gwpcorMapper: an interactive mapping tool for exploring geographically weighted correlation and partial correlation in high-dimensional geospatial datasets.

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Abstract: Exploratory spatial data analysis (ESDA) plays a key role in research that includes geographic data. In ESDA, analysts often want to be able to visualize observations and local relationships on a map. However, software dedicated to visualizing local spatial relations between multiple variables in high dimensional datasets remains undeveloped. This paper introduces gwpcorMapper, a newly developed software application for mapping geographically weighted correlation and partial correlation in large multivariate datasets. gwpcorMapper facilitates ESDA by giving researchers the ability to interact with map components that describe local correlative relationships. We built gwpcorMapper using the R Shiny framework. The software inherits its core algorithm from GWpcor, an R library for calculating the geographically weighted correlation and partial correlation statistics. We demonstrate the application of gwpcorMapper by using it to explore census data in order to find meaningful relationships that describe the work-life environment in the 23 special wards of Tokyo, Japan. We show that gwpcorMapper is useful in both variable selection and parameter tuning for geographically weighted statistics. gwpcorMapper highlights that there are strong statistically clear local variations in the relationship between the number of commuters and the total number of hours worked when considering the total population in each district across the 23 special wards of Tokyo. Our application demonstrates that the ESDA process with high-dimensional geospatial data using gwpcorMapper has applications across multiple fields.

Keywords: spatial statistics; exploratory spatial data analysis; visualization; software.

1. Introduction

Exploratory spatial data analysis (ESDA) is the process of investigation in order to detect meaningful characteristics in geospatial data [1-3]. It is a direct extension of exploratory data analysis (EDA) in that it incorporates explicit methods and procedures that take the spatial context of geographic data into consideration [4-6]. In ESDA, analysts investigate spatial patterns, associations, and processes in univariate and
multivariate data using dynamic and interactive visualization tools [7-10] in order to potentially discover previously unknown associations and form hypotheses [11, 12]. The general procedure by which ESDA occurs consists of steps of collecting and selecting data according to the target topic, exploring spatial properties of data by analytical methods through an iterative process of changing variables and parameter values, and visualizing data using dynamic and interactive graphics in a Geographic Information System (GIS) [5, 6].

While the concept and the general procedure behind ESDA has changed relatively little since the late 1990s, many attributes of geospatial datasets have. In particular, the size and frequency at which geospatial data are now commonly made available have increased dramatically [13, 14]. The immense volume, strong variety, and rapid velocity at which these data are now made available make many geospatial datasets a challenge to navigate and can make analysis cumbersome and difficult to comprehend [15]. Meaningful relationships are easily hidden or can be difficult to disentangle when there are massive amounts of data with high variety. Therefore, although ESDA has experienced a long and steady history in GIS applications [6], the recent rapid surge of data is now placing a higher demand on software applications to handle large multivariate spatial datasets in ESDA [16].

Central to ESDA is examining if the data exhibit evidence of underlying spatial processes, such as spatial dependence or spatial heterogeneity. Spatial dependence has long been a major focus in ESDA [17]. Spatial dependence, often quantified by spatial autocorrelation, characterizes how data themselves may depend on both the location and the relative geographic distance to other observations of the data [18, 19]. In contrast to this, spatial heterogeneity has received far less attention in the context of ESDA [20]. Spatial heterogeneity describes the variability of observations over space and can therefore highlight spatially varying relationships [21]. Summarizing data with descriptive statistics that encompass the entirety of the dataset without any special accommodation for locality, such as a global mean or standard deviation, can be an initial step of ESDA but such simple global analyses can lead to too much descriptive data loss with geospatial data as they fail completely in detecting any level of spatial heterogeneity [20]. For this reason, localized spatial analysis provides a better means to inspect characteristics of data and to explore spatial heterogeneity.

Geographically Weighted (GW) models are a suite of localized statistical methods that have been developed for observing and handling spatial heterogeneity in data and operate by applying a distance-decay weighted moving window [22, 23]. Popular GW statistical methods include GW summary statistics (including mean, variance, and correlation) [24, 25], GW regression (GWR) [26, 27], and GW principal components analysis (GWPCA) [28, 29]. While feature-rich tools exist for either ESDA or big geospatial data analysis; for example, ESDA with geoDa [17], big data analytics with ESRI [30], or big data visualization with kepler.gl [31], these remain limited in that they fail to encompass local ESDA with high-dimensional geospatial datasets in a manner that explicitly considers spatial heterogeneity across any number of variables. Additionally, although there are powerful software to generate GW statistics [22, 23], an applicable tool complete with an interactive graphical user interface for ESDA with GW models remains less developed.
Of the many GW statistical methods, GW correlation [22-25] and GW partial correlation [32] stand out in terms of identifying local relationships in geospatial data. These methods are very effective in understanding local correlative relationships in multivariate datasets with underlying spatial heterogeneity. These local correlation analyses let analysts pay attention to local characteristics of the dataset and determine variable selection for more sophisticated successive analyses, such as GWPCA or GWR. For example, as GWR is sensitive to local collinearity between explanatory variables (see [33]), GW correlation and partial correlation can be used to not only find interesting spatial relationships of variables for the analysis, but also to highlight any local collinearity before implementing a GWR [26]. Given that GW correlation and partial correlation operate under a moving window kernel, parameters that control both the size and the shape of the moving window are crucial. Parameter selection and tuning is recognized as an important yet difficult aspect of implementing GW models, where it is often recommended to select parameters values based on data interpretation [25, 34, 35]. Including tools to aid in parameter selection during the exploratory process in GW analyses will be beneficial to any successive works that focus on other GW models, such as scalable GWR which supports large spatial datasets in GWR analysis [36].

Three parameters standout in terms of importance in GW correlative analyses: bandwidth size, kernel type, and correlation methods. The former two parameters describe the degree of neighborhood effects, while the latter defines the correlation according to the data type used for the analysis. Bandwidth size controls for the effects of spatial scale on the analysis while kernel type defines the weighting scheme employed. GW models as described by [22, 23] may have bandwidths that are either adaptive, i.e., they include some user-defined number of nearest neighbors in the analysis, or ones that are fixed, i.e., they include only variables that fall within some user-defined geographic distance. Results are very sensitive to bandwidth and differences in results across the full range of bandwidths can be very large. Exploring bandwidth size is critically important to understand the level of spatial heterogeneity in bivariate or multivariate relationships in data. The degree of spatial heterogeneity across various bandwidth sizes is also highly sensitive to the choice of bivariate and multivariate combinations and thus it is worthwhile for analysts to be able to investigate the spatial surface of correlative relationships across a full range bandwidths in an exploratory fashion. The method by which correlative analyses should be made is selected according to data type. These include parametric methods like Pearson’s correlation coefficient, which measures the linear relationship between variables, and non-parametric methods like Spearman’s or Kendall’s rank correlation coefficient, which describe monotonic relationships. Analysts may also employ partial correlation in order to discern the relationship between two variables while considering the effects of others. In partial correlation, the degree of association between a bivariate pair is measured while explicitly controlling for the effects that changes in other variables have on the relationship. In this context, as parameter settings depend on analysts’ choices, an interactive mapping tool for ESDA that can aid in parameter selection through the exploratory process is sorely needed.

This paper introduces gwpcorMapper: an exploratory interactive mapping tool of geographically weighted correlation and partial correlation statistics. It allows for ESDA using GW correlation and GW partial correlation analyses by enabling users to interactively select covariates and change bandwidth sizes, kernel types,
and correlation methods. It complements existing tools by making GW correlation and GW partial correlation analyses simpler and supports the exploratory process by giving users the ability to investigate multiple variable and parameter choices in an interactive manner. gwpcorMapper allows for easy inspection of spatial heterogeneity at various spatial scales to find relationships that are grounded in reality. We explain the usefulness of this tool and demonstrate its use with census statistics of the 23 special wards in Tokyo, Japan for the year 2005. This data consists of 228 variables (which translates to 1,949,476 combinations for 3 variables alone) that describe the urban social structure of Tokyo within the 3134 chocho-aza (the smallest administrative unit in Japan) of the 23 special wards. We investigated the data using gwpcorMapper to find meaningful covariates and parameter values of bandwidth and kernel type. We then used these results to focus on local characteristics of urban social structure to discuss the working and living environment in Tokyo in the context of the compact city paradigm, a popular urban planning concept that emphasizes high residential population density in cities with highly diversified land use [37, 38]. The diverse and tightly packed structure of compact cities encourage lower commuting times and supports both walking and more efficient public transportation systems making them often seen as a strong contributor to sustainability within cities. Our application demonstrates that the ESDA process with high-dimensional geospatial data using gwpcorMapper can have important and relevant applications in several fields, particularly in urban planning.

2. Materials and Methods

gwpcorMapper is a web application that is built with R using the Shiny framework [39, 40]. R is one of the most popular and actively used software environments for geospatial statistical analysis and R shiny provides the means for turning R programs into interactive web applications. We build gwpcorMapper from the extensive geospatial statistical libraries that R offers as open source on popular repositories like GitHub and CRAN.

The core algorithm behind gwpcorMapper is GWpcor [32]. GWpcor is hosted on CRAN and is an extension of the GW summary statistics function, gwss(), found in the popular R library GWmodel [22, 23], and it provides GW correlation and GW partial correlation analyses with a statistical t-test to test whether the correlation is observed with statistical clarity. Like GW correlation in the GWmodel library, GW partial correlation calculates the weighted partial correlation between two variables while holding one or more variables constant under a moving kernel. Both Pearson's and Spearman’s correlation types for either GW correlation or GW partial correlation is available in GWpcor. GWpcor also includes a statistical t-test and will return the p-values of correlation and partial correlation coefficients.

The calculations for both GW correlation and GW partial correlation begin by calculating the geographically weighted co-variance matrix (\( \Sigma \)) at each data point \( i \), whose location can be described by coordinates \((u_i, v_i)\).

Given a numeric matrix \( P \) of \( n \) rows by \( m \) variables such that \( m_a \) and \( m_b \) represents the \( a^{th} \) and \( b^{th} \) columns of \( P \) and each row represent the observations of each variable, we calculate the GW co-variance matrix as it is described by [29]:
\[ \Sigma(u_i, v_i) = P^T W(u_i, v_i) P \]

where \( P \) is the data matrix containing the variables of interest and \( W(u_i, v_i) \) is the diagonal matrix of geographic weights across each location \((u_i, v_i)\) that is created using one of the five kernel functions displayed in Figure 2. Following this, either the GW correlation coefficients or the GW partial correlation coefficients are calculated. Defining \( M \) as the set of \( m \) variables in \( P \), the GW correlation coefficient at any location \((u_i, v_i)\) between two variables \((m_a, m_b)\) of \( M \) as described in [23] is given by:

\[ \rho_{m_a m_b}(u_i, v_i) = \frac{\Sigma_{m_A m_B}(u_i, v_i)}{s_{m_A}(u_i, v_i)s_{m_B}(u_i, v_i)} \]

where \( \Sigma_{m_a m_b}(u_i, v_i) \) is the element of GW co-variance matrix between variables \( m_a \) and \( m_b \) at the location \((u_i, v_i)\) and both \( s_{m_a} \) and \( s_{m_b} \) are the GW standard deviations of variable \( m_a \) and \( m_b \), respectively whose calculations follow [18]. Then, following [32], the GW partial correlation coefficients at any location \((u_i, v_i)\) between two variables \((m_a, m_b)\) of the set \( M \), given all others in the set is given by:

\[ \rho_{m_a m_b \setminus (m_a, m_b)}(u_i, v_i) = \frac{C_{m_a m_b}}{\sqrt{C_{m_a m_b} C_{m_b m_b}}} \]

where \( C \) is the inverted positive definite GW co-variance matrix between two variables \((m_a, m_b)\): \( C = (\Sigma(u_i, v_i))^{-1} \), and \( C_{m_a m_b} \) is the element between variables \( m_a \) and \( m_b \). In the case that \( \Sigma(u_i, v_i) \) is not positive definite and therefore not invertible, the pseudo-inverse is calculated and applied using the Moore-Penrose inverse [41, 42]. Finally, to find either Spearman’s GW correlation coefficient or GW partial correlation coefficient, the variables of interest are ranked prior to the calculation of the GW covariance matrix (see [23] for details). GW partial correlation and GW correlation coefficients of \textit{GWpcor} can be mapped to observe spatial heterogeneity in the relationship between two or more variables in spatial data. In summary, \textit{GWpcor} provides the core R code for calculating GW correlation and GW partial correlation statistics, and \textit{gwpcorMapper} provides the graphical user interface for accessing its functions interactively. \textit{gwpcorMapper} is able to read several popular geospatial file types, including geopackage, geojson, and ESRI shapefiles, as input and accepts several input fields as parameters (Table 1, Figures 1 and 2). The \textit{gwpcorMapper} interface consists of three panels: (I) the data panel, (II) the map panel, and (III) the scatter plot panel (Figure 1). The data panel contains the controls for loading data and setting parameters (input), while the map and scatter plot panels display the resultant correlation coefficients on both a map and a scatter plot respectively (output).
Figure 1. The gwpcorMapper UI: a multi-panel user interface highlighting its core features: (I) parameter selection, (II) map, and (III) scatter plots. Input features are labelled with letters (a-l) for cross reference with Table 1.

| Input Field        | Description                                                                 | Label |
|--------------------|-----------------------------------------------------------------------------|-------|
| Load Data          | Upload component that allows users to select data files for analysis.       | a     |
| Type               | Radio selectors for GW Model. Users can choose between GW correlation and GW partial Correlation. | b     |
| Correlation Type   | Radio selectors for the correlation method to be employed. Users can choose between Pearson and Spearman. | c     |
| Correlation Pair 1 | Searchable drop-down field to select first variable for analysis.           | d     |
| Correlation Pair 2 | Searchable drop-down field to select second variable for analysis.          | e     |
| Control Variables  | Searchable drop-down field to select any number of control variables for analysis. | f     |
| Kernel Type        | Drop-down field to select kernel type for analysis. Available kernel types are described in Figure 2. | g     |
| Adaptive Kernel Size | Bandwidth selector for kernel size in GW analysis. Only adaptive kernels are currently supported. | h     |

Table 1. gwpcorMapper input fields, their descriptions, and cross-reference label to Figure 1.
Map Results: Button to trigger analysis and to map the results.

Map Opacity: Opacity control of results layer on map.

p-value Mask: Buttons to trigger masking statistical t-test using p-values at the 0.01 or 0.05 thresholds.

Variable Selector: Drop-down field to select which variable pair to plot in partial correlation analysis.

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**Figure 2.** Kernel functions available in gwpcorMapper: (a) Gaussian, (b) Exponential, (c) Box-Car, (d) Bi-Square, and (e) Tri-Cube. Spatial weights are defined by each respective kernel whose functions are given in Table 2.

**Table 2.** Kernel functions used in gwpcorMapper to calculate the diagonal matrix of geographic weights, $W$. $\omega_{ij}$ is geographic weight at the $j^{th}$ element in $W$ that is calculated for the $i^{th}$ observation in the data matrix, $P$. $d_{ij}$ is the Euclidean distance between the $j^{th}$ observation point from $i$ and $b$ is the effective bandwidth.

| Name        | Equation                                                                 |
|-------------|--------------------------------------------------------------------------|
| Gaussian    | $\omega_{ij} = \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{b}\right)^2\right)$ |
| Exponential | $\omega_{ij} = \exp\left(-\frac{|d_{ij}|}{b}\right)$                    |
| Box-Car     | $\omega_{ij} = \begin{cases} 1 & \text{if } |d_{ij}| < b \\ 0 & \text{otherwise} \end{cases}$ |
| Bi-Square   | $\omega_{ij} = \begin{cases} 1 - \left(\frac{d_{ij}}{b}\right)^2 & \text{if } |d_{ij}| < b \\ 0 & \text{otherwise} \end{cases}$ |
The national census data of the 23 special wards in Tokyo, Japan, (Figure 3) for 2005 at chocho-aza level that is used as a case study for gwpcorMapper consists of basic demographic data including total population broken down by age, gender, employment status, and other basic socio-economic indicators. We use gwpcorMapper to study the urban social structure of the 23 special wards in Tokyo by selecting various covariates and mapping both GW correlation and GW partial correlation with various parameter settings. This allows us to explore the data in order to find meaningful relationships that describe the work-life environment in Tokyo, and then discuss our findings with respect to the compact city concept.

Figure 3. The 23 special wards of Tokyo. Ward boundaries are outlined in solid black while each chocho-aza boundary is displayed with white lines.
We demonstrate an example of ESDA through the following case study. Our first step in ESDA with `gwpcorMapper` is variable selection. As our interest is to know the work-life environment, we selected the following variables to describe the exploratory process with `gwpcorMapper` in this paper: 1. The “total number of commuters between wards” (herein referred to as “commuters”), 2. The “total number of households” (herein referred to as “households”), 3. The “day-night population ratio”, 4. The “average area per person” (herein referred to as “area per person”), 5. The “total working hours in a week of employment” (“working hours”), 6. The “day time population”, and 7. The “total population”. Many other variables can be selected but we limit 7 variables only in this paper to demonstrate the ESDA procedure with `gwpcorMapper` simply. After variable selection, we then observe any spatial heterogeneity in the correlative relationships between these variables by first observing the GW correlation between bivariate pairs and then GW partial correlation. Following this, we demonstrate how we can examine statistical significance of these relationships by examining p-values on resulting maps. Finally, we pick out the relationship between `commuters` and `working hours` while controlling for `total population` to observe how the spatial patterns of the relationship copes under varying bandwidths and kernel functions. Such may inform successive studies by urban planning experts on how compact cities, with diversified urban social structure, can influence working hours and the need to commute further distances to work.

3. Results and Discussion

Examination of the seven selected census data variables reveals that there are a total of 21 bivariate pairs alone for analysis at each of the 3134 administrative regions. The ability to search and select variables from drop-down menus and have the results of GW correlation and partial correlation mapped on the fly enabled us to quickly see how certain variables may have more pronounced spatial variation than others. Figure 4 displays 6 of the 21 resulting maps of the GW correlative relationships with `gwpcorMapper`. These demonstrate a range of spatial patterns in the relationship between each pair; from the seemingly strong spatially homogenous correlation between both `commuters` and `households` (Figure 4.a) and `commuters` with `working hours` (Figure 4.f), to the weak negative spatially heterogenous relationship between both `commuters` and `day-night population ratio` (Figure 4.b) and `working hours` and `day-night population ratio` (Figure 4.d), and to the spatially heterogenous relationship between `commuters` and `area per person` (Figure 4.c) and `day-time population` with `commuters` (Figure 4.e).
Figure 4. Map panel output showing geographically weighted correlation between: a. the total number of commuters between wards and the total number of households, b. the total number of commuters between wards and the day-night population ratio, c. the total number of commuters between wards and the average area per person, d. the total working hours in a week of employment and the day-night population ratio, e. the day time population and the total number of commuters between wards, and f. the total number of commuters between wards and the total working hours in a week of employment.

In order to demonstrate the functionality of gwpcorMapper to explore the effects that changes in additional variables may have on the correlation between any two variables, we map GW partial correlation between each of the variable pairs mapped in Figure 4 while controlling for total population. Figure 5 displays how using GW partial correlation to control for a third (or more) variable can drastically change the spatial patterns between each relationship. Notably, we can see that strong patterns emerge between both commuters and households (Figure 5.a), and commuters and working hours (Figure 5.f) while controlling for total population. In Figure 5.a we can see that there is a tendency for districts in wards that are highly residential, like Nerima, Itabashi, and Adachi, to display a strong positive correlation between households and commuters, while highly commercial areas like Minato, Chuo, and Chiyoda display a strong negative correlation. Interestingly, we see less of a pronounced relationship between commuters and day-night population ratio (Figure 5.b), commuters and area per person (Figure 5.c), working hours and day-night population ratio (Figure 5.d), and day-time population and commuters (Figure 5.e) once we control for the effects that changes in total population may have on each relationship across the 23 special wards.
Figure 5. Map panel output showing geographically weighted partial correlation between: a. the total number of commuters between wards and the total number of households, b. the total number of commuters between wards and the day-night population ratio, c. the total number of commuters between wards and the average area per person, d. the total working hours in a week of employment and the day-night population ratio, e. day time population and the total number of commuters between wards, f. the total number of commuters between wards and the total working hours in a week of employment, while controlling for total population.

The weakening and levelling out of the correlations displayed in Figures 5.b through 5.e that is apparent once we control for total population suggest that these pairs may not lead to any further particular interesting analyses. Displaying these correlations while masking statistically insignificant administrative districts (with statistical significance being defined where p-value ≤ 0.01) provide further evidence to suggest these decisions. In Figure 6, we can see that the relationships between commuters and households (Figure 6.a) and commuters and working hours (Figure 6.f), while controlling for total population, display reasonably clear relationships.
Figure 6. Map panel output showing statistical insignificance masking using p-values for the geographically weighted partial correlation between: a. the total number of commuters between wards and the total number of households, b. the total number of commuters between wards and the day-night population ratio, c. the total number of commuters between wards and the average area per person, d. the total working hours in a week of employment and the day-night population ratio, e. daytime population and the total number of commuters between wards, f. the total number of commuters between wards and the total working hours in a week of employment, while controlling for total population. Statistical significance is defined where p-values are ≤ 0.01.

Figures 4, 5, and 6 all displayed either GW correlation or GW partial correlation using Pearson’s correlation statistic with a constant adaptive bandwidth of 0.25 and a Bi-Square kernel function. However, further examination of the maps under varying bandwidth sizes and kernel types reveals differences in the magnitude and direction of the correlation coefficient and their resulting spatial patterns. Focusing on the relationship between commuters and working hours while controlling for total population and keeping the application of a Bi-Square kernel enables us to see how changing the size of the bandwidth can exaggerate the scale of spatial heterogeneity. Very large bandwidths lead to significantly reduced spatial variation with correlation coefficients levelling to moderate and positive values. Smaller bandwidths reveal that there are areas where the correlation statistics are widely different across localities. Using an adaptive bandwidth of 10% of the data, we can see in Figure 7.a that there are some areas that display a strongly positive relationship between commuters and working hours (for example, in the Minato, Koto, Toshima, and Suginami wards), some that only display a weakly positive one (for example the Chiyoda and Meguro wards), and some that even display...
a negative correlation between commuters and working hours (for example, the Ota ward). Larger band-
widths (an adaptive bandwidth of 50% of the data) even out the local events and most localities display a
uniform weak-to-moderate positive correlation with more gradual spatial variation. We still see the strong
positive relation in Suginami and Minato, however there are no longer any patches of strong correlation in
Chiyoda, Shibuya, or Sumida. We also no longer see the weaker correlations in Edogawa and Itabashi. There
are consistent patterns within certain areas like Koto but not in others, like Chuo. Using `gwpcorMapper` to
explore the data, we find that setting a small scale at 10% of data (about 300 chocho-aza under the kernel)
highlights interesting spatial variation to display a clear varying relationship between commuters and work-
ing hours (Figure 7).

![Figure 7](image_url)

**Figure 7.** Resulting maps of GW partial correlation coefficients between commuters and working hours while controlling for
total population using a Bi-Square kernel and apply varying adaptive bandwidth sizes (in terms of proportions of the total
data): (a) 0.1, (b) 0.25, (c) 0.5, (d) 0.75, (e) 1.0.

Finally, we can observe the effects of the weighting scheme that is applied to the data by varying the kernel
function (Figure 8). Up until this point, we have been using a Bi-Square kernel to apply spatial weights to
the data. However, there are four other kernel functions available in `gwpcorMapper`. Resultant maps by
Gaussian and Exponential kernel functions which apply weights to all observations display gradual spatial
variations of the correlative relationship while maps made using Box-Car, Bi-Square, and Tri-Cube kernel
functions, which apply weights to only observations that fall within the bandwidth size, display distinct
localized variations of the relationship. These local patterns describe interesting features of the data and suggest that any of the piece-wise kernel functions may be more appropriate for this data. To date, there has been little research that focuses on the selection procedure of kernel functions. Research that focuses on the selection process and influence of the different kernel functions may be an area for further study and we believe that *gwpcorMapper* may aid in such future research.

![Figure 8](image)

**Figure 8.** Resulting maps of GW partial correlation coefficients between commuters and working hours while controlling for total population using a constant (proportional) bandwidth size of 0.1 while applying varying kernel types: (a) Gaussian, (b) Exponential, (c) Bi-Square, (d) Box-Car, and (e) Tri-Cube.

With *gwpcorMapper*, we were able to uncover meaningful spatial relationships between a subset of variables describing the urban social structure of Tokyo. Particularly, we discovered that there is a clear relation between the commuting working population and the total number of hours worked and that this relationship varied across each *chocho-aza* in the 23 special wards of Tokyo when accounting for the differences in the total population. The magnitude of this relationship depended on locality and the visualizations that *gwpcorMapper* provided helped inform decisions about parameter settings, including bandwidth. This leads to the question: does the need to commute lead to longer working hours? Answering this question may support recent work that suggests that worker sleep problems within city may be related to longer commuting times [43]. Our results from ESDA suggest that either having to commute further distances may encourage longer working hours, or that jobs with longer working hours are concentrated in the city center where many
workers need to commute to. If working hours can be reduced by removing the need to commute far, then workers can spend more time doing other things. If commuting is correlated with longer working hours, then on top of losing time during commute, people have even less time to perform social functions due to their longer working hours.

4. Conclusions

gwpcorMapper offers a way to perform exploratory spatial data analysis using geographically weighted correlation and partial correlation analyses on high-dimensional geospatial datasets. This tool may aid analysts in discovering which covariates might be interesting for successive investigations, such as scalable GWR, as well as to help determine parameter values, such as bandwidth size or kernel type. Beyond providing the visual tools to subjectively select parameters, gwpcorMapper offers geospatial analysts a simple interactive approach to explore GW correlations and GW partial correlation on a map. It allows users to quickly determine and visualize any spatial heterogeneity that may exist in the data and is supportive of the idea that big geospatial data analysis should be investigation driven with theoretical underpinnings [16]. The interactive features of gwpcorMapper enable users to achieve quick visualization of localized correlative relationships amongst multivariate data which can be selected and changed easily from searchable drop-down lists. It is applicable to many popular geospatial data formats and it is not limited to census data analysis in the urban planning domain as shown in our case study.

Given that gwpcorMapper is built with R, it is easily extendable to include other GW statistical methods that exist in R’s extensive geospatial libraries, such as GWmodel. gwpcorMapper may act as a steppingstone for additional dedicated visualization software for GW statistics. Another interesting area for further development may be to introduce a “recommendation tool” that operates by analyzing the correlation coefficients between bivariate pairs and parameter combinations of selected variables and then gives suggestions for which pairs and parameter combinations may prove interesting for finer tuned visual inspections. Such an extension may be used to dramatically reduce the number of pairs that are necessary for analysis and can be addressed in future development work.

gwpcorMapper is built to run in a web-browser and thus is lightweight and can be easily run on any operating system. gwpcorMapper is open source and can be found on GitHub at https://github.com/naru-T/gwpcormapper. It can also be launched from docker, and the latest docker image can be found at https://hub.docker.com/r/iosefa/gwpcormapper.

Author Contributions: NT conceived the original idea behind gwpcorMapper and both JEHP and NT developed the software with JEHP being the main contributor. JEHP prepared the initial draft of the manuscript and produced the visualizations. All authors contributed to the writing of the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Joint Support Center for Data Science Research at Research Organization of Information and Systems (ROIS-DS-JOINT) under Grant 006RP2018, 004RP2019, and 003RP2020.
Data Availability Statement: In The geographic data used in the case study of this paper can be found at https://github.com/naru-T/gwpcormapper/tree/master/data.

Acknowledgments: TBA.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References
1. Fotheringham, A. Exploratory Spatial Data Analysis and GIS. Environment and Planning A 1992, 12, 1675–1678.
2. Unwin, A.; Unwin, D. Exploratory Spatial Data Analysis with Local Statistics. J Royal Statistical Soc Ser D Statistician 1998, 47, 415–421.
3. Haining, R.; Wise, S.; Ma, J. Exploratory Spatial Data Analysis. J Royal Statistical Soc Ser D Statistician 1998, 47, 457–469, doi:10.1111/1467-9884.00147.
4. Tukey, J. Exploratory data analysis; Addison-Wesley Publishing Company, 1977; Vol. 2; ISBN 9780201076165.
5. Dall’erba, S. Exploratory Spatial Data Analysis. In International Encyclopedia of Human Geography; Kitchin, R., Thrift, N., Eds.; Elsevier: Oxford, 2009; pp. 683–690 ISBN 9780080449104.
6. Bivand, R. S. Exploratory Spatial Data Analysis. In Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications; Fisher, M., Getis, A., Eds.; Springer: Heidelberg, 2010; pp. 219–254 ISBN 9783642036460.
7. Brunsdon, C. Exploratory spatial data analysis and local indicators of spatial association with XLISP-STAT. J Royal Statistical Soc Ser D Statistician 1998, 47, 471–484, doi:10.1111/1467-9884.00148.
8. Dykes, J. Cartographic Visualization. J Royal Statistical Soc Ser D Statistician 1998, 47, 485–497, doi:10.1111/1467-9884.00149.
9. Dykes, J.; Brunsdon, C. Geographically Weighted Visualization: Interactive Graphics for Scale-Varying Exploratory Analysis. Ieee T Vis Comput Gr 2007, 13, 1161–1168, doi:10.1109/tvcg.2007.70558.
10. Anselin, L. The Future of Spatial Analysis in the Social Sciences. Ann Gis 1999, 5, 67–76, doi:10.1080/10824009909480516.
11. Anselin, L. Interactive techniques and exploratory spatial data analysis. In Geographical Information Systems: Principles, Techniques, Management and Applications. 2nd Edition. Longley, P. A., Goodchild, M. F., Maguire, D. J., Rhind, D. W., Eds.; Wiley: London, 2005; pp. 253–266 ISBN 978-0-471-73545-8.
12. Andrienko, N.; Andrienko, G. Exploratory Analysis of Spatial and Temporal Data, A Systematic Approach. 2006, doi:10.1007/3-540-31190-4.
13. Coetzee, S.; Ivánová, I.; Mitasova, H.; Brovelli, M.A. Open Geospatial Software and Data: A Review of the Current State and A Perspective into the Future. Isprs Int Geo-inf 2020, 9, 90, doi:10.3390/ijgi9020090.
14. Mobasher, A.; Mitasova, H.; Neteler, M.; Singleton, A.; Ledoux, H.; Brovelli, M.A. Highlighting recent trends in open source geospatial science and software. T Gis 2020, 24, 1141–1146, doi:10.1111/tgis.12703.
15. Lee, J.-G.; Kang, M. Geospatial Big Data: Challenges and Opportunities. Big Data Res 2015, 2, 74–81, doi:10.1016/j.bdr.2015.01.003.
16. Harris, R.; O’Sullivan, D.; Gahegan, M.; Charlton, M.; Comber, L.; Longley, P.; Brunsdon, C.; Malleson, N.; Heppenstall, A.; Singleton, A.; et al. More bark than bytes? Reflections on 21+ years of geocomputation. Environ Plan B Urban Anal City Sci 2017, 44, 598–617, doi:10.1177/2399808317710132.
17. Anselin, L.; Syabri, I.; Kho, Y. GeoDa: An Introduction to Spatial Data Analysis. Geogr Anal 2006, 38, 5–22, doi:10.1111/j.0016-7363.2005.00671.x.
18. Cliff, A.D.; Ord, J.K. Spatial Autocorrelation; Monographs in spatial and environmental systems analysis; 1973; ISBN 0850860369.
19. Anselin, L. Spatial Econometrics: Methods and Models. *Stud Oper R* **1988**, doi:10.1007/978-94-015-7799-1.

20. Lee, S.-I. Neighborhood Effects. In *International Encyclopedia of Human Geography*; Kitchin, R., Thrift, N., Eds.; Elsevier: Oxford, 2009; pp. 349–353 ISBN 9780080449104.

21. Goodchild, M.F. The Validity and Usefulness of Laws in Geographic Information Science and Geography. *Ann Assoc Am Geogr* **2004**, *94*, 300–303, doi:10.1111/j.1467-8306.2004.09402008.x.

22. Lu, B.; Harris, P.; Charlton, M.; Brunsdon, C. The GWmodel R package: further topics for exploring spatial heterogeneity using geographically weighted models. Geo-spatial Information Sci **2014**, *17*, 85–101, doi:10.1080/10095020.2014.917453.

23. Gollini, I.; Lu, B.; Charlton, M.; Brunsdon, C.; Harris, P. GWmodel: An R Package for Exploring Spatial Heterogeneity Using Geographically Weighted Models. Journal of Statistical Software **2015**, 63.

24. Brunsdon, C.; Fotheringham, A.S.; Charlton, M. Geographically weighted summary statistics — a framework for localised exploratory data analysis. *Comput Environ Urban Syst* **2002**, *26*, 501–524, doi:10.1016/s0198-9715(01)00009-6.

25. Harris, P.; Brunsdon, C. Exploring spatial variation and spatial relationships in a freshwater acidification critical load data set for Great Britain using geographically weighted summary statistics. *Comput Geosci* **2010**, *36*, 54–70, doi:10.1016/j.cageo.2009.04.012.

26. Brunsdon, C.; Fotheringham, A.S.; Charlton, M.E. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geogr Anal* **1996**, *28*, 281–298, doi:10.1111/j.1538-4632.1996.tb00936.x.

27. Fotheringham, A.S.; Charlton, M.; Brunsdon, C. Recent Developments in Spatial Analysis, Spatial Statistics, Behavioural Modelling, and Computational Intelligence. *Adv Spat Sci* **1997**, 60–82, doi:10.1007/978-3-662-03499-6_4.

28. Lloyd, C.D. Analysing population characteristics using geographically weighted principal components analysis: A case study of Northern Ireland in 2001. *Comput Environ Urban Syst* **2010**, *34*, 389–399, doi:10.1016/j.compenvurbis.2010.02.005.

29. Harris, P.; Brunsdon, C.; Charlton, M. Geographically weighted principal components analysis. *Int J Geogr Inf Sci* **2011**, *25*, 1717–1736, doi:10.1080/13658816.2011.554838.

30. ESRI. Spatial Analysis and Data Science: Big Data Analytics. Available online: https://www.esri.com/en-us/arcgis/products/spatial-analytics-data-science/capabilities/real-time-big-data-analytics (accessed on 4 December 2020).

31. kepler.gl. Available online: https://kepler.gl/ (accessed on 4 December 2020).

32. Percival, J.; Tsutsumida, N. Geographically Weighted Partial Correlation for Spatial Analysis. Gi_forum 2017, 1, 36–43, doi:10.1553/gisience2017_01_s36.

33. Wheeler, D.C. Diagnostic Tools and a Remedial Method for Collinearity in Geographically Weighted Regression. *Environ Plann A* **2005**, *39*, 2464–2481, doi:10.1068/a38325.

34. Fotheringham, S.A.; Brunsdon, C.; Charlton, M. *Geographically Weighted Regression—The Analysis of Spatially Varying Relationships*; John Wiley & Sons, 2003;

35. Tsutsumida, N.; Rodriguez-Veiga, P.; Harris, P.; Balzter, H.; Comber, A. Investigating spatial error structures in continuous raster data. *Int J Appl Earth Obs* **2019**, *74*, 259–268, doi:10.1016/j.jag.2018.09.020.

36. Murakami, D.; Tsutsumida, N.; Yoshida, T.; Nakaya, T.; Lu, B. Scalable GWR: A Linear-Time Algorithm for Large-Scale Geographically Weighted Regression with Polynomial Kernels. *Ann Am Assoc Geogr* **2020**, *1–22*, doi:10.1080/24694452.2020.1774350.

37. Dantzig, G.; Saaty, T.L. *Compact City: a Plan for a Livable Urban Environment*; W. H. Freeman, 1973; ISBN 0716707942.

38. Bibri, S.E.; Krogstie, J.; Kärrholm, M. Compact City Planning and Development: Emerging Practices and Strategies for Achieving the Goals of Sustainable Development. *Dev Built Environ* **2020**, *4*, 100021, doi:10.1016/j.dibe.2020.100021.

39. R Core Team R. A Language and Environment for Statistical Computing; R Foundation for Statistical Computing: Vienna, Austria, 2020; Available online: https://www.r-project.org/ (accessed on 4 December 2020).
40. Chang, W.; Cheng, J.; Allaire, JJ.; Xie, Y.; McPherson, J. Shiny: Web Application Framework for R; R package version 1.5.0; 2020; Available online: https://CRAN.R-project.org/package=shiny (accessed on 4 December 2020).

41. Penrose, R. A generalized inverse for matrices. *Math Proc Cambridge* 1955, 51, 406–413, doi:10.1017/s0305004100030401.

42. Schafer, J.; Opgen-Rhein, R.; Zuber, V.; Ahdesmaki, M.; Silva, A. P. D.; Strimmer, K. corpcor: Efficient Estimation of Covariance and (Partial) Correlation; R package version 1.6.9; 2017; Available online: https://CRAN.R-project.org/package=corpcor (accessed on 4 December 2020).

43. Kim, S.; Kim, Y.; Lim, S.-S.; Ryoo, J.-H.; Yoon, J.-H. Long Commute Time and Sleep Problems with Gender Difference in Work–Life Balance: A Cross-sectional Study of More than 25,000 Workers. *Saf Heal Work* 2019, 10, 470–475, doi:10.1016/j.shaw.2019.08.001.