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LiDAR-based Sinkhole Detection and Mapping in Knox County, Tennessee

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Cover Page Footnote
We would like to thank Will Fontanez of KGIS for providing the LiDAR data and Dr. Robert Washington-Allen for help with data processing and analysis.

LiDAR-based sinkhole detection and mapping in Knox County, Tennessee

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Abstract

Sinkholes are one of the major causes of damage to roads, buildings, and other infrastructure throughout the US. Sinkholes near or on roads are especially costly and occasionally deadly. Knox County and much of East Tennessee are located within karst areas (comprised of porous and soluble limestone and dolomite), deeming it at risk for sinkholes. Currently, Knox County uses contour maps to manually identify sinkholes. Supported by a geographic information system (GIS), we developed a streamlined model to identify the locations and extents of potential sinkholes using 1-m resolution LiDAR (Light Detection and Ranging) data and applied it to the Dutchtown area of Knox County. This model consists of creating a Digital Elevation Model (DEM), filling the depressions in the DEM, extracting the depressions with a DEM difference, converting the depressions to a polygon shapefile, and analyzing the shape characteristics of the depressions. This work provides a pilot study for Knox County Stormwater Management in identifying potential sinkholes and has the potential to be used in other similar regions.

Introduction

A sinkhole is a depression in the ground that has no natural external surface drainage. It becomes dangerous when the geology of the area is made up of water absorbent rock, such as limestone and dolomite[1]. The water from rainfall moves down through the soil and begins to dissolve the rock, forming spaces and caverns underground. These spaces eventually compromise the support of the surface to the point where the surface collapses, forming a sinkhole. The collapse of sinkhole could cause severe damage to human properties and infrastructures[2,3]. Sinkholes near or on roads are especially costly and occasionally deadly. Over the last fifteen years, they have caused an average of 300 million dollars of damage per year nation-wide[1].

Much of East Tennessee contains porous, soluble limestone and dolomite, deeming it at risk for sinkholes[4]. Sinkholes in the Dutchtown Road and Cedar Bluff Road areas of Knoxville serve as the primary drainage feature for stormwater runoff. Over three square miles of residential and commercial property drain to a series of sinkholes in this area[5]. Sinkholes are hard to detect and trace due to the lack of data and effective methods in identifying sinkholes[2,3]. An accurate method of detecting and mapping potential sinkholes is of critical importance to help establish sinkhole inventory maps and understand geomorphic and hydrological processes related to the sinkhole development. This information is also important for companies, city and county officials, and homeowners to avoid constructions around sinkhole areas and prepare suitable techniques to mitigate sinkhole hazard.

Traditional methods to identify sinkholes were mainly based on the visual interpretation of the topographic maps or aerial photos and followed by field validation[2,3]. These approaches are usually not efficient and labor-intensive. The availability of high-resolution digital elevation models (DEMs) have allowed for the detection of potential sinkholes using geographic information systems (GIS) and spatial analysis tools[2,3, 6-10]. In East Tennessee, the high-resolution DEMs (about 1 meter) based on airborne LiDAR (Light Detection and Ranging) technology have been available recently[11]. This new dataset provides a potential to map potential sinkholes at a much finer scale.

The primary objective of this project was to develop a streamlined workflow model using a geographic information system, ArcGIS[12], to identify and map potential sinkholes and conduct a case study in the Dutchtown Road area of Knox County based on the recently available high-resolution LiDAR digital elevation data (Figure 1). The project provided a pilot study for Knox County Stormwater Management and has the potential to be used to identify the potential sinkholes for the entire Knox County and other similar areas.

Data and Methods

Two datasets were used in this project: a LiDAR dataset consisting of 60 tiled point-cloud LAS files and a geodatabase of Knox County drainage infrastructure. The former dataset was provided by the Knoxville, Knox County, Knoxville Utilities Board Geographic Information System (KGIS)[13] and the latter by the Knox County Stormwater Management[14]. Knox County Stormwater Management also provided a shapefile of the study site.

We developed a conceptual model to derive sinkhole-like depressions from the point cloud data collected using LiDAR (Figure 2). The model involved first creating a digital elevation model (DEM) from the LAS files, filling the DEM with ArcGIS hydrology tools, subtracting the two DEMs, converting the resulting layer to a polygon shapefile, and analyzing the shapefile to derive the potential sinkholes. Based on this conceptual model, we created a GIS model using ArcGIS model-builder[12] to automate the processes.

(1) Creating a DEM

The LAS point cloud files were imported into Applied Imagery's Quick Terrain Modeler image processing software (QT Modeler)[15] as a gridded surface model (Figure 3). Only the classified bare ground points were chosen to generate a DEM. These points represent the surface topography and exclude other features such as buildings and vegetation. These files were then merged into one gridded surface model using QT Modeler's *Merge* tool and exported as a 32 bit GeoTiff DEM. The DEM has horizontal resolution of 1.3 foot (Figure 4). It was loaded into ArcMap for further processing.

(2) Fill the DEM

The DEM was clipped using the study boundary shapefile. The *Focal Median* tool with a 7x7 kernel was used to smooth the DEM and reduce the noise (Figure 5). The *Fill* tool was then used to fill all depressions in the DEM (Figure 6). This tool is usually used to remove erroneous depressions before running other hydrology tools, but it is used to identify possible sinkholes in this model.

(3) Subtract the DEMs

We subtracted the smoothed DEM from the filled DEM using the *Minus* tool. The result is a raster of all the potential depressions in the study area with depth values (Figure 7). This step removes all non-depression surfaces from the image because cells that are the same will result in a zero, whereas cell values that were changed by the fill tool will result in a positive value equal to the depth of the depression.

(4) Convert to shapefile

Several tools were used before the conversion: *Set Null, Region Group, Zonal Statistics, and Greater Than* tools. These tools were used to reduce the dominating number of spurious depressions that were created by the random errors of the DEMs, rather than the “real” depressions. The random errors of the DEMs are likely related to pre-processing of the original LiDAR data, such as the removal of individual trees or buildings. These errors are usually just a few pixels. We applied a threshold of <1 m^2 (about 9 ft^2) in area to filter the spurious depressions. The average spacing of the original LiDAR dataset we used is about 1/3 m and it is usually smoothed to 1-m DEM for terrain analysis (make sure each pixel of the DEM has representative LiDAR point measurement). The threshold of <1 m^2 in area is the size of one pixel of the 1 m DEM, and most of them are likely caused by the random errors. After removing the spurious depressions, the *Raster to Polygon* tool was used with the “simplify polygons” option to convert the raster layer of depressions to a polygon shapefile (Figure 8). This step is necessary because many analyses may be performed on a shapefile that may not be performed on a raster file.

(5) Analyze the shapefile

The last process was to analyze the depression shapefile to eliminate depressions that were unlikely sinkholes based on two thresholds for the polygon circularity index and the polygon area. The circularity index was calculated using the equation

$$CI = \frac{\sqrt{4\pi A}}{P} \tag{1}$$

where CI is the circularity index, *A* is the area, and *P* is the perimeter of a polygon. The closer a circularity index is to 1, the more circular the polygon is, indicating it is more likely to be a sinkhole. Based on a similar study in Missouri[6], a minimum circularity index of 0.85 and a minimum area of 50 ft^2 were used as the thresholds to identify potential sinkholes. All polygons that did not meet these specifications were removed.

(6) Refine the potential sinkhole layer

We also compared the potential sinkholes with the Knox County drainage infrastructure layer. The *Select by Location* tool was used to select and remove all polygons that were intersected with the infrastructure because these depressions were likely man-made depressions or constructions (Figure 9). The resulting polygon layer represents the potential sinkholes for further analysis.

We used ArcGIS model builder to streamline the whole processes, so that the users can use this model to conduct their own analysis (Figure 10).

Results

The difference between the original and filled DEMs produced a new raster image (Figure 7) in which all pixels with a value greater than 0 were contained in a depression. After removing the spurious depressions using the threshold of <1 m^2 in area, we converted 72,324 depressions to a shapefile using the simplify polygons option. The number of depressions was subsequently reduced to about 5000 after applying the thresholds of the circularity index of 0.85 and the minimum polygon area of 50 ft^2. We also overlaid the depressions with the Knox County drainage infrastructure dataset and eliminated the depressions contained by the infrastructure. This step further reduced the number of depressions to 3,724. Figure 11 displays the spatial distribution of the final 3,724 depressions (potential sinkholes), ranging in area from 50 to 62881 ft^2. Note that many small depressions are spatially clustered together and appeared as larger polygons in this figure. We recommend government officials and homeowners to check these large spatial clusters first to evaluate the potential risk of sinkhole hazard in these regions and them move to check other small and isolated depressions.

Discussion and Conclusions

The primary goal of this work is to develop a method for identifying sinkhole locations from LiDAR data. We accomplished this goal and identified over 3,700 possible sinkholes in the Dutchtown Road Area. These potential sinkholes can be used by Knox County Stormwater Management to field-check and locate potential sinkholes. The refined sinkhole maps can help government officials and homeowners to assess the risk of sinkhole hazard, avoid constructions around sinkhole areas, and mitigate potential sinkhole collapses using suitable treatments.

One main challenge in this work was the size of the dataset. For example, we spent an immense amount of time attempting to create the DEM with ArcGIS and were unable to produce a usable DEM. We then used QT Modeler to create the DEM. The subsequent steps for mapping sinkholes were relatively straightforward in ArcGIS. This learning process helped us understand the pros and cons of different software packages and provided a useful guidance for future data processing associated with LiDAR-related datasets.

Due to limited time, we did not conduct field tests to validate the identified sinkholes and assess the accuracy of the derived map. It is important to note that the identified sinkholes layer does not necessarily represent the “real” sinkhole locations. They cannot be interpreted to real-world sinkholes until field validation is conducted. Another way to test the accuracy is to compare the map with maps of known sinkhole locations in Tennessee. If no current sinkhole maps are available at a fine scale, our method could also be applied to an area where maps of known sinkholes do exist. The model-identified results could be compared against those maps to assess the accuracy of the potential sinkholes mapped using our model.

Further work needs to explore additional methods to separate sinkholes from non-sinkhole depressions. The qualifications and thresholds used in this study were subjective and mainly based on our intuition since no metrics were provided. More research is needed to determine what size and circularity index level should be used as thresholds and if there are other variables that can be used to identify “real” sinkholes.

References

1. USGS. 2016. *USGS FAQs*. Retrieved February 23, 2017
2. Miao, X., Qiu, X., Wu, S.S., Luo, J., Gouzie, D.R., Xie, H., 2013. Developing efficient procedures for automated sinkhole extraction from Lidar DEMs. *Photogrammetric Engineering & Remote Sensing* 79, 545–554.
3. Wu Q.S., Deng, C.B., Chen, Z.Q., 2016. Automated delineation of karst sinkholes from LiDAR-derived digital elevation models. Geomorphology 266, 1-10.
4. Dunigan, T. 2017. *Tennessee Sinkholes*. Retrieved February 23, 2017
5. Ogden Environmental and Energy Services Co., I. 1999. *Dutchtown Road Flood Study Report.* Knoxville: Knox County.
6. Zhu, J., Taylor, T. P., Currens, J. C., & Crawford, M. M. 2014. Improved Karst Sinkhole Mapping in Kentucky Using LiDAR Techniques: A Pilot Study in Floyds Fork Watershed. *Journal of Cave and Karst Studies*, 207-216.
7. Al-Kouri, O., Al-Rawashdeh, S., Sadoun, B., Sadoun, B., Pradhan, B., 2013. Geospatial modeling for sinkholes hazard map based on GIS & RS data. *Journal of Geographic Information System* 5, 584.
8. Basso, A., Bruno, E., Parise, M., Pepe, M., 2013. Morphometric analysis of sinkholes in a karst coastal area of southern Apulia (Italy). *Environmental Earth Sciences* 70, 2545–2559.
9. Gutiérrez, F., Galve, J.P., Lucha, P., Castañeda, C., Bonachea, J., Guerrero, J., 2011. Integrating geomorphological mapping, trenching, InSAR and GPR for the identification and characterization of sinkholes: a review and application in the mantled evaporite karst of the Ebro Valley (NE Spain). *Geomorphology* 134, 144–156.

10. Lindsay, J.B., Creed, I.F., 2006. Distinguishing actual and artefact depressions in digital elevation data. *Computers & Geosciences* 32, 1192–1204.
11. USGS. 2018. 3D Elevation Program. https://www.usgs.gov/core-science-systems/ngp/3dep.
12. ESRI. 2014. ArcGIS 10.3 software. http://www.esri.com/
13. KGIS. 2017. Aerial LiDAR data for Dutchtown Road study site.
14. Knox County Stormwater Management Database. 2017. Knox County Drainage Infrastructure.
15. Applied Imagery. 2009. Quick Terrain Modeler software. http://appliedimagery.com/

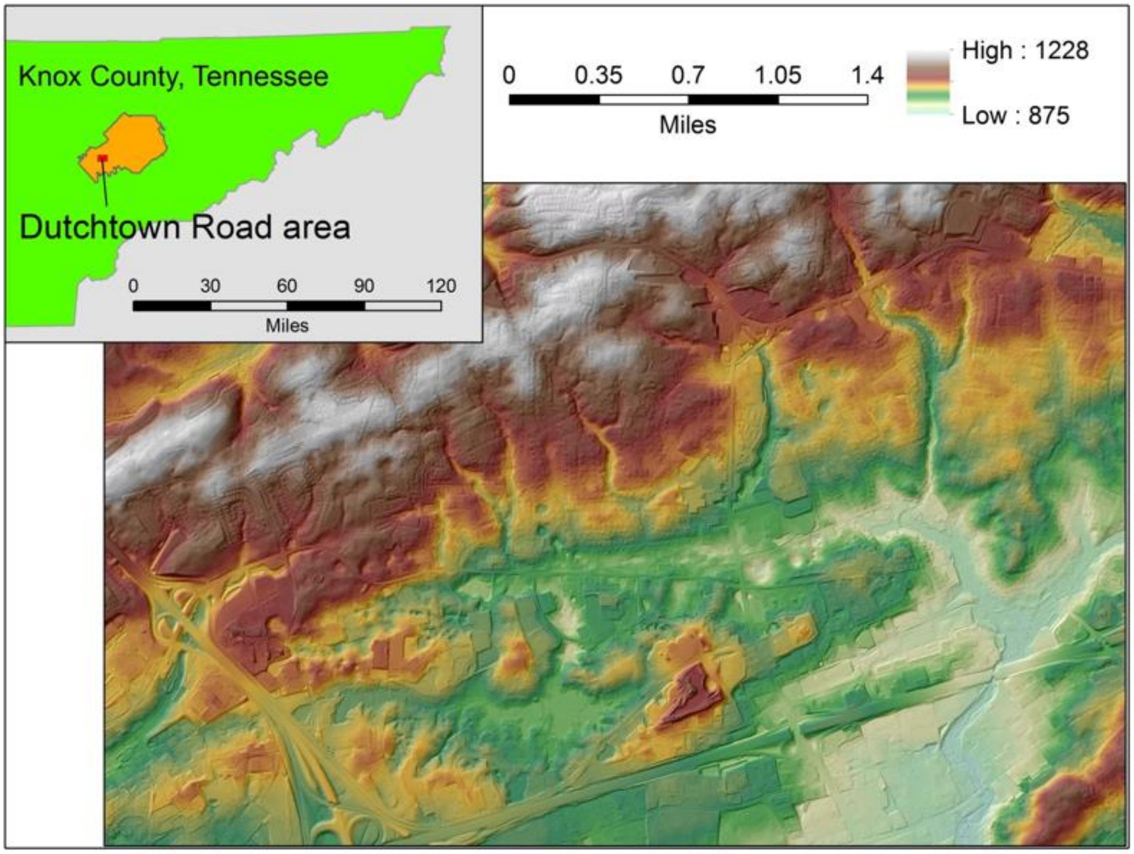

Figure 1. The study site of the Dutchtown Road area in Knox County.

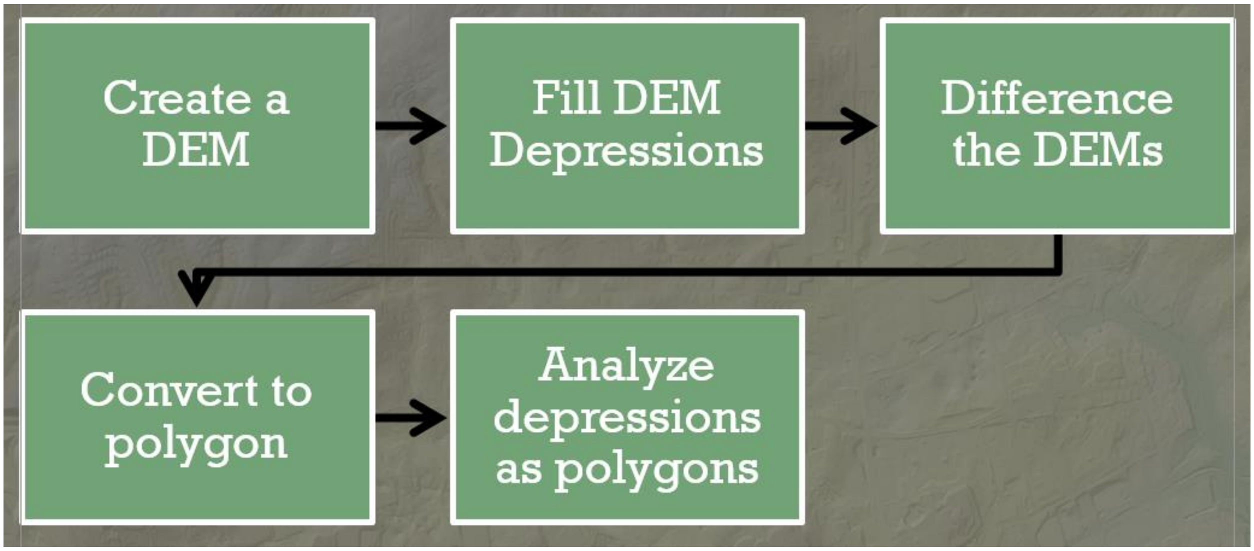

Figure 2. The conceptual model of the proposed sinkhole identification method.

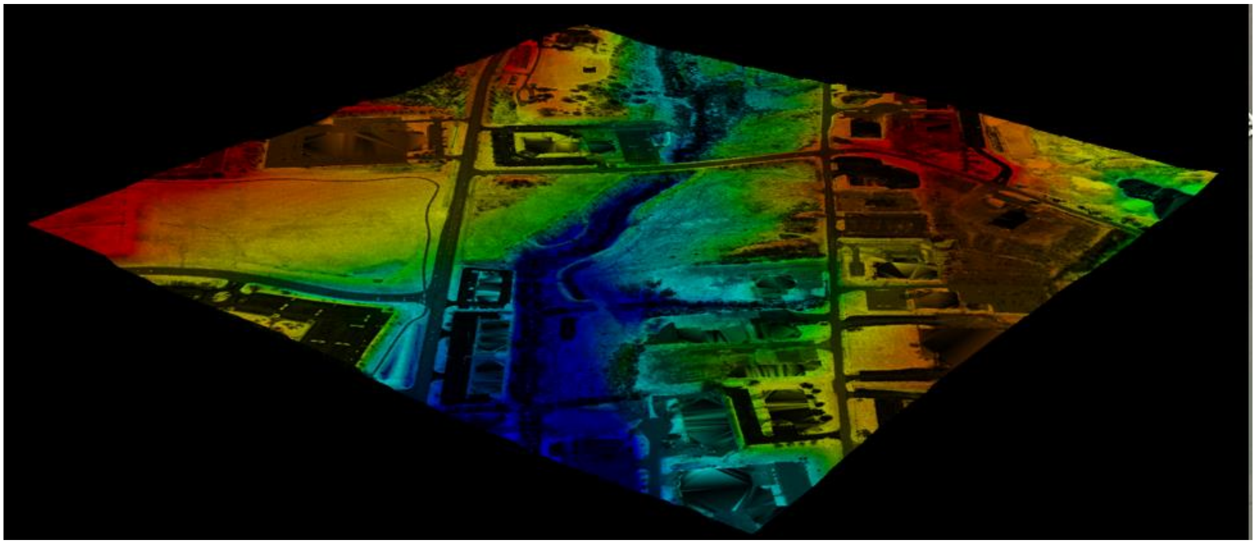
Figure 3. An example of a gridded surface model in Quick Terrain Modeler.

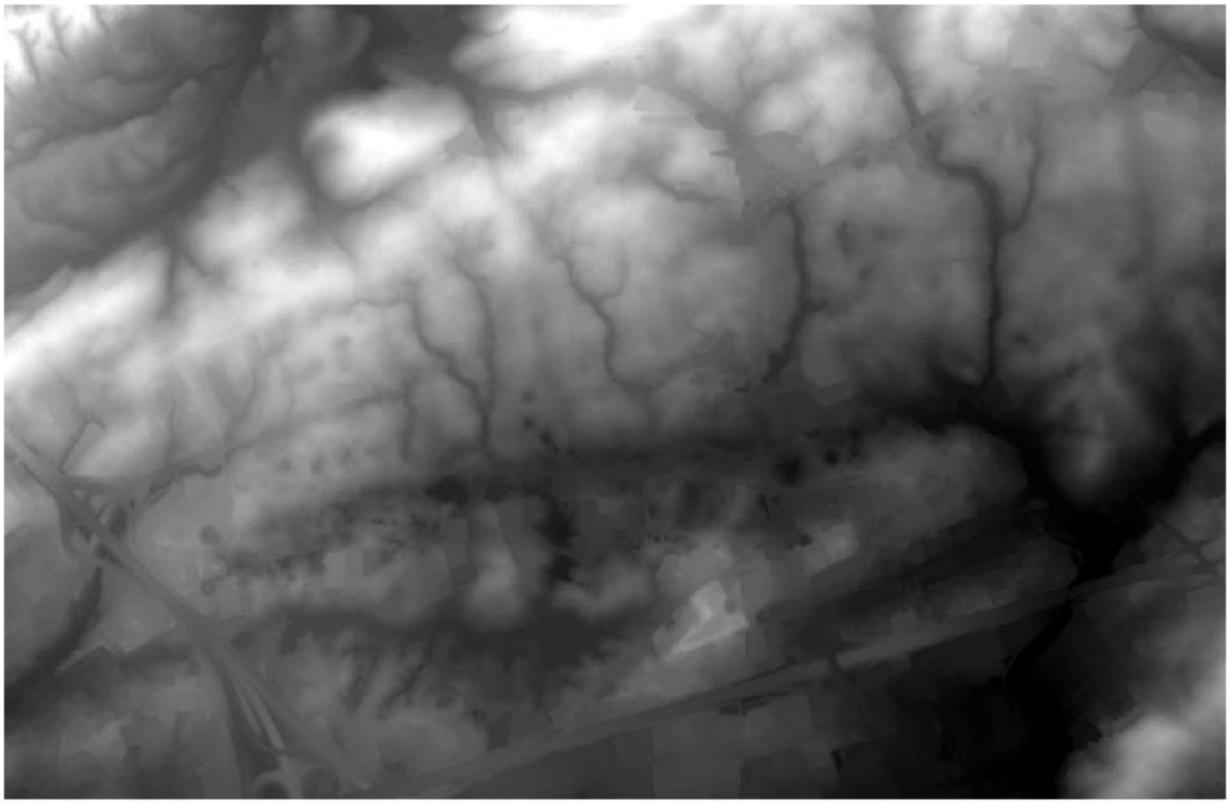

Figure 4. Clipped DEM of the study area.

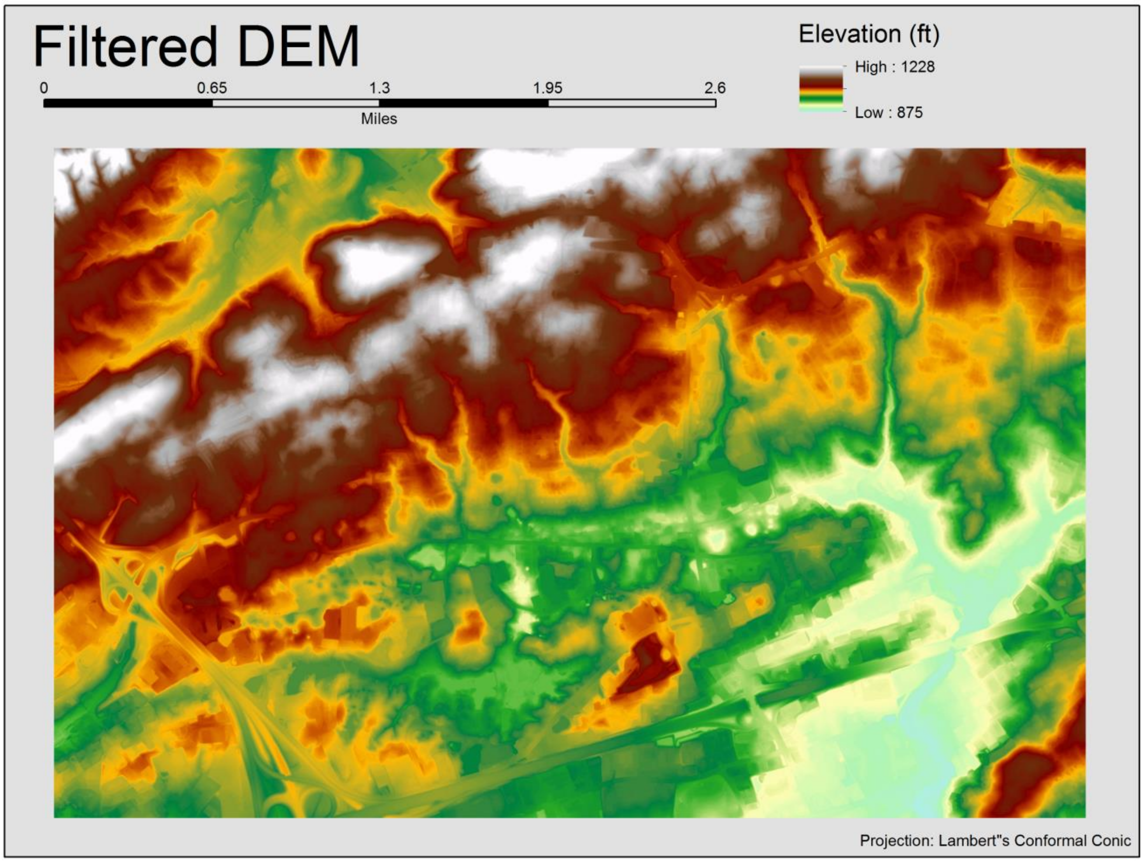

Figure 5. Smoothed DEM using the *Focal Median* tool in ArcGIS.

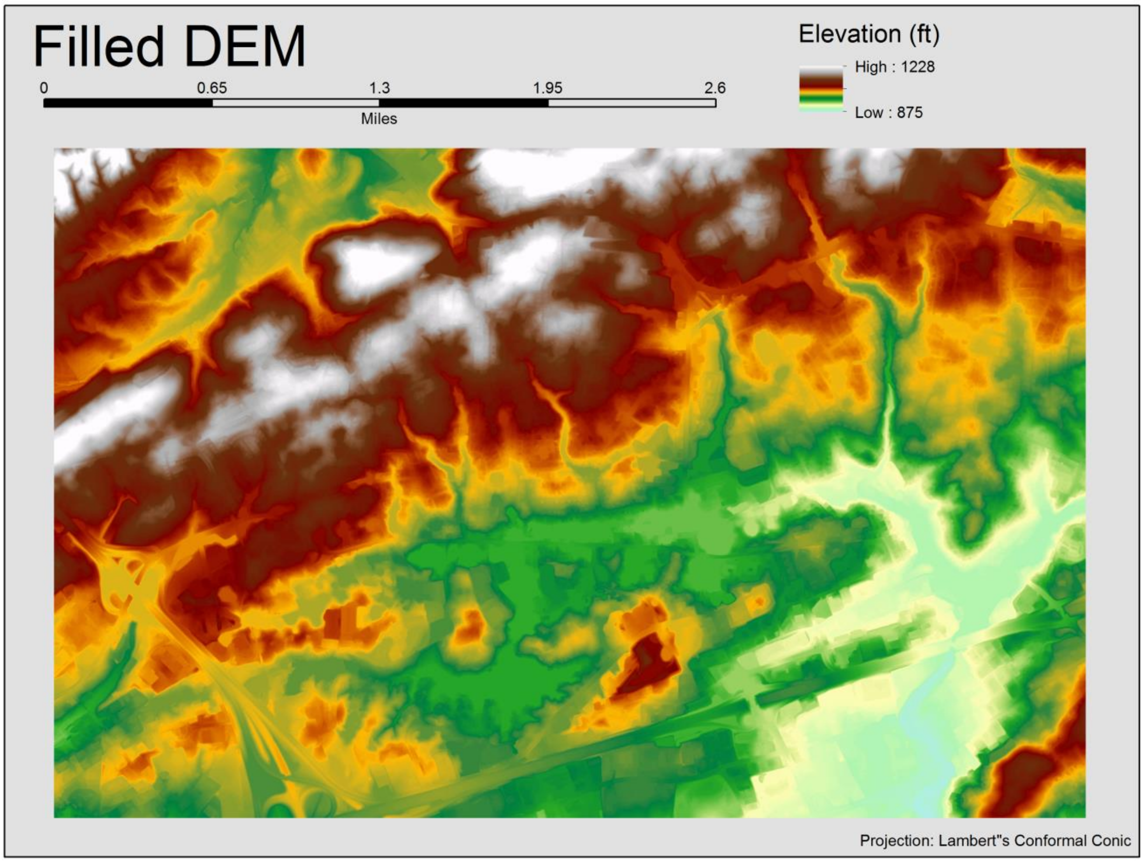

Figure 6. Filled DEM using the *Fill* tool in ArcGIS.

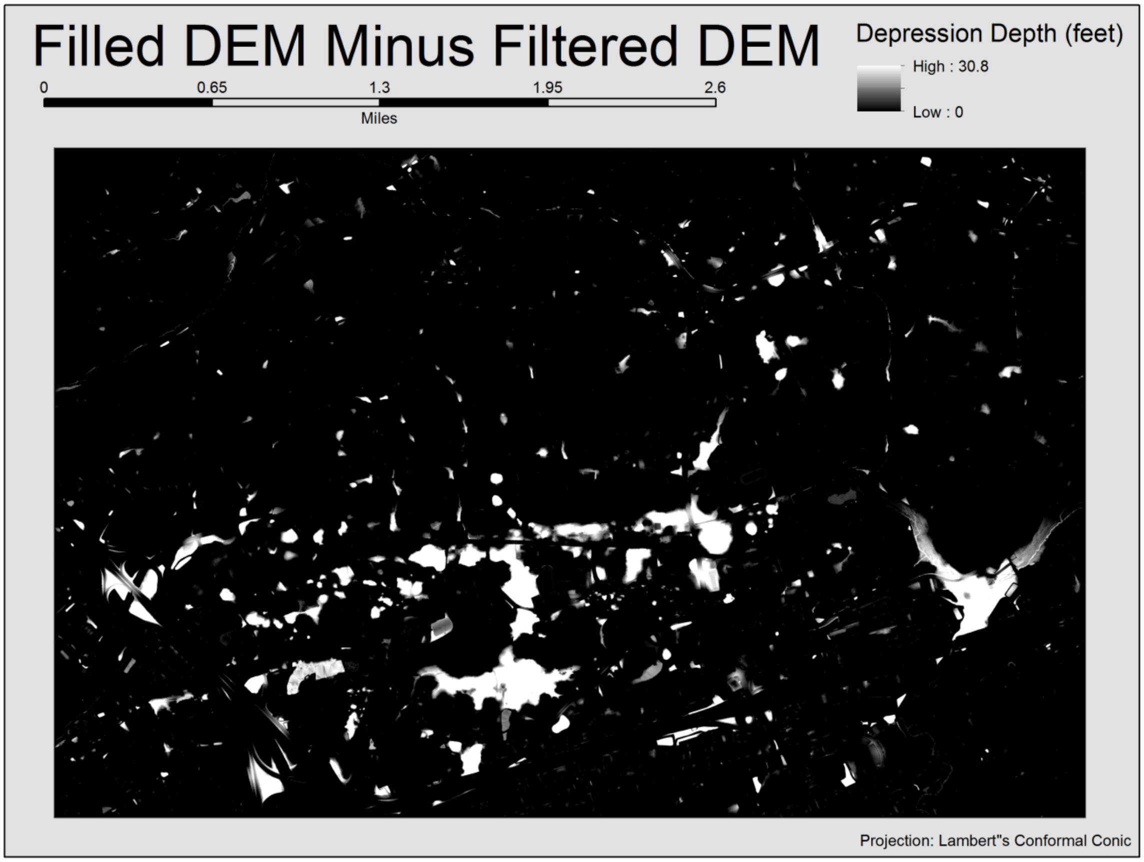

Figure 7. The difference between the original and filled DEMs using the *Minus* tool in ArcGIS.

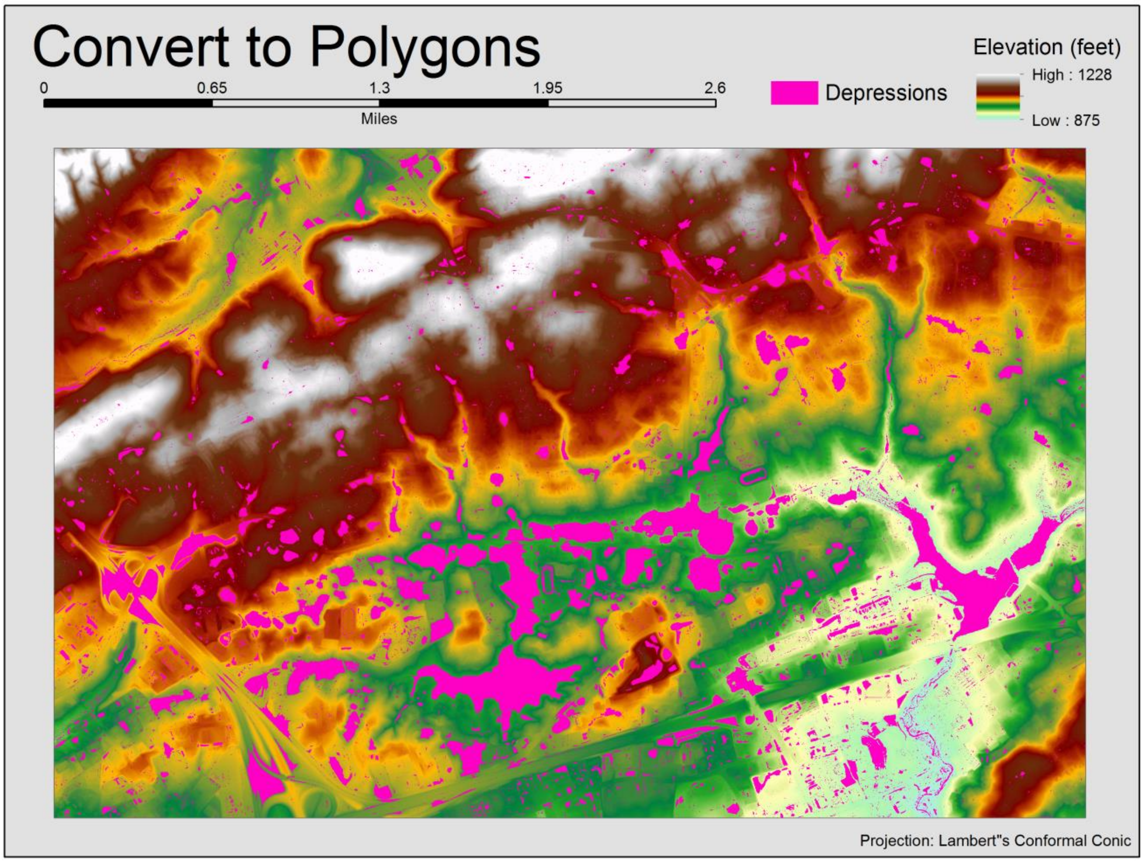

Figure 8. The map of depression polygons after converting the depression raster (DEM difference) to a shapefile.

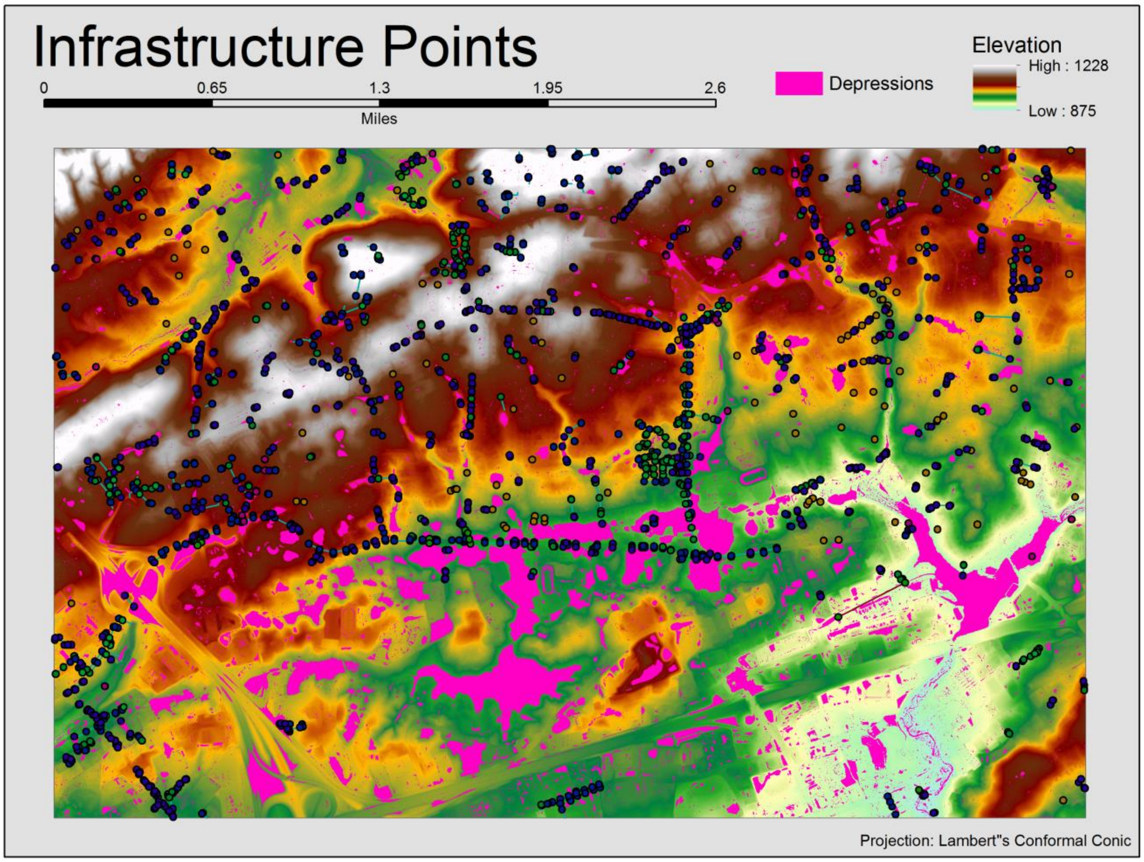

Figure 9. Overlapping Knox County Drainage infrastructure over the depression polygon layer to remove the man-made depressions.

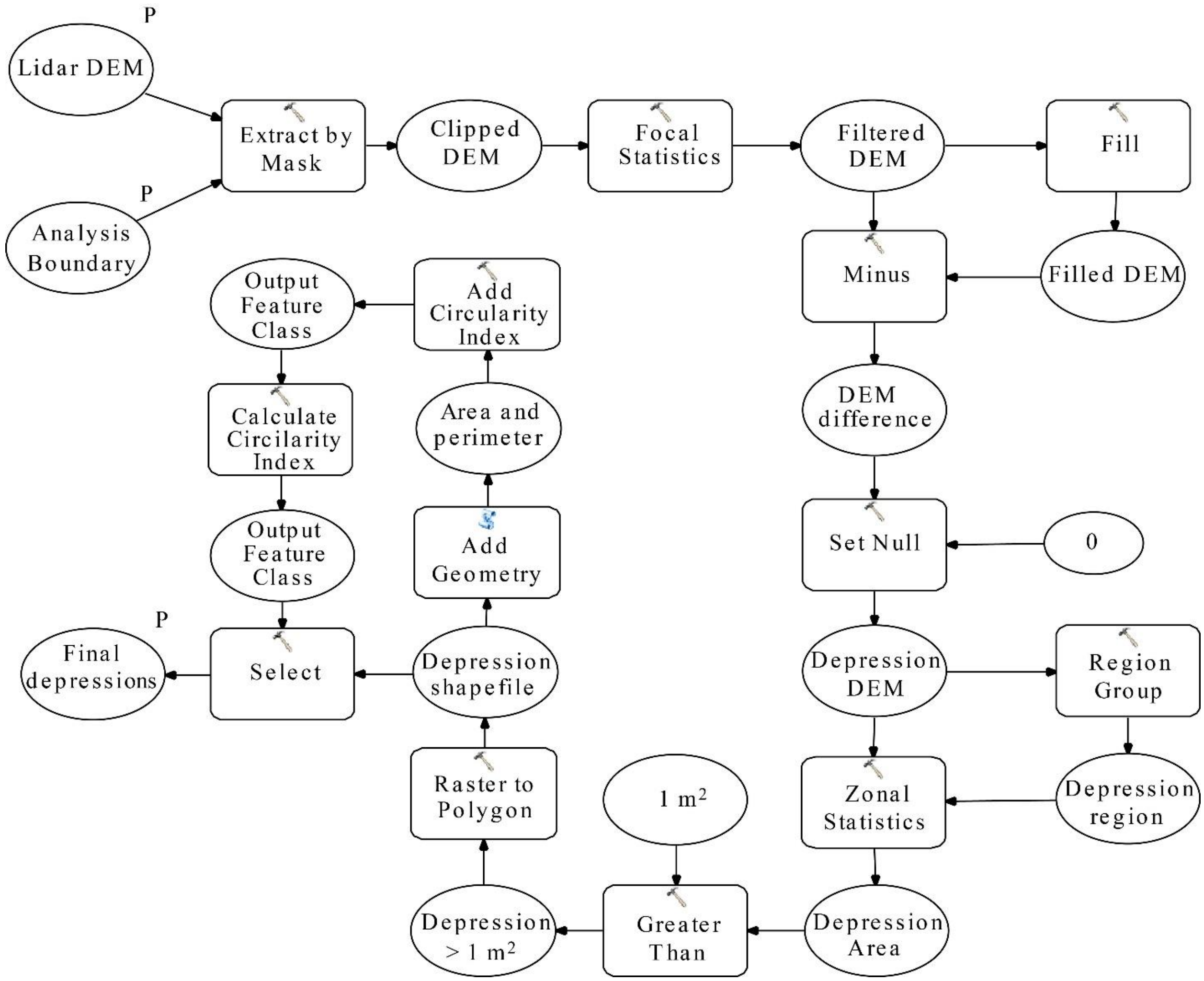

Figure 10. The ArcGIS Model to automate the whole analysis.

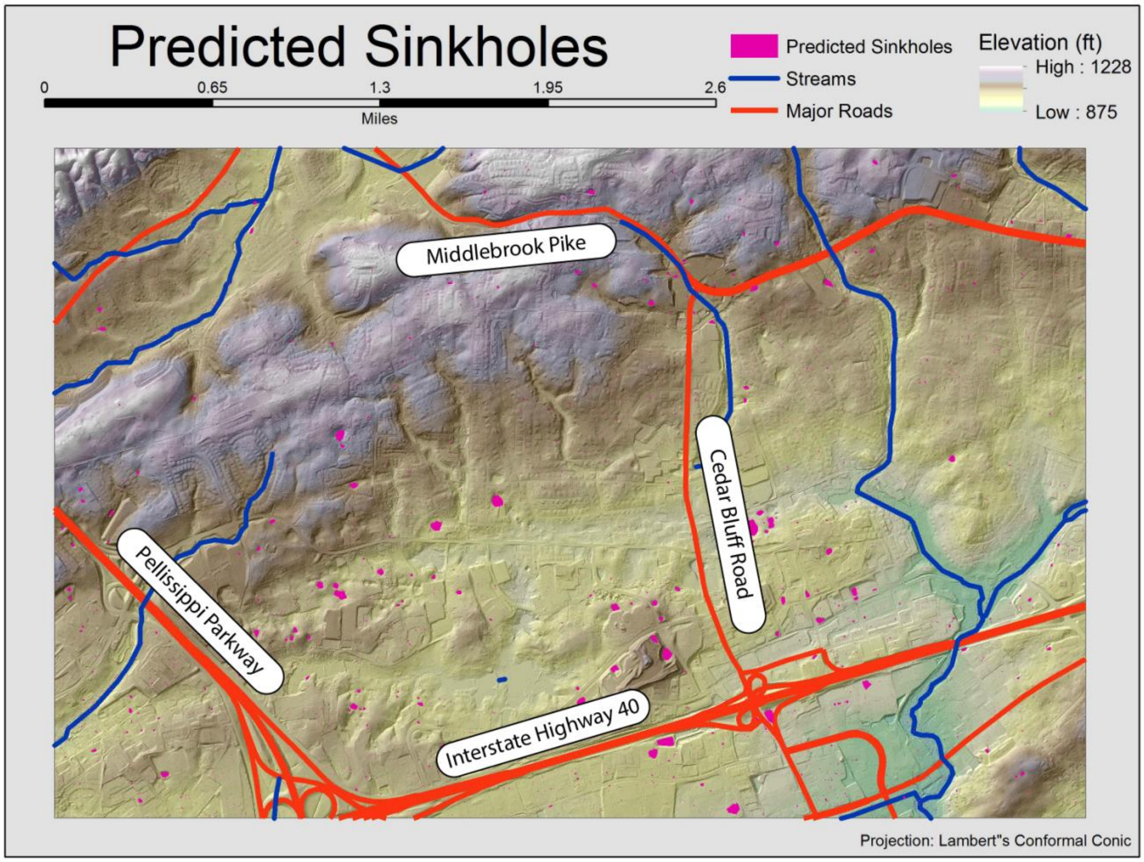

Figure 11. The distribution of predicted sinkholes after using the circularity index and polygon area thresholds and the removal of likely infrastructure depressions.