Gully-erosion estimation and terrain reconstruction using analyses of microtopographic roughness and LiDAR

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ABSTRACT

Gully mapping techniques successfully identify gullies over a large range of breadths and depths in complex landscapes but practices for estimating gully volumes need further development. Gully gap-interpolation for estimation of gully volume does not often factor in landscape microtopography in the generation of the new surface. These approaches can thus overestimate large classical gully volumes, averaging over depressions, or underestimate volumes by creating overly-smooth highly curved surfaces. Microtopographic methodology was developed to estimate the pre-gully surface and gully volume across the Calhoun Critical Zone Observatory (CCZO) in South Carolina, USA. The CCZO is a Southern Piedmont landscape severely gullied by historic agriculture with upland Ultisols many meters deep. Our gully-mapping and gully-filling approaches used 1 m² LiDAR elevation data and is based on the premise that gullies are local depressions on uplands which are deeply incised with high microtopographic roughness. Our smoothing-via-filling-rough-depressions (SvFRD) algorithm iteratively fills gullies until landscape microtopographic roughness is reduced andunchanging after a subsequent iteration. Results were evaluated in the context of prior landscape bulk erosion estimates ranging from 1483 to 3708 m²/ha as well as field surveys of gullies. Minimally eroded reference and highly-eroded post-agricultural terrain were compared to test gully-mapping and volume accuracy. Comparing gully-volume estimation techniques, inverse-distance-weighting (IDW) yielded the highest volume (1072 m³/ha) followed by ANUDEM (638 m³/ha) while spline-interpolation yielded the lowest estimate (555 m³/ha). SvFRD landscape gully volume estimates (615.5 m³/ha) were most similar to ANUDEM interpolation with roughness and gully extent results most similar to spline interpolation. Spline interpolation is effective and easily implemented but if microtopographic accuracy and mapping of fine-scale erosions features is desired to hindcast pre-gully terrain conditions, our depression-filling approach, implemented using free GIS and statistical software, is an effective method to estimate reasonable erosion volumes.

1. Introduction

1.1. Gully mapping

Much research has been conducted on gully processes and mapping in a variety of landscapes around the world, including the Calhoun Critical Zone Observatory (CCZO) in SC, USA (Bastola et al., 2018; Bergonse and Reis, 2015, 2016; Bocco, 1991; Evans and Lindsay, 2010; Frankl et al., 2015; Noto et al., 2017; Perroy et al., 2010; Zheng et al., 2008). Gully erosion is an indicator of land degradation as slopes become unstable and soils are lost as sediments downslope and down-stream (Poesen, 2011; Poesen et al., 2003; Torri and Poesen, 2014). As such, mapping gullies and measuring their extent and volume is important for quantifying land degradation. Field-based mapping and aerial photo interpretation were classically used for gully delineation before LiDAR (light detection and ranging) remote sensing technologies enabled fine-resolution geospatial analyses of terrain across landscapes, though photogrammetry techniques continue to be used and developed with field surveys being the only means of true validation (Casali et al., 2006; Daba et al., 2003; James et al., 2007; Poesen, 2011; Poesen et al., 2003; Wells et al., 2016). Bare ground surface topographic data can be obtained by filtering vegetation and other objects on the surface from

Abbreviations: SvFRD, smoothing via filling rough depressions; IDW, inverse distance weighting; LiDAR, light detection and ranging; TPI, topographic position index; ANUDEM, Australian National University Digital Elevation Modeling

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LiDAR data using different algorithms based on the likelihood of curvature or slope values between different combinations of points in 3D space to represent the ground surface (Hudak et al., 2010; Roussel and Auty, 2019). Aerial and terrestrial LiDAR scanning has revolutionized our ability to map and analyze terrain surfaces via point clouds and derived high resolution DEMs (digital elevation models) with sub-meter pixel resolution now possible (Barbosa et al., 2014; Brechiesen et al., 2019; Brubaker et al., 2013; Cavalli et al., 2008; Höfle et al., 2013; Hudak et al., 2010; Jackson et al., 1988; James et al., 2007; Johansen et al., 2012; Maxwell and Strager, 2013; Noto et al., 2017; Perroy et al., 2010; Pike et al., 2012; Roering et al., 2013). Here, LiDAR DEM data form the basis for gully mapping and volume estimation research.

Gully mapping can be considered to fall in two general categories: analyses of rasters that are pixel- (Evans and Lindsay, 2010; James et al., 2007) or object-based (Francipane et al., 2020; Johansen et al., 2012; Shruthi et al., 2014, 2015). An advantage of object-based image applications for such gully mapping is the potential for temporal monitoring of gullies as features in space rather than individually-mapped pixels. Object-based analyses rely on flexible classification criteria (Shruthi et al., 2014) and offer the advantage of reducing the need for thresholding decisions on the part of researchers to define gullies, though there are also recent developments in “fuzzy” classification criteria in pixel-based approaches as well (Noto et al., 2017). In pixel-based gully mapping, different terrain metrics are used to set rules or thresholds to define and identify gullied terrain across a landscape. For example, terrain curvature exceeding a certain range may be used to classify gullies (Bastola et al., 2018; Evans and Lindsay, 2010; Noto et al., 2017). A disadvantage of object-based mapping is that it is generally more complicated in the level of programming required and may not be practical for as many researchers to execute compared with pixel-based raster algebra that can be implemented in most GIS software programs (Conrad et al., 2015; GRASS Development Team, 2017; Hijmans, 2020; QGIS Development Team, 2016; R Core Team, 2020).

Our desire to develop mapping techniques accessible to a wider readership led us to build on pixel-based terrain metric thresholding approaches, though our approach could be easily adapted to be more flexible using the same gully-diagnostic terrain variables as predictive inputs to machine learning models like Random Forests (Shruthi et al., 2014).

Pixel-based gully identification and mapping generally uses a combination of DEM-derived terrain attributes rather than a single diagnostic geomorphometric variable. Some useful terrain attributes include topographic position indices (TPIs), topographic roughness, slope, curvature, and simulated surface-flow accumulation among other possible terrain metrics (Evans and Lindsay, 2010; Hengl and Evans, 2009; Höfle et al., 2013; James et al., 2007; Noto et al., 2017; Perroy et al., 2010). For example, Evans and Lindsay (2010) developed a pixel-based approach to gully mapping using a combination of difference from mean elevation, a type of TPI, within a moving focal window (i.e. a filter or kernel) and high positive plan curvature. Evans and Lindsay also determined that the optimal filter size used to calculate focal statistics on raster data like DEMs, should be at least as wide as the width of the gullies to be mapped.

Once gullies have been mapped in 2-dimensions, a second stage of gully depth estimation is needed to obtain a 3rd dimension for gully volume estimation. Several approaches for estimating gully depth and volume with GIS (geographic information systems) have been used to interpolate or average across gullies in DEMs. Techniques range from simple inverse-distance weighting (IDW), kriging, splines, LiDAR DEM-regeneration from point clouds omitting gully-points, DEM down sampling at coarser resolutions, and a more hydrologically-informed methods of interpolating 2 or 3-dimensional depth-surfaces like ANUDEM (Bastola et al., 2018; Borgese and Reis, 2015, 2016; Castillo et al., 2019; Doucette and Beard, 2000; Evans and Lindsay, 2010; Hancock et al., 2000, 2013; Hengl and Evans, 2009; Hutchinson et al., 2011; Noto et al., 2017; Perroy et al., 2010). Spline-based interpolation techniques are generally favored for complex, high-curvature surfaces and can be implemented in most GIS programs like SAGA, QGIS, and ArcGIS (Arun, 2013; Borgese and Reis, 2015; Conrad et al., 2015; Hengl and Evans, 2009; QGIS Development Team, 2016). A disadvantage all interpolation methods share is that they necessitate deleting the portions of the terrain mapped as gullies by converting their elevation data to “NO DATA.” Because of this, any inaccuracies in mapping the edges or borders of gullies can have a potentially detrimental effect on the validity of the interpolated surface. A second disadvantage of most interpolation techniques, except for ANUDEM (Hutchinson et al., 2011), is that the surfaces generated are purely mathematical functions which do not consider the characteristics of local or landscape microtopography. Here, we aim to develop an alternative to common gully gap-spanning interpolation. This is done by approximating a pre-erosional surface based on microtopographic roughness characteristics via σ (slope) analyses (Brechiesen et al., 2019) of the broader landscape as well as the neighborhood around and inside the gullies using a 1 m² resolution LiDAR DEM (CCZ0, 2014). This is qualitatively different from the ANUDEM raster interpolation software (Hutchinson et al., 2011) employed in ArcGIS which aims to interpolate “hydrologically correct” terrain rasters from vector data inputs by filling in sinks along simulated flow paths.

The smoothing via filling rough depressions (SvFRD) approach to gully volume estimation described here does not rely on interpolation of any sort. Rather it operates under the simple premise that rough depressions considered likely to be gullies based on gully-mapping terrain criteria will have elevation added to them until their depth and steepness are reduced to the point that they match the characteristics of local topography (Fig. 1). SvFRD, as well as IDW and spline interpolation, is executed entirely within the free R statistical program using freely available packages and command-line executable GIS software programs: WhiteBox Tools, TuDEM, and SAGA GIS (Conrad et al., 2015; Hijmans, 2020; Lindsay, 2019; R Core Team, 2020; RStudio Team, 2016; Tarboton, 2015). ANUDEM interpolation which was also in...

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*Fig. 1. Gully-mapping, volume estimation, and validation conceptual framework flow diagram for the Smoothing via Filling Rough Depressions (SvFRD) methodology developed in this study.*
cluded in the evaluation was executed in ArcMap 10.7.7. The SvFRD approach is not mechanistic in terms of hydrologically reversing the erosive processes in time that gullied the initial landscape. Rather it is a first attempt at landscape reconstruction based on the characteristics of local microtopography.

1.2. Calhoun Critical Zone Observatory (CCZO) erosion research history

Hillslopes at the 190 km² Calhoun CZO in the Piedmont region in South Carolina, USA (Fig. 2) were biogeomorphologically stable under forest cover for many millennia before the landscape was fundamentally transformed by colonial agriculture starting in the 1700s (Richter and Markewitz, 2001; Trimble, 2008). This led to extreme gully-erosion over the following two-hundred years due to accelerated runoff from agricultural fields. Cultivation-based agriculture was abandoned across most of the Southern Piedmont due to soil erosion, declining agricultural productivity, and the growth of agricultural economies in other regions (Coughlan et al., 2017). Since this time, mixed pine forests dominated by loblolly pine (Pinus taeda) have reclaimed the landscape covering rough gullied terrain under a blanket of green vegetation (Billings, 1938; Brechelsen et al., 2019; Hansen, 1991; Metz, 1958). This landscape writ with enduring legacies of human activity has a rich body of research on soil erosion with erosion estimates derived from two perspectives: upland soil loss and sediment delivery to bottomlands (Daniels, 1987; Daniels et al., 1985; Galang et al., 2007; Ireland et al., 1939; Metz, 1958; Richter and Markewitz, 2001). Estimates of bulk upland soil loss for this region of the Piedmont range from 18 to 30 cm across the landscape (James et al., 2007; Meade, 1982; Trimble, 1975a, 2008) with estimates of alluvial sediment depths in bottomlands generally ranging from 1.2 to 3 m, though deeper in some places (Happ, 1945; James, 2013; Meade, 1982; Meade and Trimble, 1974; Trimble, 1975a, 1975b). These bulk soil erosion estimates are aggregating sheet, rill, and gully erosion across the uplands of the Southern Piedmont in the United States. Examples of itemized sheet, rill, and gully erosion and sediment delivery budgets exist for some regions, e.g. Trimble’s erosion study in Wisconsin (1999), but not currently the Southern Piedmont. This manuscript is focused on estimating the gully-erosion portion of eroded soils in the CCZO Piedmont landscape.

LiDAR (Light Detection and Ranging) data and terrain processing algorithms have been used to conduct high spatial resolution analyses of this gully-roughened surface (Fig. 3) to map and estimate the magnitude of historic gully erosion (Brechelsen et al., 2019; Francipane et al., 2020; Noto et al., 2017). Recent gully-mapping work within Holcombe’s Branch of the Calhoun CZO (Noto et al., 2017) appears to have mapped classical gullies with the omission of smaller gullies that might be considered “ephemeral gullies” were the CCZO landscape still under cultivation (Bennett and Wells, 2019; Jackson et al., 1988; Nachtergaele et al., 2002; Poens et al., 2003). Ephemeral gullies are defined as existing in agricultural fields and being small enough to be smoothed over by plowing though they tend to reappear each year (Casali et al., 2006; Castillo et al., 2019; Jackson et al., 1988; Nachtergaele et al., 2002; Wells et al., 2016; Zheng et al., 2008). Because of this reappearing characteristic they are termed “ephemeral” in agricultural settings. In the case of the Calhoun CZO, we often see small erosional features less than a meter deep and only a few meters across that likely formed during or immediately after land abandonment. Following the re-stabilization of soils by secondary forest growth after agricultural abandonment (Bastola et al., 2018; Metz, 1958; Richter and Markewitz, 2001), gullies that might have been considered “ephemeral” if agriculture been maintained have instead remained persistent features through nearly a century of old-field forest succession (Billings et al., 2018; Metz, 1958). We believe this warrants special consideration of how we refer to and conceptualize small erosional features like these. Small gullies, though generally shallower and narrower than larger classical gullies are ubiquitous across the erosion-roughened landscape of the CCZO when visualized via (slope) raster analyses.

**Fig. 2.** Regional map of South Carolina in the Southeastern United States. General transitions from Appalachia (red) to Piedmont (orange and yellow) to the coastal plain (green, blue, and purple) are visible across the pseudo-colored DEM. The 190 km² Calhoun CZO landscape is to the southwest of Union, SC with its 190 km² DEM colored in black and white. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Fig. 3. 190 km² Calhoun CZO landscape with elevation pseudo-color and rough microtopographic features colored darker by high $\sigma$(slope) in moving window analyses as employed by Brecheisen et al. (2019). Features visible here due to high $\sigma$(slope) values include gullies, road-cuts, and incised channels in floodplains. Minimally-eroded reference hardwood forest (light) and post-agricultural old-field (dark) watersheds used for comparative analyses of gully volume and $\sigma$(slope) roughness reduction after gully-filling and interpolation are delineated.

(Brecheisen et al., 2019) (Fig. 3) and thus may factor heavily in obtaining accurate estimates of gully-eroded soil volumes across the landscape.

2. Materials and methods

2.1. Spatial gully mapping

In order to identify and map gullies, we first define them as upland flow-accumulating erosional depressions that are sharply incised with abrupt changes in terrain slope and curvature (Table 1, Equation 1). Raster DEM terrain-derivative datasets representing these gully characteristics were used to map gullies across the CCZO: deviation from mean elevation (Dev. Mean Elev.), local mean flow accumulation (Mean Fl. Acc.), local mean profile curvature (Mean Prof. Curv.), topographic position index (TPI), and microtopographic roughness via $\sigma$(slope) analyses.

Gullies are upland features qualitatively different from bottomland streams and incised channels and so we first eliminated floodplain bottomlands from consideration using analyses of deviation from mean elevation in a 3 km × 3 km window with values below −1.15 considered to correspond with bottomland floodplains. This determination was made as it covered sediment depositional areas spanning both very broad alluvial regions along major rivers corresponding to mapped wetlands (U.S. Fish & Wildlife Service, 1979-1994) as well as much smaller sediment-filled floodplains like those associated with historic mill dams and more modern sediment retention ponds across the CCZO (Walter and Merritts, 2008). Along with floodplains, perennial stream channel valleys were excluded as potential gully locations referencing the National Hydrography Dataset (NHD) (Geological Survey (U.S.), 2002) of mapped streams obtained via South Carolina’s Department of Natural Resources (SC DNR, 2008). Because national stream vector (i.e. polyline) datasets are generally not perfectly aligned with drainages mapped via raster analyses of DEMs, streams and smaller drainages were mapped via focal mean analyses flow-accumulation within a 21 m window of the 1 m² DEM using TauDEM (Tarboton, 2015) and whitebox tools (Lindsay, 2019) command-line software via R in RStudio with the Raster package (R Core Team, 2020; RStudio Team, 2016). NHD-mapping of perennial streams in the CCZO correspond to approximately 15 ha or more of upland contributing area. In
Table 1
Gully-mapping metrics derived from 1 m² resolution LiDAR DEM at the Calhoun Critical Zone Observatory. The kernel sizes listed were used for focal statistic calculation with thresholds employed to isolate gullied pixels. Units of measure are listed for each terrain variable along with the empirical cumulative distribution function (ECDF) drawn from a random sample of 100,000 raster values across the CCZO. Final depth thresholding was employed at > 70 m of depression filling after SwFRD in order to generate a potential gully location mask for IDW, spline, and ANUDEM interpolation analyses. Final depth thresholding was employed at > **0.5 m for final gully volume analyses for all four pre-gully surface generation methods as per the NRCS (2019) gully definition.

<table>
<thead>
<tr>
<th>Gully-mapping raster metric</th>
<th>Kernel size</th>
<th>Threshold values</th>
<th>Measurement units</th>
<th>ECDF percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviation From Mean Elevation</td>
<td>3 km × 3 km</td>
<td>&gt;−1.15</td>
<td>local z-score</td>
<td>12th</td>
</tr>
<tr>
<td>Local mean flow accumulation</td>
<td>21 m × 21 m</td>
<td>&gt;15 to</td>
<td>m²</td>
<td>14th to</td>
</tr>
<tr>
<td>Local mean profile curvature abs. val.</td>
<td>21 m × 21 m</td>
<td>&gt;4.09</td>
<td>degrees</td>
<td>96th</td>
</tr>
<tr>
<td>TPI</td>
<td>21 m × 21 m</td>
<td>&lt;0</td>
<td>meters</td>
<td>56th</td>
</tr>
<tr>
<td>Microtopographic roughness, σ (slope)</td>
<td>21 m × 21 m</td>
<td>&gt;3.42</td>
<td>degrees</td>
<td>50th</td>
</tr>
<tr>
<td>Final depth thresholding</td>
<td>NA</td>
<td>&gt;0°</td>
<td>meters</td>
<td>Method dependent</td>
</tr>
</tbody>
</table>

order to exclude these stream channels the 21 m × 21 m focal mean flow-accumulation raster was classified such that only pixels with a range of 15–7000 m² of contributing area were considered as potential gully locations. The lower limit of 15 m² of average upslope contributing area corresponds to the minimum value needed to map gullies as previously delineated for field validation by Noto et al. (2017) at the CCZO.

Gullies, in addition to being relatively small flow-accumulating features, are characterized by having high positive curvature along their top edges and high negative curvature at the bottom of their incised channels. A focal mean (21 m window) profile-curvature raster for the CCZO was generated using the Whitebox tools command-line utility (Lindsay, 2019) in the R-studio R scripting environment (Hijmans, 2020; R Core Team, 2020; RStudio Team, 2016). Because terrain curvature can be either positive or negative (convex or concave) with high values on both ends being characteristic of gully edges and bottoms, the absolute values were generated for the focal mean profile curvature raster using Whitebox tools and it was determined that values above the median value of 4.09° correspond to gullies mapped in the field by Noto et al. (2017) which we used for validation.

Depressions were identified across the landscape via local TPI calculation within a 21 m × 21 m window (Wilson and Gallant, 2000). In this TPI raster, pixels with lower elevation than the average of their neighbors are considered to be depressions. In previous work, rough microtopographic erosional terrain at the CCZO has been observed and described on the basis of σ(slope) (Brechese et al., 2019). Based on this a σ(slope) raster was created using a 21 m × 21 m focal window and Whitebox tools in R (Hijmans, 2020; Lindsay, 2019; R Core Team, 2020; RStudio Team, 2016). The distribution of σ(slope) values across the CCZO was strongly right-skewed with the median value of 3.42° offset from the mode. Though gullied terrain is an important facet of the landscape’s microtopography, at no point was it expected that anywhere near half of the landscape area would correspond to gullies. Rather, the extreme σ(slope) values above the landscape median within the long left-skewed tail of the σ(slope) distribution were be targeted for filling and smoothing. Given this, σ(slope) values greater than the median likely correspond with gully locations at the CCZO and so areas with microtopographic roughness values greater than the median value were considered as potential gully locations.

The 21 m × 21 m kernel window size used for flow accumulation, profile curvature, TPI, and σ(slope) focal analyses was chosen in order to map gullies on a similar scale as previously mapped in the SC Piedmont by James and Hansen (2007) and within the CCZO by Noto et al. (2017). This was done following the logic proposed by Evans and Lindsay (2010) that filters should be approximately the same size as the width of the gullies observed which are generally less than 21 m across at the CCZO.

The final criterion for gully mapping is that gullies must meet a minimum depth to separate them from smaller erosional features like rills. The USDA NRCS (2019) uses a minimum depth threshold of 0.5 m for mapping gullies in the field and that was employed for final gully map generation across the CCZO. Given that gully depth can only be measured after estimating a pre-erosional surface, this final stage of gully mapping must happen after the execution of the SwFRD algorithm and after each of the three interpolation methods used for comparison. For the three interpolation methods evaluated, the input potential gully pixels masked as NO DATA for interpolation were those which received any filling (i.e. depth > 0 m) via the SwFRD algorithm described in the next section. In total there are five terrain raster metrics employed to isolate potential gully pixels across the CCZO DEM and a final depression depth thresholding employed to map gullies across the landscape in Table 1 and Equation 1 below.

Equation 1. Terrain raster rules for gully-mapping at the CCZO

\[
\text{Gullied DEM pixel} \rightarrow \text{Dec. Mean Elev.} > -1.15 \& \text{ Mea. Fl. Acc.} > 15 \text{ m}^2 \& \text{ Mea. Fl. Acc.} < 7000 \text{ m}^2 \\
\& \left| \text{Mean Prof. Curv.} \right| > 4.09^\circ \& \text{TPI} < 0 \text{ m} \\
\& \sigma(\text{slope}) > 3.42^\circ \& \text{Final Depth} > 0.5 \text{ m}
\] (1)

2.2. Smoothing-via-Filling-Rough-Depressions (SwFRD) algorithm

Smoothing-via-Filling-Rough-Depressions (SwFRD) is an iterative process in which the initial 2014 LiDAR DEM (CCZO, 2014) was analyzed to isolate rough depression pixels, fill them proportionately to their local σ(slope) microtopographic roughness, then analyze the change in landscape average σ(slope), and to recycle the partially gully-filled DEM back into the beginning until rough depressions were sufficiently filled to reduce landscape σ(slope) until stabilized (Fig. 4). SwFRD was implemented using Whitebox tools in R along with the R Raster package (Hijmans, 2020; Lindsay, 2019; R Core Team, 2020; RStudio Team, 2016). It was our aim to isolate the right-skewed tail of the 2014 DEM σ(slope) microtopographic roughness distribution (Supplemental Fig. 1) and to aggressively fill in the roughest upland depressions such that the resulting SwFRD gully-filled DEM σ(slope) histogram would have a median more centered near the mode. To do this

Fig. 4. Smoothing via Filling Rough Depressions algorithm simplified flow-chart illustrating the iterative gully-filling process to generate and export a final smoothed DEM.
we scaled the degree of gully smoothing-via-filling proportionately to the magnitude of $\sigma$(slope) microtopographic roughness. The function developed to scale filling is a logarithmic increase from no filling at the original median $\sigma$(slope) value of 3.42° up to maximum filling beyond the 95th percentile value of 8.90°.

Topographic depression pixels were filled with elevation values up to the difference between their elevation and the average elevation around them from the TPI calculation. The magnitude of this filling was scaled from 0 to 1 based on $\sigma$(slope) roughness analyses (Supplemental Fig. 1) so that the most steeply-walled gullies received the most filling in order to approximate local pre-gully elevation. Finally, the change in upland landscape average microtopographic roughness, $\sigma$ (slope), relative to the previous landscape was calculated as a ratio. In the case of the first iteration, the initial average landscape $\sigma$(slope) value was divided by the first SvFRD iteration landscape average $\sigma$(slope). As the algorithm iterates, each time this division yielded a ratio greater than 1 it indicated that landscape roughness had been reduced between iterations and so the lowest partially gully-filled DEM was cycled back into the process until the algorithm reached stability with a fraction less than or equal to 1 indicating no reduction in average landscape microtopographic roughness between iterations had been achieved. At that point the t-iteration SvFRD DEM was exported. See detailed SvFRD variable definitions, functions used, and the final algorithm implementation below.

SvFRD variable definitions:

- “DEM” = CGIZO Digital Elevation Model raster
- “Potential gully mask” = Local binary raster of initial potential gullied terrain pixels satisfying the first 5 terrain metrics of Table 1 (1 = possible gully, 0 = non-gully)
- “DEM$_{\sigma}$slope” = Microtopographic roughness $\sigma$(slope) raster
- “LS$_{avg\_\sigma\_slope}$” = average value of the DEM$_{\sigma}$ slope raster across the landscape
- “TSL” = 3.42° = Threshold $\sigma$(slope) low, only depressions with roughness greater than this value are filled
- “TSH” = 8.903° = Threshold $\sigma$(slope) high, above this value maximum filling occurs
- “DEM$_{TPI}$” = 21 m x 21 m topographic position index raster with positive and negative pixel values corresponding to DEM pixel elevation difference from local mean elevation in meters
- “DEM$_{DEP}$” = Local depressions binary raster (1 = depression, 0 = rise) = DEM$_{TPI} < 0$
- “GULLY_FILL” = Raster of the elevation values to be added to the input DEM to fill gullies
- “DEMMILED” = DEM with elevation added to (partially) fill gullies across the landscape
- “SvFRD.DEM” = DEM with sufficient elevation added to fill gullies to smooth the landscape
- “SvFRD.GULLY_VOL” = final raster of SvFRD estimated gully depth across the landscape

SvFRD functions:

- “$f_{\sigma\_slope}$” = $\sigma$(slope) within a 21 m x 21 m focal window via Whitebox Tools (Lindsay, 2019)
- “$f_{TPI}$” = Topographic position index = 21 m x 21 m focal average of DEM minus DEM
- “cellsStats.mean” = Whole-raster calculation of mean via the R raster package (Hijmans, 2020)
- “Con(statement, statement is true action, statement is false action)” = Conditional logic

SvFRD algorithm:

1. Generate DEM$_{\sigma}$ slope: $f_{\sigma\_slope}$(DEM)

2. Calculate landscape average starting $\sigma$(slope) at time “t” in order to track the reduction in microtopographic roughness as gullies are iteratively filled: $LS_{avg\_\sigma\_slope}(t) = cellsStats.mean$(DEM$_{\sigma}$ slope)

3. Reclassify DEM$_{\sigma}$ slope such that the values less than TSL and higher than TSH are equal to each threshold respectively: $DEM_{\sigma}$ slope ≤ TSL = TSL & $DEM_{\sigma}$ slope ≥ TSH = TSH

4. Reclassify DEM$_{\sigma}$ slope values to a 0–10 value range for base-10 logarithmic rescaling of DEM$_{\sigma}$ slope to a 0–1 value range: $DEM_{\sigma}$ slope = $log_{10}$((10 – 1)/(TSH-TSL))$(DEM_{\sigma}$ slope-TSH) + 10

5. Generate DEM$_{TPI}$ and DEM$_{DEP}$: $DEM_{DEP} = (f_{TPI}(DEM)) < 0$

6. Generate gully-filling depth raster by multiplying the Potential_gully_mask, DEM$_{TPI}$, DEM$_{DEP}$, and the newly rescaled DEM$_{\sigma}$ slope raster. The Potential_gully_mask removes floodplains, perennial streams and rivers, and low-curvature non-flow accumulating terrain areas from consideration as possible gully locations. The absolute value of DEM$_{TPI}$ is taken in order to add positive elevation to qualifying depressions and to bring them closer to the elevation of the neighboring, un-gullied, DEM pixels. Multiplying against the log-scaled DEM$_{\sigma}$ slope raster scales the final amount of elevation added to gullies to the magnitude of their microtopographic roughness such that the most sharply incised gullies receive the most filling and less incised depressions are filled less (Supplemental Fig. 1): $GULLY\_FILL = Potential\_gully\_mask * \{DEM\_TPI\} * DEM\_DEP * DEM\_\sigma\_slope$

7. Gully-filling raster is added to the DEM to add elevation to gullied locations: $DEM\_FILLED = DEM + GULLY\_FILL$

8. DEM$_{\sigma}$ slope is recalculated for the new DEM with (partially) filled gullies and LS$_{avg\_\sigma\_slope}(t + 1)$ is calculated. The ratio of LS$_{avg\_\sigma\_slope}(t)/LS_{avg\_\sigma\_slope}(t + 1)$ is calculated comparing the current gully-filling microtopographic roughness result to the previous DEM’s LS$_{avg\_\sigma\_slope}$: $LS_{avg\_\sigma\_slope}(t)/LS_{avg\_\sigma\_slope}(t + 1) = LS_{avg\_\sigma\_slope}(t)/(cellsStats.mean(f_{\sigma\_slope}(DEM\_FILLED)))$

9. If there has been a reduction in LS$_{avg\_\sigma\_slope}$ roughness, i.e., LS$_{avg\_\sigma\_slope}(t)/LS_{avg\_\sigma\_slope}(t + 1) > 1$, the current DEM$_{FILLED}$ is cycled back into step 1 of the SvFRD algorithm (Fig. 4) as the input DEM and the process is repeated until there is no reduction in LS$_{avg\_\sigma\_slope}$ between runs. If there has not been a reduction LS$_{avg\_\sigma\_slope}$, i.e., the ratio is less than or equal to 1, the process stops and DEM$_{FILLED}(t)$ is saved as the SvFRD DEM: $Con(if\ LS_{avg\_\sigma\_slope}(t)/LS_{avg\_\sigma\_slope}(t + 1) \leq 1, save DEM\_FILLED(t) as SvFRD\_DEM, otherwise repeat SvFRD with DEM\_FILLED(t + 1) as the input)$

10. Final gully-depth estimation across the landscape via subtraction of the initial input DEM from the final SvFRD DEM yielding a spatial gully-depth raster (units in meters) where non-zero values greater than 0.5 m (Natural Resources Conservation Service, 2019) indicate the location of filled gullies: $SvFRD\_GULLY\_VOL = (SvFRD\_DEM - DEM) > 0.5 m$

2.3. SvFRD validation and comparison to common interpolation techniques

The efficacy of the SvFRD algorithm was validated by comparing gully-filling changes in $\sigma$(slope) at the landscape scale and between minimally eroded reference hardwood watersheds which had minimal anthropogenic enhancement of erosion (Brechelsen et al., 2019) and proximal post-agricultural secondary forest watersheds with more erosive land use history. Landscape and watershed gully-filling volume was calculated as the sum of the gully-filling depth raster values with units in cubic meters reported on a per-hectare basis (m³/ha). This eval-
utation addresses one aspect of the necessary functionality of this approach, which is that the landscape must successively become less rough in its surface, but it must also scale gully filling to the magnitude of erosion such that areas with less historic agricultural impacts should have lesser gully volume estimates than more heavily eroded post-agricultural terrain. The reference hardwood watersheds are not considered to be completely free of human erosion. These areas were grazed by livestock, trees were cut for timber and fuelwood, and homes were built in these locations all of which enhanced the erosive flow of water in these small catchments. Having never been completely cleared of forest cover or plowed for cultivation, however, the magnitude of anthropogenic soil erosion is much lower in the reference hardwood forest watersheds (Brechensei et al., 2019; Richter and Markewitz, 2001).

Field gully-mapping validation was conducted via comparison of SvFRD mapped gullies to field surveys of two gullies in the CCZO by Noto et al. (2017) with agreement between SvFRD mapping and field surveys analyzed via confusion matrices and both Cohen’s Kappa and the Matthews Correlation Coefficient analyses of binary (1 = gully, 0 = not-gully) rasters in R (Delgado and Tibau, 2019; Gorman, 2018; Hijmans, 2020; McHugh, 2012; Meyer et al., 2017; R Core Team, 2020; RStudio Team, 2016).

The magnitude of filling via SvFRD was compared to that from common gap-interpolation techniques of inverse distance weighting (IDW), splines, and the ANUDEM elevation gridding procedure (Hutchinson et al., 2011). For the purpose of comparing gully volume estimates from SvFRD and the three interpolation procedures, only pixels with greater than 0.5 m of filling were considered to represent gullies in the analyses following the National Soil Survey Handbook (Natural Resources Conservation Service, 2019). Analyses of terrain roughness via σ(slope) were conducted across the landscape and included the filling or interpolation of rough depressions of any depth. The same erosion map output from the SvFRD procedure was used in the three interpolation methods with depressions that had received any filling being masked and set to NO DATA for interpolation. As each of these tools function to mathematically interpolate across NO DATA daps in DEMs, it is possible in areas with complex topography that the resulting interpolated surfaces can have a lower elevation than the original DEM. Though the magnitude of this phenomenon was observed to be quite small, the resulting negative “filling” values were set to equal “0”, i.e. no-filling, for interpolated surface pixels. Statistical comparisons were made at both bulk landscape scale averages and between reference hardwood (Ref. HW) and post-agricultural old-field (OF) watersheds. Sub-catchment gully profile visualizations were generated in CCZO research area 8 for the SvFRD, IDW, spline, and ANUDEM gully-spanning surfaces generated.

IDW was implemented using the “FillMissingData” function in Whitebox Tools (Lindsay, 2019) with weight = 10 and filter = 31. The filter dimensions were chosen in order to exceed the width of the largest gullies at the CCZO ensuring that there were elevation data pixels available for surface interpolation at all points within gullies. A high weight of 10 ensures that only the pixels immediately along the edges of mapped gullies were used to interpolate elevation across the gullies reducing the potential for over-filling. A lower weight value for IDW could result in pixels further from the gully edges being used to interpolate elevation which can be problematic in complex topography. IDW could, for example, interpolate a convex surface across a gully inside a concave valley. With the chosen approach of a large kernel and high power there should be fairly flat or stair-stepped surfaces interpolated when viewing cross-sections of interpolated gully surfaces.

Spline interpolation was employed using the SAGA “Close Gaps with Spline” function with default settings in R using the Rsagacmd package (Conrad et al., 2015; Hijmans, 2020; Lindsay, 2014; Pawley, 2020). The spline radius was set to 22 m in order to match the maximum filter distance of IDW interpolation which is 21.9 m from the center to each corner of the 31 m × 31 m window. The ANUDEM (Hutchinson et al., 2011) interpolation procedure was implemented in ArcMap 10.7.7 via the “Topo to Raster” tool. As the inputs for this tool in ArcGIS are vector shapefile format, the DEM pixels bordering the mapped rough depressions were converted to point shapefile format. All default settings were used with drainage enforcement selected to generate 1 m² DEM surfaces across rough depressions. The intermediate elevation point dataset and resulting gully-spanning rasters were several gigabytes in size which can be problematic depending on the amount of computer system memory and whether or not the tool is executed in foreground or background processing when using ArcMap. Newer ArcPro GIS software may be less hindered by these issues. As such users should exercise caution when running the tool on large raster datasets and anticipate troubleshooting if running ANUDEM in ArcGIS software across large landscapes. As the rough depression areas were desired as the interpolation output, the SvFRD filling depth > 0 m was used as a mask in the ANUDEM “raster analysis” environment setting in ArcMap 10.7.7.

Analyses of σ(slope) smoothing between watershed treatments for SvFRD and the three filling or interpolation techniques were conducted via t-tests and Wilcoxon-Mann-Whitney U-tests in R using the stats and raster packages (Hijmans, 2020; R Core Team, 2020). For evaluation of landscape smoothing, all interpolated or filled depressions were preserved regardless of depth. For evaluation of gully volume estimation only interpolated or filled depression pixels greater than 0.5 m depth were retained as per the definition of gullies provided by the USDA NRCS (2019). Further validation of the SvFRD approach was conducted by comparing the landscape-average gully volume estimates of the four gully-filling techniques to studies in the soil science literature in order to determine if the gully volume estimates match previous field-based estimates (James et al., 2007; Meade and Trimble, 1974; Noto et al., 2017; Trimble, 1975a, 1999, 2008).

3. Results

3.1. SvFRD spatial gully mapping and validation

The smoothing via Filling Rough Depressions (SvFRD) algorithm iterated until landscape average σ(slope) stability was achieved. Stability was achieved upon SvFRD iterations not having reduced landscape average upland microtopographic roughness from one iteration to the next yielding a ratio ≤1 (Fig. 5). Calhoun CZO average upland σ(slope) was reduced from 3.58’ to 2.94’ and reached stability after 5 iterations. Gully mapping following the gully pixel identification methodology outlined in section 2.1 based on floodplain masking, profile curvature, surface flow accumulation, local topographic position, σ(slope), and SvFRD depression filling > 0.5 m resulted in 4.47% of the CCZO land-

![Fig. 5. Smoothing-via-Filling-Rough-Depressions (SvFRD) iterations resulted in a reduction of CCZO landscape average σ(slope) which reached stability after 5 iterations. Y-axis is calculated as the landscape average σ(slope) from a 21 m × 21 m kernel of the input DEM (iteration “n”) divided by the newest iteration of filling (t + 1) landscape average σ(slope).](image-url)
landscape being mapped as gullied terrain totaling ~8.9 km² across the 190 km² landscape (Fig. 6).

Field validation results conducted using survey delineations from Noto et al. (Noto et al., 2017) for two gullies in the CCZ0 indicate that the gully mapping approach employed here functions well at identifying large gullies with an 82.3% true-positive detection rate and a 96.4% true-negative detection rate. The 17.7% of false-negative rate results primarily from the mapped SvFRD gully borders being just inside the gully perimeter delineated in the field by Noto et al. (2017). This suggests that our 2D spatial mapping of classical gullies should be considered a reasonable and conservative estimate. Interestingly, however, the 6.8% of apparent false-positive gully identification is partially attributable to a smaller more ephemeral-sized gully branching off of the northern gully edge in the western validation area (Fig. 7). In aggregate our gully pixel identification accuracy was very high, approximately equal to that of Noto et al., with Kappa and MCC indices (Delgado and Tibau, 2019) both equal to 0.81.

### 3.2. Smoothing-via-Filling-Rough-Depressions comparison to common interpolation techniques at landscape, small catchment, and transect profile scales

As described in Section 2.1, the mask applied to the original DEM to implement the three interpolation methods was such that any DEM pixels that received any filling via SvFRD were set to NO DATA with the resulting gap-filled surfaces analyzed for e(slope) and for gully volume for any gully pixels deeper than 0.5 m. The SvFRD estimates of upland gully volume across the CCZ0 were 615 m³/ha covering 4.47% of the landscape and reduced landscape average e(slope) from 3.58° to 2.94° (Table 2). In comparison, IDW interpolation across gullies resulted in a much higher estimate of gullying at 1072 m³/ha covering 6.67% of the landscape while only slightly reducing landscape average e(slope) to 3.45°. Spline interpolation yielded the lowest gully volume estimation at 555 m³/ha covering 4.22% percent of the landscape, the most similar gully-cover reduction to SvFRD. Spline interpolation also had the

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**Fig. 6.** 190 km² Calhoun CZO landscape elevation (m) colored from white to black. The bottomland floodplain mask covers most of the dark low-elevation areas. National Hydrography Dataset mapped streams are in blue. Minimally-eroded reference (light) and post-agricultural (dark) watersheds used for validation and comparative analyses are also delineated. Local depression gully pixels having high flow accumulation, profile curvature, and e(slope) suggestive of gullies are colored in red. The final SvFRD mapped gully pixels are mapped in yellow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Fig. 7. Field validation of gully-mapping procedure. Field delineation of two gullies by Noto et al. (2017) are delineated in blue and compared to the gully mapping delineation obtained from our SvFRD approach in red. Statistical analyses conducted via confusion matrices of binary raster classification (gully = 1, not gully = 0) agreement comparisons and calculation of Cohen’s Kappa and Matthews Correlation Coefficient are embedded. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2

<table>
<thead>
<tr>
<th>Raster volume and ( \sigma ) (slope) statistical results at watershed and landscape scales for SvFRD and the three gully interpolation methods: Inverse Distance Weighting (IDW), splines, and ANUDEM.</th>
<th>Mean Ref. HW WS ( \sigma ) (slope)</th>
<th>Mean OF WS ( \sigma ) (slope)</th>
<th>Mean diff. ( \mu ) (df), ( \sigma ) (df), p-val.</th>
<th>U-stat. ( \mu ), p-val.</th>
<th>CCZO mean ( \mu ) (upland ( \sigma ) (slope))</th>
<th>Median Ref. HW WS ( \mu ) gully estimate ( \text{m}^3/\text{ha} )</th>
<th>Median OF WS ( \mu ) gully estimate ( \text{m}^3/\text{ha} )</th>
<th>Estimated CCZO gully terrain</th>
<th>Estimated CCZO gully vol ( \text{m}^3/\text{ha} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial 2014 LiDAR DEM</td>
<td>3.19’</td>
<td>5.04’</td>
<td>1.85’</td>
<td>−6.55’ (36), 1.30e-7</td>
<td>12, 2.01e-7</td>
<td>3.58’</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>IDW gully interpolation</td>
<td>3.55’</td>
<td>4.78’</td>
<td>1.23’</td>
<td>−4.00’ (36), 9.00003</td>
<td>41, 0.0001</td>
<td>3.45’</td>
<td>323.17 ± 532.49</td>
<td>3144.70 ± 2062.39</td>
<td>6.67%</td>
</tr>
<tr>
<td>Spline gully interpolation</td>
<td>3.12’</td>
<td>3.47’</td>
<td>0.35’</td>
<td>−2.37’ (36), 0.02</td>
<td>83, 0.02</td>
<td>2.84’</td>
<td>62.92 ± 170.10</td>
<td>1715.09 ± 1197.63</td>
<td>4.22%</td>
</tr>
<tr>
<td>ANUDEM gully interpolation</td>
<td>3.19’</td>
<td>4.38’</td>
<td>1.19’</td>
<td>−5.96’ (34.27), 9.40e-7</td>
<td>26, 7.73e-6</td>
<td>3.29’</td>
<td>107.61 ± 397.96</td>
<td>1915.87 ± 1556.45</td>
<td>3.69%</td>
</tr>
<tr>
<td>SvFRD gully filling</td>
<td>3.23’</td>
<td>3.59’</td>
<td>0.36’</td>
<td>−2.35’ (36), 0.02</td>
<td>39, 9.28e-5</td>
<td>2.94’</td>
<td>305.52 ± 485.05</td>
<td>1473.12 ± 1064.02</td>
<td>4.47%</td>
</tr>
</tbody>
</table>

The greatest reduction in landscape average \( \sigma \) (slope) to 2.84’ also being closest to the SvFRD result. ANUDEM interpolation yielded the most similar estimate of gully volumes to SvFRD at 638 m³/ha while covering only 3.69% percent of the landscape with a low reduction in landscape average \( \sigma \) (slope) to 3.29’.

Analyses of the change in \( \sigma \) (slope) between reference hardwood (Ref. HW) watersheds and old-field (OF) post-agricultural watersheds as a result of the different gully mapping methods generally matched the landscape results for gully volumes and \( \sigma \) (slope) microtopographic roughness reduction (Table 2). Comparisons indicate that estimated gully volumes are as much as ~5 times (via SvFRD) to ~28 times (via splines) higher in OF watersheds than in minimally-eroded Ref. HW watersheds, though there is extremely high variation in the amount of filling within the watershed treatments. Statistical analyses of \( \sigma \) (slope) show the greatest reduction in roughness via splines followed by SvFRD with the differences in average \( \sigma \) (slope) reduced the most in these two methods (Table 2). Both SvFRD and IDW interpolation actually increased average \( \sigma \) (slope) in the Ref. HW watershed treatment, but this effect was very slight for SvFRD at 0.04’ and much more substantial for IDW at 0.36’. IDW and ANUDEM had the lowest reductions in OF watershed average \( \sigma \) (slope) at 0.26’ and 0.66’ respectively. Splines and SvFRD both had high reduction in OF watershed average \( \sigma \) (slope) at 1.57’ and 1.45’ reflecting high microtopographic smoothing by both procedures (Table 2).

In order to visualize the gully-spanning surfaces of SvFRD, IDW, spline, and ANUDEM relative to the 2014 LiDAR DEM terrain, elevation profiles were generated across Ref. HW and OF watersheds in CCZO research area 8 (Fig. 8). Transect profiles A and B each cross two reference hardwood and old-field watersheds with approximately the same elevation ranges. Close inspection of the LiDAR DEM profile reveals a jagged roughening of the terrain surface in panel B along which both drainage lines were mapped as having been gullied due to historic erosion. One to two meters of eroded soils are estimated to have been lost from the interpolated and SvFRD surfaces in the middle of the incised channels. In comparison panel A is much smoother with only one of the two drainage lines having gully incision mapped with just ~0.5 to 1 m of soil loss in the larger catchment. Panel C corresponds to a cross section of a headwater gully-complex in an OF watershed and panel D to a long in-gully profile in an OF watershed. In panels A-D, IDW displays the expected flat to stair-stepped interpolation surface which does not realistically match the terrain surface to either side. This view of IDW supports the previous results suggesting that IDW seems to greatly
overestimate gully volumes due to over-filling. The spline surface generally appears much better with smoother curvature melding more naturally to the non-gully terrain on either side though there is some unusual jaggedness to the profiles in some places. ANUDEM interpolated surface results are generally intermediate between spline and IDW with surfaces being more natural in appearance than IDW but also having some of the jaggedness seen in the spline surfaces. Particularly in the OF watersheds it seems that the ANUDEM interpolation likely leads to an overestimation of gullied volumes. The jagged portions of the profiles interpolated by ANUDEM and splines are likely interpolation artifacts due to small irregularities in the elevation along the edges of masked rough depressions. In comparison, the SvFRD surface is free of jaggedness along the gully-filled surfaces. SvFRD profiles tend to fall in the midst of the interpolated surfaces or even lower than the interpolated surfaces in many cases.

4. Discussion

4.1. Gully erosion estimates in the context of previous research

Soil erosion and degradation of agricultural land is one of the most pressing problems humanity will continue to contend with in coming decades. We feel that there are needs for the identification and quantification of these erosive environmental impacts in many areas across the world (Castillo and Gómez, 2016). There is an incredible growing body of research at landscape- and watershed-scale on gullying susceptibility, simulation, and rehabilitation (Akgun and Turk, 2011; Barnhardt, 1989; Bastola et al., 2018; Bergonce and Reis, 2016; Bernatek-Jakiel and Wroński-Walach, 2018; Bocco, 1991; Conoscenti et al., 2013; Dewitte et al., 2015; Hancock et al., 2013; Höflé et al., 2013; Poesen et al., 2003; Torri and Poesen, 2014; Zheng et al., 2008). Despite this research effort and gains made in the spatial mapping of gullies (Evans
and Lindsay, 2010; Hengl and Evans, 2009; Höfle et al., 2013; James et al., 2007; Noto et al., 2017; Perroy et al., 2010), techniques frequently used to remotely estimate gully volumes generally rely on simple gap-interpolation, function only in two-dimensional profiles, or utilize paid black-box software (Bastola et al., 2018; Bergonse and Reis, 2015, 2016; Castillo et al., 2019; Evans and Lindsay, 2010; Hancock et al., 2000, 2013; Hengl and Evans, 2009; Noto et al., 2017; Perroy et al., 2010). In comparison, the SvFRD approach taken here relies on straightforward geomorphometric analyses and basic geomorphic principles. Though SvFRD was implemented as part of the gully mapping procedure in this study, it could be employed to fill gullies mapped by any means. Our goal in using a thresholding approach to gully mapping in this study (Table 1) was to maximize clarity of how gullied DEM pixels were identified. Instead of defining terrain variable threshold values statistically or based on heuristics as a manual a gully-ID decision tree, we could readily employ classification models like random forests (Shruthi et al., 2014) without making any thresholding decisions. Random forests trained using the same continuous terrain variable datasets would, however, be less transparent in terms of classification results.

Gully erosion estimates for the Southern Piedmont region are discussed from two perspectives: sediment depth delivered to bottomlands and soil depth lost from uplands with both estimates generally in agreement. Sediment depth estimates in bottomlands are reported to range between 3 m and 1.2 m (Happ, 1945; James et al., 2007; Meade, 1982). With ~11% of the landscape estimated to be bottomlands, this results in a total historic erosion sediment-volume between 3707 and 1483 m³/ha derived from uplands. Bulk soil erosion depth estimates made on uplands are between 30 cm and 18 cm (Ireland et al., 1939; James et al., 2007; Meade, 1982; Trimble, 1975a, 2008). Considering upland area as the remaining ~89% of the landscape results in a total erosion rate of 3000 m³/ha to 1800 m³/ha. Averaging high and low estimates from both sediment depth and upland erosion depth perspectives yields a gully-erosion percentage of 18-37% of total erosion based on the 615 m³/ha SvFRD gully volume estimate. Though this research is not budgeting total soil erosion volumes among sheet, rill, and gully erosion, comparison to prior estimates of gross soil erosion for the region provides context for our results and a validity check of our gully volume estimates. Trimble’s erosion budget for Coon Creek, Wisconsin for the period of 1800-1938 estimated that upland gullies accounted for ~16.5% of eroded soils transported into fluvial systems (Trimble, 1999). In this context our gully volume estimates in the SE Piedmont (Fig. 2) are reasonable with the unglaciated and warmer more rain-dominated climate likely enhancing gully erosion compared to the US Midwest. In comparison, Noto et al.‘s (2017) Calhoun CZO study which focused on gully-mapping in the Holcombe’s Branch watershed may be underestimating the magnitude of gullying in the region accounting for only 9-19% of eroded soil volume at 306 m³/ha with part of the difference likely being due to the omission of smaller more ephemeralized gully features (Fig. 7).

The identification and inclusion of relatively small gullies along with large classical gullies using high resolution LiDAR data yielded reasonable gully volume estimates based on previous bulk soil erosion estimates across the region (Brechelsen et al., 2019; Happ, 1945; Ireland et al., 1939; James et al., 2007; Meade, 1982; Metz, 1958; Richter and Markewitz, 2001; Trimble, 1975a, 2008). The inclusion of these smaller erosional features in our mapping which were not mapped during the previous field survey are considered to be false-positives in Cohen’s Kappa and MCC calculations. Rather than viewing this as a negative result, we believe this highlights the importance of how our definitions and preconceptions of erosional features can shape our efforts in quantifying them. Though smaller gullies are individually less voluminous than classical gullies, in aggregate their inclusion contrasted with Noto et al.‘s (2017) matching results in a doubling of our landscape gully erosion volume estimates compared to their results. Given the increasingly high resolution of LiDAR terrain data, we have an unprecedented ability to identify and measure small gullies using microporographic analyses (Brecheisen et al., 2019) and possibly enhance targeted soil erosion remediation efforts. This is especially important as we are seeing that small gullies are much more permanent across the post-agricultural CCZO landscape after nearly a century of reforesta-
tion than a possible designation of “ephemeral” might lead researchers, managers, and practitioners to anticipate (Bennett and Wells, 2019; Jackson et al., 1988; Nachtergaele et al., 2002; Poesen et al., 2003). These techniques were developed and implemented using free software making them widely available for academics and practitioners (Hijmans, 2020; Lindsay, 2019; R Core Team, 2020; RStudio Team, 2016; Tarboton, 2015). Future research activities will include more extensive field validation of mapped gullies as well as the possible pairing of geospatial gully mapping and initial surface approximation with landscape evolution models and geochemical analyses of buried sediments to improve pre-gully surface reconstruction (Belyaev et al., 2004; Chen et al., 2014; Dotterweich, 2005; Dotterweich et al., 2013; Hancock et al., 2016, 2011).

It is important to note that some areas within the reference watersheds were mapped as gullies in this work. This isn’t considered to be erroneous as “reference” does not equate to “zero anthropogenic enhancement of soil erosion.” Relatively open canopies and individual trees were easily distinguishable in reference watersheds in 1933 (Fig. 8) (Brechelsen et al., 2019). These reference forests were harvested for timber and fuelwood and used for grazing and homesteading. Another characteristic of the reference versus post-agricultural watersheds is that microtopographic terrain roughness remains significantly higher in post-agricultural areas relative to the reference watersheds (Table 2, Fig. 8) even after gullies were filled in across landscape. This is because the human fingerprint of terrain-roughening across the landscape also includes terracing, road cuts, and less extreme forms of erosion and other earth-moving features in addition to gullies. In fact there are many gullies across the CCZO in areas which were already reforested in 1933 due to the fact that agricultural land abandonment and old-field succession was already several decades underway in much of the SE US Piedmont by this time (Coughlan et al., 2017; Galang et al., 2007).

4.2. Comparisons among interpolation and smoothing via filling rough depression techniques

Common approaches to gully volume estimation entail manual or algometric delineation of gullies in space and interpolation across the two banks to create a new surface. Some examples of gully interpolation cited in the scientific literature include ANUDEM as employed by Noto et al. (2017), splines by Bergonse and Reis (2015), a customized IDW bilinear interpolation by Evans and Lindsay (2010), and complete DEM regeneration following the exclusion of LiDAR elevation points determined to lie in gullies by Perroy et al. (2010). SvFRD results compare very favorably to both ANUDEM and spline interpolation results and while not requiring the regeneration of the entire landscape DEM from hundreds of gigabytes of raw LiDAR point cloud data. The cross-sectional profiles generated by SvFRD are qualitatively very similar in appearance to the interpolated gully profiles of generated by Evans and Lindsay (2010). Comparisons in this study among IDW, spline, and ANUDEM techniques show that interpolation-based gap-filling methods can produce starkly contrasting surfaces from the same gully map (Fig. 8). This is problematic because some forms of interpolation like IDW employed here will overfill valleys within which gullies may have formed (Fig. 8). Slight changes in where and how slope-breaks are identified in gully mapping can also greatly affect the resulting interpolation. For example, it can be seen in Fig. 8 transects A-B that if gully edges had been mapped further downslope, IDW may have performed better. IDW will likely yield good results in locations where gullies have advanced upwards and cut into broader and more planar hillslopes as
in Fig. 8 transect C but IDW is otherwise inappropriate for use in more complex terrain with greater curvature.

The SvFRD approach appears to be less sensitive to the exact delineation of gully borders because it is, fundamentally, not an interpolation procedure. SvFRD never requires the masking of DEM data as NO DATA. SvFRD is instead a non-binary operator that iteratively adds elevation to fill gullies which reduces the likelihood of surface artifacts as observed in spline and ANUDEM surface profiles. Gullying intensity varies greatly across the CCZO landscape and with the SvFRD algorithm, areas which were less scoured and roughened by erosion received correspondingly lesser filling. SvFRD can even be run completely in the absence of any gully mapping, though it results in rough topographic depressions everywhere being filled, not only limited to gullies. Our SvFRD terrain smoothing algorithm operates under the premise that the initial biogeomorphologically stable landscape had smooth microtopography and attempts to approximate pre-gully surfaces with those characteristics. SvFRD tuning via σ(slope) analyses (Fig. 5, Supplemental Fig. 1) yielded reasonable gully volume estimates within the ranges resulting from the three interpolation techniques (Table 2, Fig. 8). Spline and ANUDEM results were very similar to those of SvFRD with SvFRD being slightly rougher in σ(slope) with a higher gully estimate than splines but smoother with lower landscape gully volume estimates than ANUDEM (Table 2).

Splines and IDW considered together indicate that interpolation methodologies are susceptible to either under- or over-estimation of gully volumes depending on the tuning of their parameters. Though interpolation techniques can be tuned to adjust the resulting surface curvature, confidently determining appropriate adjustments with would not be easier than the calibration of our SvFRD algorithm (Supplemental Fig. 1). In cases where the characteristics of the microtopography of the interpolated surface isn’t priority, spline and ANUDEM interpolation appear to be very reasonable interpolation techniques though the execution of ANUDEM requires converting terrain data formats and requires either paid ArcGIS software as implemented here or purchase of the standalone ANUDEM program. In contrast our Smoothing via Filling Rough Depressions approach yielded reasonable intermediate gully volume estimates, utilizes free software, and is explicitly founded in geomorphometry.

5. Conclusions

Gully erosion is a growing problem across the world as cycles of deforestation, conversion to agriculture, soil erosion, land abandonment, and the clearing of new land, as occurred at the CCZO, has resulted in massive environmental degradation. Irregular, roughened, gullied terrain features predominate the Calhoun Critical Zone Observatory in the Southeastern US where historic agriculture gullied and eroded much of the landscape (Figs. 3 and 8). Genenal estimates of total historic soil erosion have been made for the region previously, but few efforts have been made specifically to quantify the impact of gully erosion in this subtropical Piedmont region (Fig. 2). The Smoothing via Filling Rough Depressions approach developed and employed here iteratively fills in gullies (Fig. 5) to approximate local microtopography enabling accurate gully volume estimation and is a promising initial approach at pre-gully terrain approximation (Fig. 8). Whether for ecological conservation and study, analyzing the effects of land management practices, or for aiding in the remediation of degraded areas, we believe that the Smoothing via Filling Rough Depressions approach employed here has a special ability to inform land management and help us to understand erosional environmental processes in many parts of the world.

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Declaration of Competing Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2021.105264.

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