Mapping and modeling toxic metal concentration in soil

based on multi-spectral images and environmental variables

Yuehui

02/04/2022

Industrial activities and sites (like solid waste landfill) **are great contributor to soil contamination and toxic metal concentration**

Published: 20 December 2009

Mineral composite assessment of Kelkit River Basin in Turkey by means of remote sensing

Hakan Mete Dogan

Journal of Earth System Science **118**, Article number: 701 (2009) | Cite this article

Abstract

Utilizing remote sensing (RS) and geographic information systems (GIS) tools, mineral composite characteristics (ferrous minerals (FM), iron oxide (IO), and clay minerals (CM)) the Kelkit River Basin (15913.07 km^2) in Turkey were investigated and mapped. Mineral composite (MC) index maps were produced from three LANDSAT-ETM+ satellite images taken in 2000. Resulting MC index maps were summarized in nine classes by using 'natura breaks' classification method in GIS. Employing bi-variety correlation analysis, relationshi among index maps were investigated. According to the results, FM and IO index maps sho positive correlation, while CM index map is negatively correlated with FM and IO index ma

https://link.springer.com/article/10.1007/s12040-009-0059-9

Article | Open Access | Published: 03 June 2021

Estimating the heavy metal concentrations in topsoil in the Daxigou mining area, China, using multispectral satellite imagery

Yun Yang, Qinfang Cui, Peng Jia, Jinbao Liu & Han Bai

Scientific Reports **11**, Article number: 11718 (2021) | Cite this article

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A precise estimation of the heavy metal concentrations in soils using multispectral remote sensing technology is challenging. Herein, Landsat8 imagery, a digital elevation model, and geochemical data derived from soil samples are integrated to improve the accuracy of estimating the Cu, Pb, and As concentrations in topsoil, using the Daxigou mining area in Shaanxi Province, China, as a case study. The relationships between the three heavy metals and soil environmental factors were investigated. The optimal combination of factors associated with the elevated concentrations of each heavy metal was determined combining correlation analysis with collinearity tests. A back propagation network optimised using a genetic algorithm was trained with 80% of the data for samples and subsequently employed to estimate the heavy metal concentrations in the area. The validation results show that the

https://www.nature.com/articles/s41598-021-91103-8

Modeling the distribution of heavy metals in lands irrigated by wastewater using satellite images of Sentinel-2

Farhad Mirzaei, Yasser Abbasi, Teymour Sohrabi

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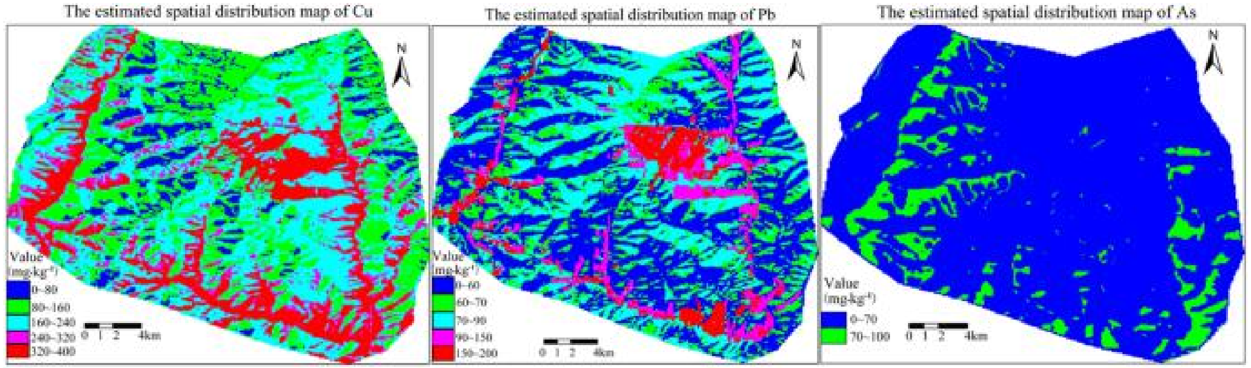
https://doi.org/10.1016/j.ejrs.2021.03.002

Abstract

The pollution of heavy metals is considered as one of the main problems of u wastewater for irrigation purposes. Frequent experimental measurements, tin cost are essential for evaluating the pollution of heavy metals in a large area. T using satellite images and establishing a relationship between the images and concentration of heavy metals can be regarded as a solution for estimating the

https://www.sciencedirect.com/science/article/pii/S1110982321000223#f0025



The Map Generated by ArcGIS 10.1 Software(https://support.esri.com/zh-cn/Products/Desktop/arcgis-desktop/arcmap/10-1#downloads)

Remote sensing provides a new opportunity to model and detect the toxic metal concentration in soil over time

Published: 20 December 2009

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352 Accesses | 19 Citations | Metrics

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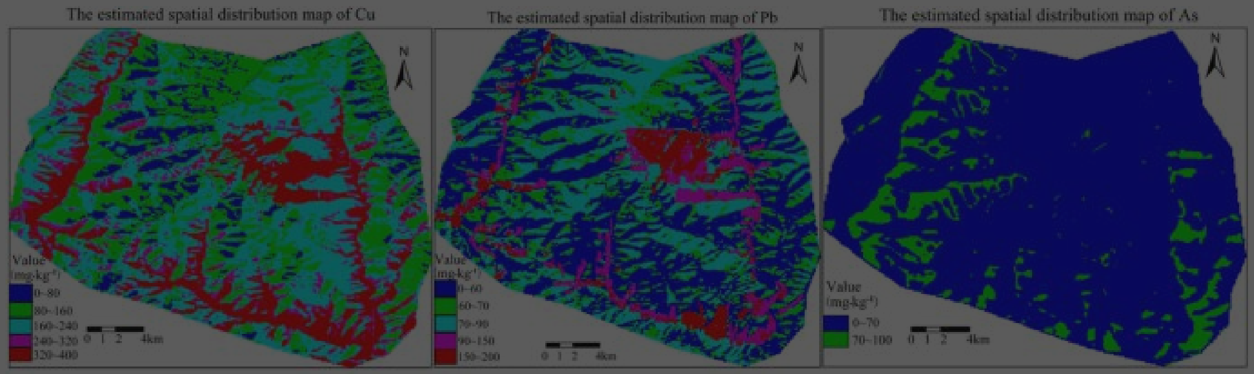

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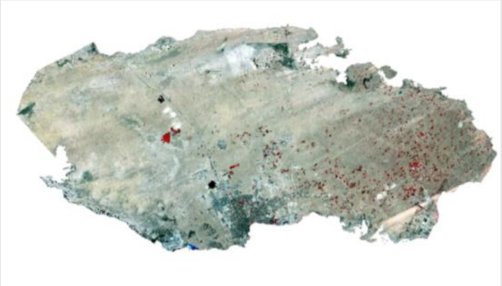
Methodology



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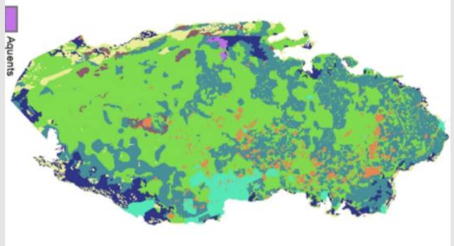

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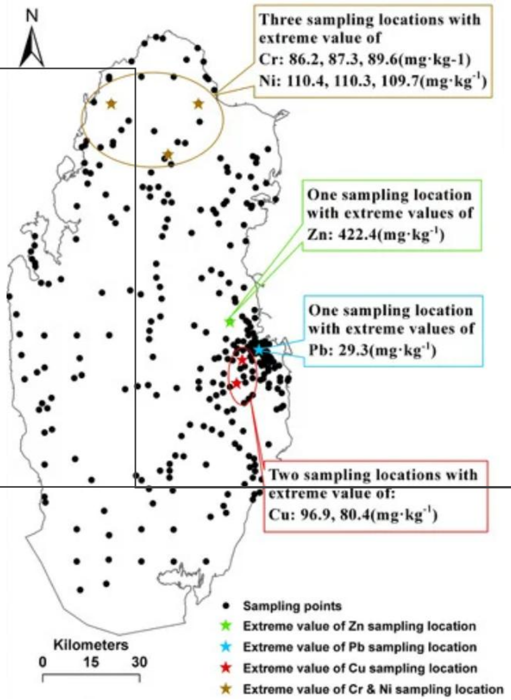
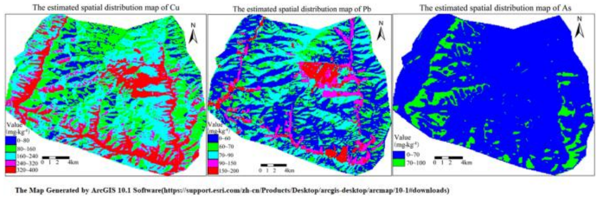


Soil Sample and Analysis

Regression Relations of the Images

Model building

Spatial distribution mapping



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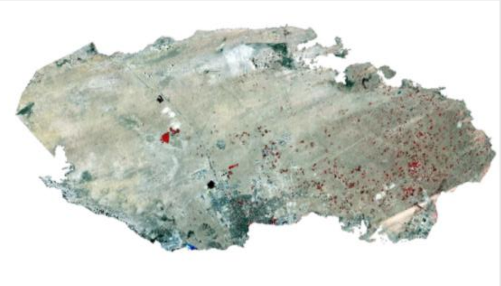

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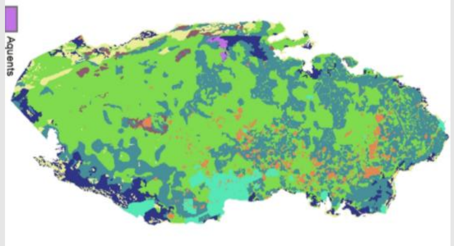
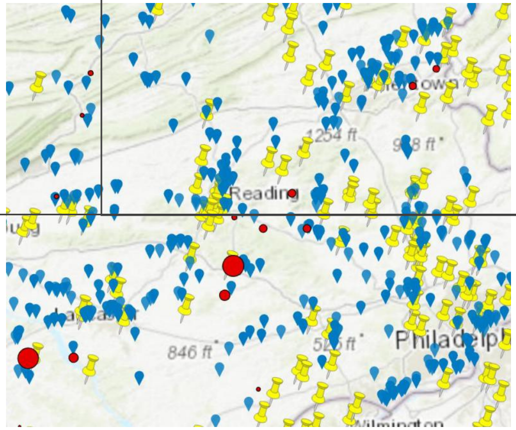


Geological Factors

Anthropogenic Factors

Real-time: precipitation?

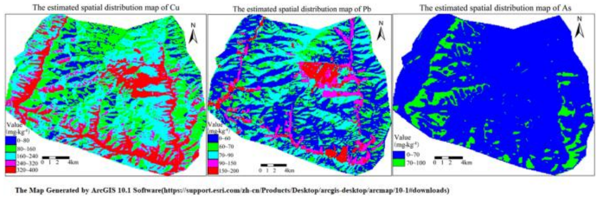


Soil Monitor from open data

Regression Relations of the Images

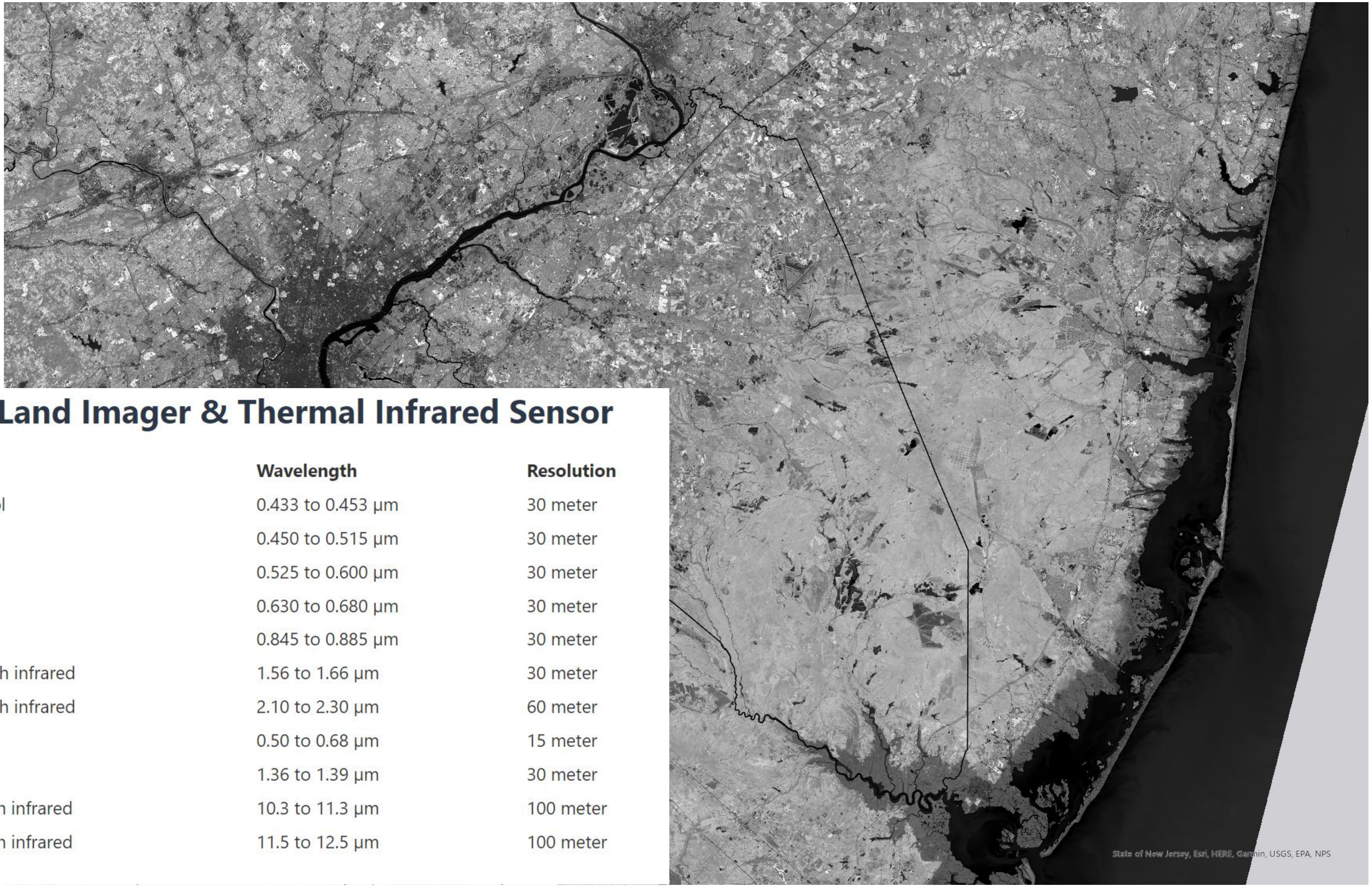
Model building

Spatial distribution mapping



Multi-spectral Satellite Images

Landsat 8

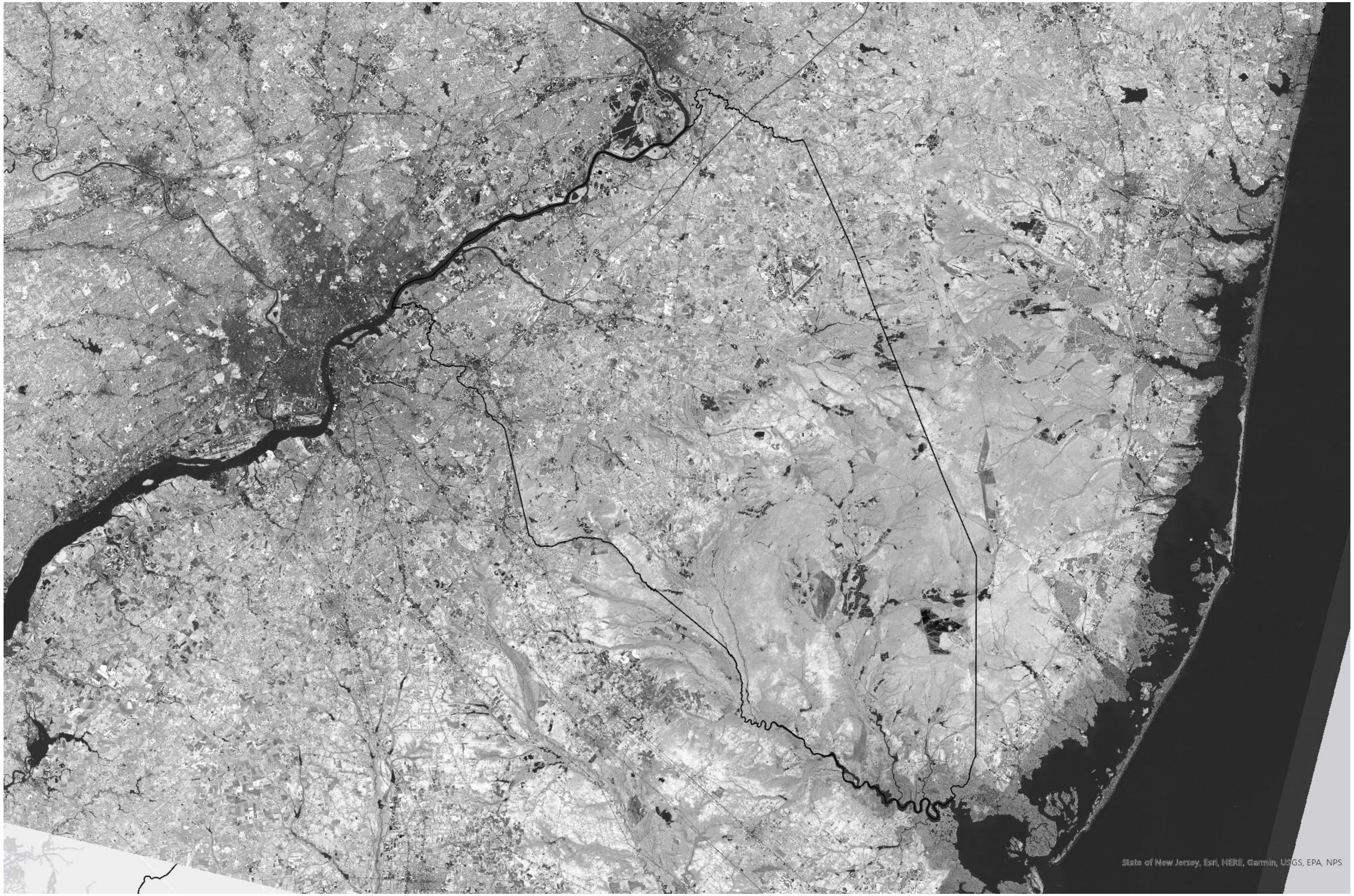


Landsat-8 Operational Land Imager & Thermal Infrared Sensor

Band Number	Description	Wavelength	Resolution
Band 1	Coastal / Aerosol	0.433 to 0.453 µm	30 meter
Band 2	Visible blue	0.450 to 0.515 µm	30 meter
Band 3	Visible green	0.525 to 0.600 µm	30 meter
Band 4	Visible red	0.630 to 0.680 µm	30 meter
Band 5	Near-infrared	0.845 to 0.885 µm	30 meter
Band 6	Short wavelength infrared	1.56 to 1.66 µm	30 meter
Band 7	Short wavelength infrared	2.10 to 2.30 µm	60 meter
Band 8	Panchromatic	0.50 to 0.68 µm	15 meter
Band 9	Cirrus	1.36 to 1.39 µm	30 meter
Band 10	Long wavelength infrared	10.3 to 11.3 µm	100 meter
Band 11	Long wavelength infrared	11.5 to 12.5 µm	100 meter

Multi-spectral Satellite Images

Landsat 8



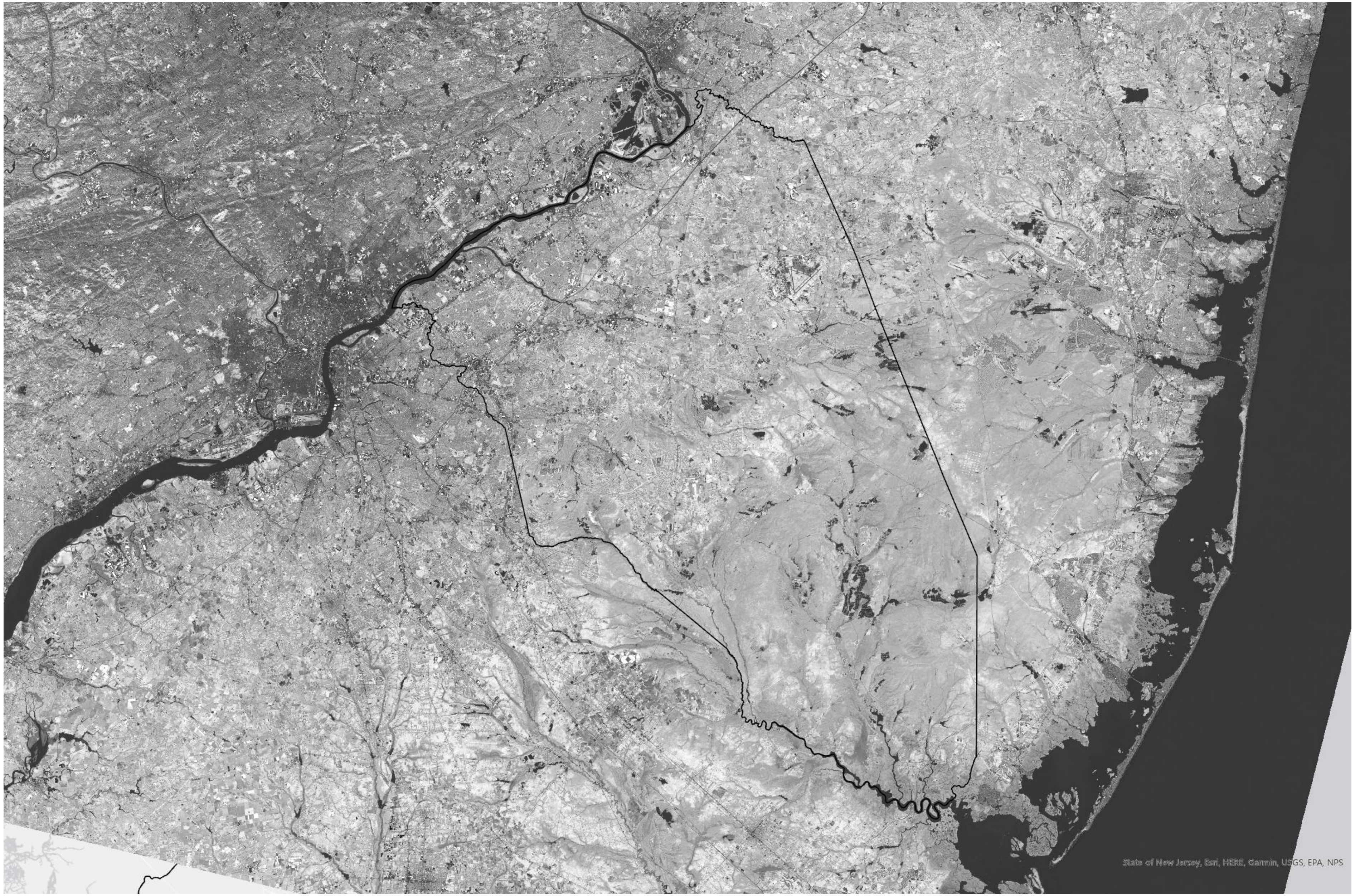
Clay mineral ratio
(CMR)
=Band6/Band7

2013-03

source: USGS

Multi-spectral Satellite Images

Landsat 8



Clay mineral ratio
(CMR)
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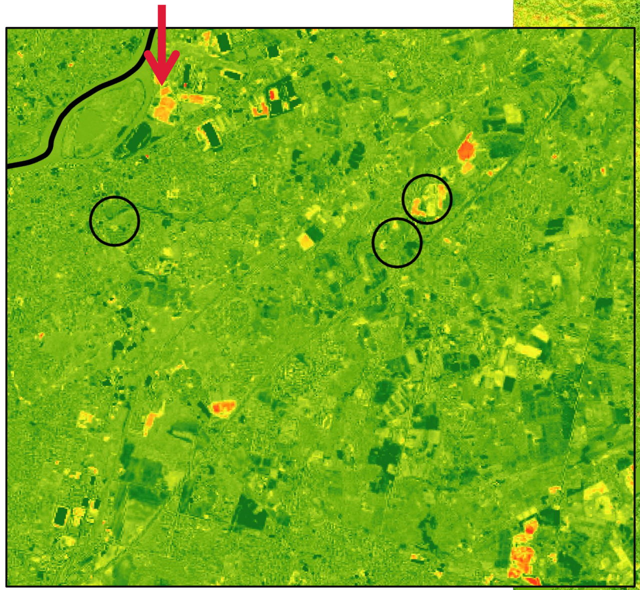
2021-03

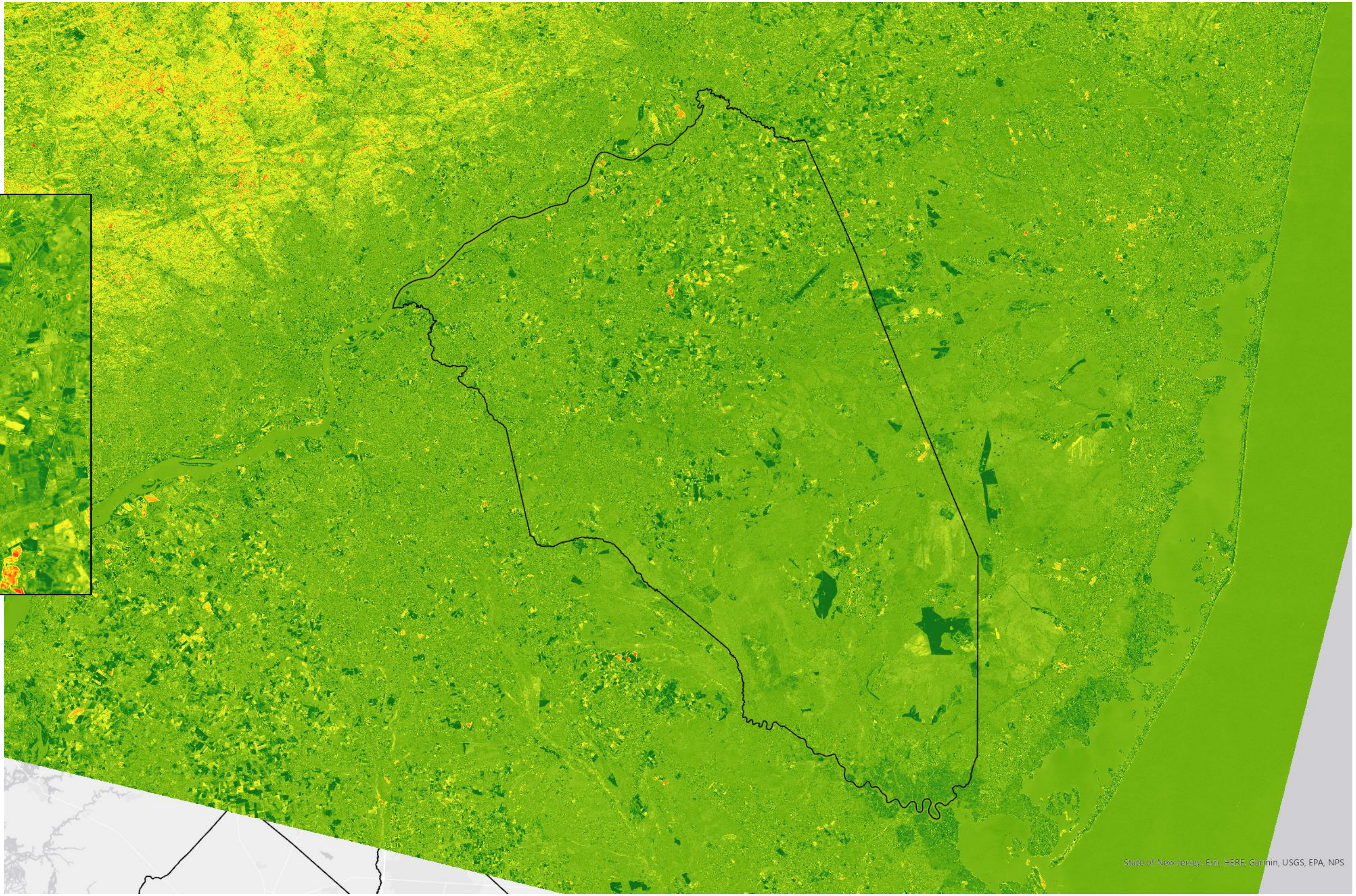
source: USGS

Multi-spectral Satellite Images
Landsat 8

Might indicate increase of metal concentration in soil



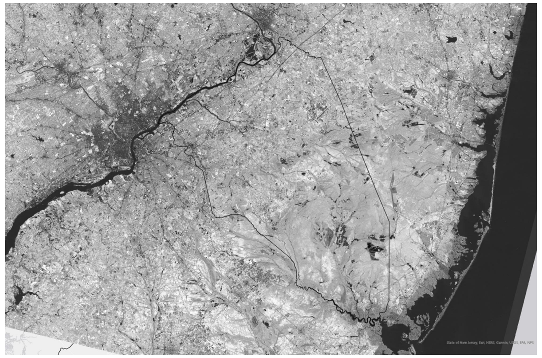
2013-2021

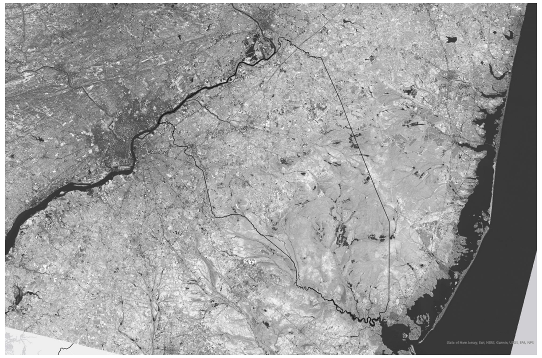


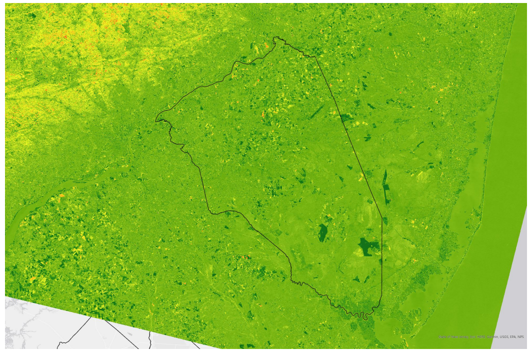
source: USGS

Multi-spectral Satellite Images
Landsat 8

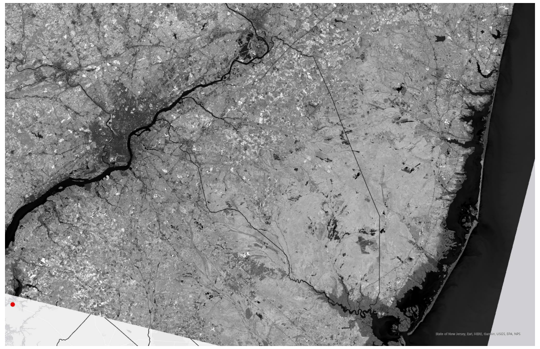
Clay mineral ratio = Band6/Band7

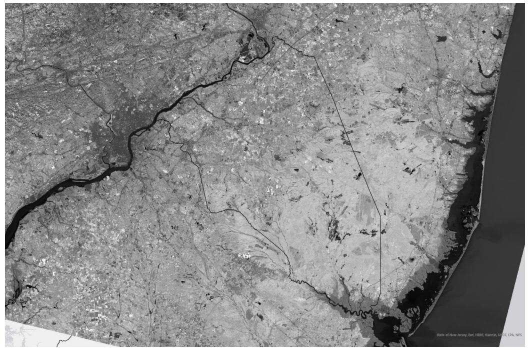


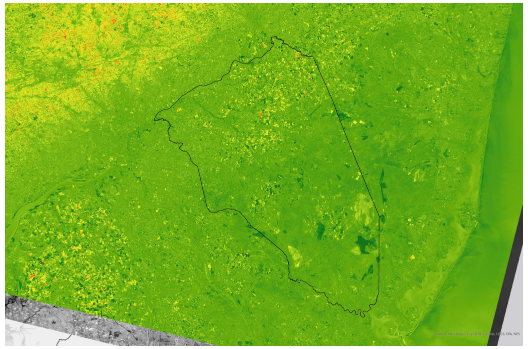




normalised vegetation index = (Band5 − Band4)/(Ban5+Ban4)





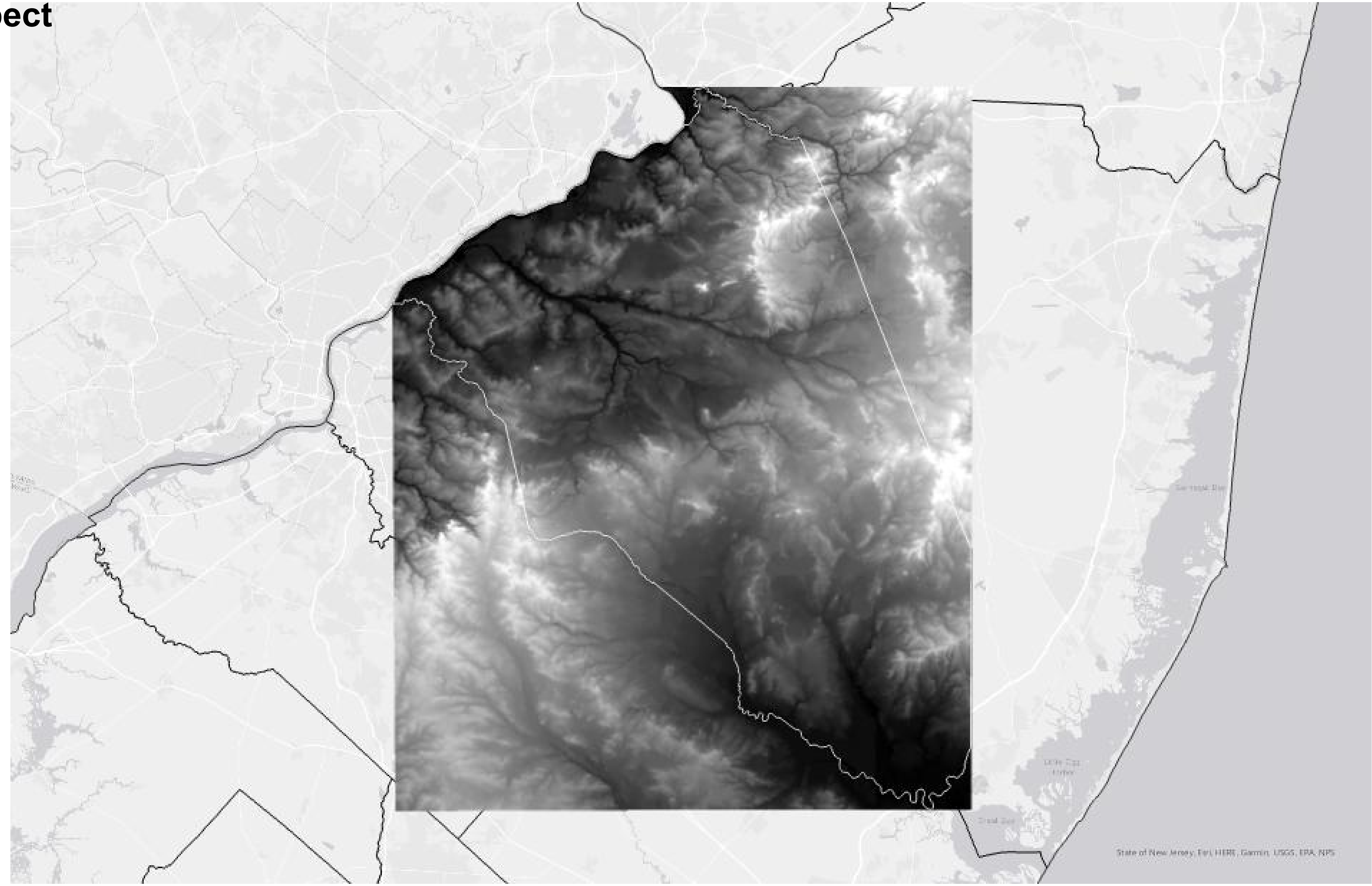


MNDWI = (B3−B6)/(B3+B6) …… …… ……

DVI = B5/B4 …… …… ……

Environmental Parameters

Elevation/ Slope/ Aspect



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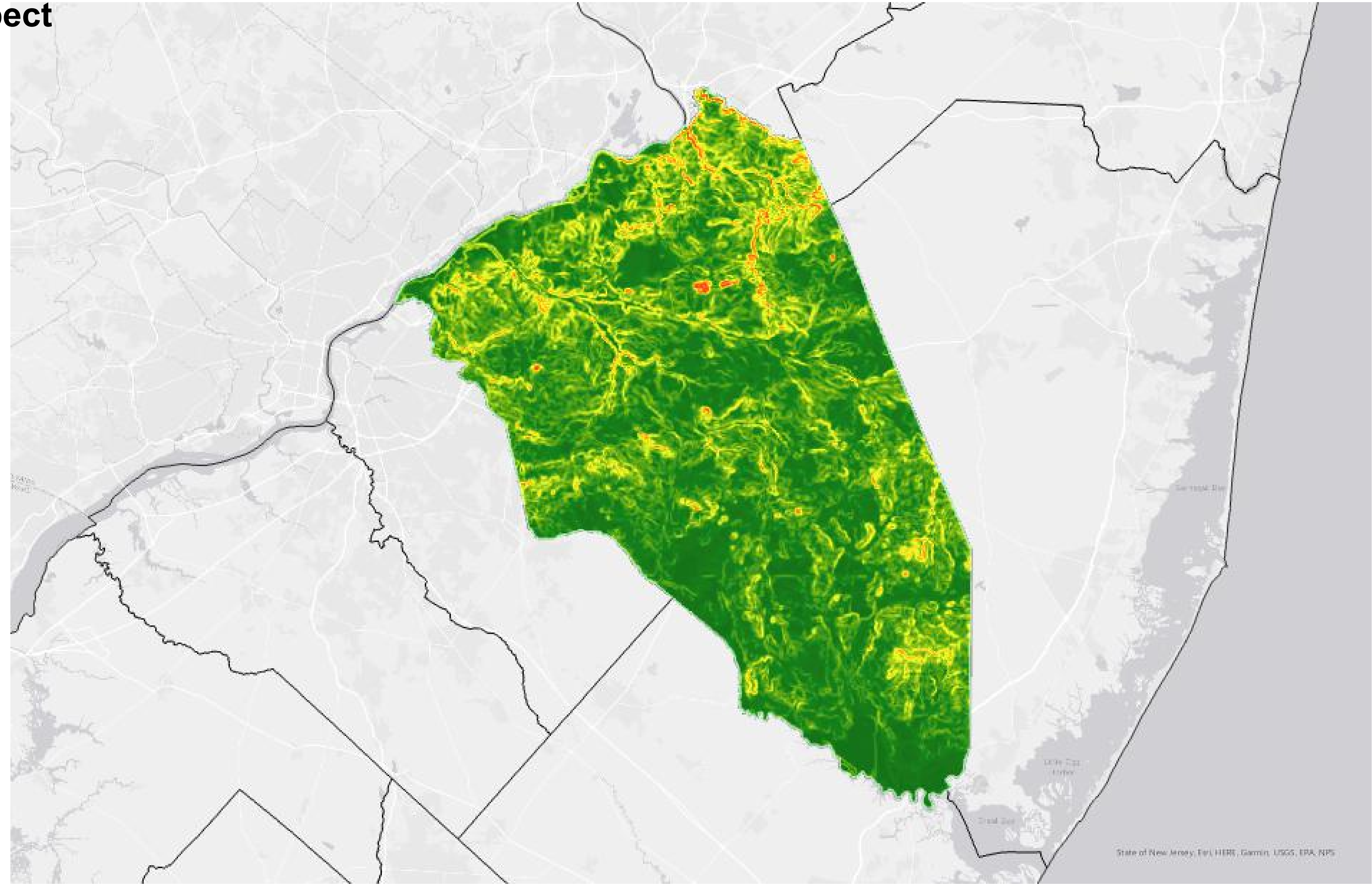
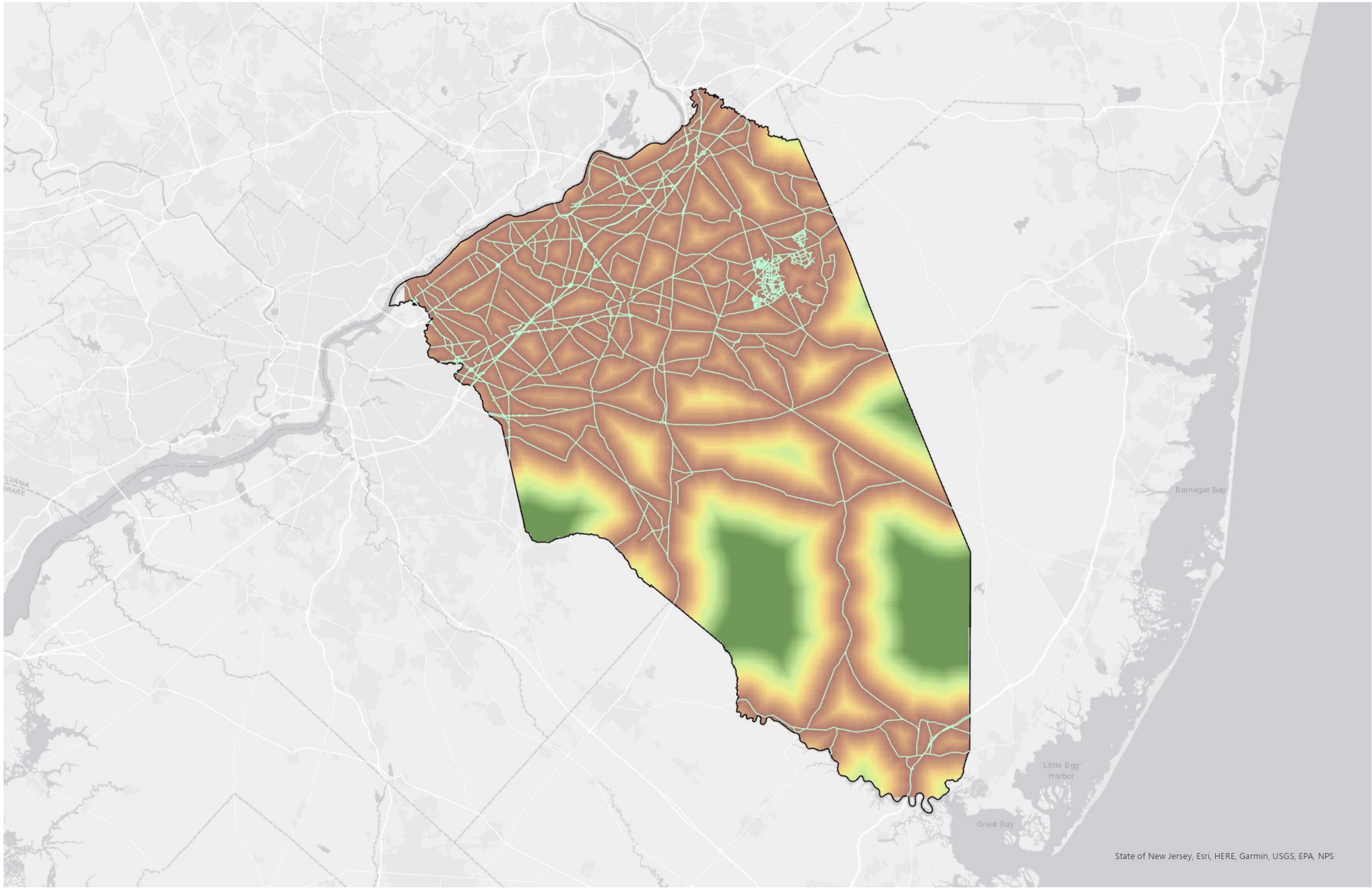


Environmental Parameters

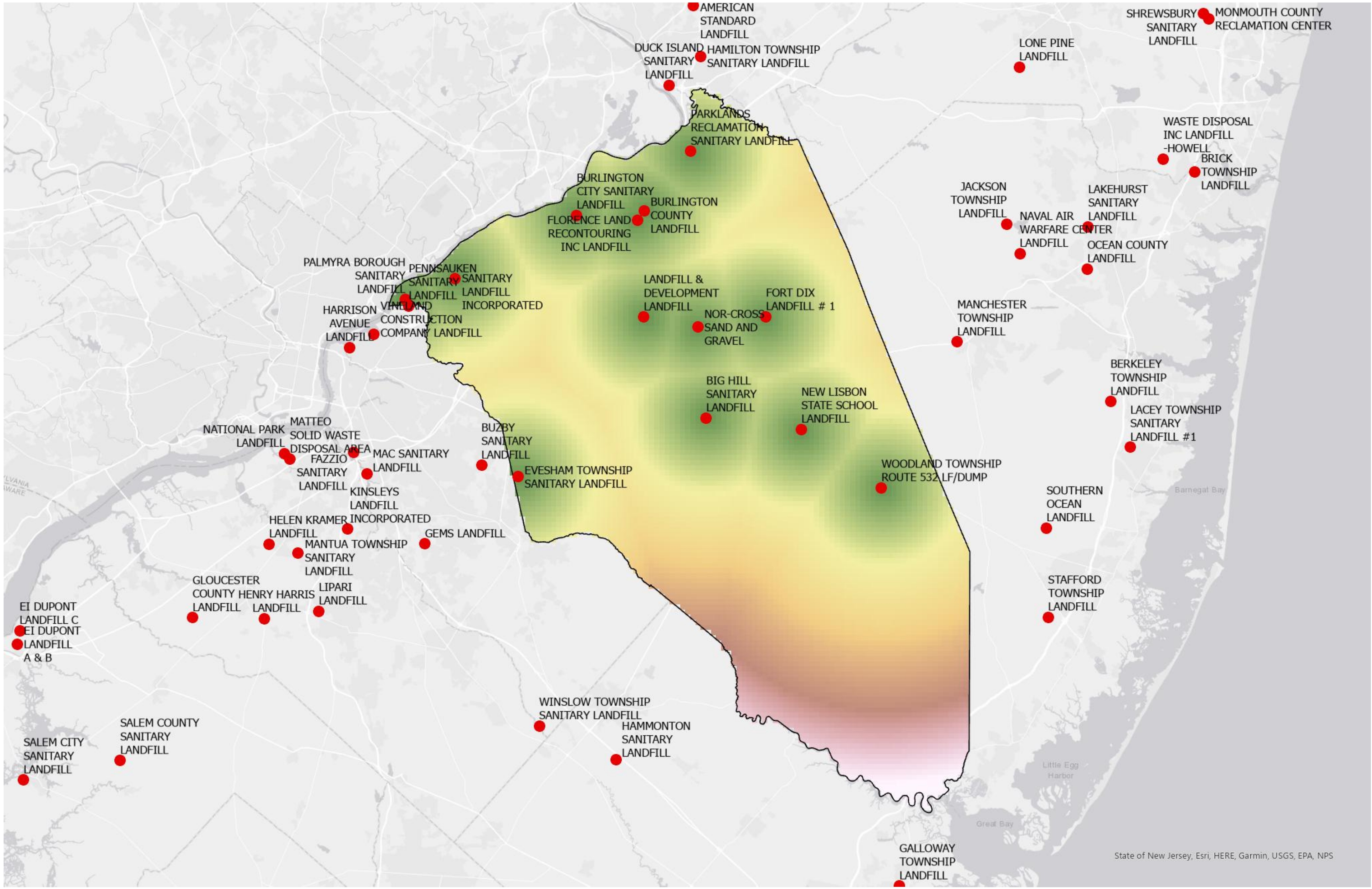
Distance to Roads



Data: Burlington County road

Environmental Parameters

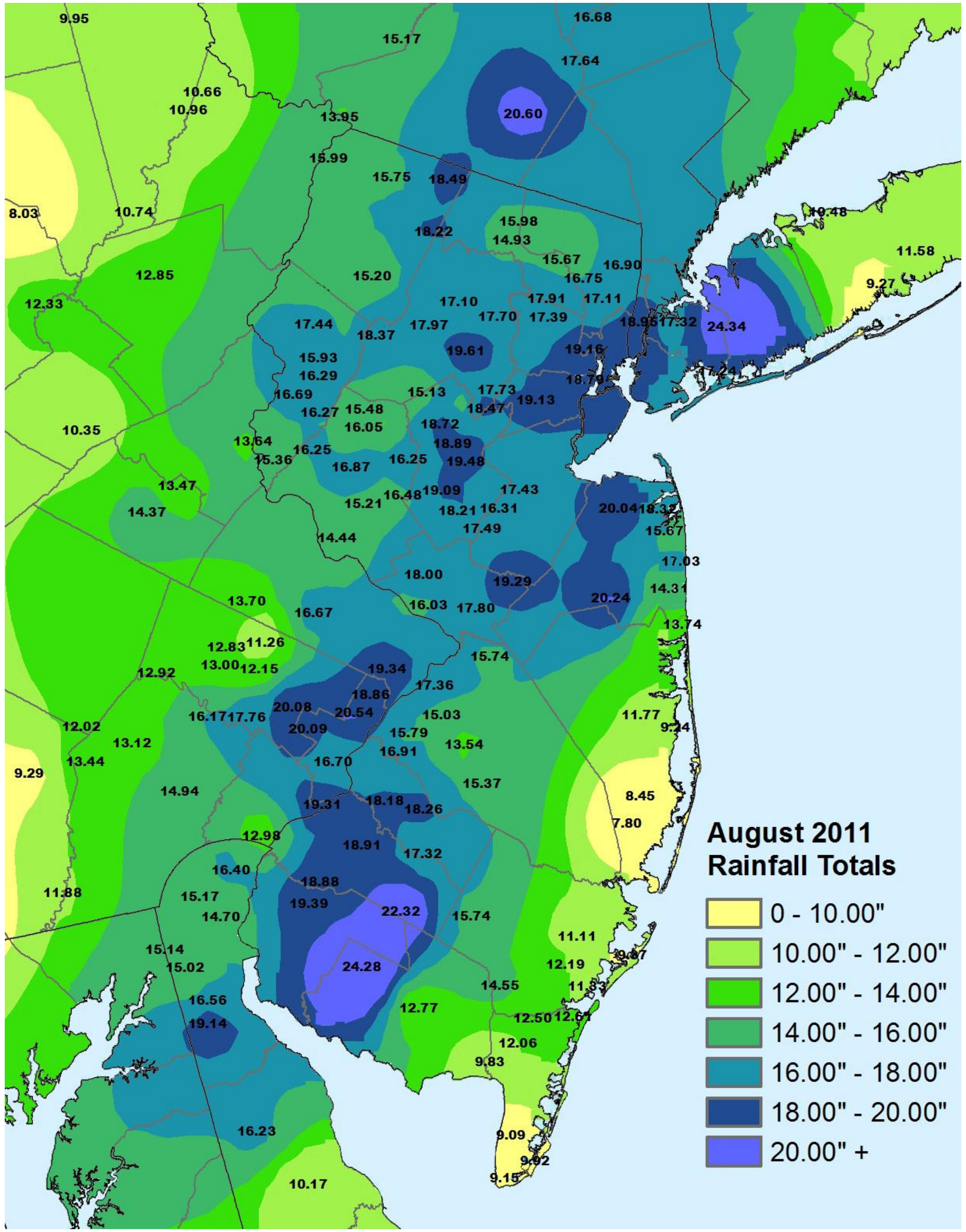
Distance to Landfill



Data: Solid Waste Landfill Sites (35 Acres and Above)

Publisher: NJ Department of Environmental Protection (NJDEP)
Publication_Date: 201105

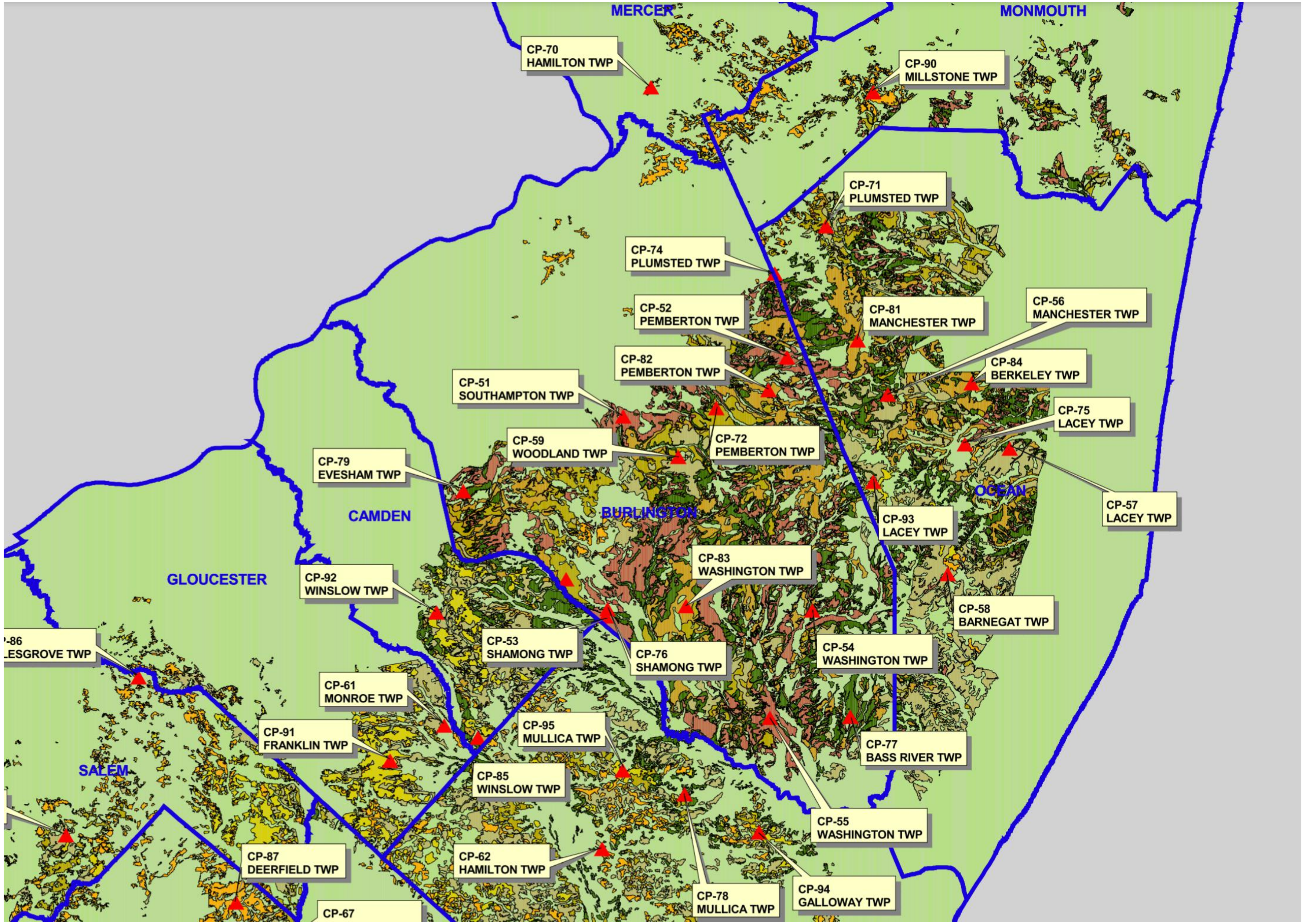
Environmental Parameters
Changing: precipitation/ temperature



Source: Office of the New Jersey State Climatologist

Contamination on Sample Points

Historic Soil Sample Data



Data: NJDEP

https://www.nj.gov/dep/dsr/publications/Characterization%20of%20Ambient%20Levels%20of%20Selected%20Metals%20and%20cPAHs%20in%20NJ%20Soils_Year%20Three_Highlands,%20Valley%20and%20Ridge,%20and%20Coastal%20Plain%20_Full%20Report.pdf

Contamination on Sample Points
Historic Soil Sample Data

TABLE 11

SUMMARY OF COASTAL PLAIN RURAL SOIL DATA

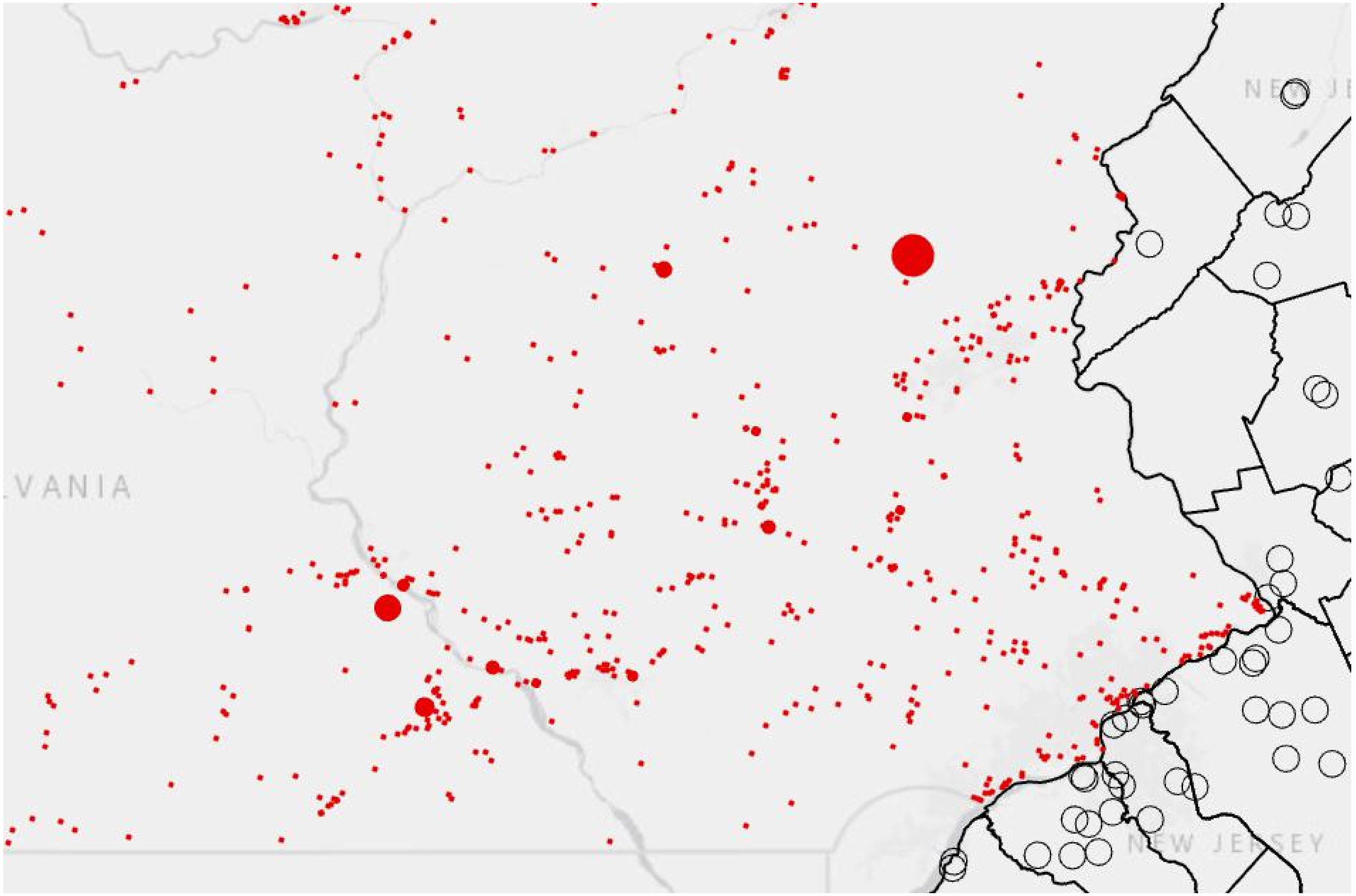
Analyte	Sample ID: / Date:	NJDEP NRDC Cleanup Criteria 03-May-1999	NJDEP RDC Cleanup Criteria 03-May-1999	CP-92 15-Jun-2001	CP-93 12-Jun-2001	CP-94 27-May-2001	CP-95 27-May-2001
Metals							
Silver		4100	110	0.20 U	0.18 U	0.22 U	0.22 U
Aluminum		NA	NA	990	2240	964	1350
Arsenic		20	20	0.97 B	0.92 B	0.98 B	1.8
Barium		47000	700	5.4 B	8.5 B	8.0 B	25.5 B
Beryllium		2	2	0.063 U	0.057 U	0.069 U	0.069 U
Calcium		NA	NA	36.1 B	210 B	144 B	126 B
Cadmium		100	39	0.076 U	0.069 U	0.082 U	0.11 B
Cobalt		NA	NA	0.13 B	0.53 B	0.31 B	0.47 B
Chromium		NA	120000	2.0	4.0	2.1	3.5
Copper		600	600	3.3	3.3	3.2 B	6.6
Iron		NA	NA	1130	2520	1100	1910
Mercury		270	14	0.029 U	0.027 U	0.040 B	0.087
Potassium		NA	NA	51.4 B	101 B	127 B	124 B
Magnesium		NA	NA	52.1 B	135 B	81.7 B	77.6 B
Manganese		NA	NA	4.6	11.6	10.1	11.7
Sodium		NA	NA	75.9 B	47.5 B	39 U	39 U
Nickel		2400	250	0.34 U	0.93 B	1.4 B	1.6 B
Lead		600	400	10.4	14.8	25.3 J	49.5 J
Antimony		340	14	0.38 U	0.34 U	0.41 U L	0.49 BL
Selenium		3100	63	0.44 U	0.40 U	0.48 U	0.48 U
Thallium		2	2	0.79 U	0.72 U	0.86 U	0.87 U
Vanadium		7100	370	4.5 B	10	5.1 B	8.6
Zinc		1500	1500	2.7	5.0	10.2 J	9.6 J

Data: NJDEP

https://www.nj.gov/dep/dsr/publications/Characterization%2
mbient%20Levels%20of%20Selected%20Metals%20and%
%20in%20NJ%20Soils_Year%20Three_Highlands,%20Va
d%20Ridge,%20and%20Coastal%20Plain%20_Full%20Re

Contamination on Sample Points
Toxics Release Inventory Database

Toxics release inventory database by EPA has covered the chemical data of the soil samples taken from monitoring sites. These separated metal sample data could be used for model calibration and validation. (Cubist tool or GA–BP model are used in relevant research)



Data: EPA

Contamination on Sample Points

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TRIPA_XYTableToPoint

Field: Add Calculate **Selection:** Select By Attributes Zoom To Switch Clear Delete Copy

	V_TRI_FORM_R_EZ.CHEM_PROCESSING_AID	V_TRI_FORM_R_EZ.CI...	V_TRI_FORM_R_EZ.DISP_LANDFILL_SURF_IMP	V_TRI_FORM_R_EZ.DISP_LAND_TREATMENT	V_TRI_FORM_R_EZ.DISP_OTHER_LAND_DISP	V_TRI_
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57	0	NEW BRIGHTON	179	0	0	<Null>
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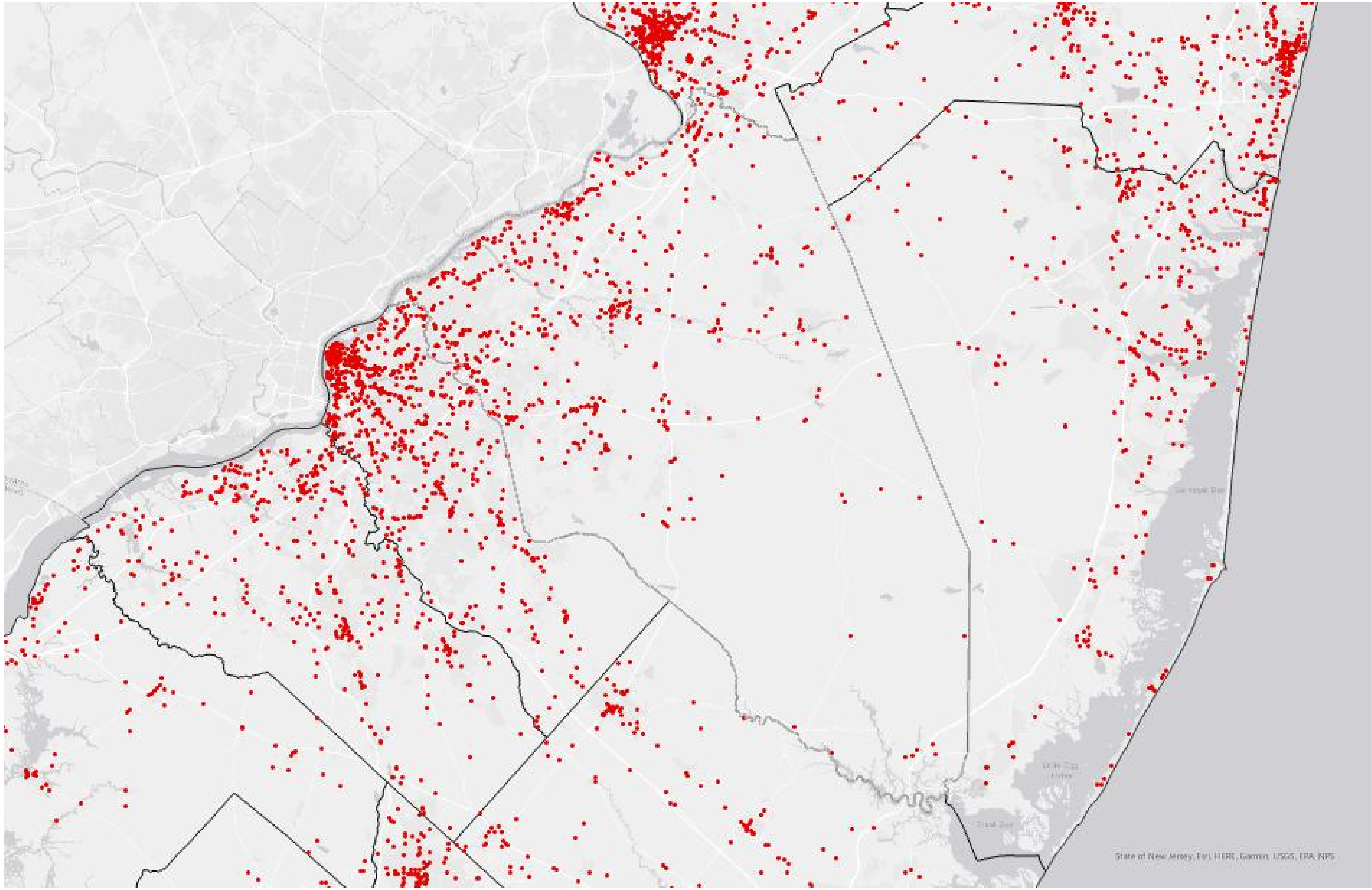
Data: EPA

Contamination on Sample Points

Known_Contaminated_Site



Data: EPA

Questions:

-How to define the scale and extent of the study site?

-Is there any other soil sample open data available?

-What is the best model to use?

....