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Assessing the Impacts of Acid Mine Drainage Reclamation in Pennsylvania

DEVELOP Technical Report

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1. Abstract

Acid mine drainage associated with abandoned coal mine lands contaminates waterways, degrades land, and causes public health concerns. Earth Conservancy (EC) is a Pennsylvania non-profit that addresses the legacy of anthracite coal mining through economic and ecological restoration of abandoned mine lands (AMLs). EC collaborates with the United States Geological Survey (USGS) to employ on-site monitoring of reclamation projects, which can be time and cost intensive. We aimed to assess the feasibility of incorporating remote sensing techniques to describe the impact of such projects on land use land cover (LULC), vegetation, runoff, and social vulnerability status. We used Landsat 4–5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) Earth observations to map changes in LULC, Normalized Difference Vegetation Index (NDVI), and surface runoff. LULC analysis revealed forested land had the greatest increase in acreage from 1986 to 2023 within the Upper Susquehanna-Lackawanna Watershed study area. Within EC's holdings, we identified NDVI and surface runoff reflected changes associated with known ecological and economic development sites. Variations in green-up time for dates of available Landsat data caused limitations in LULC and NDVI analyses, as land appeared more barren than reality. Additionally, our team conducted a social vulnerability analysis which investigated disadvantaged census tracts within the study area. We found that many of EC's land holdings were within low-income census tracts that were not federally recognized as disadvantaged areas, despite meeting the criteria. Overall, our results show promise for pairing remote sensing and environmental justice data to support Earth Conservancy's goals in addressing the diverse impacts of AML reclamation.

Key Terms

remote sensing, Landsat, LULC, NDVI, surface runoff, social vulnerability, abandoned mine land, reclamation

2. Introduction

Northeastern Pennsylvania was a 20th century hotspot for anthracite coal mining, bringing rapid development to the Wyoming Valley. The anthracite coal industry declined in the latter half of the century leaving behind a landscape riddled with abandoned mine lands (AMLs), which are historic sites of coal extraction, processing, and waste deposition (Liu et al., 2012). AMLs are associated with a wide range of legacy environmental issues, notably the contamination of groundwater, surface water, and soil through acid mine drainage (AMD; Liu et al., 2012; Zhang et al., 2023; Hosseinjanizadeh et al., 2023). AMD is the product of oxidizing chemical reactions between sulfur-bearing minerals and water in the presence of oxygen, resulting in sulfuric acid. As such, AMD has low pH and contains high concentrations of toxic metalloids and metal ions (Sakala et al., 2017; Hosseinjanizadeh et al., 2023; Zhang et al., 2023; Chalkley et al., 2022). Due to the highly acidic and toxic nature of the contamination, AMD negatively impacts ecosystem and human health in various ways, from land degradation to deteriorated quality of drinking water resources that expose children and adults to carcinogenic heavy metals (Townsend et al., 2008; Zhang et al., 2023; Singovszka et al., 2020). Furthermore, the decline of the coal industry and the resulting legacy pollution are associated with economic burden due to the loss of mining jobs as well as loss of productive land (Bowen et al., 2021). These burdens, in conjunction with historic redlining policies, have disproportionately affected low income and racially/ethnically marginalized communities in the Wyoming Valley (The Institute for Public Policy and Economic Development, 2021). As such, a full understanding of the environmental and societal legacy impacts of historic mining operations requires improved land monitoring techniques combined with the critical use of an environmental reclamation lens.

Remote sensing techniques have been powerful tools in observing effects of AMD which suggests these techniques could be helpful in assessing the impacts of reclamation and remediation efforts. These efforts would restore and revitalize degraded land and contaminated waterways (Hosseinjanizadeh et al., 2023; Chalkley et al., 2022). Comparing measurements taken from Earth observations provides an extensive source of cost-effective high-accuracy data regarding environmental changes (Rogan & Chen, 2004). A second advantage is the temporal breadth of satellite remote sensing data as Landsat data is available starting in the mid-1970s. Townsend et al. (2008) found that retrospective remote sensing is useful for tracking land use land cover (LULC) changes associated with mine land reclamation efforts over long study periods. Additionally, assessing changes in vegetation density in AMLs is critical for understanding the impacts of reclamation efforts. Calculating Normalized Difference Vegetation Index (NDVI) using remote sensing data is a powerful and effective tool for conducting vegetation analyses over a large study area and study period (Townsend et al., 2008). Furthermore, Griffith et al. (2002) found that NDVI values correlated to water quality field data, highlighting past success of utilizing remote sensing techniques as an accurate alternative to field observations and measurements.

A similar scientific research can inform and support the work of Earth Conservancy, a nonprofit organization addressing the impacts of past anthracite coal mining in northeastern Pennsylvania. Since 1992, Earth Conservancy has been reclaiming, restoring, and redeveloping AMLs within their nearly 16,500 acres of landholdings (Earth Conservancy, n.d.). As of September 2024, Earth Conservancy has reclaimed over 2,000 acres of this land as sites for economic development or ecological reclamation. To support their efforts, Earth Conservancy collaborates with the United States Geological Survey (USGS) Geology, Energy, and Minerals Science Center who provide streamflow and water quality measurements as well as assess potential strategies to address issues associated with AMD (Chaplin et al., 2007). Remote sensing data visualizations can supplement field observations and greatly support Earth Conservancy's assessment of AML reclamation and AMD remediation projects. These visualizations support their community engagement efforts and provide information within grant proposals. In addition to remote sensing data, an investigation into federal environmental justice data can provide key information regarding Earth Conservancy landholdings' disadvantaged community status. Pairing remote sensing data with an understanding of the environmental characteristics of the land with federal environmental justice data can support Earth Conservancy's goals in addressing (e.g., remediating) the diverse impacts of AMLs and AMD.

To support Earth Conservancy's work, this study assessed the feasibility of integrating Earth observations into Earth Conservancy's AML reclamation and watershed restoration efforts. Our main objectives were to visualize LULC changes in Earth Conservancy's land holdings, assess the impact of AMD reclamation on surrounding vegetation and surface water runoff over time, and investigate changes to landholdings' federal environmental justice disadvantaged community status. The study area is a subregion within the Upper Susquehanna-Lackawanna Watershed (seven sub-watersheds) in which Earth Conservancy has landholdings (Figure 1). The study's particular interest was in the Newport and Nanticoke Creek watersheds as these contain the majority of Earth Conservancy's landholdings.

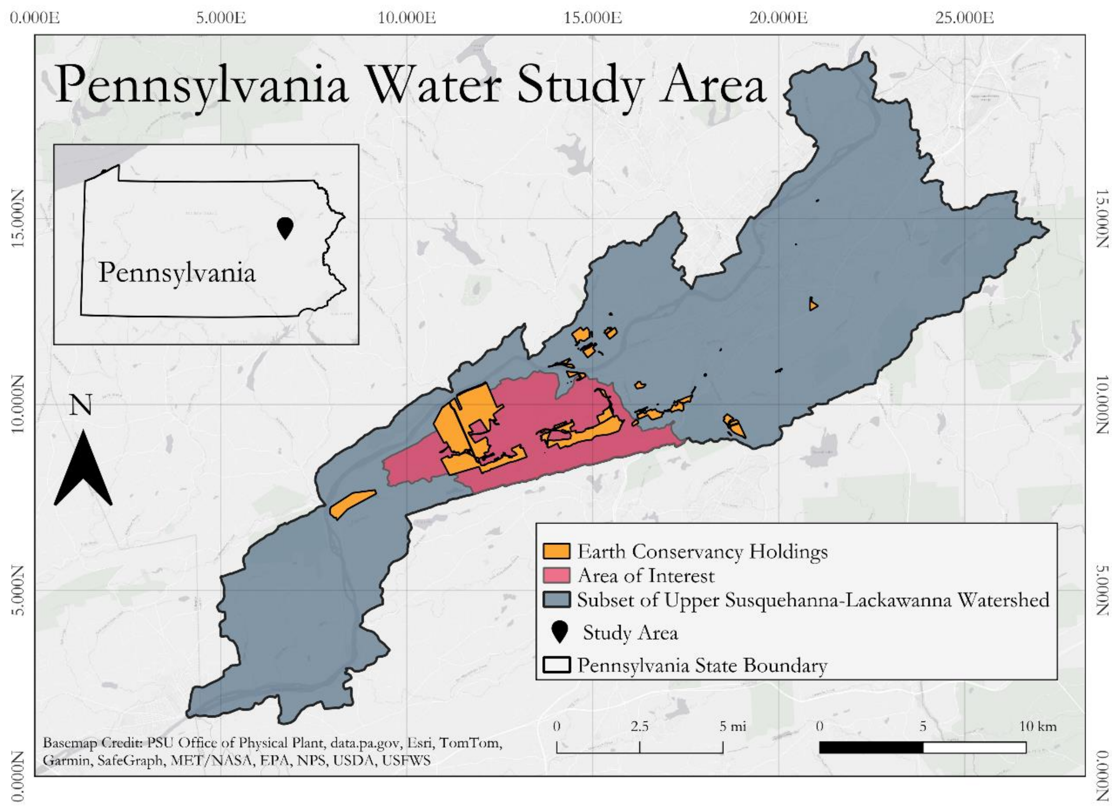

Figure 1. Subset of Upper Susquehanna-Lackawanna Watershed, encompassing Earth Conservancy's land holdings.

We visualized changes associated with Earth Conservancy's reclamation efforts using NASA Earth observations through LULC change, NDVI, and surface runoff analysis. We examined LULC over a study period of 1986 to 2023 to assess long-term change. We compared differences in NDVI from May 2015 to May 2023 to track vegetation changes in recent years. Over the same period, we mapped surface runoff with abandoned mine locations to provide insight into how reclamation efforts have impacted the surface runoff patterns of the landscape. Finally, we used information from federal environmental justice indices and screening tools to investigate changes in disadvantaged status from 2023 to 2024 in the study area.

3. Methodology

3.1 Data Acquisition

To analyze LULC change over time, we selected Landsat images from May of each decade beginning in the 1980s: 1986, 1994, 2004, 2014, and 2023 (Table A1). As seasonal variability causes changes in land appearance throughout the year, we chose dates in May to account for green-up time. This is an important aspect of our imagery as LULC analyzed in winter or leaf off periods may appear more barren than in reality. For the same reasons, we also assessed NDVI and surface runoff in May of 2015 and 2023. We chose this study period as the earliest Earth Conservancy project of interest (the Warrior Run-Slope Street project) began work in May of 2015. We utilized Landsat 4-5 Thematic Mapper (TM) Collection 2 Level–2 surface reflectance data for dates between 1986 and 2004, and Landsat 8 Operational Land Imager (OLI) Collection 2 Level–2 surface reflectance data for dates between 2014 and 2023 (Table 1). We acquired all Earth observation data from USGS Earth Explorer.

Table 1
Quantifying LULC changes from 1986–2023 over the study area for barren, developed, forest, and herbaceous land.

Land Class	Acres over whole study area: 1986	Acres over whole study area: 2023	Change in acreage (acres): 1986 – 2023	Percent change in acreage: 1986 – 2023	Percent of study area*: 2023
Barren	17,339	802	– 16,537	– 95%	0.80%
Developed	27,866	30,199	2333	8%	30%
Forest	24,038	62,232	38,194	159%	62%
Herbaceous	30,435	7210	23,225	– 76%	72%

*Not including land classified as water.

We used five environmental justice indices and screening datasets to analyze social vulnerability: the Council on Environmental Quality (CEQ) Climate and Economic Justice Screening Tool (CEJST) 1.0, the Environmental Protection Agency (EPA) Inflation Reduction Act (IRA) Disadvantaged Communities 1.0, the EPA IRA Disadvantaged Communities 2.0, EPA EJScreen: Environmental Justice Screening and Mapping Tool (EJScreen) 2.2, and EJScreen 2.3 (Table A1). We acquired CEJST data as a geodatabase file which included key information such as demographic and socioeconomic data as well as environmental and health indicators of burden data. We downloaded EPA IRA 1.0 and 2.0 geodatabases from the EPA public directory. EPA IRA 1.0 is based on EJScreen 2.2 data (released June 2023), and the EPA IRA 2.0 is based on EJScreen 2.3 (released July 2024). The EPA IRA 1.0 and 2.0 included information regarding disadvantaged status but did not include demographic or indicators of burden data. We downloaded the EJScreen 2.2 geodatabase (September 2023) and EJScreen 2.3 geodatabase (August 2024) from the EPA public directory to supplement social vulnerability metrics from the EPA IRA geodatabase (Table A2).

Ancillary datasets included Pennsylvania Department of Environmental Protection Abandoned Mine Land Inventory, and Earth Conservancy's land holdings. We downloaded data of seven HUC-12 watersheds from the USGS to define the boundaries of our study area. We used the Department of the Interior Abandoned Mine Land Inventory System (e-AMLIS) dataset from the Office of Surface Mining Reclamation and Enforcement to investigate whether all AMLs in our study area are included in this dataset, which is utilized in CEJST 1.0. Finally, we acquired a shapefile of Earth Conservancy's land holdings from Earth Conservancy, as well as abandoned mine land points. We overlaid these points on NDVI and surface runoff maps to analyze change and/or intensity and relation to mine land proximity.

3.2 Data Processing

We utilized Esri's ArcGIS Pro 3.3 to conduct data processing throughout the project. We used the "composite band" feature in ArcGIS Pro to pre-process Landsat 4–5 TM and Landsat 8 OLI data to combine the data range bands 1–7. We then symbolized these data to reflect a true color image where the red, green, and blue bands were matched respectively.

To calculate the LULC layer, we used two methodologies. For data collected from the Landsat 4–5 TM (1986, 1994, and 2004) we used the "Classification Wizard" feature in ArcGIS Pro, which utilized a supervised classification method. We trained this model by drawing polygons over a true color image classifying pixels as either water, developed, barren, forest, or herbaceous. The model used the example pixels within these polygons to output a fully classified raster reflecting the classification schema. If the model misidentified large groups of pixels, we used the reclassification function within supervised classification to reclassify these pixels from one land type to another. We used the "Classify Pixels Using Deep Learning" feature which utilized a Landsat 8 OLI model trained by Esri to apply the LULC National Land Cover Database classification scheme to the composite band data of 2014 and 2023. We then simplified the output of these data to reflect the classification schema of water, developed, barren, herbaceous, and wetlands.

To calculate NDVI, we rescaled Landsat 8 OLI Collection–2 Level–2 data from May 29, 2015, and May 27, 2023 to be in surface reflectance as opposed to digital number values. To rescale the data, we used the "Band Arithmetic Properties" feature within Raster Functions. We set the Band Indices to Equation 1 (Table B1; US

Geological Survey, 2022). We then processed the bands with the "Con" tool to remove negative values. We set values greater than or equal to 0 to the raster value and set values less than 0 to 0. After removing negative values, we combined the rescaled bands into a single raster through the "Composite Bands" feature. We then calculated NDVI for the rescaled rasters with raster band arithmetic in ArcGIS Pro by inputting the rescaled near–infrared (NIR) and red bands into Equation 2 (Table B1; Kriegler et al., 1969).

To calculate surface runoff, we used a phenology–based dynamic curve number (CN) approach which utilized the NDVI rasters previously calculated. ArcGIS Pro outputs the NDVI rasters with a scale from -1 to 1. To apply the runoff curve equation we needed the NDVI rasters in an 8–bit scale instead of floating point values. We calculated NDVI on an 8–bit scale with raster math with Equation 3 (Table B1; Kriegler et al., 1969). To calculate the CN, we ran the 8–bit NDVI rasters through a raster math calculation in ArcGIS Pro using Equation 4 (Table B1).

We used the EPA IRA geodatabase to conduct an exploratory analysis of changes of disadvantaged status within the study area between 2023 and 2024. We joined the attribute tables in ArcGIS Pro for the two indices and created a new column to calculate the change in status using field calculator. We defined four distinct categories: (1) added – disadvantaged status changed from "No" to "Yes", (2) removed – disadvantaged status changed from "Yes" to "No", (3) retains status – disadvantaged status remains "Yes", and (4) no change – disadvantaged status remains "No". Next, we reviewed the CEJST 1.0 geodatabase, and EJScreen data, which includes descriptive social vulnerability statistics to identify key variables, low–income percentile, and abandoned mine land proximity. An examination of CEJST criteria revealed that a community may be labeled as disadvantaged if they meet both the threshold for low income (65th percentile or greater) as well as the criteria for any CEJST defined category of burden. Finally, we created a social vulnerability map of the study area using thresholds from the CEJST 1.0 and data from EPA EJScreen tools (Table A2).

3.3 Data Analysis

We conducted temporal comparisons of calculated LULC, NDVI, and surface runoff maps. To analyze LULC change over time, we used the "Change Detection" feature in ArcGIS Pro. We created LULC change maps investigating change from barren land to any other land class in the schema for years 1986 to 1994, 1994 to 2004, and 2014 to 2023. We then overlaid Earth Conservancy's land holdings on these LULC change maps. We exported this data to R v4.4 as a TIFF file and summed the number of pixels that each land category occupied in the raster. We multiplied these pixels by the resolution of the raster to obtain a measure of area occupied by each land category. We then plotted the results for the years 1986 to 2023 to visualize changes in land use. We exported the area occupied by each land category to MATLAB R2023b and calculated the change in occupied area per land category from 1986 to 2023 (Table B1, Equation 5), the percent change in area occupied per land category from 1986 to 2023 (Table B1, Equation 6), and the percent of study area occupied per land category in 2023 (Table B1, Equation 7).

For both NDVI and surface runoff, we conducted a percent of normal calculation to 2015 and 2023 maps to analyze the change in potential vegetation and runoff over the study period (Table B1, Equation 8). We overlaid NDVI and surface runoff percent change maps with Earth Conservancy's land holdings and abandoned mine locations. To assess changes in environmental justice disadvantaged status, we compared areas designated as disadvantaged on the EPA IRA 1.0 (2023) versus EPA IRA 2.0 index (2024). We conducted an analysis of social vulnerability regardless of official disadvantaged designations using EJScreen 2.3 socioeconomic data from 2024. We selected census tracts within the study area that met the CEJST percentile threshold for low–income status and mapped low–income communities with AML points.

4. Results

4.1 Analysis of Results

4.1.1 Land Use Land Cover

We computed LULC maps from Landsat data for the years 1986, 1994, 2004, 2014, and 2023 using the classification schema outlined in Section 3.3. LULC maps for the years 1986 and 2023 were of particular interest, as they visualized land before any reclamation work and most recently (Figure 2). To visualize LULC change over the entire study period, we created a map depicting change from barren land to any other land class between 1986 and 2023 (Figure 3A). Within Earth Conservancy's holdings, we saw the greatest increase in developed land (Figure 3B). In the whole study area, forested land showed the greatest increase.

A) B)

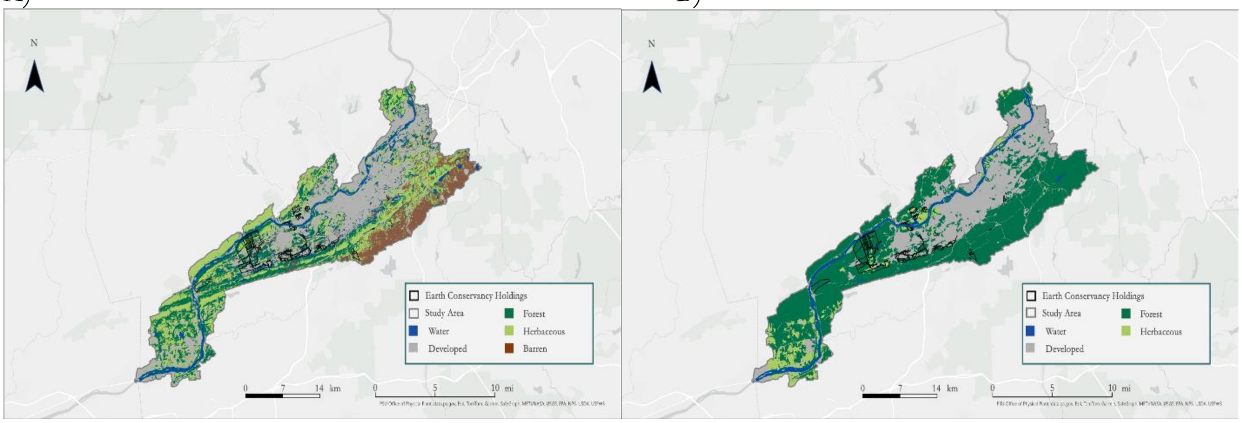

Figure 2. Two LULC maps showing water, developed, barren, forested, and herbaceous lands from A) 1986 and B) 2023.

A) B)

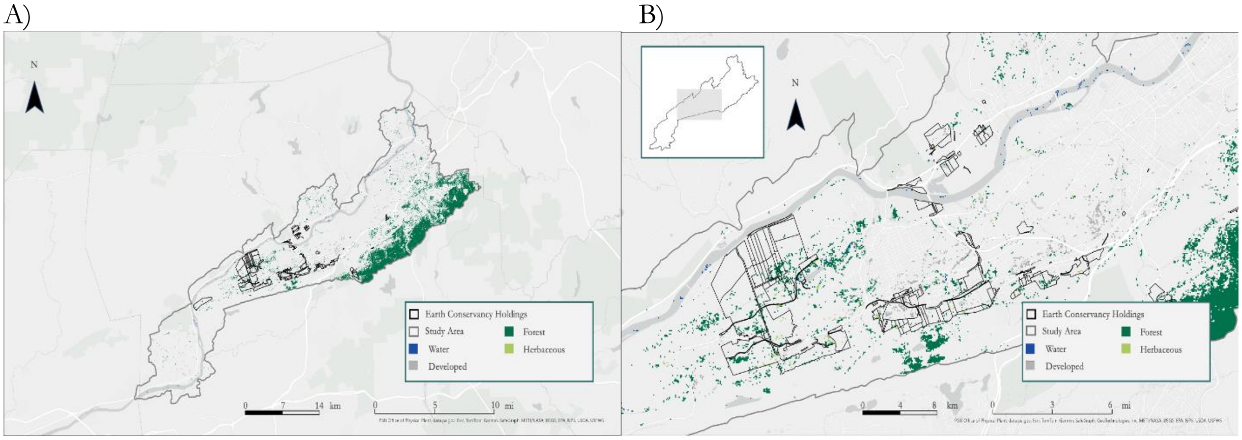

Figure 3. A) The change from barren land to water, developed, forested, or herbaceous land from 1986 to 2023. B) Investigating the change in Figure 3A zoomed in on the Area of Interest.

To quantify these LULC changes, we created a line graph representing the acreage of developed, barren, forested, and herbaceous land per decade of the study period (Figure 4). Forested land increased the most over the study area, with a 159% increase, or almost 40,000 acres. Conversely, barren land decreased the most over the entire study area, with a 95% decrease, or approximately 16,500 acres (Table 1).

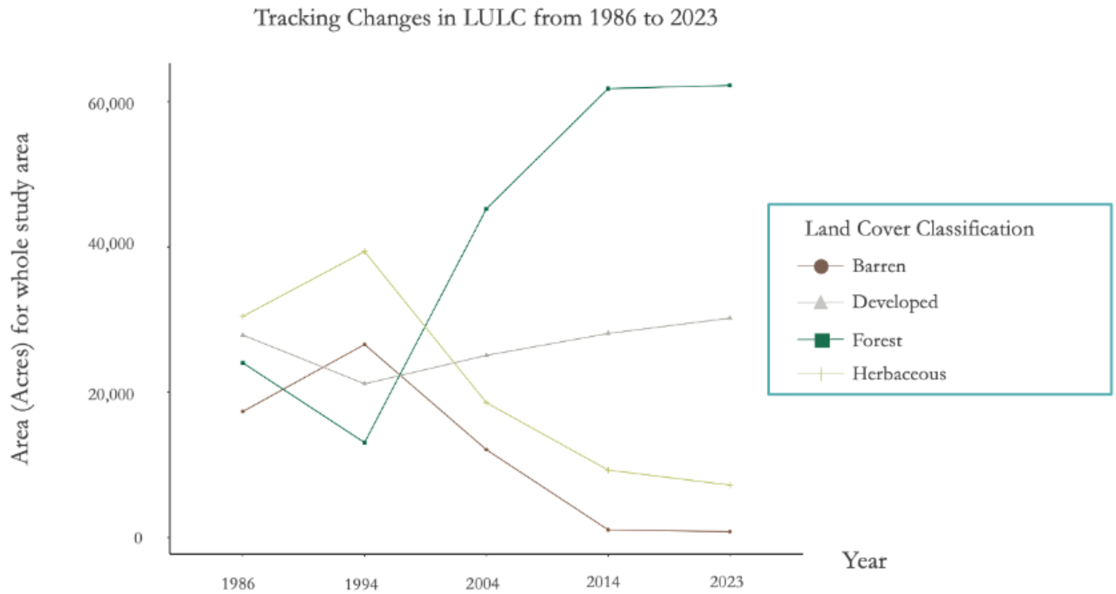

Figure 4. A time series tracking acreage of developed, barren, forested, and herbaceous lands in 1986, 1994, 2004, 2014, and 2023.

4.1.2 NDVI

We conducted an NDVI analysis for May 2015 and May 2023 using the data processing methods outlined in Section 3.2 (Figure D1). To compare changes in vegetation between the two years, we calculated the percent of normal and mapped the results as described in Section 3.3. Much of the study area did not experience great changes in vegetation density (Figure 5). However, focusing on specific landholdings in which Earth Conservancy conducted reclamation projects between 2015 and 2023 revealed changes consistent with our expectations. In those landholdings in which Earth Conservancy reclaimed AMLs for commercial development, NDVI decreased between 2015 and 2023 (Figure 5). This was consistent with our expectations, as LULC changed from a mix of forested and developed to fully developed over roughly the same period of time (Figure C1). In landholdings that Earth Conservancy reclaimed for ecological revitalization, NDVI increased which is consistent with our expectations as these projects typically include seeding the reclaimed land to increase vegetative growth (Figure 5).

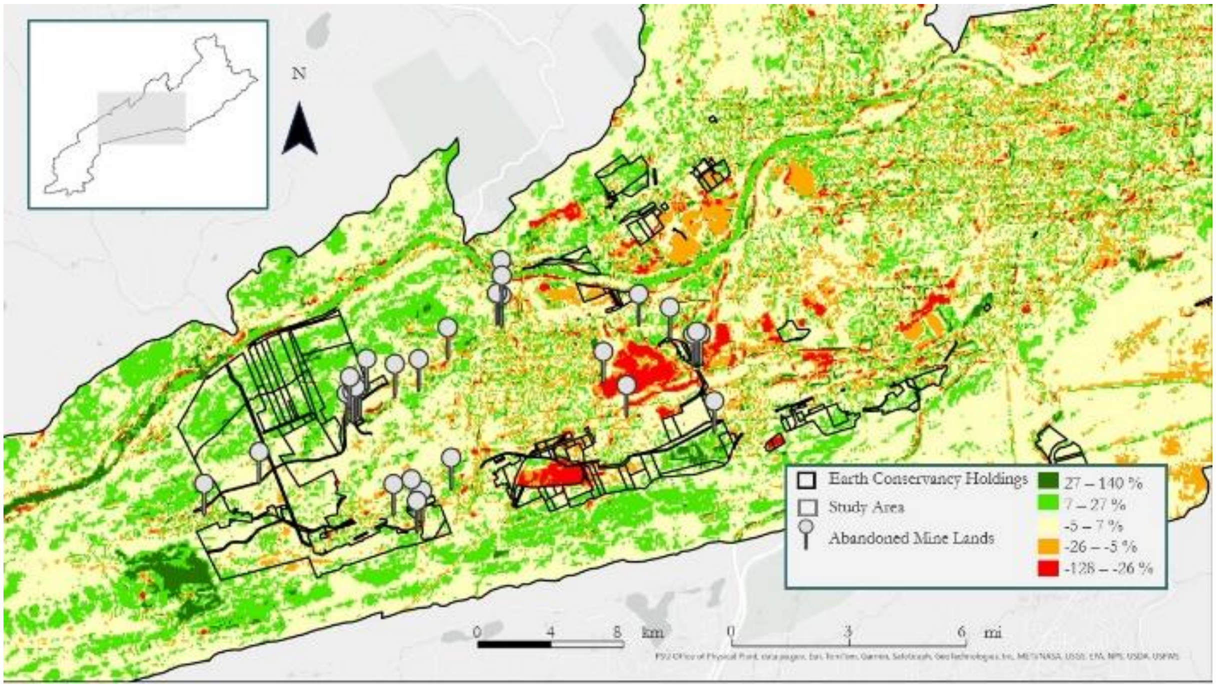

Figure 5. Percent of Normal NDVI (2015 versus 2023) with Earth Conservancy holdings and AML points overlaid. Areas in green represent areas of increased vegetation greenness, whereas areas in red represent decreased vegetation greenness between 2015 and 2023.

4.1.3 Surface Runoff

We created surface runoff maps for the years 2015 and 2023 (Figure E1). To identify areas of change in surface runoff, we created a percent of normal map (Figure 6). The percent of normal map revealed that the majority of the study area did not experience great changes in surface runoff, but portions of the study area and Earth Conservancy's landholdings did show notable differences. Landholdings that Earth Conservancy reclaimed for economic development purposes showed an increase in surface runoff (less infiltration to groundwater) and areas reclaimed for ecological restoration showed surface runoff decrease (an increase in infiltration capacity). These results are consistent with expectations given LULC type and NDVI changes as well, as we expected landholdings that experienced an increase in NDVI or a LULC type change from barren to forested to have an associated decrease in surface runoff (Ding et al., 2022).

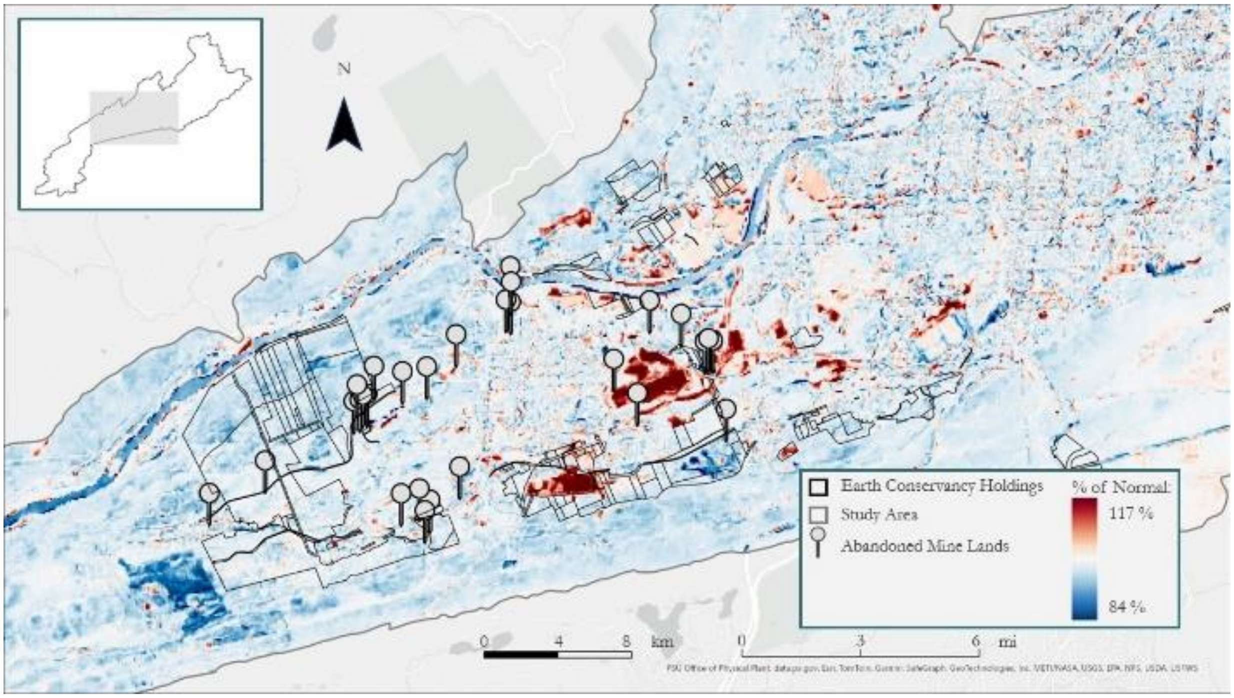

Figure 6. Surface Runoff Curve Percent of Normal Graph visualized changes observed from 2015 to 2023. Areas symbolized in red indicate an increase in the surface runoff curve number, while areas in blue symbolized a decrease in surface runoff curve numbers.

4.1.4 Social Vulnerability

We investigated changes in the disadvantaged community status between 2023 and 2024 using the EPA IRA 1.0 and 2.0 indices. Out of the 163 census tracts which are partially or completely contained within the study area, we found that 29 census tracts were added to the disadvantaged community list, 48 retained their disadvantaged status, and 20 were removed in 2024 (Figure 7).

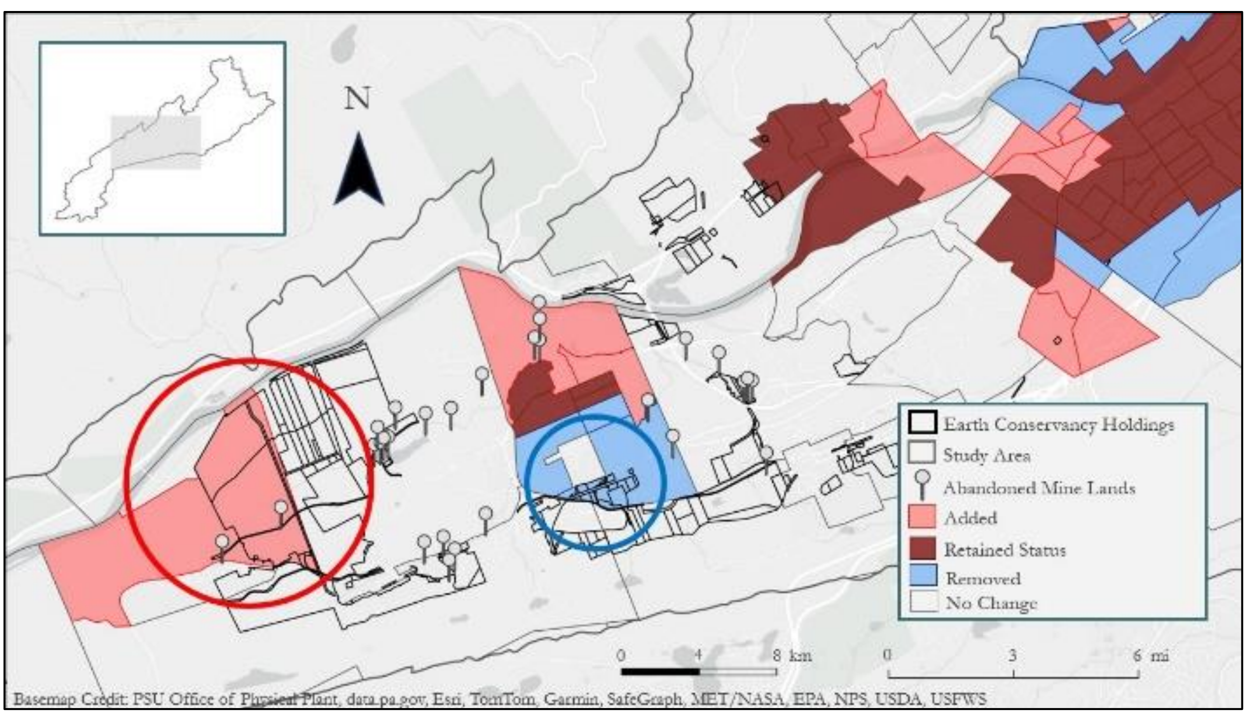

Figure 7. Change in EPA IRA "Disadvantaged Communities" Census Tract Designation between 2023 and 2024. Several of Earth Conservancy's land holdings are located in the census tract highlighted in the red circle (ID: 420792156005) which was added to the EPA IRA Disadvantaged list in 2024. Several land holdings are also located in the census tract highlighted in the blue circle (ID: 420792143002) which lost federal "disadvantaged" status in 2024.

We identified two census tracts of interest, one of which was removed from the EPA IRA Disadvantaged communities list (Census Tract ID: 420792143002) and one of which was added (Census Tract ID: 420792156005), as these areas contain several of Earth Conservancy's landholdings. We found that Census Tract 420792143002 was removed due to a change in CEJST disadvantaged community status between 2023 and 2024. However, CEJST data was only available from 2022. Due to this limitation, we were unable to identify the specific factors which led to the designation change, such as an increase in average household income or a decrease in asthma prevalence (Table A2). We found that Census Tract 420792156005 was added due to the percentile for lead paint prevalence in households increasing from the 83^{rd} percentile to the 90^{th} percentile. Meeting the EPA IRA criteria of 90^{th} percentile or greater, compared to the national average for any category of burden.

We were also interested in identifying census tracts that were considered low income and met the criteria for the "legacy pollution" category of burden. A way that a census tract can meet the "legacy pollution" criteria is by the presence of at least one AML left by legacy coal mining operations (Climate and Economic Justice Screening Tool, 2022b). The CEJST index uses e–AMLIS data from 2017 to determine whether a census tract meets this criterion. We found that the 2017 e–AMLIS database does not include all AMLs present within our study area. As such, we created a map visualizing low–income communities based upon EJScreen 2.3 data from 2024 for those census tracts at or above the 65^{th} percentile for low income and overlaid AML locations. We represented the census tracts that were considered disadvantaged versus not disadvantaged on the EPA IRA Disadvantaged Communities 2.0 list to highlight that many low–income areas with AMLs are not federally recognized as disadvantaged despite meeting the CEJST criteria. Out of the seven census tracts that contain at least one AMLs in the study area, three were designated as disadvantaged and four were not (Figure 8).

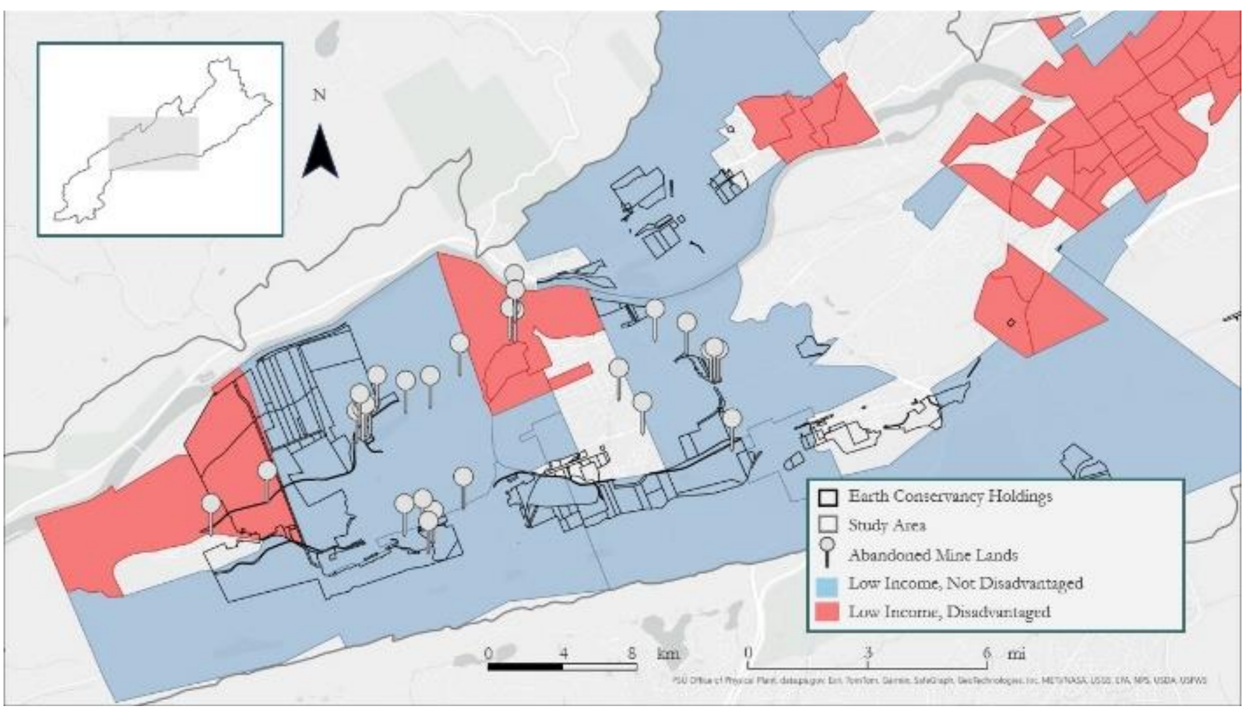

Figure 8. Low Income Communities based on EJ Screen 2.3 data from 2024, including federal disadvantaged communities and non-disadvantaged communities. Overlaid with Earth Conservancy's AML point data.

4.2 Errors & Uncertainties

We faced limitations with the classification models available for LULC analysis. The deep learning method described in Section 3.2 was compatible with Landsat 8 OLI data but not Landsat 4–5 TM data. We used supervised classification for 1986, 1994, and 2004 which is associated with greater potential errors and uncertainties as it relies on user identification of land cover to train the model. As such, results of traditional supervised LULC classifications can vary between users and yield less accurate and consistent results than the computer-classified deep learning model. Furthermore, if a certain land class is over or under-represented in training pixel quantity, the traditional supervised classification method may over or under-classify this land cover in the output. If our partners utilize this method for future work, it is important they keep an approximately equal quantity of training pixel for each land class to minimize this source of error. Additionally, the supervised classification methods classify LULC based on pixel color. However, certain land covers may appear similar in color and thus be misidentified. For example, water and certain forested land can sometimes be similarly colored in true color satellite images (e.g., on the 1986 imagery), potentially introducing error through misidentification of these land covers. Overall, the maps produced with supervised classification do provide generally accurate visualizations of land cover, but there were issues with certain land types being overrepresented and thus pixels misclassified, nonetheless. This is especially prevalent with water in place of forests or developed areas, as the color of the river changed drastically over the study period.

Sampling date and variation in green-up time caused limitations in several of our analyses. Green–up time can vary widely during the month of May. Four of the six Landsat datasets used in the LULC analysis were from late May, whereas the 1986 and 1994 datasets were from mid–May and early May, respectively (Table A1). The 1994 sampling date was a likely source of inaccuracies for the LULC change analysis. As the early May date was before or during green–up, the land appeared more barren than reality and was overclassified as barren land in the 1994 LULC map (Figure C2). This led to an apparent increase in barren land between 1986 and 1994, which was likely inaccurate given the consistent downward trend across the full study period. Additionally, the study aimed to assess LULC once every decade, however it was necessary to select data from 1986 rather than 1984 due to limitations in May data availability this year.

Furthermore, green–up time could have also impacted NDVI. Variation in precipitation and temperature between years may lead to non–anthropogenic NDVI variations. As such, changes in NDVI in areas which Earth Conservancy conducted reclamation projects cannot be attributed solely to their work. To limit the impact of precipitation variations, we consulted USGS stream gauge data for the two spring seasons (Spring 2015 and Spring 2023) we ran a t-test in Microsoft Excel and found no statistically significant difference between the two time periods (p-value = 0.392). However, historical precipitation and temperature variations along with other factors such as disease could have impacted vegetation cover and growth and consequently, impact our NDVI results. NDVI was also limited to land vegetation as we were unable to characterize aquatic vegetation in waterways as water greenness can fluctuate greatly over a short timespan depending on local precipitation events, surface runoff, and land cover changes.

The limitations associated with NDVI can also lead to uncertainties in our surface runoff analysis as the method we used to calculate runoff curve number used the NDVI values we calculated. Surface runoff does not account for any subsurface movement of water, limiting the conclusions we were able to draw from our results. While surface runoff is helpful for determining how reclamation has impacted the land surface through visualizing runoff and drainage, subsurface runoff is an important aspect of acid mine drainage investigation.

Our social vulnerability analysis was limited to 2023–2024 as the EPA IRA Disadvantaged communities list was only available beginning in 2023. As such, we are unable to examine changes in disadvantaged community status prior to this period, limiting the conclusions we were able to draw regarding potential impacts of Earth Conservancy's work in addressing environmental justice issues. While the Justice 40 CEJST list was available for 2022, the EPA IRA and the CEJST lists use different census tract boundaries, prohibiting a direct comparison of disadvantaged communities across these two indices. However, the EPA IRA lists incorporate CEJST disadvantaged community designations in their methodology. If a community is labeled as disadvantaged on the CEJST list, it is automatically considered disadvantaged by the EPA IRA list. However, the EPA IRA 1.0 and 2.0 comparison revealed that some census tracts were removed from the CEJST between 2023 and 2024, but the only CEJST data publicly available was from 2022. As such, we were unable to investigate specific factors that changed within these census tracts between 2023 and 2024 which led to the change in disadvantaged status.

5. Conclusions

5.1 Interpretation of Results

Earth Conservancy's mission is to revitalize both the environment and the economy through its reclamation efforts in the Wyoming Valley. We found NASA Earth observations and social vulnerability mapping are viable strategies for visualizing environmental and economic changes in the region. Our results provide key information to guide the partners' decision–making processes and supplement their overall knowledge base. Our LULC analysis revealed that forested land increased the most by acre within the study area, though some of the 1986 forested area was under classified. Although our study cannot attribute this finding to Earth Conservancy's reclamation work alone, it presents promising news of overall greening within and around Earth Conservancy's holdings which are often left ecologically scarred due to historic anthracite coal mining. Within Earth Conservancy's holdings, we found the greatest increase to be in developed land. Through cross referencing areas showing increased development and locations of known Earth Conservancy economic development projects, we found consistency between expected and observed increases in development. For example, Earth Conservancy launched their Bliss Bank Reclamation project in 2005 and finished up the development phase of the project in 2022. The project transformed the abandoned mine site of former culm banks and pits into a site of economic growth with the construction of two large warehouses (Earth Conservancy, 2023). LULC analyses reflected this change from barren to developed land for this site location, highlighting the feasibility of employing remote sensing LULC techniques for tracking changes associated with AML reclamation (Figure C1).

Similarly, our NDVI and surface runoff results show a negative correlation as well as LULC changes for certain reclamation sites; the Bliss Bank project site showed a decrease in NDVI and an increase in surface runoff, which is consistent with expectations for developed land. However, we found this method was not always consistent with expectations, exhibited by the Warrior Run project area. Beginning in 2013 and completed in 2015, this AML reclamation project involved the removal of mine spoils, grading of the land, and seeding the area (Earth Conservancy, 2016). As such, we expected to observe an increase in NDVI from 2015 to 2023, as the seeded area grows and becomes revegetated, and a decrease in surface runoff from 2015 to 2023, as more water can infiltrate through the soil. However, NDVI and surface runoff maps show a decrease in NDVI and increase in surface runoff. An examination of true color satellite images as well as LULC maps reveal this area does have an herbaceous landcover, leading us to the conclusion that NDVI and surface runoff mapping are subject to limitations and errors as discussed in Section 4.2. Despite these limitations, NDVI and surface runoff analyses are useful tools for analyzing environmental and land cover changes over a large study area and show promise for being integrated into Earth Conservancy's work in the future.

5.2 Feasibility & Partner Implementation

The methods presented in this feasibility study focused on whether remote sensing techniques are useful in observing long–term impacts of reclamation work by our partners, Earth Conservancy. Our feasibility study found that Earth Conservancy can utilize remote sensing to observe long–term trends pre- and post–reclamation. These trends can be observed through LULC changes, and trends in vegetation and surface runoff over reclamation sites. Additionally, the methods allowed the partners to build foundational knowledge of their land holdings including surface water dynamics, vegetation patterns, and changes in land cover over time. This knowledge can provide the partners with background information before they start reclamation projects to determine the best course of action for successful restoration. Additionally, the team's social vulnerability visualizations will enable Earth Conservancy to visualize socio–economic factors and their relation to abandoned mine lands efficiently.

This feasibility study also provided clear visualizations of Earth Conservancy's impact over their 30+ years of reclamation work in the Wyoming Valley. Earth Conservancy aims to share their mission through public outreach and education. This feasibility study provided visualizations and maps that can be used to demonstrate to the public some of the direct impacts their work has had on their community. For example, NDVI maps present scientific visualizations of vegetation increase following the Bliss Bank reclamation project, and LULC maps provide easily digestible viewing of long-term land changes over the course of Earth Conservancy's work. Furthermore, these maps help bridge the gap between complex scientific and sociodemographic data and the real world by presenting information in an engaging manner. General public audiences, especially those who reside around or within the study area, may feel more personally invested in the topics at hand as maps evoke a sense of place. Audience members can orient themselves within the community discussed and more readily understand their place in the larger story of progress that these maps are telling.

If the partner were to take our methodology further, Earth Conservancy could investigate for more recent years utilizing data that has a higher resolution. Higher spatial resolution data, such as those provided by Maxar or Planet SuperDove, can provide more detailed results on land use land cover changes. This may be specifically helpful in investigating the discrepancy between NDVI and LULC change results for the Warrior Run project. Furthermore, future investigation can be conducted into the specific variables that led to disadvantaged community status changes.

6. Acknowledgements

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7. Glossary

- Acid mine drainage – the release of highly acidic water that is rich in heavy metals from mining sites
- Abandoned mine land – historic sites of coal extraction, processing, and waste deposition
- Anthracite coal – also known as "hard" coal
- Culm banks – coal mining spoil piles, or mining waste left after mine abandonment
- Curve number – parameter used in hydrology for predicting direct runoff or infiltration from rainfall
- Environmental justice – the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to environmental laws, regulations and policies
- Green-up – onset of new vegetation growth following the dry season / winter
- Groundwater – water found underground which is stored in and moves slowly through soil and rocks formations called aquifers
- Land use land cover – classification of land based on human activities (land use) or environmental characteristics (land cover)
- NDVI – Normalized Difference Vegetation Index, quantifies vegetation by measuring the difference of near-infrared absorbed or reflected
- NLCD – National Land Cover Database
- Phenology – the study of cyclic and seasonal natural phenomena
- Raster – A fundamental data structure consisting of a matrix of equally sized cells representing a location on the earth's surface and contains a numeric value that represents a particular attribute
- Surface runoff – flow of water from precipitation or snowmelt across the surface of a landscape

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9. Appendices

Appendix A: Data

Table A1

Description of Earth observation and environmental justice data collection and uses.

<table>
<tr><th>Platform/Sensor</th><th>Source</th><th>Date</th><th>Use</th></tr>
<tr><td rowspan="3">Landsat 4–5 TM</td><td rowspan="6">Earth Explorer</td><td>May 13, 1986</td><td rowspan="4">LULC</td></tr>
<tr><td>May 3, 1994</td></tr>
<tr><td>May 30, 2004</td></tr>
<tr><td rowspan="3">Landsat 8 OLI</td><td>May 26, 2014</td></tr>
<tr><td>May 29, 2015</td><td>NDVI & Surface Runoff</td></tr>
<tr><td>May 27, 2023</td><td>NDVI, Surface Runoff, & LULC</td></tr>
<tr><td>CEJST 1.0</td><td>CEQ</td><td>Released November 2022</td><td rowspan="5">Social Vulnerability Index</td></tr>
<tr><td>EPA IRA 1.0</td><td>EPA</td><td>Released June 2023*</td></tr>
<tr><td>EPA IRA 2.0</td><td>EPA</td><td>Released July 2024*</td></tr>
<tr><td>EJScreen 2.2</td><td>EPA</td><td>September 2023</td></tr>
<tr><td>EJScreen 2.3</td><td>EPA</td><td>August 2024</td></tr>
</table>

*Release dates of EJScreen 2.2 and EJScreen 2.3 datasets (US Environmental Protection Agency, 2024)
CEJST: Climate and Economic Justice Screening Tool, CEQ: Council on Environmental Quality, EPA: Environmental Protection Agency, IRA: Inflation Reduction Act, EJScreen: Environmental Justice Screening and Mapping Tool

Table A2

Description of relevant contents of each dataset used for the social vulnerability index. These metrics include criteria used for social vulnerability analysis.

Dataset	Social Vulnerability Metrics Used
CEJST 1.0	CEJST disadvantaged status
	Adjusted percent of individuals below 200% Federal Poverty Line (percentile)
	Identified as low income (65th percentile or above)
EPA IRA 1.0 and 2.0	EPA IRA disadvantaged status
	CEJST disadvantaged status
	US Supplemental Index ≥ 90th percentile status
EJScreen 2.2 and 2.3	Low-income percentile

CEJST: Climate and Environmental Justice Screening Tool, EPA: Environmental Protection Agency, IRA: Inflation Reduction Act, EJScreen: Environmental Justice Screening and Mapping Tool

Appendix B: Equations

Table B1

All equations outlined in text and their corresponding equation number.

Equation Number	Equation
1	$\text{Rescale} = (0.0000275 \times \text{Band}) - 0.2$
2	$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$
3	$\text{NDVI}_{8-\text{bit}} = \text{NDVI} \times 100 + 100$
4	$\text{CN} = -0.11 \times \text{NDVI} + 100$
5	$\text{Area}_{\text{landclass},2023} - \text{Area}_{\text{landclass},1986}$
6	$\frac{\text{Area}_{\text{landclass},2023} - \text{Area}_{\text{landclass},1986}}{\text{Area}_{\text{landclass},1986}} \times 100$
7	$\frac{\text{Area}_{\text{landclass},2023}}{\Sigma\text{Area}_{\text{landclass},2023}} \times 100$
8	$\frac{\text{NDVI}_{2023}}{\text{NDVI}_{2015}} \times 100$ $\frac{\text{CN}_{2023}}{\text{CN}_{2015}} \times 100$

Appendix C: *LULC*

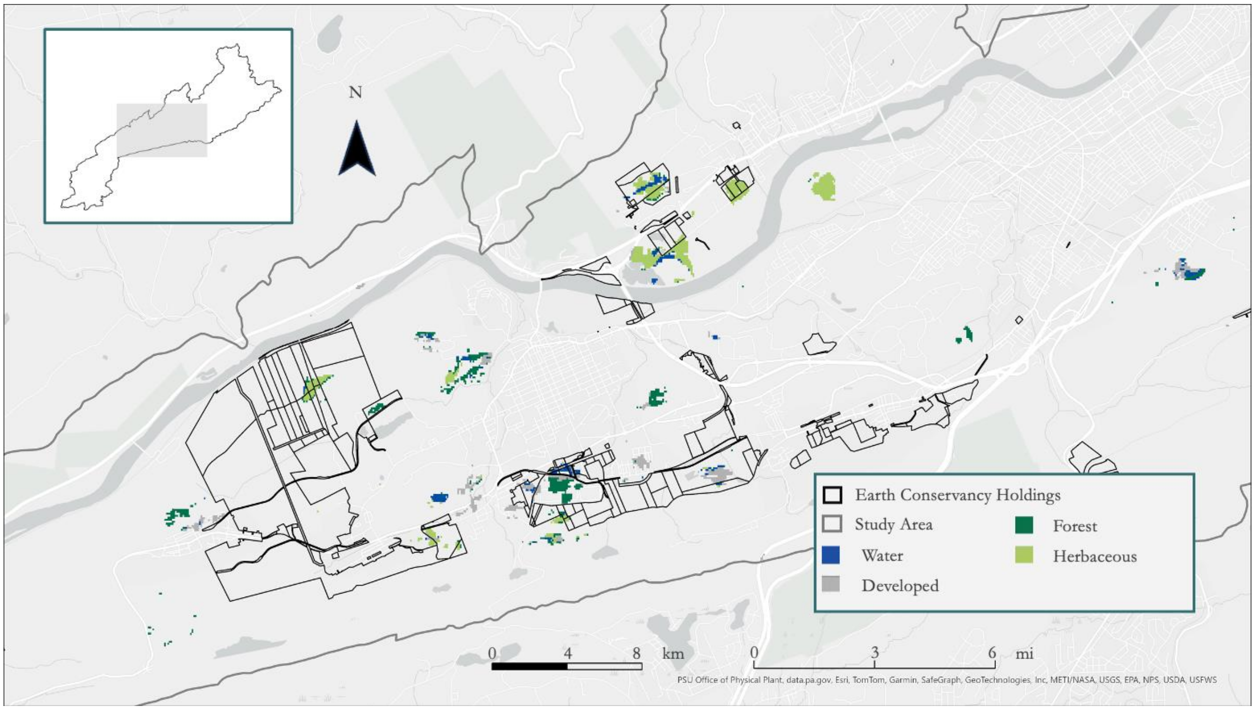


Figure C1. LULC change from 2014 to 2023, zoomed in on the majority of on Earth Conservancy's holdings to better investigate changes in these areas.

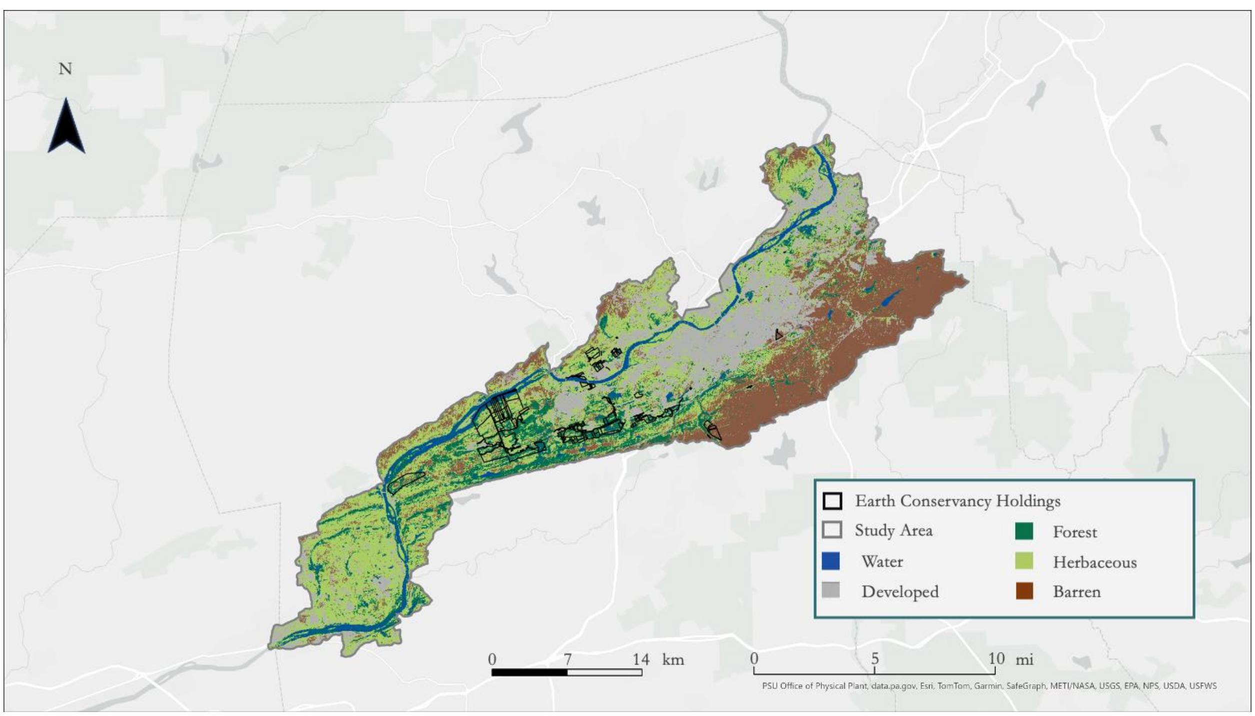
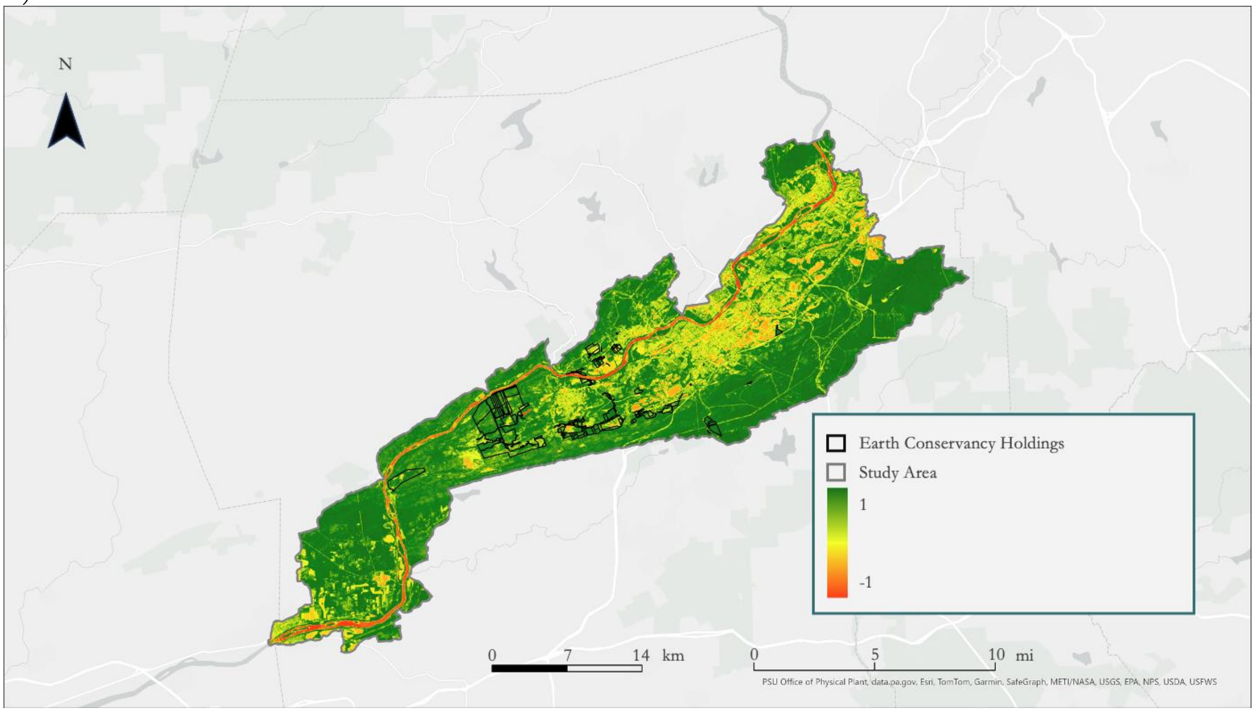


Figure C2. LULC in 1994 exhibits more barren land than any other date likely due to discrepancies between sampling date and green-up time for that year rather than land becoming more barren from 1986 to 1994.

Appendix D: *NDVI*

A)



B)

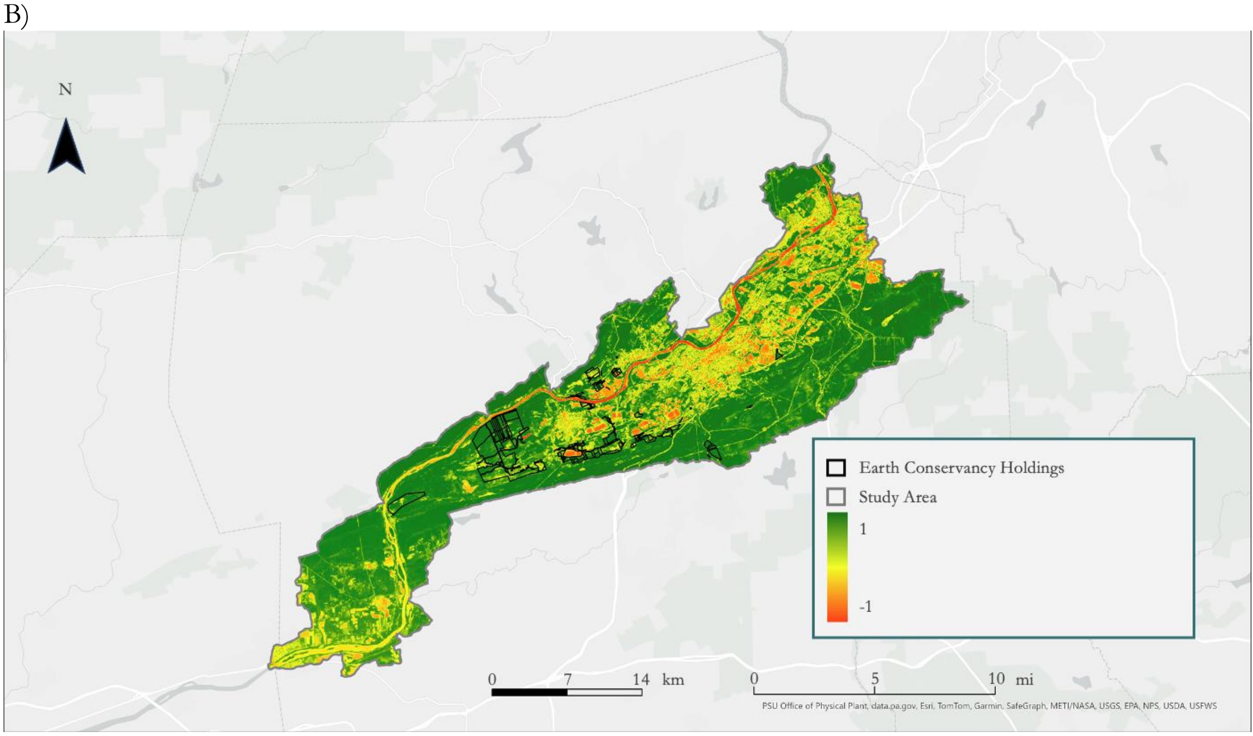
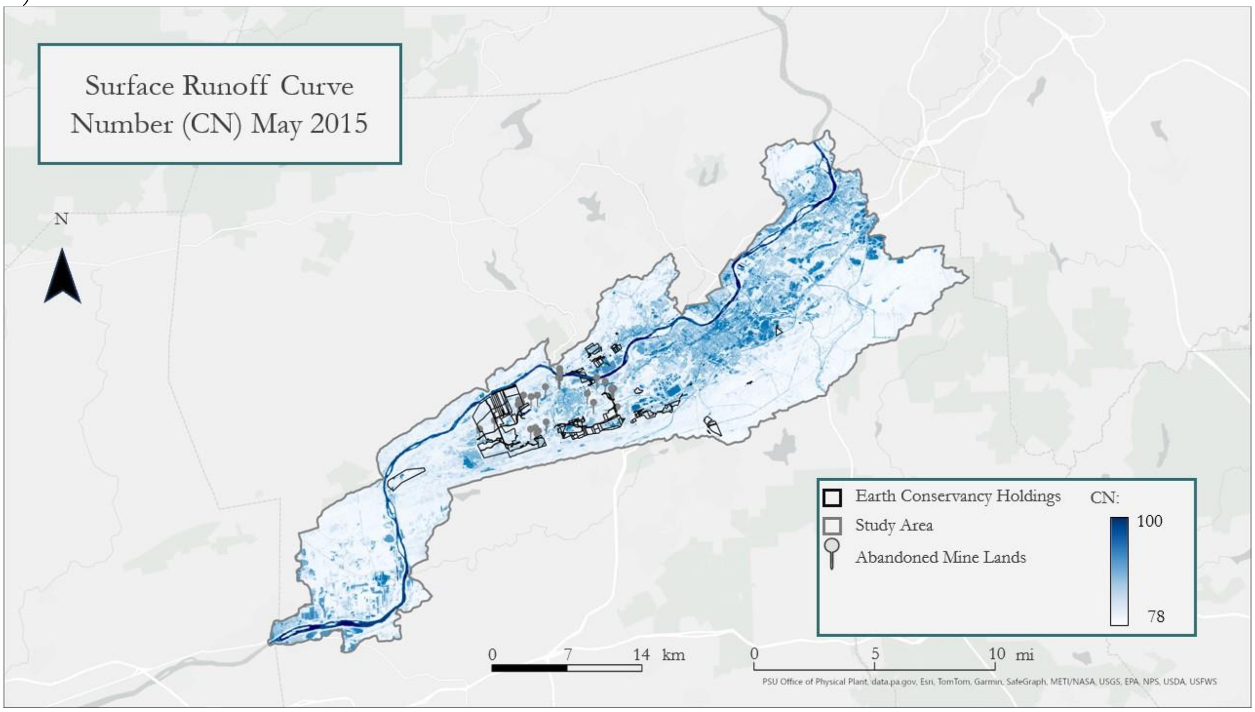


Figure D1. Visualizing NDVI in A) May 2015, and B) May 2023. Green represents areas of high vegetation, such as forests, and red represents areas of little to no vegetation, such as water or developed land.

Appendix E: *Surface Runoff*

A)



B)

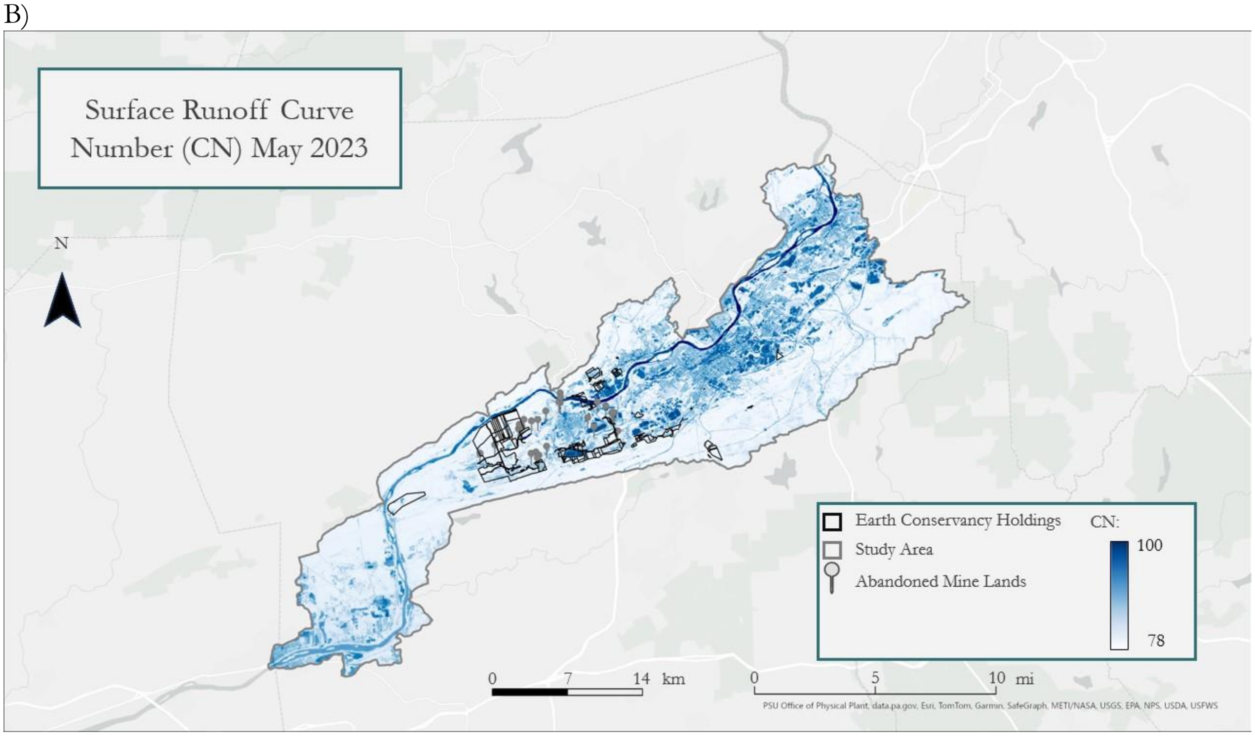


Figure E1. Visualizing surface runoff in A) May 2015, and B) May 2023. The runoff curve number varies from 78 to a maximum of 100. White areas represent lower runoff potential, and dark blue areas represent the highest runoff potential, where 100% of water will runoff.