Implementing Machine Learning to Establish a Relationship Between Coal Ash Spread and Lined vs. Unlined Sites Using Publicly Available Data

Research Paper

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Paper is a non-peer reviewed preprint submitted to EarthArXiv, but we have recently submitted to the National High School Journal of Science and is currently under peer review.

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1 Abstract

The fuel combustion process within coal power plants causes a significant amount of waste, called coal ash, often stored in slush basins. Due to low maintenance and lack of proper regulations, coal ash ponds have a high tendency to contaminate nearby groundwater sources. Without a simple way to ascertain whether the drinking water and soil near a private residential area is contaminated, citizens are unaware of the environmental risk surrounding them. To resolve this issue, this study aims to establish a correlation between the heavy metal concentrations in soil that are publicly available and the locations of coal ash plants. Thereafter, a user-friendly map will be created to determine the risk levels of their locations. To establish the correlation, four regression models and two classification models were implemented. Out of these models, the Support Vector Machine (SVM) proved to be the most accurate model in risk prediction, and the Mean Squared Error (MSE) reached the value of 0.01 in some cases. By running the models to compare the risks between the lined and unlined coal ash ponds, it was evident that the contamination levels surrounding unlined ponds were significantly greater than those near lined ponds. The results of this study will make a direct and positive impact on the community.

2 Introduction

In recent years, certain cases have brought into light the various effects of coal ash on the environmental issues as well as the health and well-being of the residents in contaminated areas. In spite of this recent increase in the concerns regarding the contamination of many toxic metals related to Coal Combustion Residuals (CCRs), and the lack of effective methods to detect coal ash, an immediate solution must be provided to the countless residents who are at risk from not knowing whether their private property is contaminated with coal ash. Without a simple and effective method to detect the coal ash sites, the residents have to perform actual lab tests on water quality, which is a more laborious, expensive, and convoluted process. This involves a complicated method to measure the contamination levels, which may prevent them from addressing the potential contamination issues. This study primarily aims to solve this issue with a simple, inexpensive, and effective computational approach.

Globally, coal's share of the energy market has decreased; however, total consumption of coal is still projected to be 43.95 trillion kilowatts of power by 2040 ((L. Doman (2017). EIA projects a 28% increase in world energy use by 2040. Homepage - U.S. Energy Information Administration (EIA). Retrieved February 19, 2023, from https://www.eia.gov/todayinenergy/detail.php?id=32912)). In 2014, approximately 8,000 metric tons of coal were produced among the major coal producing countries, with the largest source of production coming from China ((A.D. Lemly. (2015). Damage cost of the Dan River Coal Ash Spill. *Environmental Pollution*, **197**, 55–61.)). Approximately 65.5% of primary coal produced is used globally for electricity and commercial heat ((L. Ruhl, A. Vengosh, G. S. Dwyer, H. Hsu-Kim, A. Deonarine, M. Bergin, J. Kravchenko. (2009). Survey of the potential environmental and health impacts in the immediate aftermath of the coal ash spill in Kingston, Tennessee. *Environmental Science & Technology*, **43**(16), 6326–6333.)).

Over the past decade, coal ash has become a prominent issue in many parts of the United States and around the world. This issue has been followed by a series of laws imposed by the Environmental Protection Agency (EPA) requiring transparency regarding coal ash combustion and disposal. These laws were officially signed in 2014 and published in the Federal Register (FR) the following year, in 2015 ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)). Since the announcement of these rules, researchers have drawn connections between CCR contamination in groundwater and the prevalence of many diseases among the residents living within the contaminated areas. The CCRs have been considered a cause of cancer, heart disease, reproductive failure, and stroke, and they also can inflict lasting brain damage in children ((Mapping the coal ash contamination. Earthjustice. (2022, November 3). Retrieved January 24, 2023, from https://earthjustice.org/features/coal-ash-contaminated-sites-map)).

One of the major incidents related to Coal Ash is the Kingston station spill. A review on a coal ash spill case in Kingston, Tennessee gave a more in-depth view of potentially drastic environmental impacts. The first-responders and individuals coming into primary contact were prone to severe risk of contracting the illnesses associated with coal ash. In addition, other drastic environmental impacts such as an imbalance in biodiversity were revealed in the area ((P. Revas, (2013, January). Support Vector Machines for Regression: A Succinct Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, **3**(1), 5-14.)).

Without direct access to test private properties for potential coal ash contamination, a wide variety of environmental impacts and health risks go unnoticed ((P. Revas, (2013, January). Support Vector Machines for Regression: A Succinct Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, **3**(1), 5-14.)). Along the same lines, improper reporting of the coal ash sites and the contaminants results in inaccurate data regarding the contamination sites. Due to the faulty data reported by Coal Companies and the limitations on the locations where the water can be tested, many private residents are facing the dilemma of not knowing whether their water is contaminated and the relevant health concerns associated with it. More recent laws imposed by the EPA have produced the current emergence of knowledge regarding this well-hidden subject. On the other hand, there is extensive data collection and compilation by the Environmental Integrity Project (EIP). These new developments provide an opportunity to find a link between coal ash sites and relevant contamination levels in nearby areas ((Mapping the coal ash contamination. Earthjustice. (2022, November 3). Retrieved January 24, 2023, from https://earthjustice.org/features/coal-ash-contaminated-sites-map)).

It is imperative that this problem be addressed, because not only does it affect the health and well being of humans and ecosystems, the coal ash contamination also results in large sums of losses in economic revenue. With the Dan River accident alone, the combined cost of ecological damage, recreational impacts, effects on human health and consumptive use, and esthetic value accounted for loss totals of 295 billion dollars ((A.D. Lemly. (2015). Damage cost of the Dan River Coal Ash Spill. *Environmental Pollution*, **197**, 55–61. https://doi.org/10.1016/j.envpol.2014.11.027)).

Over the last few years, Artificial Intelligence and Machine learning have gained immense interest; as a result, they have improved in terms of quality and functionality. Therefore, we believe that applications of artificial intelligence and machine learning approaches are viable paths in the development of various regression and classification models, such as K-Nearest Neighbors, Support Vector Machine, and Random Forest. This can allow us to discover a correlation between heavy metal and toxic coal ash concentrations and the nearest coal ash sites.

3 Results

Support Vector Regression (SVR) Output

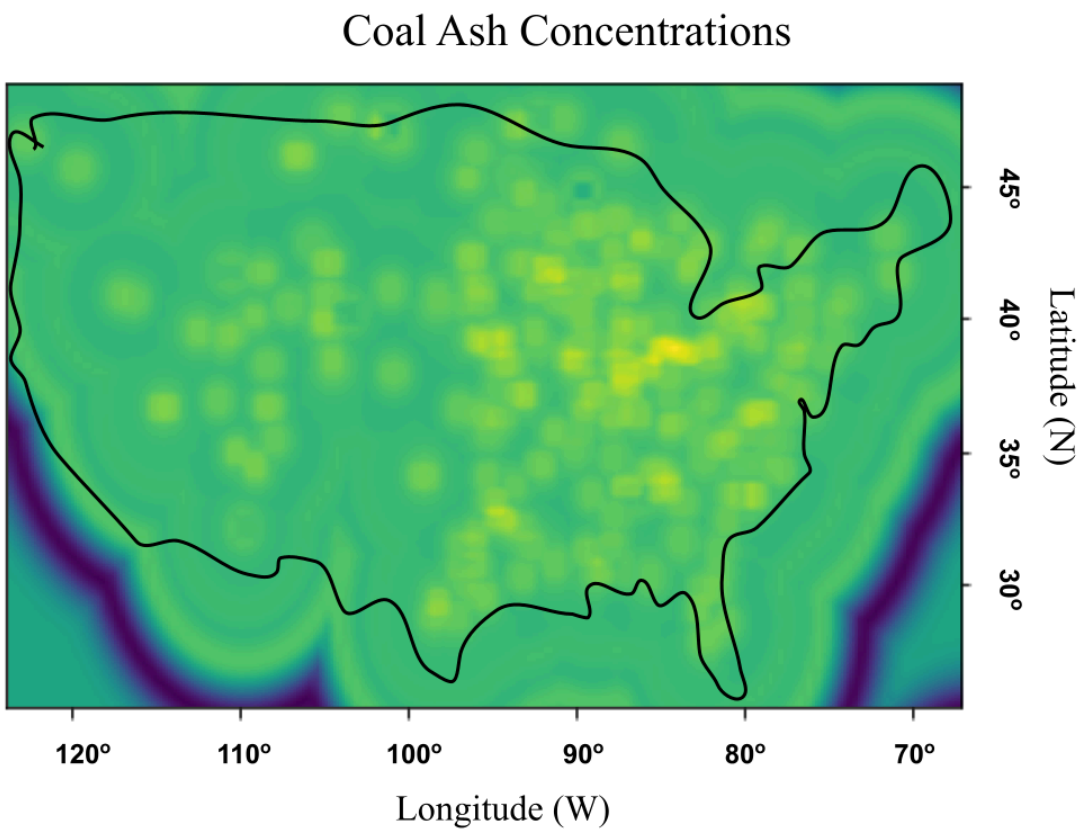


Figure 11: A map predicted by the model of the average concentrations of the 4 heavy metals across the United States for modeling coal ash spread.

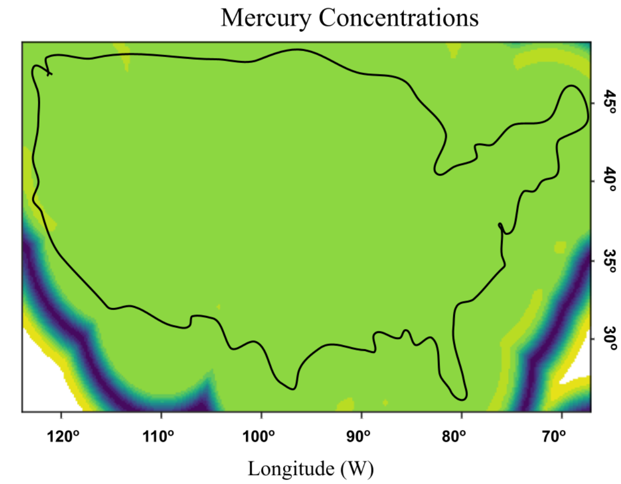


Figure 12: A map generated by the model of the concentrations Mercury across the United States

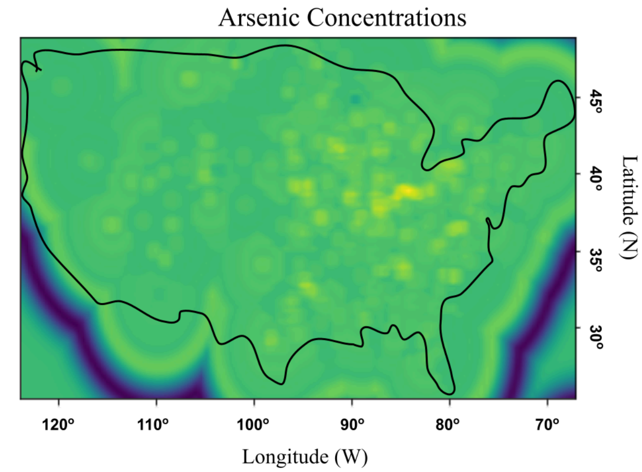


Figure 13: A map generated by the model of the concentrations Arsenic across the United States

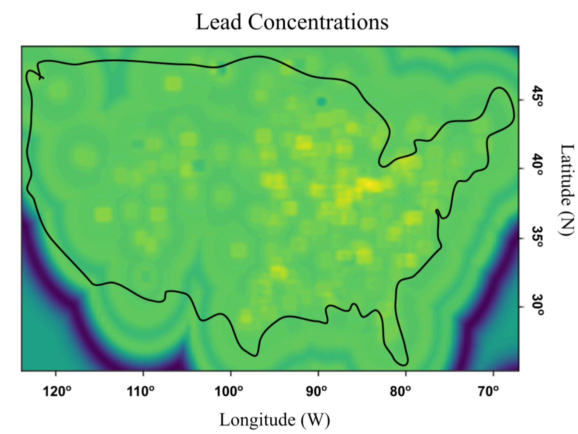


Figure 14: A map generated by the model of the concentrations Lead across the United States

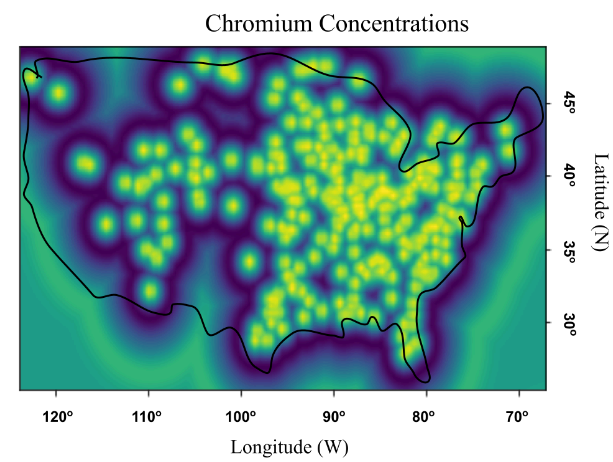
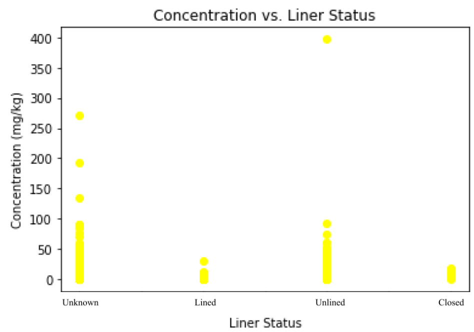


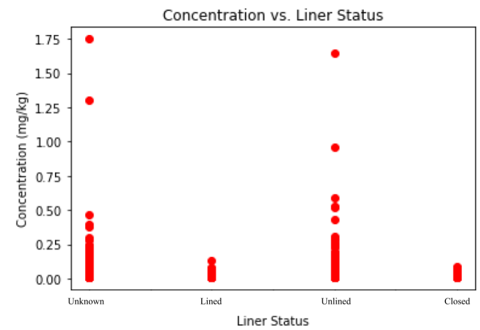
Figure 15: A map generated by the model of the concentrations Chromium across the United States

The maps above were made with matplotlib in python to model the predicted concentrations from the Support Vector Regressor (SVR) for each metal. The SVM model resulted in the highest R^2 value, and a reasonably low Mean Squared Error (MSE) compared to the other models. The average map represents the average concentrations of all four metals across the 10,000 spots. Different colors on the maps represent varying concentrations of the toxic metals focused on this paper. Following the average concentration are the individual concentrations in the maps with Mercury (Hg), Arsenic (As), Lead (Pb), and Chromium (Cr). This data shows the distribution of each heavy metal per longitude and latitude in the United States. There is no clear correlation to the Coal Ash sites. However, with extensive testing, and overlay it is possible to see that some of the concentrations average in the same areas where the coal ash sites are located, indicating a relationship between these heavy metal concentrations and the coal ash contamination.

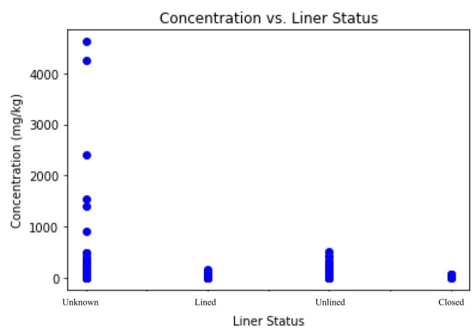
3.1 Lined vs. Unlined Coal Ash Sites



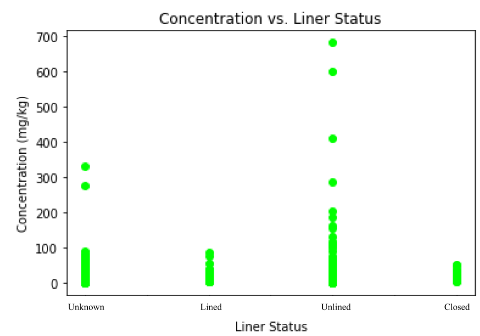
Arsenic



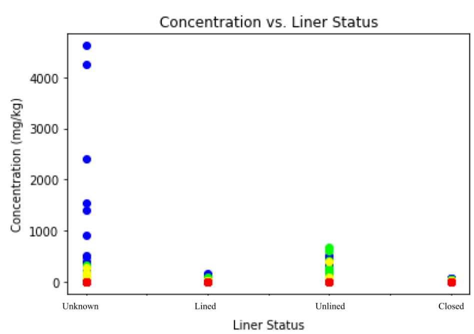
Mercury



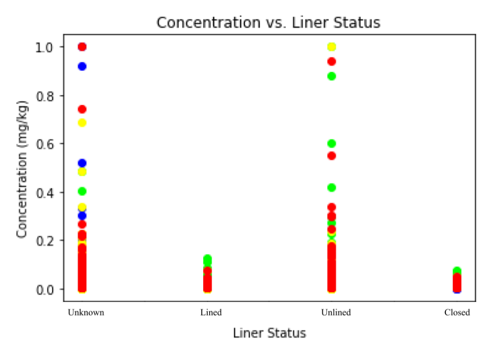
Chromium



Lead



Unscaled



Scaled

Figure 16: Graphs of Concentration of Metals with respect to Liner Status

The graphs above were made using the scatter plot function in matplotlib. Each color represents a different metal. On the y-axis is the concentration of the metal in mg/kg and on the x-axis is the type of liner. The graphs were constructed using the dataset on the concentration of a metal at a soil site and the type of liner used on the coal site closest to the soil site.

		Mercury	Arsenic	Lead	Chromium
Average Concentration (mg/kg)	Landfill (Unspecified)	0.0341	7.06	15.	45.3
	Lined	0.0237	5.1	17.8	26.0
	Unlined	0.0312	7.13	17.5	33.4
	Closed	0.0312	6.89	16.	33.0
	% Diff. Lined vs. Unlined	22.96%	27.48%	1.77%	18.69%

Table 1: Concentrations of Metals vs. Type of Liner

Table 1 displays the concentrations of each metal found in soil with respect to the liner type of the nearest coal ash site. This data was obtained through running the first algorithm to find the nearest coal ash site to a soil site and recording the coal ash landfill liner type. It is important to note that a majority of the metals have a significant percent difference in metal concentrations between the lined and unlined coal ash sites.

3.2 Regressors

For the regressors below, R^2 and MSE were used to evaluate the fit of the models. R^2 represents the correlation between the model and the data, while MSE represents the amount of error between the model and the data.

Linear Regression (Control)				
	R^2	MSE	Coefficients	Intercept
Mercury	0.00405	0.01	[-1.40975008e-04, -6.01653387e-04, -9.65629778e-04, 1.15518859e-05, -1.32736820e-03]	0.0411
Arsenic	-0.01409	43.91	[0.07137822, -0.028329, 0.42295849, 0.00388225, 0.03078834]	6.2788
Lead	0.01038	536.76	[0.2372456, -1.22251273, -0.22199772, -0.00688673, 0.74957017]	16.8838
Chromium	-0.04168	1148.7	[0.35535761, -3.99634693, 6.89917393, 0.10018364, -5.90608605]	28.1442

Table 2: Metrics for Linear Regression (Control)

Nearest Neighbors Regressor		
	R^2	MSE

Random Forest Regressor		
	R^2	MSE

Mercury	0.002129	0.009952
Arsenic	-0.03360	55.65269
Lead	-0.02396	173.0116
Chromium	-0.3153	1159.4693

Table 3: Metrics for Nearest Neighbors Regressor

Mercury	-0.06342	0.01012
Arsenic	-0.4725	76.8642
Lead	-0.2075	398.6080
Chromium	0.05413	18432.9054

Table 4: Metrics for Random Forest Regressor

Support Vector Regressor				
	C	ε	R^2	MSE
Mercury	1000	0.01	-0.022048	0.009782
Arsenic	1000	1	-0.94869	0.429278
Lead	1000	1	-0.085644	2.065493
Chromium	0.1	1	-0.240114	2.119605

Table 5: Metrics for Support Vector Regressor

3.3 Classifiers

Below are the metrics to evaluate the performance of the classifiers. Accuracy and precision are the two main metrics measured. Accuracy is the percentage of those classified correctly, and precision is the consistency of the model.

Random Forest Classifier			
	Accuracy	Precision	Trees
Mercury	0.5955334988	0.5906755342	3
Arsenic	0.8127615063	0.7763878864	1
Lead	0.9989539749	0.997909044	1
Chromium	0.6066945607	0.5665151763	1

Table 6: Metrics for Random Forest Classifier

Nearest Neighbors Classifier			
	Accuracy	Precision	Neighbors
Mercury	0.7009925558	0.6192040905	56
Arsenic	0.870292887	0.7911088978	7
Lead	0.9958158996	0.9916493059	1
Chromium	0.6976987448	0.787242441	54

Table 7: Metrics for Nearest Neighbors Classifier

The tables below demonstrate the statistics on the outputs of the two models. It is worth noting that many outputs are skewed.

Random Forest

Nearest Neighbors

	Min	Mean	Max
Arsenic	5	5.120292887	8
Mercury	5	5.730769231	7
Lead	5	5.73325062	7
Chromium	5	5.304393305	6

Table 8: Metrics for Output of Random Forest Classifier

	Min	Mean	Max
Arsenic	5	5	5
Mercury	5	5.919354839	6
Lead	5	5	5
Chromium	5	5.10251046	6

Table 9: Metrics for Output of Nearest Neighbors Classifier

4 Discussion

4.1 Regression

From Tables 3, 4, and 5, the regressors were not successful as expected. All of the R^2 values for the non-control regressors were below 0.5. Additionally, The results in Table 5 indicate that the SVR is the best regressor because of the consistently low MSE. Other models on occasion had low MSE, but only the SVR had all four MSE below 5. This establishes an acceptable proof-of-concept meaning the SVR would be the most appropriate candidate for implementation onto the user-friendly map, the final end product. This is precisely our goal, to create the map of average concentration of the toxic heavy metals selected in this project.

4.2 Classification

From Tables 8 and 9, it is evident that the accuracy and precision of both classifiers are relatively high, which should be a positive sign. However, when the outputs were analyzed more closely, it was shown that for some metals, a significant majority of the predictions were the same value. As seen in Table 9, the mean is close to the max or min, indicating that a majority of the predictions must be the same number to skew the data so far. This result might indicate that for the nearest neighbors model the vast majority of the United States is predicted to be at safe levels. However, this is not consistent with the results shown in Figures 2, 3, and 4. The likely cause of this disaccord is that the Nearest Neighbors model is not as resistant to imbalanced data as the Random Forest model is. This is reasonable since the Random Forest model implements randomization which would be less affected by imbalanced data compared to nearest neighbors which is not randomized. Thus, we abandoned this in the final step of the map creation in the project, due to the potential fallacy within the process.

4.3 Lined v. Unlined

It can be seen in Figure 16 that there is a much higher concentration of heavy metals for unlined coal ash sites when compared to lined sites. In addition to this, from Table 1, it is clear that the percent differences for three out of the four metals are greater than 5%. This indicates that the type of lining of a coal ash site has an effect on the concentrations of heavy metals around it. This is supported by the idea that lining the site would allow for a barrier between the environment and the toxic waste contained within.

This result supports that more coal ash sites need to be lined. Current data suggests that only about 6% of coal ash sites are lined[7], and the unlined sites have high instances of leaching, causing ecological damage, posing a health hazard and resulting in economical losses.

4.4 Limitations

Although the overall project led to positive results, there are some limitations for the current status of this project. First, the soil data that was utilized did not have enough samples as preferred, and the lack of a robust dataset made it difficult to train a good model. Second, the soil data used in this project was collected from the years 2007 to 2013, indicating that the data was at least 10 years old. Lastly, burning coal is not the only way for toxic metals to be released. Sources such as mines, industrial production, untreated sewage sludge, and diffuse sources such as metal piping also release toxic metals into the environment. Regardless of these limitations this project can be improved in the future to bypass these limitations.

4.5 Future Plans

In order to continue this fundamental research based on current results, there will be various important aspects to pursue for constructing a more effective and user-friendly model. The plan includes: 1) To collect robust data, whether it is from other public sources or from the field. A larger dataset and additional data mining will allow the model to reach a greater accuracy, leading to a better map. 2) Along with the robust data, to use more components of coal ash with appropriate weights to determine, or at the very least, to increase the likelihood of the final output being a representation of coal ash rather than locations with overlapping concentrations of the chosen heavy metals (as was the case with the current research). 3) To implement a deeper learning algorithm, for example, a neural network, so that the model has a better chance to create a more accurate prediction. This would be a more achievable goal as Tensorflow and Keras framework have already been included in Google Colaboratory. 4) To use data for metal concentrations across multiple years to create a prediction model. This would have direct implications for policymaking because the regulators can look at what is going to happen based on current contamination levels.

This project can address the current social problems and has direct impacts on the community because of the goal to create a map of the United States with levels of hazardous coal ash contamination. Beyond this, improving the current model and eventually working towards a prediction model will further increase its impact on the general public, by expanding the audience from residents to policymakers.

4.6 Conclusion

Through completing the main parts of this project, a map was derived on the coal ash concentrations based on four toxic metals of interest. This final product allows the general public to understand whether they live in a toxic coal ash-contaminated environment and whether they should invest in actual contamination testing, which often requires an accredited laboratory setting and is a time-intensive process.

Regardless of the measures taken to avoid dilemmas throughout the research process, there were some remaining issues. One primary concern was why the final map showed higher concentrations in the Midwest, whereas the original coal ash dataset contained a substantial number of sites in the East. This, as discussed, may be due to the effects of the natural environment and groundwater flow. There may be a higher concentration of mines and other such locations in the midwest causing a natural increase in the toxic metals of interest within this study ((L. Ruhl, A. Vengosh, G. S. Dwyer, H. Hsu-Kim, A. Deonarine, M. Bergin, J. Kravchenko. (2009). Survey of the potential environmental and health impacts in the immediate aftermath of the coal ash spill in Kingston, Tennessee. *Environmental Science & Technology*, **43**(16), 6326–6333. https://doi.org/10.1021/es900714p)).

The primary question we were asking was whether it was possible to create an effective map of the coal ash concentrations using publicly available data with regards to lined and unlined ponds. In the end, it has come to a conclusion that the SVM worked best in regards to the accuracy in the regression model with a reasonable MSE and R^2 values. According to the modeled data, the unlined ponds had significantly less contamination in nearby areas than the lined ponds, supporting our hypothesis regarding the importance lining the coal ash sites play. This will allow for policy changes regarding the proper disposal and maintenance of CCRs.

In conclusion, the project was executed to test our hypotheses thoroughly, and the data from the results supported our hypotheses. The results from this project will be helpful in solving the issue that many common residents face regarding the contamination of their private properties with these toxic heavy metals.

5 Methods

The primary goal of this project was to determine if there exists a significant correlation between the concentrations of the four primary toxic constituents of coal ash, Mercury (Hg), Arsenic (As), Lead (Pb), and Chromium (Cr), and the number of coal ash sites, with respect to whether it is lined or unlined. Data from several public sources including the United States Geological Survey (USGS) were collected and the Python programming language was used. The number of coal ash sites within a 50 kilometer (km) radius of each soil site were taken into account during the implementation phase of the project. The Jupyter Notebook: Google Colaboratory environment was utilized because of its functionalities in implementing machine learning algorithms and running on the cloud. Four distinct regression-based models and two classification models were constructed, and the four heavy metals of interest were run with each model as a preliminary stage for our final project. The validated method was then utilized to classify the regions in the United States into a low, medium, or high risk of coal ash contamination. The classifications prompt residents to take appropriate actions for their well-being, per the initial motivation of this project. All work was completed over the course of a few months using standard home-suited laptops, open-source python packages, numpy, and matplotlib, indicating the potential and versatility of this method for the general public. A concise representation of the major steps throughout the project is diagrammed in Figure 1. The details regarding these major steps were followed.

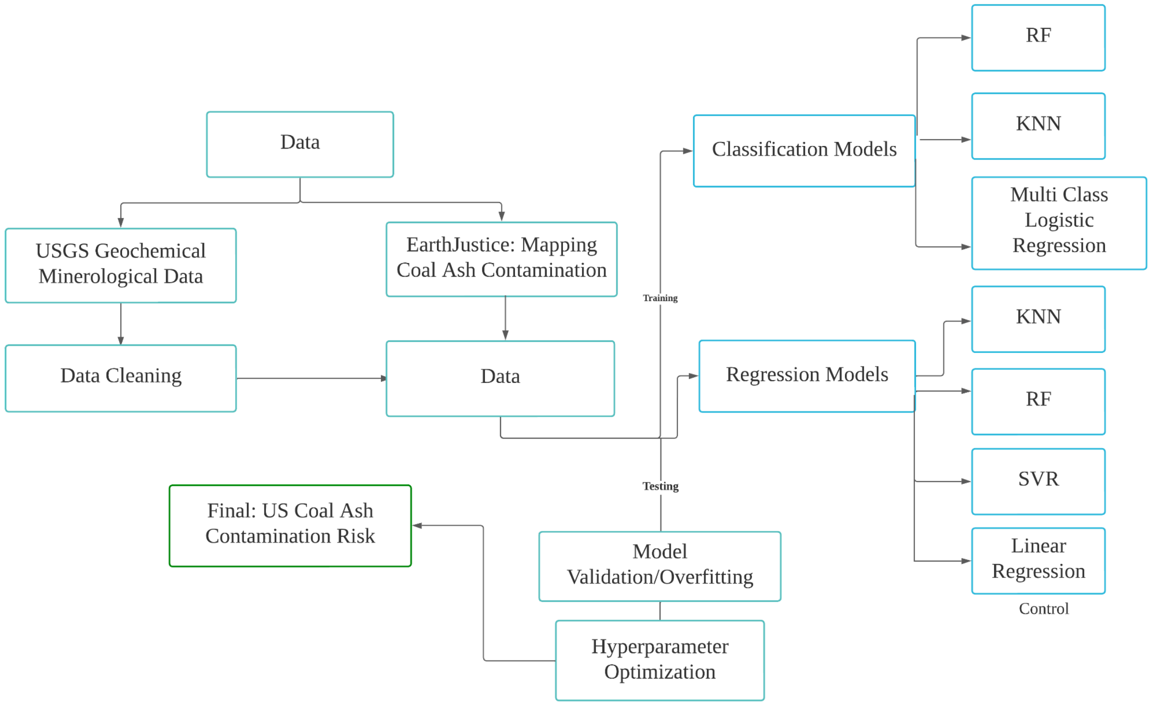


Figure 1. Workflow diagram of process relating to establishing a correlation between heavy metal concentrations and coal ash plants.

Due to the lack of robust datasets on the specific measurement of coal ash concentrations in the environment with a focus on soil, a select amount of components that constitute coal ash was selected as the primary method of testing, for the best application to our project. To obtain the data regarding the concentrations of the toxic constituents of coal ash, specifically, Mercury (Hg), Arsenic (As), Lead (Pb), and Chromium (Cr), the USGS Mineral Resources Online Spatial Data site was utilized ((Survey, U. S. G. (n.d.). *USGS mineral resources on-line spatial data*. USGS Mineral Resources On-Line Spatial Data. Retrieved January 30, 2023, from https://mrdata.usgs.gov/)).

After examining the contamination levels of these four metals throughout the United States, a dataset, including different concentrations of the minerals measured in the soil from 2007 to 2013, was constructed. One benefit of this particular dataset is the fact that it was measured before the first series of laws imposed by the EPA regarding the transparency of coal ash were signed ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)). Based on the information from Agency for Toxic Substance and Disease Registry (ATSDR) at Center for Disease Control (CDC)'s and the EPA's soil contaminant regulations, the toxic levels for Mercury (Hg), Arsenic (As), Lead (Pb), and Chromium (Cr) were set to above 0.002 mg/kg ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)), 0.010 mg/kg ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)), 400 mg/kg in soil (15 µg/L in drinking water) ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)), and 250 mg/kg ((M. Izquierdo, X. Querol, (2011, October 15). Leaching behaviour of elements from coal combustion fly ash: An overview. International Journal of Coal Geology. Retrieved January 24, 2023, from https://www.sciencedirect.com/science/article/pii/S0166516211002230)), respectively. With these parameters, the chosen dataset was an appropriate representation of the correlation between the concentrations of these measured chemicals in the soil and their locations. Exploring this dataset led to the collection of over 4,500 robust points of data for processing. One site per 1,600 square kilometers with three distinct measurements regarding the depth of the soil sample was evaluated, including samples from depths of 0-5 cm (Figure 2), the A Horizon (Figure 3), and the C Horizon sample (Figure 4).

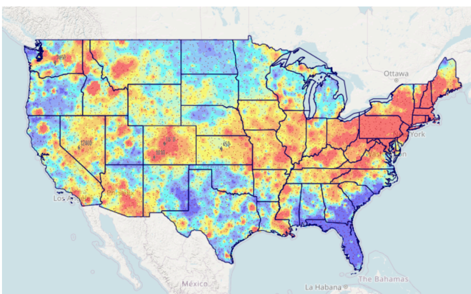


Figure 2 Map of Concentrations of Lead found in Top 5 cm Soil (Used for Data) [Credit USGS]

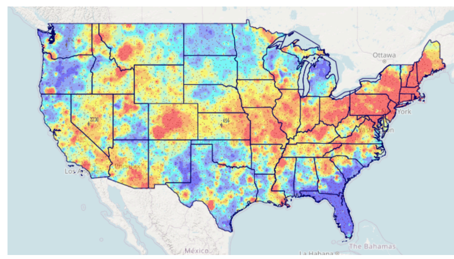


Figure 3 Map of Concentrations of Lead found in Horizon A Soil (Used for Data) [Credit USGS]

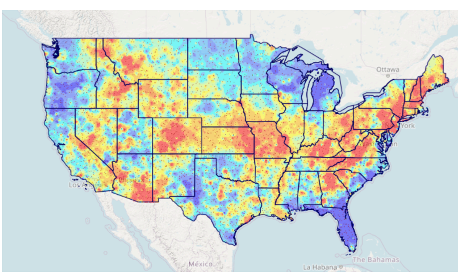
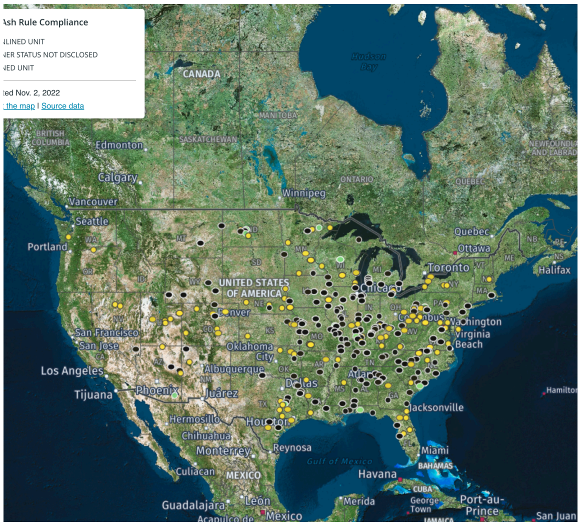
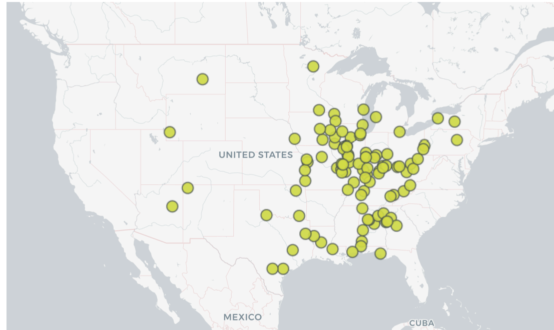


Figure 4 Map of Concentrations of Lead found in Horizon C Soil (Used for Data) [Credit USGS]





(Figure 5 & 6) Earthjustice Coal Ash Sites

To correlate the data set, the data referring to the location of the coal ash sites along with whether it was lined or unlined was found through extensive searching on public databases. This record was credited to the Earth Justice Organization, where a map of the dataset that was required in this project was located. Through exploring this dataset, it was evident that about 94% of the coal ash sites in the United States were unlined ((Mapping the coal ash contamination. Earthjustice. (2022, November 3). Retrieved January 24, 2023, from https://earthjustice.org/features/coal-ash-contaminated-sites-map)), which added valuable information to this study. As shown in Figure 5, the data of a total of 746 coal ash sites was used, of which, 101 coal ash sites were within five feet of a water source, potentially resulting in toxic sludge and thereafter further contamination. It is evident that the idea of using data from across the United States increases the applicability of the model in other areas and types of land covers due to the fact that the model now accounts for a lot of these terrain changes and forms a versatile and adaptable model.

The data was further processed in order to be analyzed by the machine learning models. To find the correlation between the dataset that contained the soil concentration calculations and the dataset that contained the location and unlined vs. lined data, two primary algorithms were implemented. The first algorithm was used to find the nearest coal ash site relative to the soil contaminant concentration using a radial measure of 50 kilometers, and the other was used to assign the contamination data set points to the nearest coal ash site, taking into account the lined vs. unlined parameters. Post-processing was performed on these two datasets in order to obtain the datasets of the corresponding nearest coal ash pond. Finally, the machine learning algorithms were performed to determine a correlation.

5.1 Implementing Models

Various regression models were tested, of which linear regression was used as a control. The models of K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) were implemented on the chosen processed datasets.

Linear regression is one of the simplest machine learning algorithms for regression while not compromising on accuracy. In that light, the aim was to keep linear regression as the control to see which type of the most basic models could arise. After running this model, there was a baseline of R^2 values to base the rest of the research and models off of, a comparison of sorts. This linear regression model (Figure 6) was run on the four toxic metals of interest in this project, based on the equation below.

$$\mathrm{y} = \mathrm{b} + \mathrm{m}_1 x_1 + m_2 x_2 + m_3 x_3 + m_4 x_4 + m_5 x_5$$

Figure 6: Mathematical equation of linear regression

```
[ ] from sklearn.model_selection import train_test_split
    X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.2)
```

```
[ ] from sklearn import linear_model
    from sklearn.metrics import mean_squared_error, r2_score
    model = linear_model.LinearRegression()
    model.fit(X_train, Y_train)

    LinearRegression()
```

Figure 7: Basic code used for running the linear regression model on dataset

The next primary regression model of interest was KNN, the results showed that this particular form of regressor was a simple yet effective model. KNN models are easy to implement and are capable of handling non-linearities effectively. Fitting the model also tends to be a quick process ((Miller, M. (2019, October 18). The basics: KNN for classification and regression. Medium. Retrieved January 24, 2023, from https://towardsdatascience.com/the-basics-knn-for-classification-and-regression-c1e8a6c955)), all of which would be essential in the expansion of our research. The tradeoffs made for these benefits were relatively low, often associated with simple overfitting options and data optimization. There are multiple ways to make sure that a KNN model executes its function properly. However, the primary methods to calculate distance are the Manhattan distance, Minkowski distance, and Euclidean distance, which are illustrated below. After running the KNN machine learning algorithm on the particular datasets and obtaining the results needed, the Support Vector Machine (SVM) was run as the next machine learning approach.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

Figure 8: Euclidean distance calculation in KNNs

The next model used was the Support Vector Machine, in the context of regression. This ML algorithm is known to have extensive uses in sorting and regression-based applications, and it has been chosen as one of the regressors used in this research. The benefits of the SVM include being robust to outliers, decision models having the capability to be easily updated, and excellent generalization capability with high prediction accuracy ((P. Revas, (2013, January). Support Vector Machines for Regression: A Succinct Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, **3**(1), 5-14. https://10.4236/ijis.2013.31002)). The way in which execution happens depends on a number of factors. Suppose we have a set of training data where x_n is a multivariate set of N observations with observed response values y_n ((P. Revas, (2013, January). Support Vector Machines for Regression: A Succinct Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, **3**(1), 5-14. https://10.4236/ijis.2013.31002)), resulting in:

$$f(x) = x'\beta + b$$

Figure 9: linear function SVM

Through the solving of convex optimization problems, we are able to get the primal formula related to SVMs ((P. Revas, (2013, January). Support Vector Machines for Regression: A Succinct Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, **3**(1), 5-14. https://10.4236/ijis.2013.31002)):

$$J(\beta) = \frac{1}{2}\beta'\beta + C\sum_{n=1}^{N}\left(\xi_n + \xi_n^*\right)$$

Figure 10: primal function SVM

After running the model on the SVM, the last regressor that was considered was Random Forest (RF). After completing our research on understanding the way RF is implemented, it seemed to be the most effective in similar research involving regression and establishing a correlation between two different sets of data ((Alhamid, M. (2021, June 26). LSTM and bidirectional LSTM for regression. Medium. Retrieved January 24, 2023, from https://towardsdatascience.com/lstm-and-bidirectional-lstm-for-regression-4fddf910c655)).

5.2 Classification Models

Through the process of implementation and data analysis in this particular project, the idea of using classification models on these datasets surfaced. Gaining traction, the classification models of SVM, and KNN were utilized to understand what would happen. In order to implement this form of classification, the guidelines regarding the safe concentration levels of Mercury (Hg), Arsenic (As), Lead (Pb), and Chromium (Cr), were used as a categorization method. When these datasets were categorized with the EPA guideline data ((Environmental Protection Agency. (2023). Disposal of Coal Combustion Residuals from Electric Utilities Rulemakings. EPA. Retrieved January 24, 2023, from https://www.epa.gov/coalash/coal-ash-rule)), the data became extremely skewed in a manner, indicating that the classification models were ineffective for the purposes of this project. Regardless, the process did allow for some insights into the process of how the machine learning models work and what may or may not need to be changed without existing models.

With all these methods having been executed, the final data and correlations were processed into a map showing the concentrations of each of these toxic metals, as well as an average, representing the coal ash concentrations in a region. These were then interpreted to come up with the final results of the project, as follows.

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