



ASPECTS OF MAPPING AND GIS SERVICE IN A HIGHER EDUCATION LIBRARY

PENN LIBRARIES

Research Data and Digital Scholarship

IU Bloomington GIS Day
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Objective

- Based on my experience at the Penn Libraries, I will explore the landscape of Mapping and GIS services at higher education institutions, and the role and core competency of the GIS librarian in promoting spatial literacy on campus through presentation of several examples.
- The examples cover applications across various disciplines from the Social sciences, humanities, health sciences, and physical sciences.

Example Projects

- Penn Map Room/Map Table
- COVID Twitter Sentiment Dashboard
- Accessibility Mapping Project (Crowd Sourcing Web App)
- Mapping the Mughal Empire
- Miscellaneous consultation
 - Land Suitability Analyses, Population Diversity Index, Water Pollution Externality, COVID vs Redlining, Philadelphia 1939 Social Base Map, Landuse crowd sourcing web app

Map Room/Map Table

- Collaborative mapping where people draw their lived experience and their own unique perspectives on a basic map. Then various layers of civic data are projected on to it to gain further insight.
- The idea came about as the [Price Lab for Digital Humanities](#) and the Penn Program in Environmental Humanities were planning a a day long symposium on [Community Mapping and Civic Data](#)
- The objective of the event was to “stimulate thought and conversation about how humanists might approach data and mapping not as simply analytical representations of reality but as products that emerge from relationships of power and, simultaneously, as tools for imagination and storytelling.”
- We were asked if we might consider hosting a map room activity
- We drew inspiration from St. Louis Map Room
- and spoke with the creator, Jer Thorp, from the Office for Creative Research (a New York based Non- Profit).

St. Louis Map Room

Community mapping in action



Image Credit: <https://www.jerthorp.com/stlmaproom>

“Interactive projections allowed viewers to overlay these community maps with census data, historic city-planning maps, live policing data, and more, to understand how the community has been shaped by acts of mapping.”

“If mapping is a source of power, people can claim power by making maps of their community that reflect them as they are, or that communicate what they’d like them to be.”

People draw their lived experience and their own unique perspectives on a basic analog map.



Image Credit: <https://www.jerthorp.com/stlmaproom>

Map Room/Map Table

Designing process



- We drew inspiration from St. Louis Map Room to develop something similar but that would be flexible for our purpose - a mobile map room that we plan to re-deploy over time around Philadelphia, across disciplines, and in a variety of contexts and locations.
- A truss rig, short throw projector, and table.

Our First Map Room/Map Table Event



Image Credit: David Toccafondi



Video credit: Paul Farber



Image credit: Girmaye Misgna

Mapping disparity in Philadelphia



On July 23, 2019, TRL hosted a Map Room event for Prof. Krystal Strong's *Re/Member Black Philadelphia Project*, which brought undergraduates and graduate students from Penn and students from the School District of Philadelphia into conversation about maps, resource disparity, and Philadelphia. The mapping workshop was taught by myself and [Girmaye Misgna](#), the Mapping and Geospatial Data Librarian.

[Mapping disparity in Philadelphia](#)

From urban renewal to today, tracking the struggles of America's cities

Equipped with SEPTA Key cards, Brent Cebul's students are taking a deep dive into Philadelphia's history, looking into the past and present challenges facing cities.



After going on a walking tour of West Philadelphia, students marked what they observed on huge maps of the neighborhood.

It's standing room only in an electronic classroom in the Van Pelt-Dietrich Library, and clusters of students are gathered around large maps of West Philadelphia. Each group is adding landmarks they saw while on a recent assignment to walk around the neighborhood and collect observations.

The obvious entries—the Market-Frankford Line, schools, churches, Clark and Malcolm X parks—go up first. Pacing around the room, Brent Cebul, an assistant professor of history, challenges the students to dig a little deeper. Create a key, he advises them. Mark the interesting,

CREDITS
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Eric Sacar
Photographer

DATE
February 27, 2019

SUBTOPICS
West Philadelphia,
Undergraduate Students,
Demography,

[Featured classroom story on PennToday](#)



Cebul drew on the resources of the Penn Libraries, including this digital classroom, to help his students understand how to map data.

Images Credit: Eric Sucar, University Communications

Currently integrated into an Urban History class curriculum



Cebul encouraged students to list what they saw on their walk, not just the typical landmarks, on their maps.



In collaboration with the Architectural Archives, School of Design, we did a map room event at the Free Library of Philadelphia as part of the Archives Month Philly event at the Central Branch.



COVID Twitter Sentiment Dashboard

- Penn Medicine Center for Digital Health and the World Well-Being Project
- Collects tweets about the coronavirus and plots their location across the country on a rapid build timeline.
- Between four million and five million coronavirus-related tweets a day and analyze them for positive or negative sentiment
- Maps changes in language about stress, anxiety, and overall sentiment of the pandemic; common topics people are discussing like health care, panic buying, politics, and economic concerns; COVID-19 symptoms; and tweets per capita by state.
- Helps physicians and health officials identify new hotspots for the virus and track how the pandemic is evolving.
- [Featured story on PennToday](#)

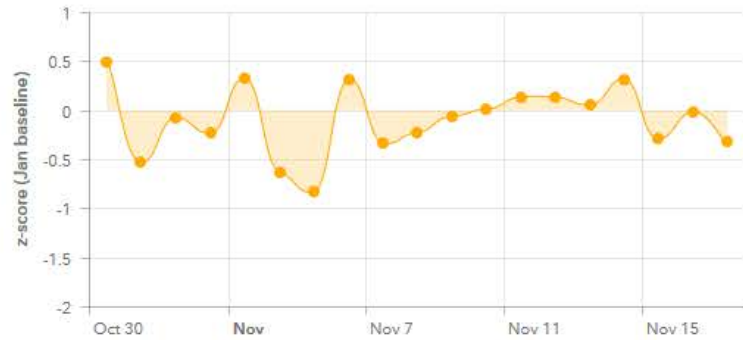


Penn COVID-19 US Twitter Map

by the Penn Medicine Center for Digital Health and the World Well-Being Project



Change in Anxiety



Anxiety | Sentiment | Loneliness

Common topics: Panic Buying

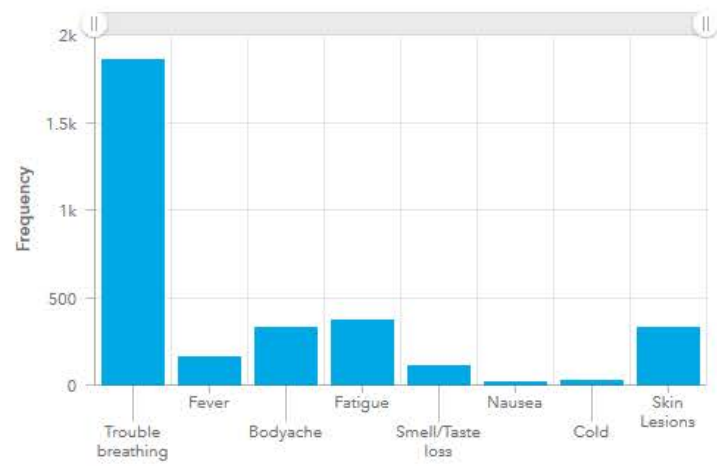


Healthcare | Panic Buying | Politics | Economic Concerns

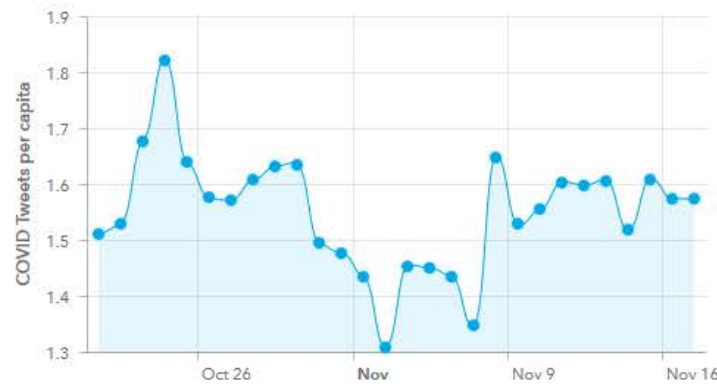
Top Twitter topics in each state

No data to show here at this point...

Top symptom mentions on Twitter in the US



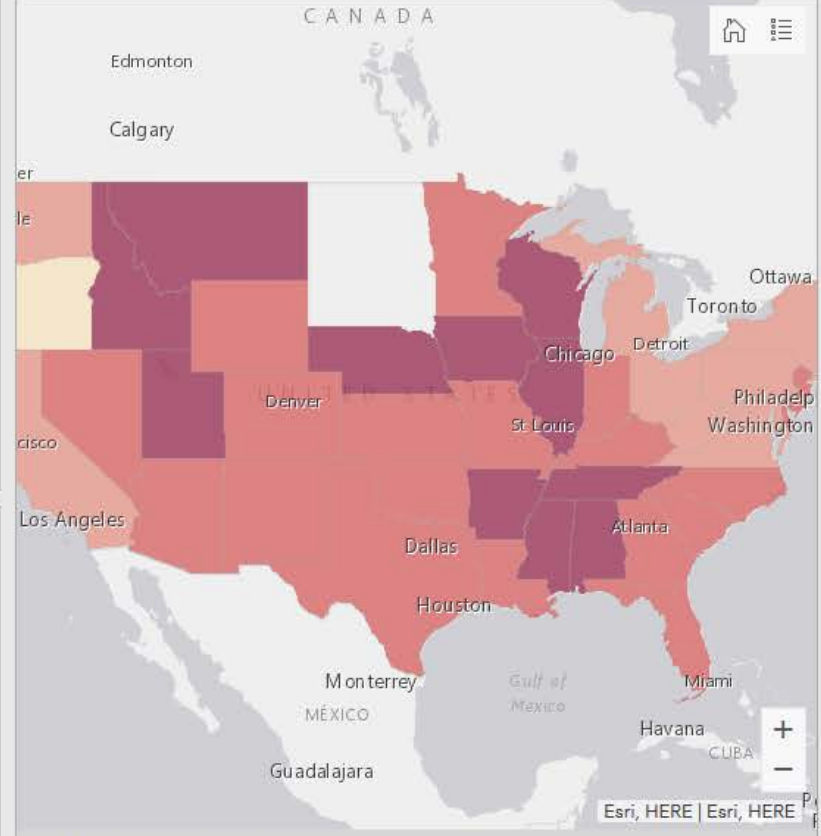
COVID Tweets per capita



No Data | No Data | No Data | No Data

Updated: 11/17/2020, 7:00:00 PM UTC

Cases per 1 million in the US



(click on each state for more)

Sentiment | Engagement | Cases per 1 million

Mobile version: [Click Here](#) ; Paper: JGIM

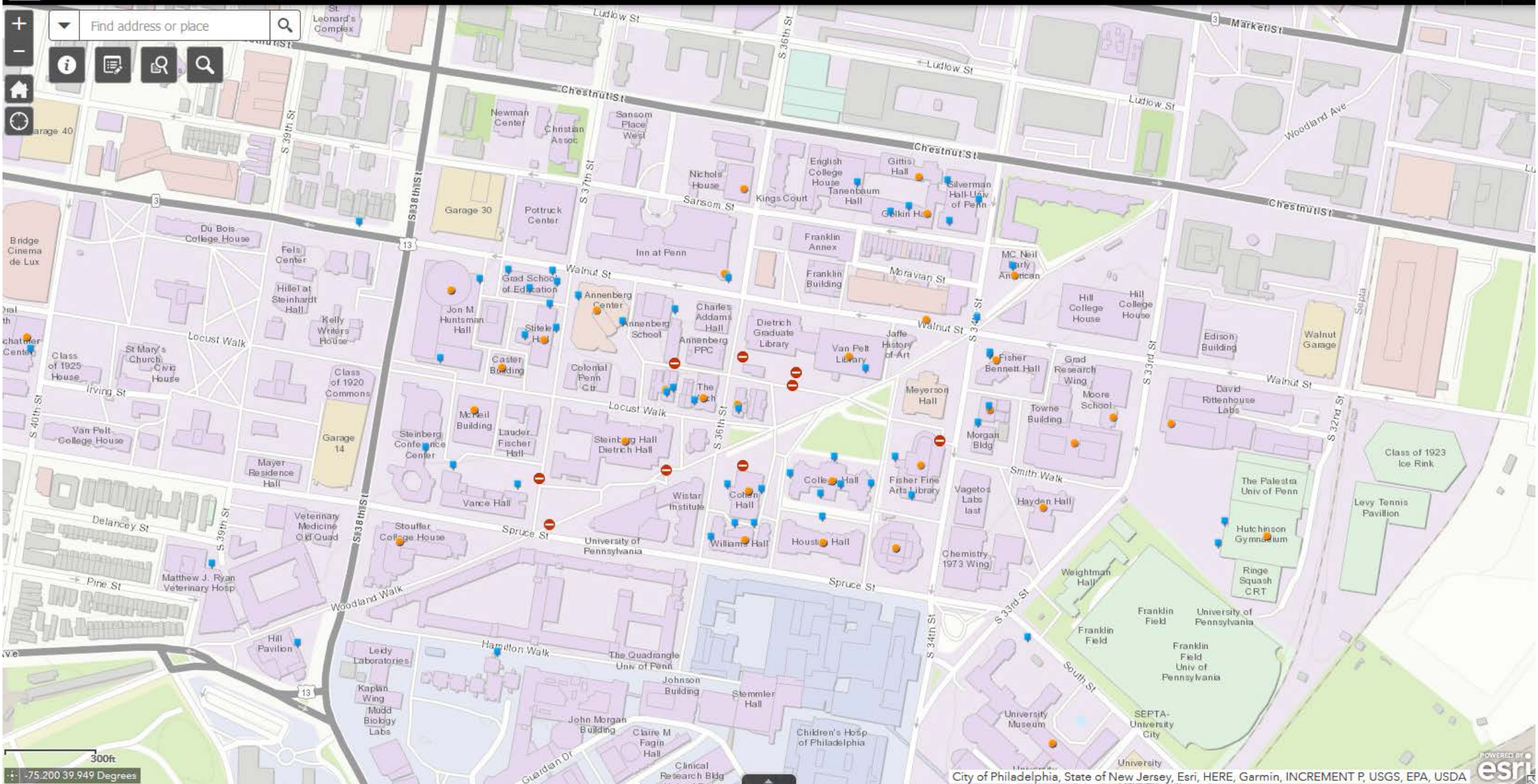
Map Key: - DateTimes shown on the map are in UTC. -- The number of COVID related tweets per capita (#Twitter users) in each state is used as a proxy for Engagement (darker indicates more tweets per capita). The dashboard shows data for the US. -- [Positive - Negative] Sentiment per state is used as a proxy for Sentiment (darker indicates more negative). -- Cases per capita are calculated by divided the confirmed cases in each state by the state population (darker indicates more cases per 1 million people in the state). The data is updated once a day around 12 am EST.

COVID Twitter Map

Accessibility Mapping Project

Crowd Sourcing Web App

- Graduate and Professional Student Assembly (GAPSA)
- Digital interface for mapping the emergence of physical and social barriers at Penn.
- The AMP uses crowdsourced data to illustrate both existing and desired features of access on campus in real-time.
- <https://web.sas.upenn.edu/access-map/who-we-are/>



AMP Web App

Mapping the Mughal Empire

Penn Undergraduate Research Mentoring (PURM)

- Each year Penn supports undergraduate involvement in faculty research through the Penn Undergraduate Research Mentoring Program (PURM), which provides students completing their first or second undergraduate year the opportunity to spend a summer conducting research with a Penn faculty member.
- PURM Digital Humanity project using Deep Mapping method
- Has components of what deep mapping does. It's a huge temporal space. There are empires, language, migration, kinship, genealogy, and layers of experiences that have to be visualized and expressed through a diverse set of tools.
- Exemplifies collaboration: Research Data & Digital Scholarship Penn Libraries, South Asian Studies Subject Librarian, and PURM faculty
- [Featured story on PennToday](#)

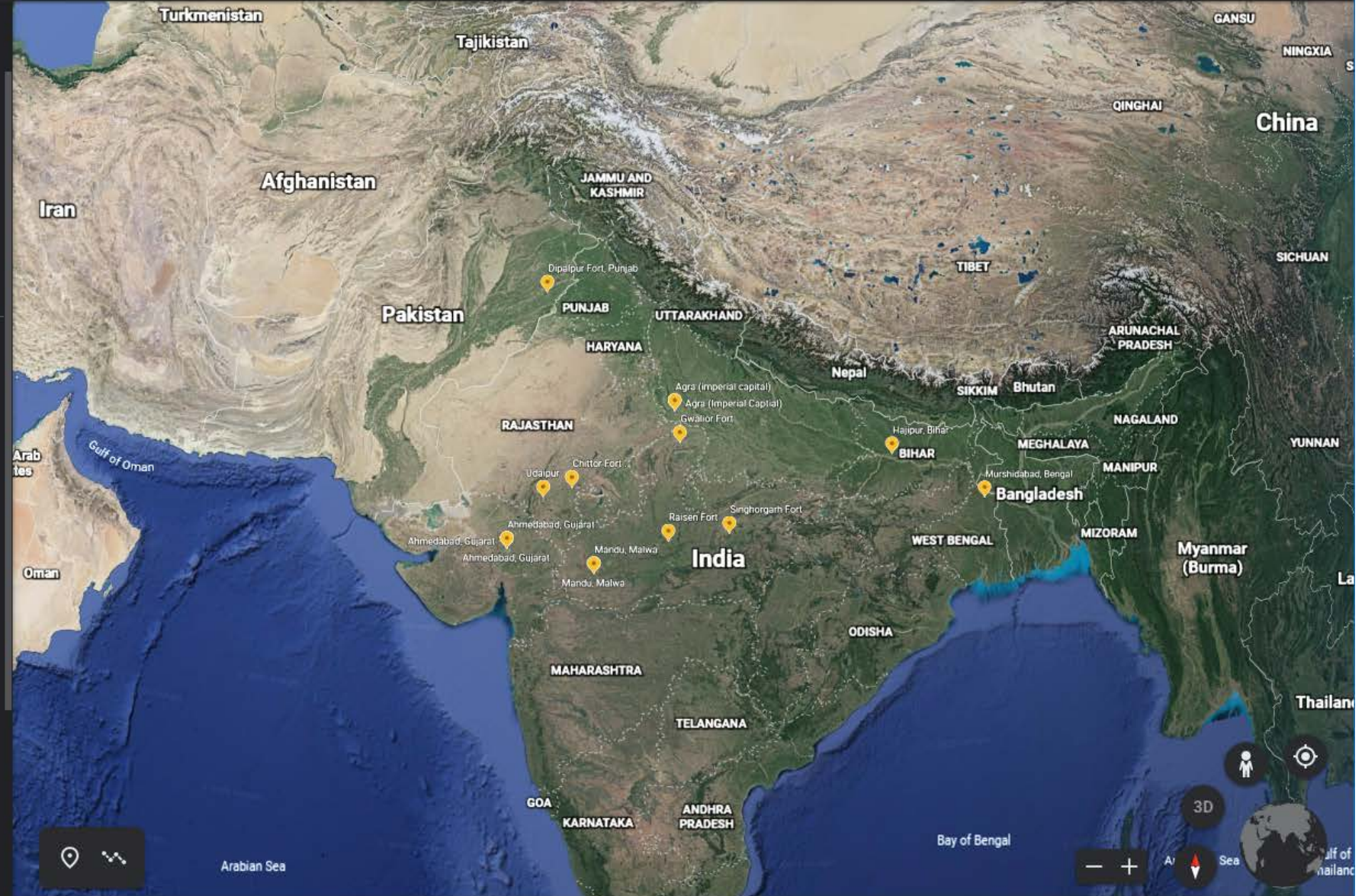
Mirza Aziz Koka Timeline

R Rachel Jessamy

New feature

 Present

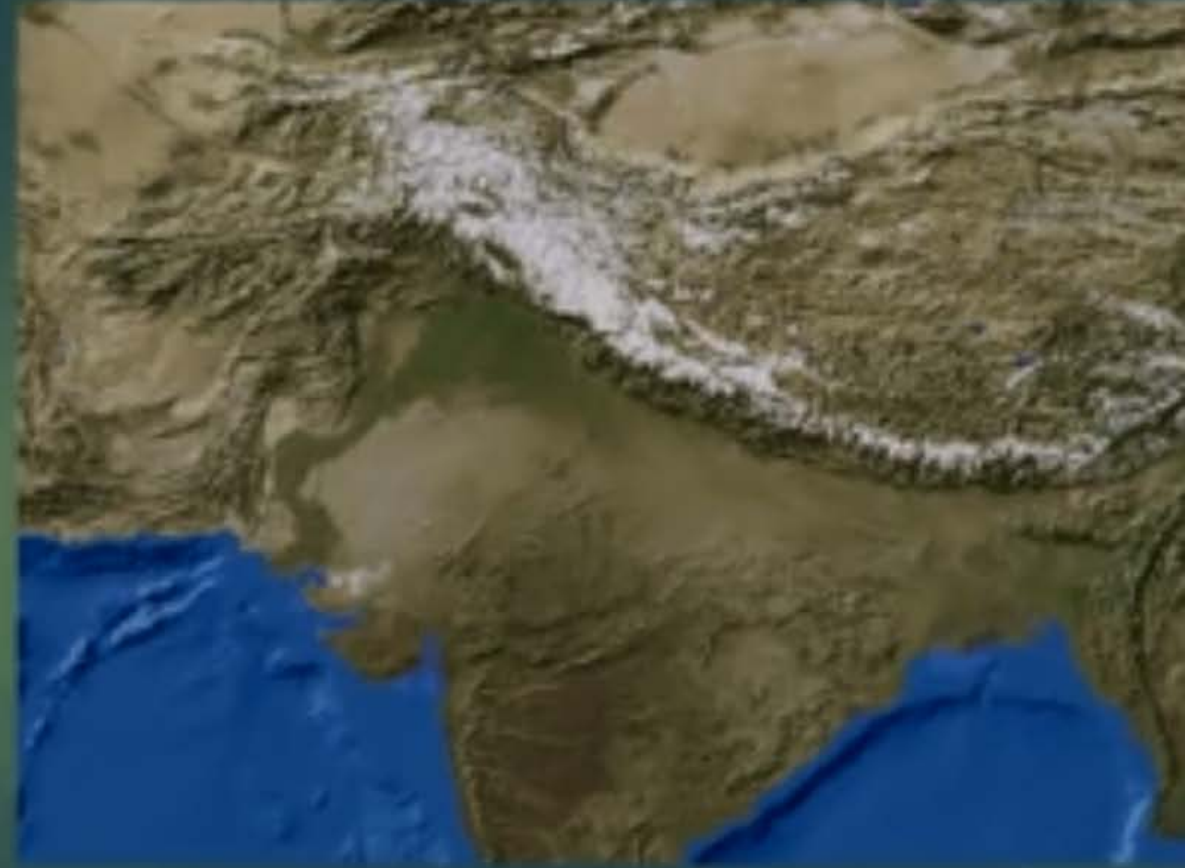
- 📍 Dipalpur Fort, Punjab
- 📍 Ahmedabad, Gujarat
- 📍 Agra (imperial capital)
- 📍 Murshidabad, Bengal
- 📍 Hajipur, Bihar
- 📍 Singhorgarh Fort
- 📍 Raisen Fort
- 📍 Ahmedabad, Gujarat
- 📍 Mandu, Malwa
- 📍 Mecca
- 📍 Agra (Imperial Capital)



[Mughal Empire Google Earth](#)

MUGHAL EMPIRE

1500 AD to 1700 AD



1881

Land Suitability Analyses

What is the potential to develop coffee production for export in the countries below?

- Madagascar
- Congo
- Bolivia
- Puerto Rico
- Myanmar
- Laos

Key question:	What is the potential to develop coffee production for export in the countries below?					
Countries	Madagascar	Congo	Bolivia	Puerto Rico	Myanmar	Laos
Supply chain						
Physical infrastructure to move coffee from field to port:						
-Roads						
-Port locations and capabilities						
-Export routes	(most coffee will flow to European and US markets)					
Production						
Land availability	(Actual agricultural area available for cultivation)					
Land accesability						
	(Proximity to physical infrastructure to move from field to port (eg, road, towns)					
Existing production	(Where are existing coffee plantations in the region?)					
Climate conditions						
<u>Climate factors</u>	<u>Topography</u>	<u>Soil type</u>	<u>Elevation</u>			
Rainfall	Slope	Depth				
Temperature		Drainage				
Weather data		Texture				
Light intensity		pH				
		Cation exchange capacity				
		Organic matter				
		Total porosities				
		Erodibility				

Steps and Data

- Roughly the problem can be broken down into the following objectives and steps:1.

❖ 1. Objective 1:

- Identify suitable coffee production sites in each country using the land-use, climate, topography, slope, elevation, soil criteria (criteria can also be weighed). Identify interactions between the criteria (example: what are the suitable factors for coffee growth in terms of the specified criteria). Slope < x, Soil = type x or PH < x, Land not urban or forest, elevation < x, precipitation and temperature in a certain range, etc.
- Steps: Use the suitability analysis tool and model builder in ArcGIS (detailed process modeling steps can be constructed).
- Data: Global land cover, climate (temperature, precipitation), elevation (DEM), slope (derive from DEM), soil cover

❖ 2. Objective 2:

- Calculate and rate the identified coffee production areas in terms of accessibility, size (production estimate), supply chain, export route, and other relevant factors. Close to a transportation road network, short distance to a port, etc.
- Steps: Use tools in ArcGIS to calculate the distance to roads and ports, and land area suitable for coffee production.
- Data: Roads network, Ports, supply chain and export route information.

❖ 3. Objective 3:

- Build a scorecard for each country based on the results of the above two steps and perform the evaluation.
- Steps: Use Multicriteria Evaluation tool in EXCEL or another platform to conduct the evaluation.
- Data: gather and collate values from outputs of the previous steps into a table.

❖ 4. Verify results

Population Diversity Index Map

- A quantitative measure that reflects how many different types (such as species) there are in a dataset (a community), and simultaneously takes into account how evenly the basic entities (such as individuals) are distributed among those types. (Wikipedia)
- When used in a population-diversity-by-race context, the index Shows the likelihood that two persons, chosen at random from the same area, belong to different race or ethnic groups.
- Simpson's Diversity index: Commonly used in biodiversity studies. Adapted here to measure population diversity by race.
- The value ranges from 0 to 1 and higher value represents greater diversity.

Calculations

$$D = 1 - \frac{\sum n(n-1)}{N(N-1)}$$

Where:

- n = number of individuals of each species
- N = total number of individuals of all species

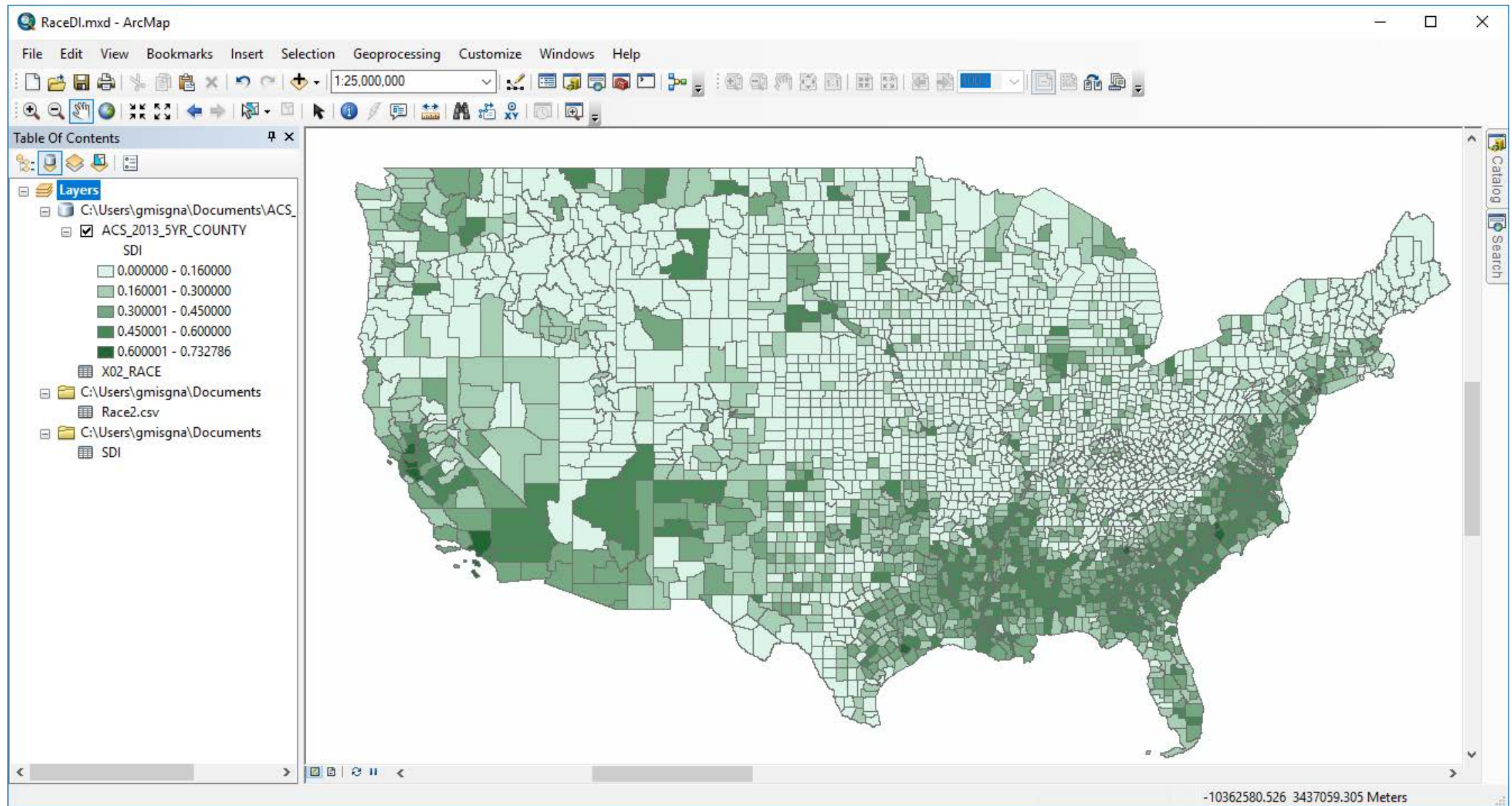
Race demographic data by county, from Census Bureau

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	OBJECTID	GEOID	B02001e1	B02001e2	B02001e3	B02001e4	B02001e5	B02001e6	B02001e7	B02001e8	B02001e9	B02001e10	B02001m10	C02003e1	C02003m1	C02003e2	C02003m2	C02003e3	C02003m3
2	1	05000US0:	54907	42997	10076	138	525	15	401	755	55	700	217	54907	0	54152	224	42997	
3	2	05000US0:	187114	161737	17733	1157	1331	5	2454	2697	273	2424	517	187114	0	184417	615	161737	
4	3	05000US0:	27321	12960	12675	55	152	0	990	489	31	458	118	27321	0	26832	126	12960	
5	4	05000US0:	22754	17461	4937	105	25	0	8	218	0	218	209	22754	0	22536	209	17461	
6	5	05000US0:	57623	54890	818	197	58	0	681	979	27	952	214	57623	0	56644	229	54890	
7	6	05000US0:	10746	3001	7614	4	6	32	0	89	0	89	76	10746	0	10657	76	3001	
8	7	05000US0:	20624	11300	9024	24	106	0	42	128	34	94	48	20624	0	20496	79	11300	
9	8	05000US0:	117714	88358	24385	314	854	24	1694	2085	158	1927	404	117714	0	115629	435	88358	
10	9	05000US0:	34145	19881	13737	30	186	13	25	273	18	255	125	34145	0	33872	125	19881	
11	10	05000US0:	26034	24216	1257	126	73	4	38	320	12	308	93	26034	0	25714	97	24216	
12	11	05000US0:	43744	37447	4358	152	108	0	1249	430	47	383	125	43744	0	43314	156	37447	
13	12	05000US0:	13687	7621	5888	0	8	0	0	170	17	153	115	13687	0	13517	118	7621	
14	13	05000US0:	25573	13798	11336	137	26	68	43	165	0	165	138	25573	0	25408	138	13798	
15	14	05000US0:	13703	11240	2090	12	0	0	140	221	13	208	139	13703	0	13482	138	11240	
16	15	05000US0:	14945	14143	530	34	47	0	25	166	15	151	71	14945	0	14779	77	14143	
17	16	05000US0:	50468	38896	8563	419	732	0	320	1538	30	1508	261	50468	0	48930	269	38896	
18	17	05000US0:	54456	43672	8853	323	222	7	512	867	192	675	256	54456	0	53589	334	43672	
19	18	05000US0:	13104	6836	5856	68	8	0	0	336	0	336	194	13104	0	12768	194	6836	
20	19	05000US0:	11198	7587	3424	8	0	0	10	169	0	169	133	11198	0	11029	133	7587	
21	20	05000US0:	37847	31992	4799	201	128	26	213	488	91	397	161	37847	0	37359	185	31992	
22	21	05000US0:	13955	10131	3172	62	203	0	64	323	0	323	155	13955	0	13632	155	10131	
23	22	05000US0:	80499	77157	917	304	394	44	635	1048	113	935	165	80499	0	79451	189	77157	
24	23	05000US0:	50102	37616	9690	194	633	45	431	1493	99	1394	281	50102	0	48609	283	37616	
25	24	05000US0:	43091	12600	29630	42	152	19	98	550	6	544	281	43091	0	42541	281	12600	
26	25	05000US0:	71076	64749	1293	944	239	5	1956	1890	184	1706	400	71076	0	69186	444	64749	1
27	26	05000US0:	79895	60425	16365	296	561	0	997	1251	60	1191	291	79895	0	78644	283	60425	
28	27	05000US0:	38169	23832	12370	1337	109	15	113	393	85	308	108	38169	0	37776	142	23832	
29	28	05000US0:	104260	85307	15862	430	682	61	453	1465	141	1324	249	104260	0	102795	292	85307	
30	29	05000US0:	17110	14813	1952	36	34	0	0	275	48	227	102	17110	0	16835	114	14813	
31	30	05000US0:	31666	27962	1485	194	26	15	1733	251	67	184	128	31666	0	31415	158	27962	

- B02001e2 (White)
- B02001e3 (Black-AA)
- B02001e4 (AI-AN)
- B02001e5 (Asian)
- B02001e6 (HA-PA)
- B02001e7 (Other)

[https://www2.census.gov/geo/tiger/TIGER_DP/2013ACS/Metadata/County and Place Metadata 2013.txt](https://www2.census.gov/geo/tiger/TIGER_DP/2013ACS/Metadata/County_and_Place_Metadata_2013.txt)

Diversity Index Map



Historical Landuse Crowd Sourcing Application

- GIS project to collect global land use data in the past.
- The data will be entered by a number of different researchers spread across the world.
- [Historical Landuse crowd sourcing Web App](#)

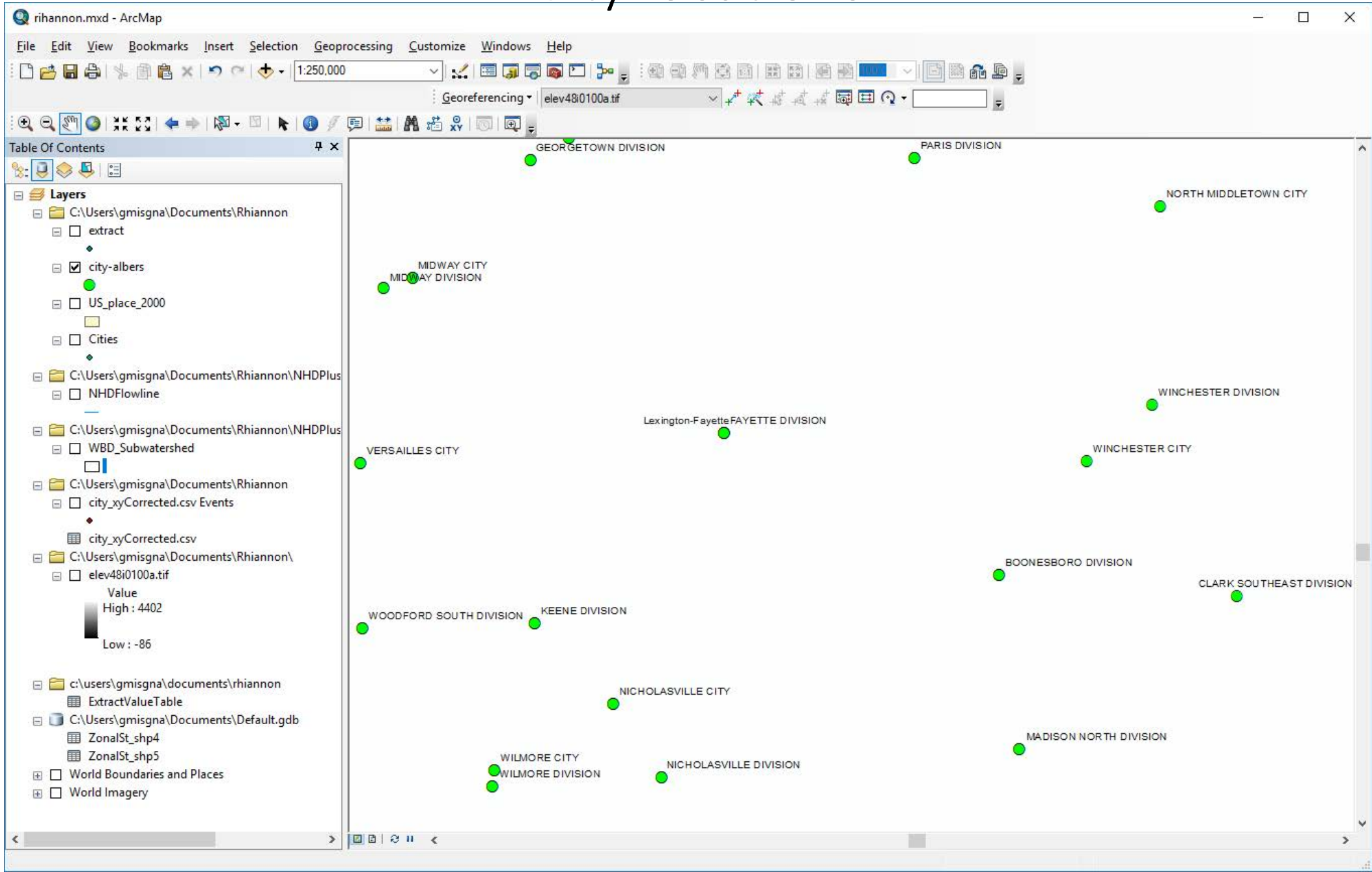
Philadelphia 1939 Social Base Map

- Digitized and Georectified 1939 Philadelphia base map.
- [Social Base webmap](#)

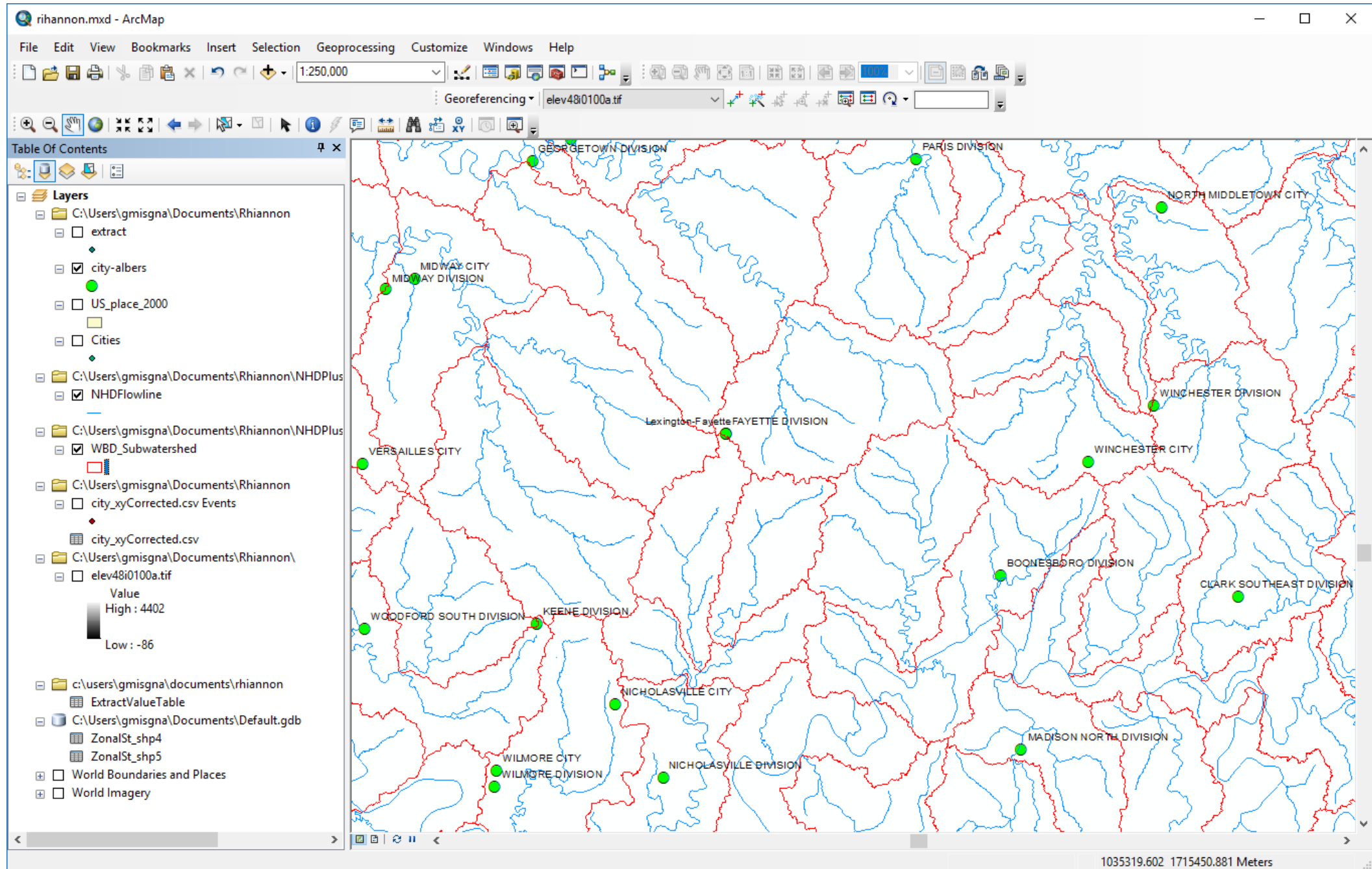
Water Pollution Externality

- **Goal:** To identify cities that are most likely to impose a water pollution externality on their downstream neighbors.
- The overarching goal is to understand the determinants of wastewater treatment technology adoption in the mid-early 20th century.
- Some cities had proper wastewater technology long before the 1972 Clean Water Act regulations ("proper", meaning, the technology imposed under the 1972 CWA). Some cities did not.
- Trying to understand why some cities adopted the technology; and others did not.
- **Hypothesis** is that adoption of the proper technology has to do with pressure from downstream neighboring cities;

City locations



Streams and Watershed boundaries



COVID vs Redlining

- Collaborating with Dr. Carmen Guerra, Penn Medicine
- Relationship between COVID-19 infections and the history of [redlining](#).
- Systematic denial of various services by federal government and agencies by selective raising of prices. Affected high proportion of minority neighborhoods. Related to National Housing Act of 1934.
- Project to test the hypothesis that COVID-19 cases and death rates in Philadelphia has disproportionately affected redlined neighborhoods.
- variables on house holds below poverty level, house holds without vehicles, and households receiving food stamps.
- [COVID Incident Map and Redlining](#)