Geospatial Project and Web Mapping

Semester 2 – 2024 – S4649801

Spatial Analysis: The Influence of Infrastructure on Crime Incidents

Introduction

Every crime is inherently tied to a location, whether it be a street, address, district, or postal code. Geographic Information Systems (GIS) have proven to be powerful tools for analysing these locational aspects [1]. By connecting crime data with geographical information, crime mapping offers invaluable insights into spatial patterns and trends. As crime statistics are influenced by several factors—including population size, infrastructure and seasonal trends [2]. This study focuses on Chermside and Capalaba, suburbs in Queensland to explore the relationship between infrastructure and crime incidents using spatial analysis techniques. By analysing offence data from Queensland Police Services, the research aims to identify the influence of infrastructure on crime incidents and to investigate the distance decay relationship between these incidents and the infrastructure in the suburb.

Method

I followed the steps below to identify the influence of infrastructure on crime incidents for Chermside first.

Step 1: Prepare Data for the Analysis

Crime incident data for Chermside were obtained from the Queensland Police Service, covering five years from 2019 to 2024. Infrastructure data were sourced from the Australian Bureau of Statistics (ABS) census 2021, which includes land use of Queensland. I used ArcGIS Online and GeoPandas as the main tools to develop the results and visualisations.

To improve the processing efficiency, only target suburb data was accessed through the URL.

```python
# Connect to QPS REST API for offences? using Python requests library
import requests, json
import pandas

# Set the URL for the REST API for offences
off_url = "https://a5c7zwf7e5.execute-api.ap-southeast-2.amazonaws.com/dev/offences?"

# Query string parameters
startDate = "10-15-2023"
endDate =   "10-15-2024"
locationType = "SUBURB"
locationName = "Chermside"
format = "JSON"

# Build the URL for the REST API
off_query = off_url + "locationType="+locationType + "&locationName="+locationName + \
            "&startDate="+startDate + "&endDate="+endDate + "&format="+format

# Send the request to the REST API
response = requests.get(off_query)

# Check if the request was successful
if response.status_code == 200:
    # Convert the response to JSON
    data = response.json()
    off_df = pandas.json_normalize(data)

else:
    print('Get location request failed')
```

Fig. 1

	Type	Date	Postcode	Area of Interest	ABS Meshblock
0	Other Theft (excl. Unlawful Entry)	2019-10-20 23:30:00	4032	Chermside	30052610000
1	Other Theft (excl. Unlawful Entry)	2019-10-21 08:47:00	4032	Chermside	30562359500
2	Other Theft (excl. Unlawful Entry)	2019-10-21 12:55:00	4032	Chermside	30052420000
3	Assault	2019-10-21 15:50:00	4032	Chermside	30562359500
4	Other Theft (excl. Unlawful Entry)	2019-10-21 16:40:00	4032	Chermside	30052420000

Fig. 2: Data used

The second data set is the ABS Mesh block data which includes geometries and land use of each block.

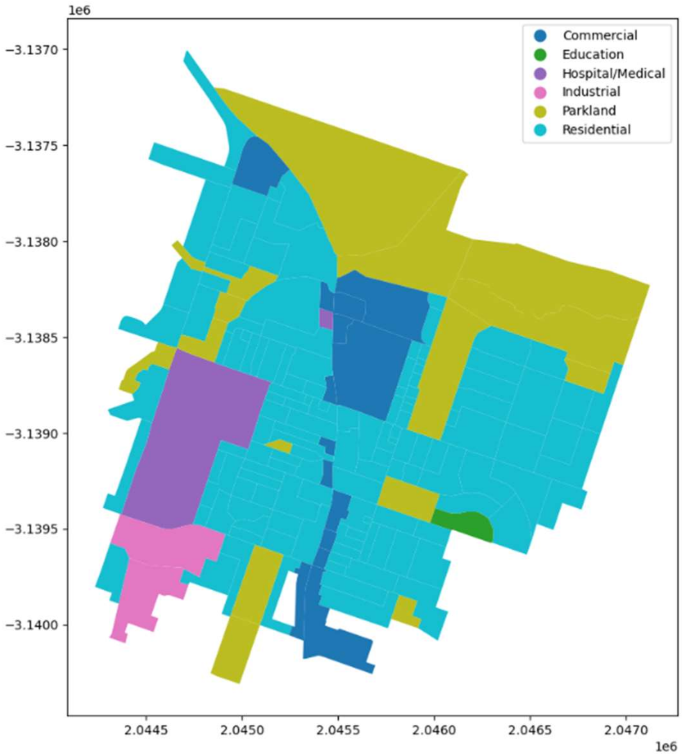

Fig. 3: Land use of Chermside

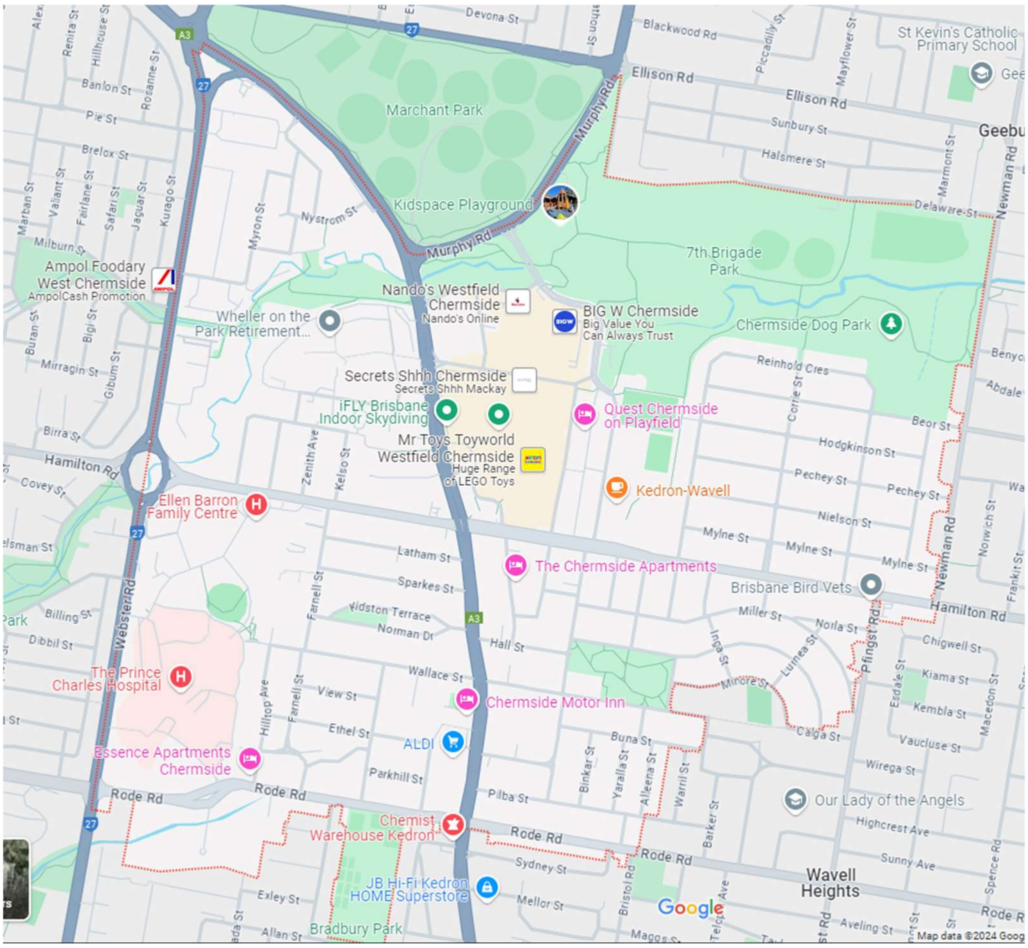

Fig 4: Google Map of Chermside

Step 2: Extract Data for the Analysis

I investigated the other theft (excl. Unlawful Entry) as the major offence in Chermside in the last five years. After categorising these mesh blocks and mapping them I identified the corresponding land uses of Chermside, where these incidents have happened.

```
off_df.value_counts('Type')

Type
Other Theft (excl. Unlawful Entry)    6413
Drug Offences                         1531
Unlawful Entry                         899
Good Order Offences                    772
Fraud                                  626
Assault                                603
Other Property Damage                  602
Traffic and Related Offences           509
Handling Stolen Goods                  313
Unlawful Use of Motor Vehicle          261
Weapons Act Offences                   185
Trespassing and Vagrancy               127
Robbery                                101
Other Offences Against the Person       91
Miscellaneous Offences                  24
Arson                                   12
Liquor (excl. Drunkenness)              12
Homicide (Murder)                        1
Other Homicide                           1
Name: count, dtype: int64
```

Fig. 5: All Offences during the last 5 years in Chermside

The following plot shows that the majority of these incidents have happened in commercial areas.

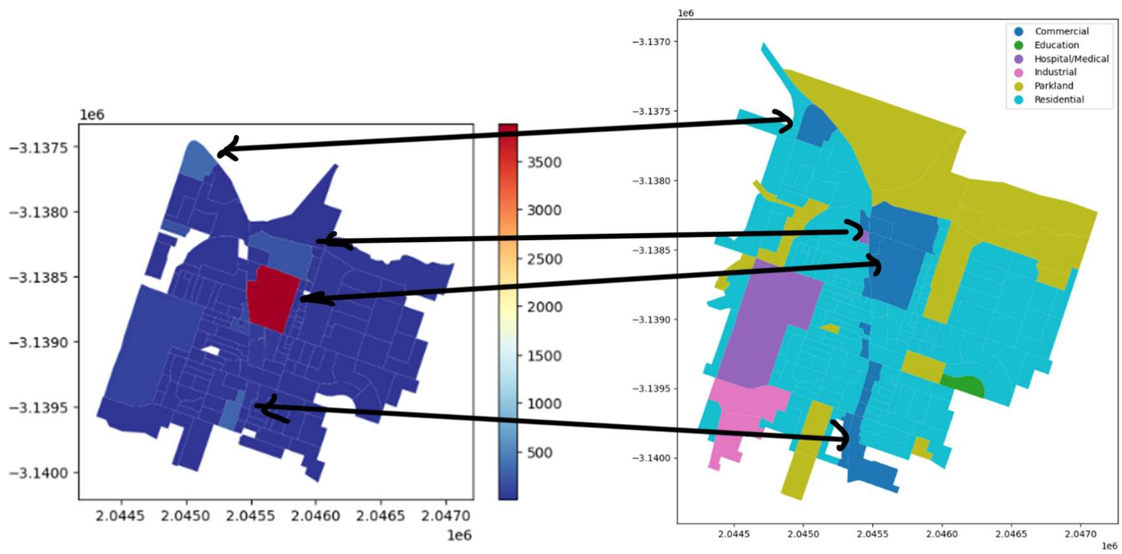

Fig 6: Mesh Blocks with High Crime Rate

Then I obtained the number of ‘Other Theft’ incidents that happened in a particular mesh block. For that, I filtered the offence data by ‘Other Theft’ and got the count of recorded incidents by the mesh block.

```python
# Step 1: Join the offence data for counts of assaults only

# Slice to get Other Theft (excl. Unlawful Entry) only
crime_df = off_df[off_df.Type=='Other Theft (excl. Unlawful Entry)']

# Summarise the offences by mesh block
crime_counts = crime_df.groupby('ABS Meshblock').agg({'Type':'count'})
crime_counts.reset_index(inplace=True)

# Join the mesh block data with the offence data
gdf_mb_crime = gdf_mb.merge(crime_counts, right_on='ABS Meshblock', left_on='MB_CODE21')

# filter necessary columns to view
gdf_mb_crime[['MB_CODE21', 'MB_CAT21', 'SA2_NAME21','Type']].head()
```

	MB_CODE21	MB_CAT21	SA2_NAME21	Type
0	30052200000	Residential	Chermside	16
1	30052210000	Residential	Chermside	5
2	30052220000	Residential	Chermside	13
3	30052230000	Parkland	Chermside	2
4	30052240000	Residential	Chermside	11

Fig. 7: Output

Figure 6 output gives the number of 'other theft' incidents that happened in each mesh block and the land use of each mesh block.

Step 3: Compute the distance between the offence to commercial areas

Next, I filtered out all the commercial areas and then combined them to be considered as one unit. Then calculate the distance from individual mesh blocks to the combined commercial unit.

```python
from shapely.ops import unary_union

# To filter the land use by commercial
target_landuse = 'Commercial'
gdf_mb_lu = gdf_mb.query("MB_CAT21=='{}'".format(target_landuse))

# Combine all the commercial areas together
unioned_mb_target_lu = unary_union(gdf_mb_lu['geometry'])

# Calculate the distances
gdf_mb_crime["dist_decay"] = gdf_mb_crime.geometry.distance(unioned_mb_target_lu)

gdf_mb_crime[["MB_CAT21","Count","dist_decay"]].head()
```

	MB_CAT21	Count	dist_decay
0	Residential	16	238.518214
1	Residential	5	58.544616
2	Residential	13	117.853006
3	Parkland	2	136.702525
4	Residential	11	92.963008

Fig. 8: Output with Distance values

Results:

To visualise the distance decay relationship between Other Theft (excl. Unlawful Entry) and commercial areas in Chermside, I used histogram and mapping. The below diagram shows there are a very high number of incidents have happened with in 200m of the commercial areas. And the number of incidents is reducing with the increase of the distance from the commercial areas.

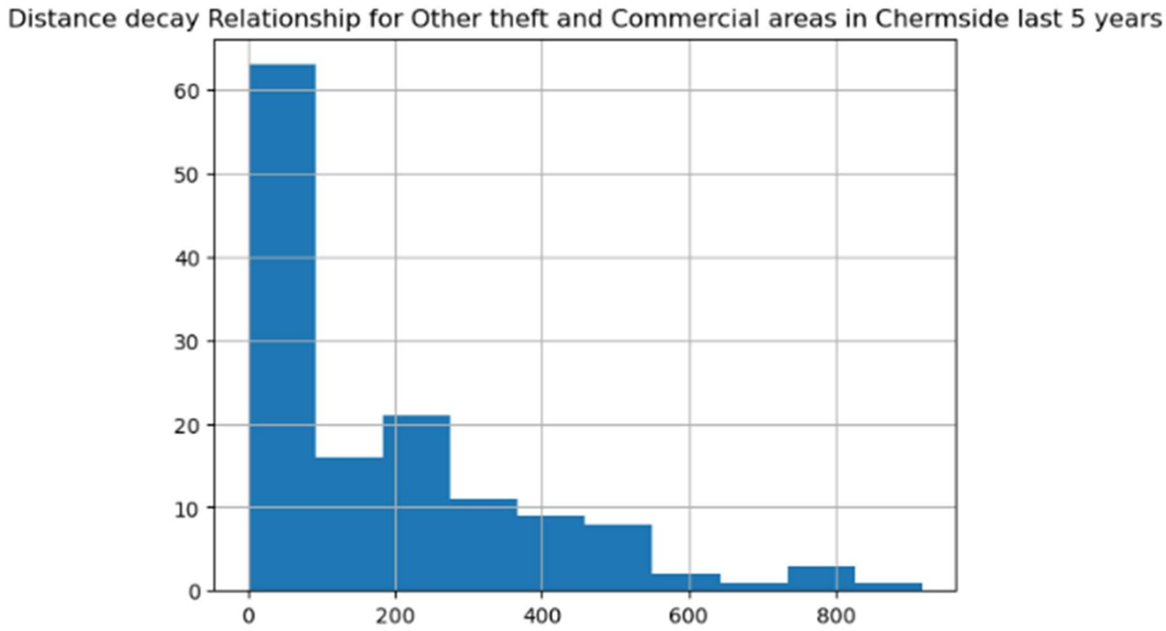

Fig. 9

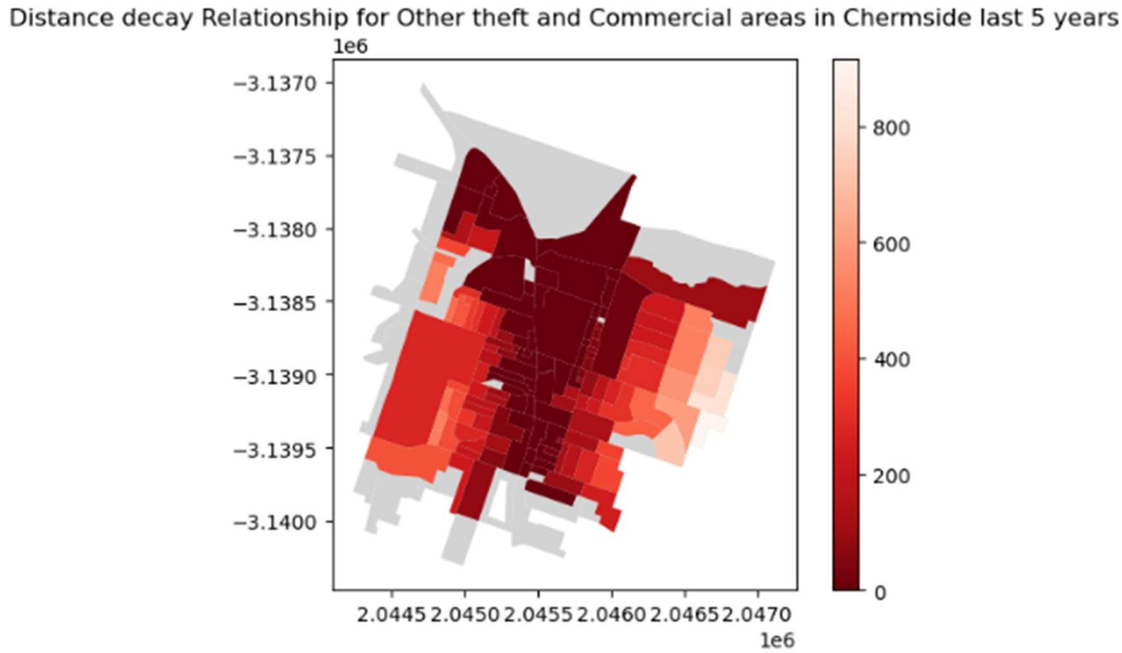

Fig. 10

In Figure 10, darker colours show mesh blocks near commercial areas with 'other theft' incidents. Crime declines significantly with distance. I further investigated how major offences have developed in Chermside over the past five years.

Trend of Other Theft in Chermside

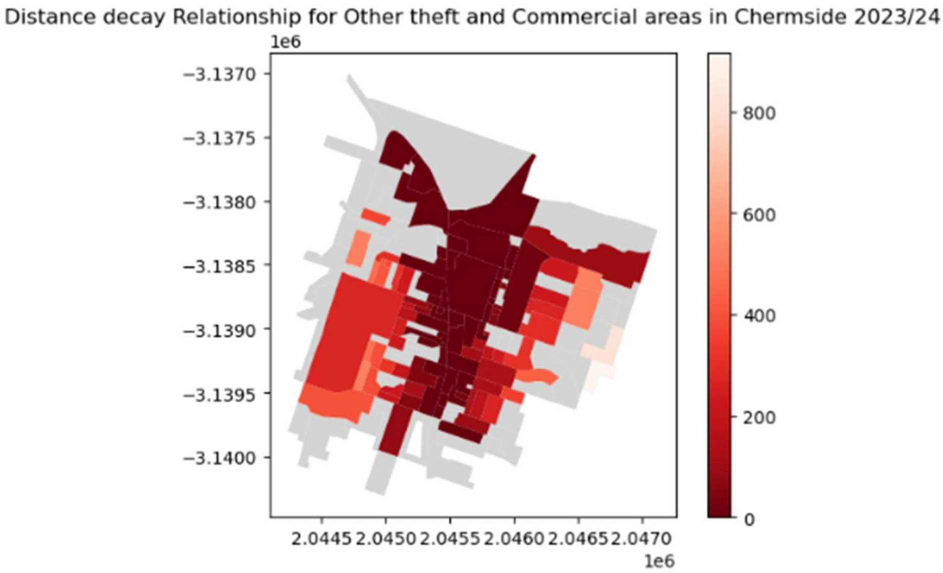

Fig. 11

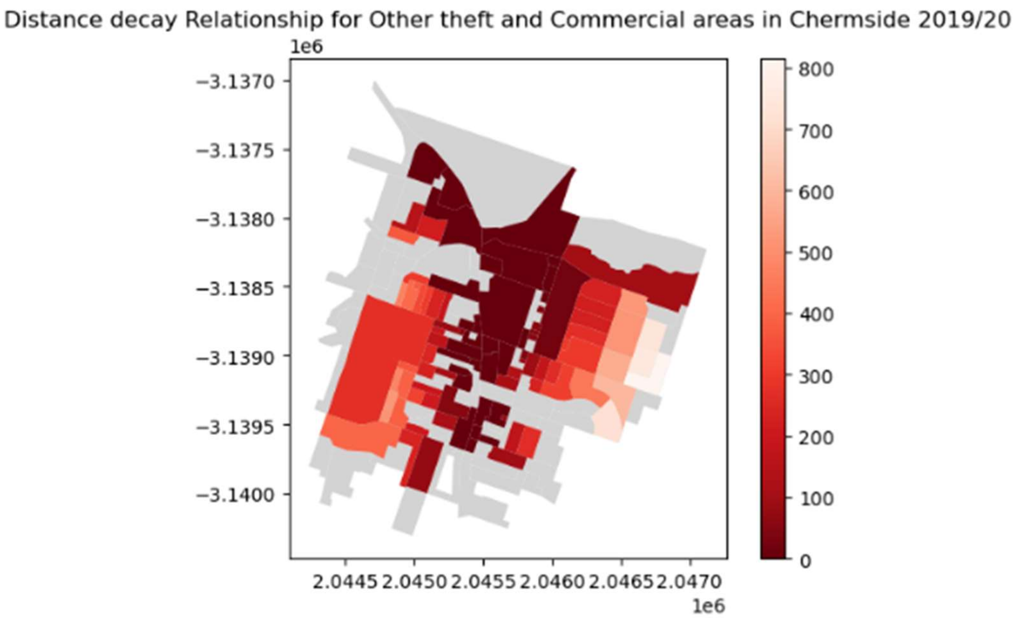

Fig. 12

A significant increase in crime has been observed in central and southern Chermside over the past five years according to figure 11 and 12.

Trend of Drug offence in Chermside

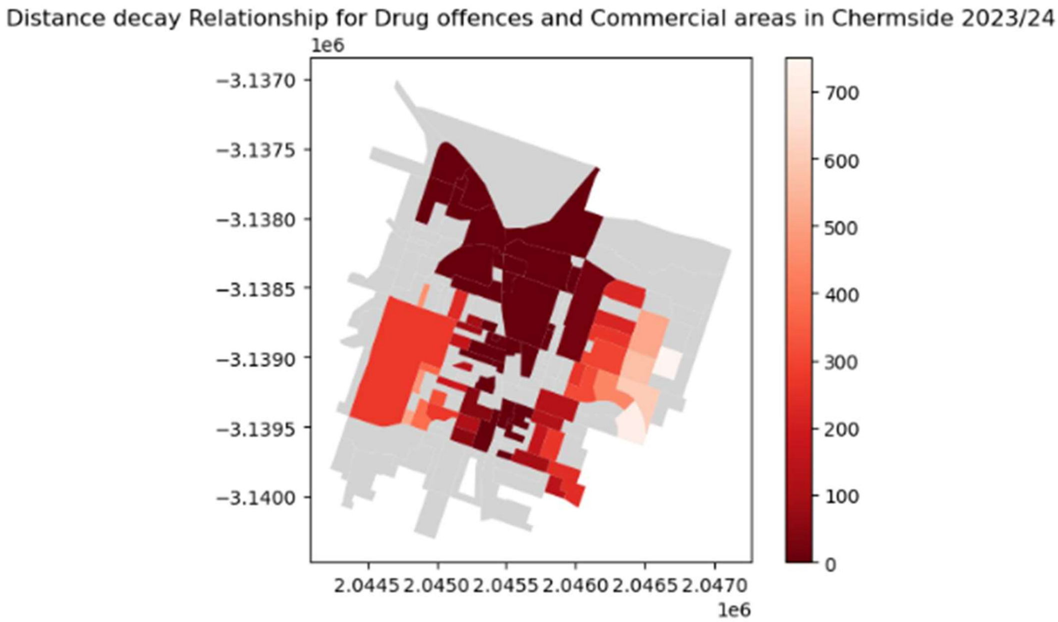

Fig. 13

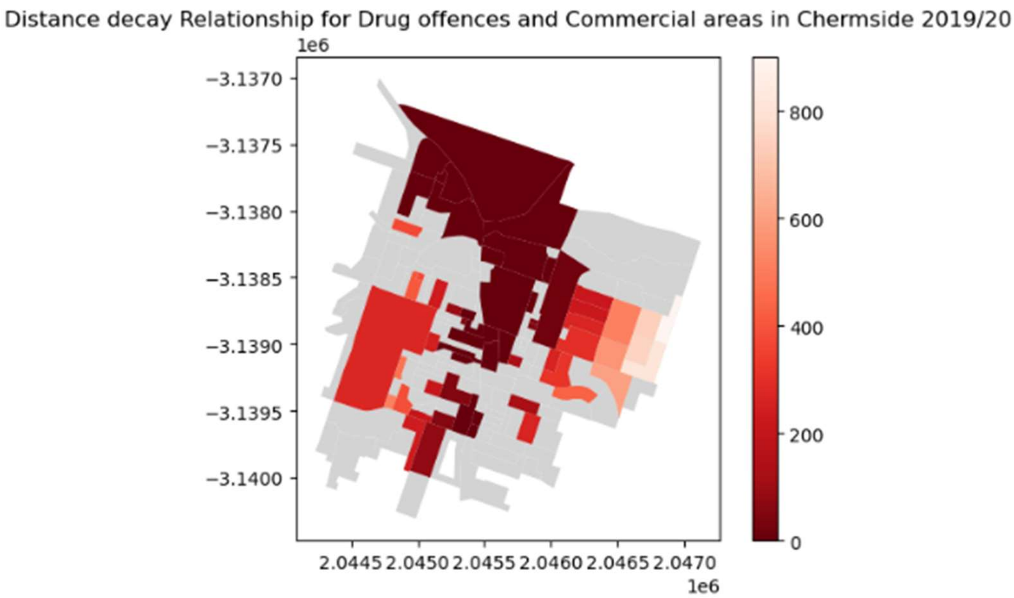

Fig. 14

Figures 13 and 14 indicate an increase in drug offence incidents in South-East Chermside over the past year compared to 2019.

Pattern of Assaulting in Chermside

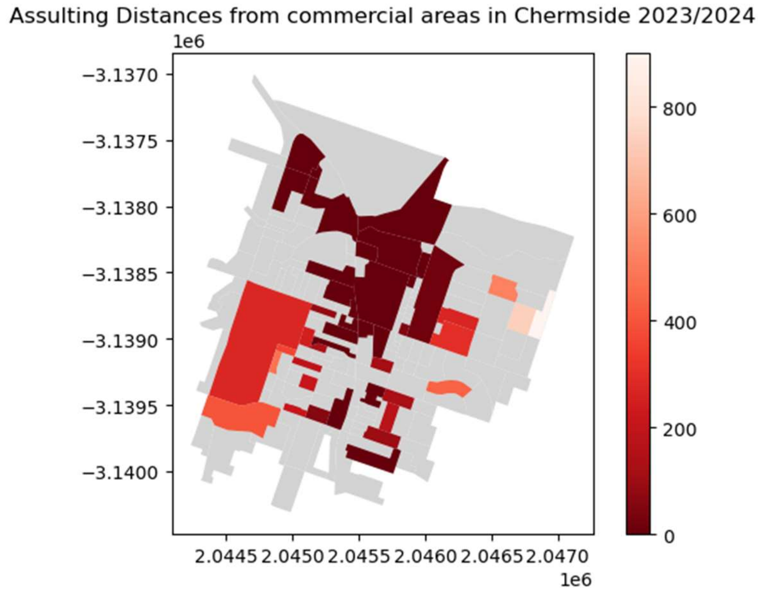

Fig. 15

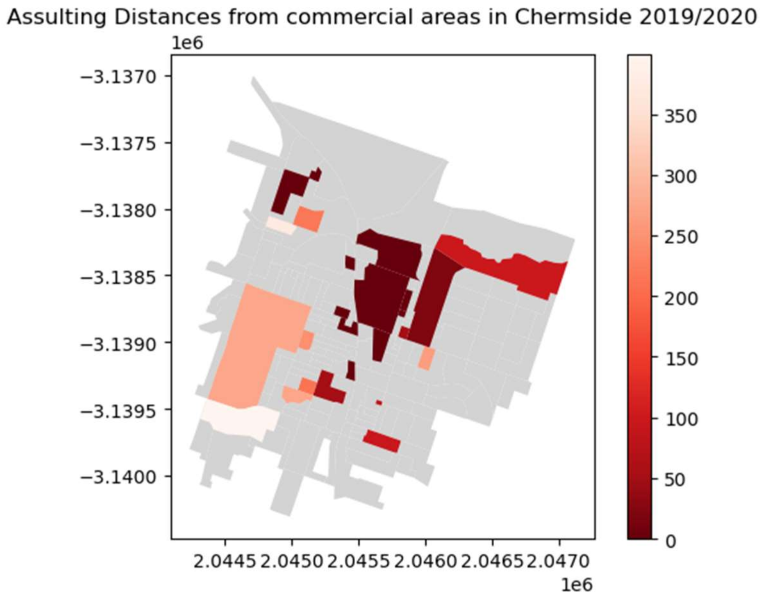

Fig. 16

Figures 15 and 16 indicate a significant increase in assaults in the last 5 years in Chermside.

Suburb: Capalaba

To investigate the distance decay relationship between Other Theft (excl. Unlawful Entry) and commercial areas I followed the same steps for another suburb, Capalaba. Figure 17 and 18 shows the similar pattern to Chermside.

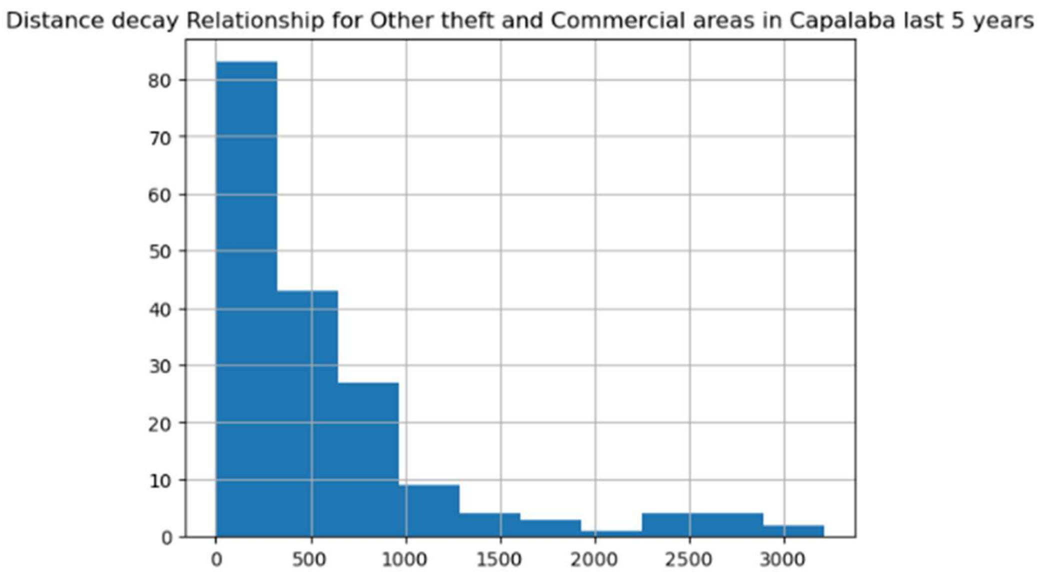

Fig. 17

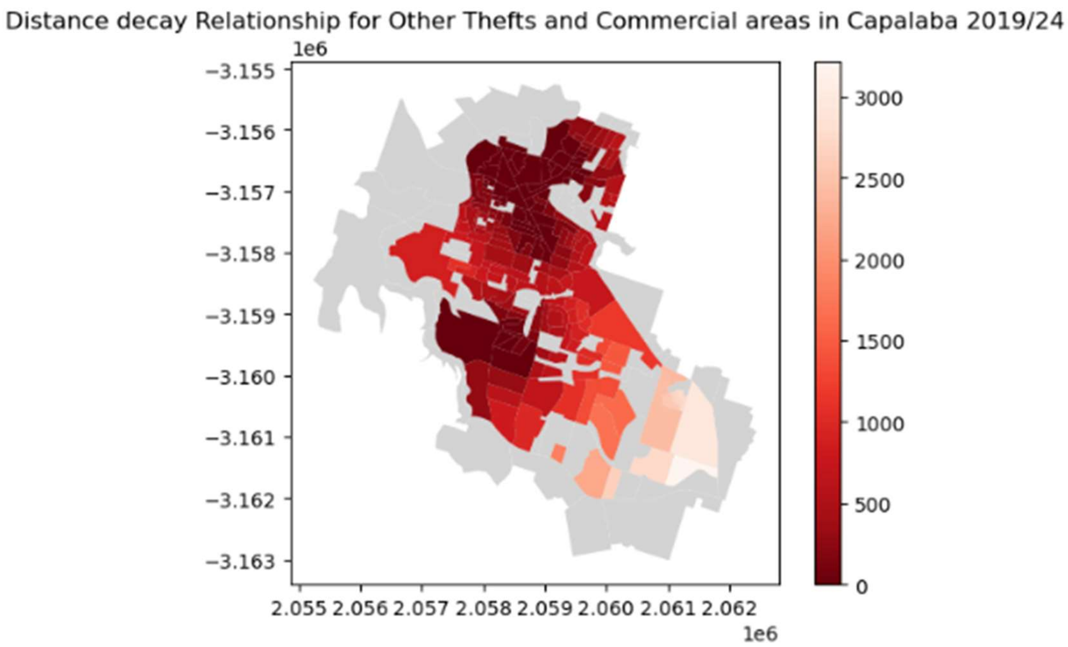

Fig.18

Discussion

Spatial analysis is an effective tool for gaining insights into location-related issues. This study demonstrates its use in examining the influence of infrastructure on crime incidents. The findings highlight that infrastructure, particularly commercial areas, significantly impacts crime patterns. Spatial analysis enables the visualization and interpretation of complex crime data, revealing that crime is not evenly distributed across a suburb. The distance decay analysis shows that most crimes occur near commercial hubs, with crime rates decreasing as the distance from key infrastructures increases. Overall, this study provides valuable insights into the relationship between infrastructure and crime incidents, offering a foundation for targeted interventions.

References

1. Esri. (n.d.). *Crime analysis and geographic information systems*. https://www.esri.com/content/dam/esrisites/sitecore-archive/Files/Pdfs/library/brochures/pdfs/crime-analysis.pdf

2. Western Australia Police Force. (n.d.). *Crime statistics*. Western Australian Government. https://www.wa.gov.au/organisation/western-australia-police-force/crime-statistics