COMP 693 Industry Project

Final Report

RESIDENTIAL SALES PRICE ANALYSIS FOR CHRISTCHURCH

(Research Project)

Submitted

By

Name: Junhua Tang
Student ID: 1161432

Host Company: Department of Land Management and Systems, Lincoln University
Name of Mentor: David Dyason

Mentor Email: David.Dyason@lincoln.ac.nz
Company Address: Ross building, Office nr. 121 PO Box 85084, Lincoln University

Date: 18/10/2025

Lincoln University

EXECUTIVE SUMMARY

Problem Addressed:

It has not been determined whether housing prices are influenced by the proximity of liquor stores. If an influence exists, it remains unclear whether it is positive or negative and where it varies spatially across different areas. The research aims to examine the impact of liquor stores on housing prices in Christchurch.

Goal:

The goal of the research is to investigate whether and how the proximity of liquor store affects housing prices in Christchurch.

Methods:

The research adopts GIS analysis to explore the impact of liquor stores on housing prices in Christchurch. Through the Moran's I and Geographic Weighted Regression (GWR) modeling, the research examines the impact of liquor stores on housing prices in spatial terms. The visualization of spatial patterns in locations and impact extent is used for a better understanding.

Outcome:

There is a strong positive spatial correlation in housing prices in Christchurch. The model owns excellent goodness of fit, independence of residual and predictive performance. The proximity of liquor store does not have significantly determined influence on the housing pricing. The liquor store impact displays a marked regional variation.

TABLE OF CONTENT

GLOSSARY/ACRONYMS

Geographically Weighted Regression (GWR): A spatial regression technique that allows model coefficients to vary across locations, capturing spatial heterogeneity in relationships between dependent and independent variables.

Variance Inflation Factor (VIF): A spatial regression technique that allows model coefficients to vary across locations, capturing spatial heterogeneity in relationships between dependent and independent variables.

Multicollinearity: A condition in which two or more independent variables in a regression model are highly correlated, making it difficult to isolate the individual effect of each variable.

Residual: The difference between the observed value and the predicted value of the dependent variable. Residuals indicate model error — ideally, they should be randomly distributed without spatial autocorrelation.

Mean Absolute Percentage Error (MAPE): A measure of prediction accuracy, expressing the average absolute difference between predicted and actual values as a percentage of actual values. Lower MAPE indicates higher prediction accuracy.

Moran's I: A spatial statistic that measures the degree of spatial autocorrelation — how similar or dissimilar values are across nearby locations.

Coefficient of Determination (R^2): A goodness-of-fit measure that represents the proportion of variance in the dependent variable explained by the model. Higher R^2indicates better model performance.

1. BACKGROUND

1.1 Overview

This project research is around the spatial analysis on the housing prices and proximity of liquor stores in Christchurch, which covers spatial correlation analysis and the influence extent of liquor stores on housing prices. The housing prices are a longstanding popular topic and there are many factors that influence them, like floor area, location, layout and so on. Liquor store is a factor familiar to the people, but rarely examined or taken into account in research. Based on the case, David Dyason, Department of Land Management and Systems, Lincoln University, initiated this research project.

This project aims to examine the influence extent of liquor store proximity on housing prices in Christchurch. If the influence is statistically significant, this research will help city planning, foster right municipal decision, provide a good reference to the evaluation of housing price and guide the investment on real estate. It also can fill the research gap in this field.

1.2 Problem

It is unclear whether the housing prices in Christchurch are spatially correlated. It's precondition of further subsequent research. If Moran's I of housing prices stands at close to 0, subsequent research will make no sense.

The impact of liquor store on the housing prices remains unknown. As a result, an appropriate model need be chosen to quantify the impact. The quantitative approach enables to give a marked indication. The appropriateness of model is measured by goodness of fit (i.e. R^2), independence of residuals, predictive performance (i.e. MAPE). In order to improve these indicators, test for multicollinearity, introduction of new variable and performance of transformation on data will possibly be employed. Otherwise, the model will be less of explanatory power.

1.3 Project Team

Junhua Tang acted as the owner of the project who was in charge of the whole research, data processing, modeling and analysis.

David Dyason acted as the academic supervisors who offered property data and guideline on research.

2. REQUIREMENTS AND GOALS

2.1 Overall Goal

Find an appropriate model to indicate the impact of liquor store proximity in quantitative terms. To realise the over goal, the following subgoals should be fulfilled:

a) All coding can run smoothly.

b) Moran's I of the housing prices is either more than 0.25 or less than -0.25.

c) R^2 is more than 0.25.

d) Residuals of the model are independent.

e) In terms of predicative performance, MAPE is less than 10%.

f) Moran's I of coefficient of the liquor store variable (i.e. the proximity of liquor store) is more than 0.5.

g) The results in the maps are consistent with the conclusions in the research.

2.2 Literature Review

The research that will be conducted aims to examine whether the housing prices in Christchurch presents a spatial heterogeneity in terms of distance to liquor stores, using TGWR (Time Geographically Weighted Regression) models or GWR (Geographically Weighted Regression). This model is employed very much widely in the literature, especially in the field of real estate prices. Cellmer et al. (2020) used GWR assess an impact of socio-economic factors on the prices and housing market activity on the national level for the area of Poland. Jeffrey et al. (2020) added a time dimension to the GWR framework and found TGWR performs better than GWR that ignores the time dimension.

Few research is conducted to explore the spatial relationship of liquor stores with housing price. Most researches that related to liquor stores are associated with crime. Michael (2015) applied FWR approach in his research about alcohol outlet density and violence, with no reference to how it influences the housing price. Heather et al. (2005) conducted spatial analysis on the relationship between alcohol outlet density and criminal violence at the small area level. In their research, the influence of alcohol outlet on the housing price is not examined either. In such case, this research into the spatial influence becomes increasingly meaningful.

3. METHODS

3.1 Overview

This project adopted a structured approach to spatial data analysis, focusing on data processing, mapping, and statistical modeling. To achieve these objectives, GIS-related libraries in Python were primarily employed throughout the workflow.

For data processing, the libraries NumPy, Pandas, and GeoPandas were used to handle and manipulate spatial and tabular datasets.

For data visualization, Matplotlib and Seaborn were applied to illustrate correlations among variables.

For mapping, Geopy and Shapely were utilized to generate and process geographic features.

For modeling, esda, libpysal, mgwr, scikit-learn, statsmodels, and SciPy were employed to implement the Geographically Weighted Regression (GWR) model.

In addition, several underlying statistical techniques supported the modeling process, including Variance Inflation Factor (VIF) analysis, correlation coefficient calculation, independence testing, and residual diagnostics.

3.2 Design

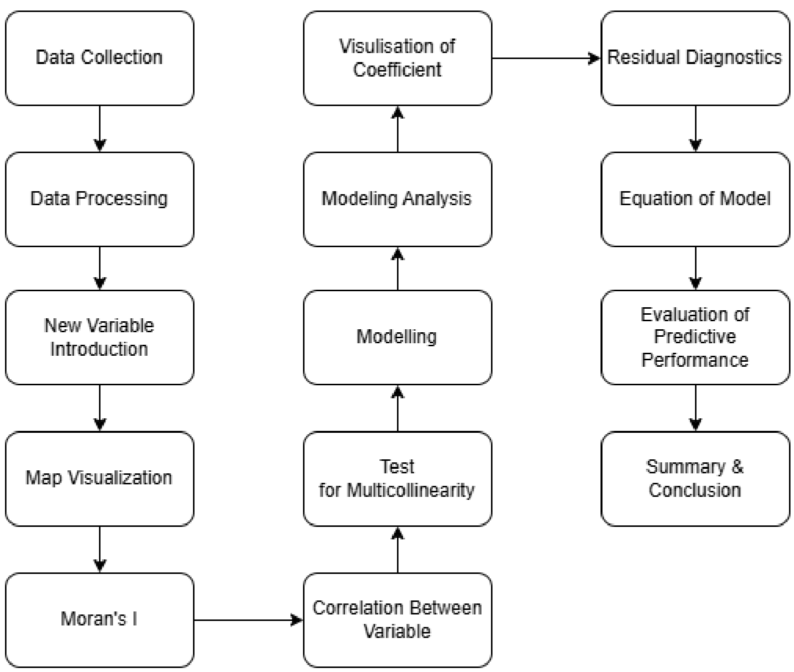


Figure 1: Diagram and Architecture of Design

Data Collection: Collected data and layers used for research, including location of sold property, selling pricing, areas, age, the layer of Christchurch.

Data Processing: Processed data by removing redundant variables, unifying format of data, renaming column names, anomaly processing, etc.

New Variables Introduction: Introduced new variables like the unit price of house per square meter, the nearest distance to liquor store for each house, the nearest distance to supermarket for each house, the distance to the center of Christchurch. Introduction of new variables enable the model to be fully interpretable.

Map Visualization: Visualized all locations of sold houses, liquor stores, supermarkets on the map of Christchurch.

Moran's I: Worked out the Moran's I of housing prices, which will serve as the precondition of further research.

Correlation Among Variables: Got a preliminary idea of correlation among variables and visualized it. The correlation coefficient matrix was employed.

Test for Multicollinearity: To avoid multicollinearity, the test for it should be performed. Variance Inflation Factor (VIF) is commonly used for the test and the variable whose VIF is more than 5 must be removed.

Modelling: Built on the selected variables, constructed the Geographically Weighted Regression (GWR) model and generated the summary report of the model.

Modelling Analysis: Evaluated key indices of model based on Coefficient of Determination (R^2), significance of coefficients.

Visualization of Coefficients: Boxplot was utilized to display the range of coefficients of variables. Coefficient of the variable related to liquor store (i.e. the nearest distance to liquor store) was also visualized on the map to demonstrate the regional variation of the liquor store impact.

Residual Diagnostics: The main purpose was to test residuals for independence, proving all information of data was extracted.

Equation of Model: Generated the math expression of the model.

Evaluation of Predictive Performance: Used MAPE to measure the predictive performance of model.

Summary & Conclusion: summarized what were achieved and drew conclusion about the impact of liquor store on the housing prices.

3.3 Risks and Challenges

What were the main risks and challenges that you had during your project? If so, how did you overcome them? What was their impact on the project?

Abnormal Data Handling

The raw dataset contained a considerable number of abnormal or inconsistent records that were not easily identifiable. For instance, some properties had a building area recorded as zero. After verification through online sources, it was found that in certain cases, the properties were sold as vacant land and therefore legitimately had no building area, only non-building area. However, in other cases, the building area and non-building area were mistakenly combined and recorded entirely under non-building area. Such abnormal records will cause a poor performance of modelling, but they required manual verification on a case-by-case basis. Ultimately, to maintain the reliability of the analysis while ensuring a sufficient sample size, unverified or untraceable data entries were removed to avoid compromising the accuracy of the study results.

Poor Model Fit of GRW

The original dataset included variables such as building area, non-building area, age, and the nearest distance to liquor store. However, these variables alone were insufficient to explain the overall sale price. This was reflected in the model's performance, as indicated by a low R^2 value and poor goodness of fit, resulting in limited explanatory power.

Additionally, the model residuals failed to pass the independence test for independence, suggesting that some underlying information in the data had not been captured. Therefore, it was necessary to introduce new variables, such as the nearest distance to supermarket, distance to cathedral, or dummy variables, and to apply logarithmic transformations to certain variables.

With the inclusion of these new variables and data transformations, the R^2 value improved significantly, and the model residuals successfully passed the independence test, indicating a better model fit and enhanced explanatory ability.

3.4 Implementation

The implementation of this project was carried out in a Python environment using Jupyter Notebook as the primary development platform. The overall process followed a reproducible workflow, integrating data preparation, spatial analysis, and model evaluation.

Data Processing: The libraries NumPy, Pandas, and GeoPandas were employed to clean, transform, and integrate spatial and tabular datasets.

Map Visualization: Matplotlib was used to produce static map visualizations of housing prices and other spatial variables.

Spatial Autocorrelation (Moran's I): The esda and libpysal packages were applied to calculate Moran's I, identifying the presence of spatial dependence in housing prices.

Correlation Among Variables: Correlation analysis was conducted using correlation coefficient matrices, visualized with Matplotlib and Seaborn to explore relationships among explanatory variables.

Test for Multicollinearity: Variance Inflation Factor (VIF) was used to detect multicollinearity. Since Python does not provide a built-in VIF function, a custom function was defined to calculate VIF values and exclude variables exceeding the threshold.

Modelling and Analysis: The mgwr package, specifically the functions mgwr.gwr and mgwr.sel, was employed to perform bandwidth selection and fit the Geographically Weighted Regression (GWR) model.

Visualization of Coefficients: Matplotlib was used to visualize coefficient distributions and spatial variations across the study area.

Residual Diagnostics: The Independency test was applied to examine residual independence and assess model adequacy.

Evaluation of Predictive Performance: The Mean Absolute Percentage Error (MAPE) was calculated to evaluate the model's predictive accuracy.

Summary and Reporting: The analytical results, figures, and interpretations were compiled into the final report, summarizing findings and drawing conclusions on the spatial impact of liquor stores on housing prices.

4. RESULTS AND OUTCOMES

4.1 Evidence of Deliverables

Data Collection

Data collected were imported successfully in Python for further processing.

Import files and data

```
[3]: roads = gpd.read_file(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\lds-nz-primary-land-parcels-SHP\nz-primary-land-parcels.shp")
liquor_store_original = gpd.read_file(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\vwLicenceDetailPoints20240924\vwLicenceDetailPoints
CHC_address = gpd.read_file(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\lds-nz-addresses-SHP\nz-addresses.shp")
property_address_original=pd.read_excel(r"D:\个人文件\Lincoln University\COMP693 Industry Project\Christchurch property sales v2.xlsx")
```

Data Processing

All data were processed and turned into analysis-ready datas.

[10]:

	date	address	geometry	building_area	nonbuilding_area	age	sale_price	nearest_dist_liquor	nearest_dist_supermarket	dist_to_cathedral	time
0	2023-10-31	92 Mustang Avenue, Wigram, Christchurch	POINT (1563239.448 5177508.159)	240	602	2.0	960000	966.20	1073.99	7845.25	10
1	2023-03-29	78 Kerrs Road, Avonside, Christchurch	POINT (1574263.834 5180981.602)	104	774	9.0	345000	1202.10	1176.15	3733.86	3
2	2023-12-06	374A Pages Road, Aranui, Christchurch	POINT (1576051.79 5181730.722)	43	0	6.0	280000	2199.24	982.50	5652.26	12
3	2023-12-23	64 Tovey Street, New Brighton, Christchurch	POINT (1578120.564 5181665.05)	91	630	9.0	758500	1064.41	1216.90	7648.86	12
4	2023-03-16	5/6 Hendon Street, Edgeware, Christchurch	POINT (1571607.246 5182195.933)	60	0	6.0	325000	495.76	964.17	2253.62	3

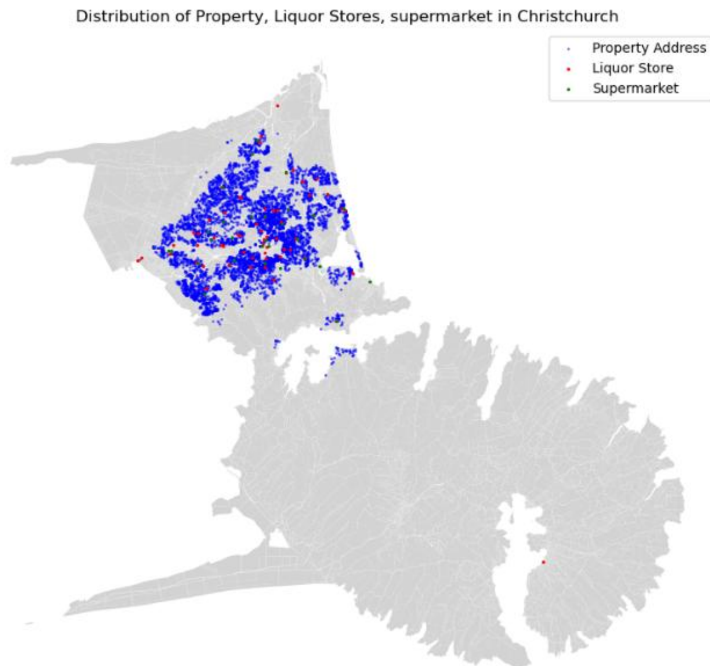
```
[11]: # [Optional] Export data
liquor_store.to_excel(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\Exported\liquor_store.xlsx")
property_address.to_excel(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\Exported\property_address.xlsx")
supermarket.to_excel(r"D:\个人文件\Lincoln University\COMP693 Industry Project\data\Exported\supermarket.xlsx")
```

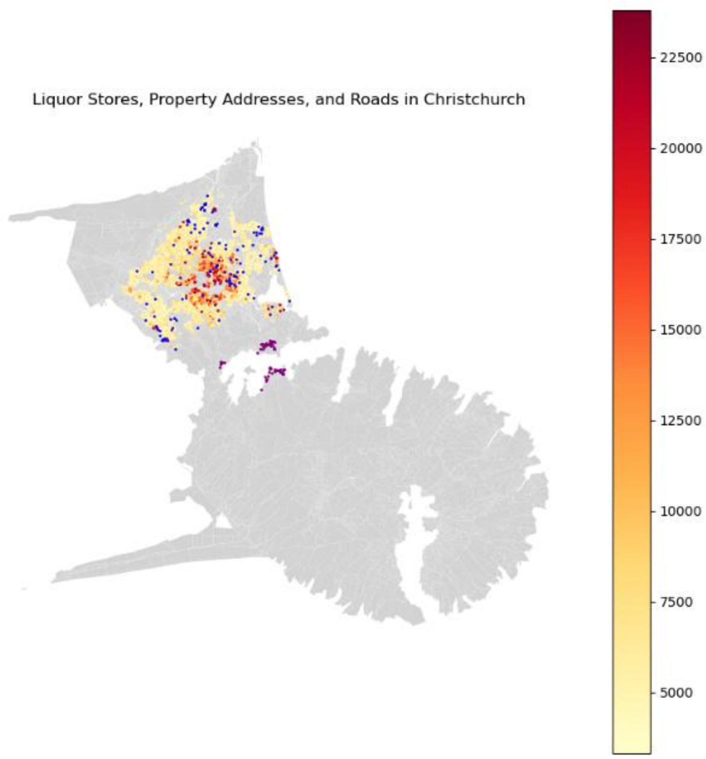
Spatial Autocorrelation (Moran's I)

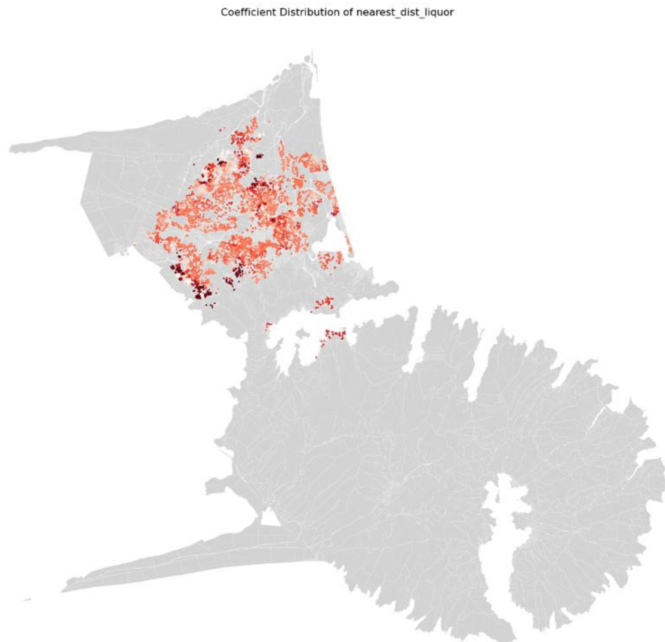
$$I = \frac{n}{W} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

```
Queen:
Moran's I: 0.4835947469845572
p-value  : 0.001

Rook:
Moran's I: 0.4835947469845572
p-value  : 0.001
```

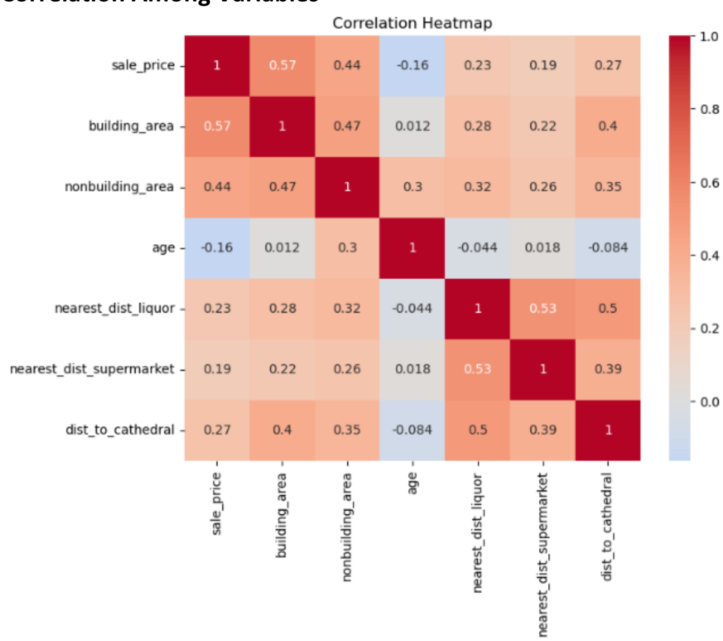
Map Visualization

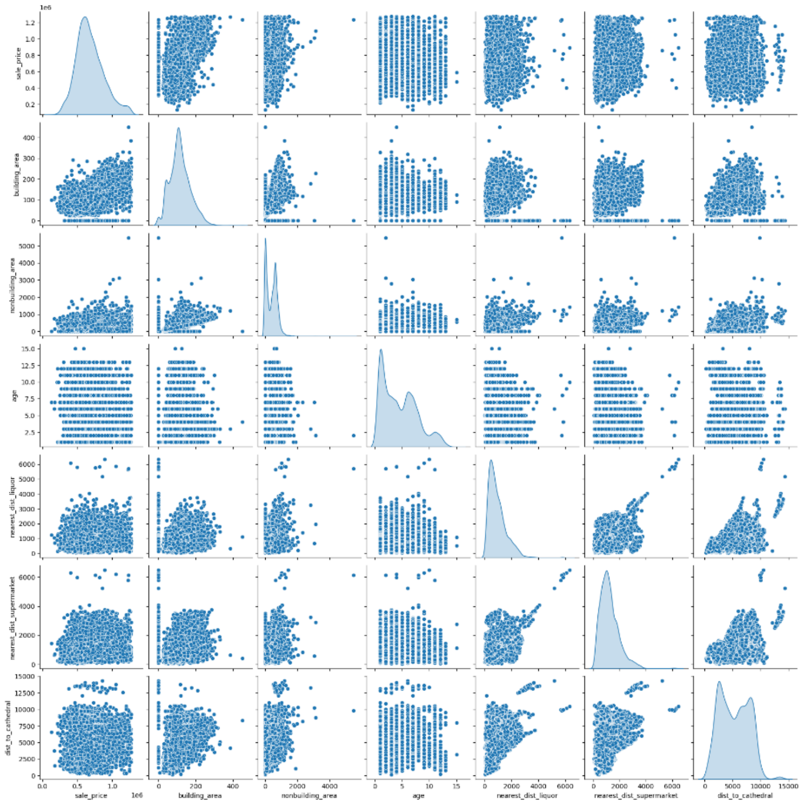

Distribution of Property, Liquor Stores, supermarket in Christchurch
Property Address
Liquor Store
Supermarket


Liquor Stores, Property Addresses, and Roads in Christchurch
22500
20000
17500
15000
12500
10000
7500
5000



Correlation Among Variables





Modelling

Models

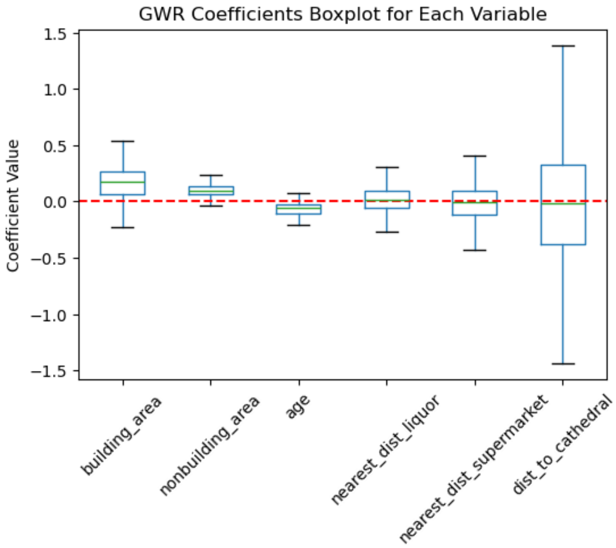
```python
display(Math(r'y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{p} \beta_k(u_i,v_i) x_{ik} + \varepsilon_i'))
display(Math(r'''
\boldsymbol{\hat{\beta}}(u_i,v_i) = (\mathbf{X}^T \mathbf{W}(u_i,v_i) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(u_i,v_i)
'''))
```

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{p} \beta_k(u_i,v_i) x_{ik} + \varepsilon_i$$

$$\boldsymbol{\hat{\beta}}(u_i,v_i) = (\mathbf{X}^T \mathbf{W}(u_i,v_i) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(u_i,v_i)$$

```python
property_address['geometry'] = property_address['geometry']
gdf_property = gpd.GeoDataFrame(property_address, geometry='geometry')
Y = gdf_property['sale_price'].values.reshape((-1, 1))
X = gdf_property[['building_area', 'nonbuilding_area', 'age', 'nearest_dist_liquor', 'nearest_dist_supermarket','dist_to_cathedral']].values
X = StandardScaler().fit_transform(X)
coords = np.array([[point.y, point.x] for point in gdf_property.geometry])

selector = Sel_BW(coords, Y, X)
bw = selector.search()

print(f'Optimal bandwidth: {bw}')

gwr_model = GWR(coords, Y, X, bw)
gwr_results = gwr_model.fit()

print(gwr_results.summary())
```

Boxplot of Coefficient



4.2 Testing/Validation

Test for Multicollinearity

```
[54]: display(Math(r'\mathrm{VIF}_j = \frac{1}{1 - R_j^2}'))
```

$$\mathrm{VIF}_j = \frac{1}{1 - R_j^2}$$

```
[19]: def calculate_vif(X):
    vif_dict = {}
    for i in range(X.shape[1]):
        y = X.iloc[:, i]
        X_other = X.drop(X.columns[i], axis=1)
        coef = np.linalg.lstsq(X_other, y, rcond=None)[0]
        y_pred = X_other.dot(coef)
        ss_res = ((y - y_pred)**2).sum()
        ss_tot = ((y - y.mean())**2).sum()
        r_squared = 1 - ss_res/ss_tot
        vif = 1 / (1 - r_squared)
        vif_dict[X.columns[i]] = vif
    return pd.DataFrame.from_dict(vif_dict, orient='index', columns=['VIF'])

data = property_address[['building_area','nonbuilding_area','age','nearest_dist_liquor','nearest_dist_supermarket','dist_to_cathedral']]

vif_result = calculate_vif(data)
print(vif_result)
```

```
                               VIF
building_area             1.052642
nonbuilding_area          1.077567
age                       1.000270
nearest_dist_liquor       1.481009
nearest_dist_supermarket  1.087638
dist_to_cathedral         0.923545
```

Test for Independence

```
[38]: w = KNN.from_dataframe(gdf_property, k=8)
w.transform = 'r'

moran = Moran(gdf_property['residuals'], w)

print(f"Moran's I: {moran.I:.4f}")
print(f"p-value: {moran.p_sim:.4f}")
```

```
D:\anaconda3\envs\gis_env\lib\site-packages\libpysal\weights\distance.py:153: UserWarning: The weights matrix is not fully connected:
 There are 7 disconnected components.
  W.__init__(self, neighbors, id_order=ids, **kwargs)
Moran's I: -0.0144
p-value: 0.0020
```

Model Equation

```
[40]: i = 110
coef = gwr_results.params[i]
variables = ['Intercept', 'building_area', 'nonbuilding_area','age', 'nearest_dist_liquor', 'nearest_dist_supermarket','dist_to_cathedral']
formula_parts = [f"{coef[j]:.3f}*{variables[j]}" if j > 0 else f"{coef[j]:.3f}" for j in range(len(coef))]
formula_str = " + ".join(formula_parts)
print(f"y = {formula_str}")
```

```
y = 14.383 + 0.055*building_area + 0.074*nonbuilding_area + -0.174*age + -0.065*nearest_dist_liquor + 0.051*nearest_dist_supermarket + -0.934*dist_to_c
athedral
```

Predictive Performance

```
[47]: display(Math(r'\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%'))
```

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

```
[44]: y_pred = gwr_results.predy.flatten()
y_true = Y.flatten()

mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100
print(f"MAPE: {mape:.2f}%")
```

```
MAPE: 0.78%
```

5. REFLECTIONS

5.1 Reflections

The overall goal and all subgoals are achieved.

a) All coding runs smoothly.
b) Moran's I of the housing prices is 0.48.
c) R^2 is 0.308.
d) Residuals of the model are independent.
e) In terms of predicative performance, MAPE is 0.78%.
f) Moran's I of coefficient of the liquor store variable (i.e. the proximity of liquor store) is 0.77.
g) The results in the maps are consistent with the conclusions in the research.

In the beginning, the model result was poor. For example, the residuals of models were not independent, which indicated that there is still some undiscovered information, i.e. new variables need be introduced. With the introduction of the new variables and log transformation performed on data, the performance of the model improved a lot.

The first learning to achieve the project goal is to manipulate data via Python libraries such as pandas and Numpy. Secondly, this project research expected me to know GIS and its approach into problems in real life. In addition, mastery of the statistics fundamentals is equally essential. Without any one of these skills, the project research cannot go. Most importantly, all of analysis and visualization of result should be realized via Python coding. Through this project, I accumulate the hands-on experience of data cleaning, processing and preparation. It also sparkles my interest in GIS using Python. I come to realize previous expertise in statistics will come in handy in spatial data analysis. The combination of GIS, programming and statistics will allow me to go far.

5.2 Conclusions

On the whole, the result of research shows that the proximity of liquor stores has no absolutely positive or negative influence on the housing price. Locally, nevertheless, the impact of liquor stores proximity takes on a strong regional variation.

Strengths

This project falls within the scope of spatial data analysis and employs GIS-related libraries in Python rather than relying on commercial ArcGIS software, which represents a significant cost saving. Moreover, it demonstrates substantial efficiency gains in data processing and modeling.

In GIS analysis, the mapping functionality allows results to be presented in a more intuitive and visually comprehensible way compared with traditional visualization methods.

The introduction of new variables and data transformations has improved the model's goodness of fit, while the residuals meet the independence assumption, resulting in better predictive performance.

Compared with the traditional Ordinary Least Squares (OLS) regression, the Geographically Weighted Regression (GWR) model takes spatial location into account, which is consistent with the study of the influence of liquor store proximity.

Limitations

Some property data were identified as outliers and consequently removed from the dataset, which may have an impact on the model results. The variable – the distance to the city centre - has a wide parameter range, which may cause certain unexplained information to be absorbed by this variable. In addition, housing prices tend to vary over time; however, due to the limited time span of the data, temporal variations could not be fully taken into account.

Suggestions for the future

It is recommended that future studies employ a larger dataset for analysis when available. At that stage, the Temporally Geographically Weighted Regression (TGWR) model could be applied to incorporate the temporal dimension. Web-scraping techniques may also help to correct anomalies in property data, thereby improving the model's accuracy. Furthermore, additional variables could be considered, such as the distribution of educational resources, accessibility of transportation, and the availability of green spaces.

If I were to start this project again, I would begin by learning more GIS analytical methods and applying a wider range of GIS techniques to investigate the research problem. In addition, I would aim to acquire web-scraping skills to extract authentic property data from official websites in order to correct data anomalies.

6. REFERENCES

Cellmer, R., Cichulska, A., & Belej, M. (2020). Spatial analysis of housing prices and market activity with the geographically weighted regression. *ISPRS International Journal of Geo-Information 9(6)*, 380. https://doi.org/10.3390/ijgi9060380

Bonny P. M. (2022) Python for geospatial data analysis. *O'Reilly Media, Inc.*

Datawhale, & GYH. (2020, December 7). Joyful Pandas (Release 1.0) Onlinetextbook. https://github.com/datawhalechina/team-learning-data-mining/tree/master/joyful-pandas

Kenett, R. S., Zacks, S., & Gedeck, P. (2022). Modern statistics: A computer-based approach with Python. *Birkhäuser*. https://doi.org/10.1007/978-3-031-07566-7

Hongtai, H., Lu, X., Cherry, C., Liu, X., & Li, Y. (2017). Spatial variations in active mode trip volume at intersections: A local analysis utilizing geographically weighted regression. *Journal of Transport Geography*, 64, 184–194. https://doi.org/10.1016/j.jtrangeo.2017.09.007

Bao, J., Shi, X., & Zhang, H. (2018). Spatial analysis of bikeshare ridership with smart card and POI data using geographically weighted regression method. *IEEE Access*, 6, 76049–76059. https://doi.org/10.1109/ACCESS.2018.2883462

Sirajum, M., & Sener, I. N. (2020). A geographically weighted regression model to examine the spatial variation of the socioeconomic and land-use factors associated with Strava bike activity in Austin, Texas. *Journal of Transport Geography*, 88, 102865. https://doi.org/10.1016/j.jtrangeo.2020.102865

Wei, Z., Zhen, F., Mo, H., & others. (2021). Travel behaviours of sharing bicycles in the central urban area based on geographically weighted regression: The case of Guangzhou, China. *Chinese Geographical Science*, 31, 54–69. https://doi.org/10.1007/s11769-020-1159-3

Cohen, J. P., Coughlin, C. C., & Zabel, J. (2020). Time-geographically weighted regressions and residential property value assessment. *The Journal of Real Estate Finance and Economics*, 60, 134–154. https://doi.org/10.1007/s11146-019-09708-3

Cameron, M. P., Cochrane, W., Gordon, C., & Livingston, M. (2015). Alcohol outlet density and violence: A geographically weighted regression approach. *Drug and Alcohol Review*, 34(4), 437–445. https://doi.org/10.1111/dar.12295

Britt, H. R., Carlin, B. P., Toomey, T. L., & Wagenaar, A. C. (2005). Neighborhood level spatial analysis of the relationship between alcohol outlet density and criminal violence. *Environmental and Ecological Statistics*, 12, 411–426. https://doi.org/10.1007/s10651-005-1290-0

7. APPENDICES

Put all supplementary Materials that you need to show but not necessary to be in the main report in Appendices here. If you have more than one Appendix, label them as Appendix A, Appendix B etc. (Note: In the text where you want the reader to refer to Appendices, specify where and what to look for, for example, Figure A1, Table A1 in Appendix A etc.)