

Advancing Sinkhole Identification and Mapping in Kentucky using Lidar and Machine Learning



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Abstract

The original Kentucky karst sinkhole database was limited in accuracy because the database was compiled from the outdated 1:24,000 scale topographic maps. Lidar (Light Detection and Ranging), which measures the Earth's surface using lasers, provides high resolution and high accuracy elevation data for improving sinkhole identification and mapping. We use a four-step process to map sinkholes from lidar data. The process involves creating a digital elevation model (DEM) using Lidar point clouds, extracting surficial depression features from the DEM, inspecting these features for potential sinkholes, and conducting field-checks for verification. To expedite the inspection of depression features, a trained neural network classifier is implemented, dramatically reducing the time for inspection. This project represents a continuation effort to update the sinkhole database in Kentucky using lidar and machine learning. This work results in a fivefold increase in mapped sinkholes in an area encompassing Carroll, Gallatin, Grant, Henry, and Spencer Counties.

Purpose

The state of Kentucky is a predominantly karst environment -- a landscape underlain by limestone which has been eroded by dissolution, with around 55% of the state containing rocks with karst potential. A common hazard in karst environments is sinkholes which form due to carbonate rock being dissolved, and overlying soil being carried away underground (Currens, 2002). Sinkholes cost the state of Kentucky over 23 million dollars a year and have the potential of causing severe damage to both people and property (Zhu et al., 2014). It is of great importance to collect and record accurate and detailed locations where sinkholes have formed. The Kentucky sinkhole database is currently being updated from its original database, which uses USGS topographic maps created prior to the 1970s, to using a newer and more accurate elevation data from lidar. A neural network machine learning model was also used to help expedite the sinkhole classification process. The counties which have been chosen to have their sinkholes mapped using this process are Carroll, Gallatin, Grant, Henry, and Spencer (Figure 1).

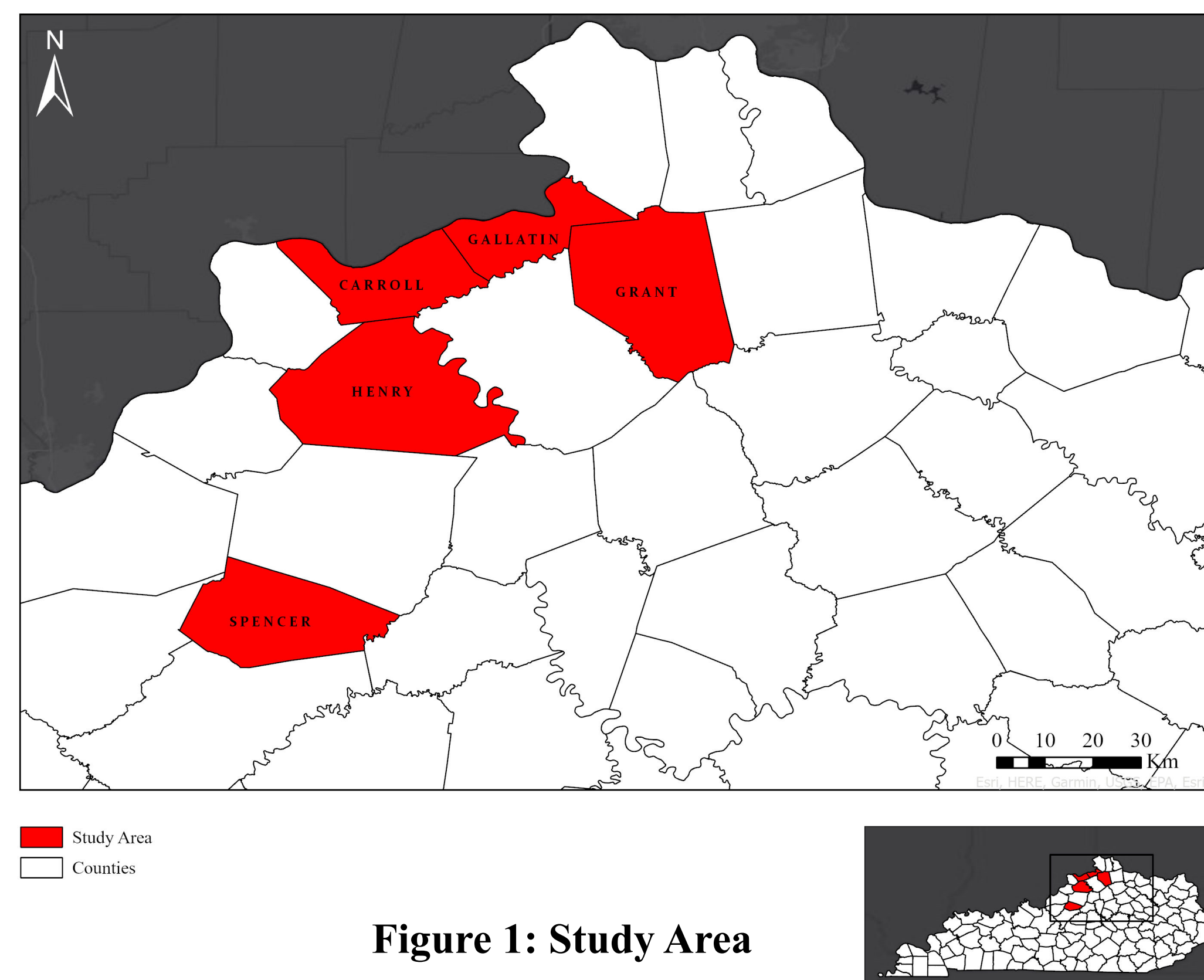


Figure 1: Study Area

Method

1. Extracting Surficial Depression Features from DEM:

1. Depressions were extracted using the fill tool, generating a new filled DEM.
2. Depressions were then obtained by subtracting the filled DEM from the original DEM.
3. Depressions were converted from raster to polygon format.

2. Machine Learning Assist:

1. Morphometric attributes of the depression polygons were extracted and fed into a pre-trained neural network model to identify polygons as either sinkholes or non-sinkholes.
2. The neural network model provides a probability of a polygon being a sinkhole, which can be used to distinguish sinkhole polygons from other depressions like ponds, rivers, and streams.

3. Inspecting Depression Features:

1. With neural network predictions, polygons manually categorized into sinkholes, non-sinkholes, and suspicious sinkholes.
2. Data reviewed by a separate party to ensure consistent classification and minimize human error, reaching final classifications through discussion.

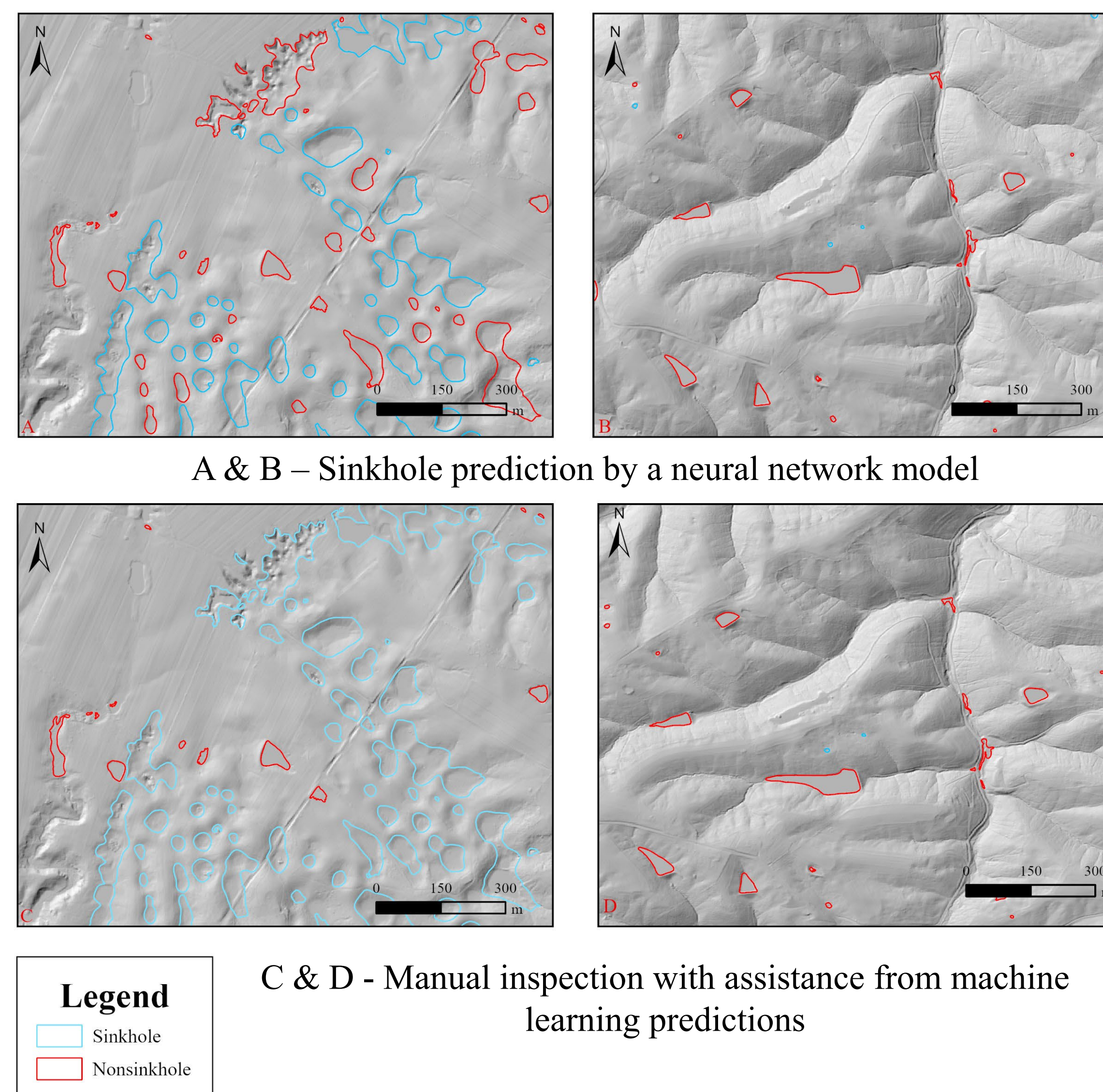


Figure 2: Neural Network Sinkhole Prediction & Manual Mapping

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Results and Discussion

A total of 949 sinkholes were discovered across the five mapped counties, with 789 of them being previously unmapped, resulting in a fivefold increase in the mapped sinkhole count for the area. The initial topographic sinkhole database had only 221 sinkholes mapped, out of which merely 160 were identified through the lidar mapping technique. This indicates that some of the formerly mapped sinkholes were either incorrect or have vanished due to human or natural disturbances. This highlights the dynamic nature of karst environments and underscores the importance of sinkhole mapping efforts to capture the temporal changes of karst features.

The successful integration of lidar technology and neural network classification presents a promising approach for comprehensive sinkhole mapping, offering valuable insights into karst landscapes and contributing to improved land management practices. The enhanced sinkhole database will serve as a valuable resource for geohazard assessments, conservation planning, and infrastructure development in regions susceptible to karst formations.

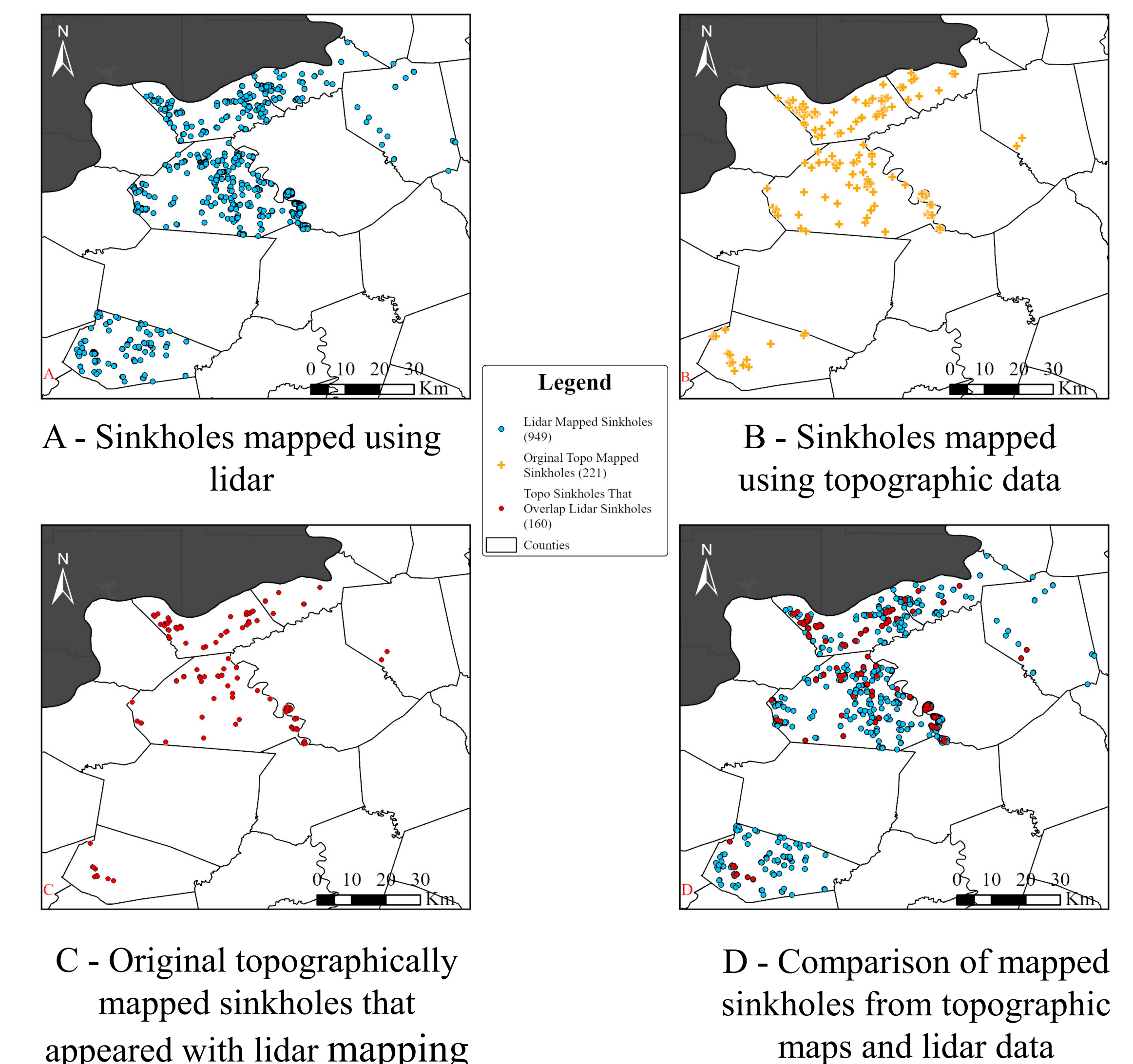


Figure 3: Sinkhole Mapping Results

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