JOURNAL OF UNDERGRADUATE RESEARCH

A Multiscalar Assessment of Mining in River Floodplains of the Southeastern United States

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Abstract

The mining of sediment is a profitable activity involving clearing and digging out large tracts of land and transformation of the topography. Often, these mines, as well as the pits, ponds, and piles of sediment are near or within the floodplains of a fluvial system. During flood events, the river can overtop and erode riparian areas that separate it from the mine, flowing into the pit and causing planform changes including avulsions. The United States Geological Survey (USGS) has mapped mining sites across the United States, but there are still multiple omissions. Google Earth Pro was used to collect geospatial point data on mines that are within the floodplain boundaries of rivers and creeks in the southeast, a region of high biodiversity. Google Earth extracted data were compared to USGS data using ArcGIS Pro, and their proximity to floodplains and channels was analyzed. Distances between the channels and pits prior to avulsion were referenced from literature (Mossa & Marks, 2011) and used to assess potential risk for other sites. It was found that out of the 1,856 total pits from USGS and Google Earth data, 25.9% were omitted from the USGS data set. This supported the conclusion that current data sets, while thorough, are still incomplete and that a better understanding of site location can reduce the risk of avulsions, which can impact infrastructure, property boundaries, flood risk, and ecological health.

Keywords: sediment mining, southeastern United States, Google Earth, pit avulsion

Introduction

The floodplains of alluvial rivers in the southeastern United States are crucial locations for the mining of sediments such as sand and gravel. These sediments, also known as aggregates, are necessary to make concrete. As a result, floodplain aggregate mines are important for critical infrastructure such as roadways, buildings, and bridges (Langer, 1988, Figure 1). A slew of methods are used to mine these sediments including in-channel mining, skimming sandbars and other floodplain deposits using heavy machinery, and the creation of pits using hydraulic dredges (Mossa & Marks, 2011). As a result, sediment mining in alluvial channels is known for a variety of hydrologic, geomorphic, and ecologic effects (Rinaldi et al., 2005).

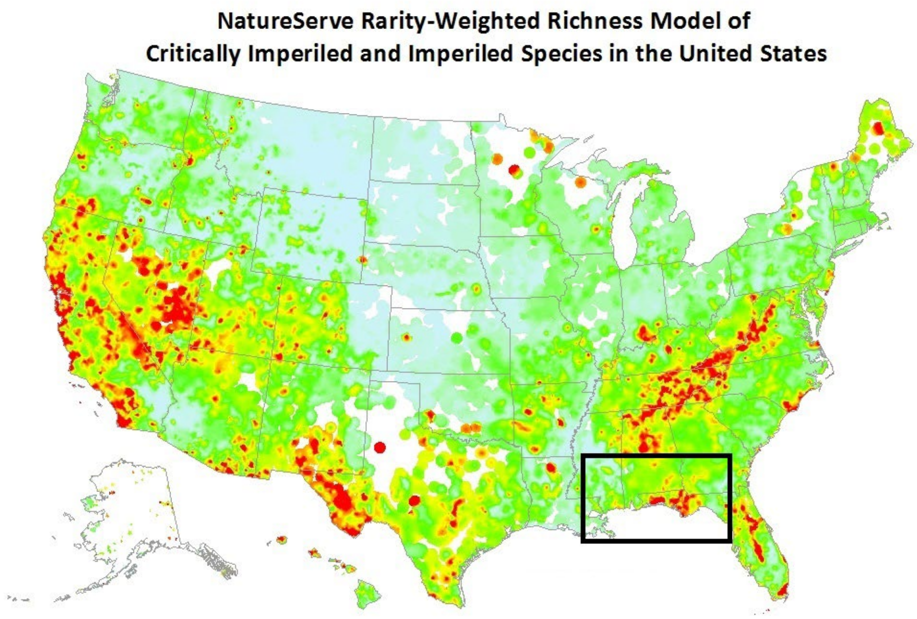

Figure 1. Map of biodiversity hotspots scaled by rarity weight in the United States, with red being the most weighted (Stein et al., 2000). The area of this study is included within the black box.

One common geomorphic effect is pit avulsion, when the river's main channel diverts into a nearby pit created in the process of sediment mining. The propensity for a river to avulse into a nearby pit is increased during a flood event when the river overtops the earthen embankments between it and the pit. This can cause permanent planform changes such as lateral migration and channel shifting (Mossa & Marks, 2011). After mining has ceased, the pits fill with rainwater and continue to pose a risk to the rivers alongside them for an indefinite amount of time (Figure 2). Along with geomorphic effects, mining can aggravate flooding through aggradation and cause problems with bridge safety by degradation.

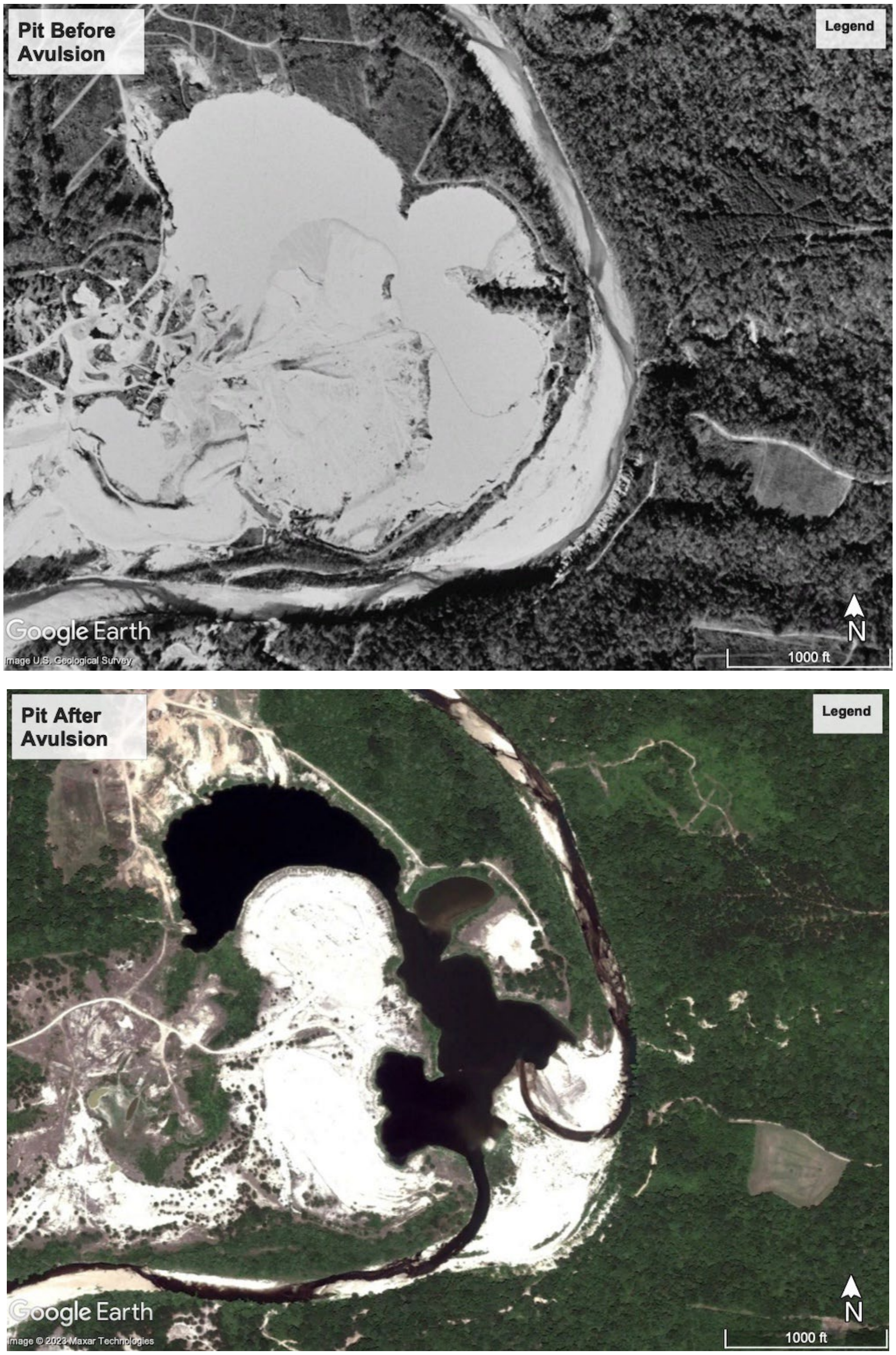

Figure 2. Section of Bayou Sara, Louisiana, before and after pit avulsion.

Currently, available data sets of global mining locations (Maus et al., 2020) have done a poor job of pinpointing mining sites in the southeastern United States. A quick comparison of National data sets (Horton & San Juan, 2016; U.S. Geological Survey, 2005) to global sets shows a disparity of data for the southeastern United States. While better than the global, the National data sets still have many omissions in the two databases available compared to sites described in the literature. These omissions occur in the active mining site database because the sites identified by the United States Geological Survey (USGS) in 2005 only include those active as of 2003, do not include aggregate mines with less than a 30,000-ton production, and do not include all specific aggregate pits. Because of this reason, the active mining site database from USGS was omitted from the data in this study. A database of mining features from USGS 7.5- and 15-minute topographic quadrangle maps of the United States, made by USGS researchers Horton and San Juan (2016), has continued to be revised into 2023. Because of its detail and use of historical data, this is an exhaustive database that is extremely useful in identifying mining sites that may pose a risk.

Despite this large database, it is hypothesized that more recent mining sites are still flying under the radar of researchers. The literature (see, e.g., Mossa & James, 2021; Mossa & Marks, 2011) includes some published rivers with mining not included in the historical database (Horton & San Juan, 2021); however, there is room for a more intensive search using geospatial data to identify more sites of individual pits. Current geospatial data tools, such as Google Earth Pro, are useful in doing this due to the user-friendly interface. Google Earth Pro's Time Machine feature is especially useful to properly identify older pits with historical data. Once these sites are identified, a comparison with USGS data can be made to better understand the gaps in current datasets. The combined data can help identify pits that pose the risk of lateral channel instability, water table lowering, aquatic and floodplain habitat destruction, and anthropogenic structure damage. This will be a valuable guide to researchers focused on river morphology and flood risk as it will give them locations to focus their efforts.

Methodology

To better understand gaps in current data sets of sediment mining sites in the southeastern United States, original geospatial data was first found. After that, USGS-sourced data sets (Horton & San Juan, 2016) were sorted into a geographical information system (GIS) application to be compared to the geospatial data. Once this was completed, GIS analysis tools were used to compare the locations of the mining sites, as well as better understand the potential risks (Rinaldi et al., 2005) of new and previously logged sites.

Study Area

The states included in this study were Florida, Alabama, Mississippi, and Louisiana (Figure 3). USGS data sets (Horton & San Juan, 2016) include the entirety of each state's area. The data acquired using geospatial methods included the entirety of each state listed between the longitudes of -84.978482 and -92.920560.

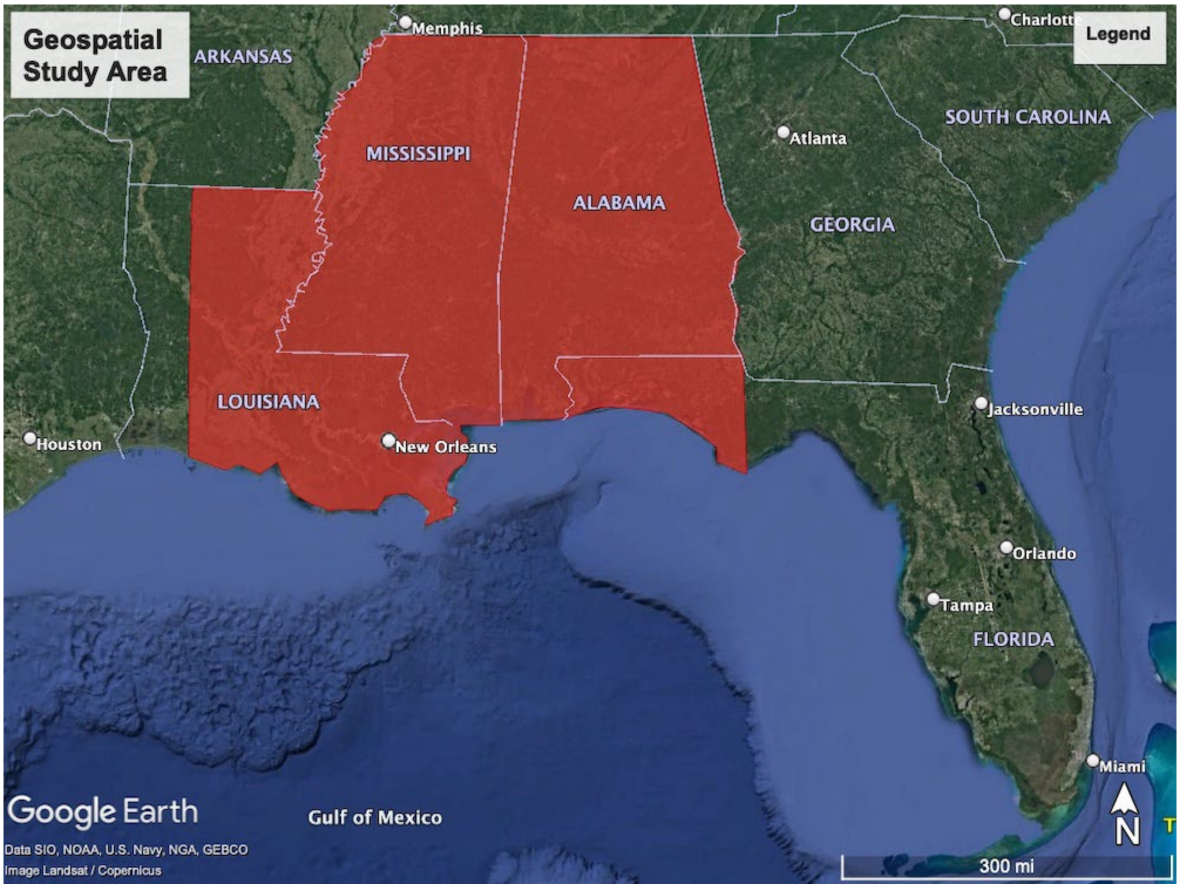

Figure 3. Geospatial study area in red.

Geospatial Data Collection

Google Earth Pro was used to collect geospatial data by conducting a longitudinal grid pattern up and down the study area. To do this, the eye altitude was set at 25000 feet, and the R key was used to ensure the field of view (FOV) was completely top-down, this confirmed a straight north-to-south route. With this FOV, starting at the southwestmost point of Alabama, a pin labeled WB1 was dropped on the western FOV edge, indicating the western boundary of the route. Using only the up and down keys, a south-to-north route was taken up the entirety of the state until the northern state border was reached. At that point, the “Measure” tool was used to measure the length across the FOV, ensuring that the line was perpendicular to the east and west edges of the FOV. 80% of this value was calculated and the “Measure” tool was once again used to mark this distance going east, away from the western edge of the FOV. A pin was dropped at this distance, on the state boundary, and labeled WB2. Using the left and right keys, the FOV was shifted until the western edge aligned with WB2. A north-to-south route was then taken until the Gulf of Mexico coastline was reached and the process was repeated until the most eastern boundary of Alabama was reached including most of the Florida Panhandle. The same process was done going westbound, using the pin label EB#, until the western boundary of the study area was reached.

While going up and down the grid route, anything in proximity of a river or creek that resembled a new or old mine site was thoroughly inspected by zooming in and using the time machine tool to look at historical aerial imagery. A site was not marked unless there was clear evidence that sediment mining was occurring. This was determined by the presence of dredges, aggregate conveyors, or conical piles of aggregate. Pits were marked with a pin labeled P. Areas bare of vegetation, presumably due to skimming with heavy machinery, were marked with a pin labeled NVA, for non-vegetated area. Areas where a pit avulsion had evidently occurred were marked with a pin labeled, PC. Lastly, river course changes were marked with a pin labeled, CC. All pins were placed where the extent of the feature was closest to the main channel of the river or creek.

Inputting Data into GIS Application

To eventually compare data using GIS analysis tools, all data was organized into individual shape files and raster images, then inputted into ArcGIS Pro as individual layers. The layers and methods of input are detailed as follows.

geospatial data input.

Google Earth Pro point data was converted from its Keyhole Markup Language (KMZ) file into a Microsoft Excel Open XML Spreadsheet (XLSX) file and sorted into its labeled categories in Microsoft Excel. Each category was moved into its own project and then inputted in ArcGIS Pro using the “XY Table to Point” tool. Since only the sites of pits were being evaluated against the

USGS data (Horton & San Juan, 2016), only points in the P category were added. A Shape (SHP) file of state boundaries was then added to break up the data by state. The “Select by Location” tool was used to select points within a state’s boundaries, with Alabama and Florida being combined. Each of these selections was made into a layer, and each layer was made into a SHP file using the “Feature Class to Feature Class” tool. This resulted in a layer for each state, with Alabama and Florida combined, for the geospatial data.

USGS data input.

The database of mining features from USGS 7.5- and 15-minute topographic quadrangle maps of the United States (Horton & San Juan, 2016) contained state-by-state KMZ files with thousands of mining feature points, including aggregate mining sites. The KMZ was downloaded for each state and was converted into an ArcGIS Pro layer using the “KML to Layer” conversion tool. Each of these layers was then inputted into the “Feature Class to Feature Class” tool with the clause of, “Symbol ID = 0”, which resulted in a SHP file that only contained pit mines for each state. All state SHP files were then combined into one layer using the “Append” tool. The SHP files for Alabama and Florida were also appended into one layer.

floodplain raster input.

Because the entirety of each state did not have a 100-year floodplain map associated with it, an estimated floodplain map of the conterminous United States (Woznicki et al., 2019) was used so that floodplain mining sites could be better documented. The map used random forest data to model unmapped floodplains. The resulting model captured 79% of the U.S. Federal Emergency Management Agency’s (FEMA) Special Flood Hazard Areas. The raster had a 30-meter resolution and indicated floodplains with the attribute 1 and non-floodplain areas with 0. This was put into ArcGIS Pro as a raster layer for further use.

flowline data input.

To be able to accurately assess the proximity of pit mines to river channels, the National Hydrography Dataset (NHD) (U.S. Geological Survey & National Geospatial Program, 2023) was downloaded for each state in SHP format. The NHD Flowline SHP files for each state were then inputted into ArcGIS Pro as individual layers, with each state containing multiple flowline layers. Each state's layers were appended using the "Append" tool to create one SHP file for all the flowlines of that state, Alabama and Florida's flowlines were combined.

Analysis

After all datasets had been organized into ArcGIS Pro, they were analyzed to confirm gaps in USGS pit mining data (Horton & San Juan, 2016), identify trends of spatial distribution, and assess risk for pit avulsions.

quantity of mines.

The number of pit mines and mining features from each data set was first recorded. To do this, the total and state quantities of mines were recorded for both USGS data, (Horton & San Juan, 2016) and for each of the geospatial data categories of features in their respective XLSX projects. The quantity of geospatially sourced pit data was then compared to the USGS (Horton & San Juan, 2016) pit data. It is important to note that the scale of USGS data was larger than that of the geospatial data scale.

comparison of data.

Using ArcGIS Pro's "Select by Location" tool, the amount of geospatially discovered pit mines that were within 1,164 meters of USGS (Horton & San Juan, 2016) pit mines was recorded. Eleven hundred sixty-four meters was sourced from previous literature (Mossa & Marks, 2011), which recorded the largest pit mine of the study having an area of 1,064,000 square meters. Assuming the pit as circular results in an estimated diameter of 1,164 meters. The mines that were within this distance were recorded per state as "shared pits", with Florida and Alabama being combined.

spatial distribution of pit data

The total amount of pits within the estimated floodplain (Woznicki et al., 2019) was first found. This was done by using the "Extract Multi Values to Points" tool, with the shared points and floodplain raster being the inputs, and then using the "Select by Attribute" tool to extract points with the floodplain raster attribute of 1. This was done for each state, with Alabama and Florida being combined, as well as the shared pits layer. The shared pits were manually divided using the

"Select by Polygon" tool. Next, the proximity of floodplain pits to the NHD flowlines (U.S. Geological Survey & National Geospatial Program, 2023) for both datasets and the shared pits were analyzed. A study by Mossa and Marks (2011) that recorded the distance from the river channel to the nearest point of an avulsed pit was used to find a pit-channel distance that indicated pits that posed a potential risk to rivers. The average distance found in the study was 66 meters (Mossa & Marks, 2011). Each layer of floodplain pit data was inputted into the "Select by Location" tool. Pits within 66 meters of the flowline respective to their state were selected, and the quantities were recorded by state with Alabama and Florida being combined. Quantities for each pit dataset were totaled and a ratio of selected floodplain pits to non-selected for each set was calculated.

Results

All data was put into ArcGIS Pro as individual layers for analysis, the results are as follows.

Geospatial Data

Table 1 details the results of geospatial data collection.

Table 1. Geospatial data

Feature	Number
Pits	742
Non-Vegetated Areas	478
Pit Captures	47
Course Change	18
Total	1285

Note. Geospatial data results collected with Google Earth Pro

Quantity of Pit Mines

Table 2 details the pit mines by state and the totals for both data sets.

Table 2. Quantity of pit mines

Data Source and State	Number of Pits
Geospatial FL/AL	375
Geospatial MS	81
Geospatial LA	286
Geospatial Total	742
USGS FL/AL	4615
USGS MS	4280
USGS LA	2238
USGS Total	11131

Total	11873

Note. Quantities of pit mines from two datasets, USGS data (Horton & San Juan, 2016) and the geospatial data.

Comparison of Datasets

Comparison of the geospatial dataset to USGS data (Horton & San Juan, 2016) was done by determining the quantity of the 742 geospatial data pits within 1,164 meters of pit mines shown in USGS data. The table is by each state, then the total, and ending with the number of shared points within the estimated floodplain (Woznicki et al., 2019).

Table 3. Comparison of Datasets

State	Number of Shared Pits
FL and AL	17
LA	235
MS	9
Total	261
In Floodplains	164

Note. Quantity of the 742 geospatial data pits within 1,164 meters of the USGS data pits (Horton & San Juan, 2016) as well as the number of shared points within the estimated floodplain (Woznicki et al., 2019).

Spatial Distribution of Pit Data

The pits that were fully contained within the estimated floodplain raster layer (Woznicki et al., 2019) were divided at a dataset and state level as well as the total of shared pits in the floodplain.

Table 4. Pits within floodplain

Dataset/State	Floodplain Pits	Floodplain Pits/Total Pits
Geospatial LA	226	0.79
Geospatial MS	52	0.64
Geospatial FL AL	237	0.63
Geospatial Total	515	0.69

USGS LA	558	0.25
USGS MS	347	0.08
USGS FL AL	600	0.13
USGS Total	1505	0.13
Shared Total	164	0.62
Total	1856	0.16

Note. Geospatial and USGS (Horton & San Juan, 2016) data pits within estimated floodplain (Woznicki et al., 2019).

The number of these floodplain pits that were within 66 meters of the NHD Flowlines (U.S. Geological Survey & National Geospatial Program, 2023) is shown in Table 5.

Table 5. Floodplain pits within 66 meters of channel

Dataset/State	Floodplain Pits<66m	Floodplain Pits<66m / Total Floodplain Pits
Geospatial LA	52	0.18
Geospatial MS	35	0.43
Geospatial FL AL	77	0.21
Geospatial Total	164	0.22
USGS LA	97	0.04
USGS MS	144	0.03
USGS FL AL	62	0.01
USGS Total	303	0.03
Shared Total	64	0.39
Total	403	0.04

Note. Amount of floodplain pits by state, according to geospatial and USGS (Horton & San Juan, 2016) data, within 66 meters of NHD Flowlines, (U.S. Geological Survey & National Geospatial Program, 2023) and its ratio to total pits.

The above tables can be used to give an understanding of omitted site data from national datasets, as well as the risk that it poses to river systems. This is illustrated in Table 6 by subtracting the shared values for each analysis from the total amount of geospatial data.

Table 6. Omitted pits

Type of Omitted Pits	Quantity
Total Omitted Pits	481
Total Omitted Pits in Floodplains	351
Total Omitted Floodplain Pits <66m from NHD Flowline	100

Note. Omitted data from each analysis, quantified by subtracting the shared data from the total geospatial data.

Discussion

The results of the study provide valuable insight into sediment mining in the southeastern United States. While the national datasets are immense, with USGS data (Horton & San Juan, 2016) including over 11,000 pit mining sites in the study area, omissions are still being made. Table 6 details the number of omissions as an estimated 481 pits, with 100 of them posing a risk to avulse and be captured by the river. Despite omissions, the USGS data (Horton & San Juan, 2016) serves as an invaluable data set to locate older mining sites that have a potential for pit avulsion. This is shown in table 5, which details total USGS pit mines less than 66 meters of the river channel as more than 300. The USGS data in Table 4 also gives insight into the spatial distribution of sediment mining depending on the state. The data indicates that a quarter of all sediment mining in Louisiana occurs within the floodplain. This could be due to the ease of access to higher quality aggregates such as sands, with low organic matter loads, that are more desired as concrete aggregates. Together, the geospatial dataset and USGS dataset are useful in assessing the risks of sediment mining in floodplains and what regions are more prone to pit avulsions.

It must be understood that much of the data is based on broad estimation. Each pit mining site is different in size, shape, and proximity to the river, and this can cause discrepancies in the data as a result. One such discrepancy can be caused by the assumption that omitted sites have maximum diameter of 1664 meters. While this is a safe assumption, since many sites are smaller in diameter, the fact that many pits are oblong in shape can create errors in this assumption. Along with this, it is not described in the methods of USGS data (Horton & San Juan, 2016) collection of where within the pit the point is being placed. This can cause discrepancies in the omitted data analysis as well as the analysis of river proximity. Another potential error to be observed is in the estimated floodplain (Woznicki et al., 2019), which is based on random forest data. Since non-vegetated areas are common to mining sites, there could be breaks in raster data. Further research would help to better understand which geospatially located mines have also been located by USGS and the validity of estimated floodplains in a mined environment.

USGS has done a spectacular job in creating an immense dataset of mining features in the southeast. The ability to look back on maps as far as 1884 grants the ability to find pits that are overgrown and impossible to find using Google Earth Pro alone. Despite this, there is still a clear lack of data for more recent mining sites in the southeast. Further research on mining sites using geospatial methods is crucial to better understand risks posed by pit mining in floodplains of the southeastern United States.

Acknowledgements

Sincerest thanks is extended to the faculty members whose answers to questions and invaluable advice helped this study be completed: Dr. Joann Mossa, University Scholars Program advisor, Dr. Patrick Inglett, Soil, Water, and Ecosystem Sciences Honors Coordinator, and Joe Aufmuth, University of Florida GIS Librarian. A special thank you is also extended to the University Scholars Program for funding this study.

References

Horton, J.D., & San Juan, C.A. (2016). Prospect- and mine-related features from U.S. Geological Survey 7.5- and 15-minute topographic quadrangle maps of the United States (ver. 9.0, January 2023): U.S. Geological Survey data release, https://doi.org/10.5066/F78W3CHG.

Langer, W. H. (1988). *Natural aggregates of the conterminous United States*. Washington, DC: US Government Printing Office.

Maus, V., Giljum, S., Gutschlhofer, J., da Silva, D. M., Probst, M., Gass, S. L. B., Luckeneder, S., Lieber, M., & McCallum, I. (2020). A global-scale data set of mining areas. *Scientific Data*, *7*(1). https://doi.org/10.1038/s41597-020-00624-w

Mossa, J., & James, L. A. (2013). 13.6 Impacts of Mining on Geomorphic Systems. *Treatise on Geomorphology*, 74–95. https://doi.org/10.1016/b978-0-12-374739-6.00344-4

Mossa, J., & Marks, S. R. (2011). Pit Avulsions and Planform Change on a Mined River Floodplain: Tangipahoa River, Louisiana. *Physical Geography*, *32*(6), 512–532. https://doi.org/10.2747/0272-3646.32.6.512

Rinaldi, M., Wyżga, B., & Surian, N. (2005). Sediment mining in alluvial channels: physical effects and management perspectives. *River Research and Applications*, *21*(7), 805–828. https://doi.org/10.1002/rra.884

Stein, Kutner, L. S., Adams, J. S., & Rousmaniere, N. S. (2000). *Precious heritage : the status of biodiversity in the United States*. Oxford University Press.

U.S. Geological Survey. (2005). *Active Mines and Mineral Processing Plants in the United States in 2003* [Review of *Active Mines and Mineral Processing Plants in the United States in 2003*]. U.S. Geological Survey. https://mrdata.usgs.gov/mineplant/

U.S. Geological Survey, & National Geospatial Program. (2023). *USGS National Hydrography Dataset Best Resolution (NHD) - Alabama* (20230305) [Shapefile]. U.S. Geological Survey. https://apps.nationalmap.gov/downloader/

U.S. Geological Survey, & National Geospatial Program. (2023). *USGS National Hydrography Dataset Best Resolution (NHD) - Florida* (20230305) [Shapefile]. U.S. Geological Survey. https://apps.nationalmap.gov/downloader/

U.S. Geological Survey, & National Geospatial Program. (2023). *USGS National Hydrography Dataset Best Resolution (NHD) - Louisiana* (20230306) [Shapefile]. U.S. Geological Survey. https://apps.nationalmap.gov/downloader/

U.S. Geological Survey, & National Geospatial Program. (2023). *USGS National Hydrography Dataset Best Resolution (NHD) - Mississippi* (20230305) [Shapefile]. U.S. Geological Survey. https://apps.nationalmap.gov/downloader/

Woznicki, S. A., Baynes, J., Panlasigui, S., Mehaffey, M., & Neale, A. (2019). Development of a spatially complete floodplain map of the conterminous United States using random forest. *Science of the Total Environment*, *647*, 942–953. https://doi.org/10.1016/j.scitotenv.2018.07.353