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EXPLORING THE SPATIAL VARIATION OF THE EFFECT OF COVID-19 ON PROPERTY MARKET ACTIVITY IN KAMPALA DISTRICT

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Abstract

The real estate sector in Uganda has been substantially impacted by the onset of COVID-19 in this country. Studies conducted worldwide have indicated that, pandemics affect property market activities differently. Additionally, the effect of pandemics on property market activity varies from one place to another. Studies conducted in Uganda, however, have not captured how the effect of COVID-19 on property market activities varies from one place to another. This study therefore explored the spatial variability of the effect of COVID-19 on property market activities in Kampala district, Uganda. The study took advantage of the spatial statistical analytical models advocated by GIS (Getis-Ord Gi, OLS, GWPR) and a unique dataset of property transactions registered by the Ministry of Lands, Housing and Urban Development (MLHUD) during the outbreak of the deadly disease. Whereas the study observed high volumes of property transactions registered in the residential outskirts of the city, low volumes were observed in the Central Business District (CBD) and the low-income areas of the eastern and western parts of the district. On the other hand, the local model approach of GWPR exposed the substantial effects of COVID-19 on property market activities that varied from -39% to 10%. It was further established that COVID-19 generated negative effects in areas with low and high prices of land per acre, to the extent of increasing as the prices dropped or increased. On the contrary, a positive effect was realized in the residential outskirts of the city where prices of land per acre were moderate. Work from home, land parcel size as well as the composition of the population, proved to be the main drivers of the changes in property market transactions (activity). The findings of the study underpin the earlier postulations of various researchers that pandemics affect property market activity. However, the effects of the pandemics vary from one pandemic to another and from one place to another.*

Key words: *Property Market Activity; COVID-19; Spatial statistical analytical models (OLS, Getis-Ord Gi*, GWPR)*

1. Background

The outbreak of COVID-19 in Wuhan, China, in the late 2019 (UNDP-Uganda, 2020), and the eventual declaration by the World Health Organization (WHO) of it as a global pandemic on 11 March 2020 (WHO, 2020) stretched the global economy to unprecedented levels. Prior to its declaration as a global pandemic, COVID-19 had infected 118,326 people with 4,292 deaths across 113 countries (WHO, 2020). The number of COVID-19 cases and deaths increased exponentially, and more than tripled within just a month from its declaration as a global pandemic (WHO, 2020). In order to control and mitigate its rapid spread, countries, including Uganda, introduced a number of restrictions, which included, amongst others, the mandatory observance of the Standard Operating Procedures (SOPs), restrictions on the movement of both cargo and people, stay-at-home regulations, business closures, social distancing, and partial and total lockdowns, all of which were implemented in phases (Del Giudice, De Paola and Del Giudice, 2020). The implementation of these unique mitigation strategies, however, affected different sectors of the economy including the real estate sector. To this, was added an increase in the level of unemployment (Bennett *et al.*, 2020; Del Giudice, De Paola and Del Giudice, 2020) and loss of income. As a consequence, people were not in a position to maintain their loan and mortgage repayments (Daily Monitor, 2021). At this point in time, the relationship between the real estate sector and the spread of COVID-19 was becoming quite well-defined.

Evidence from past pandemics indicates that property market activities are greatly impacted by the occurrence of pandemics (Koen, Tatiana and Okmyung, 2018; Tanrıvermiş, 2020; Yoruk, 2020; Francke and Korevaar, 2021; Yang and Zhou, 2021). For example, while investigating how property markets react to extreme events, Wong (2008) used a unique panel data set of the weekly transaction prices of 44 properties and the spread of SARS in Hong Kong. The results of the study indicated that property transactions were reduced by 1-3% in those areas that were moderately affected, and by 1.6% in other areas. Francke and Korevaar (2021) used micro-level transaction data to examine the effect of the plague in the 17th-century Amsterdam and cholera in the19th-century on property market activities. The results of the study indicated that property market volumes were reduced by 25% in Amsterdam. However, the effect of these pandemic outbreaks was not permanent. In contrast, while investigating the effect of a cholera epidemic in the 19th-century London on housing prices, Ambrus, Field and Gonzalez, (2016) supported that property prices remained significantly lower in the epidemic-stricken areas of London as compared to the unaffected areas of the city. However, the results of the study stood in opposition to the fact that the effects of these epidemics were transitory. The study showed that the effects persisted for almost a decade after the occurrence of the epidemic. In comparison, and on a broader scale, prior studies on pandemics and natural disasters suggest that the effects of pandemics on property market activities vary from one pandemic to another and from one place to another. This withstanding, the spatial variation of the effect of COVID-19 on property market activities in Kampala has not been quantified.

In this study, the spatial variation of the effects of COVID-19 on property market activities in Kampala-Uganda is explored, with particular focus being on COVID-19 cases registered during the first wave of the outbreak of the deadly disease between 21 March 2020 and 27 March 2021, and property transactions registered by the Ministry of Lands, Housing and Urban Development (MLHUD) during the same period. The study combined geocoded property transactions with COVID-19 cases per parish, leveraging Geographically Weighted Poisson Regression (GWPR) models to estimate the relationship between the rising COVID-19 cases and the property transactions. Unlike the findings of previous studies, such as those of Attakora-Amaniampong, Ebenezer and Dacosta, (2016), Bos, Li and Sanders, (2018), Koen, Tatiana and Okmyung, (2018), Del Giudice, De Paola and Del Giudice, (2020), and Francke and Korevaar, (2021), this study adopted GWPR models. As opposed to previous studies, that applied simple comparisons, hedonic regression, and spatial error and spatial lag models to hide local differences and also highlight contrasts in the relationships across the study area, this study detected how relationships between property market activities and their multi-dimensional determinants vary from one place to another.

The aim of this study is, therefore, to explore the spatial variability of the effect of COVID-19 on property market activity in Kampala by using the Geographically Weighted Poisson Regression (GWPR) models. Generally, the GWPR model allows for the local parameter estimates and coefficients to be modelled and visualized on a map. This is possible because the GWPR model combines the geo-visualization power of GIS to generate an output. The research contributes to the existing literature and to the body of knowledge, and in turn offers useful insights to property developers, policy-makers, financial institutions and other key players in the property market arena as to the front-runners to and laggards subsequent to the occurrence of COVID-19 within the Kampala district.

2. Study area and Methods

2.1. Study area

Data for this study were collected from the 95 parishes (administrative boundaries) of Kampala, the capital city of Uganda, and its Central Business District (CBD) which are geographically located at 0°19′N and 32°35′E. According to Uganda Bureau of Statistics (UBOS), Kampala has a night population of about 1.5 million people, while the day population is established at 4 million people. With a population growth of 5.2%, the highest in Africa, Kampala's population is projected to amount to 10 million people by 2040 (UBOS, 2017). Consequently, the Greater Kampala Metropolitan Area (GKMA) has been earmarked in the Country's Vision 2040 as an economic and administrative hub and a major investment destination for Uganda, in that it accommodates 10% of the country's population and contributes almost 60% to the GDP. Like other cities around the world, Kampala was equally hit by the outbreak of the deadly COVID-19 pandemic. The outbreak of COVID-19 in Kampala has seen the rates of infection increasing exponentially from the first case registered on 21

March, 2020 and to date, Kampala accounts for almost 50% of Uganda's COVID-19 cases (MOH, 2021). The study area is further illustrated by Figure 1.

2.2. Methods

2.2.1. Data

The data used in this study is divided into two parts, namely, spatial and non-spatial datasets. The spatial dataset comprising of the vector map of Kampala District (at a parish scale) was downloaded from the UBOS database. The non-spatial data on the other hand consists of statistical figures on COVID-19 cases, property transactions, and the socio economic and demographic factors collected from the Ministry of Health (MOH), Ministry of Lands, Housing and Urban Development (MLHUD), and UBOS respectively.

2.2.2. Covid-19 cases

COVID-19 data included COVID-19 positive cases obtained from the MOH database. Each record consisted of date of collection, district of collection, testing center (sample collection point name), nationality, transmission type, age group and sex/gender of the applicant. Modelling was subsequently conducted using COVID-19 positive cases accumulated in Kampala district over a period of one year from 17 March 2020 to 27 March 2021 for a total of 40,766 occurrences. The locations of the positive COVID-19 cases were tagged on the testing centers, which were randomly distributed across the district and which tested the people closest to them. An excerpt of COVID-19 positive cases is attached in Appendix I.

2.2.3. Property transactions

Property market activity in the study was examined in the form of volumes or number of transactions in the form of transfers, property subdivisions, and mortgages registered with MLUHD. Transaction data for the period running from 17 March 2020 to 27 March 2021 with sufficient information about land parcel size, date of registration, average value, as well as the location of the land parcel were obtained from MLHUD and used during the analysis. The advantage of this source is that it gives sufficient information about the property and its location (parish). An excerpt of the property market transactions registered is attached in Appendix I.

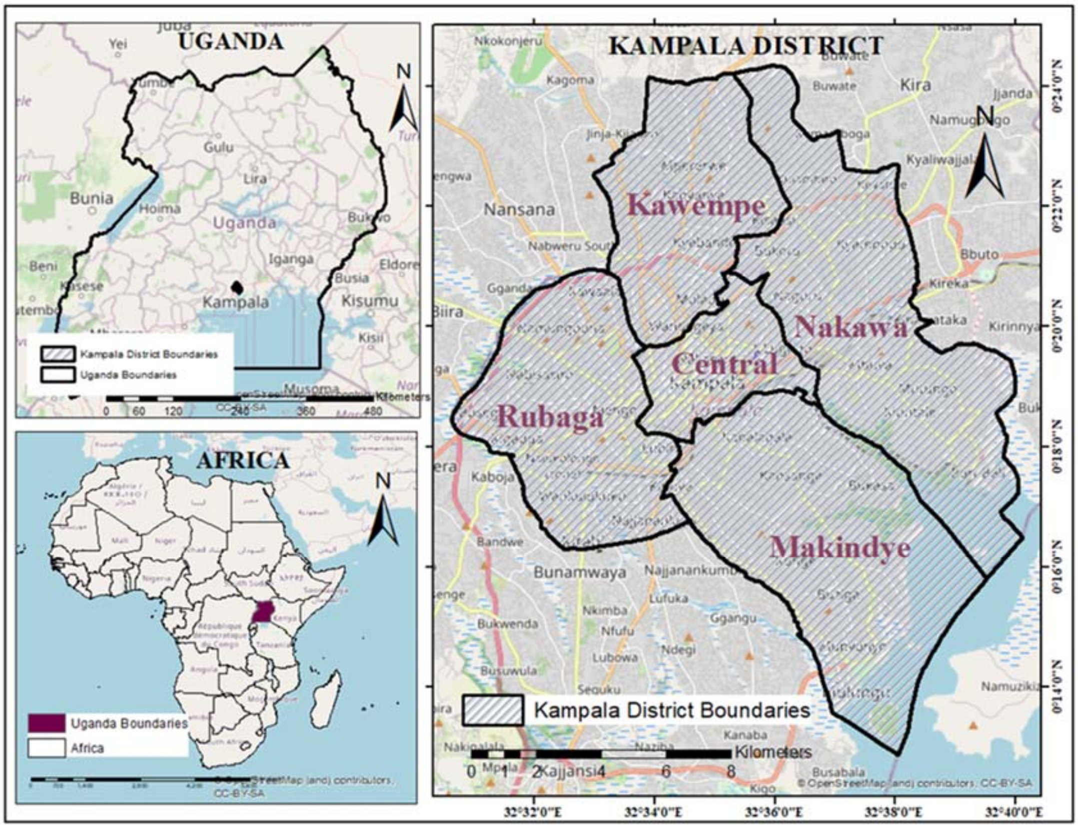


Figure 1: Kampala District

2.2.4. *Methodological workflow*

To quantify the effect of COVID-19 on property market activities, the study adopted a quantitative study approach. The study workflow followed the Organization for Economic Co-operation and Development (OECD) guidelines (OECD, 2008) and included five (5) major components, namely, 1) Data collection (primary and secondary data) where primary data involved taking coordinates of COVID-19 sample collection points whereas secondary data involved the mining of existing data from government departments such as MLHUD, UBOS, and MOH; 2) Data preparation; 3) Spatial data distribution and hotspot analysis; 4) Modelling the relationship between property market activities and COVID-19 cases, and 5) Determining the effect of COVID-19 on property market activity. The methodological workflow design is presented in Figure 2.

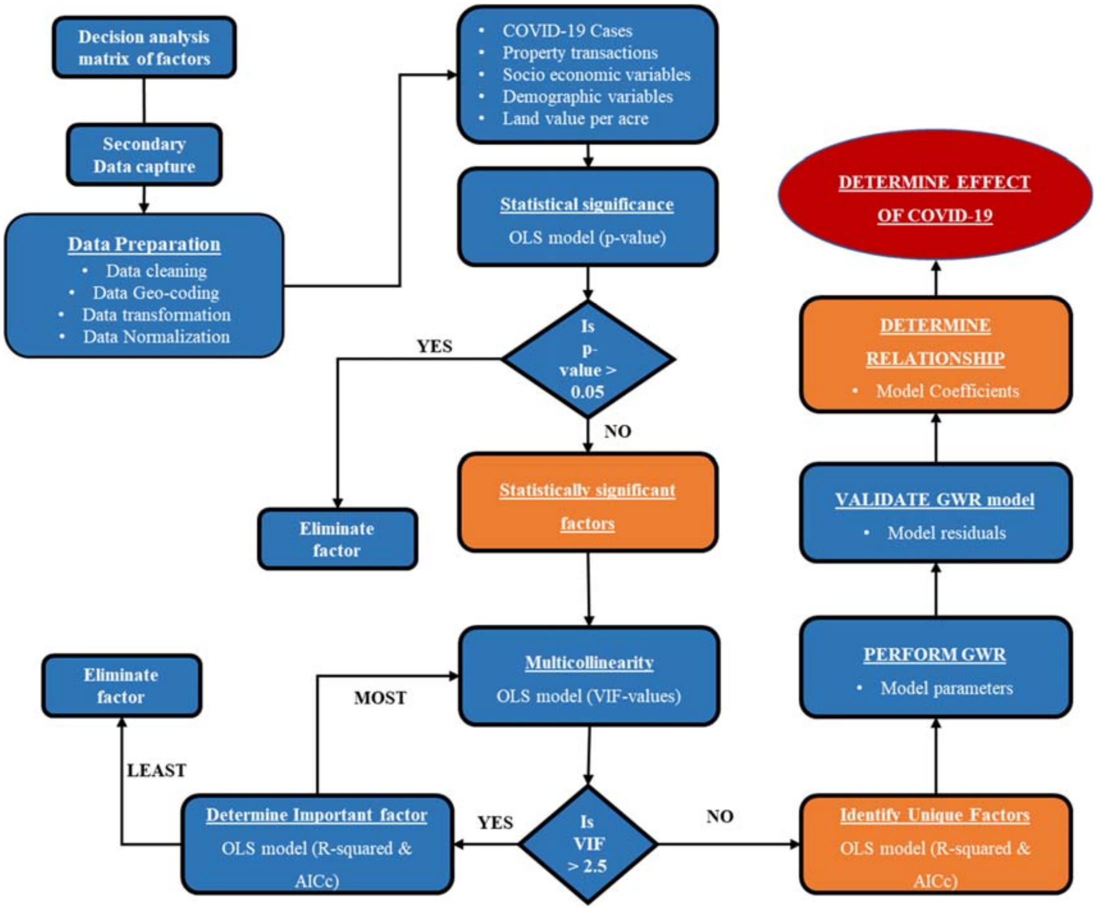


Figure 2: Detailed methodological workflow and study design

2.2.5. Data collection

Depending on the availability of the data at the required spatial scale, a number of factors influencing property market activities were defined through a review of the literature, and selected for the study. Tables 1 and 2 highlight the factors reviewed from the literature and selected on the basis of selection criteria in respect of data availability at the required spatial scale for the study respectively. Secondary data were captured for the study and involved the mining of existing data sources, such as MLHUD, MOH, and UBOS. On the other hand, the coordinates of the locations of the respective COVID-19 testing centers (sample collection points) were obtained using a web scraping algorithm that returns coordinates from the search result pages of Google Maps.

Table 1: Review of factors influencing property market activities from the literature

SN.	Factor	Author (s)	Unit
1.	Population density	Cellmer et al. (2020); Pashardes & Savva (2009)	persons/Km^2
2.	Percentage of the working population (18 – 65 years of age)	Cellmer et al. (2020); Pashardes & Savva (2009)	%
3.	Level of unemployment	Cellmer et al. (2020); Radonjić et al. (2019)	%
4.	Percentage of male population (gender/sex)	Gu (2018); Joseph (2019); wan Rodi et al. (2013)	%
5.	Level of education of the population (literacy rate)	Joseph (2019); Pashardes & Savva (2009)	%
6.	Percentage of the population with access to health services	Ge & Du (2007); Koen et al. (2018); Limsombunchai (2004)	%
7.	Percentage of the population with access to schools	Ge & Du (2007); Koen et al. (2018); Limsombunchai (2004)	%
8.	Percentage of the population with access to piped water	Ge & Du (2007); Koen et al. (2018); Limsombunchai (2004)	%
9.	Average value of land per acre	Cellmer et al. (2020); Pashardes & Savva (2009); San Ong (2013); XU et al. (2017)	shillings
10.	Average property size	Cellmer et al. (2020); Koen et al. (2018)	m^2
11.	Average monthly income	(Francke & Korevaar, 2021; Ge & Du, 2007)	shillings
12.	GDP	(Pashardes & Savva, 2009; San Ong, 2013)	%
13.	Inflation rates	(Ge & Du, 2007; Gu, 2018)	%
14.	Mortgage availability	(Cellmer et al., 2020)	%
15.	Loan interest rates	(Ge & Du, 2007; Grybauskas et al., 2021; Koen et al., 2018)	%
16.	Migration index	(Cheshire et al., 2021)	ratio
17.	Emission of particulate pollutants	(Francke & Korevaar, 2021; San Ong, 2013)	mm
18.	Government policies and legislations (tax exemptions)	(Cheshire et al., 2021; Wan Rodi et al., 2013)	varies

2.2.6. Data preparation

Before analysis could be conducted, COVID-19 positive cases and property transactions were "cleaned" by eliminating duplicate records and those with missing fields. In addition, data pertaining to COVID-19 cases and property transactions were re-projected and transformed to realize a uniform coordinate system.

2.2.7. Data normalization

The different variables selected for the study had different measurement scales, and as such, normalization was carried out to render them comparable before analysis could be conducted. A number of normalization techniques proved to be possible. The dependent variable was log transformed to achieve a normal distribution of property transactions, whereas, the min-max method was adopted in the case of the independent variables in order to preserve the relationships within the data, (OECD, 2008). The factors were consequently assigned an identical range from 0 – 1. Under the min-max normalization method, each factor I_q^t for a generic country c and time t, is transformed by;

$$\mathbf{I_{qc}^t} = \frac{\mathbf{X_{qc}^t} - \mathbf{min_c}(\mathbf{X_q^t})}{\mathbf{max_c}(\mathbf{X_q^t}) - \mathbf{min_c}(\mathbf{X_q^t})}$$

where $min_c(X_q^t)$ and $max_c(X_q^t)$ are the minimum and maximum values of X_{qc}^t across all countries c at time t. In this way, the normalized factors I_{qc} have values lying between 0 (laggard, $X_{qc}^t = min_c(X_q^t)$), 1 (leader, $X_{qc}^t = max_c(X_q^t)$).

Table 2: Variables selected for the study

SN.	Factors (Variables)	Data availability	Availability of proxy data	Spatial scale	Decision
1.	Population density	Yes		Yes	Yes
2.	Land value per acre	Yes		Yes	Yes
3.	Unemployment rates	Yes		Yes	Yes
4.	Gender composition	Yes		Yes	Yes
5.	Average property size	Yes		Yes	Yes
6.	Working population	Yes		Yes	Yes
7.	Literacy levels	Yes		Yes	Yes
8.	Access to social amenities (health care)	Yes		Yes	Yes
9.	Access to social amenities (water)	Yes		Yes	Yes
10.	Access to social amenities (schools)	Yes		Yes	Yes

2.2.8. Spatial data distribution and hotspot analysis

To understand the spatial pattern of distribution of both property transactions and COVID-19 cases, an initial classification of data was conducted. COVID-19 cases and property transactions data in this study were classified using the natural breaks method, which is based on the Jenks Natural Breaks algorithm (Nkeki and Osirike, 2013). The Jenks Natural Breaks algorithm method produced class breaks that identified the best group of similar values and maximized the differences between the classes of the registered COVID-19 cases and property transactions. Based on this classification method, COVID-19 cases and property transactions were divided into classes, the boundaries of which were set in cases where there were relatively large differences.

Finally, a Getis–Ord Gi* statistical model was used to model the spatial diffusion of COVID-19 cases and property transactions in Kampala. The application of this model was based on the number of COVID-19 cases and property transactions in each parish and on the number of testing centers (sample collection centers) in Kampala District (Murad and Khashoggi, 2020). The hotspot analysis tool was used to calculate the Getis–Ord Gi* statistic for each parish in the district. The resultant z-scores and p-values determined the location of parishes with either high or low values which were then clustered spatially. In the case of statistically significant positive z-scores, the larger the z-score, the more intense the clustering of the high values (hot spots). For statistically significant negative z-scores, the lower the z-score, the more intense the clustering of the low values (cold spots) (Murad and Khashoggi, 2020).

2.2.9. Modelling the relationship between property market activities and COVID-19 cases

In this study, the Ordinally Least Squares (OLS) and Geographically Weighted Poisson Regression (GWPR) statistical analytical models were employed to model the respective spatial relationships between property transactions and COVID-19 cases. The OLS was used as a diagnostic tool and for selecting the appropriate statistically significant and noncollinear factors influencing property market activities during the outbreak of COVID-19. On the other hand, the GWPR model is an extension of the conventional linear regression model obtained by taking into account the spatial relationships by assigning weights to individual observations depending on their location in space. The GWPR model is derived from the non-parametric regression model, and its underlying principle lies in the formation of a local linear regression at each point where a quantity has been measured (Alves, Nobre and Waller, 2016).

The OLS can automatically test for statistical significance and multicollinearity (redundancy) among factors. The statistical significance and multicollinearity were assessed using the p-values and the variance inflation factor (VIF) values of the OLS model respectively. Variables with a p-value of <0.05 were considered statistically significant and therefore subjected to a multicollinearity test. A VIF value greater than 2.5 indicated the existence of multicollinearity between factors, and was therefore excluded from the model (Fik, Ling and Mulligan, 2003; Ge and Du, 2007). The process of determining significant and unique factors was iteratively carried out using the OLS model. To validate the model, the global Moran's Index was applied to detect whether spatial autocorrelation or the clustering of model residuals was evident, which would then violate the assumption of OLS (Alves, Nobre and Waller, 2016).

The weighting function, the bandwidth size, as well as the best model in the GWPR model, were determined using the Corrected Akaike Information Criterion (AIC). Given the large variations in the density of both COVID-19 cases and property transactions, an adaptive bi-square kernel function was specified within the GWPR environment (Cellmer, Cichulska and Bełej, 2020). It was specified within the GWPR environment so that in parishes where data points were sparse, the kernel bandwidth would increase and decrease in size in parishes where data points were abundant. The GWPR model returns a set of model parameter estimates (coefficients) and diagnostic statistics (R^2 and AICc) which can be visualized within a GIS environment. The maps generated can thus be used to explain the level of association in the spatial relationships, as well as the influence each factor has on the dependent variable.

To determine the robustness of the GWPR model in explaining property market activities in Kampala, the spatial autocorrelation of GWPR model residuals was examined. Spatial autocorrelation occurs when observations of one parish correlate with observations of other nearby parishes within the study area. The global Moran's index has been commonly used as a measure of the presence or absence of spatial autocorrelation (Binbin *et al.*, 2014). The Moran's index ranges from -1 (data are perfectly dispersed) to 1 (data are perfectly clustered). However, when the Moran's index reaches zero, there is no spatial autocorrelation (randomness of observations). In regression models, spatial autocorrelation is a commonly encountered issue when the model cannot adjust for existing spatial heterogeneity. In the Geographically weighted Poisson Regression- (GWPR) environment, after accounting for non-stationary effects of observations, it is expected that the estimated errors (model residuals) should display a random distribution (Fotheringham, Brunsdon and M., 2003; Nakaya *et al.*, 2005; Cellmer, Cichulska and Bełej, 2020). In this study, the global Moran's index value was employed to examine randomness in the estimated errors (model residuals) of the GWPR model to validate model performance (Kauhl *et al.*, 2015; Bui *et al.*, 2018).

3. Results and Discussions

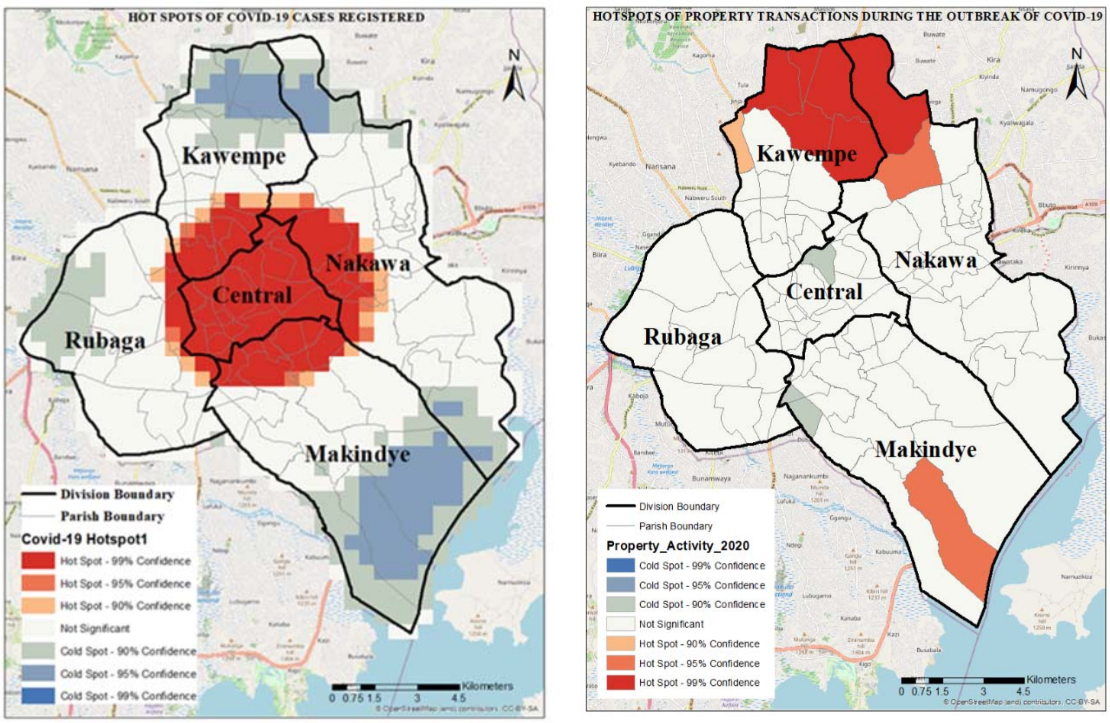
3.1. Spatial data distribution and hotspot analysis

The results of the GIS data classification indicated a disproportionate distribution of both COVID-19 cases and property transactions in Kampala district. Whereas the central and surrounding parts of the district registered high numbers of COVID-19 cases, the residential outskirts of the city registered low numbers. On the other hand, high volumes of property transactions were registered in the northern residential areas of Kampala district where the population density is high and land values are average.

In this study, a Getis–Ord Gi* statistical hotspot model was applied to both COVID-19 cases and property transactions in Kampala district to model the spatial distribution of the same. The results of the hotspot analysis displayed an amoebic shaped distribution pattern of COVID-19 cases, as displayed in Figure 3, with hotspot locations in the central division and cold spot locations in the outskirts of the city center. At a parish level, hotspots of COVID-19 cases were registered in the parishes of Kamwokya I, Kamwokya II, Mulago, Nakasero and the surrounding areas (areas of concentration) whereas the remaining areas proved to be insignificant. While assessing and evaluating COVID-19 susceptibility in the GKMA, Bamweyana *et al.* (2020) established that the CBD was more susceptible, with the levels of susceptibility declining as one moves to the city outskirts. In fact, the results of this study were established to be in line with the findings of the current study. The concentration of COVID-19 cases in the central area can be attributed to the fact that it incorporates the CBD and is therefore an area of concentration in terms of office space, presents with a high road density, and is in close proximity to trade and business facilities, and with considerable interactions taking place around human activities. The findings of the study further concur with those of a UN

Habitat report on cities and pandemics that highlights the role of the connectedness of cities in the spread of the deadly disease (UNDP-Uganda, 2020).

Furthermore, hotspots of property transactions were registered in the northern (Kyanja, Komamboga, Kisaasi, Mpererwe) areas of the district. These areas are typically residential with relatively low land values per acre and a high population density. Cold spots in terms of property transactions were registered in the city center and the eastern and western parts of Kampala. Whereas land values per acre are relatively high in the city center, the eastern and western parts of the district are predominantly low-income areas with the majority of property transactions being informal (unregistered).



3a) Hotspots of COVID-19 cases registered

3b) Hotspots of property transactions registered

Figure 3: Hotspots of COVID-19 cases and property transactions

4. Modelling the relationship between property market activities and COVID-19

4.1. Statistical significance and multicollinearity

Most of the variables (six) selected for inclusion in the study, where property market activity is measured in terms of volume of transactions, were response variables, which proved to be statistically significant at a level of significance below 0.05. However, the highest percentage of those variables subject to multi-collinearity occurred where the VIF was established to be higher than 2.5. They were, therefore, eliminated from the model. Table 1 highlights the statistical significance (p-value), and the collinearity (VIF values) of the selected variables.

Consequently, an OLS model was developed and included only those variables that were statistically significant and unique. The results of the model suggest that population density, average land parcel size, and the number of COVID-19 cases had the greatest impact on property market activities. The results of this study concur with those of several other studies that highlight population density and the physical characteristics of the properties as dominant determinants of property transactions (Ge and Du, 2007). The number of property transactions was log transformed to ensure a normal distribution of the dependent variable. Table 2 details the parameter estimates and model's diagnostic statistics.

Table 3: Analysis of the statistical significance and collinearity of variables

SN.	Factors (Variables)	Statistical significance (p-value)	Variance Inflation Factor (VIF value)
1.	Population density	0.008	1.42
2.	Land value per acre	0.823	
3.	Unemployment rate	0.137	
4.	Gender composition (male population)	0.152	
5.	Average property size	0.044	1.10
6.	Working population (18-65 years)	0.038	282.23
7.	Literacy level	0.131	
8.	Access to social amenities (health care)	0.013	2.89
9.	Access to social amenities (water)	0.218	
10.	Access to social amenities (schools)	0.017	3.74
11.	COVID-19 cases	0.029	1.24

KEY

Statistical significance:

p-value < 0.05 significant

p-value > 0.05 Not significant

Multi Collinearity (Uniqueness):

VIF-value < 2.5 Unique variables

VIF-value > 2.5 Collinear variables

Table 4: Diagnostic statistics of the OLS model

SN.	Parameter	Estimate	p-value	VIF
1.	Intercept	0.66	0.000	-
2.	Working population	0.92	0.038	1.15
3.	Average land parcel size	1.54	0.049	1.08
4.	Population density	-14.54	0.039	1.18
5.	COVID-19 cases	-0.95	0.025	1.11

4.2. Determining GWPR model estimates and diagnostic statistics

One of the benefits of GWPR is the ability of the model to scrutinize the spatial variation in the independent variables, that are considered as the explanatory variables. According to Table 3, the model registers a moderate R^2 of 0.61. An R^2 of 0.61 suggests that the GWPR model could explain 61% of the total variations in the property market activities in Kampala district. However, this does not exclude the situation where the R^2 value of the GWPR model varies from one parish to another. The parameter estimates, as well as the diagnostic statistics of the GWPR model, are further presented in Table 5.

Table 5: Estimates and diagnostic statistics of the GWPR model

SN.	Parameter	Min	Mean	Max	Standard Deviation
1.	Intercept	-0.70	0.23	1.36	0.40
2.	Residual	-1.27	-0.02	1.53	0.54
3.	Population density	-68.00	-10.70	12.68	16.81
4.	Percentage of the working population	-2.73	0.78	4.02	1.63
5.	Average land parcel size	-1.68	4.73	12.41	4.04
6.	COVID-19 case	-3.89	-0.91	0.89	0.89
7.	Local R^2	0.02	0.33	0.73	0.20
	R^2 = 0.61, Adjusted R^2 = 0.45, AIC = 216.71				

Figure 4 presents the values of R^2 for the specific locations of the GWPR model. The maps show that the model has a poor fit with the data for parishes located in the central, western and eastern areas of the district, particularly in Nakawa (e.g., Mutungo, Banda, Kiswa). The poor fit of the model in the region can be attributed to the low turnover in property transactions as a result of informal transactions, the high percentage of the retired population (65 years and above), as well as the relevant areas predominantly reflected as low-income areas. However, the model accurately describes property market activities in the northern and southern parts of the district, in the parishes of Komamboga, Kanyanya, Kabowa (e.g., where R^2 is greater than 0.51). The good fit of the model can be attributed to the large turnover in property transactions registered in the region that are motivated by the low value of the land, coupled with an influx of the employed population. The results further indicate that, although the model is able to accurately define property transactions in some areas within Kampala, the model presents with a poor fit in most of the parishes.

An investigation of the R^2 hotspots and cold spots reveals that the northern and southern parts of the district are statistically significant hotspot areas reflecting a goodness-of-fit model, whereas, the eastern and western are classified as cold spots. Elsewhere, the R^2 was found to be insignificant. Figure 4 illustrates the R^2 hotspot and cold spot areas of Kampala.

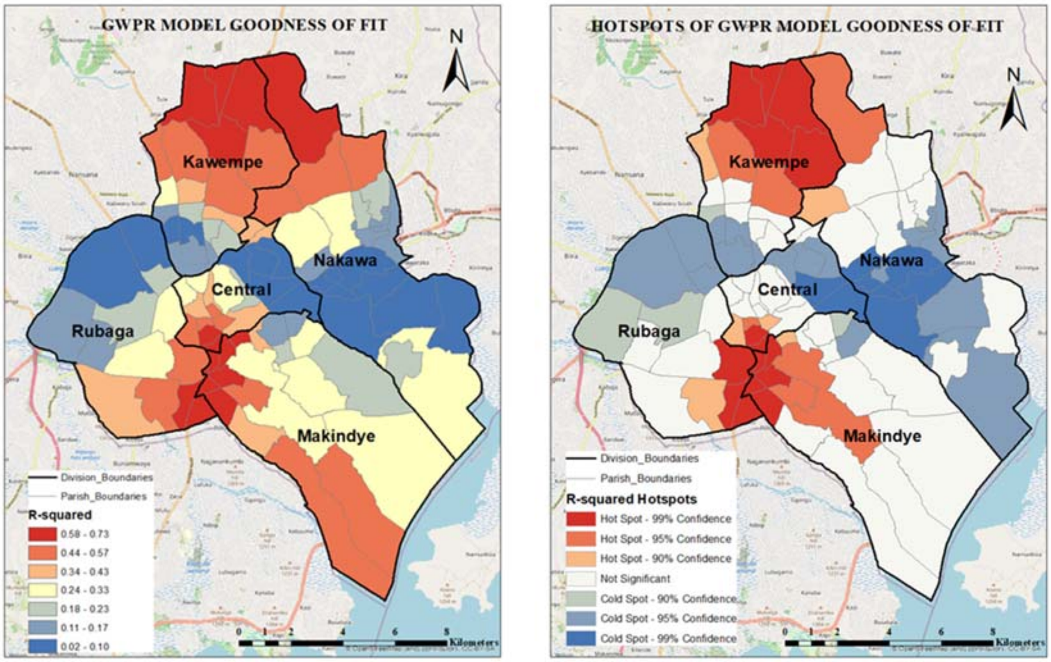


Figure 4: Goodness of fit (model performance) of the GWPR model based on R^2 values

The spatial distribution of the COVID-19 coefficient values (relationship with Property transactions) reveals both a positive and negative relationship between COVID-19 cases and property market activities. A positive relationship is evident in the north-eastern parts of Kampala, whereas the relationship registered elsewhere is negative. The results of the analysis further display the severe negative effect of COVID-19 cases on property market activities in parts of the central, western and south-eastern portions of the district. An analysis of the results show that the western and central parts of the district are mainly slum areas occupied by low-income earners, but also incorporating a concentration of retired people (65years and above). The south-eastern parts of the district are characterized by high values per acre for the land, thus acting as a de-stimulant for property transactions. On the other hand, a positive COVID-19 impact on property market activities can be observed in the northern parts of the district (e.g., Kanyanya, Kulambiro, and other settlements). In fact, these areas register low COVID-19 cases; furthermore, they are majorly residential areas characterized by low values of land per acre and coupled with high population densities. The details of the spatial distribution of the COVID-19 coefficients are explained in Figure 5.

The phenomenon of clustering coefficients of similar values in Kampala also occurred in that case. Thus, hotspots were registered in some parts of the central, north and north-eastern parts of the district. Likewise, cold spot areas were registered in the western, south east, and parts of the central district. The remaining areas proved to be insignificant; their details are explained by the hotspot map in Figure 5.

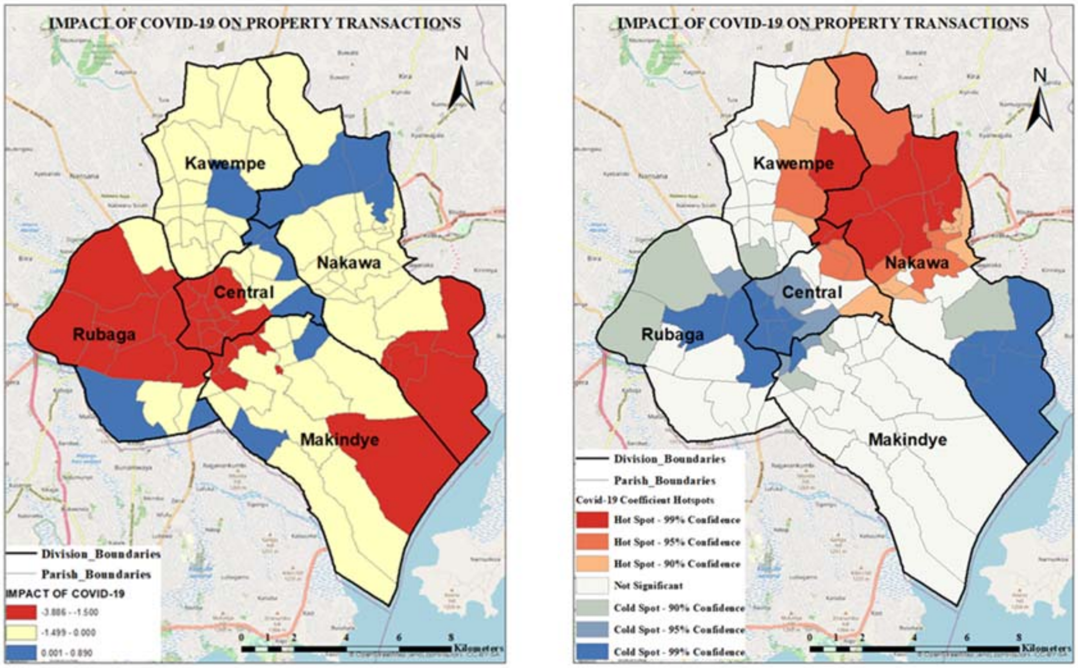


Figure 5: Relationship between COVID-19 cases and property transactions based on model coefficients

To evaluate the accuracy, reliability, and predictive power of the GWPR model, a global Moran's Index was evaluated using the GWPR model residuals. The spatial distribution of GWPR model residuals displayed a non-statistically significant random distribution with a Moran's Index of -0.005 (p=0.922). Given a z-score of 0.098, the pattern of residuals of the GWPR model did not appear to be significantly different from the random distribution. The random distribution of GWPR model residuals implies that the model was able to account for the non-stationarity of the determinants of property market activity in Kampala district and therefore the results of the model are not biased.

5. Conclusions and Recommendations

For the last ten years, the real estate market in Uganda has been growing progressively, with its contribution to the national GDP rising from 7.3% in 2010 (AFDB et al., 2012) to 11% in 2020 (Gardner et al., 2020). This continued growth has been threatened by the outbreak of COVID-19, and the unique mitigation and control strategies that were adopted to control its rapid spread, including amongst others, business closures, restrictions on the movement of goods and people, stay-at-home regulations, and partial and total lockdowns. Despite government interventions for lowering the prime lending rate, and putting a seal on evictions, property transactions during the outbreak of COVID-19 declined by 74%.

This study quantified the spatial variation in the effects of COVID-19 on property market activity in Kampala. Basing on the findings of the study, it can be concluded that COVID-19 has proved to be a significant determinant in property market activity. Its intensity has varied in geographical space, with a positive relationship being observed in the northern parts (a middle-class population) and a negative relationship in the central, western, and south-eastern portions of the district (the high and low-income extremities of the income distribution curve). In addition, GWPR has proved to be an effective model for spatial data analysis, although it has not shown sufficient goodness-of-fit in respect of the data for all of the analyzed parishes.

Exploring the spatial variation of the effects of COVID-19 on property market activity is a pre-requisite that underpins any new policy in terms of property tax, stamp duty, and waivers following the occurrence of a pandemic. A better understanding of front-runners to and laggards subsequent to the occurrence of a pandemic allows policy makers to introduce policies that are relevant to an area of interest. This study explored the effects of COVID-19 on property market activity, and using the turnover in transactions and data on a parish scale, future research should take into account property types (residential, commercial, industrial).

A notable limitation of the study is that most of the variables (factors), for example, the average monthly income of the people, the GDP, mortgage availability, and interest rates amongst others that influence property market activities in Kampala district are available on a global scale. This is in sharp contrast to the disaggregate scale considered for this study. The research therefore recommends that further studies should explore the concept of integrating data at varying spatial scales.

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Appendices

Appendix I: Data collection and Capture

(a) Selection of variables from literature

SN.	Factors (Variables)	Data availability	Availability of Proxy data	Spatial scale	Decision
1.	GDP	Yes		No	No
2.	Inflation rates	Yes		No	No
3.	Population density	Yes		Yes	Yes
4.	Land value per acre	Yes		Yes	Yes
5.	Unemployment rates	Yes		Yes	Yes
6.	Gender composition	Yes		Yes	Yes
7.	Average property size	Yes		Yes	Yes
8.	Working population	Yes		Yes	Yes
9.	Literacy levels	Yes		Yes	Yes
10.	Average monthly income	No	No	No	No
11.	Access to social amenities (Health care)	Yes		Yes	Yes
12.	Access to social amenities (water)	Yes		Yes	Yes
13.	Access to social amenities (schools)	Yes		Yes	Yes
14.	Mortgage availability	No	No	No	No
15.	Loan interest rates	Yes		No	No
16.	Migration index	No	No	No	No
17.	Emission of particulate pollutants	Yes		No	No
18.	Government policies and legislations (tax exemptions)	Yes		No	No

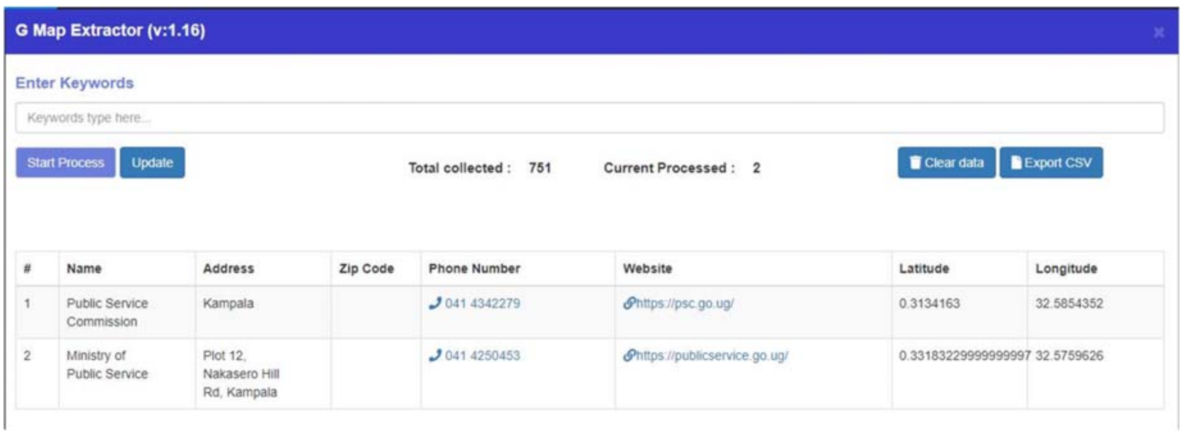
(b) Extract of the National COVID-19 positive cases log register

Age	Age group	Sex	Nationality of the client	Sample collection Point Name	District of Sample Collection	Region	Date of confirmation of COVID-19	Date of sample collection	Transmission
38	30-39yrs	M	Ugandan	Airport	Wakiso	South Central	21-Mar-20	21-Mar-20	Imported
37	30-39yrs	M	Ugandan	Airport	Wakiso	South Central	23-Mar-20	22-Mar-20	Imported
35	30-39yrs	M	Ugandan	Airport	Wakiso	South Central	23-Mar-20	21-Mar-20	Imported
34	30-39yrs	M	Ugandan	Airport	Wakiso	South Central	23-Mar-20	22-Mar-20	Imported
30	30-39yrs	M	Ugandan	Airport	Wakiso	South Central	23-Mar-20	21-Mar-20	Imported
38	30-39yrs	M	Ugandan	Kayunga Hosp	Kayunga	North Central	23-Mar-20	21-Mar-20	Imported
38	30-39yrs	M	Ugandan	Kayunga Hosp	Kayunga	North Central	23-Mar-20	21-Mar-20	Local
31	30-39yrs	M	Ugandan	Kampala, Kyengera	Kampala	Kampala	23-Mar-20	22-Mar-20	Imported
60	60-69yrs	M	Ugandan	Masaka RRH	Masaka	South Central	23-Mar-20	22-Mar-20	Imported
63	60-69yrs	M	Ugandan	Wakiso, Imperial Gold Ebbs	Wakiso	South Central	25-Mar-20	23-Mar-20	Imported
57	50-59yrs	M	Ugandan	Adjumani hospital	Adjumani	West Nile	25-Mar-20	23-Mar-20	Local
1	0-9yrs	F	Ugandan	Iganga	Iganga	Busoga	25-Mar-20	22-Mar-20	Local
31	30-39yrs	M	Ugandan	Kampala, IQC Douglas Villa	Kampala	Kampala	26-Mar-20	25-Mar-20	Imported
39	30-39yrs	M	Ugandan	Wakiso, Mission IQC	Wakiso	South Central	26-Mar-20	25-Mar-20	Imported
55	50-59yrs	M	Ugandan	Hoima RRH	Hoima	Bunyoro	26-Mar-20	25-Mar-20	Imported

(c) Extract of the sorted Kampala District COVID-19 case log register

Age	Age group	Sex	Nationality of the client	Sample collection Point Name	District of Sample Collection	Region	Date of confirmation of COVID-19	Date of sample collection	Transmission
26	20-29yrs	F	Ugandan	Kawempe Hospital	Kampala	Kampala	05-Sep-20	01-Sep-20	Local
24	20-29yrs	M	Ugandan	Kiswa HC III	Kampala	Kampala	05-Sep-20	01-Sep-20	Local
36	30-39yrs	M	Ugandan	Jubilee	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
41	40-49yrs	M	Ugandan	ABSA	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
50	50-59yrs	M	Ugandan	IGG	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
29	20-29yrs	M	Ugandan	City Hall	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
35	30-39yrs	M	Ugandan	Jubilee	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
25	20-29yrs	F	Ugandan	Jubilee	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
32	30-39yrs	F	Ugandan	IGG	Kampala	Kampala	05-Sep-20	28-Aug-20	Local
64	60-69yrs	M	Ugandan	Mengo Hospital	Kampala	Kampala	05-Sep-20	03-Sep-20	Local
38	30-39yrs	M	Ugandan	Mulago NRH	Kampala	Kampala	05-Sep-20	04-Sep-20	Local
74	70-79yrs	M	Ugandan	Nakasero Hospital	Kampala	Kampala	05-Sep-20	04-Sep-20	Local
32	30-39yrs	M	Ugandan	Makerere University Hospita	Kampala	Kampala	05-Sep-20	04-Sep-20	Local
57	50-59yrs	F	Ugandan	Mulago NRH	Kampala	Kampala	05-Sep-20	03-Sep-20	Local
36	30-39yrs	F	Ugandan	RMC	Kampala	Kampala	05-Sep-20	04-Sep-20	Local
55	50-59yrs	M	Ugandan	Makerere University Hospita	Kampala	Kampala	05-Sep-20	04-Sep-20	Local

(d) Geo coding of sample collection centers using Web scraping algorithm (G-Map extractor tool)



(e) Extract of the Geo coded sample collection centers

FID	SN	Sample collection center	Longitude	Latitude	covid_case
45	46	Bunga	32.63666	0.264221	1
46	47	Busega	32.523167	0.31078	1
47	48	Butabika	32.658353	0.3145	17
48	49	Butabika Hospital	32.657728	0.314781	62
49	50	Buziga	32.625812	0.246097	2
50	51	Buziga State House, Kansanga-Muyenga	32.608738	0.289041	1
51	52	Bwaise	32.567034	0.357371	1
52	53	Cabinet Secretariate, Wandegeya	32.573928	0.33467	28
53	54	Cambridge Health Medical Center	32.605465	0.327614	42
54	55	Case Medical Centre	32.575145	0.324705	85
55	56	CCCC, Kololo	32.593767	0.32903	3
56	57	Charms Uganda Limited	32.617891	0.33623	6
57	58	China-Uganda Friendship hospital	32.605822	0.329644	536
58	59	Church Raod, Kansanga	32.608738	0.289041	1
59	60	CID, Kibuli	32.590256	0.309351	1
60	61	City Ambulance	32.588078	0.334445	1
61	62	City Medicals Kampala	32.603703	0.317589	183
62	63	CityOil, Kira Road	32.585463	0.338296	1
63	64	CMC Motors	32.613678	0.330794	4
64	65	CMS Clinic Bakuli	32.563141	0.312291	1
65	66	CPHL, Butabika	32.659973	0.313761	355
66	67	Crane Plaza	32.588333	0.3387	1
67	68	Cure Medical Centre	32.567104	0.27875	2
68	69	Datamine Technical Business School	32.573066	0.32586	1

(f) Extract of the Property transactions data

SN	Date of Registration	Title Location	Legal Area	legal area unit type
0	2021-08-17 15:34:48	KAMPALA	0.3703	area_unit_type_hectares
1	2021-08-17 15:34:48	KAMPALA	0.3703	area_unit_type_hectares
2	2021-08-17 15:34:48	KAMPALA	0.3703	area_unit_type_hectares
3	2021-08-17 15:25:22	BUYE	0.158	area_unit_type_hectares
4	2021-08-17 15:25:22	BUYE	0.5	area_unit_type_acres
5	2021-08-17 15:25:22	BUYE	0.5	area_unit_type_acres
6	2021-08-17 12:32:43	BULANGE	0.13	area_unit_type_hectares
7	2021-08-13 12:12:43	NATETE	0.2	area_unit_type_hectares
8	2021-08-13 12:12:43	NATETE	0.2	area_unit_type_hectares
9	2021-08-13 12:12:43	NATETE	0.2	area_unit_type_hectares
10	2021-08-12 15:59:14	KAMPALA	0.252	area_unit_type_hectares
11	2021-08-12 15:59:14	KAMPALA	0.252	area_unit_type_hectares
12	2021-08-11 16:36:45	KAMPALA	0.368	area_unit_type_acres
13	2021-08-11 16:36:45	KAMPALA	0.368	area_unit_type_acres
14	2021-08-11 14:07:07	KYANJA	0.136	area_unit_type_hectares
15	2021-08-11 14:07:07	KYANJA	0.136	area_unit_type_hectares
16	2021-08-11 14:07:07	KYANJA	0.136	area_unit_type_hectares
17	2021-08-11 14:07:07	KYANJA	0.136	area_unit_type_hectares
18	2021-08-06 16:50:44	BULANGE	0.568	area_unit_type_hectares
19	2021-08-06 16:37:06	KAMPALA	0.084	area_unit_type_hectares

(g) Extract of the Kampala district Socio-economic data

Parish	Population Size by Parish				Population composition by age				Acess to socio amenities		Population 18+ who are illiterate		%age of working population		Distance to any Primary school		Distance to any Health facility	
	Male	Female	age of ma	Total	18 - 65 Years		%age composition		Acess to piped Water		Both Sexes		Working (14-64)		5 Kms or More		5 Kms or More	
					18 years	65 years	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Bukesa	4326	4711	0.61	9037	5937	126	5811	0.69	2363	0.69	272	0.56	3676	0.61	27	0.22	20	0.11
Civic Centre	224	151	0.03	375	298	7	291	0.03	137	0.04	4	0.01	228	0.04	1	0.01	1	0.01
Industrial Area	383	262	0.05	645	457	3	454	0.05	229	0.07	32	0.07	395	0.07	27	0.22	21	0.12
Kagugube	2983	3246	0.42	6229	4467	83	4384	0.52	2312	0.68	259	0.53	2637	0.44	40	0.32	38	0.21
Kamwokya Ii	9041	9599	1.27	18640	11524	157	11367	1.35	5064	1.48	725	1.49	8519	1.42	18	0.14	32	0.18
Kamwokya I	938	963	0.13	1901	1253	39	1214	0.14	462	0.14	36	0.07	854	0.14	13	0.10	0	0.00
Kisenyi I	561	559	0.08	1120	737	15	722	0.09	302	0.09	73	0.15	473	0.08	0	0.00	0	0.00
Kisenyi Ii	4134	4195	0.58	8329	4687	116	4571	0.54	1806	0.53	768	1.58	2878	0.48	70	0.56	94	0.53
Kisenyi Iii	2285	2274	0.32	4559	2611	57	2554	0.30	1082	0.32	265	0.55	1730	0.29	2	0.02	2	0.01
Kololo I	494	497	0.07	991	701	43	658	0.08	215	0.06	19	0.04	488	0.08	0	0.00	0	0.00
Kololo Ii	580	552	0.08	1132	750	48	702	0.08	270	0.08	17	0.03	684	0.11	9	0.07	11	0.06
Kololo Iii	574	442	0.08	1016	691	31	660	0.08	270	0.08	6	0.01	525	0.09	8	0.06	0	0.00
Kololo Iv	955	962	0.13	1917	1272	32	1240	0.15	494	0.14	35	0.07	932	0.16	1	0.01	3	0.02
Mengo	5741	5947	0.81	11688	7300	137	7163	0.85	2864	0.84	516	1.06	5180	0.86	8	0.06	17	0.10
Nakasero I	352	266	0.05	618	444	14	430	0.05	216	0.06	22	0.05	336	0.06	3	0.02	2	0.01
Nakasero Ii	977	818	0.14	1795	1380	41	1339	0.16	475	0.14	37	0.08	1066	0.18	1	0.01	3	0.02
Nakasero Iii	539	457	0.08	996	710	18	692	0.08	343	0.10	33	0.07	468	0.08	0	0.00	0	0.00
Nakasero Iv	509	284	0.07	793	644	6	638	0.08	273	0.08	25	0.05	505	0.08	5	0.04	3	0.02
Nakivubo Shauriyaako	687	461	0.10	1148	869	23	846	0.10	347	0.10	46	0.09	686	0.11	0	0.00	0	0.00
Old Kampala	1152	1087	0.16	2239	1435	35	1400	0.17	334	0.10	21	0.04	1090	0.18	6	0.05	10	0.06
Bwaise I	8892	10166	1.25	19058	10282	211	10071	1.19	4303	1.26	660	1.36	7231	1.20	143	1.14	153	0.86
Bwaise Ii	8577	9692	1.20	18269	10230	206	10024	1.19	4155	1.22	756	1.56	7802	1.30	125	1.00	164	0.92
Bwaise Iii	3797	4386	0.53	8183	4426	108	4318	0.51	1153	0.34	355	0.73	3219	0.54	16	0.13	27	0.15
Kanyanya	11959	14885	1.68	26844	14680	328	14352	1.70	5194	1.52	864	1.78	10484	1.75	429	3.43	568	3.20
Kawempe I	20889	23856	2.93	44745	23935	487	23448	2.77	7932	2.32	1191	2.45	16537	2.75	400	3.19	473	2.66
Kawempe Ii	10720	12519	1.50	23239	12091	233	11858	1.40	4979	1.46	719	1.48	8213	1.37	117	0.93	203	1.14
Kazo Angola	8610	9988	1.21	18598	10075	197	9878	1.17	3379	0.99	601	1.24	7379	1.23	152	1.21	126	0.71

Appendix II: Results & Discussions

Analysis of study Metrics

Item	Measurement metric	Scale (Range)	Interpretation
Multicollinearity (Uniqueness)	VIF (Variance Inflation Factor)	VIF > 10	Collinearity
		2.5 < VIF < 10	Moderate Collinearity
		VIF < 2.5	No Collinearity
Goodness of fit of regression model	R^2 (R-squared)	$R^2 > 0.5$	Good fit
		$0.25 < R^2 < 0.5$	Moderate fit
		$R^2 < 0.25$	Poor fit
Statistical significance	P-values	p-value > 0.05	Not significant
		p-value < 0.05	Significant
Spatial Autocorrelation	Moran's Index (M.I)	1	Clustered
		0	Random
		-1	Dispersed
Relationship	Model coefficients	Value	Magnitude (Strength)
		Negative (-)	Inverse relationship
		Positive (+)	Direct relationship