

# Ranjeet Gupta / SC24M138

## Lab 6: Vector data processing 2

### 1. Point in Polygon Analysis

When you have a polygon layer and a point layer - and want to know how many or which of the points fall within the bounds of each polygon, you can use this method of analysis.

```
In [1]: import geopandas as gpd
#Load point and polygon data
point_data = r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\Lab-6\1
polygon_data = r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\Lab-6

# Load the point (places) and polygon (countries) data
places = gpd.read_file(point_data)
countries = gpd.read_file(polygon_data)

# Ensure both datasets are in WGS 84 (EPSG:4326) coordinate system
places = places.to_crs('epsg:4326')
countries = countries.to_crs('epsg:4326')

print(places)
print(countries.head())
```

	scalerank	natscale	labelrank	featurecla	\
0	10	1	8	Admin-1 capital	
1	10	1	8	Admin-1 capital	
2	10	1	8	Admin-1 capital	
3	10	1	8	Admin-1 capital	
4	10	1	8	Admin-1 capital	
...	...	...	...	...	
7338	0	600	1	Admin-1 capital	
7339	0	600	1	Admin-1 capital	
7340	0	600	3	Admin-1 capital	
7341	0	600	0	Admin-0 capital	
7342	0	600	0	Admin-0 region capital	

	name	namepar	namealt	diffascii	\
0	Colonia del Sacramento	None	None	0	
1	Trinidad	None	None	0	
2	Fray Bentos	None	None	0	
3	Canelones	None	None	0	
4	Florida	None	None	0	
...	...	...	...	...	
7338	Rio de Janeiro	None	None	0	
7339	São Paulo	None	Sao Paulo Sio Paulo	0	
7340	Sydney	None	None	0	
7341	Singapore	None	None	0	
7342	Hong Kong	None	None	0	

	nameascii	adm0cap	...	rank_max	rank_min	geonameid	\
0	Colonia del Sacramento	0.0	...	7	7	3443013.0	
1	Trinidad	0.0	...	7	7	3439749.0	
2	Fray Bentos	0.0	...	7	7	3442568.0	
3	Canelones	0.0	...	6	6	3443413.0	
4	Florida	0.0	...	7	7	3442585.0	
...	...	...	...	...	...	...	
7338	Rio de Janeiro	0.0	...	14	12	3451190.0	
7339	Sao Paulo	0.0	...	14	14	3448439.0	
7340	Sydney	0.0	...	12	12	2147714.0	
7341	Singapore	1.0	...	13	12	1880252.0	
7342	Hong Kong	0.0	...	13	12	1819729.0	

	meganame	ls_name	ls_match	checkme	min_zoom	ne_id	\
0	None	None	0	0	9.0	1159112629	
1	None	None	0	0	9.0	1159112647	
2	None	None	0	0	9.0	1159112663	
3	None	None	0	0	9.0	1159112679	
4	None	None	0	0	7.0	1159112703	
...	...	...	...	...	...	...	
7338	Rio de Janeiro	Rio de Janeiro	1	0	1.7	1159151619	
7339	S	Sao Paolo	1	0	3.0	1159151621	
7340	Sydney	Sydney1	1	0	1.7	1159151623	
7341	Singapore	Singapore	1	5	2.1	1159151627	
7342	Hong Kong	Hong Kong	1	0	3.0	1159151629	

	geometry
0	POINT (-57.84 -34.48)
1	POINT (-56.901 -33.544)
2	POINT (-58.304 -33.139)
3	POINT (-56.284 -34.538)
4	POINT (-56.215 -34.099)
...	...
7338	POINT (-43.22697 -22.92308)

```

7339 POINT (-46.62697 -23.55673)
7340 POINT (151.18323 -33.91807)
7341 POINT (103.85387 1.29498)
7342 POINT (114.18306 22.30693)

```

[7343 rows x 39 columns]

	scalerank	featurecla	LABELRANK	SOVEREIGNT	SOV_A3	ADM0_DIF	\
0	3	Admin-0 country	5.0	Netherlands	NL1	1.0	
1	0	Admin-0 country	3.0	Afghanistan	AFG	0.0	
2	0	Admin-0 country	3.0	Angola	AGO	0.0	
3	3	Admin-0 country	6.0	United Kingdom	GB1	1.0	
4	0	Admin-0 country	6.0	Albania	ALB	0.0	

	LEVEL	TYPE	ADMIN	ADM0_A3	...	CONTINENT	\
0	2.0	Country	Aruba	ABW	...	North America	
1	2.0	Sovereign country	Afghanistan	AFG	...	Asia	
2	2.0	Sovereign country	Angola	AGO	...	Africa	
3	2.0	Dependency	Anguilla	AIA	...	North America	
4	2.0	Sovereign country	Albania	ALB	...	Europe	

	REGION_UN	SUBREGION	REGION_WB	NAME_LEN	LONG_LEN	\
0	Americas	Caribbean	Latin America & Caribbean	5.0	5.0	
1	Asia	Southern Asia	South Asia	11.0	11.0	
2	Africa	Middle Africa	Sub-Saharan Africa	6.0	6.0	
3	Americas	Caribbean	Latin America & Caribbean	8.0	8.0	
4	Europe	Southern Europe	Europe & Central Asia	7.0	7.0	

	ABBREV_LEN	TINY	HOMEPART	\
0	5.0	4.0	-99.0	
1	4.0	-99.0	1.0	
2	4.0	-99.0	1.0	
3	4.0	-99.0	-99.0	
4	4.0	-99.0	1.0	

	geometry
0	POLYGON ((-69.99694 12.57758, -69.93639 12.531...
1	POLYGON ((71.0498 38.40866, 71.05714 38.40903,...
2	MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...
3	MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...
4	POLYGON ((19.74777 42.5789, 19.74601 42.57993,...

[5 rows x 66 columns]

**A. Given the locations of all known significant places, we will try to find out which country has had the highest number of important places.**

```

In [2]: # Perform spatial join to find which points are within each country polygon
# 'inner': use intersection of keys from both dfs; retain only left_df geometry
points_in_countries = gpd.sjoin(places, countries, how="inner", predicate="within")
# print(points_in_countries)

# Group by country name to count the number of important places per country
places_count = points_in_countries.groupby('ADMIN').size().reset_index(name='Places')
print(places_count)

```

```
# Merge with the countries GeoDataFrame to retain the geometries for visualization
countries = countries.merge(places_count, left_on='ADMIN', right_on='ADMIN', how='left')
print(countries)

# Replace NaN values with 0 for countries with no significant places
countries['Place_Count'] = countries['Place_Count'].fillna(0).astype(int)

# Find the country with the maximum number of important places
max_places_country = countries.loc[countries['Place_Count'].idxmax()]
print(f"The country with the highest number of important places is {max_places_country['Country']}")
```

	ADMIN	Place_Count
0	Afghanistan	33
1	Aland	1
2	Albania	26
3	Algeria	51
4	American Samoa	1
..	...	...
219	Vietnam	60
220	Western Sahara	1
221	Yemen	20
222	Zambia	34
223	Zimbabwe	20

[224 rows x 2 columns]

	scalerank	featurecla	LABELRANK	SOVEREIGNT	SOV_A3	ADM0_DIF	\
0	3	Admin-0 country	5.0	Netherlands	NL1	1.0	
1	0	Admin-0 country	3.0	Afghanistan	AFG	0.0	
2	0	Admin-0 country	3.0	Angola	AGO	0.0	
3	3	Admin-0 country	6.0	United Kingdom	GB1	1.0	
4	0	Admin-0 country	6.0	Albania	ALB	0.0	
..	...	...	...	...	...	...	
250	3	Admin-0 country	4.0	Samoa	WSM	0.0	
251	0	Admin-0 country	3.0	Yemen	YEM	0.0	
252	0	Admin-0 country	2.0	South Africa	ZAF	0.0	
253	0	Admin-0 country	3.0	Zambia	ZMB	0.0	
254	0	Admin-0 country	3.0	Zimbabwe	ZWE	0.0	

	LEVEL	TYPE	ADMIN	ADM0_A3	...	REGION_UN	\
0	2.0	Country	Aruba	ABW	...	Americas	
1	2.0	Sovereign country	Afghanistan	AFG	...	Asia	
2	2.0	Sovereign country	Angola	AGO	...	Africa	
3	2.0	Dependency	Anguilla	AIA	...	Americas	
4	2.0	Sovereign country	Albania	ALB	...	Europe	
..	...	...	...	...	...	...	
250	2.0	Sovereign country	Samoa	WSM	...	Oceania	
251	2.0	Sovereign country	Yemen	YEM	...	Asia	
252	2.0	Sovereign country	South Africa	ZAF	...	Africa	
253	2.0	Sovereign country	Zambia	ZMB	...	Africa	
254	2.0	Sovereign country	Zimbabwe	ZWE	...	Africa	

	SUBREGION	REGION_WB	NAME_LEN	LONG_LEN	\
0	Caribbean	Latin America & Caribbean	5.0	5.0	
1	Southern Asia	South Asia	11.0	11.0	
2	Middle Africa	Sub-Saharan Africa	6.0	6.0	
3	Caribbean	Latin America & Caribbean	8.0	8.0	
4	Southern Europe	Europe & Central Asia	7.0	7.0	
..	...	...	...	...	
250	Polynesia	East Asia & Pacific	5.0	5.0	
251	Western Asia	Middle East & North Africa	5.0	5.0	
252	Southern Africa	Sub-Saharan Africa	12.0	12.0	
253	Eastern Africa	Sub-Saharan Africa	6.0	6.0	
254	Eastern Africa	Sub-Saharan Africa	8.0	8.0	

	ABBREV_LEN	TINY	HOMEPART	\
0	5.0	4.0	-99.0	
1	4.0	-99.0	1.0	
2	4.0	-99.0	1.0	
3	4.0	-99.0	-99.0	
4	4.0	-99.0	1.0	
..	...	...	...	

250	5.0	-99.0	1.0
251	4.0	-99.0	1.0
252	5.0	-99.0	1.0
253	6.0	-99.0	1.0
254	5.0	-99.0	1.0

	geometry	Place_Count
0	POLYGON ((-69.99694 12.57758, -69.93639 12.531...	1.0
1	POLYGON ((71.0498 38.40866, 71.05714 38.40903,...	33.0
2	MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...	48.0
3	MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...	NaN
4	POLYGON ((19.74777 42.5789, 19.74601 42.57993,...	26.0
..	...	...
250	MULTIPOLYGON (((-171.57002 -13.93816, -171.564...	1.0
251	MULTIPOLYGON (((53.30824 12.11839, 53.31027 12...	20.0
252	MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...	72.0
253	POLYGON ((31.11984 -8.61663, 31.14102 -8.60619...	34.0
254	POLYGON ((30.01065 -15.64623, 30.05024 -15.640...	20.0

[255 rows x 67 columns]

The country with the highest number of important places is United States of America with 768 places.

## B. The point dataset has places with Latitude/Longitude coordinates, choose WGS 84 EPSG:4326 as the CRS in the Coordinate Reference System Selector dialog.

```
In [3]: # Load the dataset
places = gpd.read_file(point_data)

# Reprojects the data into the WGS 84 CRS if it's in a different CRS.
places = places.to_crs("EPSG:4326")
```

## C. Open countries vector layer

```
In [4]: # Display the first few rows of the dataset
print(countries.head())
```

	scalerank	featurecla	LABELRANK	SOVEREIGNT	SOV_A3	ADM0_DIF	\
0	3	Admin-0 country	5.0	Netherlands	NL1	1.0	
1	0	Admin-0 country	3.0	Afghanistan	AFG	0.0	
2	0	Admin-0 country	3.0	Angola	AGO	0.0	
3	3	Admin-0 country	6.0	United Kingdom	GB1	1.0	
4	0	Admin-0 country	6.0	Albania	ALB	0.0	

	LEVEL	TYPE	ADMIN	ADM0_A3	...	REGION_UN	\
0	2.0	Country	Aruba	ABW	...	Americas	
1	2.0	Sovereign country	Afghanistan	AFG	...	Asia	
2	2.0	Sovereign country	Angola	AGO	...	Africa	
3	2.0	Dependency	Anguilla	AIA	...	Americas	
4	2.0	Sovereign country	Albania	ALB	...	Europe	

	SUBREGION	REGION_WB	NAME_LEN	LONG_LEN	ABBREV_LEN	\
0	Caribbean	Latin America & Caribbean	5.0	5.0	5.0	
1	Southern Asia	South Asia	11.0	11.0	4.0	
2	Middle Africa	Sub-Saharan Africa	6.0	6.0	4.0	
3	Caribbean	Latin America & Caribbean	8.0	8.0	4.0	
4	Southern Europe	Europe & Central Asia	7.0	7.0	4.0	

	TINY	HOMEPART	geometry	\
0	4.0	-99.0	POLYGON ((-69.99694 12.57758, -69.93639 12.531...	
1	-99.0	1.0	POLYGON ((71.0498 38.40866, 71.05714 38.40903,...	
2	-99.0	1.0	MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...	
3	-99.0	-99.0	MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...	
4	-99.0	1.0	POLYGON ((19.74777 42.5789, 19.74601 42.57993,...	

	Place_Count
0	1
1	33
2	48
3	0
4	26

[5 rows x 67 columns]

**D. Using point in polygon vector analysis find the number of important places in each country. Colour code accordingly (You can highlight your favourite country)**

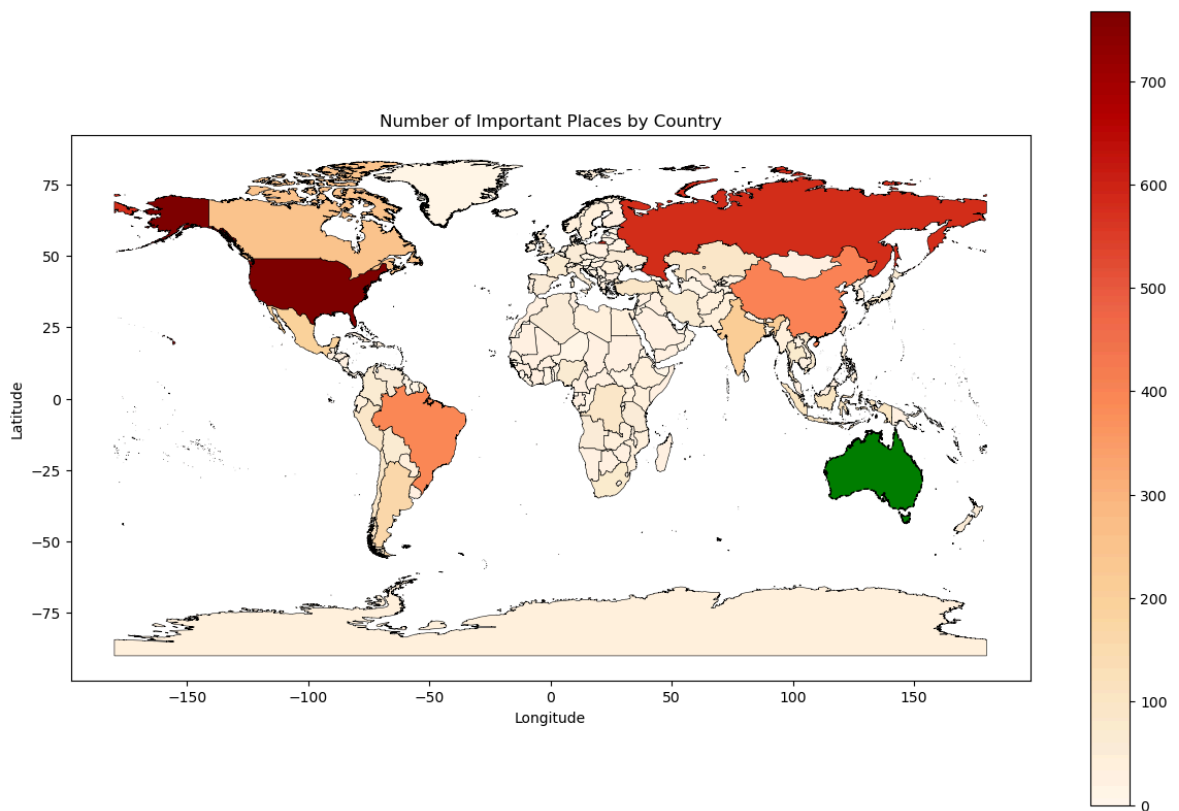
```
In [5]: import matplotlib.pyplot as plt
favourite_country = 'Australia'
# Plot the countries with color coding by the number of important places

fig, ax = plt.subplots(1, 1, figsize=(15, 10))
# Color map by the number of important places
countries.plot(column='Place_Count', cmap='OrRd', linewidth=0.4, ax=ax, edgecolor='black')

# Highlight favorite country
countries[countries['ADMIN'] == favourite_country].plot(ax=ax, color="green", edgecolor='black')

# Add title and other plot settings
```

```
ax.set_title("Number of Important Places by Country")
ax.set_xlabel("Longitude")
ax.set_ylabel("Latitude")
plt.show()
```



In [ ]:

## 2. Spatial Querying

### A. Spatial query to find all cities that are within 10 kms of a river.

```
In [6]: rivers_data = r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\Lab-6\

# Load the cities and rivers GeoDataFrames
cities = gpd.read_file(point_data).to_crs("EPSG:32643") # Replace with appropriate CRS
rivers = gpd.read_file(rivers_data).to_crs("EPSG:32643") # Same CRS as cities

# and project to a suitable CRS (e.g., UTM for accurate distance, EPSG:32643 for

# Create a 10,000-meter (10 km) buffer around each river
rivers_buffer = rivers.buffer(10000)

# Convert buffer to a GeoDataFrame for spatial operations
rivers_buffer_gdf = gpd.GeoDataFrame(rivers, geometry=rivers_buffer, crs=rivers.crs)
print(rivers_buffer_gdf, "\n")

# Spatial join: find cities that intersects with the rivers buffer
cities_near_rivers = gpd.sjoin(cities, rivers_buffer_gdf, how="inner", predicate="intersects")
print(cities_near_rivers, "\n")
```



```
print(cities_near_rivers.columns, "\n")

# Display cities near rivers
print(cities_near_rivers[['name_left', 'geometry']]) # place the actual name fi

# # Optional: plot the cities and rivers for visualization
# import matplotlib.pyplot as plt

# fig, ax = plt.subplots(figsize=(10, 10))
# rivers.plot(ax=ax, color="blue", label="Rivers")
# rivers_buffer_gdf.plot(ax=ax, color="lightblue", alpha=0.5, label="10 km Buffe
# cities_near_rivers.plot(ax=ax, color="red", label="Cities within 10 km")
# ax.legend()
# plt.show()
```



```

1451 POLYGON ((-4548785.052 7661687.108, -4549413.0...
1452                                     None
1453 POLYGON ((-4674939.259 7950052.14, -4676042.69...
1454 POLYGON ((-4008520.476 7401613.758, -4004420.6...

```

[1455 rows x 35 columns]

	scalerank_left	natscale	labelrank	featurecla	name_left	\
24	10	1	5	Admin-1 capital	Yên Bái	
26	10	1	5	Admin-1 capital	Thái Bình	
27	10	1	5	Admin-1 capital	Tuy Hòa	
30	10	1	5	Admin-1 capital	Cao Lãnh	
33	10	1	5	Admin-1 capital	Vĩnh Long	
...	...	...	...	...	...	
7331	0	600	3	Admin-0 capital	Cairo	
7332	0	600	1	Admin-1 capital	Shanghai	
7335	0	600	3	Admin-0 capital	Paris	
7337	0	600	1	Admin-1 capital	Kolkata	
7339	0	600	1	Admin-1 capital	São Paulo	

	namepar	namealt	diffascii	nameascii	adm0cap	...	\
24	None	None	0	Yen Bai	0.0	...	
26	None	None	0	Thai Binh	0.0	...	
27	None	None	0	Tuy Hoa	0.0	...	
30	None	None	0	Cao Lanh	0.0	...	
33	None	None	0	Vinh Long	0.0	...	
...	...	...	...	...	...	...	
7331	None	Al-Qahirah	0	Cairo	1.0	...	
7332	None	None	0	Shanghai	0.0	...	
7335	None	None	0	Paris	1.0	...	
7337	Calcutta	None	0	Kolkata	0.0	...	
7339	None	Sao Paulo Sio Paulo	0	Sao Paulo	0.0	...	

	name_nl	name_pl	name_pt	name_ru	name_sv	\
24	Rode Rivier	Rzeka Czerwona	Rio Vermelho	ÐŸÐ%Ð%Ð³ÑÐÐ°	RÃ¶da floden	
26	Rode Rivier	Rzeka Czerwona	Rio Vermelho	ÐŸÐ%Ð%Ð³ÑÐÐ°	RÃ¶da floden	
27	None	None	None	None	None	
30	Mekong	Mekong	Rio Mekong	ÐÐÐµÐ°Ð%Ð%Ð³	Mekong	
33	None	None	None	None	None	
...	...	...	...	...	...	
7331	Nijl	Nil	Rio Nilo	ÐÐÐ,Ð»	Nilen	
7332	None	None	None	None	None	
7335	Seine	Sekwana	Rio Sena	ÐjÐµÐ%Ð°	Seine	
7337	Ganges	Ganges	Rio Ganges	ÐÐÐ°Ð%Ð³	Ganges	
7339	TietÃª	TietÃª	Rio TietÃª	ÐŸÐ,ÐµÑÐÐµ	Rio TietÃª	

	name_tr	name_vi	name_zh	wdid_score	ne_id_right
24	KÃ±zÃ±l Nehir	SÃ´ng Há»ng	ç°Ÿæ²³	5	1159116785
26	KÃ±zÃ±l Nehir	SÃ´ng Há»ng	ç°Ÿæ²³	5	1159116785
27	None	None	None	0	1159111003
30	Mekong	MÃª KÃ´ng	æ¹ªâª-æ²³	4	1159121023
33	None	None	None	0	1159113739
...	...	...	...	...	...
7331	Nil	SÃ´ng Nin	â°çªæ²³	4	1159121589
7332	None	None	None	0	1159123017
7335	Sen Nehri	SÃ´ng Seine	âjªç°³æ²³	4	1159112177
7337	Ganj Nehri	SÃ´ng Há±ng	æªªæ²³	4	1159122643
7339	None	None	éªµª¹æ²³	4	1159125573

[1941 rows x 74 columns]

```
Index(['scalerank_left', 'natscale', 'labelrank', 'featurecla_left',
      'name_left', 'namepar', 'namealt', 'diffascii', 'nameascii', 'adm0cap',
      'capalt', 'capin', 'worldcity', 'megacity', 'sov0name', 'sov_a3',
      'adm0name', 'adm0_a3', 'adm1name', 'iso_a2', 'note_left', 'latitude',
      'longitude', 'changed', 'namediff', 'diffnote', 'pop_max', 'pop_min',
      'pop_other', 'rank_max', 'rank_min', 'geonameid', 'meganame', 'ls_name',
      'ls_match', 'checkme', 'min_zoom_left', 'ne_id_left', 'geometry',
      'index_right', 'dissolve', 'scalerank_right', 'featurecla_right',
      'name_right', 'name_alt', 'rivernum', 'note_right', 'min_zoom_right',
      'name_en', 'min_label', 'label', 'wikidataid', 'name_ar', 'name_bn',
      'name_de', 'name_es', 'name_fr', 'name_el', 'name_hi', 'name_hu',
      'name_id', 'name_it', 'name_ja', 'name_ko', 'name_nl', 'name_pl',
      'name_pt', 'name_ru', 'name_sv', 'name_tr', 'name_vi', 'name_zh',
      'wdid_score', 'ne_id_right'],
      dtype='object')
```

	name_left	geometry
24	Yên Bái	POINT (3695475.625 2729239.517)
26	Thái Bình	POINT (3896857.741 2610661.08)
27	Tuy Hòa	POINT (4436861.3 1739688.494)
30	Cao Lãnh	POINT (4013112.929 1341089.401)
33	Vĩnh Long	POINT (4057373.447 1318655.57)
...	...	...
7331	Cairo	POINT (-3909845.463 4288553.943)
7332	Shanghai	POINT (5124053.991 4581810.359)
7335	Paris	POINT (-4212632.342 8373560.534)
7337	Kolkata	POINT (1879181.673 2549954.605)
7339	São Paulo	POINT (-6179656.865 -15580440.684)

[1941 rows x 2 columns]

## B. Load the river lake line data and cities populated places data. Explore the attribute table

```
In [7]: # Check the first few rows to explore the attribute tables
print("Rivers/Lakes Data Attributes:")
print(rivers.head()) # Display the first few rows of the river
print("\nRivers/Lakes Data Columns:")
print(rivers.columns) # Display all column names for an overview

print("\nCities/Populated Places Data Attributes:")
print(cities.head()) # Display the first few rows of the cities
print("\nCities/Populated Places Data Columns:")
print(cities.columns) # Display all column names for an overview
```

		dissolve	scalerank		featurecla		name	name_alt	\
0		0River	1.0		River	Irrawaddy Delta		None	
1	1001Lake	Centerline	9.0	Lake	Centerline	Tonle Sap		None	
2		1001River	9.0		River	Tonle Sap		None	
3	1002Lake	Centerline	9.0	Lake	Centerline	Sheksna		None	
4		1002River	9.0		River	Sheksna		None	

	name_pt	name_ru	name_sv	name_tr	\
0	Rio Irauaí	Иравади	Irrawaddy	Ä°ravadi	Nehri
1	None	Иравади	None	None	
2	None	Иравади	None	None	
3	None	Иравади	Sjeksna	None	
4	None	Иравади	Sjeksna	None	

```

                                geometry
0  MULTILINESTRING ((2705619.301 2094592.654, 270...
1  MULTILINESTRING ((3731406.707 1659438.944, 373...
2  LINESTRING (3858032.783 1568315.839, 3858536.1...
3  LINESTRING (-1556543.92 7154971.481, -1554135...
4  LINESTRING (-1510524.362 7144405.677, -1509386...

```

```
Index(['dissolve', 'scalerank', 'featurecla', 'name', 'name_alt', 'rivernum',
      'note', 'min_zoom', 'name_en', 'min_label', 'label', 'wikidataid',
      'name_ar', 'name_bn', 'name_de', 'name_es', 'name_fr', 'name_el',
      'name_hi', 'name_hu', 'name_id', 'name_it', 'name_ja', 'name_ko',
      'name_nl', 'name_pl', 'name_pt', 'name_ru', 'name_sv', 'name_tr',
      'name_vi', 'name_zh', 'wdid_score', 'ne_id', 'geometry'],
      dtype='object')
```

	scalerank	natscale	labelrank	featurecla	name \
0	10	1	8	Admin-1 capital	Colonia del Sacramento
1	10	1	8	Admin-1 capital	Trinidad
2	10	1	8	Admin-1 capital	Fray Bentos
3	10	1	8	Admin-1 capital	Canelones
4	10	1	8	Admin-1 capital	Florida

	namepar	namealt	diffascii	nameascii	adm0cap	...	rank_max	\
0	None	None	0	Colonia del Sacramento	0.0	...	7	
1	None	None	0	Trinidad	0.0	...	7	
2	None	None	0	Fray Bentos	0.0	...	7	
3	None	None	0	Canelones	0.0	...	6	

4	None	None	0	Florida	0.0	...	7
---	------	------	---	---------	-----	-----	---

	rank_min	geonameid	meganame	ls_name	ls_match	checkme	min_zoom	ne_id	\
0	7	3443013.0	None	None	0	0	9.0	1159112629	
1	7	3439749.0	None	None	0	0	9.0	1159112647	
2	7	3442568.0	None	None	0	0	9.0	1159112663	
3	6	3443413.0	None	None	0	0	9.0	1159112679	
4	7	3442585.0	None	None	0	0	7.0	1159112703	

```

geometry
0 POINT (-3969096.441 -14975071.773)
1 POINT (-4131395.315 -15029487.368)
2 POINT (-4018601.143 -15163527.45)
3 POINT (-4117648.235 -14871923.154)
4 POINT (-4158131.122 -14919756.839)

```

[5 rows x 39 columns]

Cities/Populated Places Data Columns:

```

Index(['scalerank', 'natscale', 'labelrank', 'featurecla', 'name', 'namepar',
      'namealt', 'diffascii', 'nameascii', 'adm0cap', 'capalt', 'capin',
      'worldcity', 'megacity', 'sov0name', 'sov_a3', 'adm0name', 'adm0_a3',
      'adm1name', 'iso_a2', 'note', 'latitude', 'longitude', 'changed',
      'namediff', 'diffnote', 'pop_max', 'pop_min', 'pop_other', 'rank_max',
      'rank_min', 'geonameid', 'meganame', 'ls_name', 'ls_match', 'checkme',
      'min_zoom', 'ne_id', 'geometry'],
      dtype='object')

```

## C. To do buffer analysis, the layers must be in projected Coordinate Reference System (CRS). as the buffer distance would be in m or km

```

In [8]: # Choose an appropriate projected CRS (e.g., UTM Zone 43N for India, EPSG:32643)
projected_crs = "EPSG:32643" # Adjust as needed for your region

# Reproject to the chosen projected CRS
rivers_projected = rivers.to_crs(projected_crs)
cities_projected = cities.to_crs(projected_crs)

# Create a 10 km buffer around the rivers
rivers_buffer = rivers_projected.buffer(10000) # 10,000 meters (10 km)

# # Plot to visualize
# fig, ax = plt.subplots(figsize=(10, 10))
# rivers_buffer.plot(ax=ax, color="blue", edgecolor="black", alpha=0.5, label= '

# cities_projected.plot(ax=ax, color="red", markersize=1.5, label= 'Cities withi
# ax.set_title("10 km Buffer Around Rivers with Nearby Cities")
# ax.legend()
# plt.show()

# Plot to visualize
import matplotlib.patches as mpatches

fig, ax = plt.subplots(figsize=(10, 10))

```

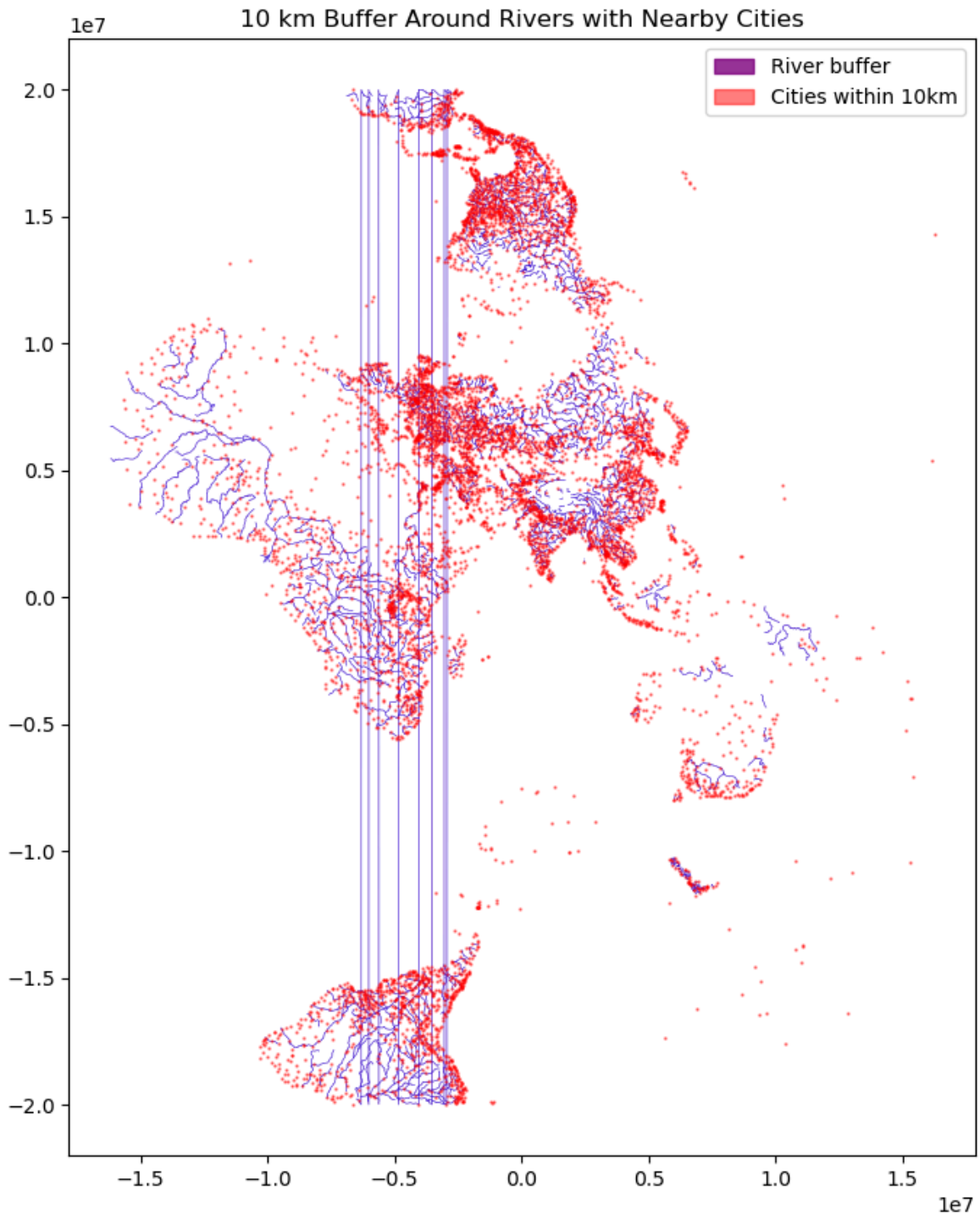
```

rivers_buffer.plot(ax=ax, color="purple", edgecolor="blue", linewidth=0.15, alpha=0.8, label="River buffer")
cities_projected.plot(ax=ax, color="red", alpha=0.5, markersize=0.5, label='Cities within 10km')

# Create custom Legend entries
buffer_patch = mpatches.Patch(color="purple", alpha=0.8, label="River buffer")
city_patch = mpatches.Patch(color="red", alpha=0.5, label="Cities within 10km")

# Add the custom Legend
ax.legend(handles=[buffer_patch, city_patch])
ax.set_title("10 km Buffer Around Rivers with Nearby Cities")
plt.show()

```



**D. Convert the files from geographic coordinate system to projected**

coordinate system. Project both the datasets to World\_Azimuthal\_Equidistant. For creating buffers, an Azimuthal Equidistant projection would be best suited as radial distances around the centre of the projection are accurate

```
In [9]: # Check the CRS of the Loaded data
print(rivers.crs)
print(cities.crs)

from pyproj import CRS

# Define the World Azimuthal Equidistant projection with a PROJ string
world_ae_proj = CRS("+proj=aeqd +lat_0=0 +lon_0=0 +datum=WGS84 +units=m +no_defs")

# Reproject rivers and cities to World Azimuthal Equidistant
rivers_ae = rivers.to_crs(world_ae_proj)
cities_ae = cities.to_crs(world_ae_proj)

# print(rivers_ae)

# Verify the new CRS
print(f"Rivers dataset CRS after projection: {rivers_ae.crs}")
print(f"Cities dataset CRS after projection: {cities_ae.crs}")

# Optional: Visualize the projected data
fig, ax = plt.subplots(figsize=(10, 10))
rivers_ae.plot(ax=ax, color='blue', label='Rivers')
cities_ae.plot(ax=ax, color='red', markersize=1.5, label='Cities')
ax.set_title("Projected Rivers and Cities in Azimuthal Equidistant")
ax.legend()
plt.show()
```

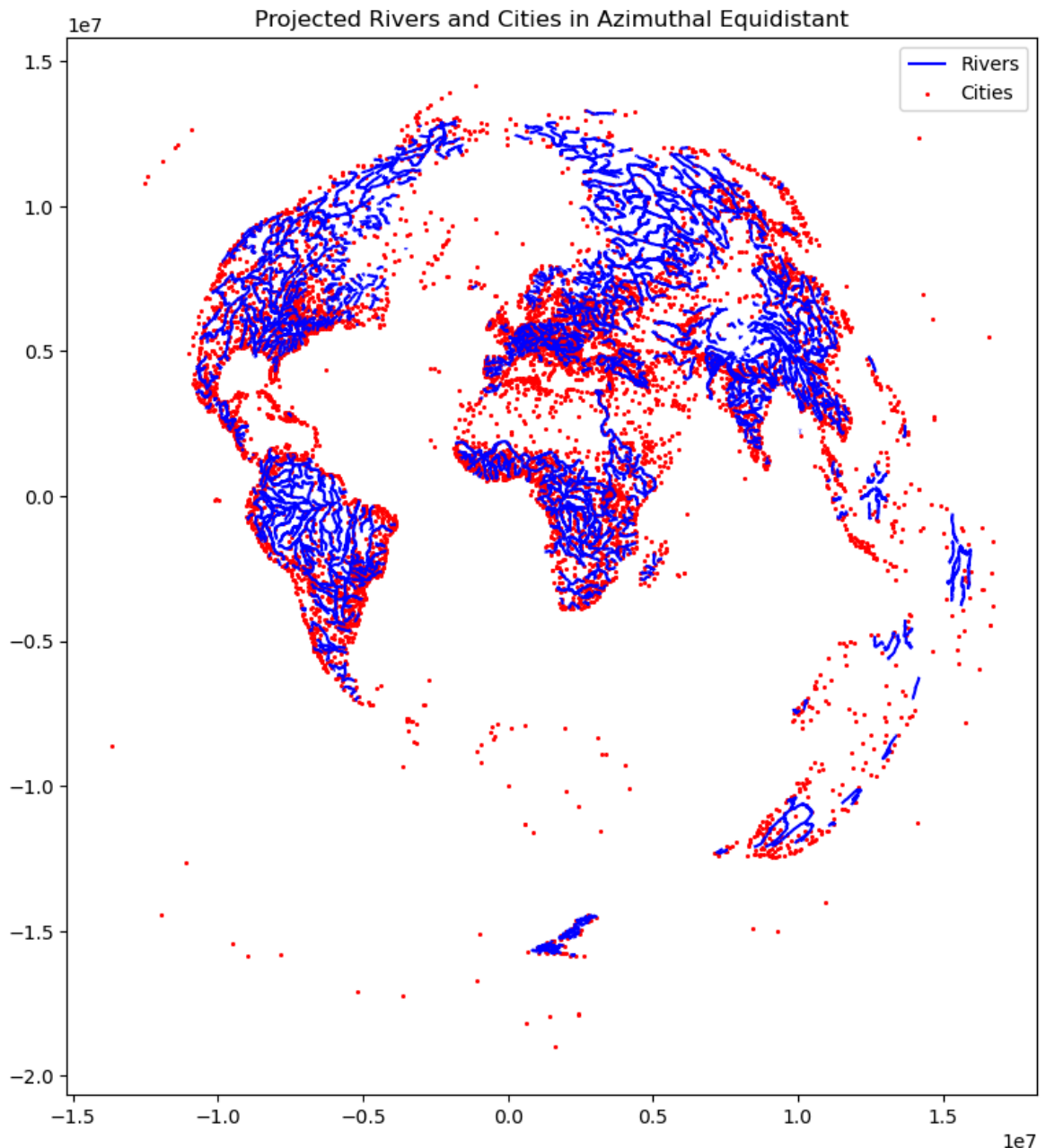
EPSG:32643

EPSG:32643

Rivers dataset CRS after projection: +proj=aeqd +lat\_0=0 +lon\_0=0 +datum=WGS84 +units=m +no\_defs +type=crs

Cities dataset CRS after projection: +proj=aeqd +lat\_0=0 +lon\_0=0 +datum=WGS84 +units=m +no\_defs +type=crs





**E. create buffer rings around the rivers and populated place. Use buffer distance as 10000 (10 Km)**

```
In [10]: import matplotlib.pyplot as plt
import matplotlib.patches as mpatches

# Create a 10 km buffer around the rivers and cities in the projected coordinate
rivers_buffer = rivers_ae.buffer(10000) # 10,000 meters = 10 km
cities_buffer = cities_ae.buffer(10000) # 10,000 meters = 10 km

# Convert these buffered objects into GeoDataFrames for easier handling
rivers_buffer_gdf = gpd.GeoDataFrame(rivers_ae, geometry=rivers_buffer, crs=rivers_ae.crs)
cities_buffer_gdf = gpd.GeoDataFrame(cities_ae, geometry=cities_buffer, crs=cities_ae.crs)
print(rivers_buffer_gdf)
print(cities_buffer_gdf)
```

```

# UserWarning: Legend does not support handles for PatchCollection instances. Fr
# # Plotting the buffer rings around rivers and populated places
# fig, ax = plt.subplots(figsize=(10, 10))

# # Plot river buffers first (could be more visually prominent)
# rivers_buffer_gdf.plot(ax=ax, color="cyan", edgecolor="black", linewidth=0.15,

# # Plot city buffers on top (may overlap)
# cities_buffer_gdf.plot(ax=ax, color="orange", edgecolor="black", linewidth=0.1

# ax.set_title("10 km Buffer Rings Around Rivers and Populated Places")
# ax.legend()
# plt.show()

# Plotting the buffer rings around rivers and populated places
fig, ax = plt.subplots(figsize=(10, 10))

# Plot river buffers first (could be more visually prominent)
rivers_buffer_gdf.plot(ax=ax, color="purple", alpha= 0.8) # No label here

# Plot city buffers on top (may overlap)
cities_buffer_gdf.plot(ax=ax, color="red", alpha=0.8) # No label here

# Create custom legend entries
river_patch = mpatches.Patch(color="purple", alpha=0.8, label="10 km River Buffe
city_patch = mpatches.Patch(color="red", alpha=0.8, label="10 km City Buffer")

# Add the custom legend
ax.legend(handles=[river_patch, city_patch])
ax.set_title("10 km Buffer Rings Around Rivers and Populated Places")
plt.show()

```



1451 POLYGON ((634107.252 4970775.329, 635297.987 4...  
 1452 None  
 1453 POLYGON ((247148.376 5224039.482, 246788.137 5...  
 1454 POLYGON ((1051399.884 5219971.477, 1055899.439...

[1455 rows x 35 columns]

	scalerank	natscale	labelrank	featurecla \
0	10	1	8	Admin-1 capital
1	10	1	8	Admin-1 capital
2	10	1	8	Admin-1 capital
3	10	1	8	Admin-1 capital
4	10	1	8	Admin-1 capital
...	...	...	...	...
7338	0	600	1	Admin-1 capital
7339	0	600	1	Admin-1 capital
7340	0	600	3	Admin-1 capital
7341	0	600	0	Admin-0 capital
7342	0	600	0	Admin-0 region capital

	name	namepar	namealt	diffascii \
0	Colonia del Sacramento	None	None	0
1	Trinidad	None	None	0
2	Fray Bentos	None	None	0
3	Canelones	None	None	0
4	Florida	None	None	0
...	...	...	...	...
7338	Rio de Janeiro	None	None	0
7339	São Paulo	None	Sao Paulo Sio Paulo	0
7340	Sydney	None	None	0
7341	Singapore	None	None	0
7342	Hong Kong	None	None	0

	nameascii	adm0cap	...	rank_max	rank_min	geonameid \
0	Colonia del Sacramento	0.0	...	7	7	3443013.0
1	Trinidad	0.0	...	7	7	3439749.0
2	Fray Bentos	0.0	...	7	7	3442568.0
3	Canelones	0.0	...	6	6	3443413.0
4	Florida	0.0	...	7	7	3442585.0
...	...	...	...	...	...	...
7338	Rio de Janeiro	0.0	...	14	12	3451190.0
7339	Sao Paulo	0.0	...	14	14	3448439.0
7340	Sydney	0.0	...	12	12	2147714.0
7341	Singapore	1.0	...	13	12	1880252.0
7342	Hong Kong	0.0	...	13	12	1819729.0

	meganame	ls_name	ls_match	checkme	min_zoom	ne_id \
0	None	None	0	0	9.0	1159112629
1	None	None	0	0	9.0	1159112647
2	None	None	0	0	9.0	1159112663
3	None	None	0	0	9.0	1159112679
4	None	None	0	0	7.0	1159112703
...	...	...	...	...	...	...
7338	Rio de Janeiro	Rio de Janeiro	1	0	1.7	1159151619
7339	S	Sao Paolo	1	0	3.0	1159151621
7340	Sydney	Sydney1	1	0	1.7	1159151623
7341	Singapore	Singapore	1	5	2.1	1159151627
7342	Hong Kong	Hong Kong	1	0	3.0	1159151629

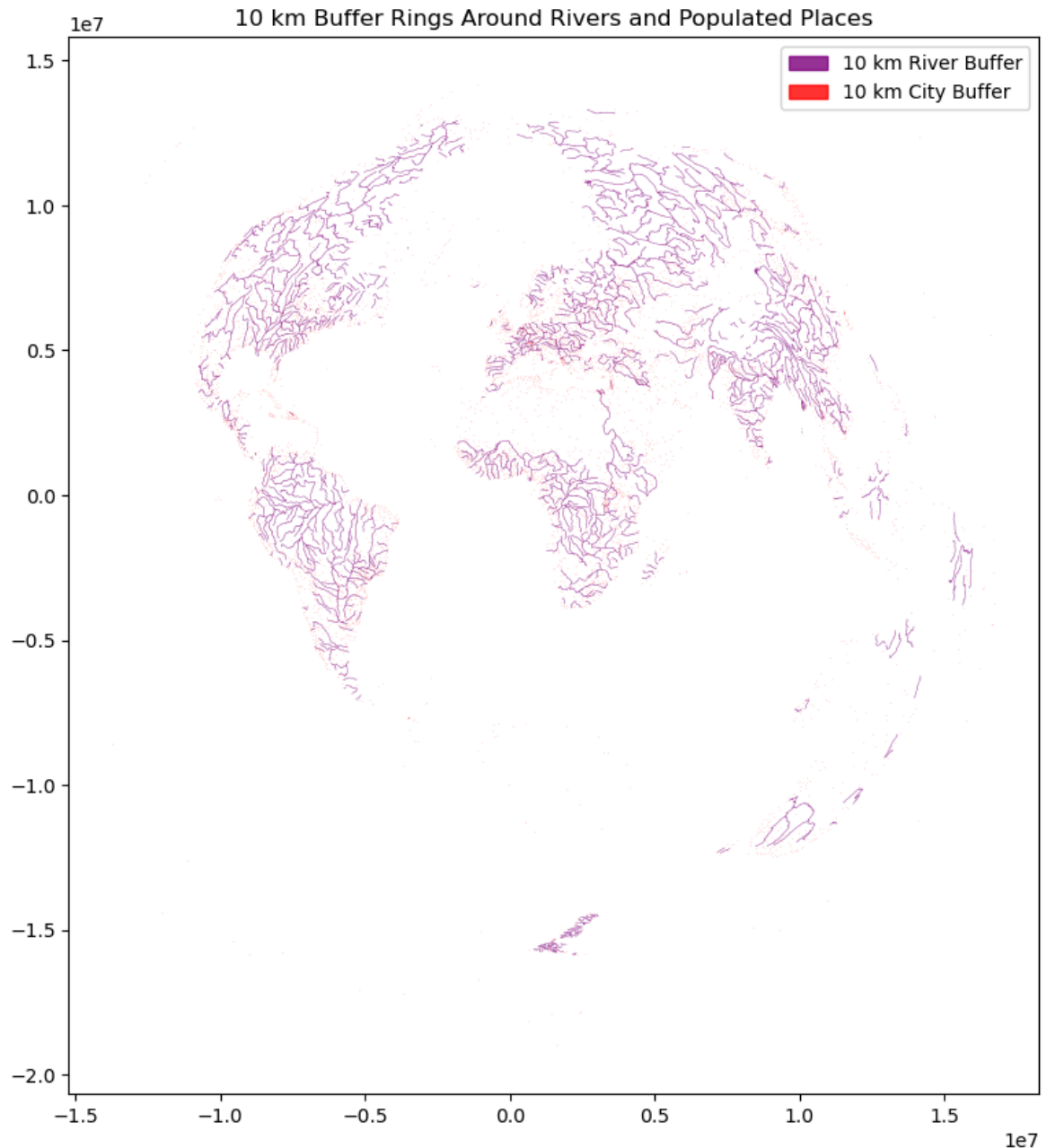
geometry  
 0 POLYGON ((-5524358.943 -4466465.068, -5524407....

```

1    POLYGON ((-5486417.74 -4327207.242, -5486465.8...
2    POLYGON ((-5636960.417 -4310525.118, -5637008....
3    POLYGON ((-5379035.389 -4435724.561, -5379083....
4    POLYGON ((-5395047.121 -4379773.605, -5395095....
...
7338 POLYGON ((-4523570.96 -2782837.179, -4523619.1...
7339 POLYGON ((-4859015.78 -2903590.001, -4859063.9...
7340 POLYGON ((8838153.443 -12379152.889, 8838105.2...
7341 POLYGON ((11567431.615 268596.058, 11567383.46...
7342 POLYGON ((11408055.84 5122887.034, 11408007.68...

```

[7343 rows x 39 columns]



## F. Now select only the rivers from the buffer created that intersect

```

In [11]: # Perform spatial intersection to get only the parts of the rivers that intersect
rivers_within_buffer = gpd.overlay(rivers_buffer_gdf, cities_buffer_gdf, how='in

```

```

# Display the resulting GeoDataFrame to check the selected rivers
print(rivers_within_buffer)
print(rivers_buffer_gdf)

# Visualize the selected rivers within the buffer
fig, ax = plt.subplots(figsize=(10, 10))

# Plot the river buffer
rivers_buffer_gdf.plot(ax=ax, color="lightblue", edgecolor='blue', linewidth=0.7)

# Plot the original cities buffer to show the area of intersection
cities_buffer_gdf.plot(ax=ax, color="green", edgecolor="green", linewidth=1, alpha=0.5)

# Plot the rivers within the city buffer
rivers_within_buffer.plot(ax=ax, color="red", edgecolor="red", linewidth=1.5, alpha=0.9)

# Custom Legend with mpatches
river_patch = mpatches.Patch(color="blue", alpha=0.5, label="River Buffer")
cities_patch = mpatches.Patch(color="green", alpha=0.8, label="City Buffer" )
intersected_rivers = mpatches.Patch(color="red", alpha=0.9, label="Rivers in the City Buffer")

# Add Legend and title
ax.set_title("Rivers within the City Buffer")
ax.legend(handles=[river_patch, cities_patch, intersected_rivers])
plt.show()

```

	dissolve	scalerank_1	featurecla_1	name_1	name_alt	rivernum	\
0	ØRiver	1.0	River	Irrawaddy Delta	None	0	
1	ØRiver	1.0	River	Irrawaddy Delta	None	0	
2	ØRiver	1.0	River	Irrawaddy Delta	None	0	
3	ØRiver	1.0	River	Irrawaddy Delta	None	0	
4	ØRiver	1.0	River	Irrawaddy Delta	None	0	
...	...	...	...	...	...	...	
2446	178River	5.0	River	Loire	None	178	
2447	178River	5.0	River	Loire	None	178	
2448	178River	5.0	River	Loire	None	178	
2449	303Drau	7.0	River	Drau	Drava	303	
2450	303Drau	7.0	River	Drau	Drava	303	

	note_1	min_zoom_1	name_en	min_label	...	rank_max	rank_min	\
0	None	2.0	Irrawaddy	3.0	...	9	7	
1	None	2.0	Irrawaddy	3.0	...	7	7	
2	None	2.0	Irrawaddy	3.0	...	3	3	
3	None	2.0	Irrawaddy	3.0	...	9	9	
4	None	2.0	Irrawaddy	3.0	...	10	9	
...	...	...	...	...	...	...	...	
2446	Changed in	4.0	4.7	Loire	5.7	...	8	7
2447	Changed in	4.0	4.7	Loire	5.7	...	10	9
2448	Changed in	4.0	4.7	Loire	5.7	...	7	7
2449	None	6.0	Drava	7.0	...	9	8	
2450	None	6.0	Drava	7.0	...	8	8	

	geonameid	meganame	ls_name	ls_match	checkme	min_zoom_2	\
0	1314042.0	None	Letpadan	1	0	6.7	
1	1289828.0	None	Wakema	1	0	6.1	
2	1315244.0	None	Labutta	1	0	6.7	
3	1325211.0	None	Hinthada	1	2	6.7	
4	1328421.0	None	Pathein	1	0	6.7	
...	...	...	...	...	...	...	
2446	2983362.0	None	Roanne	1	0	7.0	
2447	2980291.0	None	Saint-Etienne	1	0	6.7	
2448	2990474.0	None	Nevers	1	0	6.7	
2449	3195506.0	None	Maribor	1	2	6.7	
2450	2774326.0	None	Klagenfurt	1	0	6.1	

	ne_id_2	geometry
0	1159145911	POLYGON ((10109298.54 3257113.535, 10109334.13...
1	1159145943	POLYGON ((10132978.362 3033470.506, 10132961.1...
2	1159145949	POLYGON ((10111513.814 2922930.967, 10110561.2...
3	1159145963	POLYGON ((10102793.021 3225143.052, 10102462.1...
4	1159145967	POLYGON ((10081986.441 3042426.302, 10082510.3...
...	...	...
2446	1159129807	POLYGON ((343682.726 5109674.409, 343676.896 5...
2447	1159139913	POLYGON ((379670.909 5045906.978, 379717.343 5...
2448	1159141991	POLYGON ((279956.838 5206598.25, 279812.843 52...
2449	1159135827	POLYGON ((1338559.469 5199156.147, 1337948.925...
2450	1159145087	POLYGON ((1214679.971 5210510.032, 1217423.536...

[2451 rows x 73 columns]

	dissolve	scalerank	featurecla	name	\
0	ØRiver	1.0	River	Irrawaddy Delta	
1	1001Lake	Centerline	9.0	Lake Centerline	Tonle Sap
2	1001River	9.0	River	Tonle Sap	
3	1002Lake	Centerline	9.0	Lake Centerline	Sheksna
4	1002River	9.0	River	Sheksna	
...	...	...	...	...	

1450	2049Lake	Centerline	10.0	Lake Centerline	Ohau
1451		219River	6.0	River	Po
1452		178River	5.0	River	Loire
1453		178River	5.0	River	Loire
1454		303Drau	7.0	River	Drau

	name_alt	rivernum	note	min_zoom	name_en	min_label	...	\
0	None	0	None	2.0	Irrawaddy	3.0	...	
1	None	1001	None	7.1	None	8.1	...	
2	None	1001	None	7.1	None	8.1	...	
3	None	1002	None	7.1	Sheksna	8.1	...	
4	None	1002	None	7.1	Sheksna	8.1	...	
...	...	...	...	...	...	...	...	
1450	None	2049	None	7.2	Ohau	8.2	...	
1451	None	219	Version 4 edit	5.0	Po	6.0	...	
1452	None	178000	Changed in 2.0	4.7	Loire	5.7	...	
1453	None	178	Changed in 4.0	4.7	Loire	5.7	...	
1454	Drava	303	None	6.0	Drava	7.0	...	

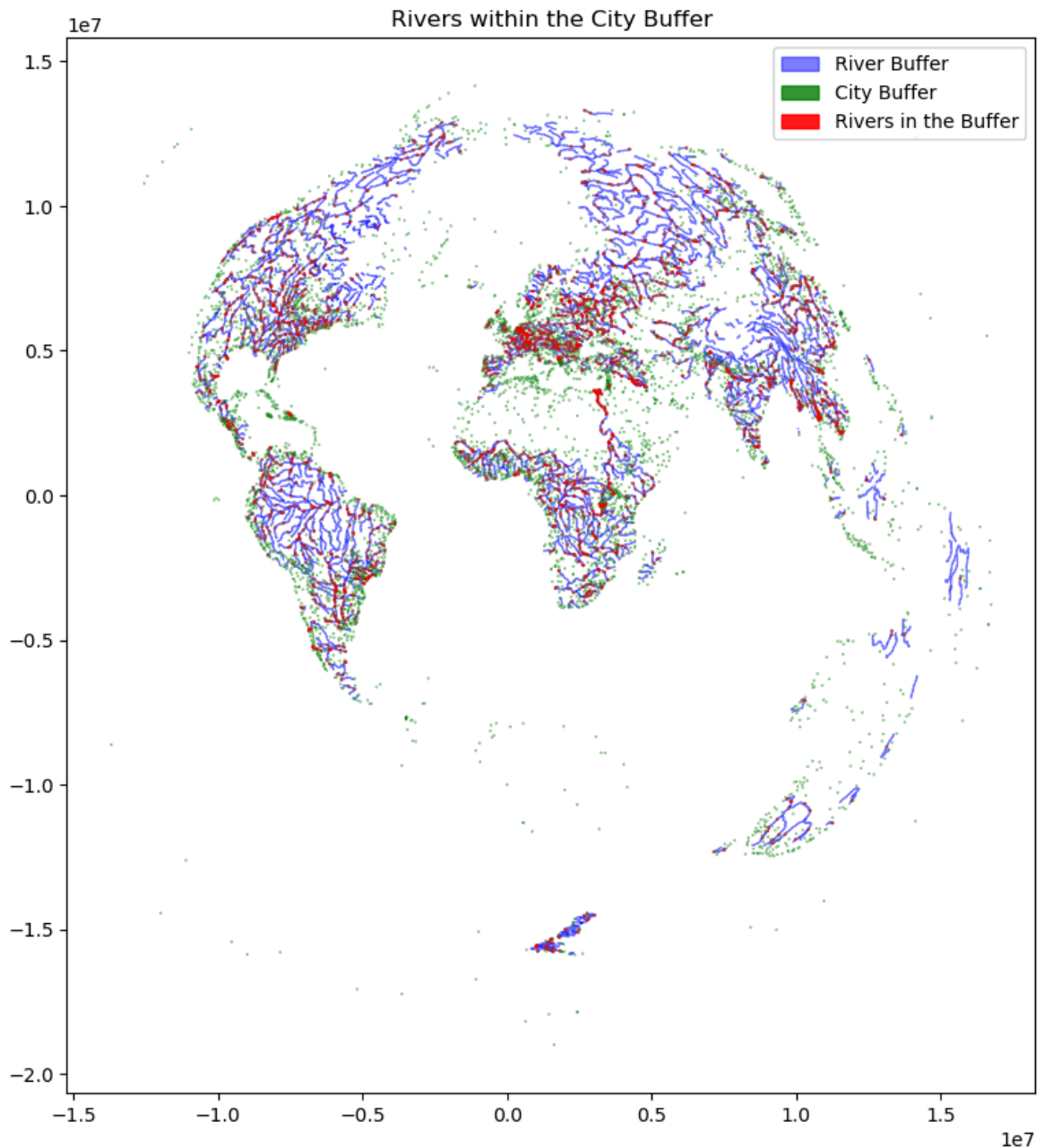
	name_pl	name_pt	name_ru	name_sv	name_tr	\
0	Irawadi	Rio IrauÃ;di	ÐÑÑÐ°Ð²Ð°Ð´,	Irrawaddy	Ä°ravadi	Nehri
1	Tonle Sap	None	Ð¢Ð%Ð%Ð»ÐµÑÑÐ°Ð¿	None	None	
2	Tonle Sap	None	Ð¢Ð%Ð%Ð»ÐµÑÑÐ°Ð¿	None	None	
3	Szeksna	None	Ð`ÐµÐ°ÑÑÐ°Ð°	Sjeksna	None	
4	Szeksna	None	Ð`ÐµÐ°ÑÑÐ°Ð°	Sjeksna	None	
...	...	...	...	...	...	
1450	None	None	None	None	None	
1451	Pad	Rio PÃ³	ÐÑÐ%	Po	Po	Nehri
1452	Loara	Rio Loire	ÐÑÑÐ°ÑÑÐ°	Loire	Loire	Nehri
1453	Loara	Rio Loire	ÐÑÑÐ°ÑÑÐ°	Loire	Loire	Nehri
1454	Drawa	Rio Drava	ÐÑÑÐ°Ð²Ð°Ð°	Drava	Drava	

	name_vi	name_zh	wdid_score	ne_id	\
0	SÃ´ng Ayeyarwaddy	ǎ%ǎ´ǎçǎ ǎ°ǎ±ǎ	2	1159109417	
1	None	None	4	1159109429	
2	None	None	4	1159109445	
3	None	èǎǎǎǎǎǎǎ´ǎ°ǎ²³	4	1159109447	
4	None	èǎǎǎǎǎǎǎ´ǎ°ǎ²³	4	1159109461	
...	...	...	...	...	
1450	None	None	4	1159129657	
1451	SÃ´ng Po	ǎ³ǎ²³	4	1159129663	
1452	SÃ´ng Loire	ǎǎǎçǎ ǎ°ǎ²³	4	1159129671	
1453	SÃ´ng Loire	ǎǎǎçǎ ǎ°ǎ²³	4	1159129677	
1454	None	ǎ%ǎǎçǎ ǎ²³	5	1159129685	

	geometry
0	MULTIPOLYGON (((10138551.54 3049624.556, 10138...
1	POLYGON ((11183514.629 2708469.621, 11184239.3...
2	POLYGON ((11322060.743 2548275.499, 11321592.1...
3	POLYGON ((2523610.596 6878389.198, 2523565.166...
4	POLYGON ((2491759.669 6980840.76, 2491289.873 ...
...	...
1450	POLYGON ((2535034.246 -14768011.839, 2534683.4...
1451	POLYGON ((634107.252 4970775.329, 635297.987 4...
1452	None
1453	POLYGON ((247148.376 5224039.482, 246788.137 5...
1454	POLYGON ((1051399.884 5219971.477, 1055899.439...

[1455 rows x 35 columns]





**G. select features from the buffered places that intersect with the buffered river lines.**

```
In [39]: import geopandas as gpd
import matplotlib.pyplot as plt

# Perform the spatial intersection between city buffers and river buffers
cities_near_rivers = gpd.overlay(cities_buffer_gdf, rivers_buffer_gdf, how='inte

# Plot to visualize the intersected features
fig, ax = plt.subplots(figsize=(10, 10))

# Plot the river buffer
rivers_buffer_gdf.plot(ax=ax, color="lightblue", edgecolor='blue', linewidth=0.7

# Plot the city buffer
```

```

cities_buffer_gdf.plot(ax=ax, color="red", edgecolor='red', linewidth=1, alpha=0.7)

# Plot only the intersecting features (cities near rivers)
cities_near_rivers.plot(ax=ax, color="black", edgecolor='green', linewidth=1.5, alpha=0.7)

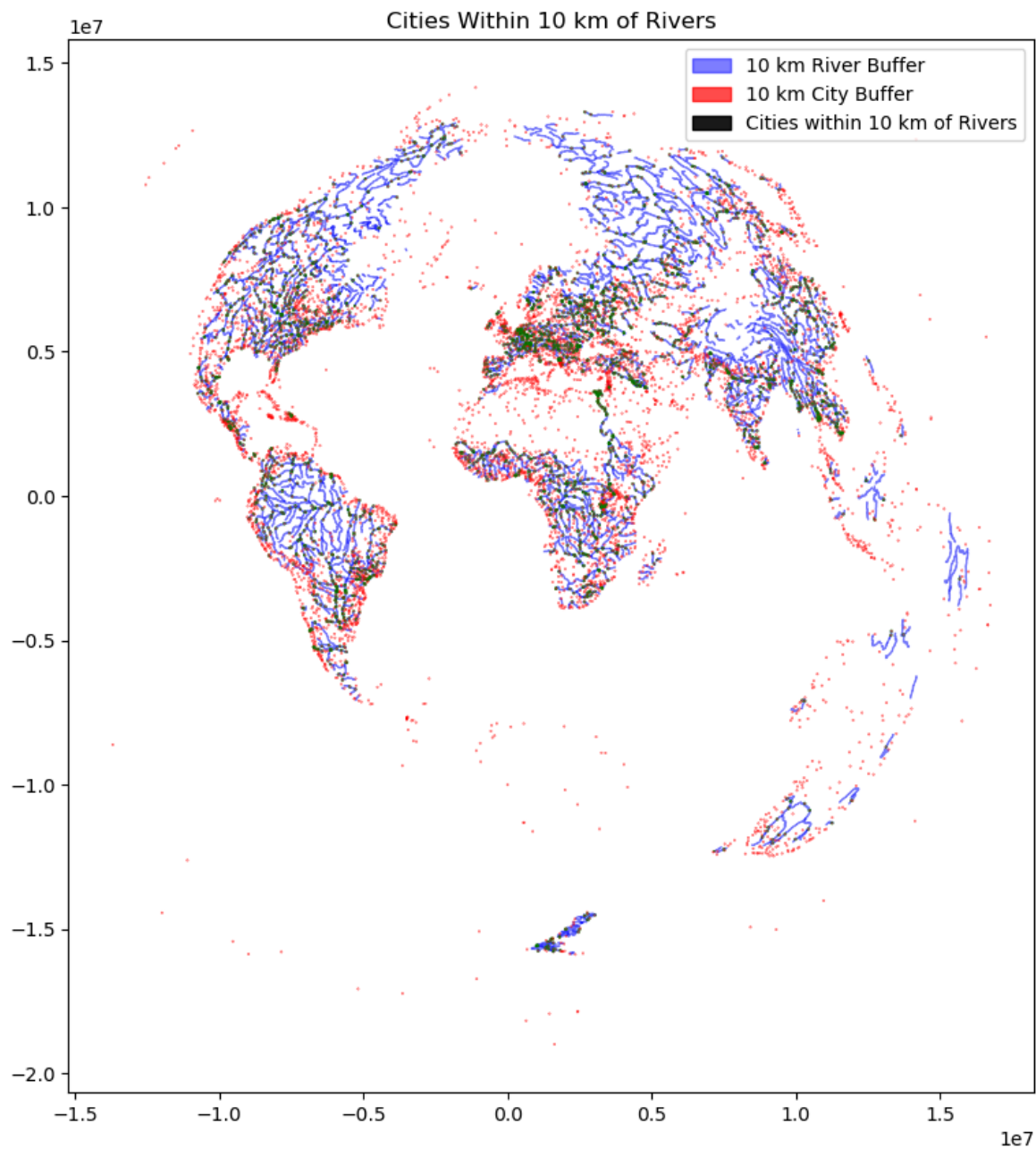
# UserWarning: Legend does not support handles for PatchCollection instances.
# # Add Legend and title
# ax.legend()
# ax.set_title("Cities Within 10 km of Rivers")
# plt.show()

# Custom Legend with mpatches
river_patch = mpatches.Patch(color="blue", alpha=0.5, label="10 km River Buffer")
city_patch = mpatches.Patch(color="red", alpha=0.7, label="10 km City Buffer")
intersection_patch = mpatches.Patch(color="black", alpha=0.9, label="Cities with River Buffer")

# Add custom Legend
ax.legend(handles=[river_patch, city_patch, intersection_patch])
ax.set_title("Cities Within 10 km of Rivers")
plt.show()

# print the intersected GeoDataFrame
print(cities_near_rivers)
print(cities_buffer_gdf)

```





2447 POLYGON ((203498.335 5415218.185, 203354.341 5...  
 2448 POLYGON ((203498.335 5415218.185, 203354.341 5...  
 2449 POLYGON ((9095777.263 3747144.52, 9094853.276 ...  
 2450 POLYGON ((-4859063.932 -2904570.173, -4859207....

[2451 rows x 73 columns]

	scalerank	natscale	labelrank	featurecla \
0	10	1	8	Admin-1 capital
1	10	1	8	Admin-1 capital
2	10	1	8	Admin-1 capital
3	10	1	8	Admin-1 capital
4	10	1	8	Admin-1 capital
...	...	...	...	...
7338	0	600	1	Admin-1 capital
7339	0	600	1	Admin-1 capital
7340	0	600	3	Admin-1 capital
7341	0	600	0	Admin-0 capital
7342	0	600	0	Admin-0 region capital

	name	namepar	namealt	diffascii \
0	Colonia del Sacramento	None	None	0
1	Trinidad	None	None	0
2	Fray Bentos	None	None	0
3	Canelones	None	None	0
4	Florida	None	None	0
...	...	...	...	...
7338	Rio de Janeiro	None	None	0
7339	São Paulo	None	Sao Paulo Sio Paulo	0
7340	Sydney	None	None	0
7341	Singapore	None	None	0
7342	Hong Kong	None	None	0

	nameascii	adm0cap	...	rank_max	rank_min	geonameid \
0	Colonia del Sacramento	0.0	...	7	7	3443013.0
1	Trinidad	0.0	...	7	7	3439749.0
2	Fray Bentos	0.0	...	7	7	3442568.0
3	Canelones	0.0	...	6	6	3443413.0
4	Florida	0.0	...	7	7	3442585.0
...	...	...	...	...	...	...
7338	Rio de Janeiro	0.0	...	14	12	3451190.0
7339	Sao Paulo	0.0	...	14	14	3448439.0
7340	Sydney	0.0	...	12	12	2147714.0
7341	Singapore	1.0	...	13	12	1880252.0
7342	Hong Kong	0.0	...	13	12	1819729.0

	meganame	ls_name	ls_match	checkme	min_zoom	ne_id \
0	None	None	0	0	9.0	1159112629
1	None	None	0	0	9.0	1159112647
2	None	None	0	0	9.0	1159112663
3	None	None	0	0	9.0	1159112679
4	None	None	0	0	7.0	1159112703
...	...	...	...	...	...	...
7338	Rio de Janeiro	Rio de Janeiro	1	0	1.7	1159151619
7339	S	Sao Paolo	1	0	3.0	1159151621
7340	Sydney	Sydney1	1	0	1.7	1159151623
7341	Singapore	Singapore	1	5	2.1	1159151627
7342	Hong Kong	Hong Kong	1	0	3.0	1159151629

geometry  
 0 POLYGON ((-5524358.943 -4466465.068, -5524407....

```

1    POLYGON ((-5486417.74 -4327207.242, -5486465.8...
2    POLYGON ((-5636960.417 -4310525.118, -5637008....
3    POLYGON ((-5379035.389 -4435724.561, -5379083....
4    POLYGON ((-5395047.121 -4379773.605, -5395095....
...
7338 POLYGON ((-4523570.96 -2782837.179, -4523619.1...
7339 POLYGON ((-4859015.78 -2903590.001, -4859063.9...
7340 POLYGON ((8838153.443 -12379152.889, 8838105.2...
7341 POLYGON ((11567431.615 268596.058, 11567383.46...
7342 POLYGON ((11408055.84 5122887.034, 11408007.68...

```

[7343 rows x 39 columns]

## H. Save this as a kml file and view on Google earth

```

In [43]: print(cities_near_rivers.columns)
         print(cities_near_rivers)

# # Save the rivers within the city buffer as a KML file
# output_kml_path = r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\

# # Save to KML
# cities_near_rivers.to_file(output_kml_path, driver='KML')
# print(f"File saved as {output_kml_path}. You can now open this file in Google
#                                     # BY using the above code we get th
#                                     # have values that cannot be fully

# Selecting essential columns for KML export
selected_columns = ['name_1', 'nameascii', 'adm0name', 'iso_a2', 'pop_max', 'pop
cities_in_river_buffer = cities_near_rivers[selected_columns]

# Save to KML
output_kml_path = r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\La
cities_in_river_buffer.to_file(output_kml_path, driver='KML')
print(f"File saved as {output_kml_path}. You can now open this file in Google Ea

```

```
Index(['scalerank_1', 'natscale', 'labelrank', 'featurecla_1', 'name_1',
      'namepar', 'namealt', 'diffascii', 'nameascii', 'adm0cap', 'capalt',
      'capin', 'worldcity', 'megacity', 'sov0name', 'sov_a3', 'adm0name',
      'adm0_a3', 'adm1name', 'iso_a2', 'note_1', 'latitude', 'longitude',
      'changed', 'namediff', 'diffnote', 'pop_max', 'pop_min', 'pop_other',
      'rank_max', 'rank_min', 'geonameid', 'meganame', 'ls_name', 'ls_match',
      'checkme', 'min_zoom_1', 'ne_id_1', 'dissolve', 'scalerank_2',
      'featurecla_2', 'name_2', 'name_alt', 'rivernum', 'note_2',
      'min_zoom_2', 'name_en', 'min_label', 'label', 'wikidataid', 'name_ar',
      'name_bn', 'name_de', 'name_es', 'name_fr', 'name_el', 'name_hi',
      'name_hu', 'name_id', 'name_it', 'name_ja', 'name_ko', 'name_nl',
      'name_pl', 'name_pt', 'name_ru', 'name_sv', 'name_tr', 'name_vi',
      'name_zh', 'wdid_score', 'ne_id_2', 'geometry'],
      dtype='object')
```

	scalerank_1	natscale	labelrank	featurecla_1	name_1	namepar	\
0	10	1	5	Admin-1 capital	Yên Bái	None	
1	10	1	5	Admin-1 capital	Thái Bình	None	
2	10	1	5	Admin-1 capital	Tuy Hòa	None	
3	10	1	5	Admin-1 capital	Cao Lãnh	None	
4	10	1	5	Admin-1 capital	Truc Giang	None	
...	...	...	...	...	...	...	
2446	0	600	1	Admin-1 capital	Shanghai	None	
2447	0	600	3	Admin-0 capital	Paris	None	
2448	0	600	3	Admin-0 capital	Paris	None	
2449	0	600	1	Admin-1 capital	Kolkata	Calcutta	
2450	0	600	1	Admin-1 capital	São Paulo	None	

	namealt	diffascii	nameascii	adm0cap	...	\
0	None	0	Yen Bai	0.0	...	
1	None	0	Thai Binh	0.0	...	
2	None	0	Tuy Hoa	0.0	...	
3	None	0	Cao Lanh	0.0	...	
4	None	0	Truc Giang	0.0	...	
...	...	...	...	...	...	
2446	None	0	Shanghai	0.0	...	
2447	None	0	Paris	1.0	...	
2448	None	0	Paris	1.0	...	
2449	None	0	Kolkata	0.0	...	
2450	Sao Paulo Sio Paulo	0	Sao Paulo	0.0	...	

	name_pl	name_pt	name_ru	name_sv	name_tr	\
0	Rzeka Czerwona	Rio Vermelho	Рѣка Чѣрво́на	RÄjda floden	KÄ±zÄ±l Nehir	
1	Rzeka Czerwona	Rio Vermelho	Рѣка Чѣрво́на	RÄjda floden	KÄ±zÄ±l Nehir	
2	None	None	None	None	None	
3	Mekong	Rio Mekong	Мѣкѣнг	Mekong	Mekong	
4	None	None	None	None	None	
...	...	...	...	...	...	
2446	None	None	None	None	None	
2447	Marna	Rio Marne	Марна	Marne	Marne Nehri	
2448	Sekwana	Rio Sena	Сѣквѣна	Seine	Sen Nehri	
2449	Ganges	Rio Ganges	Гѣнгѣс	Ganges	Ganj Nehri	
2450	TietÃ	Rio TietÃ	Тѣтѣ	Rio TietÃ	None	

	name_vi	name_zh	wdid_score	ne_id_2	\
0	SÃ'ng Há»ng	çºçæ²³	5	1159116785	
1	SÃ'ng Há»ng	çºçæ²³	5	1159116785	
2	None	None	0	1159111003	
3	MÃª KÃ'ng	æ¹ââ-æ²³	4	1159121023	
4	None	None	0	1159113739	
...	...	...	...	...	

2446	None	None	0	1159123017
2447	SÃ´ng Marne	é@-æ@æ²³	4	1159110541
2448	SÃ´ng Seine	åj@ç²³	4	1159112177
2449	SÃ´ng Há±ng	æ@æ²³	4	1159122643
2450	None	é@µç@¹²³	4	1159125573

```

                                geometry
0    POLYGON ((10695369.377 4391711.374, 10695225.3...
1    POLYGON ((10932426.633 4231744.893, 10931767.5...
2    POLYGON ((11769956.218 2891404.917, 11769812.2...
3    POLYGON ((11529816.651 2205405.833, 11529672.6...
4    POLYGON ((11601201.356 2174161.458, 11600542.3...
...
2446 POLYGON ((10577469.109 7502299.273, 10576884.5...
2447 POLYGON ((203498.335 5415218.185, 203354.341 5...
2448 POLYGON ((203498.335 5415218.185, 203354.341 5...
2449 POLYGON ((9095777.263 3747144.52, 9094853.276 ...
2450 POLYGON ((-4859063.932 -2904570.173, -4859207....

```

[2451 rows x 73 columns]

File saved as C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\Lab-6\cities\_in\_river\_buffer.kml. You can now open this file in Google Earth.

Just for visual representation of kml file by load to the OSM map by using folium

```

In [45]: import folium
          from folium import plugins
          import geopandas as gpd

          # Read the KML file using GeoPandas
          gdf = gpd.read_file(r"C:\Users\Ranjeet Gupta\Downloads\Scientific Computing Lab\

          # Create a base map
          m = folium.Map(location=[gdf.geometry.centroid.y.mean(), gdf.geometry.centroid.x

          # Add KML Layer to the map
          folium.GeoJson(gdf).add_to(m)

          # Display the map in the notebook
          m

```

C:\Users\Ranjeet Gupta\AppData\Local\Temp\ipykernel\_22988\301996777.py:9: UserWarning: Geometry is in a geographic CRS. Results from 'centroid' are likely incorrect. Use 'GeoSeries.to\_crs()' to re-project geometries to a projected CRS before this operation.

```

m = folium.Map(location=[gdf.geometry.centroid.y.mean(), gdf.geometry.centroid.x.mean()], zoom_start=2)

```



Out[45]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [ ]: