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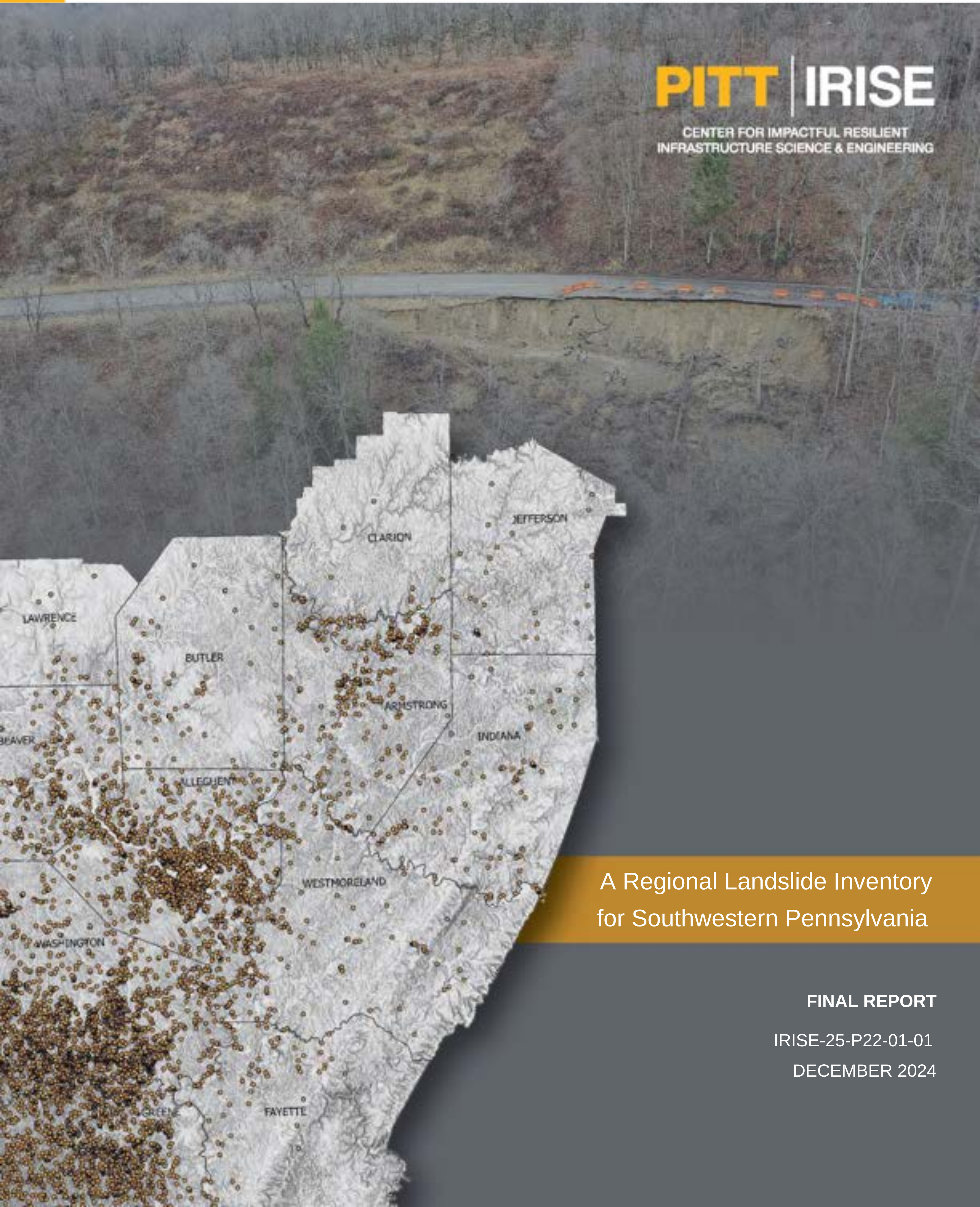

A Regional Landslide Inventory for Southwestern Pennsylvania

FINAL REPORT

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16. Abstract

Landslides are a major disruption to road networks and infrastructure in Southwestern Pennsylvania. A combination of rugged topography, clay-rich bedrock, complicated hydrogeology, and changing local climate results in numerous landslides across the region, particularly in areas where humans have modified the landscape. However, documentation of the spatial and temporal patterns of these landslides is spread across a wide range of government agencies and historical sources. This limits comprehensive planning efforts to address ongoing damage and mitigate potential future landslides. This project has inventoried over 7400 landslides from twelve agencies and/or data sources in a systematic and standardized format. Landslide events, once cataloged, were attributed with an extensive list of parameters summarizing topography, geology, soils, recent weather history, and local mining history. These data are summarized into data tables compatible with modern analysis tools and directly shared with the public when possible. In addition, case studies describing the potential for use of landslide data are presented in the report. This data framework, in conjunction with parallel and complimentary efforts, is a strong foundation for increasingly data driven approaches to landslide mitigation and management in the region.

17. Key Words

Landslides, Transportation impacts, Mining legacies, Freeze-thaw, Redbed stability, Topographic metrics, Soil characteristics

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1 .0 Introduction

1.1 Project background

Landslides are a major disruption to road networks and infrastructure in Southwestern Pennsylvania. The regionĝs clay-rich bedrock, complicated strata hydrogeology, and deeply incised valleys, when combined, lead to landsliding (Pomeroy, 1982). This propensity for landslides is worsened by emerging changes to the local climate with the region likely to be wetter and precipitation events likely to be more intense (Drum et al., 2017). Finally, Southwestern Pennsylvania (SWPA) has a legacy of deferred maintenance. Infrastructure built to address historical landsliding hazard is often close to 100 years old.

Given the scale of this disruption, transportation agencies and local governments have invested significant resources in landslide repair. However, planning for future landslides remains a challenge given the ñthresholdò responses controlling landslides occurrence and the ongoing changes in climatic conditions. Specifically, one of the impetuses for this database project was the 2018 spring, where record precipitation (National Weather Service, n.d.) caused a substantial number of landslides (Ashland, 2021). During this period, emergency costs for road repairs were estimated to be roughly ten times the funds originally budgeted for landslide repairs (KDKA News, 2018). As we prepare this report in 2024, a record single storm event (Smith, 2024) set off a series of landslides across the region. This is in stark contrast to 2023, when minimal snowfall and limited freezing conditions resulted in a relatively quiet landslide season. This temporal variability in landsliding and the resulting mismatch between anticipated and actual costs results in substantial economic burden to the region that is very likely to require sustained and significant resources over the coming decades (Kotz, Levermann and Wenz, 2024).

There is a robust cumulative experience across the region in how to fix landslides (Green, Ciloglu and Dorn, 2023). However, the history of when and where these landslides occur is not routinely recorded and curated. Comprehensive efforts to strategically engage this regional landslide challenge are strained because information about landslides is spread across multiple government and non-government agencies and organizations. Transportation agencies historically have managed landslide repair on a district-by-district basis. These records are distinct from records kept at finer jurisdictional scales (e.g., counties or municipalities). While information management continues to improve and can mitigate some challenges, landslide data collected varies widely across these sources and only recently have efforts to standardize data by following best practice emerged in the region (Green, Ciloglu and Dorn, 2023). The effort necessary to reconcile these structural data issues can challenge and truncate holistic planning responses to landslide impacts. A unified inventory of landslides and associated data provides a consistent set of information that can guide planning, mitigation, and adaptation efforts. Documentation of the relative importance of landslide causes and locations can advance an effective, proactive approach to landslide monitoring and mitigation.

This project has inventoried landslides from twelve agencies and/or data sources in a systematic and standardized format. The project 1) Designed a unified data structure for inventorying of landslides that is accessible for a wide variety of stakeholders [Section 2.1]; 2) Collected data from across the region and back through time to populate the database and provided a working database [Sections 2.2 and 3]; and 3) Used the comprehensive data collected to create illustrative case studies that document the power of the data [Section 4].

1.2 What we mean by ñlandslideò

In this report, ñlandslidesò refer to a wide variety of hillslope processes ranging from rock falls to soil creep. Part of this shorthand is enforced by the nature of the data. While some records include detailed information about the landslide, the vast majority of the records organized here do not include sufficient information to make or confirm the classification of the landslide. Therefore, ñlandslideò serves as a catchall term for all the potential hillslope processes these records may include. More important, in our interactions with the broader community, ñlandslideò is a common simplification for this range of processes, particularly for lay audiences. When technical needs dictate (e.g., a specific case is being discussed) more specific terms will be used, but, in general, landslide will be used as a general term throughout this report.

1.3 Regional stratigraphy

Lithology plays a critical role in hillslope stability. In SWPA, bedrock materials depend on relative elevation and the spatial location in the complex layers of sedimentary materials underlying most of the region. There are prominent layers closely associated with hillslope instability including multiple claystones and mudstones, for example, the Pittsburgh Red Beds, a mudstone occurring just below the Casselman/Glenshaw boundary (Winters, 1972). Likewise, the Morgantown Sandstone in the Casselman Formation is a common source of regional rockfalls (Orsborn, 2015). However, even in these commonly recognized strata, thicknesses can vary widely across the region (e.g., the isopach mapping in Winters, 1972).

To simplify our discussions, we have adapted and synthesized regional stratigraphic information to aid discussions throughout this document. Table 1.1 contains a generalized stratigraphic column for the study area following the recommendations of Berg et. al, (1983). Several resources were used to determine the estimated average thickness of various formations (Donahue and Rollins, 1979; Puglio and Iannacchione, 1979; Pomeroy, 1982; Evanek, Iannacchione and Anderson, Thomas, 2022). In addition, cores collected at limestone quarry operations in Fayette and Westmoreland Counties were used to estimate average thicknesses for Pottsville Group, Mauch Chunk and Loyalhanna Formations (Iannacchione, 2024).

Table 1.1. Generalized study area stratigraphic column with estimated average thicknesses for formations (Berg et al., 1983).

System or Period	Group	Formation	~Thickness, ft
Quaternary			0-100
Permian	Dunkard	Greene (Pg)	480
		Washington (Pw)	200
Transition		Waynesburg (PPw)	140
Pennsylvanian	Monongahela (Pm)	Uniontown	100
		Pittsburgh	300
	Conemaugh	Casselman (Pcc)	310
		Glenshaw (Pcg)	312
	Allegheny (Pa)	Freeport	100
		Kittanning	100
		Clarion	100
	Pottsville (Pp)	Homewood, Mercer, Connoquenessing	170
Mississippian		Mauch Chunk	200
		Loyalhanna	60

1.4 The database in a larger context

Landsliding is a continued challenge to southwest PA and its residents. One of the first regional compilations of landslide data was Al Ackenheil's dissertation (1954). Many of the data gathering efforts that followed are summarized in section 2.2.1. There are undoubtedly data that are missed here, but this database is intended to be regularly updated and grow. The standardized organization of a wide range of parameters will allow identification of state and local patterns in landslides and their drivers. This database is also intended to be complementary with other ongoing data organization and analysis efforts in collective efforts to ensure standardized, consistent records of landsliding in the region.

In the transportation sector, PennDOT already uses the gINT software (Bentley Systems, Incorporated, Exton, PA), a tool used to organize geotechnical data and analyze subsurface conditions. Connecting gINT software and the landslide database would enable and accelerate population of some of the data parameters (e.g., downslope displacement or depth to failure plane). However, this approach would likely only work for landslides impacting state routes. In addition, PennDOT is developing a Geotechnical Asset Management Program (GAMP) to track geotechnical assets related to known concerns, including landslides. Again, the wide range of parameters collected and organized in this database will provide substantial opportunities to enhance the GAMP as a tool and ultimately improve prioritization of projects and resultant management outcomes.

Similarly, the Pennsylvania Department of Conservation and Natural Resources (DCNR) is currently developing a geographic information system (GIS) database of all the landslides tracked by that agency over the years including some data mining from news reporting. Cross-comparison with this database creates the potential to not only expand the IRISE database, but also, populate some of the hard to reconstruct data such as the areal extent of landsliding. This state level work is intended to be incorporated into national landslide inventory efforts <https://www.usgs.gov/tools/us-landslide-inventory>. Therefore, this database will have an important role in making sure these inventories are complete and thus reflect the fundamental challenges to the region.

2 .0 Methods, method development, parameter descriptions, and quality assurance

This section describes the approach, different data sources, methods, and parameters used in the construction of the database. For each data type (i.e., Landslides, Topography, Soil, Geology, Weather) it describes the data sources used, the method through which data was analyzed, and the parameter extracted from it (i.e., each landslide is represented by a row in in the database, and each column describes a parameter that characterizes this specific landslide).

2.1 Construction of database

2.1.1 Design of the database structure

The database was designed to be easily incorporated into existing data structures used by respective end users. Proprietary data formats were avoided. A simple (i.e., flat file) structure was used to minimize necessary data manipulations by the end user. These choices resulted in a comma separated variable (.csv) file, with appropriate precision reported for each variable. In response to feedback from the IRISE Landslide Working Group (see Section 6 for information on the working group), an MSExcel version of the database will also be provided that provides more plain language variable names, filtering capabilities, etc.

Data variables to be included in the database were determined in an iterative process conducted in close collaboration with the working group. At the beginning of the project period, the Pitt Team read the landslide literature and gathered potential data sources. After a wide survey and discussions with the working group, the team did an internal evaluation weighing the relative influence of the data parameter and the feasibility of data collection. These decisions were presented to the working group during the October 4, 2022 meeting for input and approval. This list evolved to the parameter list presented to the working group in February 2024 and included in the rest of this section.

2.1.2 Database construction

Using the database structure, a set of parameter maps were created, roughly one map per spatial data field. These maps are all raster maps (i.e., the data is stored as sets of pixels rather than as polygons) and to ensure spatial consistency, these maps are all registered to the USGS 30ft digital elevation model (DEM) (Gesch et al., 2002). Descriptions of data sources and data processing necessary for each data field are described in the rest of this section.

For time series weather data, the data are stored in daily rasters by the Parameter-elevation Regressions on Independent Slopes ModŜſ (PRISM) group. In this case, the PRISM pixel where the landslide occurred was identified, and the weather time series for that pixel extracted. These time series were summarized (e.g., precipitation or freeze/thaw counts over the preceding weekly/monthly/6months) and summary values stored in the flat file database.

To simplify and standardize data collection, these rasters were then queried in a systematic process described in the next section.

2.1.3 Database workflows

Based on the construction decisions described above (section 2.1.2), the workflow for constructing the database included: 1) Reading, organizing and combining landslide datasets from various sources (section 2.2).; 2) Associating each landslide with the spatial information at its location (i.e., topography, soil, geology, sections 2.3-2.5).; and 3) Associating each landslide with the time series of weather data at its location (section 2.6). These three steps are implemented in an in-house algorithm that is run from a ómainô file, which calls a set of functions that execute each of these steps. Each of these functions calls in turn a set of sub-functions, to compute specific components.

2.2 Landslides

Landslides collected from various sources provide the basic input for the database. The landslide location and time of occurrence are used to attribute each landslide with a set of parameters. This section describes landslide data sources, processing method, and database parameters that are extracted directly from the data sources.

2.2.1 Landslide data sources

There are a wide variety of landslide data sources incorporated into the database, each with different types of information, including landslide location, date, lithology etc. In this section, these sources are described and data choices documented.

2.2.1.1 Historical landslide data

2.2.1.1.1 USGS historical data

Following the substantial landslide activity associated with Hurricane Agnes, the US Geological Survey (USGS) endeavored in the 1970s and 1980s to comprehensively map landslides in SWPA. The data and methods are described in the following documents: Briggs et al. (1975) and Pomeroy (1982). (Note there are numerous field map studies, open file reports, and other miscellaneous documents not cited here. For a comprehensive list please consult the USGS Publications Warehouse.) In addition, all of the maps of landslides are scanned, organized, and available from the PA DCNR:
<https://www.dcnr.pa.gov/Geology/GeologicHazards/Landslides/Pages/default.aspx>

The Southwestern Pennsylvania Commission (SPC) previously digitized all of the ñmodernò landslide footprints (i.e., landslides visible in 1973 aerial imagery) for SPC counties (i.e., they do not include Clarion and Jefferson counties in PennDOT District 10). These data are available on Pennsylvania Spatial Data Access (PASDA, <www.pasda.psu.edu>). These data only include the landslides occurring in the 1970s and do not include the mapping of ñOldò landslides included in the map series.

As part of the database project, in combination with other work at the University of Pittsburgh (e.g., class projects) we have been digitizing all features mapped during the USGS work. Active landslides in Jefferson and Clarion Counties mapped by the USGS on the following topo sheets are included in the database: Coolspring, Dayton, Distant, East Brady, Parker, Sigel, and Templeton.

2.2.1.1.2 William Adams dissertation data

Landslide locations in Allegheny County recorded as part of William Adamsô dissertation research were digitized from the maps in the dissertation (Adams Jr., 1986) and included in the database.

These data are directly derived from Figure 16 in the dissertation. Only slopes indicated in the dissertation as ñSlope Movements Field Visitedò and ñSlope Movements Used in Verification of Modelò were used in the database. ñSlope Movements Inventoried But Not Field Visitedò were not included in the database. The label names on Figure 16 in the dissertation were used as the original label in the database.

2.2.1.1.3 Alfred Ackenheil dissertation data

Landslide locations in Allegheny County recorded as part of Alfred Ackenheilôs dissertation research were digitized from the table of landslides in the dissertation (Ackenheil, 1954).

Some of the slides indicated in the Ackenheil thesis are separate from what we refer to as landslides, as they were trench or foundation collapses. Hence, such events were not included in this database (numbered by Ackenheil as slides 8, 38, 41, 73, 74, 88, 93).

There are multiple landslides in the Ackenheil data that have ambiguous location data. For example, there is a slide in 1938 that occurs simply in ñSewickley Fresh Air Farm, Fair Oaks Twp.ò (Slide number 4 in Ackenheilôs dissertation). While there is record of this location, it is a large parcel and there is no further information about where on the property the slide occurred. In these cases, there are no coordinates provided in the database. The slide ID numbers given in Ackenheilôs thesis were used as the original label in the database.

2.2.1.2 Contemporary landslide data

2.2.1.2.1 PennDOT district geotechnical engineering records

PennDOT districts 10, 11, and 12 all provided spreadsheets of landslides that had occurred within the relevant district over recent years. It is important to note that none of these lists were presented as comprehensive and reflect records kept as part of district operations but not necessarily an exhaustive list of landslides.

PennDOT District 10 provided a spreadsheet in February 2023 including landslides reported as early as 1975. PennDOT District 11 provided a spreadsheet in May 2022 including landslides back to 2015. PennDOT District 12 provided a list in June 2022 including landslides back to 2015, and an additional short list of older slides in October 2023.

2.2.1.2.2 Allegheny County landslide data

Allegheny County Department of Public Works provided a spreadsheet of their slide data back through 2013 to the Pitt Team in February of 2023. In addition, copies of all available digital landslide assessment and repair projects were provided at that time.

2.2.1.2.3 City of Pittsburgh landslide data

The City of Pittsburgh Department of Mobility and Infrastructure (DOMI) provided a spreadsheet of landslides in November of 2022.

2.2.1.2.4 311 Landslide data (City of Pittsburgh)

In addition to the DOMI landslide list, all reports of landslides to the 311-reporting system were accessed via the Western Pennsylvania Regional Data Center (WPRDC) (<https://data.wprdc.org/dataset/311-data>. The working list utilized in this database was accessed in December 2022 and includes landslides back through 2015. A fraction of the landslides occurring in 2019 (77 slides) were field validated, revealing that ~70% of the 311 reported slides coincided with slides observed in the field (i.e., occurred within 100m of the site reported). Of the remaining slides, about a third (7 slides) were associated with duplicate slide reports (Rohan, Wondolowski and Shelef, 2021). The 311 data is presented as downloaded and does not reflect any modification based on these QA results. The 311 data set index used by the WPRDC table is included as the original label in the database.

2.2.1.2.5 Miscellaneous Allegheny County landslide data

Forest Hills Borough provided a list of recent slides (back to 2018) in March 2023.

2.2.1.2.6 NASA global landslide data

The National Aeronautics and Space Administration (NASA) Landslide Repository (Kirschbaum et al., 2010; Kirschbaum, Stanley and Zhou, 2015) was accessed on 10/10/2023 and landslides occurring within the counties forming PennDOT D10, D11, and D12 were included in the database. Data was obtained from <https://maps.nccs.nasa.gov/arcgis/sharing/content/items/eec7aee8d2e040c7b8d3ee5fd0e0d7b9/data>,

2.2.2 Processing of landslide data

Landslides from different sources were aggregated to a unified table through an in-house algorithm coded in MATLAB. The algorithm reads each one of the landslide datasets originated from different data sources (e.g., 311, District 12 etc.), in the form of csv or xls file (i.e., comma separated variable and excel files, respectively). In some cases (e.g., PennDOT district data), coordinates were derived from inhouse location formats (i.e., the State Route/Start Segment/Segment Offset system). In these cases, while end segment data was sometimes available, it was less consistent than start segment info, so locations were based uniformly on start segment and offset. In other cases (e.g., Ackenheil, City of Pittsburgh) slides were geolocated from available location information ranging from street addresses to specific facility names. The data from the sources outlined above were used to populate a table with a consistent set of basic information about the landslide.

The original labels of the landslide, if they were provided in the data source, are preserved in the ôLabelô parameter (i.e., column) to enable easy linking between slides in the database to slides in the source list. In addition, a unique ID is assigned to each landslide based on the data source. The data source is also recorded in a 'DataSource' column to provide data tracking capabilities. At the minimum, a landslide in the table will have a data source, and an ID.

2.2.3 Landslide parameters

The parameters below are parameters extracted directly from the landslide data sources. Not all parameters exist for each landslide, as this depends on the details that were provided in the data source.

ID: Landslide ID specific for the database, includes the data source (311, USGS, D10, etc.) followed by a number (i.e., D10-1). ID numbers are based on ranked order of the landslides from each data source from south to north based on their latitudes. Slides with exactly the same latitude at database precision are ordered from west to east.

DataSource: The name of the data source (i.e., 311, USGS, D10, etc., without an ID number).

Original Label: The original labels of the landslide if they exist. This aims to enable linking between slides in the database to slides in the respective source list.

Latitude: Decimal degrees north of the Equator.

Longitude: Decimal degrees west of the Prime Meridian (by convention the westward direction is indicated by a negative value).

County: County where landslide occurred, inherited from data source or spatial query.

Municipality: Municipality where landslide occurred, inherited from data source or spatial query.

State route: Included for PennDOT data. Route number of route near landslide occurrence.

Start Segment: Included for PennDOT data. Start segment of route section where landslide occurred.

Offset from start segment (ft): Included for PennDOT data. Offset from start segment of route section where landslide occurred.

Above or below road: Describes whether the landslide is above (A) or below (B) the road in the context of local elevations. AB marks that it occurs both above and below.

Slide type (DCNR classification): Describes the landslide type following DCNR classification (Delano and Wilshusen, 2001) (Categories included in the database: Debris avalanche, Debris flow, Debris slide, Earthflow, Mudflow, Rock fall, Rock slump, Slump, and Soil creep, for more details see section 4.6).

Landslide area (ft^2): The areal extent of slide materials.

Landslide downslope displacement (ft): The magnitude of downslope displacement as recorded from the landslideȏs head scarp to the nearest occurrence of run out material (Figure 2.2.1).

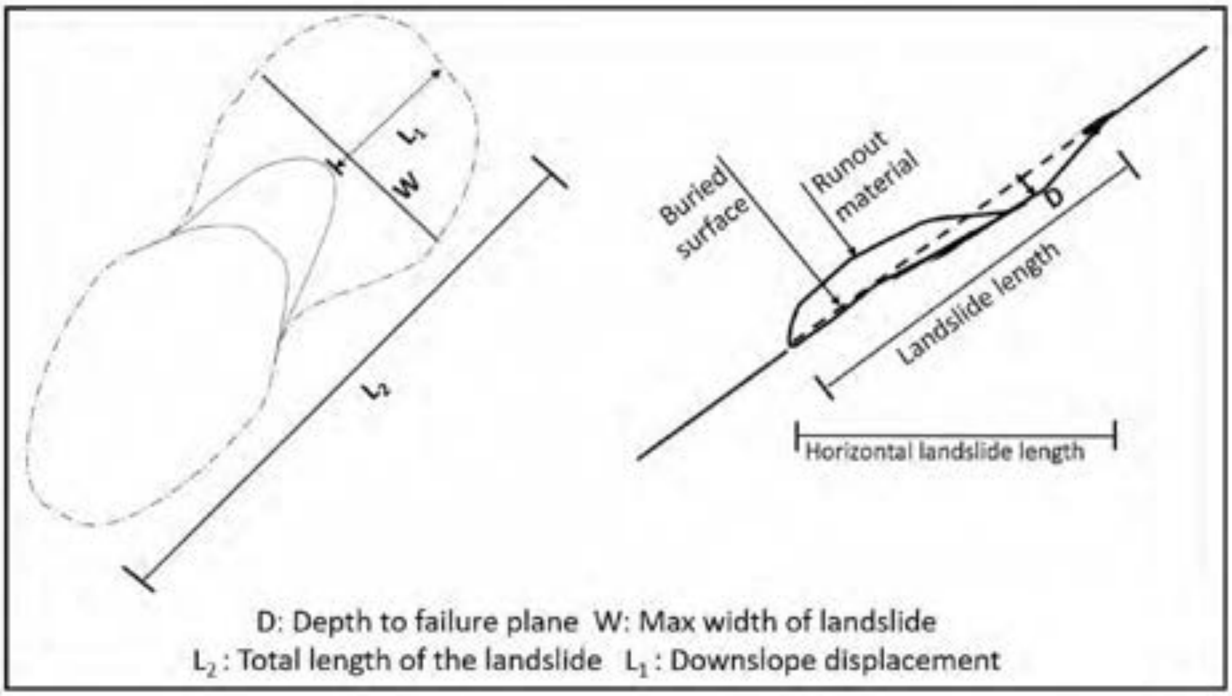

Figure 2.2.1. Schematic of key landslide dimensions included in the database. Note, this schematic may not apply to rock falls given differences in relevant processes.

Depth to failure plane (ft): The depth to the failure plain as recorded from field observations, cores or alike (Figure 2.2.1).

Month: Month of landslide occurrence.

Day: Day of landslide occurrence.

Year: Year of landslide occurrence.

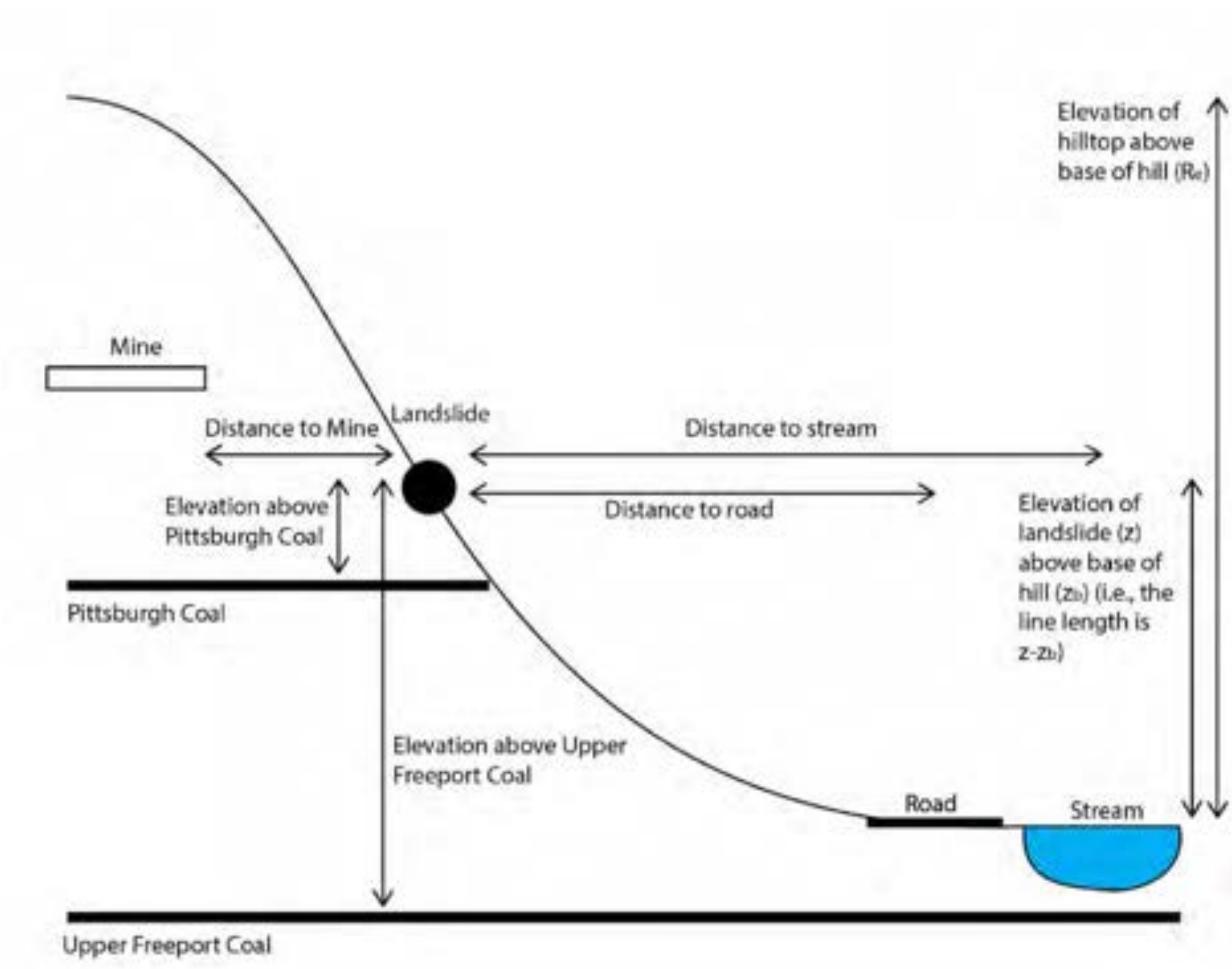

Figure 2.2.2. Schematic of key spatial metrics included in the database.

2.3 Topography

Topography influences the partitioning of water, biota, and physical stresses across the landscape and hence influence landslide occurrence. This section describes topographic data sources, processing method, and topographic parameters included in the database.

2.3.1 Topographic data sources

The topographic analysis relies on digital elevation models (DEMs) which are spatially located, uniformly gridded arrays of numerical values that describe surface elevation.

2.3.1.1 LiDAR data

The 1m resolution data was acquired 2006-2008 and is downloaded from <https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=1248>.

2.3.1.2 10m DEM data

The data is based on the USGS national elevation dataset (NED) (Gesch et al., 2002) which relies on the best available elevation data at each location, and is downloaded from <https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=10>.

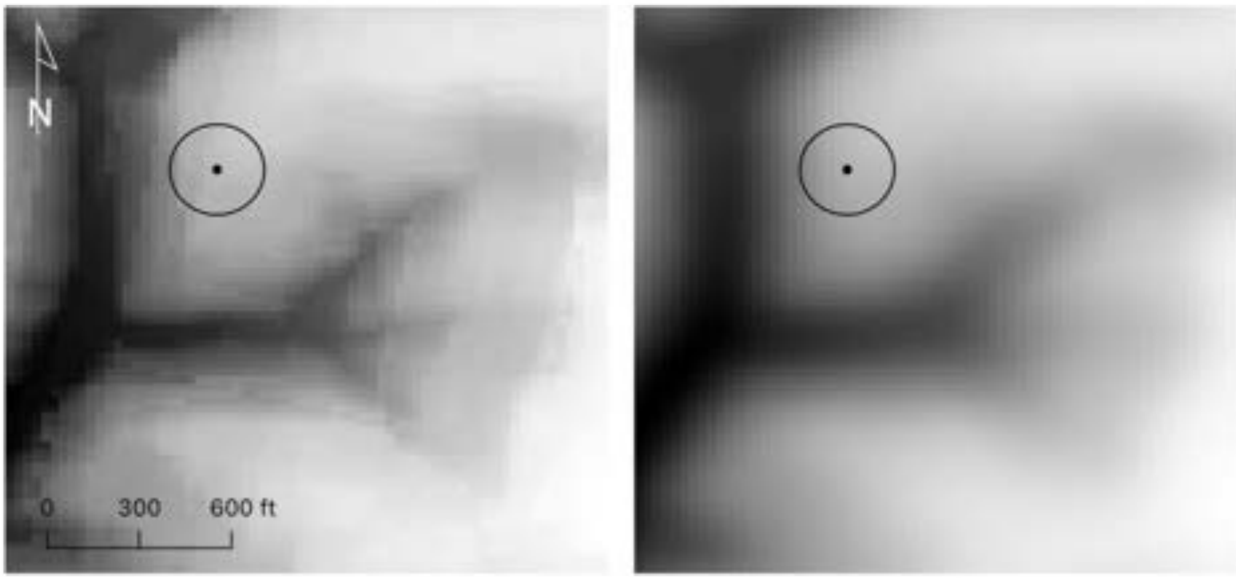

Figure 2.3.1. Raw (left) and smoothed (right) DEMs. The circle with the dot in the center illustrates the circular filter used for smoothing the DEM (the circular area is equivalent to the average area of the USGS active or recently active landslides in the study area). The smoothed DEM is produced by computing the average elevation of all raw DEM pixels within the circular filter, and assigning this average value to the pixel that the circle is centered on (where the dot is located). Repeating this procedure when the circular filter is centered on each DEM pixel produces the smoothed DEM.

2.3.2 Processing of topographic data

Topographic parameters for each landslide location were computed from the value of a raster pixel (or a neighborhood of pixels) at the landslide location. Pixel values were computed based on algorithmic processing of a DEM of the study area, mostly at a pixel resolution of ~30 ft (Section 2.3.1.2). Given that the typical area of landslide is often larger than that of a 30 by 30 ft DEM pixel, spatially averaged topography over a scale of a typical landslide is used to characterize the topographic characteristics associated with the landslide. Such averaging, often termed smoothing, also helps remove local fluctuation in the DEM pixel values that may stem from artifacts associated with the construction of DEMs. We created a smoothed DEM by applying a circular average filter (radius = 150 ft, based on the average area of active landslides in the USGS data) over the original DEM (Figure 2.3.1).

Most of the topographic parameters were computed based on this smoothed DEM. The computation was done with MATLAB, based on in house algorithms, combined with the TopoToolbox (Schwanghart and Scherler, 2014) and MATLABȏs mapping toolbox. We computed a raster (i.e., spatially located, uniformly gridded array of numerical values) of each of the topographic parameters from the aforementioned smoothed DEM. The latitude and longitude values of each landslide in the database (i.e., section 2.2.3), were then used to extract the value of each topographic parameter from the corresponding raster in the location of each landslide. In some cases (slides USGS 2, 3683, 3721, 3706, 3713, 4449, 3473,2878, 2813, 2350, 2042) landslides are very close to the study area boundary. Rasterization and smoothing resulted in edge effects where rasters were truncated at the edges. As a result, these slides do not have many of the derived parameters.

2.3.3 Topographic parameters

Elevation (ft):

Association with landslides: Elevation correlates with temperature, precipitation, and vegetation. Importantly, in areas of predominantly horizontal bedding, such as in large portions of SWPA, it also correlates with lithology. All of these parameters may affect landslide occurrence through erosion, pore pressure, freeze thaw, and substrate properties.

Description: The database shows the elevation above mean averaged sea level for the landslide polygon centroid or the landslide point location based on the smoothed DEM.

Local relief (ft):

Association with landslides: Local relief describes the range of elevation values over a prescribed scale, and hence is a general quantification of landscape steepness over this scale. Here it is calculated over a typical hillslope scale and hence represents the steepness of hill slopes as a key factor in landslide initiation.

Description: Local relief in each DEM pixel is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014)) and computes the difference between the highest and lowest elevations within a circular kernel whose radius is 820 ft (typical hillslope length) that is centered on each pixel.

Slope (degrees):

Association with landslides: Topographic slope affects the relative magnitude of the gravitational shear and normal forces that drive and resist landslide, respectively, as well as by changing the velocity of surface and groundwater flows, and associated erosion and/or pore pressure.

Description: Slope was computed from the smoothed DEM as the total gradient computed over a 3*3 kernel.

Topographic roughness (ft):

Association with landslides: Topographic roughness describes how rugged the terrain is, and ruggedness may be associated with local slopes, topographic depressions, and lithology, which may affect water flow, accumulation, and material properties, and hence propensity for landslides.

Description: Roughness was computed as the standard deviation of elevation differences between the original DEM and DEM that is smoothed with a kernel of 150 ft radius.

Aspect (azimuthal degrees, clockwise from north):

Association with landslides: Aspect (orientation of slope) is associated with the magnitude of solar radiation over the slope and orientation relative to prominent wind direction. Hence it may covary with evapotranspiration, vegetation cover, and snowpack which can affect soil saturation and cohesion and hence propensity for landslides.

Description: Aspect in each DEM pixel is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014)) and computes the slope orientation at the landslide location.

Drainage area (ft^2):

Association with landslides: Drainage area correlates with the quantity of water that drains to the landslide location, and hence its potential for landslide given the association between saturation, pore pressure, and landsliding.

Description: Drainage area in each DEM pixel is computed from the number of DEM pixels that drain to a pixel of interest, and is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014))).

Wetness index (index value):

Association with landslides: Wetness index models the potential for water accumulation in each landscape position (high values indicative of high accumulation potential), and hence its potential for landslide given the association between saturation, pore pressure, and landslide.

Description: Wetness index in each DEM pixel is computed from the natural logarithm of the ratio between the area (ft^2) that drains to the pixel and the topographic slope (ft/ft) of the pixel (both computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014))).

Hillslope Position (fraction 0-1):

Association with landslides: Parameters such as topographic gradient, curvature, soil thickness, and drainage area typically change down a hillslope (e.g., drainage area increases, soils become thicker). Given the effect of such parameters on pore pressure, soil strength, and shear stresses, such change may affect the propensity for landsliding.

Description: Hillslope position is the relative location along a hillslope, where values of 0, 0.5, and 1 represent the base, middle and top of the hill, respectively. The hillslope position is approximated as $(Z-Z_b)/R_e$, where Z is the elevation at the landslide location, Z_b is the lowermost elevation of the hill, and R_e is the hillôs topographic relief (i.e., elevation difference between the hillôs top and base, Figure 2.2.2). Z_b and R_e are approximated by finding the minimum and maximum elevations within a circular area, centered on the landslide, whose radius equals a typical hillslope length (~820 ft).

Distance to nearest stream (ft):

Association with landslides: Distance to nearest stream can capture the influence of stream incision on erosion and steepening of hill toes and induction of landslide.

Description: Based on an ArcGIS algorithm that creates a raster of Euclidean distances from the nearest stream (i.e., the ñDistance Accumulationò function), where streams are defined as landscape positions having drainage area larger than 4,500,000 ft^2 (based on a typical drainage area threshold for channel initiation). Distance from nearest stream is then sampled from this raster. See Figure 2.2.2.

Distance to nearest road (ft):

Association with landslides: Distance to nearest road can capture the influence of roads on hydrology and topographic modifications (i.e., roadcuts, road fills) and thus be associated with propensity for landslides.

Description: Based on an ArcGIS algorithm that creates a raster of Euclidean distances from the nearest road (i.e., the ñDistance Accumulationò function), where roads, including dirt roads, are based on the combination of State Roads, Local Roads, and Unpaved Roads (Penn State - Center for Dirt and Gravel Road Studies, 2012; Pennsylvania Department of Transportation, 2024a, 2024b). Distance from nearest road is then sampled from this raster. See Figure 2.2.2.

Mean curvature (ft^{-1}):

Association with landslides: Mean curvature is associated with the convergence/divergence of water in plan view (i.e., viewed from above). Mean curvature increases/decreases slope downstream, and hence combines potential hydrologic and topographic effects on landslide occurrence.

Description: Mean curvature (Figure 2.3.2) in each DEM pixel is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014)) and relies on the curvature of a two dimensional polynomial surface computed based on a 3*3 kernel centered at each DEM pixel (Schmidt, Evans and Brinkmann, 2003). Positive and negative values are indicative of concave (channels) and convex (ridges) landforms, respectively.

Planar Convex Planar Concave Profile Curvature

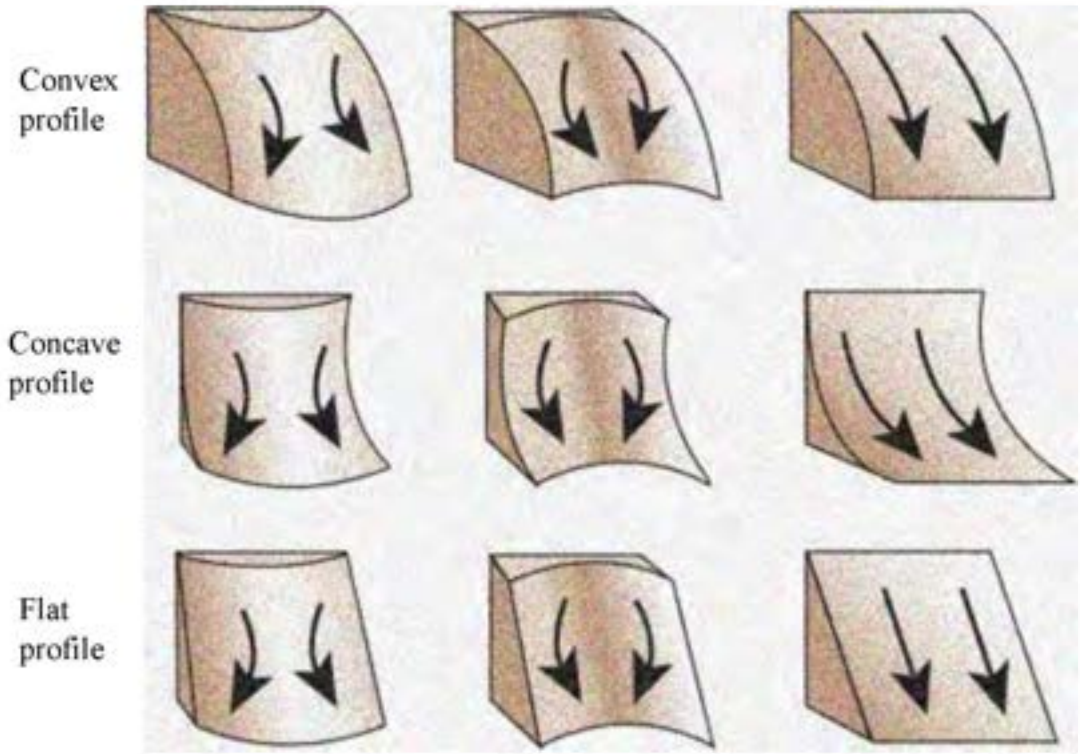

Figure 2.3.2. Illustration of curvatures. Left hand column is convex planform (i.e., map view) curvature types, center column is concave planform curvatures, and right-hand column is profile curvature types. Figure modified from <https://www.esri.com/arcgis-blog/products/product/imagery/understanding-curvature-rasters/>.

Planar curvature (ft^{-1}):

Association with landslides: Planar curvature (Figure 2.3.2) is associated with the convergence/divergence of water in plan view and hence describes topographic effects on hillslope hydrology that might be related to saturation, erosion, and landslide occurrence.

Description: Planar curvature in each DEM pixel is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014)) and relies on the curvature, perpendicular to the steepest descent of a two dimensional polynomial surface computed based on a 3*3 kernel centered at each DEM pixel (Schmidt, Evans and Brinkmann, 2003). Positive and negative values are indicative of upstream (channels) and downstream (ridges) curvature, respectively.

Profile curvature (ft^{-1}):

Association with landslides: Profile curvature (Figure 1) describes changes in topographic gradient in the direction of steepest descent and may capture potential effect of changes in gradient on landslide occurrence.

Description: Profile curvature in each DEM pixel is computed from the smoothed DEM using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014) and relies on the curvature, in the direction of steepest descent, of a two dimensional polynomial surface computed based on a 3*3 kernel centered at each DEM pixel (Schmidt, Evans and Brinkmann, 2003). Positive and negative values are indicative of decreased and increase slope downstream, respectively, which are typically associated with channels and ridges, respectively.

2.4 Soil

Soil characteristics influence the hydrology and cohesion of soils, as well as their depth, and hence affect the characteristics of landslides and their likelihood.

2.4.1 Soil data sources

Soil characteristics were extracted from the SSURGO database (Soil Survey Geographic, <https://www.nrcs.usda.gov/resources/data-and-reports/soil-survey-geographic-database-ssurgo>). SSURGO is a comprehensive soil information system maintained by the United States Department of Agriculture's Natural Resources Conservation Service (NRCS) based on the historical county soil surveys (Soil Survey Staff, 2023).

2.4.2 Processing of soil data

SSURGO database contains a series of hierarchical (mapunit Ÿ component Ÿ horizon), one-to-many tabular relationships between spatial and attribute data. The associated tables are linked by keys as follows: The mapunit key (ñmukeyò) links the data to the polygons representing the relevant soil map unit spatial extent. In turn, the mapunit table links to the component table on ñcokey.ò Likewise, the component table links to the chorizon table on ñchkey.ò (Thus, mapunits are linked to horizon characteristics through the component table). To produce a map of the spatial distribution of soil parameters, two aggregation steps are required. First, a weighted-average value was calculated for all soil horizons (i.e., chorizon data) within a soil component, weighting the average based on their relative thickness. Using these weighted component values, a weighted-average value was computed for all soil components within a soil mapping unit that considers the percentage composition of each component within that unit (e.g., the Gilpin Usher series contains characteristics of both the Gilpin soil and the Usher soil). This weighting captures the relative contribution of soil characteristics from each component. In cases where an entity did not have data, these components were removed from the weighting and the weighted average reflects only horizons or components where data was available.

Values for soil parameters were calculated using SSURGO data as described above including soil thickness, soil texture (clay, silt, and sand percentages), AASHTO [American Association of State Highway and Transportation Officials] group index, erodibility factor, porosity, and hydraulic conductivity. In contrast, soil components have values for soil properties such as soil slip potential, erosion/drainage/run off class. In these cases, only the component weighting was calculated as horizon data do not include values. Finally, parameters such as planning limitation and potential for erosion hazard are provided for soil series in the SSURGO data and therefore do not need to be aggregated.

One parameter, the porosity (dimensionless) was derived indirectly from chorizon data for each horizon by dividing the bulk density of the soil (i.e., ñwthirdbar_rò in the SSURGO database) by quartz density (2.65 g/cm3). This dividend was subtracted from one to determine the horizon porosity. Then the weighted averaging for soils, as described above, were applied to the horizon and component porosities to determine the average soil porosity.

Given the uncertainty in both the landslide location and the soil parameter values (soil mapping is generally based on a single data point every four acres), soil parameters were sampled from an average of local values. Soil parameter rasters were smoothed by applying a circular average filter (radius = 150 ft, based on the average area of active landslides in the USGS data) over the original soil parameter raster. In some cases (slides USGS 2, 3683, 3721, 3706, 3713, 4449, 3473,2878, 2813, 2350, 2042) landslides are very close to the study area boundary. Rasterization and smoothing resulted in edge effects where rasters were truncated at the edges. As a result, these slides do not have many of the derived parameters.

2.4.3 Soil parameters

Soil Unit:

Association with landslides: N/A

Description: This is a name for the soil, generally based on historical soil series names generated for county soil surveys. This name allows linkage of experience based on soil survey names to the quantitative measures presented here.

Sand content (%):

Association with landslides: Sandy soils are generally well drained. That is, high sand content results in drier, lower pore pressure, and therefore less landslide prone soils. Sand can play a conflicting role at the extreme (e.g., entirely sandy soils, 90%+) where sand's much lower cohesion can increase the likelihood of slope failure (e.g., consider sand dunes).

Description: Component proportion and horizon thickness weighted average of percent sand in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Silt content (%):

Association with landslides: Soil textures are described as a mix of clay/silt/sand. Within this mix, silt is the middle size particle and does not have the extremes in drainage and cohesion characteristics of sand and clay. A silt-rich soil is not necessarily a landslide prone soil due to particle size alone but reported here as part of the clay/silt/sand mix.

Description: Component proportion and horizon thickness weighted average of percent silt in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Clay content (%):

Association with landslides: Clay content is a primary control on soil water retention. Clay-rich soils drain poorly and therefore can have elevated landslide risk during periods of soil water saturation. In addition, clays tend to have more pore space and be more cohesive than silty or sandy soils, in both cases influencing the likelihood of landsliding.

Description: Component proportion and horizon thickness weighted average of percent clay in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Erodibility factor ($K_w$fact, unitless):

Association with landslides: This is an empirically derived factor used for erosion modelling in universal soil loss equation approaches. The erodibility reflects soil cohesion and hillslope microtopographic patterns. Both factors can influence the likelihood of a hillslope soil to slide.

Description: Component proportion and horizon thickness weighted average of soil erodibility factor in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Average soil thickness (in):

Association with landslides: Soil depth can provide information on sediment supply (i.e., soils will be relatively thin following a landslide, so thin soils can indicate lower supply and therefore lower probabilities of additional sliding). Similarly, deeper soils can retain more water, increasing pore pressure and water saturation increasing the potential for slope failure.

Description: Component proportion weighted average total thickness of soil horizons in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map. Note that SSURGO data may not report the total depth of soils, and use of this parameter should incorporate that limitation.

AASHTO soil index:

Association with landslides: The AASHTO index is a measure of sediment characteristics and resulting suitability for highway construction. It combines soil plasticity, liquid limit, and sediment size mix. These characteristics can provide insight into the propensity for soils to slide, particularly combinations of characteristics on soil cohesion. A high index value indicates high suitability and vice versa.

Description: Component proportion and horizon thickness weighted average of AASHTO soil classification in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Erosion hazard potential:

Association with landslides: This is a hazard rating generated during the compilation of the county soil surveys. As with the erosion factor, this rating incorporates information about soil cohesion and local topography, and both can provide important inference about relative slope stability.

Description: Pre-aggregated data in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location. These values are assigned to the soil map unit, so smoothing was not used for this parameter. [Class Description: Not rated, Slight, Moderate, Severe]

Erosion class:

Association with landslides: Erosion class is measure of cumulative estimated soil loss in a soil unit. Areas in the higher loss categories can reflect the impacts of landsliding on hillslope soils (landsliding removes soil materials) and thus included in the database as a means to identify areas with elevated soil loss and therefore potential landslide activity.

Description: Component percent weighted sum of erosion class in SSURGO database (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map. [Class Description: Area of sediment deposition = 0, Class 1 (0-25% soil loss) = 1, Class 2 (25-75% soil loss) = 2, Class 3 (75-99% soil loss) = 3, Class 4 (complete soil loss) = 4]

Planning Limitations - Local Roads and Streets:

Association with landslides: A qualitative measure from the county soil surveys indicating the suitability of the local soils for road emplacement. This measure includes the propensity of the soil to erode or fail and can provide insight into landslide patterns.

Description: Assigned to mapunit based on soil surveys (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location. These values are assigned to the soil map unit, so smoothing was not used for this parameter. [Class Description: Not rated, Not limited, Somewhat limited, Very limited].

Drainage class:

Association with landslides: The rate of drainage is a primary control on soil moisture. Poorly draining soils tend to accumulate water during wet weather periods, affecting soil cohesion and pore pressure, both important factors in the potential for landslides.

Description: Component percent weighted sum of drainage class in SSURGO database (Soil Survey Staff, 2023) for the mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map. [Class Description: Excessively drained =1, Somewhat excessively drained =2, Well drained = 3, Moderately well drained =4, Somewhat poorly drained = 5, Poorly drained =6, Very poorly drained =7]

Runoff class:

Association with landslides: Runoff is an important part of soil moisture content, more runoff results in lower soil water content. Water content impacts soil cohesion and pore pressure. In addition, increased runoff results in higher, faster flows which likely erode more soil.

Description: Component percent weighted sum of runoff class in SSURGO database (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map. [Class Description: Negligible =1, Very low =2, Low =3, Medium =4, High= 5, Very high =6]

Soil slip potential:

Association with landslides: An indicator of slip potential derived as part of the county soil survey series. A qualitative measure of slip potential, i.e., slide potential.

Description: Component percent weighted sum of soil slip potential in SSURGO database (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map. [Class Description: Low=1, Medium =2, High=3]

Soil porosity (in3/in3):

Association with landslides: Soil porosity is a direct constraint on soil moisture content, and therefore directly impacts soil drainage, cohesion, and pore pressure, all strong influences on the likelihood of landsliding.

Description: Component proportion and horizon thickness weighted average of soil porosity in SSURGO database (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

Saturated hydraulic conductivity (micrometers per second):

Association with landslides: An empirically measured rate of water flow through a soil. This rate is a primary control on soil water content which affects soil cohesion and pore pressure, both influence the potential for landslides. Soils with high hydraulic conductivity tend to be well drained, and vice versa.

Description: Horizon thickness and component proportion weighted average of horizon vertical conductivities in SSURGO database (Soil Survey Staff, 2023) for mapped soil unit at landslide polygon centroid or landslide point location on the smoothed parameter map.

2.5 Geology

Geologic parameters affect rock strength, hydrologic properties, and soil formation, as well as mining activities, all of which can influence landslide occurrence. This section describes geologic data sources, processing method, and geologic parameters included in the database.

2.5.1 Geologic data sources

The geologic analysis relies on both digitized geologic maps and contours of key coal horizons.

2.5.1.1 Bedrock geology

We used the digitized version of the state geologic map (Pennsylvania Bureau of Topographic and Geologic Survey, Department of Conservation and Natural Resources, 2001) for bedrock geology data. This version is available from the PA DCNR and is mapped at the formation and group level: <https://www.dcnr.pa.gov/Geology/GeologyOfPA/Pages/default.aspx>.

2.5.1.2 Coal contours

The USGS mapped the top of seam elevations of regionally important coal deposits (i.e., the Pittsburgh and Upper Freeport Coals) through a synthesis of available data (Northern and Central Appalachian Basin Coal Regions Assessment Team, 2001). These data are available here: <https://pubs.usgs.gov/pp/p1625c/>.

2.5.1.3 Mining data sources

The Pennsylvania Department of Environmental Protection (PADEP) tracks all areas undermined in their Digitized Mined Areas data set (Pennsylvania Department of Environmental Protection, 2023b) located here: <https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=257>. These data were used to evaluate the proximity of landslides to historical mining activity.

For specifics about the nature of mining, in some cases historical mine maps from the Pennsylvania Mine Map Atlas <https://www.minemaps.psu.edu/> were accessed.

In addition, mining activity was cross-checked with the abandoned mine land records maintained by the PADEP (Pennsylvania Department of Environmental Protection, 2023a) and available here: <https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=460>. These records often provide information about both surface and underground mining extents, including subsidence locations.

2.5.2 Processing of geologic data

The state geologic map and coal contours were used to extract geologic information pertinent to regional landsliding. A rasterized version of the state geologic map, where each formation is associated with an integer index value, was used to extract this index value for each landslide location. The index was then converted to a textual formation name based on a conversion table, which was placed in the database. The coal contours of the Pittsburgh (PGH) and Upper Freeport (UFR) Coals were used to create rasters of these coalbed elevations (these rasters were not smoothed). The overburden above each coalbed was computed by subtracting its coalbed elevation from the topographic elevation. The dip and aspect (dip direction) of the coalbed were computed from the coalbed rasters using TopoToolbox (Schwanghart and Scherler, 2014). The mining data was used to compute a raster of the distance between landslides and mines. For landslides located directly above mines, the elevation of the coal marker beds was used to approximate the elevation difference between the surface and the mine and store it in a raster. Values from these rasters were extracted at each landslide location. In some cases (slides USGS 2, 3683, 3721, 3706, 3713, 4449, 3473,2878, 2813, 2350, 2042) landslides are very close to the study area boundary. Rasterization and smoothing resulted in edge effects where rasters were truncated at the edges. As a result, these slides do not have many of the derived parameters.

2.5.3 Geologic parameters

Geologic Formation or Group (name):

Association with landslides: Different formations or groups are associated with different lithologic characteristics that affect the propensity for landslides.

Description: Geologic formation or group (as defined by Pennsylvania Bureau of Topographic and Geologic Survey, Department of Conservation and Natural Resources (2001)) at the landslide polygon centroid or landslide point location.

Elevation above Pittsburgh or Upper Freeport coal (ft):

Association with landslides: Given the sub-horizontal lithologic layers common across the study area, elevation above such marker beds may correlate with specific layers that are landslide prone.

Description: This is based on the elevation difference between the topographic surface and the marker bed elevation at the location of each landslide. In areas that are not underlain by a marker bed, no value is assigned. See Figure 2.2.2.

Dip of Pittsburgh or Upper Freeport coal (degrees):

Association with landslides: The dip of the marker bed may be indicative of the dip of the layers above it. Hence it may be indicative of the dip-related lithologic weakness planes, as well as the routing of groundwater, both may affect landslides.

Description: The dip was computed from the marker bed raster as the total gradient computed over a 3*3 kernel.

Aspect of Pittsburgh or Upper Freeport coal (Measured in azimuthal degrees, clockwise from north):

Association with landslides: The aspect of the marker bed describes the direction of the dip and can help identify locations where the lithology dips with or against the direction of the topographic slope. The relations between the lithologic dip and the topographic slope can dictate whether failure planes are aligned with gravitations stresses, and whether groundwater are likely to discharge at the surface, causing elevated pore pressure and promoting landsliding.

Description: Aspect in each marker bed pixel is computed using TopoToolbox (a MATLAB based set of topographic analysis algorithms, (Schwanghart and Scherler, 2014)) and reflects the orientation of the marker bed dip the landslide location.

Distance to underground mine (ft):

Association with landslides: Mined areas may be associated with hydrologic, surface, and lithologic disruptions, all of which may be associated with landslide occurrence.

Description: Based on an ArcGIS algorithm that creates a raster of Euclidean distances from the nearest underground mine (i.e., the ñDistance Accumulationò function), where underground mines are defined by the PADEP ñDigitized Mined Areasò (Pennsylvania Department of Environmental Protection, 2023b). A distance of zero implies that a mine is mapped directly below the landslide. See Figure 2.2.2.

Depth to underground mine (ft):

Association with landslides: The elevation difference between the surface and the mine may reflect the extent to which the mining activity influences surface lithology, topography, and hydrology and thus propensity to landslides.

Description: Elevation of landslide above uppermost mapped coal contours (i.e., PGH or UFR coal) if mining occurred directly below the landslide polygon centroid or point. See Figure 2.2.2.

2.6 Weather

Weather, primarily precipitation and freeze-thaw cycles, influences soil moisture status and therefore pore pressure and soil cohesion, as well as water availability and infiltration, and can hence influence landslide occurrence.

2.6.1 Weather data sources

Precipitation and temperature data are based on PRISM. The PRISM group has mapped spatially continuous daily weather data at 800m and 4km pixel resolution across the continental United States from roughly 1900 to present (PRISM Climate Group, 2014). Precipitation was recorded in the database as the average daily precipitation over different periods prior to the landslide (see section 2.6.2). Freeze thaw occurrences were determined based on the maximum and minimum daily temperatures over periods of different length prior to the landslide (see section 2.6.2).

2.6.2 Processing of weather data

The PRISM datasets, originally at a native grid resolution of 0.8km, have been coarsened to 4km resolution on the PRISM website to facilitate analysis at wider spatial scales. PRISM utilizes a weatherï elevation regression approach for interpolating values based on a combination of weather data and DEMs. In this process, weather stations contributing to the regression are assigned weights, primarily determined by the physiographic resemblance (e.g., elevation, slope, aspect, distance to ocean) of the station to the specific grid cell. In the study area, daily PRISM data exist between 1982-2022 for the study area and was downloaded using R <https://cran.r-project.org/web/packages/prism/vignettes/prism.html#download-30-year-normal-data>.

The PRISM data was processed using an in-house algorithm coded in MATLAB. For each landslide associated with a date of occurrence/reporting in the database, the algorithm reads the daily PRISM maps for a specified period prior to the landslide, locates the landslide, and records daily precipitation or temperature data for that location over the specified period. These time series of weather data at each location are then used to compute measures of weather prior to the landslide. For precipitation, the PRISM precipitation data was used to compute average daily precipitation over several time spans (1, 2, 7, 30, 90, and 180 days) prior to a given landslide. For temperature, average temperatures over different time periods preceding a landslide (7, 30 and 365 days) were calculated from the PRISM data. In addition, the number of freeze thaw cycles was computed as follows: a freeze period was considered to start when a day with a max temperature higher than 34ÁF dropped to a minimum temperature less than 28ÁF. The freeze period continues as long as the daily maximum temperature does not exceed 34ÁF. These temperature thresholds are based on temperatures necessary to freeze or thaw water at depth in a soil (Fraser, 1959). The number of times a freeze occurred was counted over the period of interest. The mean length of freeze thaw cycles was computed by dividing the length of the period by the number of cycles. The mean (and minimum) freeze temperature was computed from the average (and minimum) of the minimum and maximum daily temperatures over freeze periods.

2.6.3 Weather parameters

Weather influences landslides in several ways. Precipitation can affect pore pressure and erosion, and freeze thaw can affect soil permeability and cohesion, thus influencing conditions for landsliding.

Daily Precipitation (in):

Association with landslides: Precipitation can increase pore pressure and erosion and thus influence landslide occurrence.

Description: The mean average precipitation was computed over a period of 1, 2, 7, 30, 90, and 180 days prior to landslides that have an associated date of landslide occurrence.

Freeze thaw cycles:

Association with landslides: Water expands by ~11% upon freezing. Therefore, water freezing at depth can affect soil and rock void space. These alterations to hydrologic flowpaths change soil permeability, cohesion, and pore pressure. Multiple episodes of freezing and thawing can have additive effects (larger void spaces allow more water in, increasing the expansion during freezing, creating even larger voids, etc.). Additionally, during freeze periods, soil cohesion should increase substantially, limiting landslide activity.

Description: The number of freeze thaw alterations over periods of 7, 30 and 365 days were counted prior to landslides that have timing information. In addition, the average length of freeze and thaw periods within these time periods was calculated.

Freeze thaw temperatures (for periods of 7, 30 and 365 days prior to landslides that have timing information):

Association with landslides: Freeze thaw temperatures can affect the depth of shrink swell (expansion and contraction due to freezing of water and melting of ice) in soils, and thus mechanical properties (e.g., cohesion, permeability) and soil creep.

Description: The database includes the mean and minimum temperature of freeze periods, the mean temperature of thaw periods, and the mean temperature of all days for each period.

2.7 Quality assurance

Quality assurance (QA) procedures were developed to assure the accuracy of spatial and temporal data at landslide location and time. Given that the characterization of each landslide primarily relies on extraction of data from maps and weather datasets, the QA focused on inspecting this spatial and temporal data. Note this process was iterative, that is, when an issue was identified and fixed, a new subset of the database was sampled and subjected to the QA process.

Spatial Data QA: The spatial data was primarily extracted from rasters (spatially grided data) at landslide locations. Raster data is described in sections 2.1, 2.3-2.5. Some of the rasters were created from vector data (a data structure that uses points, lines, and polygons to represent spatial features). Relevant ArcGIS shapefiles (e.g., roads, geologic formations, soil properties, mined areas) were converted to rasters. We verified the consistency between the original shapefile and derived raster values by querying a subset of locations and making sure that shapefile and raster values are consistent.

Parameter Value QA: The numerical values stored in the database were first evaluated for illogical values and/or inconsistencies with measurement units (e.g., porosity values larger than 1 (porosity should range between 0 and 1)). Once identified these data issues were inspected to identify the causes of poor-quality data. Often these issues required fixes to the procedures described in sections 2.1.2 and 2.1.3.

QA at specific landslide locations: This was the bulk of the QA procedure and consisted of multiple steps:

A subset of ~3% of all landslides in each county was randomly selected, to provide a representative sample across space and data sources. This subset of slides (N=220) was divided among team members.

Each member QAœ̂d a portion of the slides allocated to them to identify potential problems. The QA focused on making sure that the values of all the parameters recorded in the database table for each specific landslide are consistent with the raster value at this location. We also checked if the raster values are consistent with values measured directly from the map using ArcGIS (for example, measurements of distance from road or distance from mine). Weather data for each landslide was evaluated by looking for illogical cases, for example, multiple freeze thaw cycles on summer months when such cycles are not expected, or unrealistic average temperatures given the season of landslide occurrence.

The causes for the QA issues detected in the prior step were fixed, and the QA procedure resumed focusing on making sure that the issues detected indeed were corrected while continuing to identify any additional QA issues. This procedure was repeated iteratively several times until no more QA issues were detected.

Despite this rather robust QA procedure it is likely that QA issues will be detected in the future as people work with the database. These issues can be addressed when the database is periodically updated.

2.8 How to use the database

The database will be provided in two forms: 1) a .csv file with cross-platform optimized parameter names (e.g., minimized spaces, special characters, etc.); and 2) an excel sheet with parameters grouped by data content and built in data querying tools turned on. A screen shot of a portion of the data base is shown in Figure 2.8.1.

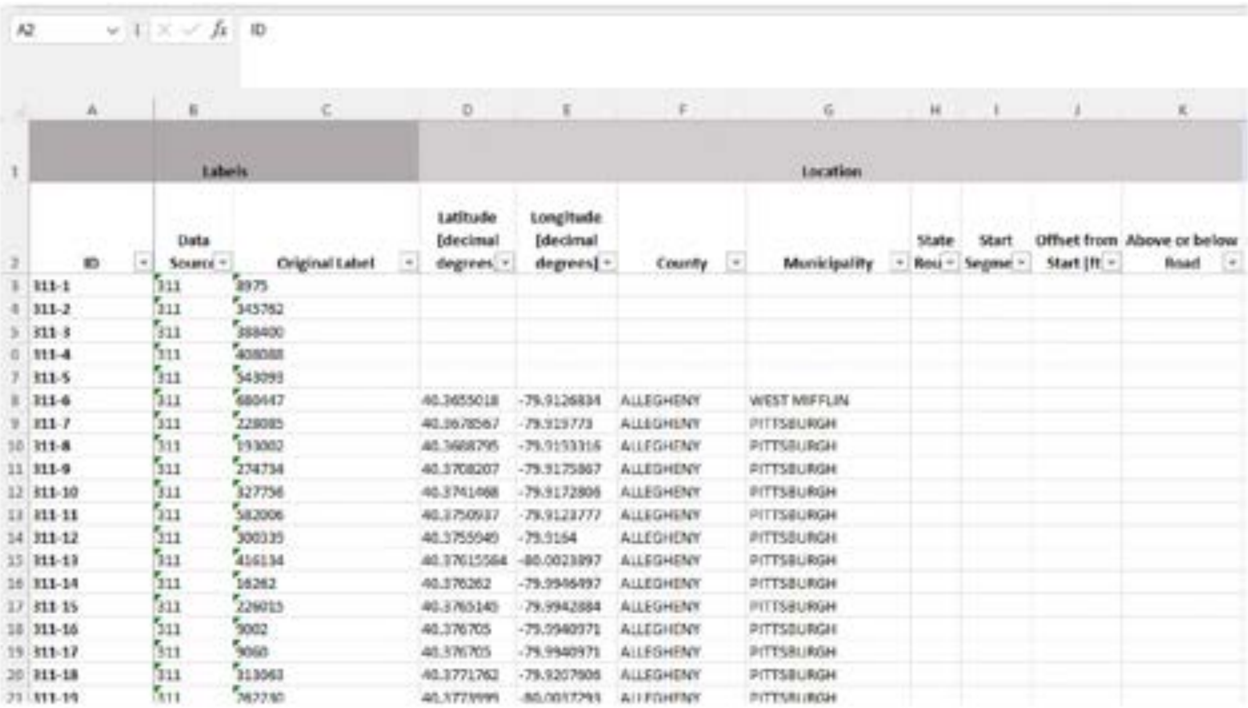

Figure 2.8.1. Screenshot of upper left corner of database table. Note the first two rows are frozen, keeping the column labels at the top of the screen as the user scrolls through the data. The parameter names (row 2) have the ñFilterò tool turned on. That allows a user to pick a specific value or range of values for a parameter and will only show those values on the table.

This set up allows the user the ability to quickly identify slides of interest using Microsoft Excel. For example, a user may want to examine slides occurring in the Glenshaw Formation following intense precipitation. The user would navigate the database, moving right in the spreadsheet to the ñGeologic Formation or groupò column, click on the column name to open the filter tool and select only the Glenshaw Formation (Figure 2.8.2a). After selecting ñOKò, this will result in the spreadsheet only displaying the 815 landslides in the Glenshaw Formation (Figure 2.8.2b). Then the user would navigate over to the weather section of the database and use the filter tool to select precipitation greater than an inch on the day of the landslide (Figure 2.8.2c).

This set of selections results in 24 landslides. This small number is primarily a result of the limited number of landslides with a reported date of occurrence, discussed at several points in this report. In this case, 479 of the 815 landslides in the Glenshaw Formation have no date associated with them, and as a result have no weather measurements.

Once these filters have been applied, the user is able to look for similarities in the parameters. For example, thirteen of the 24 landslides are either in the Tyler Silt Loam or Ginat Silt Loam, suggesting these soil series might be particularly prone to landsliding following intense precipitation. However, given the limitations of landslide date data this subset should be examined with caution as the small sample size can accentuate the influence of outliers (see section 4.1).

As for data input, these workflows will be developed by agencies as part of their operating procedures. There are several parameters where recording the data at the time of the slide (or soon after) can improve database content. These parameters include: location data, date data, location of the slide above or below the road, the slide type according to DCNR classification, landslide area, landslide downslope displacement, and depth to failure plane. These parameters should be prioritized in data entry procedures.

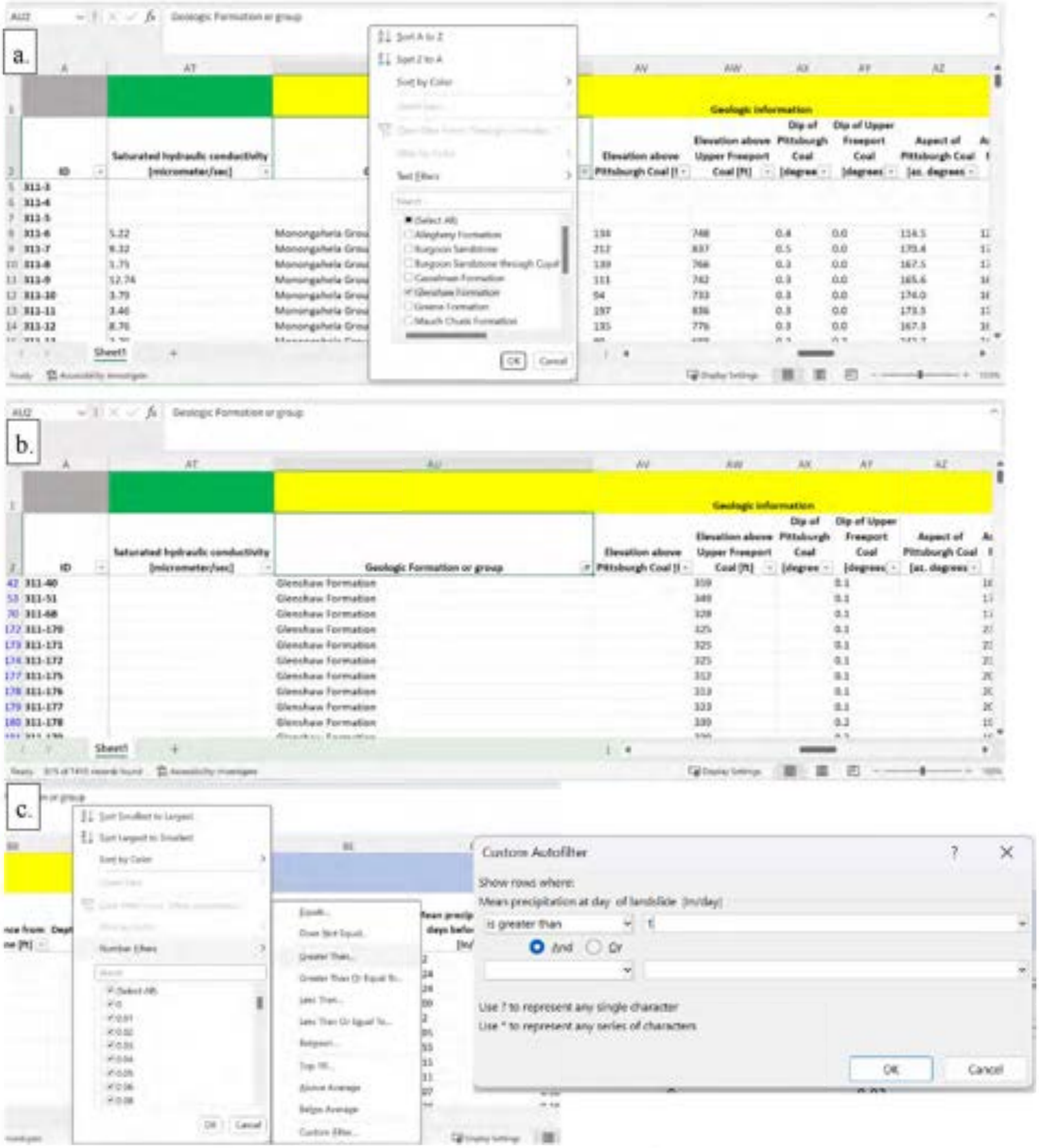

Figure 2.8.2. Screenshots of the Microsoft Excel version of the landslide database. Panel a. shows the use of the filter tool, selecting only the landslides in the Glenshaw Formation. Panel b. shows the outcome of that choice where only 815 landslides are shown, all in the Glenshaw Formation. Panel c. shows how to use the filter tool to select a range, in this case precipitation greater than one inch on the day of the landslide. The window on the right of panel c opens when the selection shown on the left of panel c is made.

3 .0 Database

3.1 Summary of data

The database contains records of over 7400 landslides (Figure 3.1.1) characterized by more than seventy parameters. These landslides occur as early as 1920 and the database includes landslides through parts of 2023. Data are drawn from a variety of sources summarized in section 2.2.1. The vast majority of landslides have location data (~99%), approximately 42% are associated with a reporting date, and approximately 37% include weather data. The numbers of landslide records pulled from each of these data sources are summarized in Table 3.1.1.

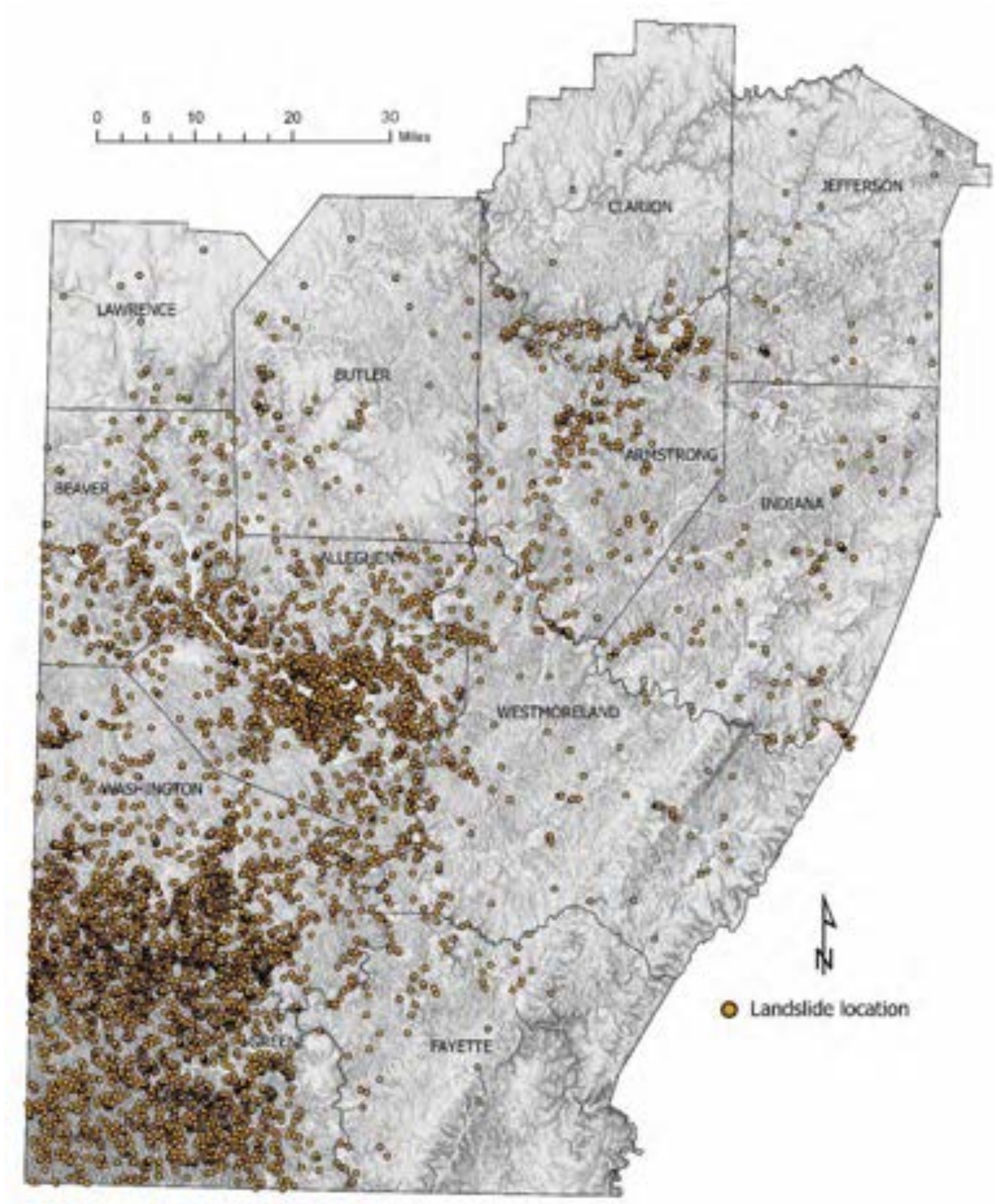

Figure 3.1.1. Hillshade map of the study area with county boundaries and locations of all reported landslides.

Table 3.1.1. Number of landslide records derived from each data source.

Data Source	Number of Slides
Ackenheil Dissertation	90
Pitt Landslides of Consequence	8
Adams Dissertation	223
USGS	4844
NASA	127
PennDOT District 10	243
PennDOT District 11	282
PennDOT District 12	427
Allegheny County	55
City of Pittsburgh	78
Pittsburgh 311	1033
Borough of Forest Hills	3

These records are not distributed evenly across space or time. Far southwestern Pennsylvania (i.e., Washington and Greene Counties) had far more landslides per area recorded in the USGS mapping than other regions. These patterns were surprising to the USGS team mapping the landslides, and they conducted field surveys to confirm the air photo interpretation (Pomeroy, 1986). There is also a concentration of landslides in and near the City of Pittsburgh. This largely is a result of data derived from the 311-reporting system,

3.1.1 Dates of landslide occurrence

Landslide records are not continuous in time. The most comprehensive historical records are the USGS landslide data (Pomeroy, 1982). These data were gathered as a reaction to widespread regional landsliding associated with intense precipitation generated by Hurricane Agnes. In addition, during this mapping, areas of apparent landsliding that were judged to pre-date 1972 (e.g., conspicuous slumps but with re-established vegetation) were also mapped.

There are other collections of landslides with reasonable temporal constraints, but most of these are focused on Allegheny County. Alfred Ackenheilȏs dissertation research includes a set of 68 landslides with time stamps (Ackenheil, 1954). The 311 data have time stamps, but these records are limited to the City of Pittsburgh. Many of the PennDOT and NASA slides are also associated with temporal information. We note that this temporal information likely reflects the time at which landslides were reported, which is not necessarily identical to when they actually occurred.

3.2 Accessing the database

The database files are hosted at the WPRDC https://data.wprdc.org/dataset/irise-regional-landslide-inventory-for-southwestern-pennsylvania. As noted in section 2.8, the database is provided for download in both a .csv and Microsoft Excel format.

In the public facing version of the document, there are portions of the data not provided. The PennDOT regional geotechnical data records [Section 2.2.1.2.1] are not included in the public facing version of the database. For access to these data, the user will need to contact PennDOT directly.

4 .0 Exploring the database

Whereas this report does not aim to analyze the landslides in the database, the following section includes examples of simple analyses. These analyses aim to demonstrate the power of the data-centered approach and explore various dimensions of the database to illustrate the forward potential of this database, as well as its limitations.

4.1 County-scale variability in landslides across the study area

Examination of landslide characteristics across counties highlights variability within the study area and demonstrates both true spatial differences as well as biases introduced by differences among data sources (Table 4.1.1).

The number of landslides and their density varies meaningfully between counties. Washington, Allegheny, and Greene counties have the highest number and density (i.e., number per area) of landslides in the database while Clarion, Lawrence and Jefferson have the lowest number and density values. These differences reflect a combination of true propensity for landslides and a reporting bias. For example, landslide reports through the 311 citizen-report system (1028 slides, about half of the slides in Allegheny County) exist only for the City of Pittsburgh, inflating the count of slides in Allegheny County.

Landslides tend to be more common over specific geologic formations, and the make-up of these formations varies between counties. The number of landslides in a given formation, however, depends not only on the local propensity of the formation for sliding, but also on the extent of formation exposure within the county. Hence, when analyzed in terms of likelihood (i.e., number of landslides per area over which each formation is exposed), patterns differ from those that rely simply on the number of landslides in a given formation. For example, whereas in Greene County most landslides occur in the Greene formation, the likelihood for landslide occurrence is higher in the Washington formation (again this arises from the common occurrence of the Greene formation in Greene County relative to the Washington Formation). Sometimes the raw counts and likelihoods converge as in Allegheny County, where landslides are both most common and most likely in the Casselman Formation.

The number, percent, and density of landslides in proximity to roads (within 100 ft) vary meaningfully between counties, and ranges between 12-1535 slides (Lawrence and Allegheny counties, respectively), ~14-88% of all slides (Washington and Jefferson counties, respectively), and ~0.1e-5 to 4e-5 slides per feet of road (Lawrence and Greene County, respectively). These differences likely reflect a combination of the effect of roads on landslide propensity in different counties, as well as bias introduced by different data sources. For example, In Fayette County, the vast majority of landslides (>80%) are sourced from PennDOT, and hence are constrained to those that influence roads (and are hence adjacent to roads). In Washington County, on the other hand, most landslides (>90%) were mapped by USGS and are therefore not necessarily constrained to those that are in proximity to road.

Table 4.1.1. Comparison of selected landslide characteristics between counties in SWPA.

County	Number of Slides	Slide Density in county [slides/ mile^2]	Geologic formation with most slides	Geologic formation in which landslides are most likely	Number of slides within 100 ft from roads [#]	Percent of slides within 100 ft from roads [%]	Number of slides within 100 ft from roads per road length in county [#slides/ft]	Average topographic slope where landslides occur [degrees]	Ratio between Average topographic slope where landslides occur and average slope in a county	Average soil clay content where landslides occur [%]	Percent of Penn DOT slides without date [%]	Average precipitation per day in the 7 days before slides [In/day]	Average number of freeze thaw cycles within 30 days prior to slides [#]
ALLEGHENY	2119	1.73	Casselman Formation	Casselman Formation	1535	72.4	3.76E-05	11.65	1.76	17.67	75.6	0.19	6.68
ARMSTRONG	315	0.29	Allegheny Formation	Pottsville Formation	122	38.7	1.40E-05	16.01	2.23	21.41	97.5	0.15	9.65
BEAVER	317	0.43	Glenshaw Formation	Allegheny Formation	169	53.3	1.63E-05	13.11	2.07	22.87	81.3	0.15	6.82
BUTLER	83	0.06	Allegheny Formation	Casselman Formation	39	46.9	1.91E-06	9.78	2.04	20.80	100.0	0.09	5.84
CLARION	25	0.02	Allegheny Formation	Pottsville Formation	14	56.0	2.35E-06	11.45	2.24	17.00	91.7	0.15	9.91
FAYETTE	78	0.06	Monongahela Group	Monongahela Group	62	79.5	5.22E-06	12.06	1.75	23.56	54.8	0.21	13.40
GREENE	1506	1.60	Greene Formation	Washington Formation	415	27.6	4.04E-05	12.02	1.23	28.52	25.6	0.25	14.97
INDIANA	86	0.06	Glenshaw Formation	Burgoon Sandstone	70	81.4	4.29E-06	12.08	2.03	20.66	97.4	0.16	6.75
JEFFERSON	24	0.02	Allegheny Formation	Allegheny Formation	21	87.5	2.37E-06	14.06	2.62	21.07	92.3	0.12	7.75
LAWRENCE	16	0.03	Allegheny Formation	Shenango Formation	12	75	1.19E-06	8.34	2.46	17.57	63.6	0.28	0.25
WASHINGTON	2301	1.63	Greene Formation	Greene Formation	326	14.2	2.81E-05	10.42	1.49	28.45	45.8	0.21	11.65
WESTMORELAND	182	0.11	Monongahela Group	Shenango Formation through Oswayo Formation, undivided	105	57.7	3.91E-06	12.21	1.98	25.64	59.0	0.21	11.98

The county average topographic slope where landslides occur ranges from ~8 to 16 degrees (Lawrence and Armstrong Counties, respectively). The ratio between the average topographic slope associated with landslides and the average topographic slope in the county is highest for Jefferson County (~2.6), and lowest for Greene County (~1.2). These different ratios likely reflect the small number of landslides in Jefferson County (24 slides) combined with a dominance of a cluster of landslides over a steep hillslope in the SW portion of Jefferson County, demonstrating statistical artifacts that occur when the number of landslides is small.

The average precipitation and number of freeze-thaw cycles prior to landslides may be sensitive to the number of slides in each county. For example, Lawrence County has the smallest number and density of slides in the database (16 slides, 0.02 slides/mile^2, respectively), and is also associated with the highest average precipitation in the 7 days before slides (0.28 inch/day) and the lowest average number of freeze thaw cycles (0.25) before slides. These extreme precipitation and freeze-thaw values demonstrate that when the number of slides in a county is small, a statistical analysis can be heavily influenced by a few outlier slides associated with extreme values (weather conditions in this example).

The examples above underline the importance of careful analysis of the database when trying to extract temporal and spatial patterns with predictive power. Whereas this project primarily focused on database construction, the simple analyses presented here, as well as others reported in the remainder of this section, provide guidelines for future analyses that rely on this database. These guidelines are as follows:

- Analysis results often depend on the data source used (i.e., 311, PennDOT, NASA, etc.), and hence careful consideration should be given to what data sources are used in an analysis.
- A unified analysis of data from the entire study area may miss important differences between sub-regions.
- Statistical analysis of a small number of landslides (e.g., when the database is parsed in space or time) is prone to the influence of outliers and should be interpreted carefully.
- Analysis of temporal data is associated with potentially high uncertainty about whether the reported date indeed represents the timing of landslide occurrence.
- Analysis of spatial data can benefit from acknowledging the spatial uncertainty and bias of different data sources (e.g., 311 reported slides are associated with spatial uncertainty of about 120m, PennDOT reported slides are reported along the road, but the centroid is likely below or above the road).
- Analysis of polygon data (where landslides are mapped as polygons) may produce different results than analysis of point data (where landslides are mapped as a point in space).
- Analysis of lithologic data is limited by the resolution of geologic maps (i.e., formation and group rather than individual horizons or rock type).

- The association between the propensity for slope failure and some parameters may be highly non-linear (e.g., the likelihood of landslide occurrence may increase abruptly when a threshold in precipitation or topographic slope is exceeded).

Future analyses that rely on this database will benefit from considering these guidelines and from careful interpretation of results and may require advanced statistical tools to address potential non-linearities and uncertainties.

4.2 Historical landslides and the importance of timing

The landslide data collected here span over a century of SWPA history. However, the data captured are not generally temporally comprehensive (Figure 4.2.1). Data drawn from consistent records through time can simplify inference. If landslides are consistently recorded through time, other related temporal processes, for example, weather, can be directly related to the landslide records and associations can be evaluated. The datasets compiled here capture different periods of time, often for specific portions of SWPA (Figure 4.2.1).

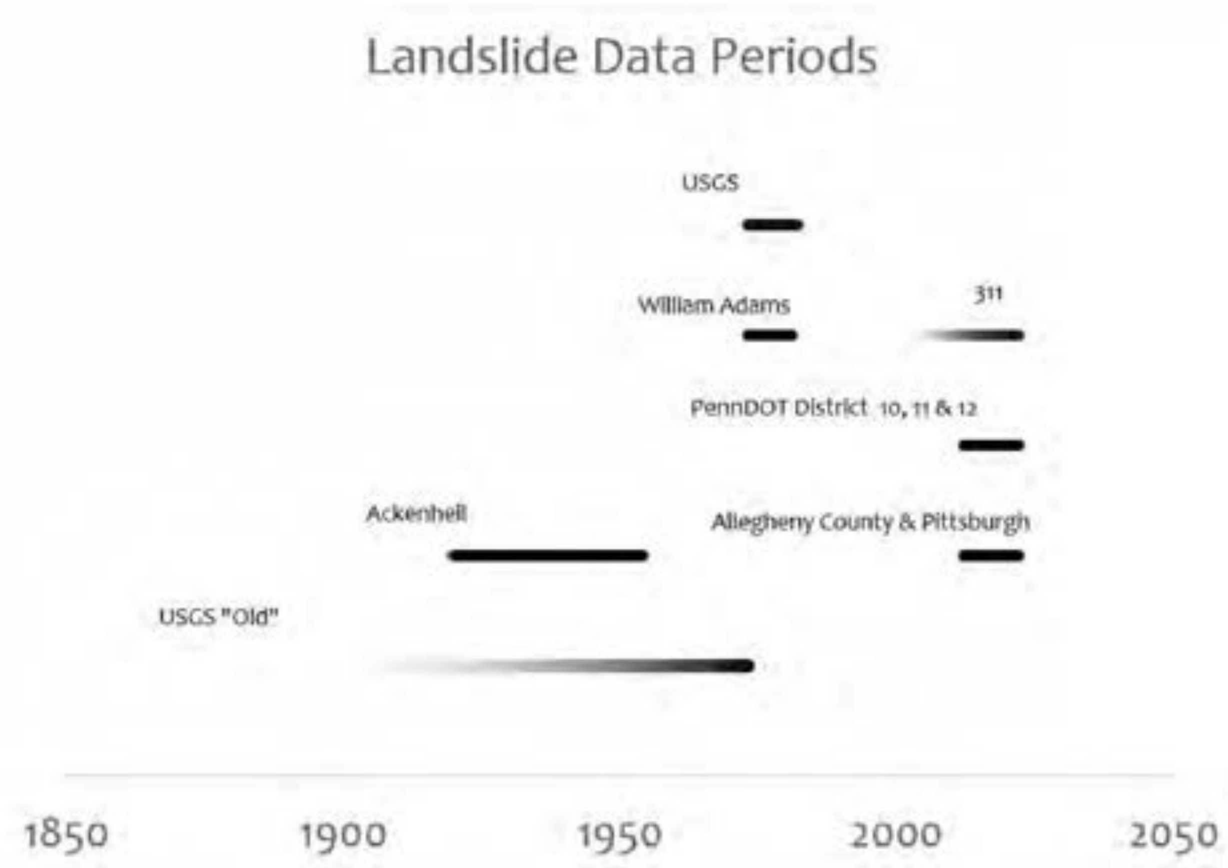

Figure 4.2.1. Relative temporal coverages of selected datasets included in the database. While the temporal coverage of the USGS ñOldò data are shown on this plot, these data are not included in the database.

There are time periods of excellent coverage. The USGS compilation captures the entire study area using aerial photography acquired ~1973 (Pomeroy, 1982). During this mapping multiple surface features were identified, ranging from ñActive or Recently Activeò landslides (i.e., landslides apparent on the photography) to ñOldò landslides (i.e., landslides apparent on the photography, but overprinted by subsequent processes such as revegetation) to ñHuman madeò features (e.g., quarries, strip mines). The Active/Recently Active landslides have decent time control (we know they occurred shortly before the aerial photos were taken), but the ñOldò landslides could have occurred a decade before the photos were taken or could reflect landslides occurring during pre-European periods or activated during early clearance for agriculture. Regardless, this results in a fundamentally uneven distribution of landslides across this history (Figure 4.2.2)

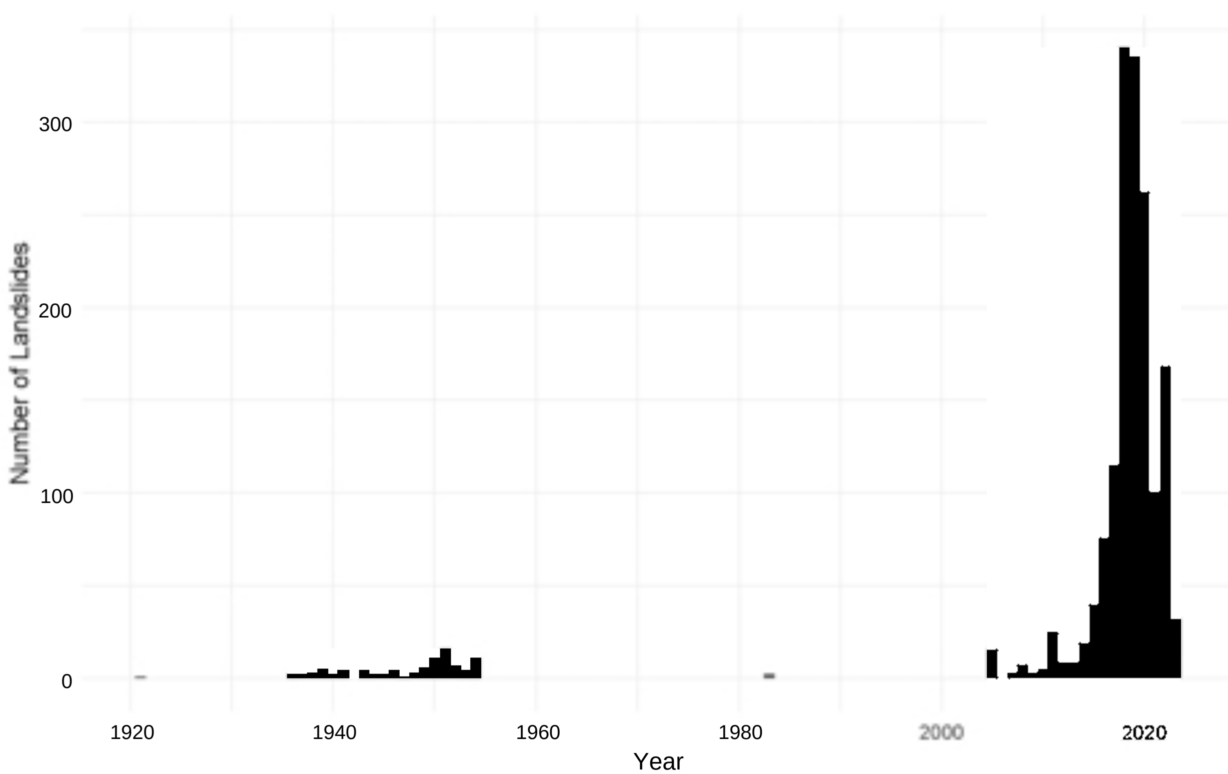

Figure 4.2.2. Temporal distribution of landslides with dates in the database.

This inconsistent recording of landslides limits our ability to evaluate the role of extreme events. The USGS mapping was a reaction to the widespread landsliding associated with Hurricane Agnes (1972) (Pomeroy, 1982) Since, there have been additional extreme events in the region, with Hurricane Ivan (2004), being potentially the most important. However, the available landslide data recorded during the aftermath of Hurricane Ivan is very minimal. This limits our ability to assess the role of extreme precipitation on regional landsliding and hence limits assessment of future risk.

It is not uncommon for landslide occurrence to depend on the volume of mobile material stored on the hillslope. Production of this material is a time-dependent process, so the question arises, did the substantial movement of material by landslides following Hurricane Agnes diminish landsliding in subsequent years? For example, Hurricane Hugo (1989) caused widespread impacts throughout West Virginia, including large portions of the Monongahela River Valley (Jacobson, 1993), however, there is no indication of increased landsliding in SWPA following that storm. Is that a function of the spatial precipitation patterns or does it reflect diminished volumes of mobile hillslope materials due to landsliding following Hurricane Agnes 17 years prior to 1989? Or, alternatively, does it result from a gap in the data record? The gaps in the data record preclude our ability to answer these sorts of questions.

Another substantial gap in the database is associated with landslides before 1972. Records for specific sub-regions in SWPA exists (e.g., the Ackenheil dissertation records near Pittsburgh) but there are very few records for the rest of the region before 1972 (it is difficult to assess the age of the ñOldò landslides mapped by the USGS as those theoretically could be prehistoric or from the 1960s). Human activities can set off landslides (from early colonial landslides triggered by forest clearance for agriculture to recent examples like the Kilbuck landslide). What is not clear is how the human contribution to landsliding has changed as human disturbances have grown more intense. It also limits our ability to assess the persistence of slope instability. That is, have some of the landslides persisted for more than a century? These bounds can provide valuable information as we formulate solutions to ongoing landslides and plan to mitigate landsliding as a result of future human disturbances.

The effort necessary to reconstruct landslide occurrence is substantial. For example, during this project we attempted to constrain the date of landslides to where we knew a landslide had occurred, but a specific date was not provided (e.g., only a year value was provided). The current data landscape is unprecedented, with tools like Google Earth providing rich sets of return aerial photography to the general public, and efforts like Allegheny Countyôs repeat LiDAR providing extremely rich volumes of technical data. We attempted to utilize PLANET data <www.planet.com>, daily satellite images of the earthôs surface with 9-foot pixels, to pinpoint the day a landslide occurred. While daily is a bit of a misnomer as cloud free conditions are necessary for usable imagery, this still provides a record that should allow constraining dates to within days. However, even at this resolution, identification of landslides was not consistently possible (Figure 4.2.3). In earlier periods where less data is preserved and the data that is preserved is less consistent, the effort necessary to reconstruct landslide timing would rapidly increase relative to the Planet data approach, if the reconstruction of time constraints is possible at all.

Figure 4.2.3. Return imagery collected by PLANET satellites of a landslide (pin marks approximate location) in Allegheny County reported by PennDOT District 11 on January 29, 2018. Note that change is very hard to detect even at this image of 3m resolution.

Given the tradeoffs between the effort necessary to reconstruct landslide timing and the relative inference this data allows, it is not clear that widespread reconstruction of historical landslide dates is advisable. That said, for specific questions, over tightly constrained spatial domains, reconstruction of landslide occurrence can provide helpful insight. Regardless, collection and inclusion of timestamps in all future landslide cataloging has clear benefits for both current and future management efforts. Recording the date of landslide initiation is one of the most important pieces of data to be preserved.

4.3 Precipitation

Over the next century, precipitation is anticipated to increase in northeastern United States (Easterling *et al.*, 2017). Changes in precipitation patterns, including increased precipitation clustering and intensity, are expected (Donat *et al.*, 2016). These changes may lead to more frequent landslides in the region. For example, the extraordinary 2018 precipitation in Pittsburgh caused a period of increased shallow soil moisture and increasing groundwater levels during reduced evapotranspiration conditions prevalent in winter. This combination of factors induced widespread landslides in the region (Ashland, 2021). As precipitation variability and magnitude continues to increase in the coming years, more landslides seem likely to occur in the region.

One substantial challenge in characterizing the interaction between precipitation and landslide timing is the limited records with information on landslide timing (section 4.2). The database contains roughly 2500 landslides with at least an approximate date of occurrence. Sometimes these data are not precise, as there can be a lag between the time of landslide occurrence and detection/reporting. Further, landslides can move very slowly for extended periods before crossing the threshold to damage or rapid movement that results in reporting, making the date of landslide occurrence hard to specify precisely. So, analysis of precipitation and landslide timing does incorporate some noise. Despite these potential uncertainties, these data remain an important way to examine the relationship between precipitation and landslides and provide a means to evaluate the impact of future climate scenarios on regional landsliding.

Ideally, there would be exact precipitation records across SWPA. However, meteorological stations are limited in both temporal and spatial coverage. These data gaps make it difficult to analyze the relationship between precipitation and landslide occurrence, as station data cannot provide the spatial and temporal continuity required for a robust analysis. Therefore, we have utilized precipitation data that has been interpolated across the region at a resolution of 4 km pixel. The PRISM project has generated high-resolution weather maps that incorporate not just precipitation but also geographical and topographical influences like elevation and slope orientation (Daly and Bryant, 2013). This method accounts for factors such as elevation, slope aspect, and proximity to coastlines in evaluating of precipitation forcings in local context. This section evaluates the relationship between local precipitation patterns derived from PRISM data and the occurrence of landslides in the study area.

4.3.1 Comparison of precipitation and landslide events 2005-2022

Understanding the relationship between precipitation and landslide occurrences is crucial for planning mitigation of landslides impacts. This section analyzes precipitation data for landslide events in our study area between 2005 and 2022 (the period with the most available dates and therefore the most weather data). The analysis focuses on the mean precipitation over the 1 and 7 days preceding each dated landslide during this period (Table 4.3.1).

Table 4.3.1. Comparison of the number of landslides with the average precipitation during 1 and 7 days before landslide event between 2005-2022

Year	Landslide number	Precipitation on day of slide (in/day)	Precipitation 7 days prior to day of landslide (in/day)
2005	16	0.69	0.27
2006	1	0.06	0.25
2007	3	0.19	0.16
2008	8	0.04	0.18
2009	2	0.21	0.06
2010	8	0.57	0.24
2011	27	0.29	0.31
2012	8	0.79	0.3
2013	12	0.55	0.35
2014	12	0.19	0.14
2015	62	0.24	0.21
2016	86	0.2	0.13
2017	119	0.16	0.16
2018	421	0.44	0.26
2019	368	0.22	0.17
2020	145	0.14	0.14
2021	136	0.24	0.18
2022	125	0.18	0.17

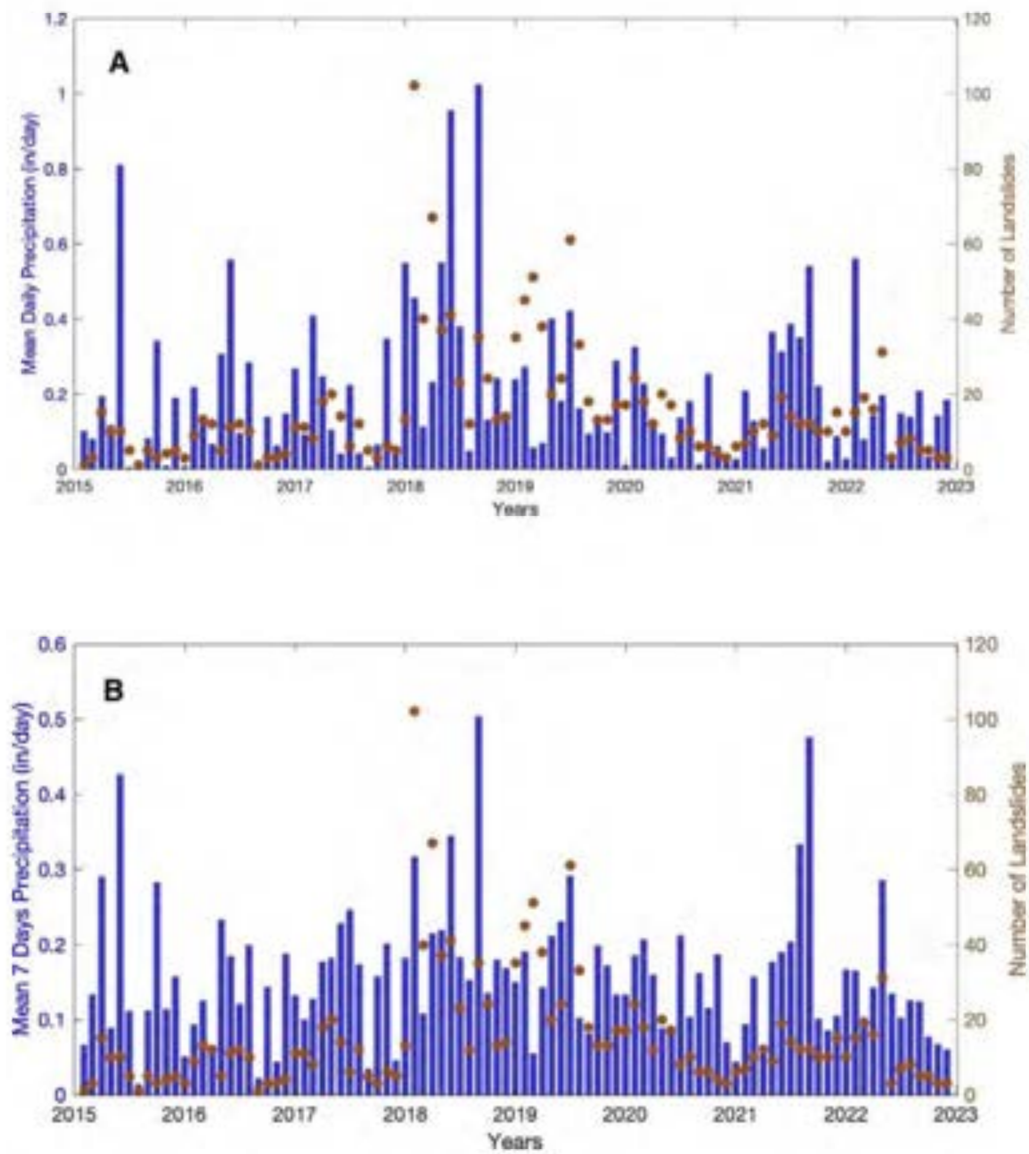

Figure 4.3.3. Comparison of total daily count of landslides occurring from 2015 to 2023 with the average precipitation over different periods preceding each dated landslide in the study area (1 and 7 days, panels a) and b) respectively). Each blue bar represents the average precipitation reported in the database for all landslides that occurred during the prior respective month, plotted on the left y-axis. The red dots represent the number of landslides during each month, plotted on the right y-axis. Note that the number of bars may vary due to the availability of complete precipitation data for the preceding periods.

There are several interesting observations that arise from Table 4.3.1. The average precipitation within 1 and 7 days prior to landslides has a considerably wider range between 2005-2014 (e.g., 0.04-0.79 In/day for the 1-day period), compared to the period between 2015-2022 (e.g., 0.14-0.44 In/day for the 1-day period). This likely reflects the small number of landslides per year

(<27) in the database during this period, resulting in a stronger outlier effect on precipitation statistics. Between 2015 to 2022, the number of landslides drastically increased (>62) because of the addition of systematically reported 311 data. The larger sample of landslides improves the robustness of the statistical analysis and reduces the range of averaged precipitations.

Figure 4.3.3 reveals interesting associations between the number of landslides and precipitation between 2015-2022. Months with high number of landslides sometimes do not have a high average precipitation within 1 day of the landslides (Figure 4.3.3a). However, this association is stronger for the average precipitation within 7 days prior to landslides (Figure 4.3.3b). This points to the importance of both punctuated (i.e., 1 day before landslide) and cumulative precipitation (i.e., 7 days prior) on landslide occurrence. Further, the high number of landslides in 2018 and 2019, compared to the lower number of landslides during months of similarly high precipitation in 2021 is intriguing. A potential interpretation is that the precipitation in 2018-2019 triggered many landslides that were ñripeò for failure, leaving fewer such landslides to fail under similar conditions in 2021.

4.3.2 Comparison of precipitation and landslide events in April 2018

April 2018 was marked by intense stormy weather and significant landslide events in and around Pittsburgh (Ashland, 2021). The database provides an opportunity to explore the association of these landslides with daily and weekly precipitation (1 and 7 days, Figures 4.3.4a and 4.3.4b, respectively). Sometimes landslide events are elevated on days of heavy precipitation. For example, on April 4 and April 16, daily precipitation exceeded one inch, resulting in multiple landslides. Specifically, April 4 daily precipitations at landslide locations averaged 1.3 inches and 1.5 inches on April 16. An elevated number of landslides (4 landslides per day) were observed for both days, suggesting an association between heavy daily precipitation and landslide occurrences (Figure 4.3.4a). However, there are also days with low or no precipitation that still had landslides, confirming that factors beyond event day precipitation, such as prior cumulative precipitation or inherent slope instability, play a role in triggering landslides. Alternatively, this may also reflect a gap between the actual day of landslide occurrence and the day on which it was reported. Average precipitation within 7 days prior to a landslide shows a reasonable relationship with the number of landslides (Figure 4.3.4b). For example, the seven days preceding April 16-19 had a relatively high average precipitation, correlating with a high landslide count during these days. However, this is not always consistent, as seen during April 25-28, where a relatively high number of slides occurred without particularly high precipitation in the preceding 7 days. It is important to note that this short analysis is based primarily on 311 data, which has limitations. In particular, the narrow spatial footprint and potential for duplicate reports in the 311 data do not necessarily reflect landslide patterns across the entire study area.

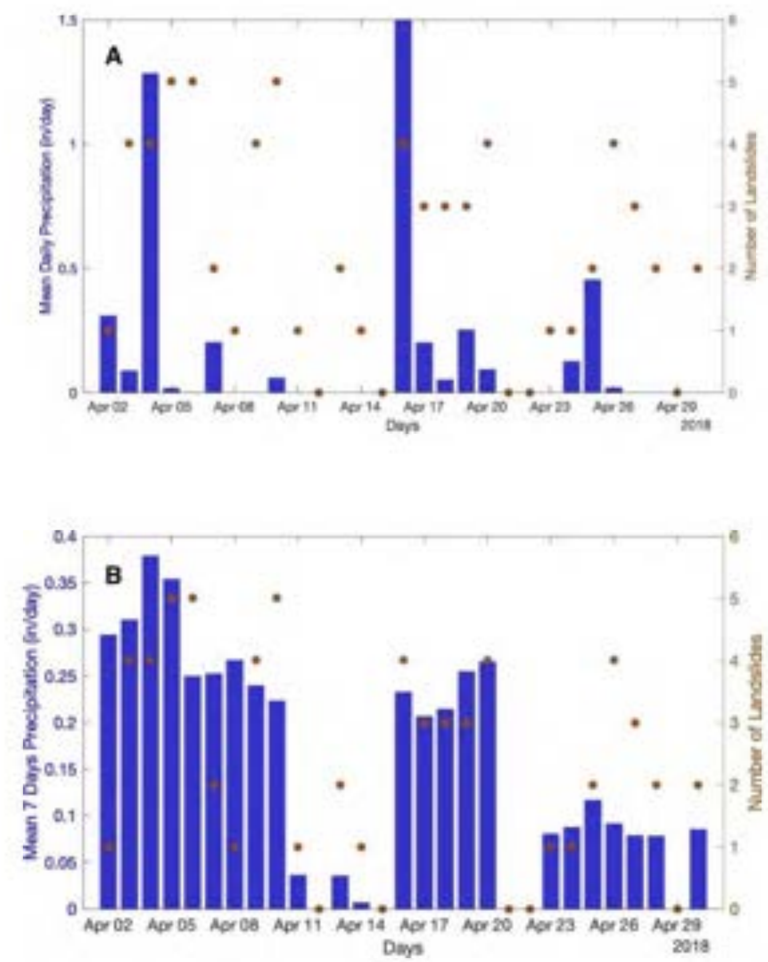

Figure 4.3.4. Relationship between daily total number of landslides and average precipitation over periods of 1 and 7 days preceding each dated landslides in April 2018. Each blue bar represents the average precipitation for these periods, plotted on the left y-axis. The red dots represent the number of landslides, plotted on the right y-axis.

This simple analysis highlights several relationships that are helpful for understanding regional landsliding. In particular, the interaction between different period average precipitation and landslide events from 2005 to 2022 indicates that both immediate and cumulative precipitation are associated with increased landslide activity in the region.

4.4 Bedrock geology and landsliding in southwestern Pennsylvania

In SWPA, the topography and geologic structure historically have dictated the location of roads. Roads often run through valley bottoms adjacent to both steep natural and/or cut rock slopes and terraces of colluvium. This places transportation corridors near landslide prone areas, and therefore can result in service interruptions, environmental impacts, and infrastructure damage.

Important geologic materials in SWPA include shale, sandstone, limestone, and coal (descriptions of regional stratigraphy rely on names and thicknesses in Table 1.1). In particular, the claystone and mudstone units have inherent weakness which when combined with other contributing factors (e.g., freeze thaw, weathering, topographic slope, etc.) can increase landslide risk.

Based on the distribution of landslides in this database (Figure 3.1.1), there appear to be three distinct geological controls across the study area. In Pittsburgh and surrounding counties, thick, weak claystones are associated with landslide occurrence including infamous strata like the Pittsburgh Red Beds. Unconsolidated, clay-rich colluvial deposits are associated with the greatest density of landslides in the database in Washington and Greene Counties. In the northwestern section of the study area (Butler and Lawrence Counties) glaciation has smoothed relief and altered soils, and landslide occurrence is lower as a result.

Although the Pittsburgh Red Beds are sometimes identified as the culprit for the considerable number of landslides in western Pennsylvania, there are other clay-rich units in the stratigraphy that also result in landsliding. Accurately mapping these strata presents significant challenges. The challenges grow from both the variability of stratigraphic thicknesses across the formation (Figure 4.4.1) and from the lack of updated geologic mapping at higher resolutions in the region. (The most recent regional mapping dates to at least 1980 and any revisions to the state geologic map during that update). However, given the strata are generally flat or gently sloping, it should be possible to use the elevation of a location relative to a deeper bed to establish if the bedrock or outcrop at a location is near the stratigraphic layer of interest. This section uses the elevation of the land surface above the mapped elevations of the Upper Freeport Coal at landslide locations (Northern and Central Appalachian Basin Coal Regions Assessment Team, 2001) to evaluate strata prone to landsliding (Figure 4.4.2).

When the distributions of land surface elevations above the UFR coal are compared with regional stratigraphies, the relative occurrence of landslides near different rock layers in the study area emerges. Specifically, a digital elevation model derived from the UFR coal contour (Northern and Central Appalachian Basin Coal Regions Assessment Team, 2001) was differenced with the surface DEM (Gesch et al., 2002) at all locations above the coalbed in the study area.

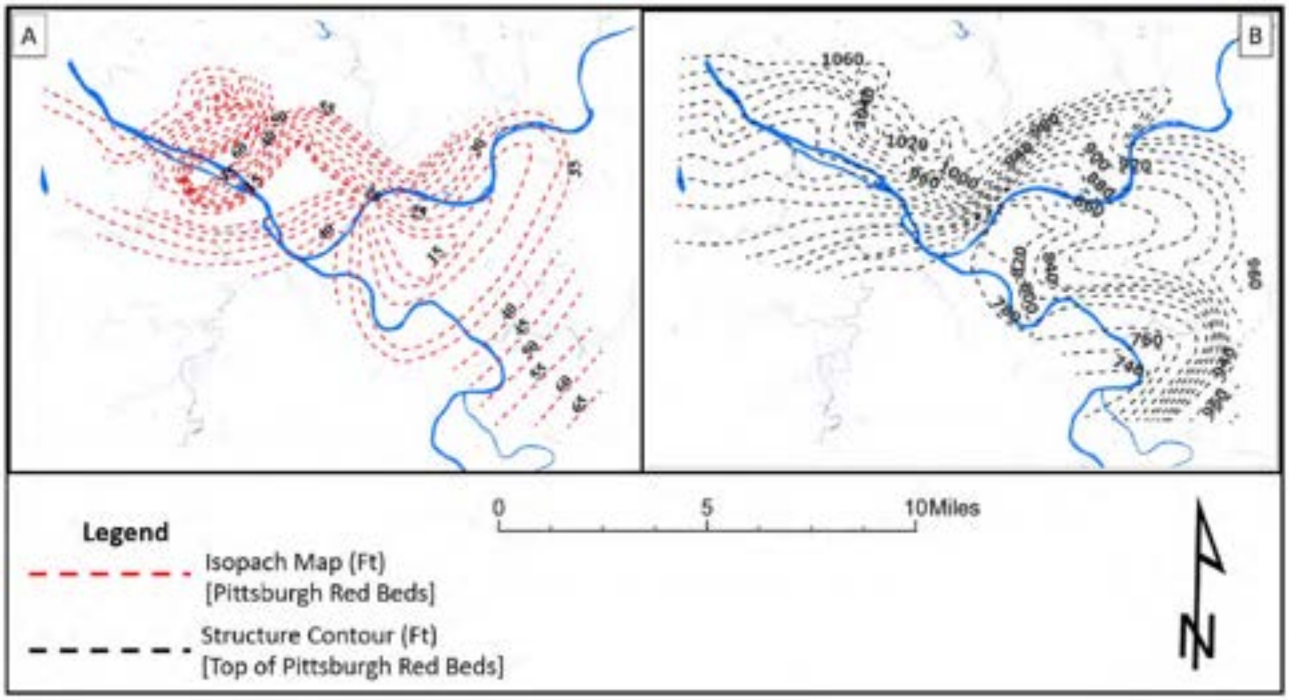

Figure 4.4.1. Structural maps a) Isopach and b) structural maps of the Pittsburgh Redbeds (digitized from Winters, 1972).

There are several peaks in landslides at specific elevations above the UFR coal: ~13,000 ft, ~700 ft, and ~ 500 ft (shown in Figure 4.4.2.). The peak at 500 ft above the UFR Coalbed is roughly 200 feet above the elevation of the Pittsburgh Red Beds (and Ames Limestone) relative to the UFR. However, this is a wide peak that stretches across multiple strata. The lower shoulder of the peak is located roughly at the elevation of the Pittsburgh Red Bed. The upper shoulder is at ~600 feet above the UFR, so the peaks span other strata including the Schenley Red Beds, the Wellersburg Red Beds, and the Clarksburg Red Beds (Figure 4.4.2). The center of the peak lines up with the elevation of the Morgantown Sandstone above the UFR coalbed. This analysis suggests that landslides in areas near Pittsburgh occur over multiple stratigraphic layers and not just the Pittsburgh Red Beds.

The second peak at around 700 feet above the UFR coal is not at the elevation of any stratigraphic layer commonly associated with regional landsliding (it lies at the rough elevations of the Sewickley Coal and Fishpot Limestone). Additional attention to this portion of the stratigraphic column could provide new insights on landslide prone strata. Additionally, the 700-foot peak is near the relative elevation of the PGH coal. The high frequency of landslides at this elevation could reflect a combination of local landslide prone strata and disturbance to local hydrology associated with mining triggering landslides above and below coalbed (see section 4.5 for more detail on mining).

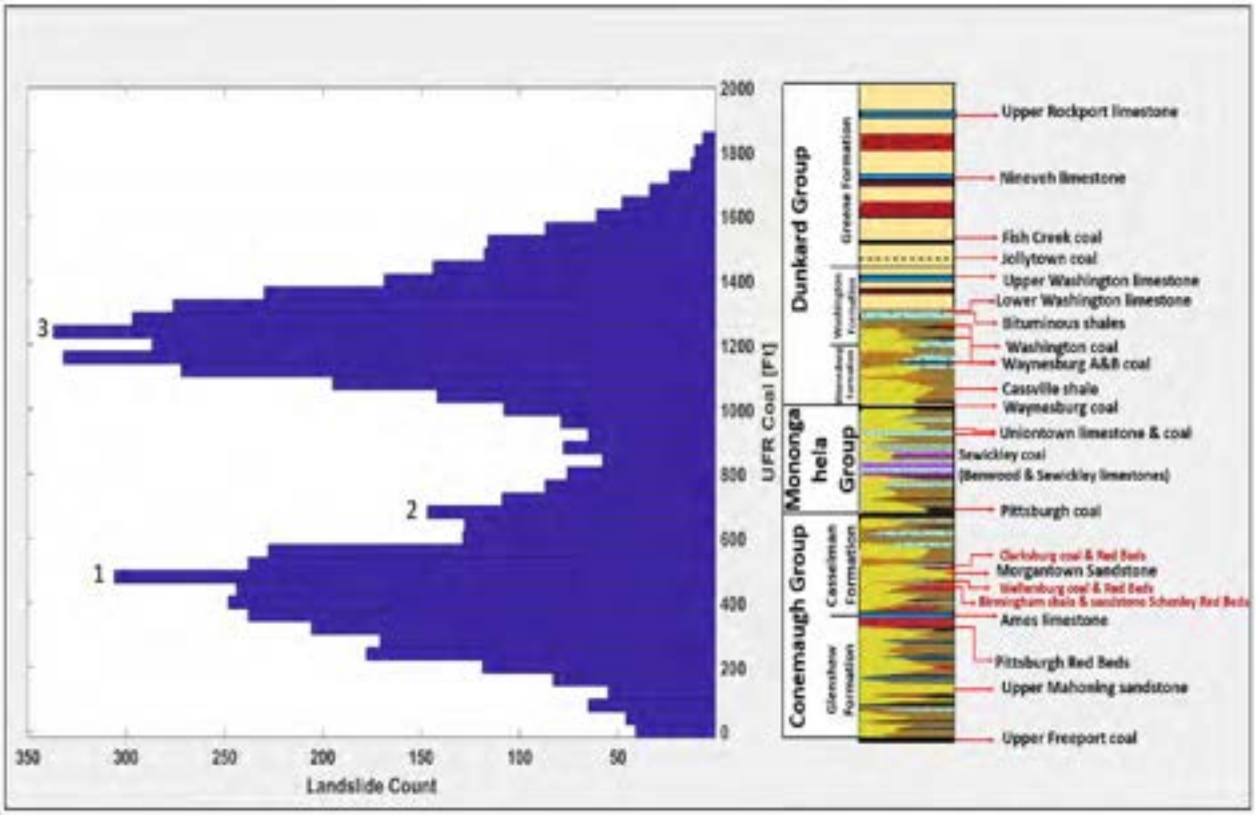

Figure 4.4.2. Landslide counts at elevations above the Upper Freeport Coal juxtaposed with generalized Pennsylvania stratigraphic columns (Harper, 2000; Fedorko and Skema, 2013). Elevations with relatively high incidence of landslides are labeled 1, 2, and 3.

The third peak (at roughly 1,300 feet above the UFR coalbed) is the most prominent peak in the set (Figure 4.4.2). However, there are no clear stratigraphic beds that could explain this peak. The Washington Limestones (Upper and Lower) coincide with the elevations where landslides peak (1300 feet about the UFR coal). These limestones may suggest a role for preferential flow at these elevations through the limestones (through karst features or otherwise). Flow through the limestone would supply focused inputs of water to hillslopes in these elevationsô ranges, increasing the chance for landsliding. In addition, there are several shale units in the Dunkard group (Cassville shale and Bituminous shale) that lie near the bottom shoulder of the peak, but neither are unusually thick nor are they associated with landsliding in Washington and Greene Counties. Pomeroy (1986) suggests that many of the landslides in this region occur at or just below sand/silt stones in contact with weaker lithology (e.g., mudstone or siltstones). In contrast to the stratigraphy in and around Allegheny County, individual lithologies in the Dunkard Group are rarely traceable for more than a couple miles (Pomeroy, 1986). This heterogeneity makes application of this approach difficult in areas underlain by rocks in the Dunkard Group. However, this geology is clearly particularly important to regional landslide activity and more detailed examination of this section may yield new insights regarding its association with landslides.

This approach has important limitations. Most importantly, the UFR coalbed only underlies parts of the study area (e.g., the Kittanning coalbeds would be better, but those data are not compiled into digital GIS data.) Moreover, it relies on assumptions of relatively similar thickness of the formations across the region. As mentioned in the previous paragraph, this assumption largely does not hold for strata in the Dunkard Group. Finally, strict counts of landslides at each location can be deceiving if there are differences in the total area of outcrops (that is, if landsliding is equally distributed across the landscape, areas with more outcrops will have more landslides). If a likelihood analysis is desired (i.e., accounting for variations in land area), the count of landslides in each elevation bin has to be divided by the total land area at the corresponding elevation bin. Ultimately, a more sophisticated analysis of the database should allow future insight into specific lithologies, particularly over more constrained spatial areas where the assumptions about elevation are more likely to be reasonable and strata thicknesses more likely to be consistent in thickness.

4.4.1 Glaciation and landslides in southwestern Pennsylvania

The relative lack of landslides in northern portions of the study area (Figure 3.1.1) is another take away from this database. There are very few landslides in Clarion, Butler, and Lawrence Counties. It is difficult to compare these areas with Allegheny, Washington, and Greene Counties, as the exposed lithology in most of this region is deeper than the Upper Freeport Coal. What is particularly striking is the extremely low frequency of landslides north of the southernmost boundary of the area glaciated during the last glacial maximum. Glaciation resulted in gentle slopes with more sand content relative to the southwestern corner of the study area (Figure 4.4.3). These conditions are less favorable for landslides and that is reflected in the patterns of landslides observed across the study area (Figure 3.1.1).

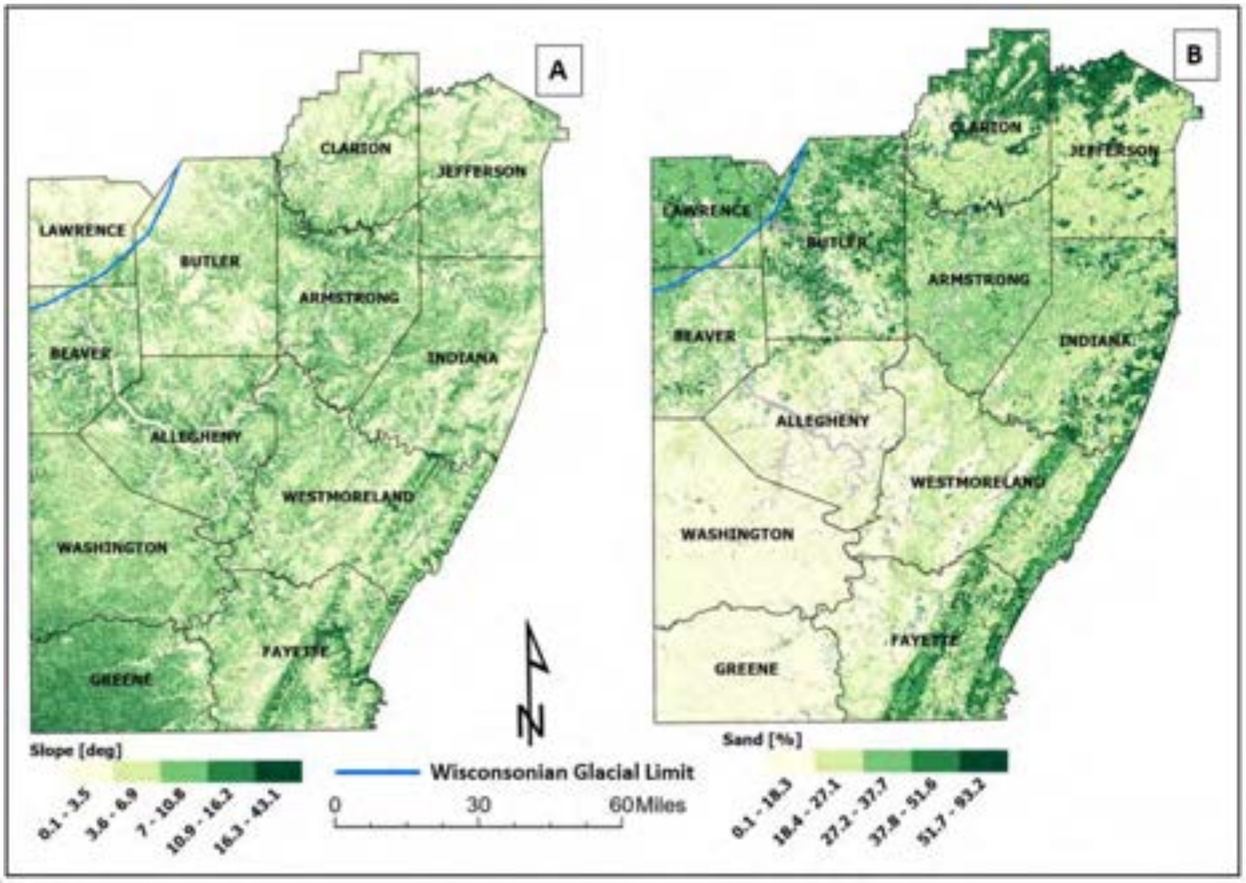

Figure 4.4.3. Impact of glaciation in the study area. a) slope in degree; b) average sand content (%). Blue line shows the most recent glacial extent in study area.

4.5 Influence of coal mining on the occurrence of landslides

4.5.1 Background on coal mining

This section examines the occurrence of landslides within surfaces that have been altered by human activity, in particular coal mining. Human-altered slopes include civil construction (roads), property development, utilities, and mineral extraction. The primary form of mineral extraction within the study area is coal mining by both surface and underground methods (documented below). The following sections examine conditions where it is likely that past coal mining influenced landslide occurrence. Some of these influences include bituminous coal mining trends, distance to mining or overburden, and mining type.

4.5.1.1 Bituminous coal mining trends

All twelve counties in the study area have had a long history of coal extraction and have significant reserves of bituminous coal (Figure 4.5.1). For example, underground coal mining along the slopes of Mount Washington was reported in the late 18th century. As shown in Figure 4.5.2, by 1983, Pennsylvania bituminous coal production increased to over 65 million short tons (Energy Information Administration assessment of the Mine Safety and Health Administration's database). This was accomplished through almost equal amounts of surface (30.6 million tons) and underground (34.5 million tons) mining methods. In 2022, the last year where annual production rates are reported, surface mining accounts for only 2.2 million tons while underground mining accounts for 35.1 million tons. For the 39 years of data available from the EIA/MSHA data (i.e., Energy Information Administration assessment of the Mine Safety and Health Administration's database), surface mining production has dropped to 7% of the 1983 totals. Conversely, underground mining has increased by almost 2%. Underground mining production increased dramatically in the 1990s largely due to the rapid expansion of longwall mining methods. However, since 1998, underground mining production has declined at an almost steady rate to its current value. As will be shown in Section 4.5.3, these trends have had a dramatic impact on how bituminous coal mines are impacting surface conditions and hence, the potential for landslide occurrence.

4.5.1.2 Mining Era in which the coal was extracted

Three distinct mining eras exist within the study area. The first is associated with early legacy mining activities, i.e., up to the passage of Pennsylvania's 1968 Land and Water Conservation and Reclamation Act and the federal Surface Mining Control and Reclamation Act of 1977 (SMCRA). Both laws have been amended several times to strength their intended outcomes. In the earliest years, before these laws, there were minimal environmental standards to control how coal mines were developed. Up-dip mining dominated, creating arguably many of the worst legacy mining issues. This is especially evident in Allegheny County and is discussed further in Section 4.5.2. As these types of above drainage mining deposits were exhausted, deeper below drainage shaft and slope mines dominated, especially in parts of Washington, Westmoreland, and Fayette Counties. In contrast, Section 4.5.3 explores landslide issues, prior to the implementation of SMCRA and its amendments, caused by surface strip mines and surface developments of underground coal mining in Armstrong County. In this part of the study area, there are multiple minable coalbeds that were often mined in unordered sequences potentially producing multiple horizons for coal mining activity. The authors believe the implementation of SMCRA and its later amendments in 1990 greatly reduced the potential for landslide occurrences (Bain et al., 2019). The third distinct mining era is associated with the introduction and expansion of longwall mining. The first longwall panel was developed in the early 1980s. Today it is by far the most dominant form of coal mining in Pennsylvania (Bain et al., 2019).

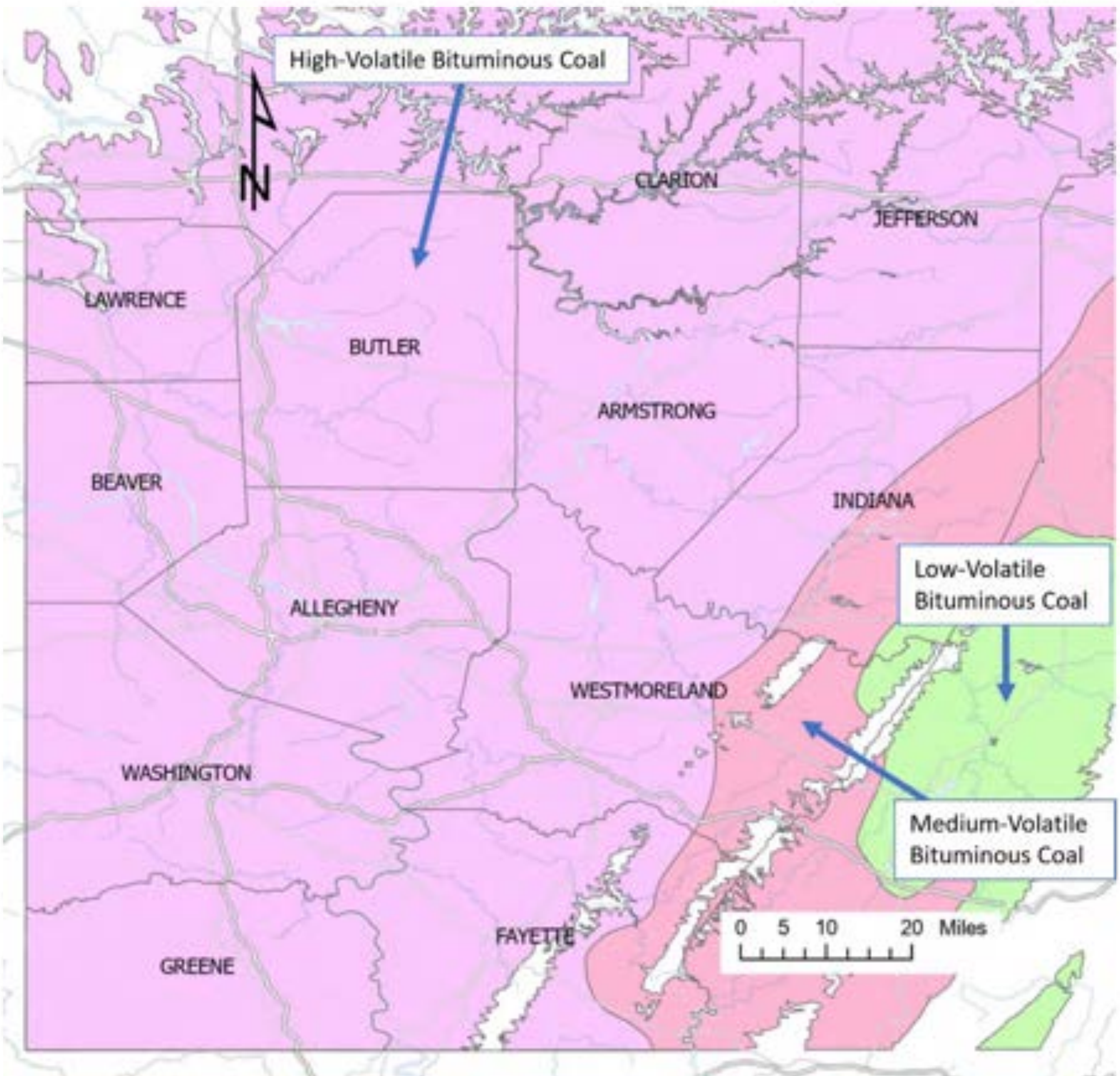

Figure 4.5.1. Areal distribution of bituminous coal reserves within the 12-county study area. Note: purple = high-volatile; pink = medium-volatile; and green = low-volatile bituminous coal reserves.

4.5.1.3 Distance to mining or overburden

The distance between a mined coalbed and the surface can greatly enhance the potential for landslide occurrence. When the overburden is low (less than 100 ft), the surface can be subjected to increased potential for water discharges, portal and highwall instabilities, and a higher potential for subsidence. The Pittsburgh Coalbed is the dominate mining horizon for Allegheny, Fayette, Westmoreland, Greene, and Washington Counties, whereas the Allegheny Group of Coalbeds (this includes the Upper and Lower Freeport; Upper, Middle, and Lower Kittanning;

and Clarion and Brookville) are the dominate mining horizons in other counties. Determining the overburden, especially above the Pittsburgh and Upper Freeport Coalbeds, allows for analyzing its relative importance in the potential landslidesô occurrence.

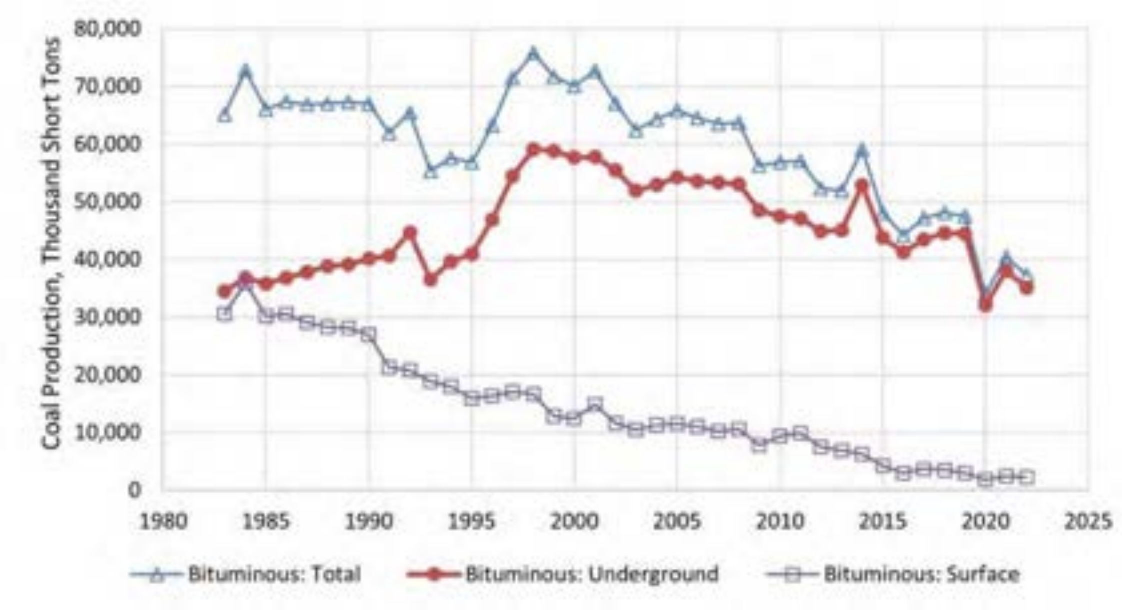

Figure 4.5.2. Graph showing the changes in Pennsylvania bituminous coal production from 1983 to 2022 (EIA analysis of MSHA database).

The following sections introduce examples of where coal mining can be an influential causal factor for landslide occurrence. These case study examples are by no means a complete treatment as to how coal mining can influence landslide occurrence. However, they can provide useful information as to how some of the important factors are manifested in different parts of the study area and illustrate how the database approach can clarify and constraint the role of mining in landslide activity.

4.5.2 Mining in the shallow Pittsburgh Coalbed

This example focuses on some of the earliest Allegheny County underground coal mining activities that have impacted landslide occurrences. Many of these mines, developed in the first half of the 20th Century have been referred to as ďegacyô mines. The Pennsylvania Bureau of Mines (Dept of Internal Affairs of Pennsylvania, Official Document #11, 1900) provides evidence of the extensive underground coal mining within Allegheny County. In 1983, the EIA reported Allegheny County surface and underground coal production at approximately 1.5 million tons. By 2022, The IEA reported no surface or underground coal mining in Allegheny

County. Most of the production was now from longwall mines in Greene and Washington Counties with lesser amounts from room-and-pillar mines in Armstrong, Beaver, Butler, Clarion, Indiana, Jefferson, and Lawrence, Counties.

4.5.2.1 Local characteristics

The underground mining case study occurs within the Glassport Quadrangle and encompasses both southeastern Allegheny County and a small portion of northwest Washington County, Pennsylvania. The outcrop of the Pittsburgh Coalbed and its structure contours with respect to sea level are shown in Figure 4.5.3. Also shown are the axes of the anticlines and synclines in the region. The strata dips in these areas are gentle (less than 3-deg) but are significant enough to affect how water moves through mines. In general, when water enters the mine, through the coalbed and roof and floor strata, it will move down dip. If there are no openings to the surface (portals) or if the coal barriers between the mine and the coal outcrop are of insufficient thickness, the water will discharge through the portals and/or inadequate coal barriers then enter the watershed. If there are no portals and the coal barriers are sufficiently thick, the water will pond against the down dip coal barrier adjacent to the Pittsburgh Coalbed outcrop. All these conditions exist in mines within the Glassport Quadrangle.

A visual examination of the landslides within the Glassport Quadrangle seems to show some clustering near the outcrop of the Pittsburgh Coalbed (dashed line on Figure 4.5.3). It would be helpful to know if this clustering is real or imagined and, if it is real, why it might occur.

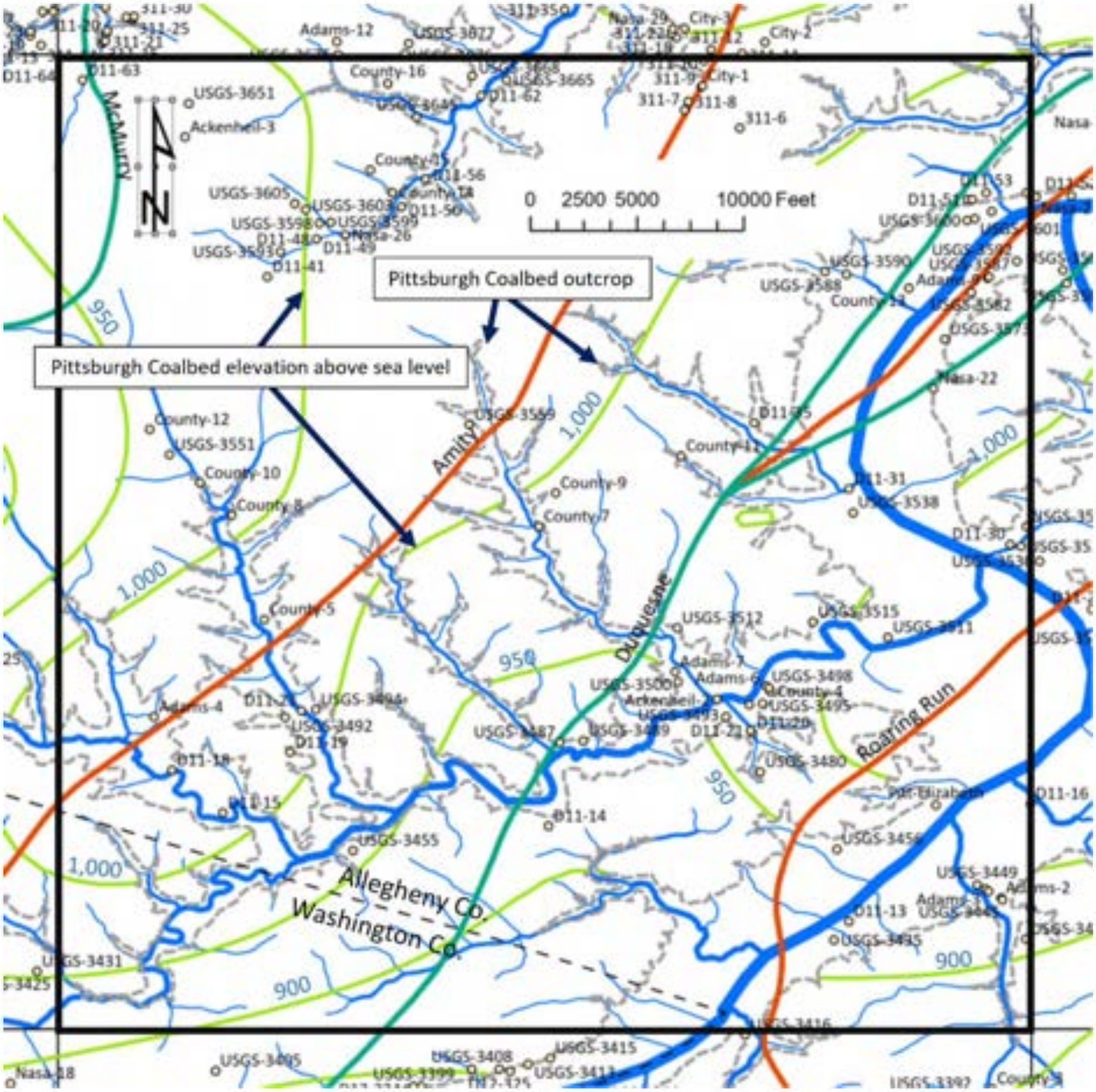

Figure 4.5.3. Landslide locations and names within the Glassport Quadrangle. Also included are gray dashed lines depicting the outcrop and thin green lines the structure contour (500 ft intervals) of the Pittsburgh Coalbed. Red-orange thick lines are axes of anticlines and dark green lines are axes of synclines. Solid blue lines are streams, the thicker the line the greater the stream order.

4.5.2.2 The influence of overburden

There are 95 landslides within the Glassport Quadrangle (Table 4.5.1). Landslide occurrence associated with the Pittsburgh Coalbed mining is thought to be influenced by a) mine water drainage saturating the slopes and b) spoil and other material casted from the mining operation producing unstable slope conditions. Both conditions would generally occur below the surface elevation of the coalbed. In the Glassport Quadrangle, 37 (39%) of all landslides occurred in areas where the surface is at or within 100 vertical feet below the projection of the Pittsburgh Coalbed. Landslide occurrence can also be influenced by disturbing mining related highwalls or subsidence of the ground above the coalbed. In the Glassport Quadrangle, 21 (22%) of all landslides occurred within 100 vertical feet above the Pittsburgh Coalbed. Adding both the below and above categories together yields a value of 58 (61%) of all landslides within the Glassport Quadrangle occur within 100 ft of the Pittsburgh Coalbed outcrop.

Table 4.5.1. The 95 landslides contained within the Glassport Quadrangle and sorted by those occurring within 100 ft either above or below the Pittsburgh Coalbed.

Data Source	Over 100 ft	Under 100 ft	Within 100 ft	Percent of Total within 100 ft	Total
311	1	0	1	20	5
Ackenheil	0	0	0	0	2
Adams	0	2	2	33	6
City	0	0	0	0	1
County	**3**	**7**	**10**	**83**	**12**
D11	**6**	**8**	**14**	**61**	**23**
Nasa	0	2	2	100	2
Pitt	0	0	0	0	1
USGS	**11**	**18**	**29**	**67**	**43**
Total	21	37	58	61	95

It should be noted that the above analysis was limited and did not consider other potentially important parameters, such as slope angle. It also lacked an analysis as to the overall area occupied by the within 100 ft category in comparison to areas outside this category. While a more rigorous analysis is needed, it is interesting that 83% of the Allegheny County, 61% of the D11, and 67% of the USGS landslides were within the 100 ft category (bold values in Table 4.5.1). A visual representation of the overall patterns shown in Table 4.5.1 is provided in Figure 4.5.4.

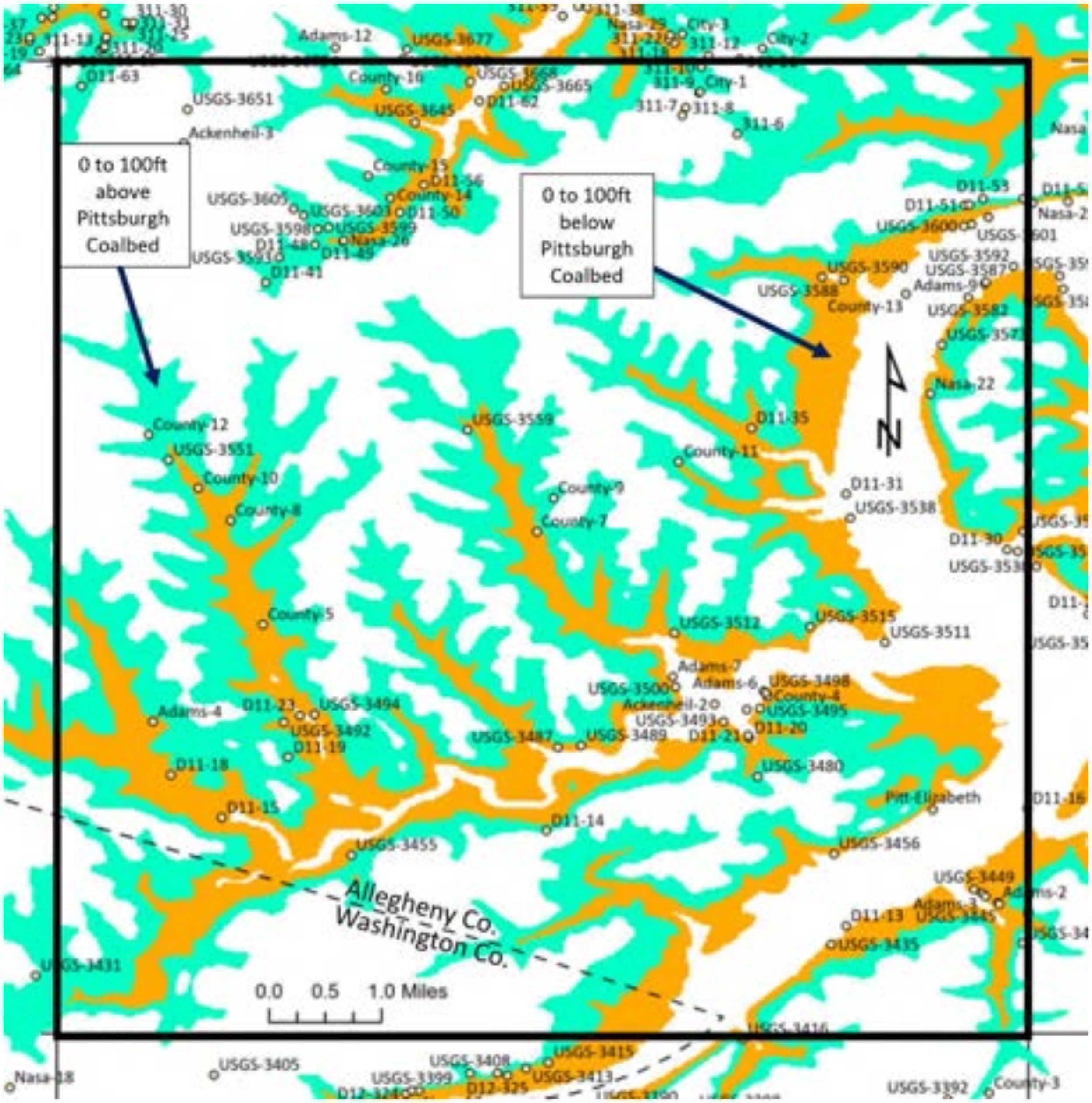

Figure 4.5.4. Location of landslides and the intervals 100 ft above (light green) and 100 ft below (orange) the Pittsburgh Coalbed.

4.5.2.3 Mining era in which much of the Glassport Quadrangle coal was extracted.
In the first half of the 20th Century, prior to the development of the continuous mining machines, rooms were developed using drill, blast, and muck processes. These development entries typically had room widths less than 18 ft wide. Production panels were driven with relatively wide entries (often greater than 18 ft). It was also common for these production rooms to be widened by extracting coal from the pillarsôribs. Production panel rooms were expected to

remain stable for a relatively short time compared to the rooms within the main entries sections. An example of this is shown in Section 4.5.2.4.

As previously discussed, many legacy mines entered the coal reserve at its lowest elevation in the hillside and mined up-dip from that location. In these cases, water can flow down-dip and discharge through the mine entrance or portals. Figure 4.5.5 shows that mines in the Glassport Quadrangle mined up to the Pittsburgh Coalbed outcrop. The coal barriers in these mines (Figure 4.5.5) are considered by todayֹs standards to be completely inadequate in controlling drainage to the watershed (Iannacchione et al., 2014). These same mines are partially, or in many cases, totally above the surface drainage. These surface drainage patterns are highlighted by the streams and rivers shown in Figure 4.5.5. In addition, the coal and overburden above the coal was often stripped along the outcrop and was either left in un-reclaimed piles or cast over the mining bench. Two significant factors in landslide occurrence are the water draining from these portals and the casted by-products of mining. It is therefore not surprising that this examination of the landslide database shows many such examples. In the latter half of the 20th Century mine layouts changed to accommodate mechanized equipment. The production panel style of mining discussed above was replaced with room-and-pillar layouts created during development that could later be either partially or fully extracted.

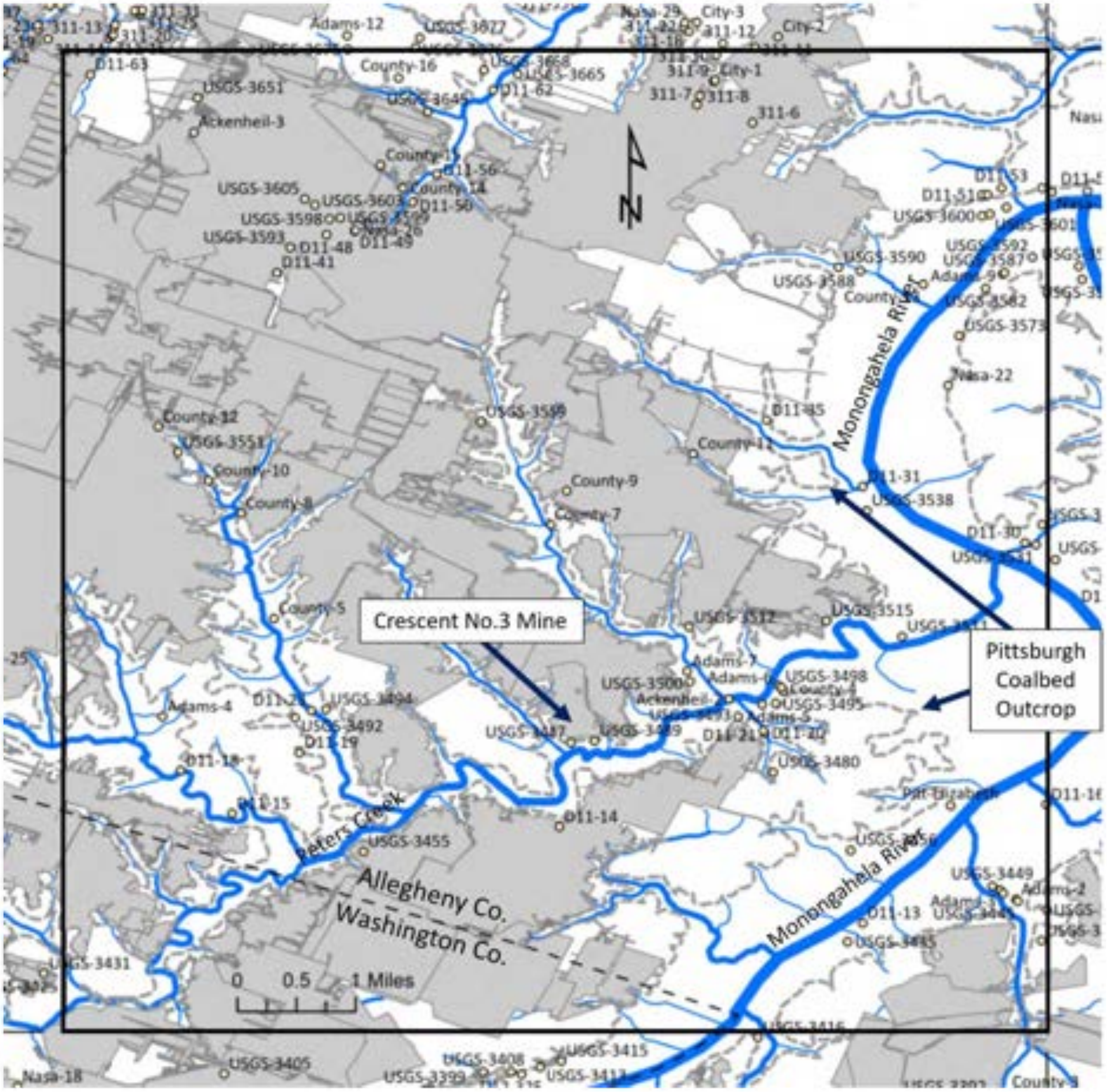

Figure 4.5.5. Underground coal mines (gray color) in the Pittsburgh Coalbed within the Glassport Quadrangle. The location of the Crescent No.3 Mine is highlighted.

4.5.2.4 The Crescent No.3 Mine example

The Crescent No.3 Mine (Figure 4.5.5) provides an example of landslide occurrence associated with a legacy mine. This mine is adjacent to a narrow bench where the Pittsburgh Coalbed was likely stripped prior to or during the underground mine's development (Figure 4.5.6a). The direction of dip is from the Amity Anticline (Red-orange line in the upper left) to the Duquesne

Syncline (Dark green line crossing the Crescent No.3 Mine, Figure 4.5.3). The structural elevations of the Pittsburgh Coalbed are shown as dashed orange-red line (Figure 4.5.6), supporting the dip and water flow directions. The Crescent No.3 Mine is an example of a mine totally above-drainage.

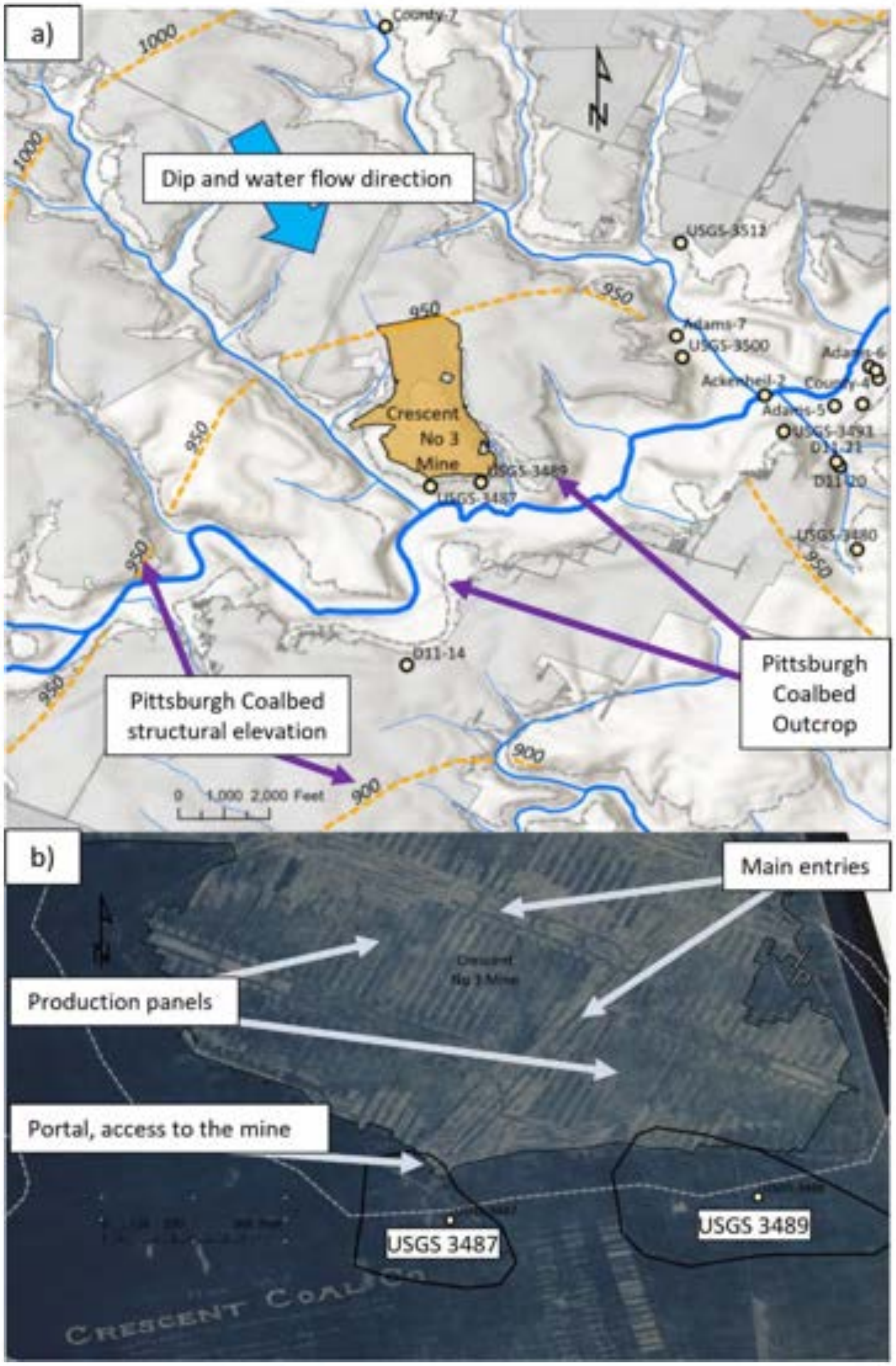

Figure 4.5.6. a) Plan view of the Crescent No.3 Mine outline showing the outcrop of the Pittsburgh Coalbed, and the direction of dip and water flow. Other mines in the Pittsburgh Coalbed are shown in light gray; b) the mine map for the Crescent No. 3 Mine showing the

location of the mineôs portals, the two USGS mapped landslides, and examples of the main entries and production panels. The polygons reflect the extent of landslides USGS 3487 and USGS 3489 as depicted in the 1979 mapping (Davies, 1979).

Two USGS landslides were mapped along and below the outcrop of the Pittsburgh Coalbed (Figure 4.5.6b). The mineôs portals are located along the Pittsburgh Coalbed outcrop. From there, the mine extended up-dip, first developing the main entries to assist in moving miners and materials (Figure 4.5.6b). Production panels are developed on either side of these main entries. At this mine, both the main entries and the development panels are oriented parallel to the dip of the coalbed. This was done to eliminate ponding at the working faces and reduce the need for pumping. However, this layout promoted the drainage of water, down-dip, towards the portals and out of the mine. It is likely that landslide USGS 3487, and potentially USGS 3489, were impacted by excessive water drainage onto the slope through the portal or thin coal barriers onto slopes where mining related materials had been cast.

4.5.3 Mining in the Allegheny Group

This case study assesses landslide occurrences associated with the outcrop of the Allegheny Group. The Allegheny Group of formations is ~300 ft thick (Table 1.1) and can potentially contain multiple mineable coals from the Upper Freeport downward through Brookville Coalbeds. This example is thought to be indicative of areas where multiple mineable coalbeds crop out in a relatively narrow band on the surface. In the northern portions of the study area, surface areas where the Allegheny Group crops out are known to display extensive remnants of both underground and surface mines.

4.5.3.1 Local characteristics

Armstrong County comprises parts of 24 Topographic quadrangles (Figure 4.5.7) and has an area of 665 square miles where strata dips slightly perpendicular to the axis of anticlines and synclines. Within this area, 315 landslides are contained within the database.

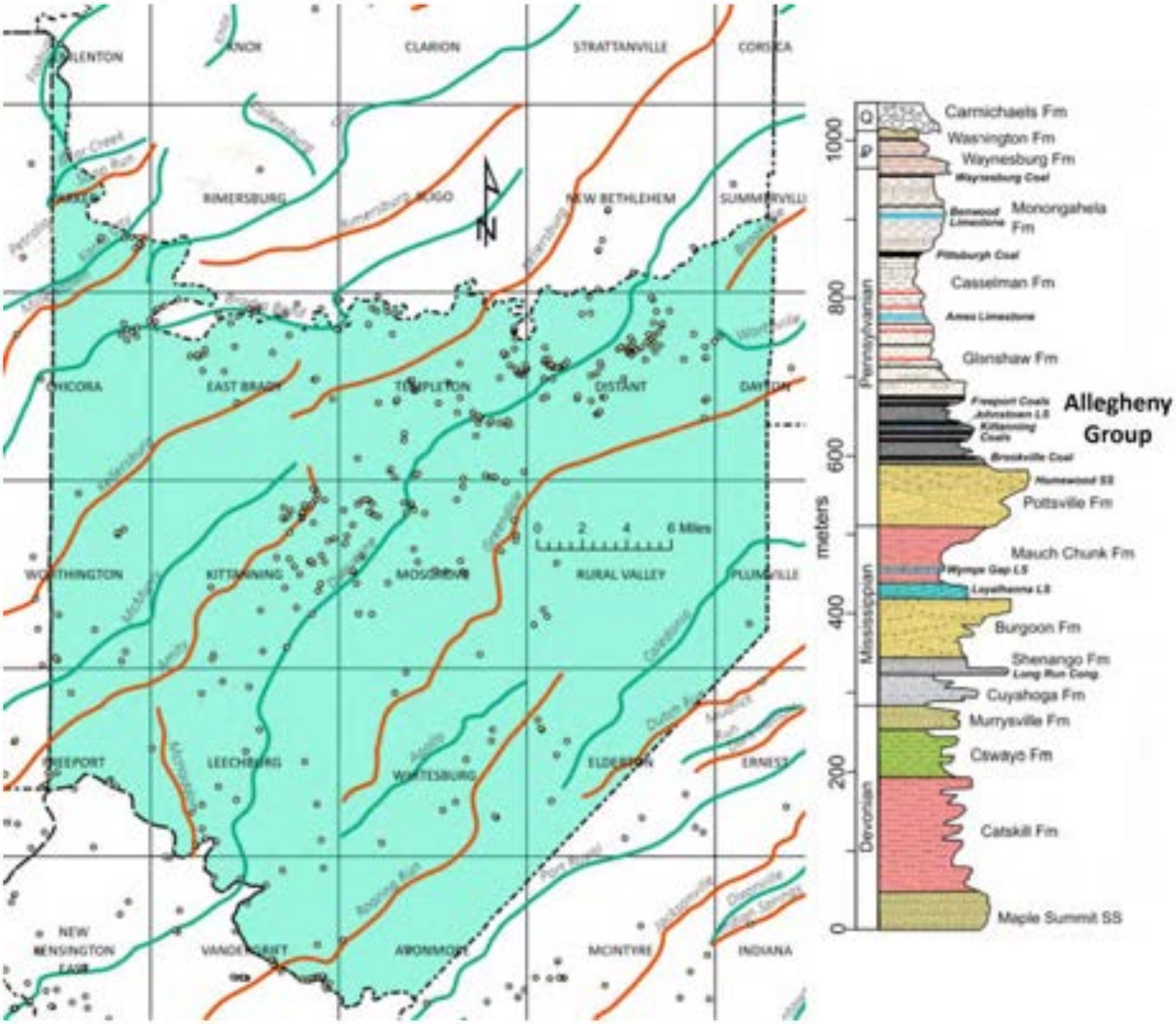

Figure 4.5.7. The Armstrong County study area is characterized by many landslides and a rich history of mining within the Allegheny Group. The map shows the locations of the landslides (open circles), the associated topographic quadrangles, and structural trends that bring the Allegheny Group to the surface over a large area of the County (anticlinal axis are in red-orange; synclinal axis in dark green). A stratigraphic column developed for the eastern portion of Fayette and Westmoreland Counties is adapted from Pazzaglia, Shaulis and Lindberg (2021).

The Allegheny Group crops out throughout Armstrong County (Figure 4.5.8). All the underground and surface coal mining take place in the Allegheny Groupês ~300 ft of strata. When visually examining this figure, a sizable portion of the landslides occur within the Allegheny Group. To help evaluate this relationship, the stratigraphic sequence found at the surface and the landslides contained within the database were overlain and counted.

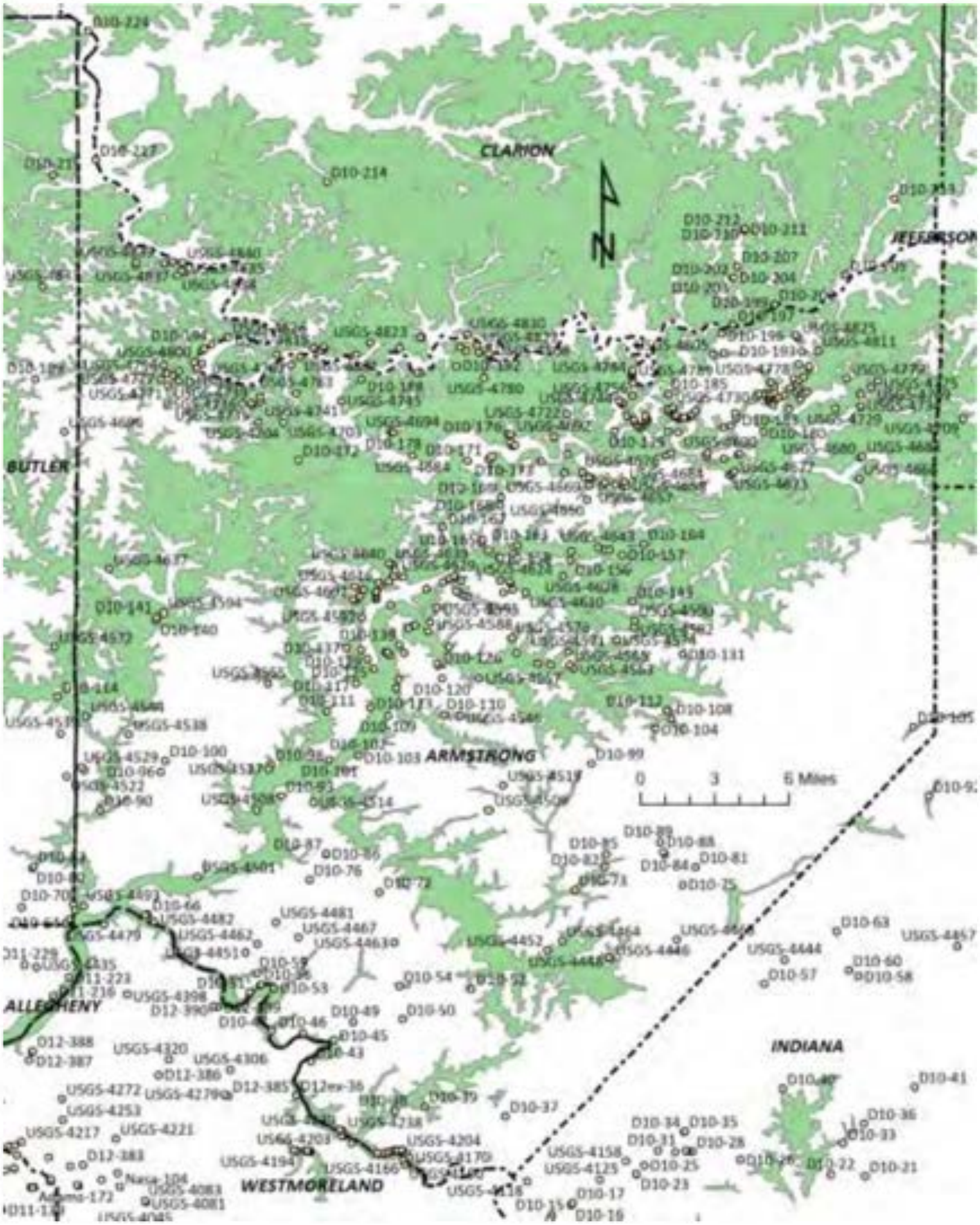

Figure 4.5.8. The green color shows the location of Allegheny Group cropping out at the surface. Also included are the locations of the 315 Armstrong County landslides in the database.

Of the 315 Armstrong County landslides, 234 or 74%, occurred within the Allegheny Group (Table 4.5.2). The next highest number, 38, occurred in the underlying Pottsville Formation. It seems reasonable to assume that the greater occurrence of landslides within the Allegheny Group are related to previous intense mining activity. All the other stratigraphic sequences contain only thin coals that are rarely mined in this area.

Table 4.5.2. Five stratigraphic sequences are found at the surface of Armstrong County. The distribution of landslides within these sequences is shown.

Stratigraphic Sequence	Number of Landslides
Allegheny Group	234
Burgoon SS through Cuyahoga Group	3
Casselman Formation	6
Glenshaw Formation	34
Pottsville Formation	38
Total	315

The data sources for landslide occurrences in Armstrong County are limited to PennDOT District 10, with 80, and the USGS, with 235. It is interesting that the number of Allegheny Group landslides from both data sources is reasonably high. Allegheny Group landslides for District 10 number 50, or 63% of the total. The number for USGS Allegheny Group landslides is 184, or 78% of the total.

Table 4.5.3. The number of landslides in the Allegheny Group by data source.

Data Source	Total Number	Number in Allegheny Group	Percentage of Total
D10	80	50	63
USGS	235	184	78
Total	315	234	74

4.5.3.2 Mining conditions

A substantial number of Armstrong County underground and surface coal mines operated prior to the passage and implementation of the 1977 SMCRA. At that time, a mining company was not required to extract coal in an environmentally acceptable manner. As a result, many of these mining sites are in a condition quite different from what existed prior to mining. The slopes in areas where mining has occurred can sometimes become unstable, producing a landslide. These mining sites consist of both surface strip or contour mines and the surface operations for underground mines. Examples of both follow. Since the passage and implementation of SMCRA and its later amendments, mining processes have continued to evolve as have the effectiveness of actions to prevent environmental harm. This is largely due to a robust mine permitting process controlled by the Commonwealth of Pennsylvania's Department of Environmental Protection. One obvious outcome is that current mining practice allows for only stable slope conditions, so landslides are not anticipated in mines permitted since the early 2000s.

The mining practices within Armstrong County are unlike those described in the Glassport Quadrangle. The Allegheny Group coalbeds differ in thickness and lateral consistency. The Pittsburgh Coalbed is known for conditions that are surprisingly uniform over great lateral distances. These Allegheny Group mining operations typically use room-and-pillar layouts and surface contour mining over multiple mining horizons. There are as many as eight minable coalbeds, but their thickness and quality can change dramatically over relatively short horizontal distances. This resulted in more widespread mining impacts that followed the entire 300 ft thickness of the Allegheny Group. This compares to only the strata directly above and below the Pittsburgh Coalbed (100 ft in thickness) in the Glassport Quad. Of course, there are exceptions to both these general trends. Let us begin by examining the relationship between underground coal mines and landslides as shown in Figure 4.5.9.

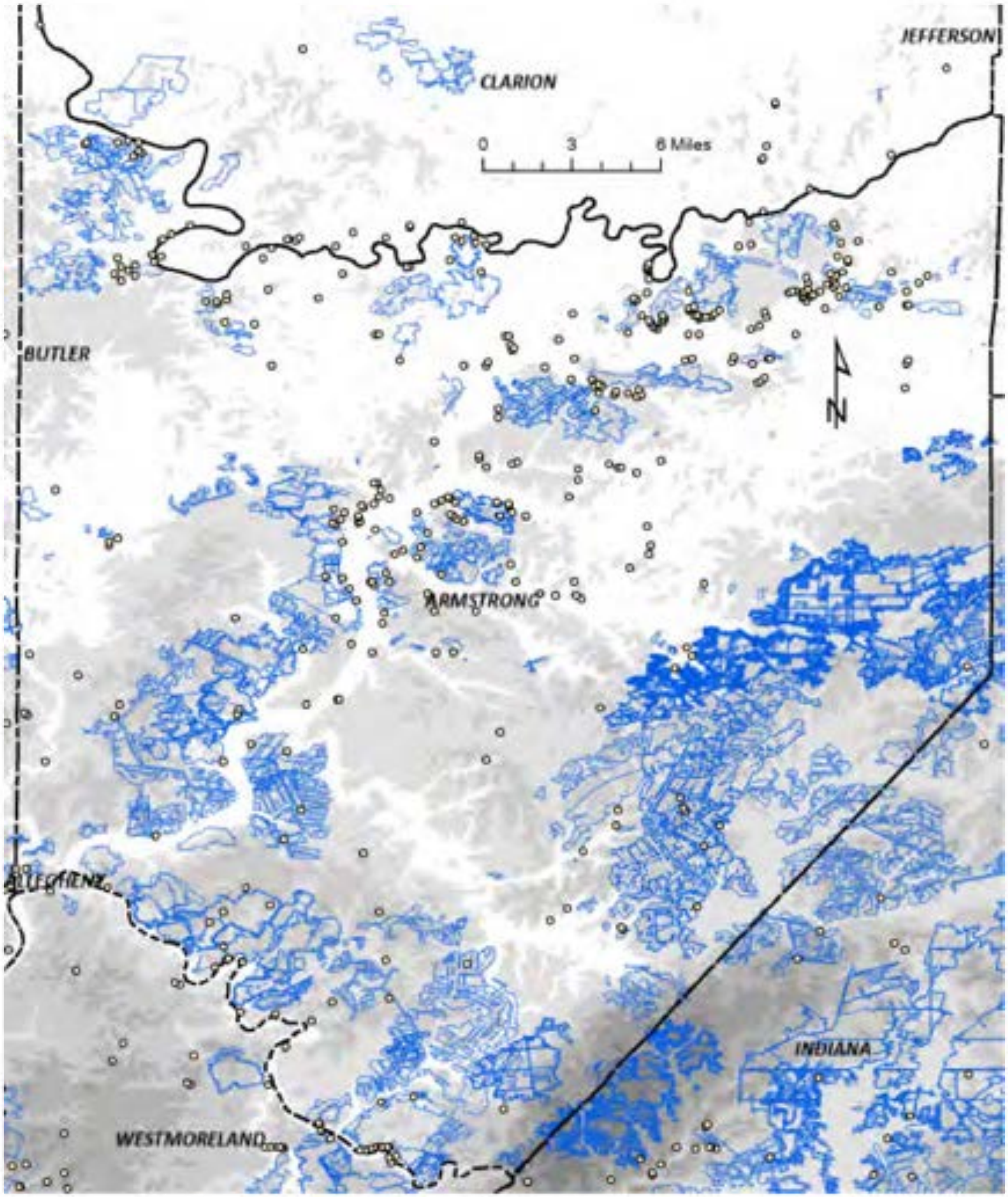

Figure 4.5.9. Map showing the distribution of Armstrong County landslides over underground coal mines. The outline of the underground mines is shown in blue. The different shades of gray represent the overburden above the Allegheny Group. The darker the gray, the greater the overburden which can range from 0 (white) to almost 800 ft (dark gray).

4.5.3.3 Impact of pre-SMCRA coal mining

There are no publicly available GIS databases that contain information on the location and characteristics of surface mining operation in Armstrong County. While this information exists, it currently resides in state and company archived files. Currently, surface coal mines and the surface operations of underground coal mines are required to be reclaimed to a standard identified in the mineǿs permit. Therefore, these mines have engineered slopes that are designed to remain stable. Unfortunately, this is not the case for surface mines developed prior to the implementation of SMRCA and its amendments. These mines lacked acceptable surface mine reclamation practices. The problem will lessen going forward due to the efforts of the federal and state agencies to reclaim these sites through taxpayer funded projects. Regrettably, there are so many of these AML (Abandoned Mine Land) sites that it will take many decades to complete these reclamation projects.

In 1983, the National Abandoned Lands Inventory (NALI) was developed. The current version of the Pennsylvania inventory is in a GIS format. The location of AML sites for Armstrong County are shown in Figure 4.5.10. The inventory is not complete and does not contain information on re-mining or other post 1983 developments at the sites. The inventory represents a reasonable approach to identifying areas where, on closure of the mining site, reclamation was not implemented. This allows for an approximate comparison of AML sites with landslide occurrences. This database is especially relevant for the USGS data source since all these landslides were identified prior to the development of the AML inventory.

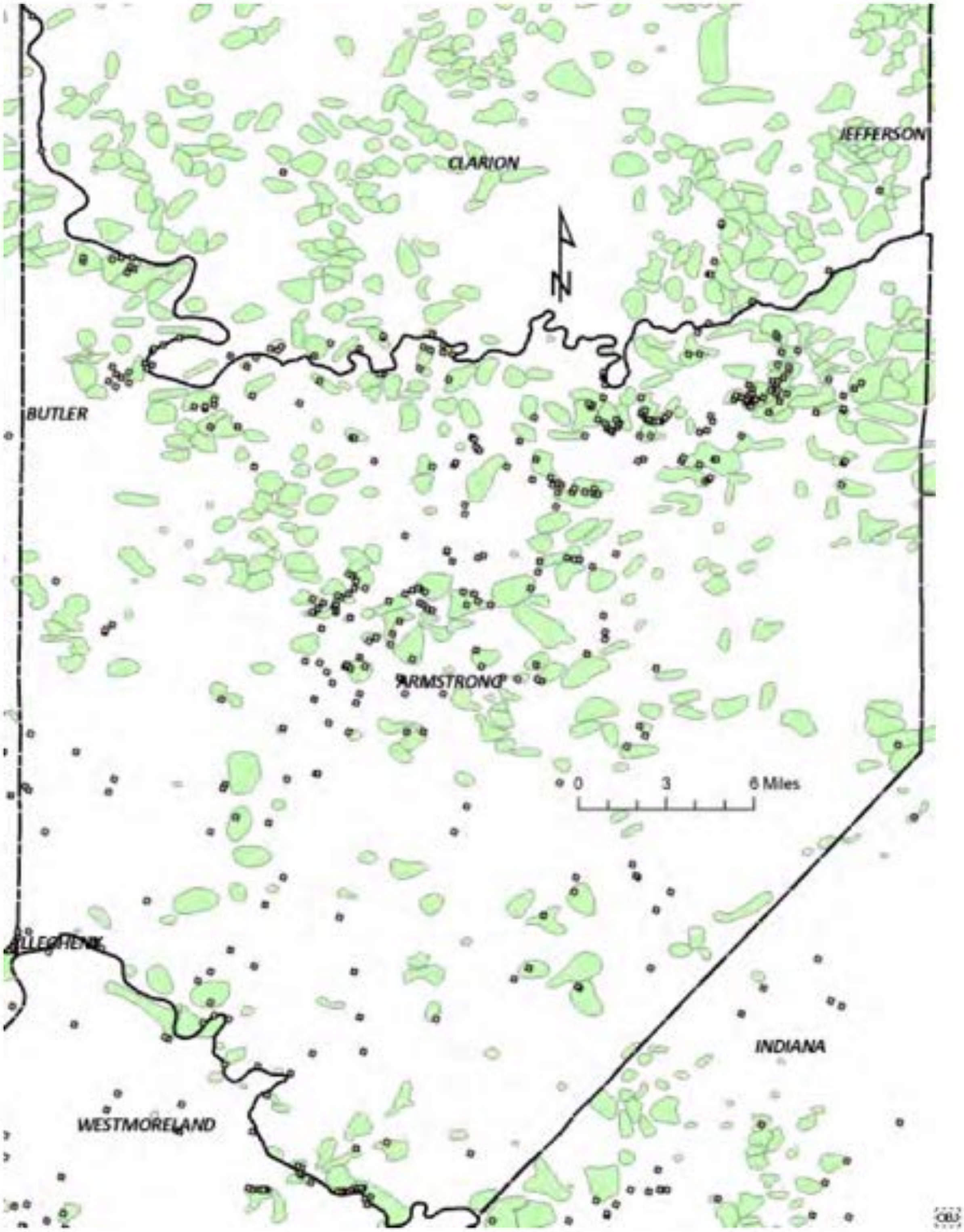

Figure 4.5.10. The light green areas represent AML sites in Armstrong County identified in NALI. Also shown are the locations of the database landslides.

When the polygons for the NALI AML sites are overlain with the landslide database for Armstrong County, a preliminary assessment is possible. Of the 315 Armstrong County landslides, 160 (51%) occurred within AML (Table 4.5.4). The number of USGS identified landslides occurring at AML sites is 143, or 61%. In comparison, only 17 (21%) of District 10 identified landslides occurred within AML sites. The high percentage of USGS landslides occurring within AML sites provides an indication that surface expressions of coal mining have a disproportionately high correlation with landslide occurrence.

Table 4.5.4. Analysis of the number of AML landslides by data source.

Data Source	Number of Landslides	Occur within AML	Percentage
D10	80	17	21
USGS	235	143	61
Total	315	160	51

4.5.3.4 A closeup look at surface conditions within AML sites

One striking example of what AML surface conditions can look like is shown in Figure 4.5.11. There are ten different AML sites contained within this figure, each containing at least one abandoned strip or underground mine and, in some cases, multiple surface mine benches. There are also several examples where the surface operation from underground coal mines have produced benches near their portals. It should be mentioned that some of these AML sites may have been recently reclaimed or re-developed and may not be reflected in this map.

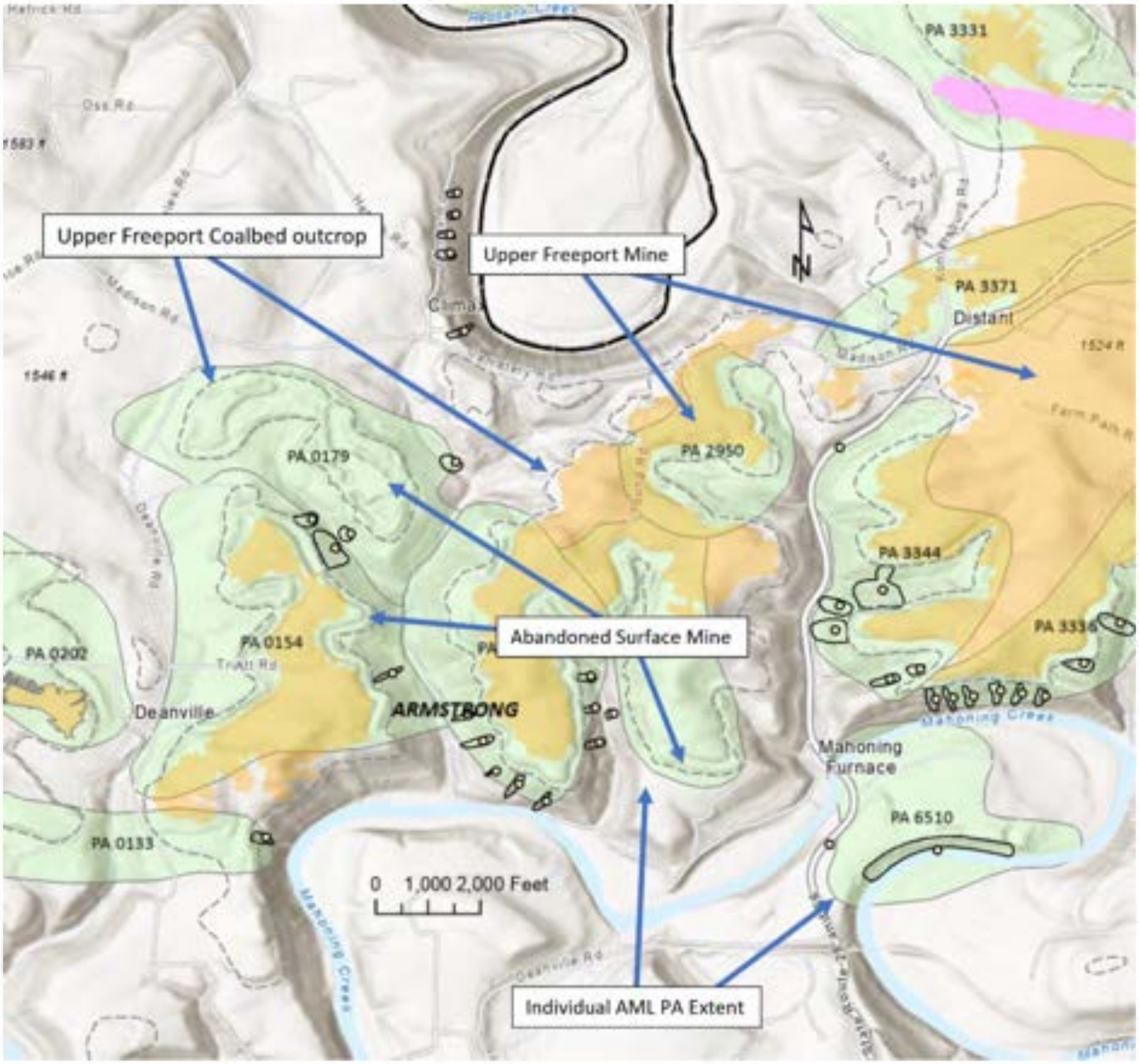

Figure 4.5.11. Closeup look at topographic conditions with AML sites PA 0202, PA 0133, PA 0154, PA 0179, PA 2950, PA0329, PA0335, PA3371, PA3344, and PA 6510. Note the occurrence of many strip mine benches as well as the surface operations for underground coal mines. Also shown is the Upper Freeport outcrop and underground coal mines (Upper Freeport = orange; Lower Freeport = pink). The polygons reflect the extent of active or recently active landsliding delineated in the 1979 USGS data (Pomeroy, 1979a, 1979b).

4.5.4 Summary of coal mining influence

Two case studies show how coal mining, especially mines developed prior to the implementation of SMCRA and its amendments, can influence landslide occurrence within the study area. The Glassport Quadrangle example is focused on legacy mines in Allegheny and Washington

Counties. The Armstrong County example is focused on surface strip mining and the surface operations for underground mines. In both cases, preliminary analysis suggests that the occurrence of landslides is elevated in these areas. This is not meant to be a thorough assessment of coal miningôs influence within the study area. Instead, these examples are meant to increase database user awareness as to how coal mining may influence landslide occurrence in different parts of the study area.

4.6 Landslide classification using geotechnical data

Landslide classification allows for the comparisons of groups of similar landslides to evaluate underlying causes. For example, rockfalls and slumps involve the sliding of different materials at different rates, and therefore need to be analyzed in distinct conceptual frameworks. The vast majority of the landslides in the database are not classified (i.e., only 245 (~3%) are classified), making these comparative analyses difficult with the existing data. One option to address this data gap is the classification of landslides using documentary information. In retrospective cases, classification of most of these landslides likely requires intense consultation of geotechnical data (if available). To explore how this classification might proceed, we used geotechnical data provided by Allegheny County to assess our ability to reconstruct classification. This section explores how geotechnical data were used and evaluated as a means for landslide classification, including the geolocation of historical slides as an avenue to accessing other spatial data resources.

First, we evaluated several classification systems and presented these options to the working group. The DCNR Landslide classification system by Delano and Wilshusen (2001) (Table 4.6.1) was preferred by the Pitt team and this decision was supported by the working group. The classification is based on Pennsylvania conditions and has a relatively simple classification system. Alternative classification systems we investigated were Cruden and Varnes (1996), and Highland and Bobrowsky (2008). Cruden and Varnesô classification system was too detailed; the extensive data required for classification does not match the level of information commonly available. Highland and Bobrowskyôs classification system was adequately simple, but it was not developed for Pennsylvaniaôs conditions. The DCNR system was therefore used as a taxonomy to classify the Allegheny County landslides based on available data.

Table 4.6.1. DCNR Landslide Classification System (from Delano and Wilshusen, 2001).

Type of Movement		Type of Material		
		Bedrock	Engineering Soil	
			Coarse- grained	Fine-grained
Fall		Rockfall		
Slide	Translational	Rockslide	Debris slide	
	Rotational	Rock slump	Slump	
Flow	Rapid		Debris avalanche	Mudflow
			Debris flow	Earthflow
	Slow	Rock creep	Talus creep	Soil creep

To illustrate the process of landslide classification from geotechnical reporting and to help guide future classification efforts, several examples are described based on the technical reports from Allegheny County (Figure 4.6.1). The first example is the Evergreen Road slide. For this slide, pictures indicating the type of material present and rate of movement (Figure 4.6.2) along with supporting descriptions from geophysical reports (DôAppolonia Engineering, 2018a) were used to classify the landslide. According to the Evergreen Road Final Report, the slide had a ñnear-vertical scarpò at the upper limit, with ñirregular mounds of soil rock and debrisò remaining on the slope below the scarp (DôAppolonia Engineering, 2018a). Additionally, the report revealed that the fill had a "heterogeneous mixture of soil, rocks, boulders and construction debrisò (DôAppolonia Engineering, 2018a). This information confirmed that the slide material (Figure 4.6.2) is coarse and unconsolidated. Moreover, Figure 4.6.2 (c) shows a rapid soil movement of the soil in discrete layers as indicated by the displaced debris over the intact lower bedrock. These pictures and report descriptions, taken together, provided evidence of a debris slide, which according to DCNR is ñthe rapid sliding movement of unconsolidated coarse soil in which the material slides as one of more discrete unitsò (Delano and Wilshusen, 2001). In this case, the combination of pictures and geotechnical reporting allowed for classification using the DCNR system.

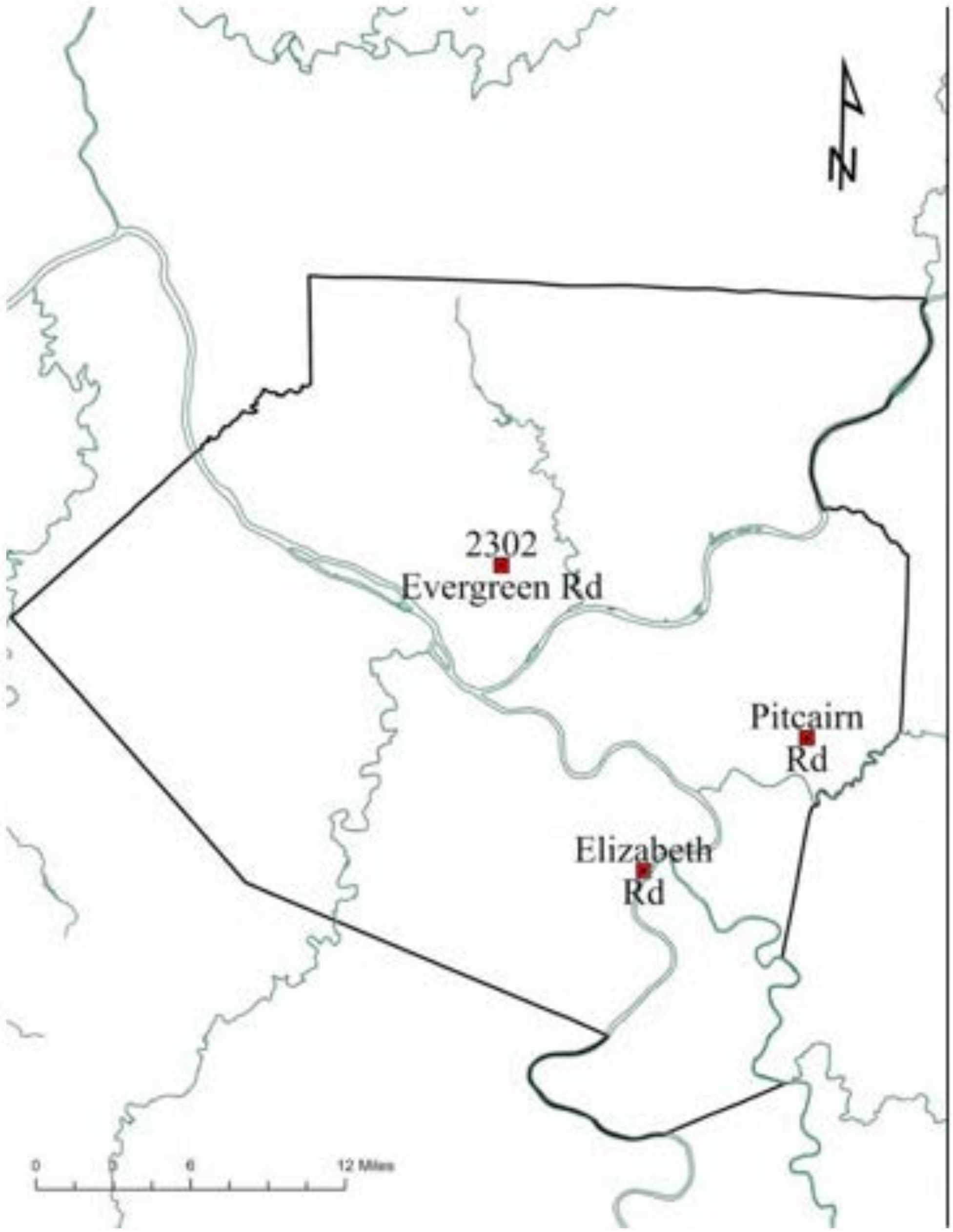

Figure 4.6.1. Map of landslide examples where geotechnical data were used. Outline of Allegheny County and locations of landslides referenced in this section are shown.

(a) (b)

(c) (d)

Figure 4.6.2. Pictures of the Evergreen road slides (from (DôAppolonia Engineering, 2018a). Panel a) upper limit of the landslide at Evergreen Road from Ricoôs Parking Lot -- looking west; b) landslide debris on slope at Evergreen Road -- looking south; c) Landslide debris on Evergreen Road ï looking west; and d) clearing of landslide debris from Evergreen Road -- looking west (DôAppolonia Engineering, 2018a).

In some cases, there were no pictures in the Countyôs geotechnical reports, so we utilized the Allegheny County Landslide Portal (ACLP) to access imagery by cross-checking location data. (Note, limited pictures of the landslide in the reports may result from landslides being cleaned up rapidly to allow road use and the geotechnical team designing repairs being engaged after this clean up.) To match the landslides, schematics in the reports were used to digitize and geolocate the footprints of all Allegheny County landslides with sufficient data. Geolocated slides were then used to find the slide in the ACLP. Once the slide was matched, this allowed for access to the pictures on the ACLP for classification (Figure 4.6.3).

Figure 4.6.3. Example of landslide image from Allegheny County Landslide Portal for Elizabeth Rd Lateral Support landslide.

However, in some cases, the ACLP pictures were still insufficient to determine the full scope of the landslide and allow classification. Hence, similar to the Evergreen Road Landslide, additional information from geophysical reports were used to classify landslides (Fig. 4.6.3). For example, the report for the Elizabeth Street slide stated ñan approximately 80- to 100-foot section of the eastern roadway embankment failed suddenly prior to February 16, 2018, resulting in an approximately 3-foot-high, near vertical scarp that encroached on the northbound travel laneò (DôAppolonia Engineering, 2018b). Moreover, the cross-section of the landside in the construction plans (Fig 4.6.4) showed rotational sliding. These data, when combined with the online imagery, were used to classify the Elizabeth Road landslide as a slump (i.e., Table 4.6.1).

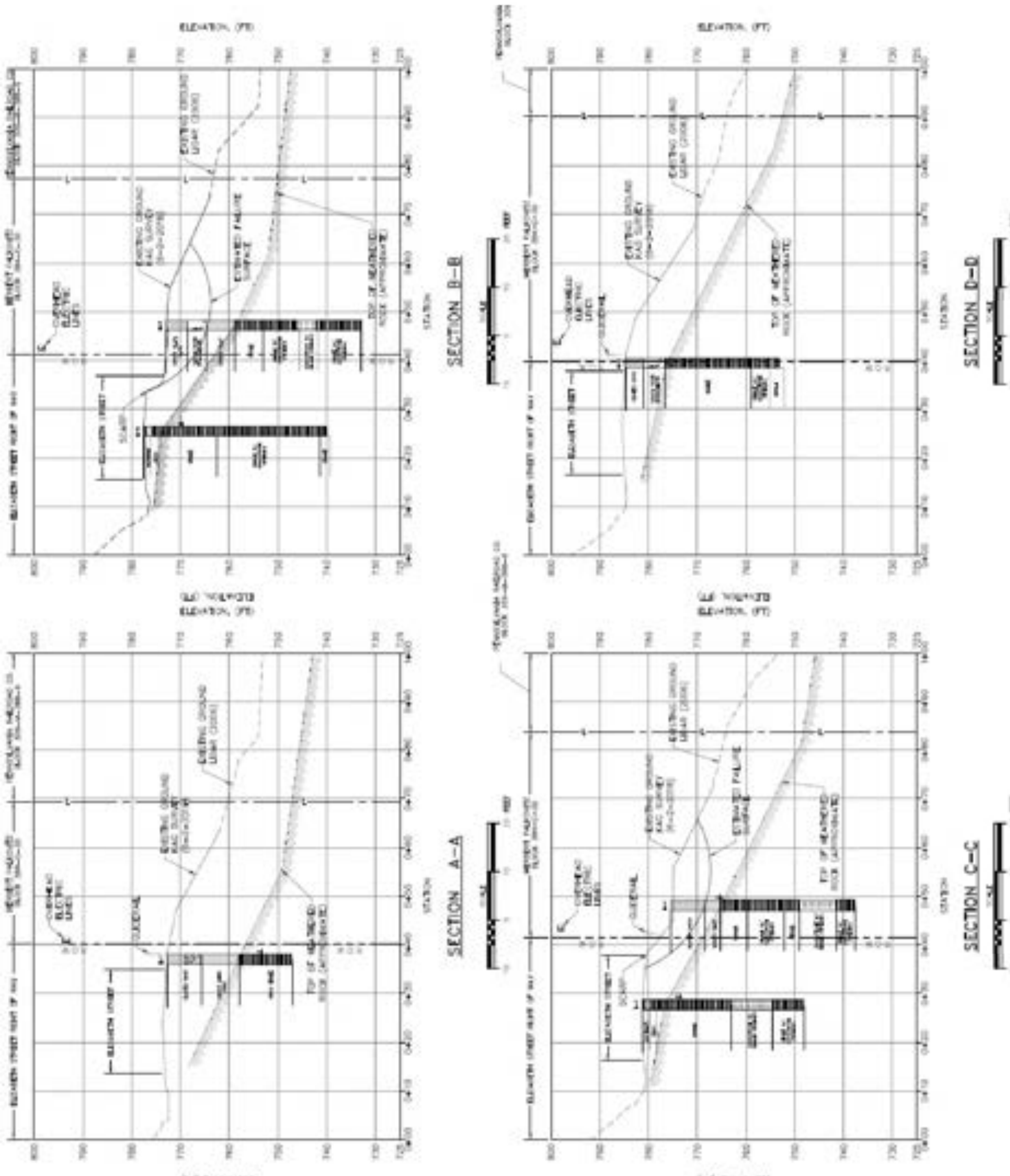

Figure 4.6.4. Cross Section of landslide at Elizabeth Road Lateral Support (DôAppolonia Engineering, 2018c).

The shape of the slide and soil depth data were also used to help classify some slides. For example, in the Pitcairn Rd. Landslide, the large, semi-circular footprint of the slide shown in the construction plans (Figure 4.6.5), along with the deep soil layer and homogenous material shown in the boring log data were used to classify this slide as a slump. According to the DCNR classification system, ñFormation of a semicircular slip surface is typically an indication that the material is not composed of layers having different strengths,ò and ñArtificially placed materials such as fill and mine waste typically fail by slumpingò (Delano and Wilshusen, 2001).

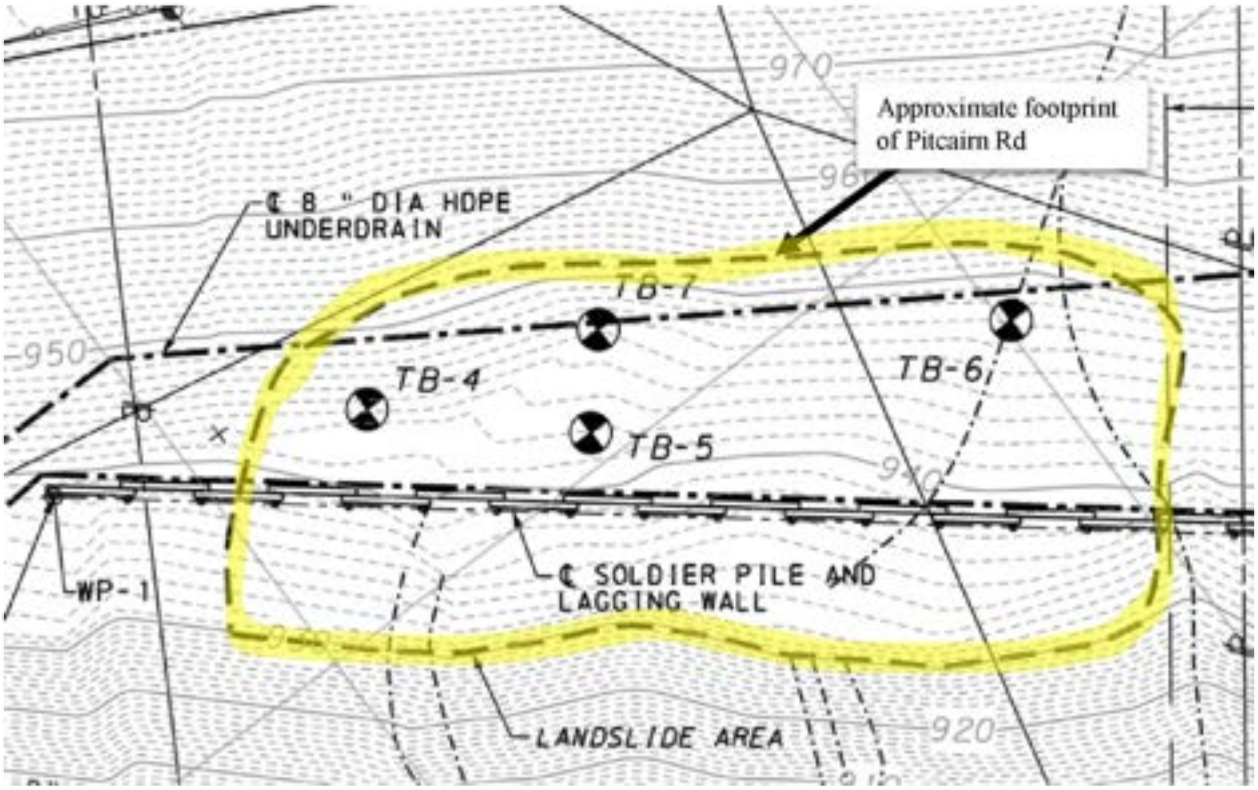

Figure 4.6.5. Pitcairn Rd landslide footprint (County of Allegheny Public Works, 2014).

This section described several cases where geotechnical data were used and evaluated to classify database landslides according to the DCNR classification system. However, while possible with sufficient information, the information was not always reliably available in these documents. Classification of landslides from geophysical reports and construction plans was possible in 7 of the 22 cases where geophysical data were available. Of the 15 slides without sufficient information, 13 had ambiguous location data. This prevented them from being included in the database since they could not be precisely located and additional data could not be accessed. The remaining two simply did not have sufficient pictures in the geophysical reports. Issues of ambiguous location data are discussed at other points in this report (section 2.2.1.1.3). Here, it is a significant barrier to building the landslide database and therefore obstructs retrospective landslide classification efforts.

This process illustrated the effort necessary for retrospective landslide classification. Location data was not reliably provided and therefore required substantial effort in evaluating all available geotechnical data. Further, sometimes location data was not useful. As the landslide database evolves, classification of landslides as near as possible to the time of occurrence is strongly encouraged. In cases where immediate classification is not possible, precise location data, copious landslide imagery, and complete event descriptions in geophysical reports would increase the potential for successful retrospective classification.

4.7 High consequence landslides in southwestern Pennsylvania

Beyond the substantial economic cost of landsliding to the region, it is also important to consider the human cost of these events. Globally, landsliding kills thousands of people per year (Froude and Petley, 2018). It is fortunate that recent landsliding in Pennsylvania has not taken much of a human toll. However, this fortune is sometimes the result of luck in ñnear missò cases. Further, historically, there have been grim tragedies that have extracted a human toll. This section describes a subset of eight landslides associated with both recent near misses and historical tragedies (i.e., fatality, non-fatal injury, vehicle damage, temporary road closure, or a near miss). Many of these landslides are not necessarily captured by the available agency records, so this section serves as a list of landslides that are at the forefront of regional experience, particularly for those who insure the publicôs health and safety.

4.7.1 High consequence landslides within the database

Ackenheilôs PhD dissertation (1954) identifies five landslides that caused vehicle accidents between 1940 and 1951. These accidents caused 22 fatal and 9 nonfatal injuries (Table 4.7.1). The most striking event occurred on December 22, 1942. A rock fall along SR 930 (currently SR 51) in Aliquippa killed 22 workers traveling on a bus from the Jones and Laughlin steel plant at the end of their shift. One worker was able to escape out the back window with only minor injuries.

Table 4.7.1. Landslide impacting roadways from Ackenheilǿs PhD dissertation that included injuries. The numerical values in the ID correspond to the numbers used in Plates 1-3 of the dissertation.

Date	ID	Injure	Characteristic	Volume, yd³	Location	Comment
5/31/1940	Ackenheil-62	4nf	Debris avalanche	30	Ohio River Blvd	Vehicle crash
12/22/1942	Ackenheil-68	22f; 1nf	Rock fall	150	West end of Ambridge Bridge	Bus crash
3/12/1943	Ackenheil-35	1nf	Rock fall	1	Bigelow Blvd	Vehicle crash
1/14/1946	Ackenheil-75	1nf	Earth flow	NA	Clairton-Elizabeth Road	Retaining wall collapse
2/9/1946	Ackenheil-1	1nf	Debris flow	NA	Monessen	Vehicle crash (8 vehicles total)
1/18/1951	Ackenheil-14	1nf	Rock fall	2	Saw Mill Run Blvd @ Woodruff	Vehicle crash

f ï fatal accident
nf ï non-fatal accident

The slide labeled Ackenheil-68 generated 150 yd^3 of material onto SR 930 (elevation 752 ft) from the adjacent cliff with a slope angle of 70 degrees (Ackenheil, 1954). The Upper Freeport Coalbed in this area is expected to be at an elevation of 750 ft and the Ames Limestone at an elevation of 1055 ft (Figure 4.7.1). These are important stratigraphic markers as they represent the boundary between the Allegheny Group (Pa), the Glenshaw Formation (Pcg) and Casselman Formation (Pcc), respectively (Figure 4.7.1). Therefore, landslide Ackenheil-68 is located in the Lower to Middle Glenshaw Formation (Pcg).

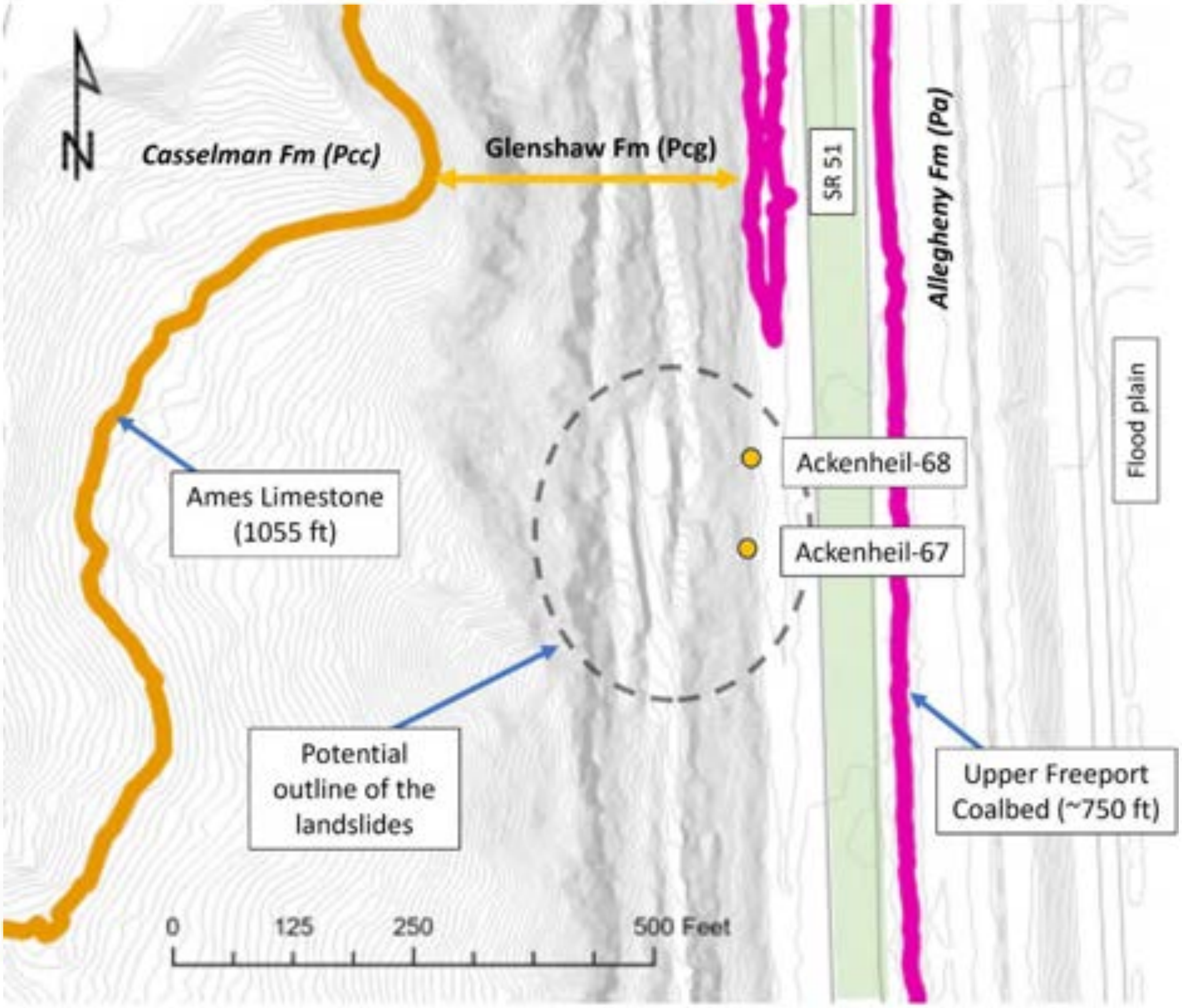

Figure 4.7.1. Surface contour (2-ft interval) showing the steep slopes at the location of slides Ackerheil-67 and Ackenheil-68. Also shown is the outcrop of the Upper Freeport Coalbed (the dividing boundary between Allegheny Group and the overlying Glenshaw Formation) and the Ames Limestone (the dividing boundary between Glenshaw Formation and the overlying Casselman Formation).

Ackenheil (1954) indicated that this section of highway, 2 miles north and south of the Ambridge Bridge has been plagued with landslides. From 1932 to the occurrence of slide Ackenheil-68 on Dec 22, 1942, four other major rock falls are reported that impacted traffic and resulting in one fatal injury. Also, for the five years after slide Ackenheil-68, six other major rock falls/earthflows were identified in this road section by Ackenheil (1954).

- Ackenheil-81 on Feb 21, 1951, where 100 yd^3 of debris blocked the road two days, no injuries

- Ackenheil-85 on Jan 29, 1952, where 150 yd^3 of debris blocked the road for three days, no injuries
- Ackenheil-87 on Sep 11, 1952, where 150 yd^3 of debris blocked two lanes for 12 hours, no injuries
- Ackenheil-67 on Apr 20, 1953, where 125 yd^3 of debris blocked the roadway for 3 days, no injuries.
- Ackenheil-66 on Jul 15, 1953, where 50,000 yd^3 of debris blocked the roadway.
- Ackenheil-88 on Feb 27, 1954, where 100 yd^3 of debris hit bus and blocked the road for 3 days

4.7.2 . High consequence landslides added to the IRISE database

There are a few high-consequence landslides not included in any of the sourced datasets. These landslides, located throughout the study area (Figure 4.7.2), are now included in the database with the source label ñPitt" (Table 4.7.2). Their individual characteristics are discussed below. These landslides were identified through historical documents, news reports, and conversations with other landslide experts.

Table 4.7.2. Location of eight high-consequence landslides impacting roads that are currently not within the IRISE database.

ID	**County**	**Date**	**Lat**	**Long**
Pitt-Woodruff1	Allegheny	Dec 1982	40.425063	-80.019022
Pitt-Woodruff2	Allegheny	17 Feb 1983	40.425063	-80.019022
Pitt-Elizabeth	Allegheny	8 Mar 1923	40.2786989	-79.8875038
Pitt-PennTwp	Westmoreland	After 2000	40.344372	-79.632701
Pitt-AmwellTwp	Washington	14 Jul 2010	40.0295856	-80.2135159
Pitt-SmithTwp	Washington	1 Oct 2018	40.3949709	-80.3983043
Pitt-Vestaburg	Washington	17 May 2011	40.012165	-79.992176
Pitt-KilbuckTwp	Allegheny	19 Sept 2006	40.5143457	-80.1148369

Figure 4.7.2. Location of eight landslides added to IRISE database by the University of Pittsburgh.

4.7.2.1 Pitt-Woodruff1 & Pitt-Woodruff2

One of the most notable high consequence landslides occurred on Feb 17, 1983. In this tragic accident, two people were fatally injured with a third suffering serious injury after being struck by a falling rock. Landslide Pitt-Woodruff2 happened suddenly during attempted stabilization of the slope along SR 51 near Woodruff Street in Pittsburgh. This engineering intervention was initiated in response to earlier landslide (Pitt-Woodruff1) at this same area ~3 months before (Figure 4.7.3).

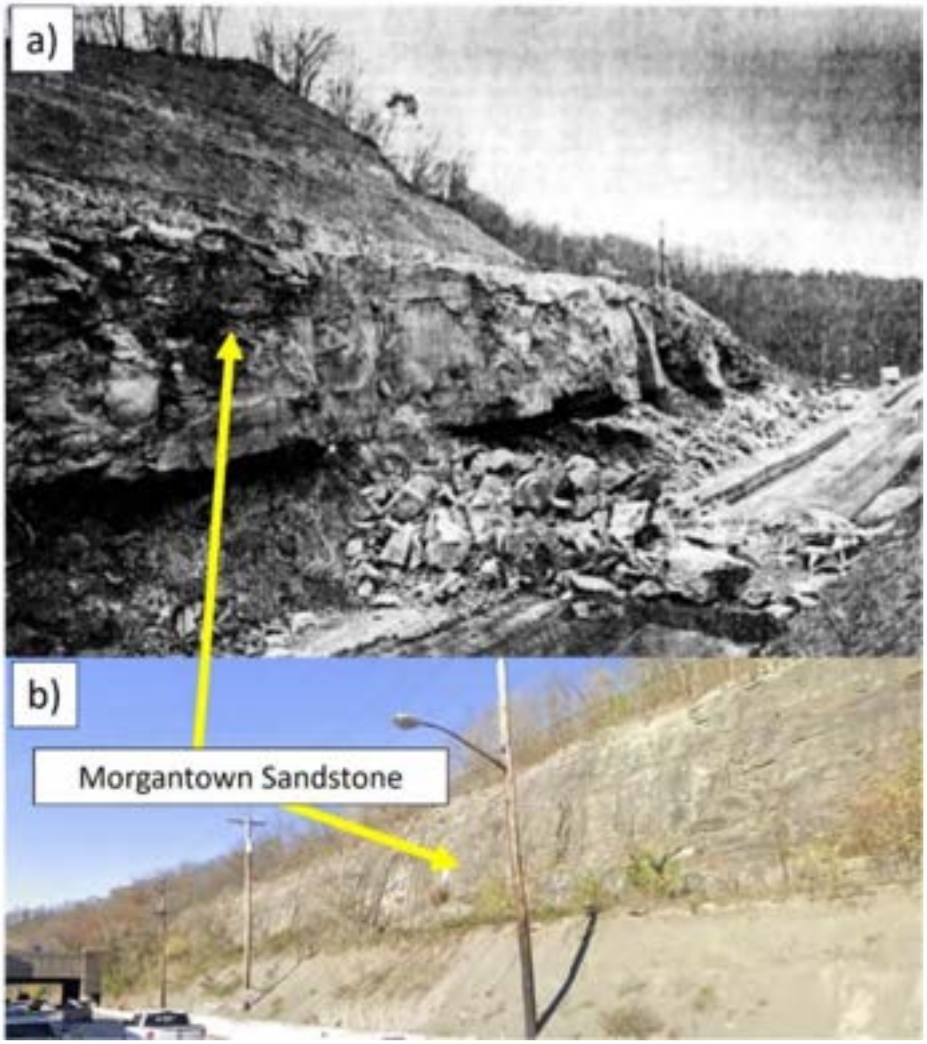

Figure 4.7.3. a) View of the SR 51 landslide near Woodruff Street after the 1983 February landslide. Note that the Morgantown Sandstone highwall was close to the roadway and underlain by a weaker rock; b) View of the current slope. [Note: the Morgantown Sandstone has been partially excavated and now forms a highwall further back from the road surface].

While there are eight landslides listed in the IRISE Database along Woodruff Street (Figure 4.7.4), the fatal 1983 events are not captured in any of the databases used to form this database. At this location, the Pittsburgh Coalbed is projected to be at an elevation of 1,014 to 1,024 ft. The top of Morgantown Sandstone has an elevation of ~870 ft. This would yield a difference of ~144 ft between the Monongahela-Casselman boundaries and the top of the Morgantown Sandstone. Therefore, the majority of the slide material originated in the Middle Casselman Formation.

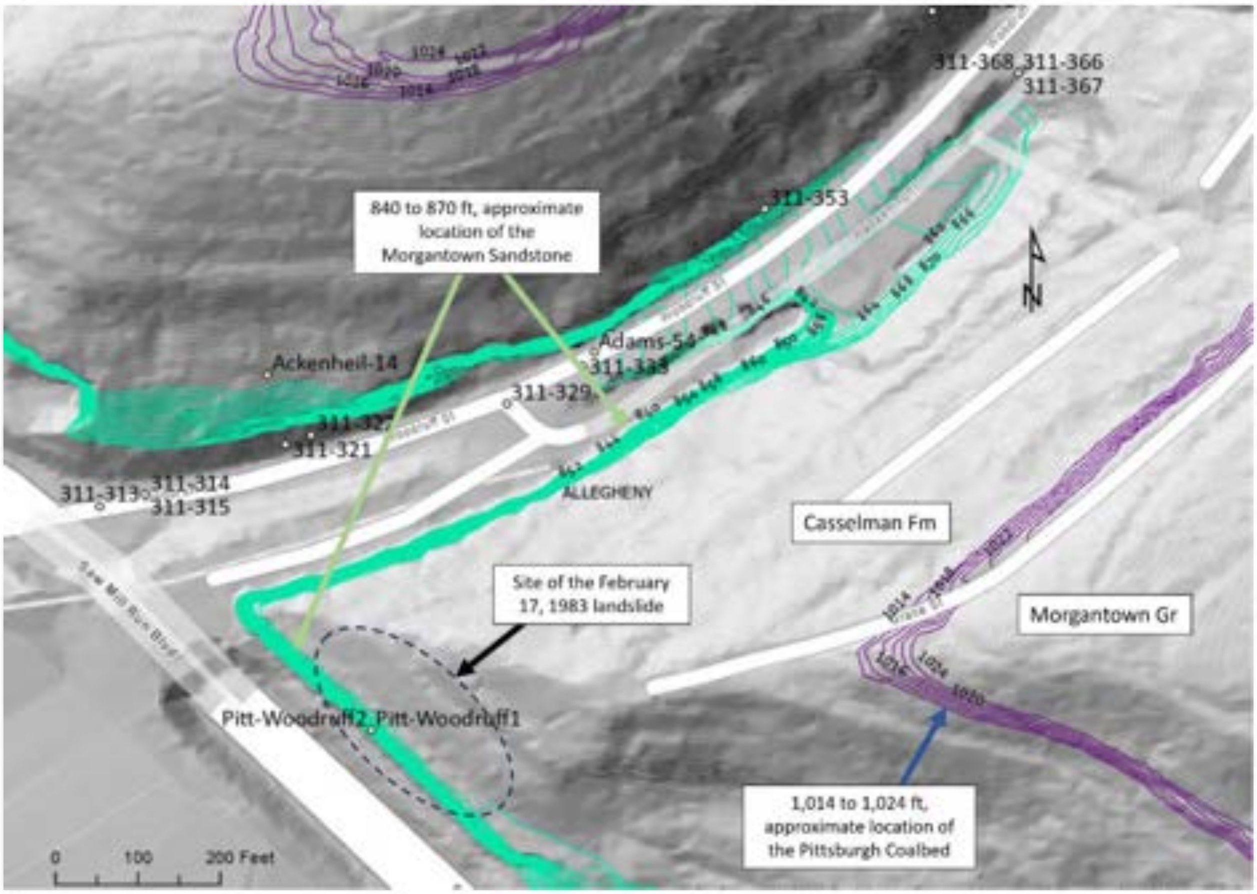

Figure 4.7.4. Topographic contour showing the location of the February 17, 1983 landslide and the approximate location of the Pittsburgh Coalbed and Morgantown Sandstone outcrops.

4.7.2.2 Pitt-Elizabeth

On March 6, 2023, a sudden massive rockfall damaged SR 837 near Elizabeth, PA (Figure 4.7.5). Fortunately, this event occurred with only minor disruption to traffic as there were no reported accidents and the roadway was closed for the two days it took to reduce the size of the large boulders and remove the debris from the road. This event is classified as a road closure and a near miss as it had the potential to harm the traveling public. This landslide originated almost exclusively from an outcrop of Morgantown Sandstone located ~80 ft above the roadway (Figure 4.7.5b). This rockfall occurred during the study period and the PennDOT districtĝs landslide data was provided to us prior to this event. Therefore, the rockfall would not be reflected in agency data and we have included it here.

Figure 4.7.5. a) Location of the March 6, 2023, landslide (Photo from WTAE News); b) landslide material originated from an outcrop of Morgantown Sandstone above SR 837.

The Morgantown Sandstone is very massive/thick in this portion of the Monongahela Vally, reported to be approximately 40 ft thick (Orsborn, 2015) in this area. The Pittsburgh Coalbed is estimated to be between 990 to 1,000 ft and the Morgantown Sandstone between 810 to 860 ft. At this site, the top of the Morgantown Sandstone lies ~130 ft below the Pittsburgh Coalbed (Figure 4.7.6). This places the landslide in the middle of the Casselman Formation (Pcc) and within the horizon of the Morgantown Sandstone.

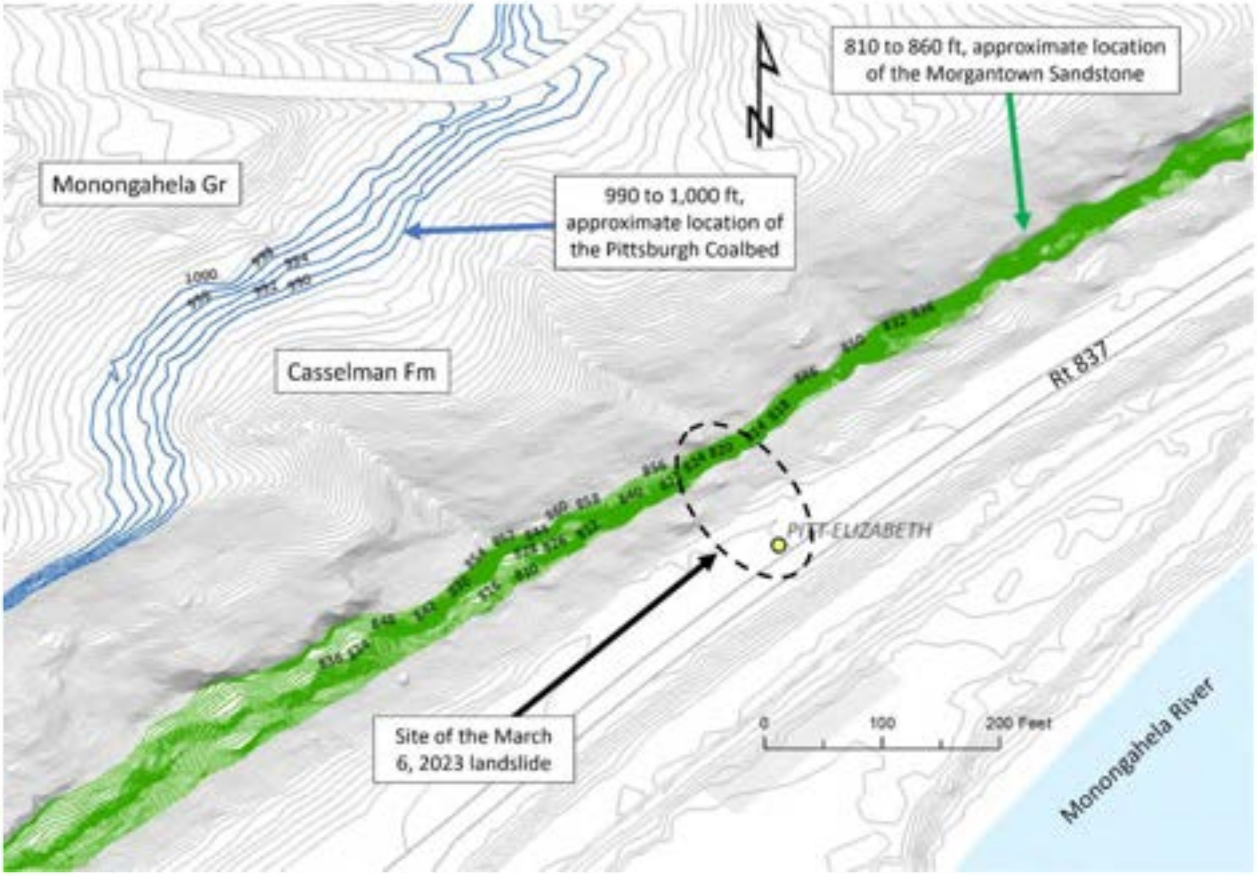

Figure 4.7.6. Surface contours showing the high relief associated with the outcrop of the Morgantown Sandstone.

4.7.2.3 Pitt-PennTwp

A fatal accident occurred on SR 130 in Penn Township and was associated with a landslide that added water to the roadway and most likely assisted in cracking the asphalt (Figure 4.7.7). The street view within Google Maps does not show an outcrop that would reveal the nature of the local strata (Figure 4.7.7b). It is therefore assumed that the landslide was most likely a debris flow and could have occurred above or below the roadway.

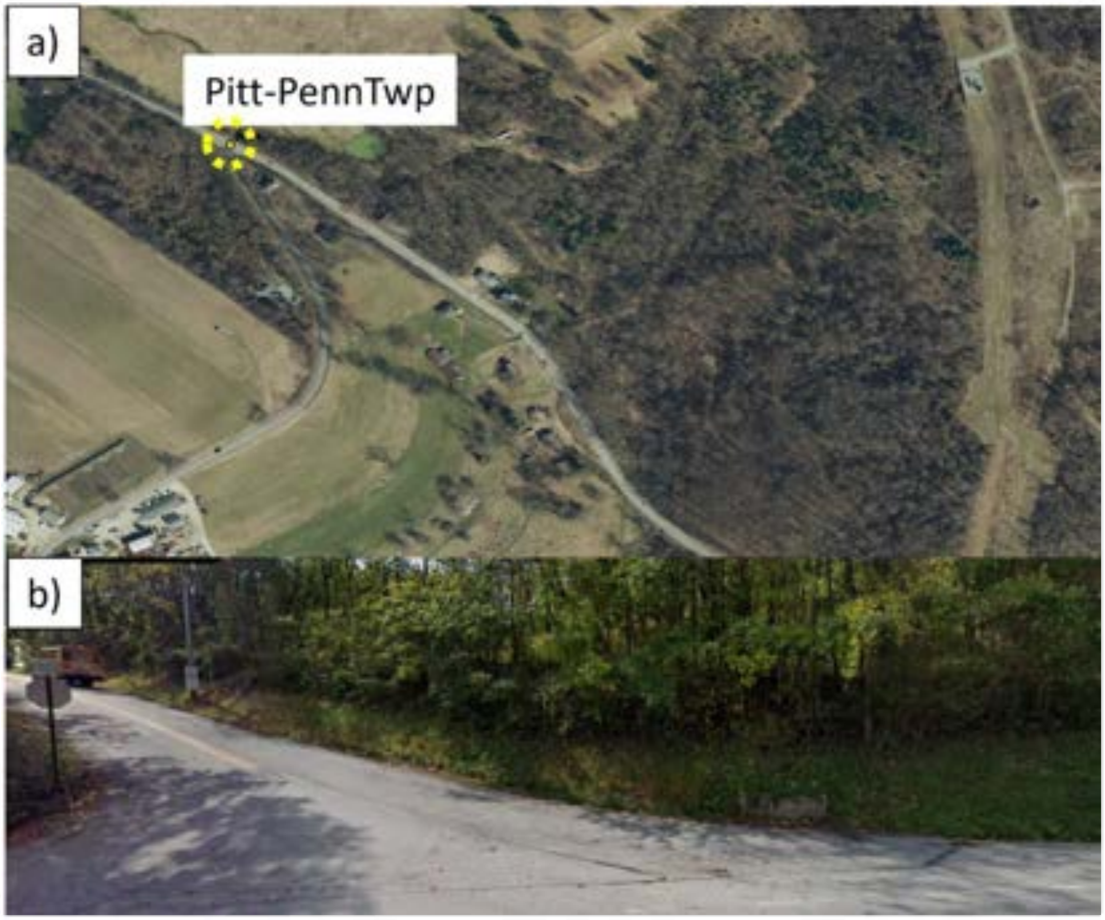

Figure 4.7.7. a) Location of Pitt-PennTwp on SR 130 in Penn Township from Google Earth. The top of the image is oriented to the north.; b) view of the hillside above the landslide location.

The stratigraphic location of slide Pitt-PennTwp was determined to be ~100 ft above the Pittsburgh Coalbed within the Middle to Lower Monongahela Group (Figure 4.7.8). This value was obtained by subtracting the Pitt-PennTwp surface elevation (1,150 ft) from the elevation of the Pittsburgh Coalbed (1,050 ft) located at the boundary between the Monongahela Group (Pm) and Casselman Formations (Pcc).

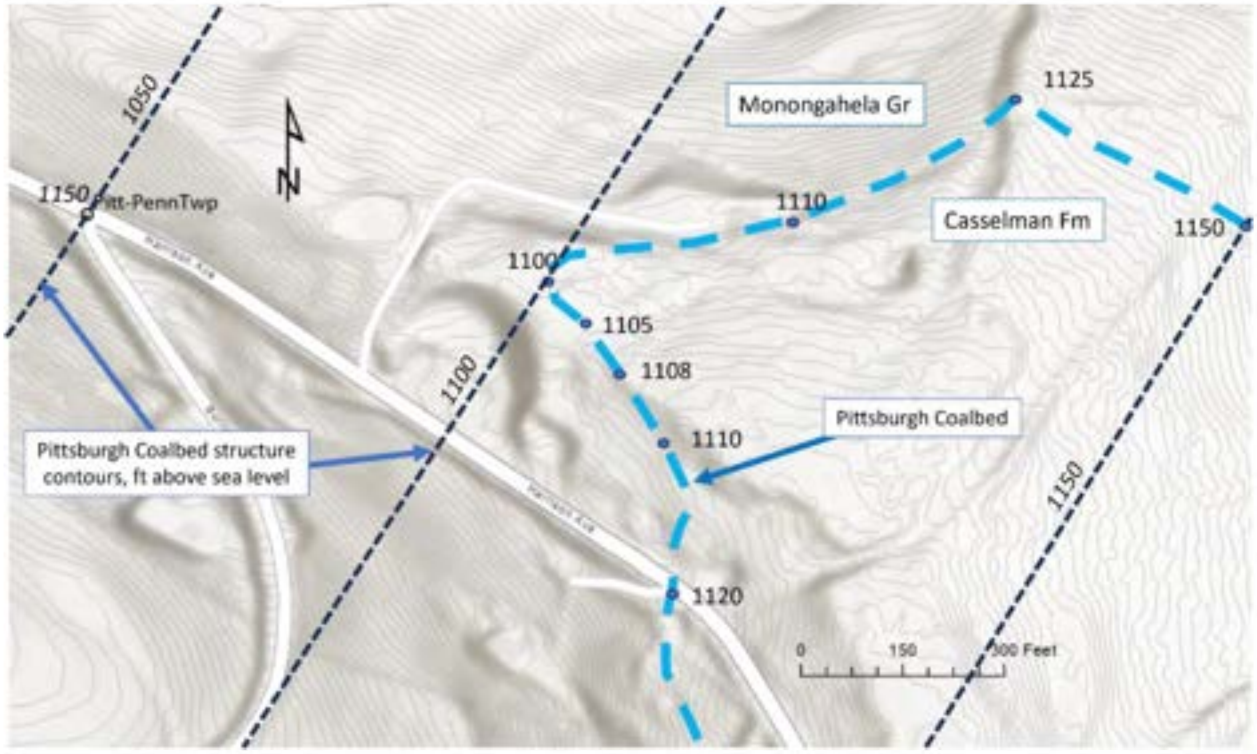

Figure 4.7.8. Surface contours (grey) and structure contours (black) on the Pittsburgh Coalbed in the area near Pitt-PennTwp.

4.7.2.5 Pitt-Amwell

A landslide occurred on July 14, 2010, along SR 2020 adjacent to Tenmile Creek ~2.5 miles from exit 23 on I-79, Washington Co., PA (Figure 4.7.11a). A vehicle carrying one person forcefully struck obstructions in the road surface injuring its driver. The vehicle encountered ñruts, gaps, openings, holes, separations, slopes, and/or cracks in the roadò due to a landslide that is thought to have been caused by the excavation in slide prone soils for the Kearney/Marcellus Well pad site below SR 2020 (Figure 4.7.11b).

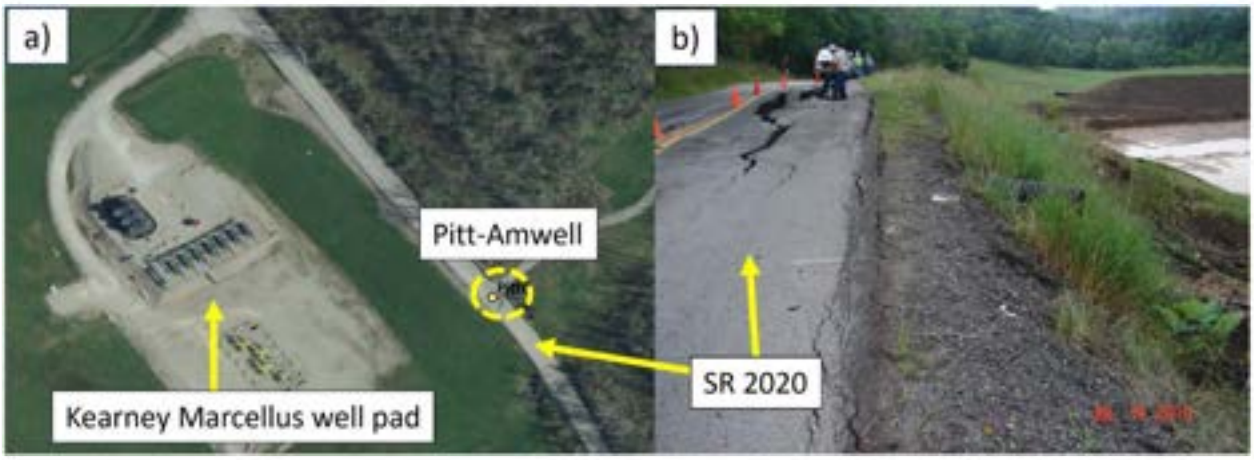

Figure 4.7.11. a) Location of the July 14, 2010, landslide along SR 2020 from Google Earth. The top of the image is oriented to the north.; b) condition of roadway adjacent to the Kearney Marcellus well pad site.

The position of the Pitt-Amwell landslide along SR 2020 is just below the boundary between the Waynesburg (PPw) and Washington (Pw) Formations. The landslide appears to have originated below the roadway although there is an area of relatively high relief above this area that may have contributed to this occurrence. If the landslide originated below the road, it would be in the Upper Waynesburg Formation. However, an area of past landsliding might have occurred above the road within the Washington Formation (Figure 4.7.12). There are two previously identified USGS landslide above the road directly southeast of Pitt-Amwell. It is also interesting to note that the general dip of the strata is to the southwest indicating water could discharge from strata above the roadway.

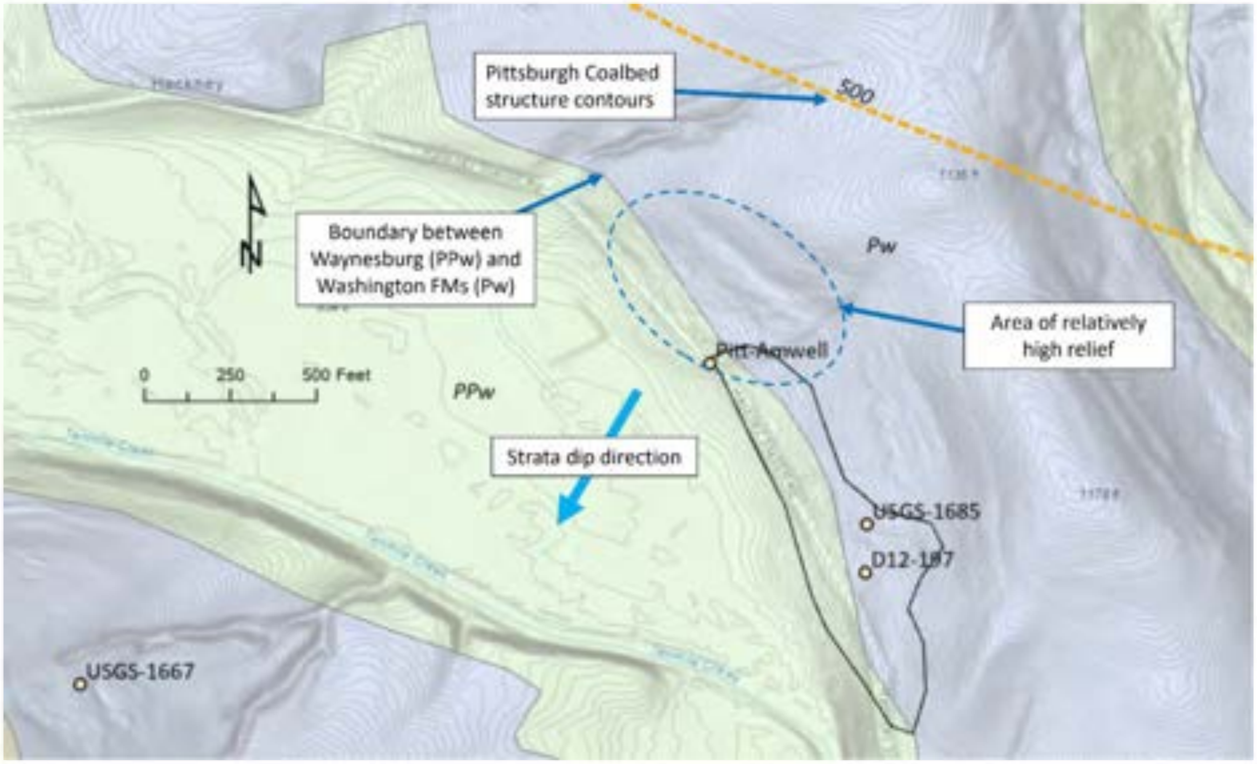

Figure 4.7.12. The Pitt-Amwell landslide is within the upper Waynesburg and lower Washington Formations. There is an area of relatively high relief above the roadway that could be related to a past landslide event. Also shown is an area of past landslides previously identified by the USGS. The polygon reflects the footprint of USGS-1685 as delineated in the 1978 mapping of the Amity Quadrangle (Pomeroy, 1978).

4.7.2.6 Pitt-SmithTwp

A vehicle crash on SR 18 in Smith Township, Washington Co., October 1, 2018 (Figure 4.7.13a) was reported caused by a landslide. The slide occurred below the roadway resulting in uneven pavement, large cracks, and asphalt sinkholes (Figure 4.7.13b). A large, abandoned surface coal mine is located above Pitt-SmithTwp. Since the site has never been repaired, mine related drainage from the surface mine could possibly be saturating the surface along the roadway.

Figure 4.7.13. a) Pitt-SmithTwp landslide occurred along SR 18 from Google Earth. The top of the image is oriented to the north.; b) uneven pavement, large cracks, and asphalt sinkholes.

Pitt-SmithTwp is below the Pittsburgh Coalbed outcrop at the Monongahela Group/Casselman Formation boundary (Figure 4.7.14). At this location, the Pittsburgh Coalbed strip mine bench is at an elevation of 1,084 ft. The road is approximately 58 ft below the Pittsburgh Coalbed placing the strata within the Upper Casselman Formation (Pcc).

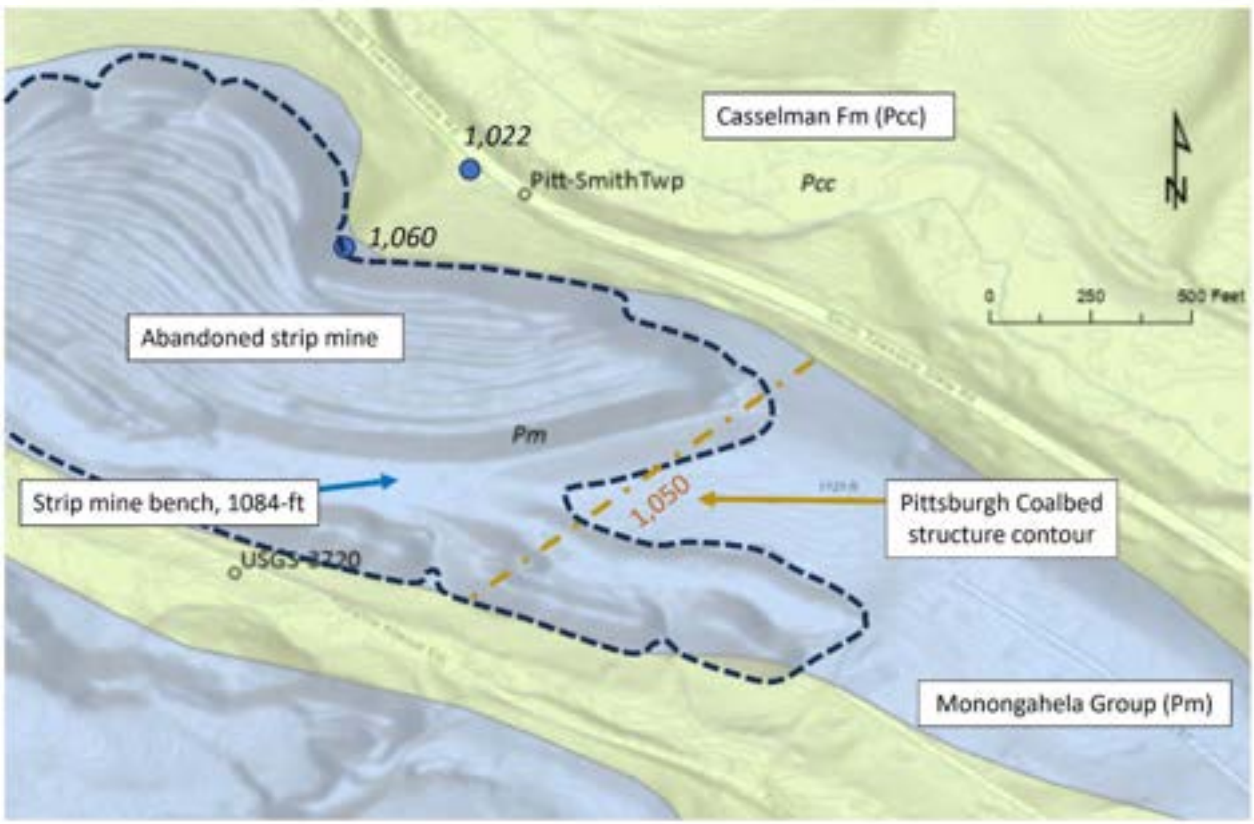

Figure 4.7.14. Surface contours showing the abandoned surface coal mine above the road and landslide location below the road. The landslide material originated in the Upper Casselman Formation (Pcc).

4.7.2.7 Pitt-Vestaburg

On May 17, 2011, a massive landslide occurred along SR 88 near Vestaburg, Washington Co. (Figure 4.7.15a). Pitt-Vestaburg occurred in an area containing an extensive coal mine bench and associated highwall along SR 88. The steepness of the slope containing the bench and highwall was originally formed by the Monongahela River cutting into the adjoining highside. While no one was injured and no vehicle damage was reported, the massive scale of this landslide denotes the potential catastrophic nature of this event (Figure 4.7.15b). The Pittsburgh Coalbed can be seen along SR 88 close to the Vesta #5 Mine portal (Figure 4.7.15c).

Figure 4.7.15. a) Location of the May 17, 2011, landslide along SR 88 (Photograph from Southwestern Pennsylvania Rural Exploration website); b) photograph of the massive Pitt-Vestaburg landslide (courtesy of Roy Painter); c) photograph of the Pittsburgh Coalbed alongside SR 88 near the Vesta #5 portal (Google Maps).

The location of Pitt-Vestaburg is directly below the outcrop of the Pittsburgh Coalbed (Figure 4.7.16a). The Vesta #5 portals are ~500 ft from Pitt-Vestaburg. This mine operated from 1908 to the mid-1980s and at one point was one of the largest coal mines in the world. The strata that encompass Pitt-Vestaburg is comprised of 30 ft of the Upper Casselman Formation (Pcc) and ~50 ft of lower Monongahela Group (Pm) (Figure 4.7.16b). In this area, the Pittsburgh Coalbed forms a bench presumably related to the Vesta #5 mining operations. The highwall above the bench has an average slope of ~63 degrees while the slope below the bench averages ~39 degrees. The differences in slope are almost certainly linked to the relative strengths of the strata. For example, the Pittsburgh Coalbed and its roof and floor are often comprised of claystone, carbonaceous shales, and thin coals. These units are known to weather in outcrop at a much faster rate than siltstones, sandstones, and limestones. The larger boulders shown in Figure 4.7.14b were most likely derived from the strata above the Pittsburgh Coalbed bench, i.e., the Lower Monongahela Group (Pm).

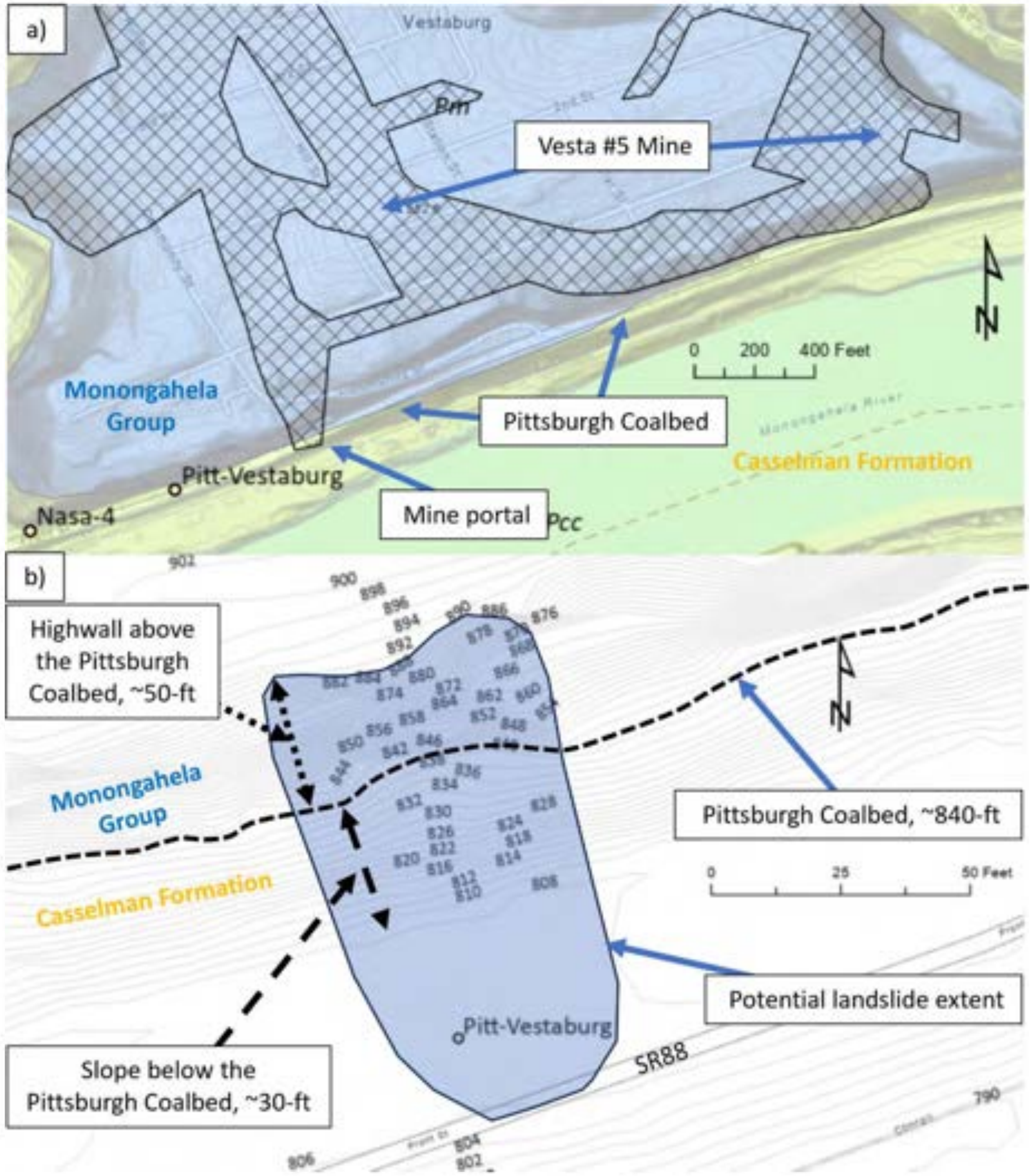

Figure 4.7.16. a) Location of the Pitt-Vestaburg and its position near the outcrop of the Pittsburgh Coalbed and the nearby sealed Vesta #5 Mine portals. Several other landslides from the USGS and NASA databases are in the general area. b) A surface contour map showing the location and elevation of Pitt-Vestaburg, the Pittsburgh Coalbed outcrop, and the highwall in the Lower Monongahela Group and the slope in the Upper Casselman Formation.

4.7.2.8 Pitt-KilbuckTwp

On September 19, 2006, a landslide 1,000 ft wide and extending 600 ft upslope displaced between 300,000 to 500,00 yd3 of rock and soil at a commercial development site in Kilbuck Township, Allegheny County (Hamel, 2020). Much of the landslide ended up covering four lanes of SR 65 as well as 3 lanes of Norfolk-Southern main line railroad tracks (Figure 4.7.19). During excavation and grading at the commercial development site, fill was placed over unrecognized colluvium until it suddenly ćcascaded down the hillsideô closing the roadway for two days. In June 2008, a taskforce commissioned to report on the Kilbuck Township Landslide indicated that remediation costs rose two million dollars with monthly monitoring cost averaging $75,000/month (Joint State Government Commission). The commercial development project was abandoned, and the site has been returned to something resembling pre-development, natural slope that includes trees and vegetation. Seven years later, Tom Fontaine wrote an article in the Pittsburgh Tribune (Feb 18, 2013) entitled ñKilbuck landslide site still not stabilized 7 years laterò indicating that some slope movements were still occurring.

Figure 4.7.19. a) The September 19, 2006, Kilbuck landslide covered SR 65 and portions of the Norfolk-Southern main line railroad tracks is recognized as one of the regionôs largest (Hamel, 2020); b) the remediation efforts took approximately 3 days to complete (Tribune photo).

This area north of the Ohio River has been the site of numerous landslides, some of which are classified as ćactiveô by the USGS as they are known to be moving, albeit at a rate and location that no longer threatens I-79 (Figure 4.7.20a). Dr. Jim Hamel has written extensively about the landsliding that occurred during the construction of I-79 from the Mt. Nebo exit to the Ohio River (Hamel and Flint, 1969). During a recent field trip sponsored by the Pittsburgh Geological Society (March 26, 2022) Dr. Hamel showed evidence of continuous minor movements almost 50 years after these slopes were first remobilized by road construction in the area.

The area near Pitt-KilbuckTwp (Kilbuck Twp. landslide) also has a history of landslides. Ackenheil identified two landslides close to Pitt-KilbuckTwp (Ackenheil, 1954). The first (Ackenheil-61) occurred on Mar 26, 1951, near the old Dixmont State Hospital. Approximately

15,000 yd3 of material containing clay and shale slide down the slope, triggered by removal of a toe of a previous landslide. The second (Ackenheil-90) occurred on April 17, 1954, where 200 yd^3 of red beds of clay and shale slide in response to nearby excavations (Figure 4.7.20b). The exact location of this landslide could not be determined.

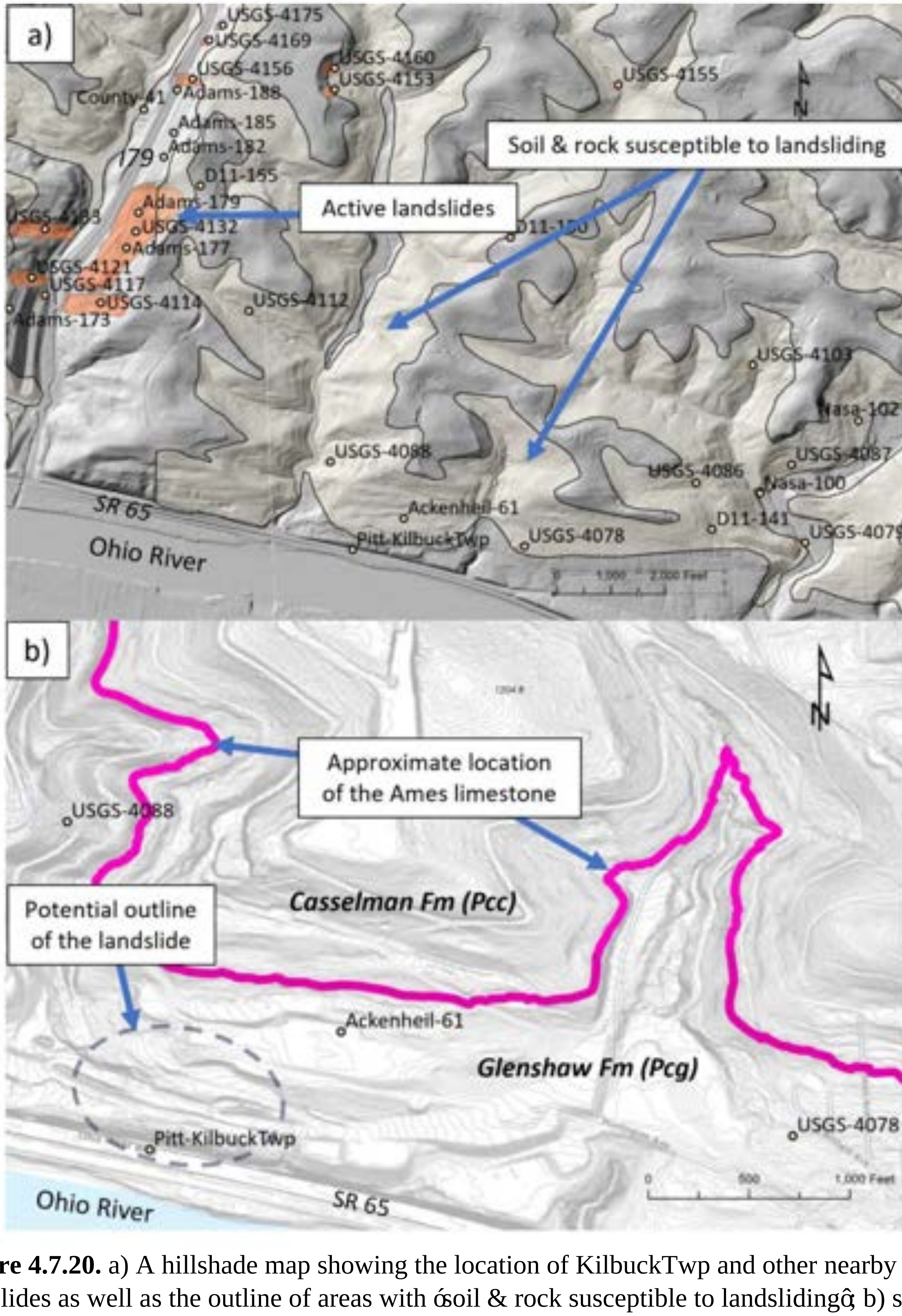

Figure 4.7.20. a) A hillshade map showing the location of KilbuckTwp and other nearby recent landslides as well as the outline of areas with "soil & rock susceptible to landsliding"; b) surface contours showing the location of the Ames Limestone and the approximate areal extent of Pitt-KilbuckTwp.

The approximate size of Pitt-KilbuckTwp as described by Hamel (2020) is shown as an ellipse with a long axis of ~1,000 ft and a minor axis of ~600 ft (Figure 4.7.20b). In addition, the approximate elevation of the Ames Limestone was determined as 950 ft based on the elevation of the Upper Freeport coalbed (~650 ft) and the average thickness of the Glenshaw Formation (Pcg) of ~300 ft. The Ames Limestone represents the boundary between the Casselman and Glenshaw Formations. SR 65 is ~220 ft below this boundary. The potential elevation at the center of Pitt-KilbuckTwp is ~825 ft. Therefore, the landslide originated within the Middle Glenshaw Formation (Pcg).

4.7.3 Unique characteristics of eight high consequence landslides impacting roads

The database of high consequence landslides impacting roads is too small to definitively identify the most important parameters responsible for these impacts. However, there are some interesting trends in the data (Table 4.7.3) For example, the high consequence landslides in this database occur over a wide range of possible stratigraphic sequences. Extending from the Glenshaw Formation (Pcg) to the Washington Formation (Pw) which includes some 1,300 ft of strata (Table 1.1). The other interesting trend is the relative speed of the landslide. There were many catastrophic rock falls but there are also three landslides that may have occurred at a slower speed.

Table 4.7.3. Characteristics of eight high-consequence landslides impacting roads not in other IRISE database sources.

ID	State Road	Formation	Injury	Vehicle damage	Near Miss	Position	Most Likely Characteristic
Pitt-Woodruff1	51	M Casselman			Y	Above	Fast moving rock fall
Pitt-Woodruff2	51	M Casselman	F-2; Nf-1	Y		Above	
Pitt-Elizabeth	837	M Casselman			Y	Above	Fast moving rock fall
Pitt-PennTwp	130	L Monongahela	F-1			?	Slower moving debris flow
Pitt-Amwell	2020	U Waynesburg	Nf - 1	Y		Below	Slower moving debris flow
Pitt-SmithTwp	18	U Casselman		Y		Below	Slower moving debris flow
Pitt-Vestaburg	88	L Monongahela			Y	Above	Fast moving rock fall
Pitt-KilbuckTwp	65	L to M Glenshaw			Y	Above	Fast moving rock fall

L ï Lower; M ï Middle; U ï Upper
F ï Fatality; Nf ï Nonfatal injury

5 .0 Next steps

This report is not an ending, rather it is a beginning. There is persuasive evidence that landslides will continue to occur in the region, particularly with expected changes in precipitation patterns. Increasing sophistication in our ability to mitigate landslide risk and prevent future impacts to our infrastructure is a cornerstone of successful adaptation to continued challenges associated with changes in climate.

With the establishment of a database, the infrastructure to continue and improve record-keeping is fundamentally improved. Individual or district level initiatives to track and plan for future landslide challenges become part of an effort that directly improves state and local decisions on how to best address the ñperfect stormò of climate, both natural and human altered terrain, and lithology driving landslides in SWPA.

5.1 What is missing from the database?

One of the opportunities in the establishment of a data structure is a careful assessment of what has been collected over time and what would be helpful to add to the collection. Through the analysis of existing landslide records and consultation with our landslide working group, there are a number of holes in the data. That is, there are potentially important pieces of information that largely have not been collected. These parameters include:

- Å Occurrence on natural or artificial slopes: One of the most notorious landslides in our database is the Kilbuck slide (Pitt-Kilbuck). This slide resulted from a poorly engineered artificial slope and impacted regional transportation networks for weeks. An ability to differentiate between landslides that occurred in artificial slopes and those that occurred in ñnaturalò slopes provides the opportunity to carefully evaluate common factors in both conditions and adjust construction, mitigation, and prevention strategies for the respective settings.
- Å Information about the relative magnitude of landslides: While the database contains over seven thousand landslides, the data necessary to assess the relative magnitude of the landslides does not exist (e.g., magnitudes of volume, area, and displacement). Minor landslides reported to the 311 system are treated the same as major slides blocking parts of important transport arteries. The parameter ñLandslide downslope displacementò a measure of displacement at the landslide scarp, has been added to the database as an encouragement to record these data going forward (it is empty or almost completely empty in this version of the database). Not only do we want to know where and when landslides occurred, we also want to know the magnitude of displacement associated with it. While other parameters regarding landslide volume or slide velocity have not been added to this iteration of the database, both would also be valuable for future analyses.
- Å Landslide footprints: In addition to the relative magnitude of the earth moved, this database does not contain polygons documenting the spatial extent of a landslide. While

these data exist for the USGS landslides, the process of reconstructing them for more recent landslides is intense (section 4.6). This leaves the database information ambiguous. For example, is the point location reported the bottom of the slide, the top of the slide, or the centroid? What is the extent of the slide? Therefore, when assessing the role of spatial factors like soils or geology, there is the potential to assign the wrong parameter value. Spatial filtering was used in the topographic measures to mitigate some of these challenges, but a clear set of footprint boundaries is a far superior option and ideally should be recorded going forward.

- A means to track landslide reoccurrence: Landslide prone slopes driven by topography and lithology tend to slide multiple times. It is difficult to reconstruct reoccurrence of landslides from the information available and ambiguous definitions (e.g., if a landslide occurs immediately adjacent to a historical slide is it a new slide or a reoccurrence?). Clear guidance on how to identify a reoccurring slide and track it in the database could clarify the role of these problem spots in regional landslide challenges.
- Costs (estimate or actual) of landslide repair: Landslide damage to infrastructure creates significant costs. The collection and assessment of cost data is a clear information and analysis need. While the database does not include these data, it is set up to be linkable to other management information systems (e.g., GAMP) that would allow these kinds of cross-comparisons.
- Likelihoods of landslides: With a large collection of a wide variety of parameters, the likelihood of a landslide at a particular location in time and space can be estimated. This database is a relatively large collection of landslides, however, there are thorny issues of sample bias that limit the utility of any potential likelihood estimates. For example, most data in the database with a date of occurrence are from the 311 dataset. Therefore, most weather information is constrained to a small spatial region that is likely not directly applicable to the larger region, particularly given the multiple slip-prone strata and intense human disturbance in Pittsburgh. A system to estimate likelihood is beyond the scope of this effort, however the data collected here contribute toward that system.
- Measures of risk: Landslide occurrence is hard to predict given the threshold nature of slide initiation. Therefore, estimating the risk of a landslide in a particular location is a much more common approach to planning and mitigating the impacts of future landsliding. However, risk requires comprehensive and complete data, including both likelihood and cost data (discussed above). While this database is an important step toward improving our estimates of risk, estimates from the database parameters would be incomplete (for example, the costs of landslide repair are an important component of risk assessment, and are not included in the database) and remain beyond the scope of this effort. In addition, the fragmented and incomplete nature of the data in this database, which have been repeatedly acknowledged, exacerbate the challenges associated with robust risk assessment.
- Monitoring data: A combination of risk assessment and monitoring data are potentially one of the most effective ways to predict landslides. However, monitoring data require a

much more dynamic database, with tools to assimilate monitoring data streams and condense these streams into useful metrics. Fundamentally, while there are promising monitoring tools emerging (e.g., return LiDAR), these monitoring data streams have not been established or centralized. Moreover, this project has always been about data gathering and organization. Development of monitoring programs and tools for data management require additional and more substantial resources.

5.2 What parameters are under reported?

Some of the parameters included in this database remain under-reported. Part of that has to do with the structure of data sources. The USGS data from the 1970s provided a comprehensive account of landslides during a period of intense geomorphic change. However, it was based on aerial photography so some factors simply cannot be reliably reconstructed. For example, the date of landslide occurrence for 4844 out of 7412 landslides in the database likely will never be populated. However, going forward, careful attention to tracking this data can have important implications for our ability to plan for landslide challenges. These factors include:

- Date of landslide occurrence (~25% of slides have a date): Temporal information on the timing of landslide occurrence can help reveal conditions that lead to landsliding. In particular, it may help link landslide occurrence with climatic conditions prior to landslide (e.g., precipitation, freeze thaw, or combinations of both), or with the effect of landscape modifications (slope modifications, road construction changes) that occurred prior to landsliding. While these data may always be less precise than we would prefer (e.g., when does a landslide start? At the first very small movement or when the flow is rapid and large? Does the time of reporting represent the time of occurrence?), having this information still provides the ability to reconstruct important factors, particularly weather.
- Type of landslide (~3% of slides are classified): Mitigation, and moreover, innovation in mitigation requires clear understanding of the underlying mechanisms of slope failure. Currently subdividing the landslides in the database by type is a challenge. Reconstruction of landslide type is a time intensive task, if it is possible at all (for example, the USGS and 311 data likely cannot reliably be classified from available information). In contrast, the DCNR classification system is simple and could be built into documentation efforts with minimal additional work. In the long run, these data can provide insight into questions ranging from the best repair strategies to novel ways to mitigate risk.
- Above/Below Road (~3% of slides have relative location information): The location of landslides relative to infrastructure often influence the relative damage the landslide causes. The limited availability of these relative location information makes it difficult to assess these influences. Recording these details during landslide tracking can make the data in the database more powerful with relatively minimal effort.

- Landslides that occur away from roads: Some data sources do a better job capturing the entire range of landslide locations (e.g., the USGS data is based on aerial imagery and can detect all landslides visible at the relevant resolution). Other data sources are biased based on their operational purpose and tend to focus on landslides near infrastructure (e.g., consider the difference between the data tracked by the City of Pittsburgh and the 311 data.) If this data is used to build predictive models, this bias will be important. It is not clear if the various tracking lists include all landslides that occur or focus on landslides that will require resources to mitigate. It is recommended that all landslides detected by an agency be included in the database. This will add an incremental level of record-keeping effort, but the increase in the utility of the data for a broad range of operation relevant analyses will be substantial.

5.3 Some parameter data need to be refined

There are several parameters that are based on relatively coarse mapping. All of the soil data, much of the geological data, and historical mine mapping are based on partial information or on mapping meant to guide broad planning decisions. Extracting this information at a point is not an optimal approach, particularly given the heterogeneity in soil and rock composition. Further, these data require expertise and judgement to make a determination (while it is easy to identify a slide as above or below a road, itôs not simple to identify a particular stratigraphic layer).

For all landslides that are repaired, soils, lithology, etc. are highly likely to be determined as part of the geophysical information generated during this planning and implementation process. Populating the database with this information as it is gathered can make determination of landsliding materials and settings more precise and therefore can improve the communityôs ability to improve mitigation of specific circumstances. Retrospective reconstruction of these data is a slog. Integration of this information into the database as it is generated seems highly preferable.

6 .0 Acknowledgements

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7 .0 Acronyms and abbreviations

AASHTO: American Association of State Highway and Transportation Officials

ACLP: Allegheny County Landslide Portal

AML: Abandoned Mine Land

csv: comma separated variable

DCNR: Department Of Conservation and Natural Resources

DEM: digital elevation model

DOMI: [City of Pittsburgh] Department of Mobility and Infrastructure

EIA: Energy Information Administration

GAMP: Geotechnical Asset Management Program

MSHA: Mine Safety and Health Administration

NASA: National Aeronautics and Space Administration

NED: National elevation dataset

NALI: National Abandoned Lands Inventory

NRCS: [United States Department of Agriculture] Natural Resources Conservation Service

PASDA: Pennsylvania Spatial Data Access

PADEP: Pennsylvania Department of Environmental Protection

PGH (coal): Pittsburgh Coalbed

PRISM: Parameter-elevation Regressions on Independent Slopes Model

SMCRA: Surface Mining Control and Reclamation Act of 1977

SPC: Southwestern Pennsylvania Commission

SSURGO: Soil Survey Geographic Database

SWPA: Southwestern Pennsylvania

UFR (coal): Upper Freeport Coalbed

USGS: US Geological Survey

WPRDC: Western Pennsylvania Regional Data Center

8 .0 References cited

Ackenheil, A.C. (1954) *A soil mechanics and engineering geology analysis of landslides in the area of Pittsburgh, Pennsylvania*. PhD. University of Pittsburgh.

Adams Jr., W.R. (1986) *Landsliding in Allegheny County, Pennsylvania: Characteristics, Causes, And Cures*. PhD. University of Pittsburgh.

Ashland, F.X. (2021) óCritical shallow and deep hydrologic conditions associated with widespread landslides during a series of storms between February and April 2018 in Pittsburgh and vicinity, western Pennsylvania, USAô, *Landslides*, 18(6), pp. 2159ï 2174.

Bain, D.J. *et al.* (2019) *The Effects of Subsidence Resulting from Underground Bituminous Coal Mining in Pennsylvania, 2013-2018: Bituminous Mine Subsidence and Land Conservation Act Act 54 Amendments 5th Five-Year Report*. Harrisburg, PA: Pennsylvania Department of Environmental Protection.

Berg, T.M. *et al.* (1983) *Stratigraphic correlation chart of Pennsylvania*. Commonwealth of Pennsylvania, Department of Environmental Resources, Bureau é (General Geology Report, 75).

Briggs, R.P. *et al.* (1975) *Landsliding in Allegheny County, Pennsylvania*. Circular 728. US Geological Survey, National Center.

County of Allegheny Public Works (2014) *Construction Plans for Pitcairn Road Landslide Stabilization Project*. Pittsburgh, PA: County of Allegheny.

Cruden, D.M. and Varnes, D. (1996) *Landslide types and processes*. Special Report 247. Transportation Research Board, pp. 36ï 57.

Daly, C. and Bryant, K. (2013) óThe PRISM climate and weather systemð an introductionô, *Corvallis, OR: PRISM climate group*, 2.

DôAppolonia Engineering (2018a) *Final Report: Subsurface Exploration and Schematic Design, 2302 Evergreen Road Landslide Remediation*. Pittsburgh, PA: County of Allegheny.

DôAppolonia Engineering (2018b) *Proposal--Subsurface Exploration, Schematic Design, and Right-Of-Way Stage Services: Elizabeth Street Lateral Support*. Pittsburgh, PA: County of Allegheny.

DôAppolonia Engineering (2018c) *Site Location Plan: Elizabeth Street Lateral Support*. Pittsburgh, PA: County of Allegheny.

Delano, H.L. and Wilshusen, J.P. (2001) *Landslides in Pennsylvania*. Pennsylvania Geological Survey (Educational Series).

Donahue, J. and Rollins, H.B. (1979) óGeology of the Northern Appalachian Coal Fieldô, in. *Ninth International Congress of Carboniferous Stratigraphy and Geology* (Guidebook, Field Trip No. 2).

Donat, M.G. *et al.* (2016) óMore extreme precipitation in the worldôs dry and wet regionsô, *Nature Climate Change*, 6(5), pp. 508ï 513. Available at: https://doi.org/10.1038/nclimate2941.

Drum, R.G. *et al.* (2017) óOhio River Basinð Formulating climate change mitigation/adaptation strategies through regional collaboration with the ORB allianceô, *Report no., US Army Corps of Engineers, Institute for Water Resources: Alexandria, VA* [Preprint].

Easterling, D.R. *et al.* (2017) óPrecipitation change in the United Statesô.

Evanek, N., Iannacchione, A.T. and Anderson, Thomas (2022) óA Case Study of Potential Geologic Factors Affecting the Occurrence of Massive Ground Collapses at an Underground Limestone Mine in Southwestern Pennsylvaniaô, in. *International Conference on Ground Control in Mining*.

Fedorko, N. and Skema, V. (2013) óA review of the stratigraphy and stratigraphic nomenclature of the Dunkard Group in West Virginia and Pennsylvania, USAô, *International Journal of Coal Geology*, 119, pp. 2ï 20. Available at: https://doi.org/10.1016/j.coal.2013.07.016.

Fraser, J.K. (1959) óFreeze-Thaw Frequencies and Mechanical Weathering in Canadaô, *ARCTIC*, 12(1), pp. 40ï 53. Available at: https://doi.org/10.14430/arctic3712.

Froude, M.J. and Petley, D.N. (2018) óGlobal fatal landslide occurrence from 2004 to 2016ô, *Natural Hazards and Earth System Sciences*, 18(8), pp. 2161ï 2181.

Gesch, D. *et al.* (2002) óThe national elevation datasetô, *PE & RS- Photogrammetric Engineering & Remote Sensing*, 68(1), pp. 5ï 11.

Green, D.R., Ciloglu, F. and Dorn, S.E. (2023) *Landslide Best Practices Handbook*. Pitt IRISE Project Reports IRISE-23-P21-03-01. Pittsburgh, PA: University of Pittsburgh.

Hamel, J.V. (2020) óFour Famous Historic Landslides of the Pittsburgh Areaô, in. *Landslide Capacity Building Virtual Seminar Series*.

Hamel, J.V. and Flint, N.K. (1969) *Analysis and Design of Highway Cuts in Rock: A Slope Stability Study on Interstate Route 279 and 79 Near Pittsburgh, Pennsylvania*. Pennsylvania Department of Highways Research Project 41472, p. 130.

Harper, J.A. (2000) óGeology of the Pittsburgh areaô, in *Pittsburgh at the Millennium: The Impact of Geoscience on a Changing Metropolitan Area, Guidebook, 65th Annual Field Conference of Pennsylvania Geologists, JA Harper, ed*, pp. 8ï 9.

Highland, L.M. and Bobrowsky, P. (2008) *The landslide handbook-A guide to understanding landslides*. US Geological Survey.

Iannacchione, A.T. *et al.* (2014) ôFactors Influencing Water Discharges from Underground Coal Mine Pools in Pennsylvaniaö, *SME Annual Meeting Preprint*, 14ï 152, p. 8.

Iannacchione, A.T. (2024) *Stratigraphic Studies from Limestone Mining Permits*. Personal Communication (from cores collected from mining permits along Chestnut Ridge in Fayette and Westmoreland Counties).

Jacobson, R.B. (1993) *Geomorphic studies of the storm and flood of November 3-5, 1985, in the upper Potomac and Cheat River basins in West Virginia and Virginia*. USGPO; US Geological Survey, Map Distribution.

Jeong, H.-G. *et al.* (2020) ôImprovement of daily precipitation estimations using PRISM with inverse-distance weightingö, *Theoretical and Applied Climatology*, 139, pp. 923ï 934.

Jeton, A.E., Watkins, S.A. and Huntington, J. (2006) *Evaluation of precipitation estimates from PRISM for the 1961-90 and 1971-2000 data sets, Nevada*. US Geological Survey.

KDKA News (2018) ôLandslide Repair Costs Adding Up as PennDOT Continues to Manage Dozens Across Districtö. Available at: https://www.cbsnews.com/pittsburgh/news/pittsburgh-landslide-repair-costs-penndot/.

Kirschbaum, D., Stanley, T. and Zhou, Y. (2015) ôSpatial and temporal analysis of a global landslide catalogö, *Geomorphology*, 249, pp. 4ï 15. Available at: https://doi.org/10.1016/j.geomorph.2015.03.016.

Kirschbaum, D.B. *et al.* (2010) ôA global landslide catalog for hazard applications: method, results, and limitationsö, *Natural Hazards*, 52(3), pp. 561ï 575. Available at: https://doi.org/10.1007/s11069-009-9401-4.

Kotz, M., Levermann, A. and Wenz, L. (2024) ôThe economic commitment of climate changeö, *Nature*, 628(8008), pp. 551ï 557.

National Weather Service (n.d.) *2018 in Context: Record Precipitation across Pennsylvania, 2018 in Context: Record Precipitation across Pennsylvania*. Available at: https://www.weather.gov/ctp/RecordPrecip2018.

Northern and Central Appalachian Basin Coal Regions Assessment Team (2001) *2000 resource assessment of selected coal beds and zones in the Northern and Central Appalachian Basin coal regions*. Professional Paper 1625ï C. US Geological Survey.

Orsborn, N. (2015) *Deposition and Structural Features of the Basal Morgantown Sandstone of the Casselman Formation (Pennsylvanian) of the Greater Pittsburgh Region*. University of Pittsburgh.

Pazzaglia, F.J., Shaulis, J. and Lindberg, S.R. (2021) ôGuidebook Ohiopyle 2021 Field Conference of Pennsylvania Geologists: Introduction and overviewö, in *Geology of Ohiopyle*

State Park and the Laurel Highlands of Southwestern Pennsylvania: 85th Annual Field Conference of Pennsylvania Geologists Guidebook, pp. 1ï 10.

Penn State - Center for Dirt and Gravel Road Studies (2012) ôUnpaved Roads of Pennsylvaniaö. PASDA. Available at: https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=111.

Pennsylvania Bureau of Topographic and Geologic Survey, Department of Conservation and Natural Resources (2001) ôDigital Bedrock Geology of Pennsylvaniaö. Harrisburg, PA: Pennsylvania Bureau of Topographic and Geologic Survey. Available at: http://www.dcnr.state.pa.us/topogeo/map1/bedmap.aspx.

Pennsylvania Department of Environmental Protection (2023a) ôAbandoned Mine Lands Inventory Sitesö.

Pennsylvania Department of Environmental Protection (2023b) ôDigitized Mined Areasö. Coal Center, PA: Bureau of District Mining Operations.

Pennsylvania Department of Transportation (2024a) ôPennDOT - Pennsylvania local roadsö. PASDA. Available at: https://www.pasdhttps://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=1038a.psu.edu/uci/DataSummary.aspx?dataset=54.

Pennsylvania Department of Transportation (2024b) ôPennDOT - Pennsylvania Stateroadsö. PASDA. Available at: https://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=54.

Pomeroy, J.S. (1982) *Landslides in the greater Pittsburgh region, Pennsylvania*. Professional Paper 1229. US Geological Survey.

Pomeroy, J.S. (1986) *Map showing slope movements in the Oak Forest Quadrangle, Greene County, southwestern Pennsylvania*. Miscellaneous Field Studies Map 1794. US Geological Survey. Available at: https://doi.org/10.3133/mf1794.

PRISM Climate Group (2014) ôPRISM Gridded Climate Dataö. Oregon State University. Available at: https://prism.oregonstate.edu (Accessed: 1 September 2023).

Puglio, D.G. and Iannacchione, A.T. (1979) *Geology, mining, and methane content of the Freeport and Kittanning coalbeds in Indiana and surrounding counties, Pa*. Report of Investigation 8406. US Department of the Interior, Bureau of Mines.

Rohan, T.J., Wondolowski, N. and Shelef, E. (2021) ôLandslide susceptibility analysis based on citizen reportsö, *Earth Surface Processes and Landforms*, 46(4), pp. 791ï 803. Available at: https://doi.org/10.1002/esp.5064.

Schmidt, J., Evans, I.S. and Brinkmann, J. (2003) ôComparison of polynomial models for land surface curvature calculationö, *International Journal of Geographical Information Science*, 17(8), pp. 797ï 814.

Schwanghart, W. and Scherler, D. (2014) óTopoToolbox 2ï MATLAB-based software for topographic analysis and modeling in Earth surface sciencesô, *Earth Surface Dynamics*, 2(1), pp. 1ï 7.

Smith, P. (2024) óRecord rain brings dangerous flash flooding and strong winds to Northeastô, *NBC News*. Available at: https://www.nbcnews.com/news/us-news/record-rain-brings-dangerous-flash-flooding-strong-winds-northeast-rcna147521.

Soil Survey Staff (2023) óSoil Survey Geographic (SSURGO) Databaseô. Natural Resources Conservation Service, United States Department of Agriculture Soil Survey Staff.

Winters, D.M. (1972) *Pittsburgh red beds: stratigraphy and slope stability in Allegheny County, Pennsylvania*. MSc thesis, University of Pittsburgh, Pennsylvania (unpubl).

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