Applied Energy 304 (2021) 117864

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Spatiotemporal analysis of water-electricity consumption in the context of the COVID-19 pandemic across six socioeconomic sectors in Doha City, Qatar

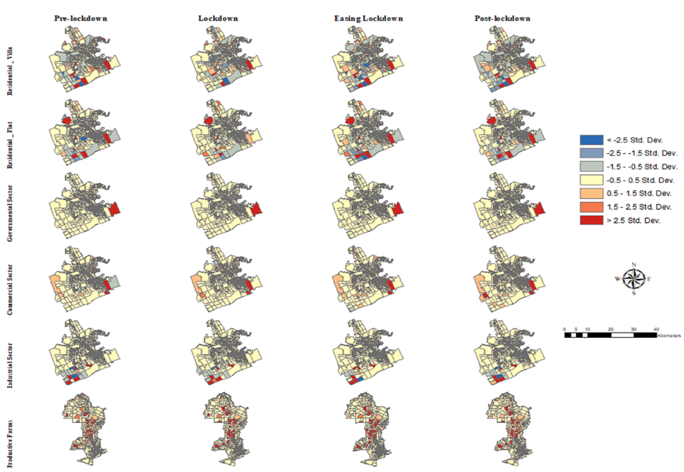
Ammar Abulibdeh

Department of Humanities, College of Arts and Sciences, Qatar University, P.O. Box: 2713, Doha, Qatar

HIGHLIGHTS

- There is an association between water and electricity consumption.
- Lockdown period increased electricity and water consumption by 30% and 6% in 2020 compared to 2019.
- The electricity consumption in the industrial and commercial sectors dropped due to the pandemic.
- The water and electricity consumption in the residential sectors increased during the summer.
- The spatial impact shows variation across the six sectors.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Water-electricity consumption
Socioeconomic sectors
Spatial modeling
Statistical modeling
Qatar

ABSTRACT

This study investigates the water – electricity consumption in the context of the COVID-19 pandemic across six socioeconomic sectors. Due to inadequate research on spatial modelling of water – electricity consumption in the context of the COVID-19 pandemic, this study investigated geographical block-level variation in water and electricity consumption in Doha city of Qatar. Spatial analyses were performed to investigate the spatial differences in each sector. Five geospatial techniques in a Geographical Information System (GIS) context were used in the study. Moran's *I*, Anselin Local Moran's *I*, and Getis-Ord G_i^* statistics tools were used to identify the hot spots and cold spots of water and electricity consumption in each sector. Furthermore, Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR) models were employed to investigate the spatial relationship between water and electricity consumption during the pandemic year. The findings show that there is a distinction in water and electricity consumption at the block level across all sectors and over time. Hot spot and spatial regression analysis reveal spatial and temporal heterogeneities in the study area across the six socioeconomic sectors. The intensity of hot spots of water and electricity consumption are found in the southern and western parts of the city due to high population density and the concentration of the commercial and industrial areas. Furthermore, analyzing the spatiotemporal correlation between the water and electricity consumption across the six sectors shows variation within and between these sectors over space and time. The results show a

https://doi.org/10.1016/j.apenergy.2021.117864
Received 30 April 2021; Received in revised form 28 August 2021; Accepted 10 September 2021
Available online 17 September 2021

positive relationship between water and electricity consumption in some blocks and over time of each sector. During the lockdown phase, strong positive correlation between water and electricity consumption have exist in the residential sector due to extra water and electricity footprints in this sector. Conversely, the water and electricity consumption were positively correlated but declined in the industrial and commercial sector due to the curtailment in production, economic activities, and reduction in people's mobility. Mapping the hot spot blocks and the blocks with high relationship between water and electricity consumption could provide useful insight to decision-makers for targeted interventions.

1. Introduction

The COVID-19 pandemic has been swiping the world since December 2019 resulting in millions of morbidity and mortality cases and forcing people to change their lifestyles. The COVID-19 pandemic has made an immensely negative impact on the global economy and imposed a crucial challenge to healthcare systems worldwide. Countries have taken various measures to contain the spread of the disease through social distancing and isolation, lockdowns, early detection, closure of many facilities (i.e., schools, restaurants, non-essential services, etc.) forcing people to spend more time at homes [1–4]. As a result, the pandemic has negatively affected many industries, including manufacturing, energy, agriculture, education, tourism, aviation, and sports among others [5]. The lockdown measures and changes in people's lifestyles have made a direct impact on water and electricity consumption patterns in many sectors, particularly the commercial and industrial sectors [6,7]. Subsequently, the lockdown policy has resulted in increasing the water and electricity consumption in the residential sector due to a larger occupancy.

Energy industry is facing great challenges due to the spread of the COVID-19 pandemic. The observations of the impact of the pandemic on the energy sector show that the existence of extra energy footprints due to mitigation measures taken by the governments and the association of structural changes in energy demand and consumption during the pandemic compared to the period prior to the pandemic. This extra demand and consumption have resulted from the increase in the residential sector due to stay-at-home policy as people have taken to teleworking and telemedicine [1,8,9]. Furthermore, the water and energy demand and consumption have been affected by the new consumption behaviour and social forms facilitated by the pandemic. The spatial and temporal heterogeneities of the pandemic impacts on energy consumption appear gradually because of the dynamics of the mitigation measures and the spread of the disease. Furthermore, the pandemic has affected the energy industry in terms of both supply and demand [6]. Meanwhile, the literature shows that the energy consumption has decreased in both the commercial and industrial sectors [10]. These studies have contributed to the understanding of the impacts of the spread of the COVID-19 pandemic on water and energy sectors from different views.

The water-electricity nexus identifies the numerous interconnected aspects between water and electricity resources [11,12]. This concept views water and electricity as part of an integrated water and energy systems, rather than as independent resources. The use of water covers all stages of the fuel cycle, from extraction of energy resources such as oil and natural gas, to energy production and electricity generation [13,14]. Electricity is needed for extraction, conveying, purification, and transfer of the water to different forms of consumers in the economy [12,15,16]. It is considered the major water consumer of all energy types and accounts for 25%−80% of the water used for energy generation [17,18]. Kiziltan [19] found that, on average, electricity consumption increases by more than 0.10% for a 1% increase in water consumption. Major development initiatives, fluctuating demographics, climate change, and more dependency on desalination have currently drawn attention to the links between water and electricity usage, and the fuels and infrastructure incorporated in their production [12]. In a situation where there is water scarcity, abundant supply of fossil fuel-derived energy, high demands for water and electricity, continuous growth in population, and increasing issues surrounding climate change, links between water and electricity can potentially reveal opportunities for enhancements in efficiency or trade-offs of mutual benefits.

The water-electricity nexus has become an essential element in development and thus in monitoring the implementation of the Sustainable Development Goals (SDGs). The aim of the water-electricity nexus is to endorse the inseparable links between the use of the resources to provide basic and universal rights of water and electricity/energy security. Analysing this nexus stimulates sustainable goals and objectives, and stability between resource users. It also facilitates the transition to a local, regional, and global integrated ecosystems through encouraging strategic and integrated management [14,17,20].

In the emergent and chaotic environment under the COVID-19 pandemic, more investigation in this impact is beneficial for the whole energy and water societies and industries by providing diverse views and more perspectives. The high variability in water and electricity consumptions across different socioeconomic sectors necessitates a national level assessment for identifying the impact of the propagation of the COVID-19 pandemic on these fundamental resources. An accurate assessment of water and electricity consumption's spatial variation is important to promote the authorities' responses and planning for water and electricity production and supply. From a micro-scale, it is expected to see an overall drop in the electricity and water consumption in industrial and commercial sectors and a rise in the residential sector due to lockdown measures. Therefore, there is a pressing need to investigate the spatial variation to arrive at a better conclusion on water and electricity demand and distribution and the areas that are more negatively affected by the spread of the disease. Furthermore, the authorities should ensure that the variation in the short-term in water and electricity consumption have no negative long-term consequences.

The research on the effect of the COVID-19 pandemic on the spatial water and electricity consumption in different socioeconomic sectors does not exist in the literature since the COVID-19 pandemic is a new phenomenon. The spatial variations in water and electricity consumption are complicated when the impact of the disease's propagation to different socioeconomic sectors is examined. The water and electricity consumption has presented apparent spatial changes, and the economic recovery in specific sectors has not been successful as water and electricity consumption has been low even when mitigation restrictions are eased in different countries. This study investigates the spatiotemporal impact of the COVID-19 pandemic on the water and electricity consumption across different socioeconomic sectors. To investigate the spatial changes in water and electricity consumptions during the COVID-19 pandemic, we consider six different socioeconomic sectors that reflect the policies that have been followed to slowdown the spread of the pandemic. These sectors include residential (villas and flats) as stay-at-home policy has forced many people not to leave their homes. Furthermore, the commercial, industrial, and productive farms sectors are taken as an indication of the impact of the pandemic on economic development and activities. Finally, the study also investigates the impact of the pandemic on the spatial water and electricity consumption by the governmental sector and explores how this sector has been affected by the pandemic.

This paper aims to investigate the spatial impact of the COVID-19 pandemic on the water and electricity consumption in different

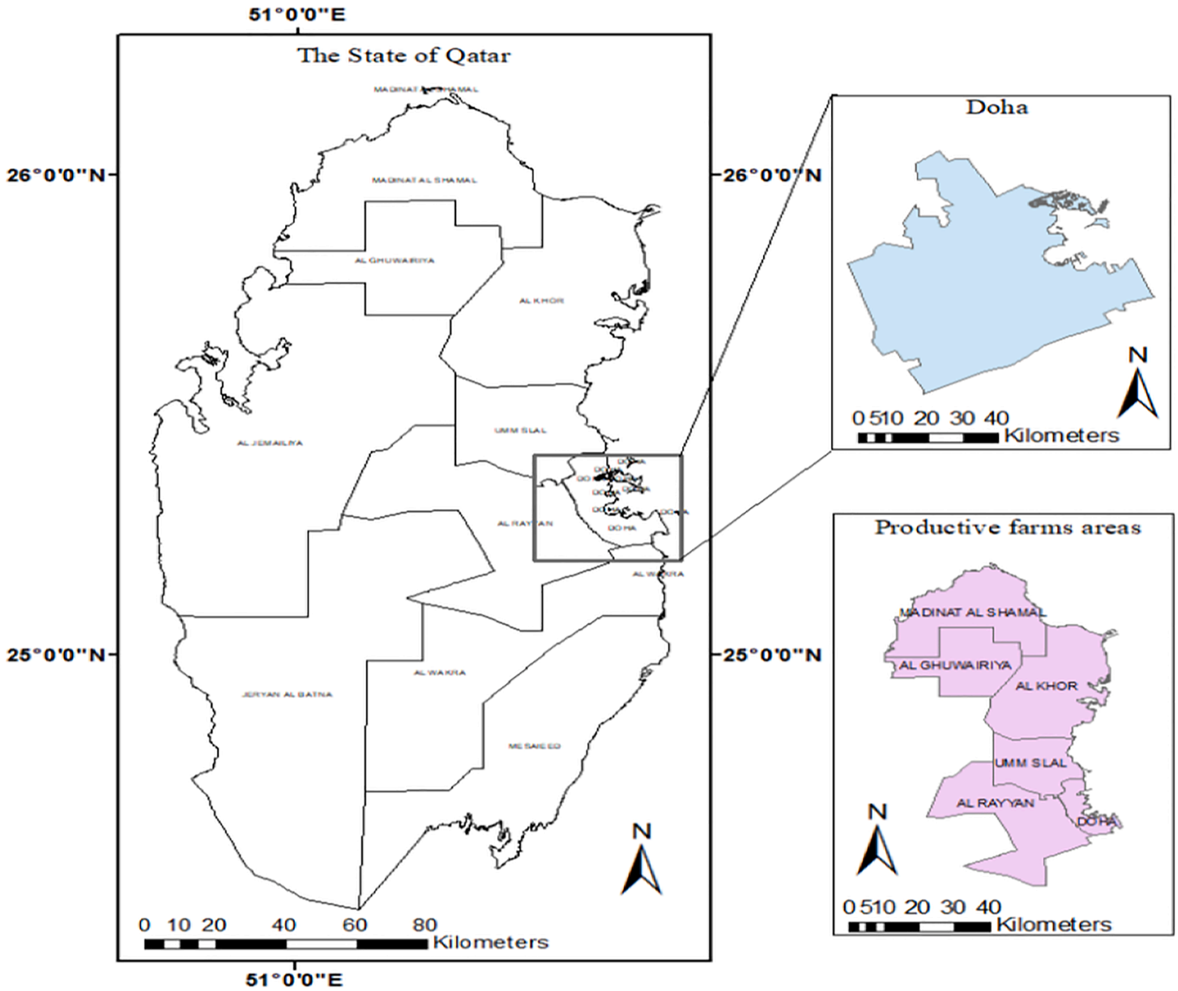


Fig. 1. The study area showing the Doha city and the productive farms area.

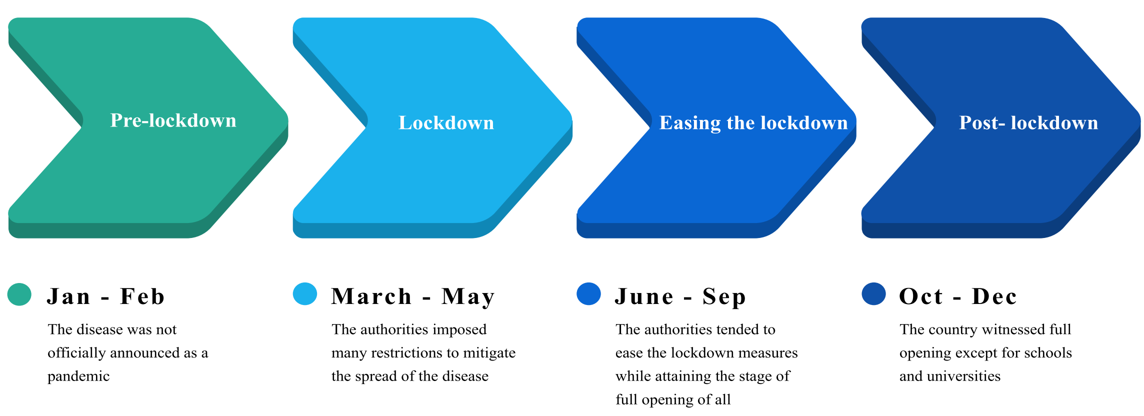


Fig. 2. Temporal framework of evaluating the impact of COVID-19 pandemic on water and electricity consumption.

socioeconomic sectors. The novelty of this paper is that it presents a different approach by studying the impact of the pandemic on water and electricity consumption. This approach focuses on analysing the impact of the pandemic on the spatial distribution of water and electricity consumption. The main contributions of this paper to the body of knowledge are summarised as follows. (1) To the best of our knowledge, no previous studies in the literature have investigated the spatial dimension of the water and electricity consumption in the context of COVID-19 pandemic. Previous studies used mainly two approaches to investigate the impact of COVID-19 pandemic on water and electricity consumption. The first approach is to compare between the water and electricity consumption prior to and during the pandemic year. The second approach is to predict the virtual electricity consumption under normal circumstances and compare it with the actual electricity consumption, where the difference was assumed to be caused by the propagation of the pandemic. None of these studies focused on the spatial dimension of the water and electricity consumption under the context of the propagation of the pandemic. Therefore, this study aims to

Table 1
Description of the socioeconomic sectors and related hypotheses of water and energy consumption.

Socioeconomic sector	Description	Number of readings	Rational and hypotheses
Residential	Villas, flats	Villa – 118934. Flat – 106970	Residential buildings in Qatar consume the highest proportion of the water and electricity resources. The propagation of COVID-19 pandemic in Qatar forced the authorities to take measures and strategies to fight the disease. These measures include stay-at-home policy, where thousands of employees and students performed their tasks from their homes. Therefore, it is expected that the water and electricity consumption has increased in this sector, particularly during the summer season where the temperature exceeds 40 °C associated with an intensive use of air conditioning for cooling.
Commercial	Banks, services institutions, SMEs, private organisations, retail, groceries and pharmacies, etc.	46415	The commercial sector is one of the pillars of Qatar's economy. Thousands of people work in this sector. The implementation of the mitigation measures to slowdown the spread of the disease forced many companies and services in this sector to shut down. Therefore, examining the water and electricity consumption is this sector can give indication on the extent of the impact of the disease on the economy of the country, particularly in the easing lockdown or post-lockdown phases.
Industrial	Liquefied natural gas, crude oil production and refining, ammonia, fertilisers, petrochemicals, steel reinforcing bars, cement, commercial ships, repairs	590	The pandemic affected all the components of industrial system in Qatar and across the world. The pandemic and the associated measures affected the procurement of raw material, process of manufacture, and production. The workforce was asked to stay at home, particularly during the lockdown phase. Therefore, assessing the water and electricity consumption in this sector can show the dynamic effect of the pandemic on the economy in general, and on the industrial sector in particular.
Government	Ministries, public schools, offices, hospitals, and universities, etc.	15551	This sector is important as it employs a large number of people. Furthermore, this sector is responsible for issuing and implementing policies to reduce the spread of the disease and many of the employees were asked to work from home. Furthermore, some public entities (i.e., public schools and university) were closed, while others (i.e., public hospitals and clinks) increased their capacity to fight the disease.
Productive farms	Farms, livestock, ranching	1450	Qatar is a semi-arid country and the agricultural sector consume high percentage of water and electricity resources. However, most of the arable land used for agricultural purposes are located outside the urban areas and hence the water and electricity consumption was not affected by the spread of the disease.

fill this gap by investigating the structural changes in water and electricity consumption patterns and visualising the interrelationship over space, time, and sector under the context of COVID-19 pandemic, (2) This study is the first of its kind in investigating the water and electricity consumption considering six socioeconomic sectors on a spatiotemporal scale. These sectors are essential in achieving economic development and human wellbeing, (3) Three different temporal levels were considered in this study (monthly, annually, and four phases related to the lockdown measures) to assess the impact of COVID-19 pandemic on water and electricity consumption, (4) This study utilizes five GIS methods in its attempt to address the research objectives. Spatial statistical and regression models are used to assess the correlation between water and electricity at the block level. Utilising and comparing between multiple methods help to ensure robust and persuasive results.

2. Study area

The State of Qatar is located to the east of the Arabian Peninsula in the Middle East, bordering the Arabian Gulf and Saudi Arabia. The area of the country is about 11,437 km^2 and the country is located at 25° 30′

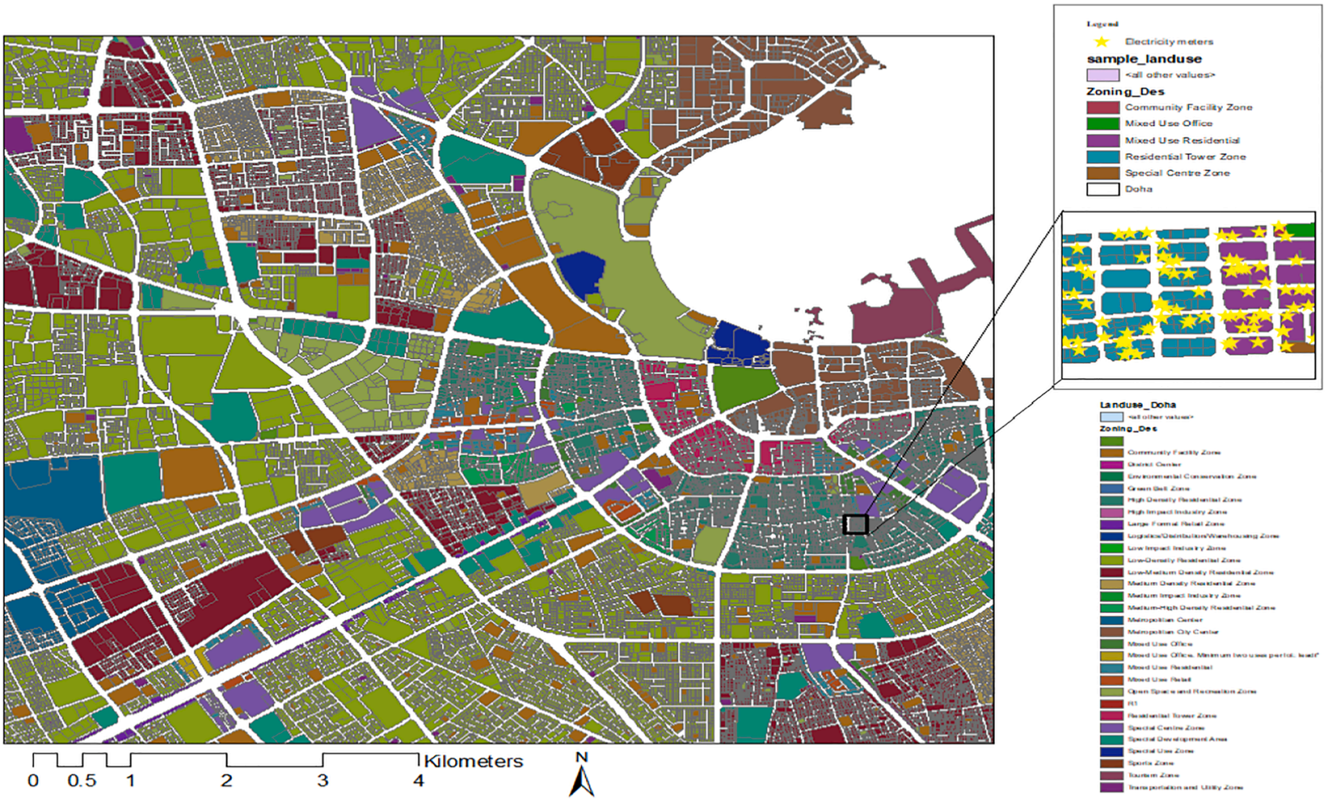


Fig. 3. Land use category in Doha City on the left, while on the right the metering system (stars in yellow) that Kahramaa uses to collect water and electricity data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Electricity (per kw) and water (per m^3) prices per sector (US Dollars) as for June 2021 (Source: Kahramaa - https://www.km.qa/CustomerService/Pages/Tariff.aspx).

Electricity (kw)	Residential (Villa)	Residential (Flat)	Commercial	Industrial	Productive farms	Government sector
1–2,000	0.03	0.03	0.035	0.036	0.02	0.087
2,001–4,000	0.035	0.035	0.035	0.036	0.02	0.087
4,001–10,000	0.05	0.05	0.047	0.036	0.02	0.087
10,001–15,000	0.05	0.05	0.06	0.036	0.02	0.087
15,001 and more	0.07	0.07	0.06	0.036	0.02	0.087
Water (M^3)						
1–20	1.5	1.5	1.65	1.5	1.4	2.5
21–50	01.9	1.9	2.4	1.5	1.4	2.5
51–250	1.9	1.9	2.4	1.5	1.4	2.5
251 and more	2.7	2.7	2.4	1.5	1.4	2.5

N and 51° 15′ E, as shown in Fig. 1. Qatar is located in one of the most water scarce regions in the world; it has the least renewable water and arable land resources [21,22], but it has rich fossil-fuel based energy resources. The energy wealth has allowed the government to generate freshwater from the sea through desalination. The revenue generated from its exporting energy resources are used to subsidise water and energy prices paid by local consumers.

Qatar has witnessed prompt economic development and population growth since the 1970s and is still among the fastest growing economies in the world [22]. Qatar's population has exponentially increased from 0.46 million in 1960 to 2.8 million in 2019 [20]. This significant increase is mainly due to the flux of the expatriate population to satisfy the economic growth and development needs of workers in the country. This economic development is attributed to the discovery of hydrocarbon energy sources [21] and the hosting of the FIFA World Cup 2022 [23,24]. The population growth and economic development have placed tremendous pressure on scarce groundwater resources in the country and led to an increase in demand on the country's limited water resources, which have resulted in overexploiting the limited natural renewable water resources in the country.

The State of Qatar has imposed many restriction measures to slow down the propagation of the COVID-19 disease. On 9 March 2020, the country announced the start of a national lockdown that included commercial, industrial, and governmental institutions and employees. Non-essential services in the country were closed including retail stores, restaurants and parks. Furthermore, the mobility of people was restricted by encouraging people to stay at their homes and by stopping public transportation services and imposing restrictions on the international visitors and flights. These restrictions reduced the number of daily infected cases and mortality rates; however, these steps have negatively affected the economy and quality of life of people. After the number of daily cases declined in the country, the government announced a four-phase plan to completely stop the lockdown orders in the country and allow all socioeconomic sectors in the country to operate normally. The first phase started on 15 June 2020 and included easing some restrictions, while the final phase started on 1 September 2020, which allowed all businesses to operate in full capacity and full opening to all socioeconomic sectors in the country. Therefore, different

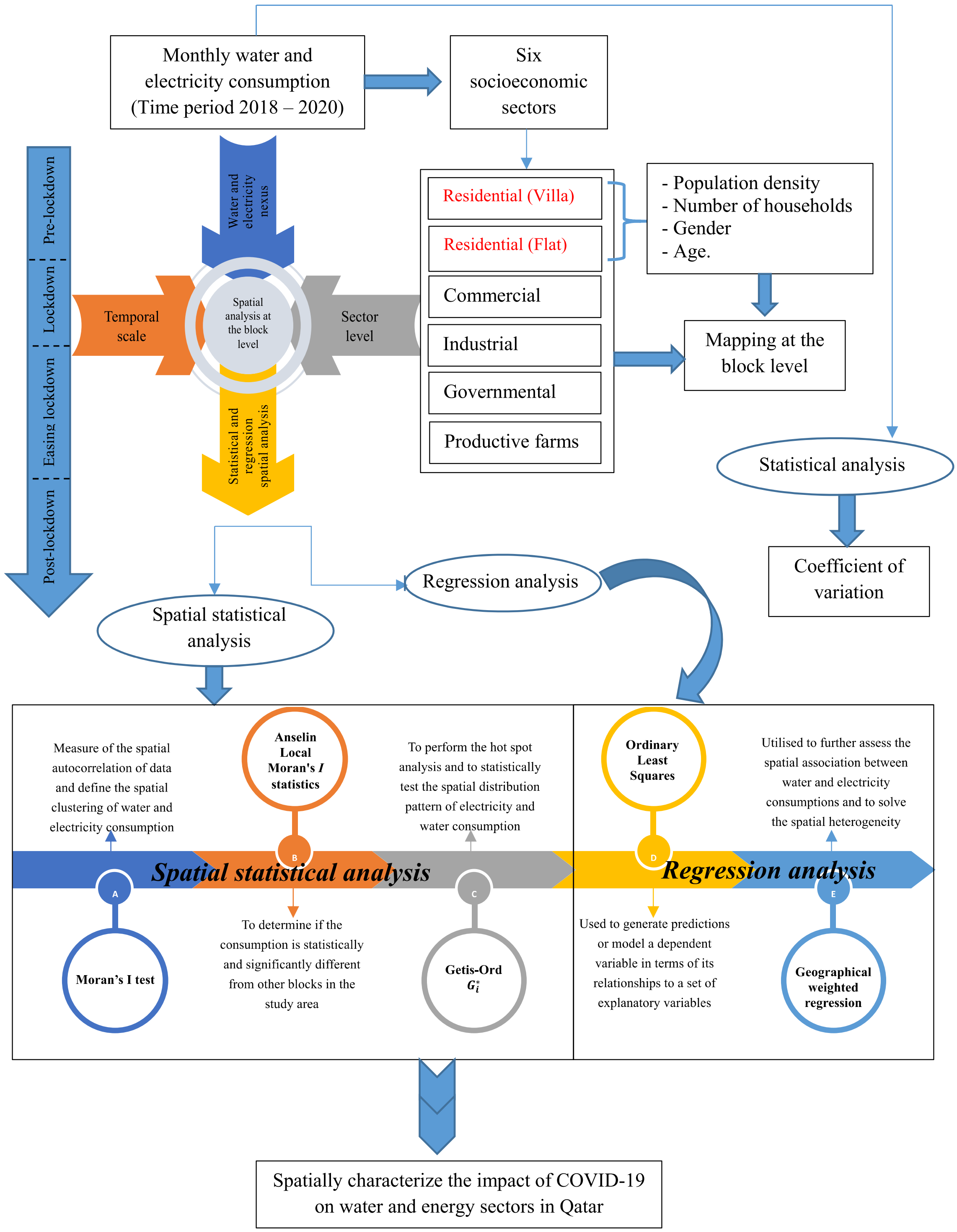


Fig. 4. The framework of this study.

temporal scales were adopted in this study. First, the water and electricity consumption was compared over time since 2018. Second, the spatial analysis was based on the annual average water and electricity consumption. Finally, the analysis was done on a finer time level taking four phases during the pandemic year (Fig. 2), while considering the changes in the propagation of the disease and the associated measures that the country took to curb the spread of the disease.

Qatar is an excellent case study to examine the water – electricity consumption. The country is semi-arid with unfavourable climatic conditions, limited annual precipitation, dryness that experiences significant water stress, the decline and shortage in water resources, rapid population and economic growth, urbanisation, relative wealth, and prolific energy supply. Historically, the population of Qatar has been small and has relied heavily on local production and imported foods from the neighbouring Saudi Arabia. Recently, the social and economic dynamics of the country has transformed significantly. In Qatar, the high-water scarcity necessitates local and regional levels of assessments for identifying the most appropriate policy directions and technologies.

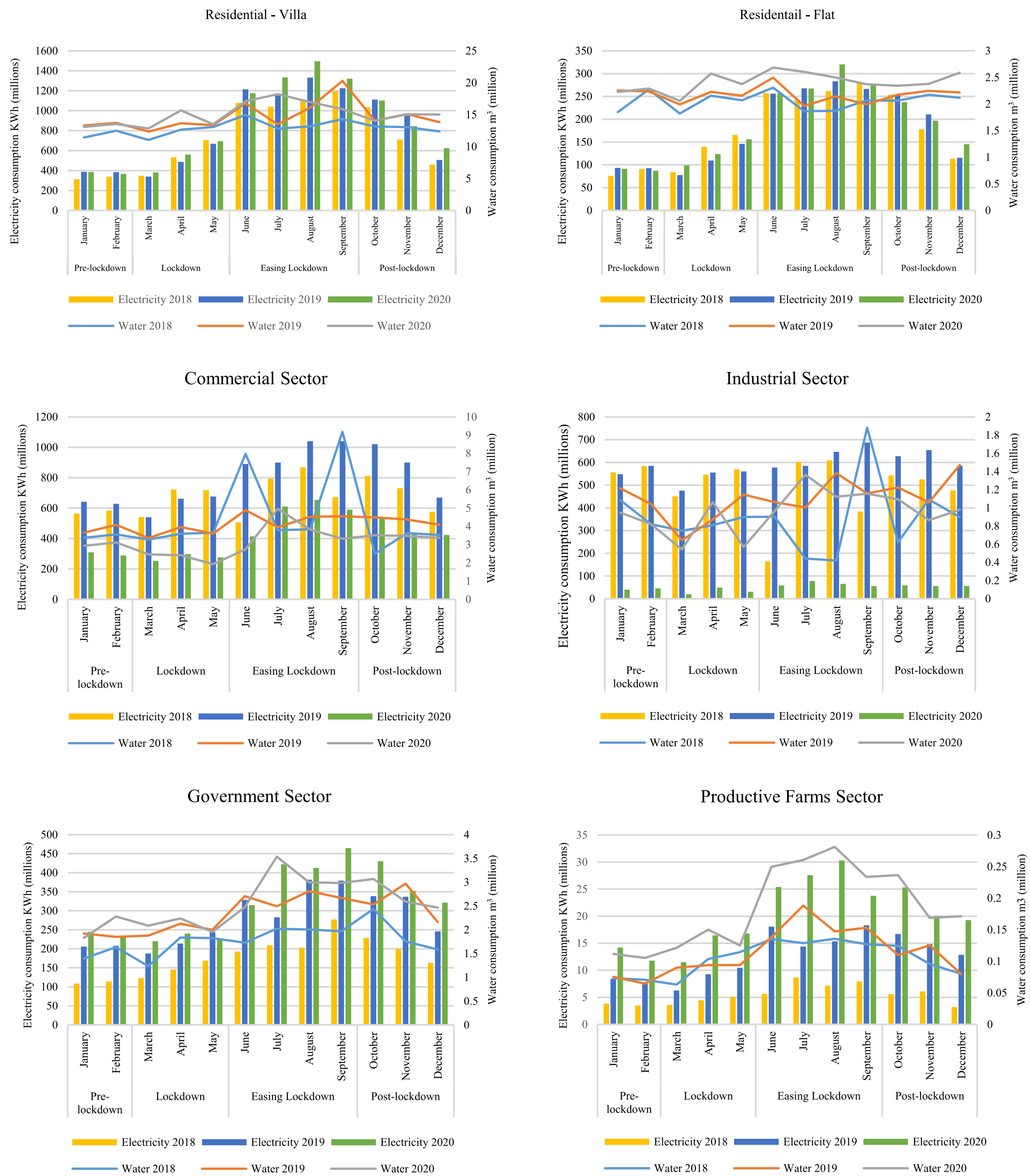


Fig. 5. Comparison of water and electricity consumption in Qatar during 2019 and 2020.

Table 3
Coefficient of variation of electricity and water consumption prior and during the pandemic year.

Year	Electricity consumption (KWh - million)					Water consumption (m^3 - million)			
	Statistics	Pre-lockdown	Lockdown	Easing lockdown	Post Lockdown	Pre-lockdown	Lockdown	Easing lockdown	Post Lockdown
2020	Mean	353	612	1782	979	7	10	18	12
	SD	298	589	1917	934	9	15	24	16
	CV	84	96	107	95	134	144	134	135
2019	Mean	631	995	2300	1428	7	10	18	12
	SD	510	760	1831	1070.	9	14	24	15
	CV	80	76	79	74	130	131	134	125
2018	Mean	555	996	1829	1170	6	10	16	10
	SD	502	811	1583	913	8	13	20	14
	CV	90	81	86	78	131	132	124	133

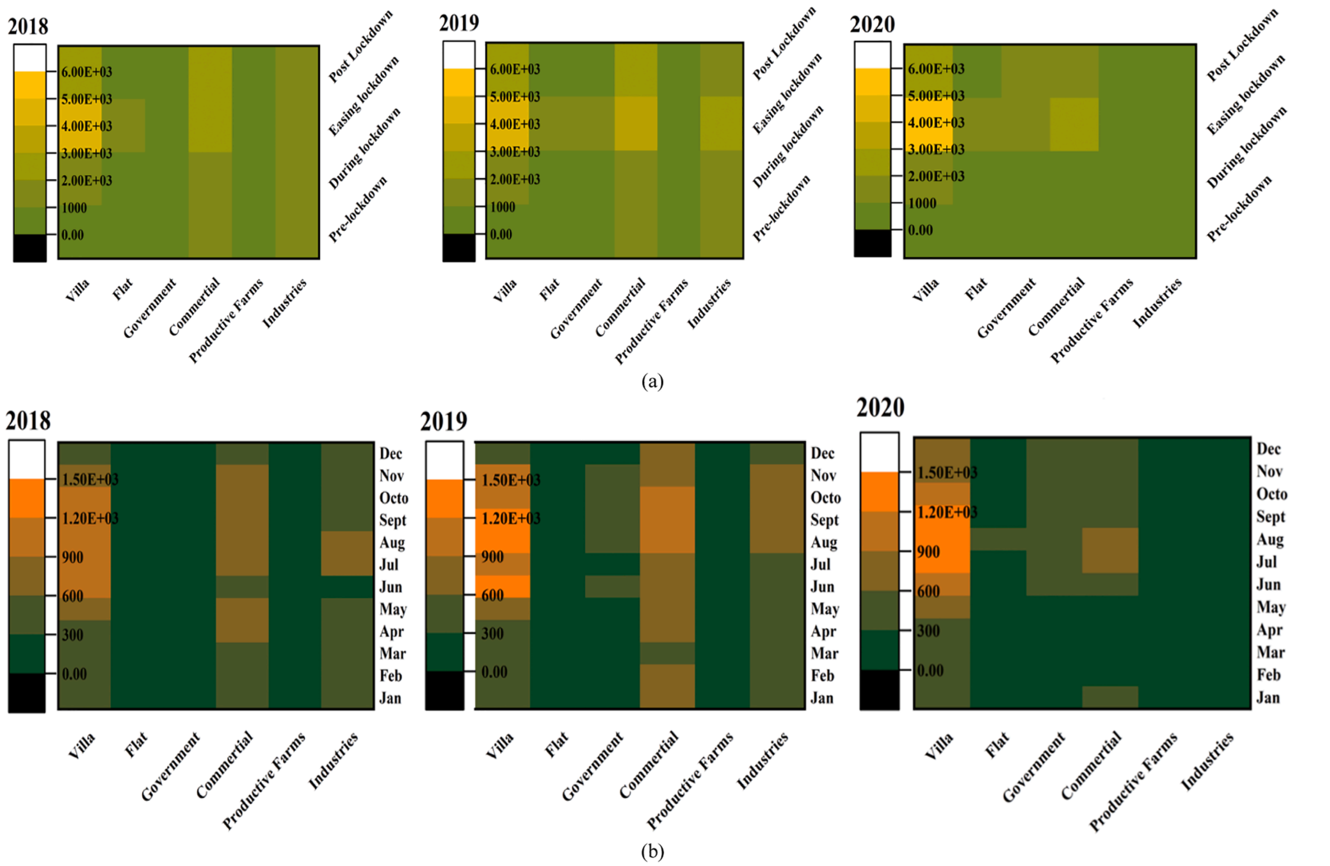


Fig. 6. (a) Electricity consumption during the four phases related to lockdown; (b) Monthly variation in electricity consumption prior and during the pandemic.

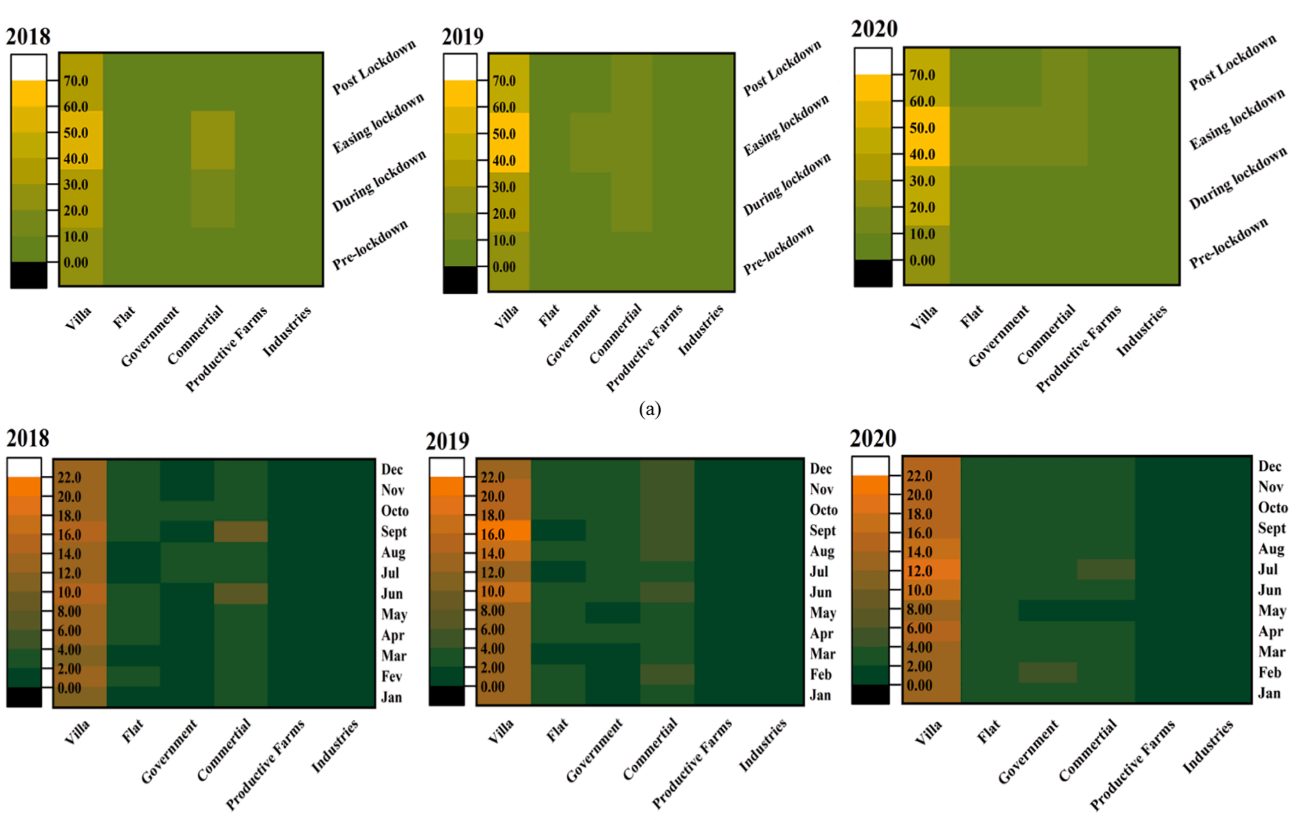


Fig. 7. (a) Water consumption during the four phases related to lockdown; (b) Monthly variation in water consumption prior and during the pandemic.

Fig. 8. The spatial distribution of electricity consumption levels across six socioeconomic sectors.

3. Dataset and methodology

3.1. Dataset

The data related to water and electricity consumption in this study were provided kindly by Qatar General Electricity and Water Corporation (KAHRAMAA) for the period starting on 1 January 2018 and ending on 31 December 2020 for different socioeconomic sectors, as shown in Table 1. Kahramaa is responsible for transmitting, distributing, regulating and maintaining the supply of electricity and water for the residence of the country. Additionally, the block shapefile map was provided by the Ministry of Municipality and Environment (MME).

Kahramaa and the MME identify land use categories in Doha city in different ways. Fig. 3 (left) shows the categories of the land use based on the MME classifications. The ministry classified the land use into 30 different categories. On the other hand, Kahramaa classify the buildings in the MME land use categories into 8 different classes and identify different tariff to each category. These categories are residential villa and flat, commercial, industrial, productive farms, government, hotels, and bulk industry. The tariff of the electricity and water in each of the six sectors is shown in Table 2. Kahramaa depends in collecting the monthly consumption rates on the meters installed in each building as shown in Fig. 3 (right). Furthermore, social explanatory variables were used to spatially explain the impact of different social parameters on water and electricity consumption. These data are population density, number of households, gender (males, females), and age categories (age cohort between 14 and 39 and age cohort between 40 and 64 years). These explanatory variables were obtained through the national GISnet, a fiber-optic network, which connects more than 90 hubs representing the main public agencies in the country that use the geospatial data. These data were obtained on the block level.

A geodatabase was developed within the GIS environment, and ArcMap 10.7 was utilised to link the water and electricity consumption rates to the blocks' boundaries shapefile of the Qatari block geographic units. The water and electricity consumption readings are spatially joined with the blocks that are located in it to analyse the water and electricity consumption on the finer scale possible.

3.2. Methodology

In this study, different methods were used to analyse the spatial distribution of water and electricity consumptions across six socioeconomic sectors by using a variety of tools embedded in the GIS software. The electricity and water consumptions data were analysed at the block level and were based according to the distribution of the socioeconomic sectors. The first aim was to discern differences visually in water and electricity consumption in the four stages between years 2019 and 2020 between different blocks. This visualisation is important to determine the blocks with a high rate of consumption and detect if this consumption varied by time due to the spread of the COVID-19 pandemic and the associated measures. This is a preliminary, but necessary, step to understand spatial variability of water and energy consumption over space and time. Hot spot analysis was performed (i.e., Moran's *I* test, the Anselin Local Moran's I statistics tool, and Getis-Ord G_i^* test) to determine the blocks with high water and electricity rates. Statistical cluster analysis can help in minimising the subjectivity in the resulted maps by identifying the meaningful clusters of the water and electricity consumption in each block. The hot spot analysis and outlier analysis tools use statistics to detect the spatial patterns of the water and electricity consumption in the study area. ArcGIS analysis provides traditional and optimised statistical cluster analysis tools. This type of analysis allows for more flexibility in defining the spatial relationships in the water and

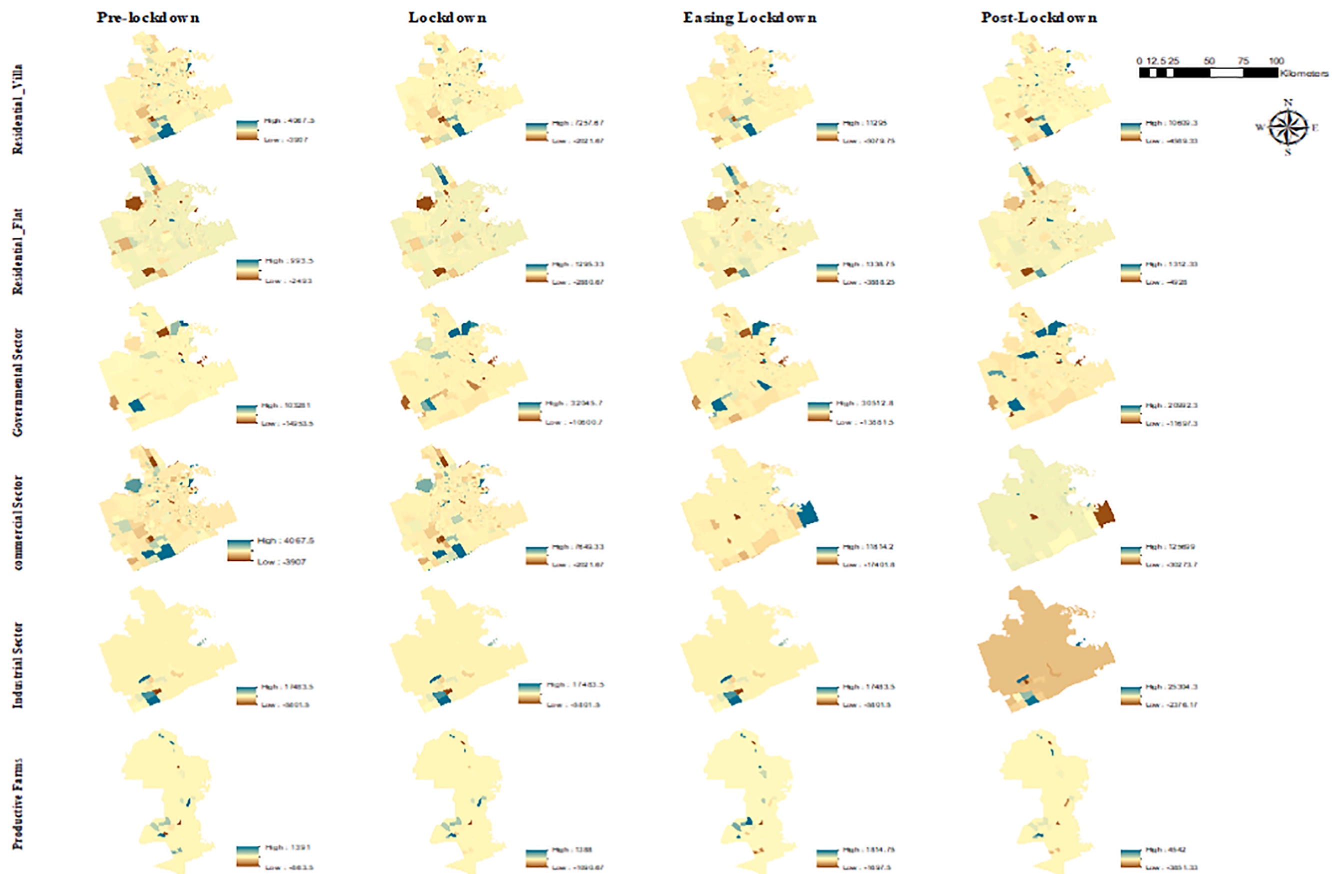


Fig. 9. The spatial distribution of water consumption levels across six socioeconomic sector.

energy consumption data. Three levels of statistical analysis are performed to analyse the impact of water and electricity consumption as shown in Fig. 4.

3.2.1. Statistical analysis

The coefficient of variation was used to investigate the relative differences in water and energy consumption concerning various socioeconomic sectors during 2020, and the results were compared with the measures of the last two years. This method was widely used previously to assess the degree of dispersion in different fields [25–28]. The spatial concentration of water and electricity consumptions in the country was described from 2018 to 2020 during the same periods of pre-lockdown, lockdown, unlock and post-lockdown periods, respectively. Seasonal correlations of water and electricity consumptions from six sectors were also explained to show the degree of relationship among various sectors from 2018 to 2020 (i.e., during different phases of lockdown).

3.2.2. Spatial statistical analysis

To define the spatial patterns and clustering of the electricity consumption across the six socioeconomic sectors, the local Moran's *I* test and Getis-Ord G_i^* test were used. These two tests are well-established and well-known geospatial statistics tools in the GIS literature for understanding the spatial patterns of any geographical phenomenon [29,30].

Moran's *I* is a measure of the spatial autocorrelation of data, allowing us to define the spatial clustering of water and electricity consumption across different socioeconomic sectors and its varying spatial densities. The values of Moran's test lie within a range of −1.0 to +1.0. The values near −1 indicate perfect dispersion of water and electricity consumptions, while values near +1 denote more clustering of water and energy consumptions. While Moran's *I* of zero denotes complete spatial randomness (i.e., no spatial autocorrelation). In this study, Local Moran's *I* has also been applied for better understanding whether the water and electricity consumption patterns are clustered, dispersed or random during the pandemic. Z- score, which is relevant statistics to Moran's *I* statistic, quantifies the degree of deviation (i.e., the dispersion or clustering around Moran's *I* value). Another relevant statistic to Moran's *I* is the P-value, which gives indications of the statistical significance of clustering outputs. Eq. (1) has been used for computing Moran's *I* [29,31].

$$I = \frac{N\sum_i\sum_j W_{i,j}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\left(\sum_i\sum_j W_{i,j}\right)\sum_j\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)^2} \tag{1}$$

where N is the number of blocks in each socioeconomic sector, X_i and X_j are the variable values at a specific location and at another location, respectively, and W_{ij} is a weight applied to the comparison between location I and location j. This distance-based weight matrix is based on the inverse distance between locations i and j (i.e., $1/d_{ij}$).

Furthermore, the Anselin Local Moran's *I* statistics tool was used to analyse the spatial pattern of water and electricity consumptions in each block in the study area to determine if the consumption is statistically and significantly different from other blocks in the study area. This test identifies statistically significant clusters of high and low water and electricity consumption rates and the outliers that have values that are statistically different spatially and temporally from their surroundings.

To statistically test the spatial distribution pattern of water and electricity consumption in Doha city, the Getis-Ord G_i^* was employed to perform the hot spot analysis in GIS platform to determine whether the highest or lowest water and electricity consumption levels tend to be spatially clustered (dependent). The results of the Z-scores and P-values in this test indicate if blocks with either high or low consumption tend to

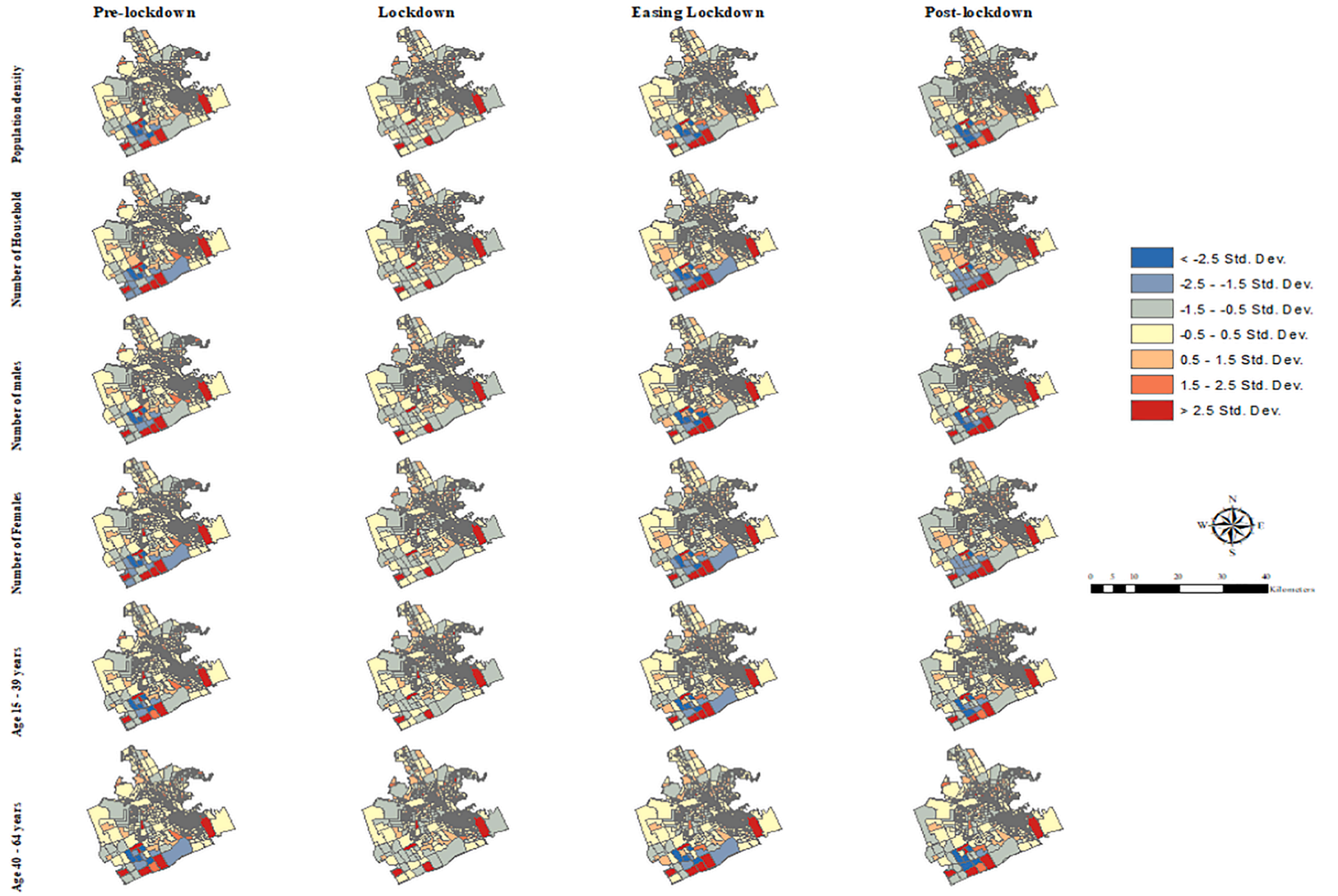


Fig. 10. The effect of social determinants on electricity consumption during the four phases in the pandemic year. Although the figure shows clustering of hot spots in the southern parts of the city, this pattern is different during the lockdown phase.

be clustered over space. This test assigns a Z-score to each location over space. Accordingly, the larger the Z-score is, the more intense the clustering of high water and electricity consumption values (hot spot) are. On the other hand, cold spots are identified when more clustering occurs on lower consumption rates [29,32]. In this case, Z-scores are smaller and considered statistically significant negative. This test is utilised in this study to identify and analyse the spatial clustering of water and electricity consumption levels across different socioeconomic sectors in Qatar during the year of pandemic. The Getis-Ord G_i^* is computed according to the following formula:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \tag{2}$$

where n is the consumption rate value, x_j is the attribute value for feature j, w_{ij} is the spatial weight between block i and block j and X is the mean of the variable. This distance-based weight matrix is based on the inverse distance between locations i and j (i.e., $1/d_{ij}$).

3.2.3. Regression analysis

Furthermore, the regression analysis using univariate OLS and GWR models with a single variable were used to examine the association between water and electricity consumptions and the spatial relationship between these two variables across the six socioeconomic sectors. Both models were performed in ArcGIS 10.7. The models' performance was assessed based on the R^2 (coefficient of determination) value, which shows the prediction ability of a regression model to fit the measured values of the dependent variable. Furthermore, the corrected Akaike Information Criterion (AICc) values were used as another tool to assess the performance of the models. This tool is an indicator of the relative information lost by the model during the estimation process. The models perform better when the value of R^2 is high and the value of the AICc is low [33,34].

The OLS tool is a global linear regression method used to generate predictions or model a dependent variable in terms of its relationships to a set of explanatory variables. OLS is the best- known regression technique and provides a good starting point for spatial regression analysis. It assumes that the relationship between these dependent and independent variables are stationary and do not vary over space [33,35]. The OLS can be computed according to the general form of [35,36]:

$$y_i = \beta_0 + x_i \beta + \varepsilon_i \tag{3}$$

where at block i, y_i is the electricity consumption rate, β_0 is the intercept and illustrates the value of y when x equel to zero, x_i denotes the water consumption at the block level, β is the vector of regression coefficients, and ε_i is a random error term. OLS minimises the sum of squared prediction errors and hence optimises the regression coefficient (β) [35,37]. However, one of the weaknesses of the global regression models is the difficulty to properly explain the spatial hetrogeneity [34].

Due to the spatial distribution of each socioeconomic sector being unbalanced and prevalence of inter-block spatial heterogeneity and spatial correlation, the global regression models such as the OLS assumptions do not hold any more. Therefore, to improve the OLS prediction, the GWR model [33] was utilised to further assess the spatial association between water and electricity consumptions and to solve the spatial heterogeneity. The GWR model is a local form of linear regression for modelling spatially varying relationships. This model is based

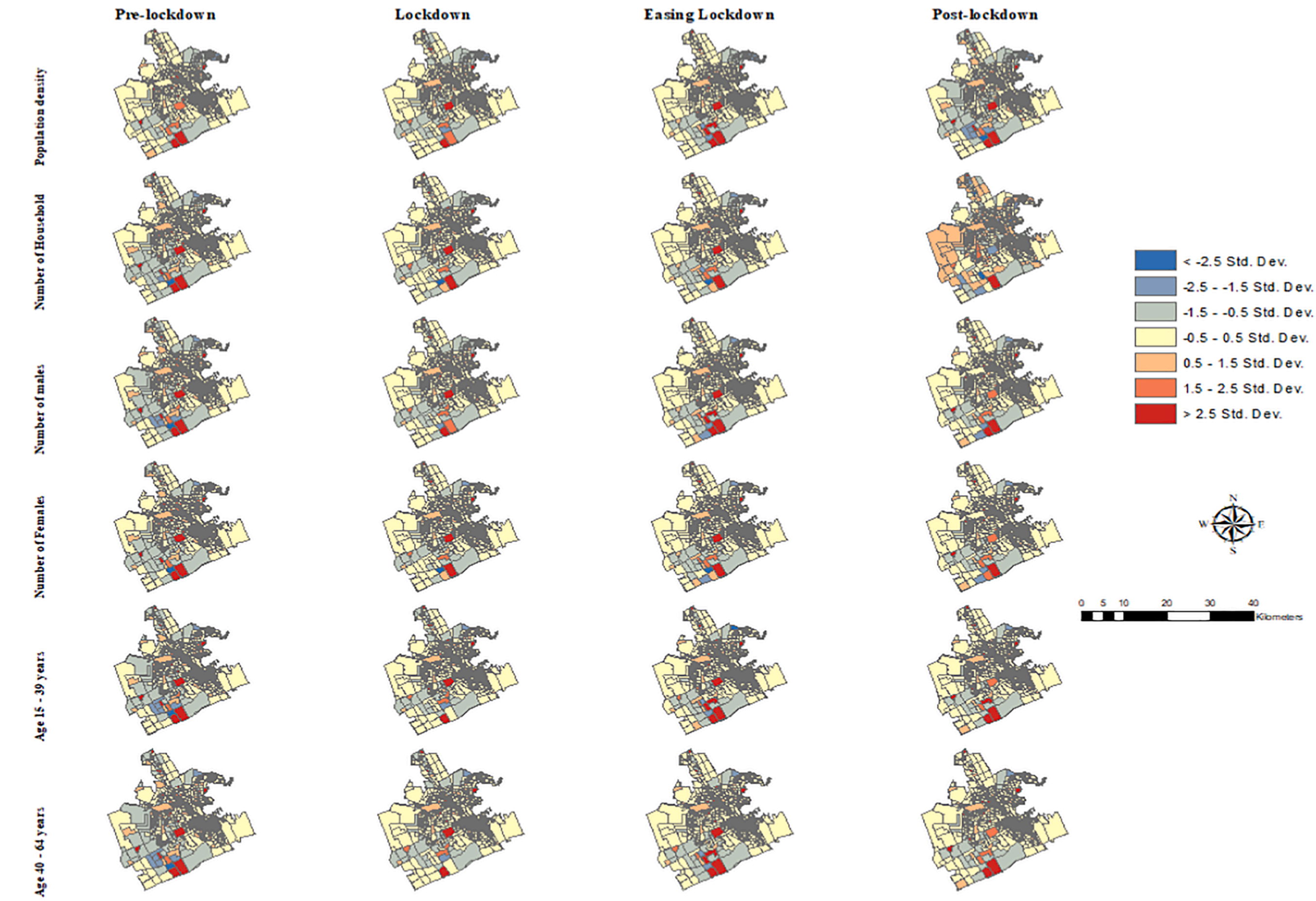


Fig. 11. The effect of social determinants on water consumption during the four phases in the pandemic year.

on kernel-weighted regression and is developed as an extension of general regression models. Mathematically, the model is represented as the following [35,38,39]:

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_{ij} X_{ij} + \varepsilon_i, i = 1, 2, \cdots, n \tag{4}$$

where at block i, y_i is the value of electricity consumption rate, β_{i0} is the intercept, β_{ij} is the j_{th} regression parameter, X_{ij} is the value of the j_{th} explanatory parameter and ε_i is a random error term. In a matrix form, parameter estimates for each explanatory variable and at each block is given as follows [35,38]:

$$\widehat{\beta}(i) = (X^{'} W(i) X)^{-1} X^{'} W(i) Y \tag{5}$$

where $\widehat{\beta}$ denotes the vector of parameter estimate (m × 1), X demonstrates the matrix of selected explanatory variables, W(i) is a diagonal matrix of spatial weights (n × n) and is constructed from the weights of each observation depending on its distance from the location i and is calibrated based on a locally weighted regression, and y represents the vector observations of electricity consumption rates (m × 1). Furthermore, a distance-decay function (w_{ij}) is employed to predict the regression coefficients as a distance-weighting factor between the study area and the observations. Since each socioeconomic sector is distributed irregularly in the study area and to increase the correspondence of the model, a variable bandwidth is used by an adaptive weight kernel, which is represented as the following [34].

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{\theta_{i(k)}}\right)^2\right)^2 d_{ij} < \theta_{i(k)} \\ 0 d_{ij} > \theta_{i(k)} \end{cases} \tag{6}$$

where d_{ij} is the distance between observations i and j in each socioeconomic sector, $\theta_{i(k)}$ is the adaptive bandwidth defined by the k^{th} nearest neighbour distance. The distance-decay function becomes zero when the distance between the observations become greater than the adaptive bandwidth.

4. Results

4.1. Temporal analysis of electricity and water consumption between 2018 and 2020

Fig. 5 shows the water and electricity consumption in Qatar during 2018 and 2020 on a monthly basis and in the four phases. The figure clearly shows that the water and electricity consumption in these sectors was affected differently due to the lockdown policies adopted by the country due to the propagation of the pandemic. Prior to the lockdown phase in 2020, the residential sector (villas and flats) witnessed an increase in electricity (15% for villas and 7% for flat) and water (11% for villa and 9% for flat) consumption compared to the consumption in the same period in 2018, and slight decrease in electricity (2% for villas and 4% for flat) and water (1% for villa and 0.6% for flat) compared to the same period of 2019 due to the population and economic growth. This increase implied as well to the government and productive farms sectors, albeit at different levels. On the one hand, the commercial and

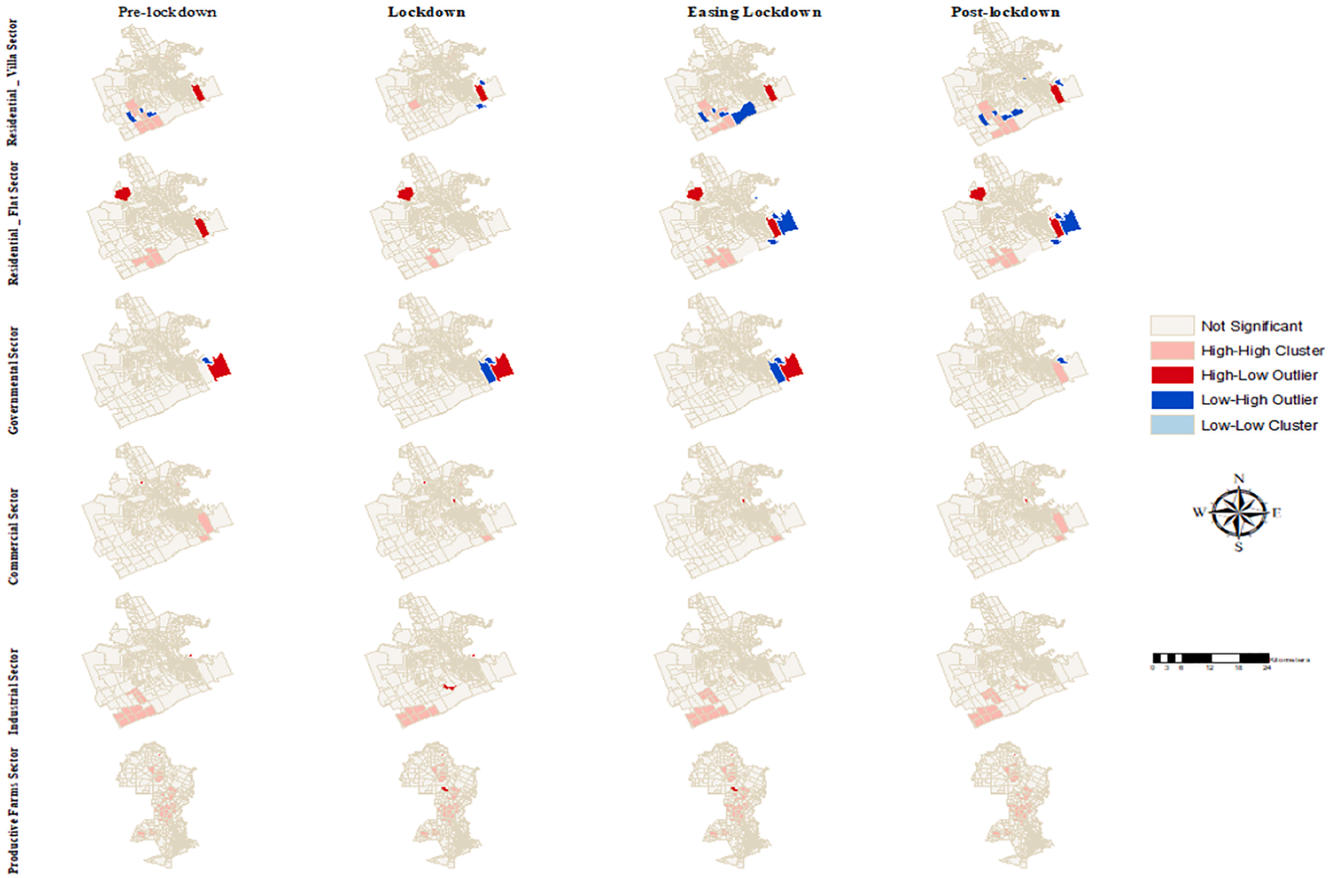


Fig. 12. The Anselin Local Moran's *I* statistics of electricity consumption across six socioeconomic sectors. Different blocks are identified as hot spots (high-high) in the residential (villa), industrial, and productive farms sectors during the four phases.

industrial sectors witnessed a decrease in water and electricity consumption. This trend continued during the lockdown phase, when the electricity and water consumption increased in the residential sector because of the stay-at-home policy that forced many employees and students to perform their activities from their homes. On the other hand, the industrial and commercial sectors witnessed the highest drop in consumption due to the closure of many related economic activities due to the lockdown. The productive farms sector was not affected by the lockdown policy, as the water and electricity consumption increased steadily during all months of the lockdown period compared to consumption in the same period in 2018 and 2019. During this phase, the water and electricity consumption dropped in the commercial sector, while only electricity consumption decreased in the industrial sector during the lockdown period. In easing lockdown phase, almost all sectors witnessed an increase in water consumption, while the electricity consumption varied in these sectors. The figure shows that the electricity consumption increased in the residential, government, and productive farms and decreased in other sectors. Overall, the figure shows that electricity consumption has decreased mainly due to the decrease in electricity consumption in the commercial and industrial sectors, which is considered the main consumption of electricity in the country. On the other hand, the water and electricity consumption increased during the summer due to travelling ban by many countries across the globe and hence many people were not able to travel outside the country due to the non-opening of the commercial and industrial activities.

The coefficient of variation statistical test was performed to examine the changes on total water and electricity consumption prior and during the pandemic year in the four phases related to the lockdown. The results in Table 3 show that there is an increasing demand from all sectors on water and electricity since 2018, and this is reflected on the different phases related to the lockdown measures. In the lockdown period, for example, the water and electricity consumption levels increased in 2020 compared to the same period in 2018 and 2019. In general, the total electricity consumption during the lockdown period increased by 18% and 30% in 2020 compared to 2018 and 2019, respectively, while the water consumption during the same time period increased by 14% and 6% compared to 2018 and 2019, respectively. The CV value of the electricity consumption increased in 2020 by 18.22% and 26% compared to 2018 and 2019, respectively, while it increased by 8% and 9% compared to 2018 and 2019, respectively in the water consumption. This variation applies to the easing lockdown and post-lockdown phases in the electricity consumption and to all other phases related to water consumption.

The variation of electricity consumption during the four phases and during the months of 2020 compared to 2018 and 2019 is shown in Fig. 6. The maximum electricity consumption is during the easing lockdown phase compared to the other phases due to the increase in consumption in the commercial and government sectors. The residential flat sector witnessed an increase in the electricity consumption during the four phases and all months of the pandemic year compared to the previous year. On the other hand, the commercial sector witnessed a decline in the electricity consumption, particularly during the lockdown phase.

The water consumption has almost the same patterns as the electricity consumption during the pandemic year, as shown in Fig. 7. During the easing of lockdown period, water consumption from the residential (villas) sector has increased compared to the same period in 2018 and 2019 due to the summer month when usually water consumption increases. The figure shows that the highest monthly water consumption was during the months of June, July and August. The

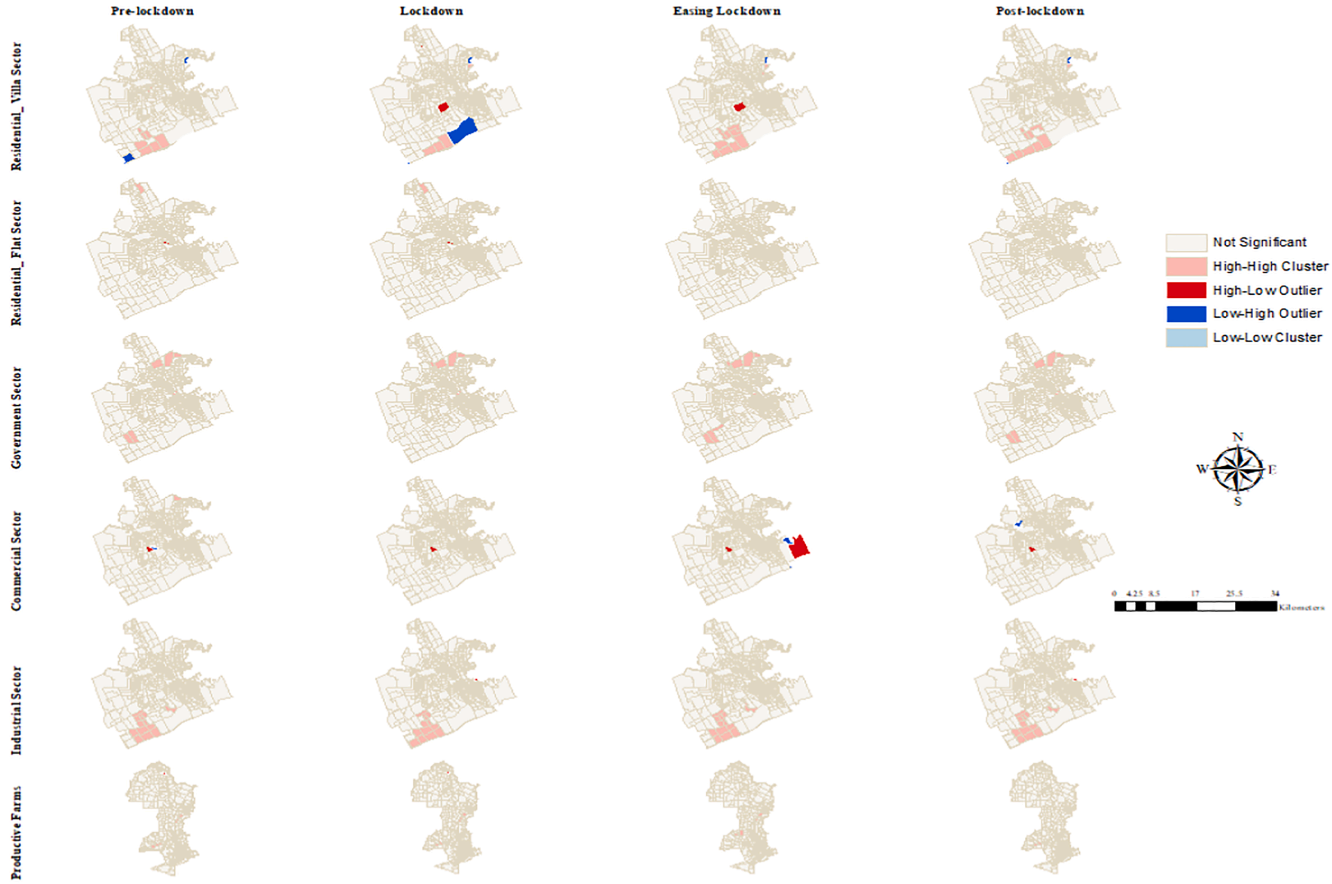


Fig. 13. The Anselin Local Moran's *I* statistics of water consumption across six socioeconomic sectors. Different blocks are identified as hot spots (high-high) in the residential (villa), government, industrial, and productive farms sectors during the four phases.

Table 4
Moran's Index for electricity and water consumption.

Electricity consumption				
Sector (electricity)	Moran's Index	Variance	z-score	p-value
Residential (Villa)	0.0816	0.000193	5.913	0.000
Residential (flat)	−0.006	0.000196	−0.379	0.705
Government	−0.001	0.00000	−0.054	0.956
Industry	0.066	0.000120	6.100	0.000
Productive Farms	0.150	0.000515	12.242	0.000
Commercial	0.121	0.000209	8.452	0.000
Water consumption				
Sector	**Moran's Index**	**Variance**	**z-score**	**p-value**
Residential (Villa)	0.102	0.000170	7.901	0.000
Residential (flat)	−0.004	0.000136	−0.274	0.784
Government	0.021	0.000040	3.445	0.000
Industry	0.045	0.000046	6.726	0.000
Productive Farms	0.020	0.000124	1.847	0.065
Commercial	−0.003	0.000124	−0.188	0.851

water consumption in the commercial sector witnessed a decline during the lockdown period in 2020 compared to the same period in previous years.

4.2. Spatial analysis of water and electricity consumption

Mapping the differences in the water and electricity consumption between 2019 and 2020 during the four phases across the six different socioeconomic sectors on the block level reveals spatial changes in the consumption rates prior to and during the pandemic, as shown in Fig. 8 and Fig. 9. The blocks with high water and electricity annual consumption changed and increased during the pandemic year (2020) in the residential (villas and flats) and the government sectors in Doha city, and the productive farms outside the city compared to 2019. While, on the other hand, the blocks with lower water and electricity consumption levels increased in both the commercial and industrial sectors. However, these blocks are scattered in different areas in the city due to the spatial distribution of each sector within the city. In the residential sector (villas and flats), for example, the electricity and water consumptions increased in the southern and eastern part of the city. While the electricity consumption increased in the governmental sector in many scattered blocks within the city.

Social factors affect the electricity and water consumption. In this study, four social parameters were considered in explaining the spatial variation in the electricity and water consumption in the residential sector. These factors are population density, number of households, gender, and age. These factors are considered on the block levels. GWR was used to examine the impact of each of these factors on electricity and water consumption. Fig. 10 shows the effects of the social determinants on the spatial distribution of electricity consumption in the residential (villa) sector during the four phases in year 2020. The figure shows that there are hot spots and cold spots in the southern parts of the city during the four phases; however, the pattern is different during the lockdown period as the areas with hot spots and cold spots are reduced. One possible explanation of this difference is that this area has many industrial and commercial activities and during the lockdown these activities were closed to reduce the propagation of the disease and hence many people either moved to other places in the city or left the country due to losing their jobs. The same applies on water consumption as shown in Fig. 11. The figure shows that water consumption are more

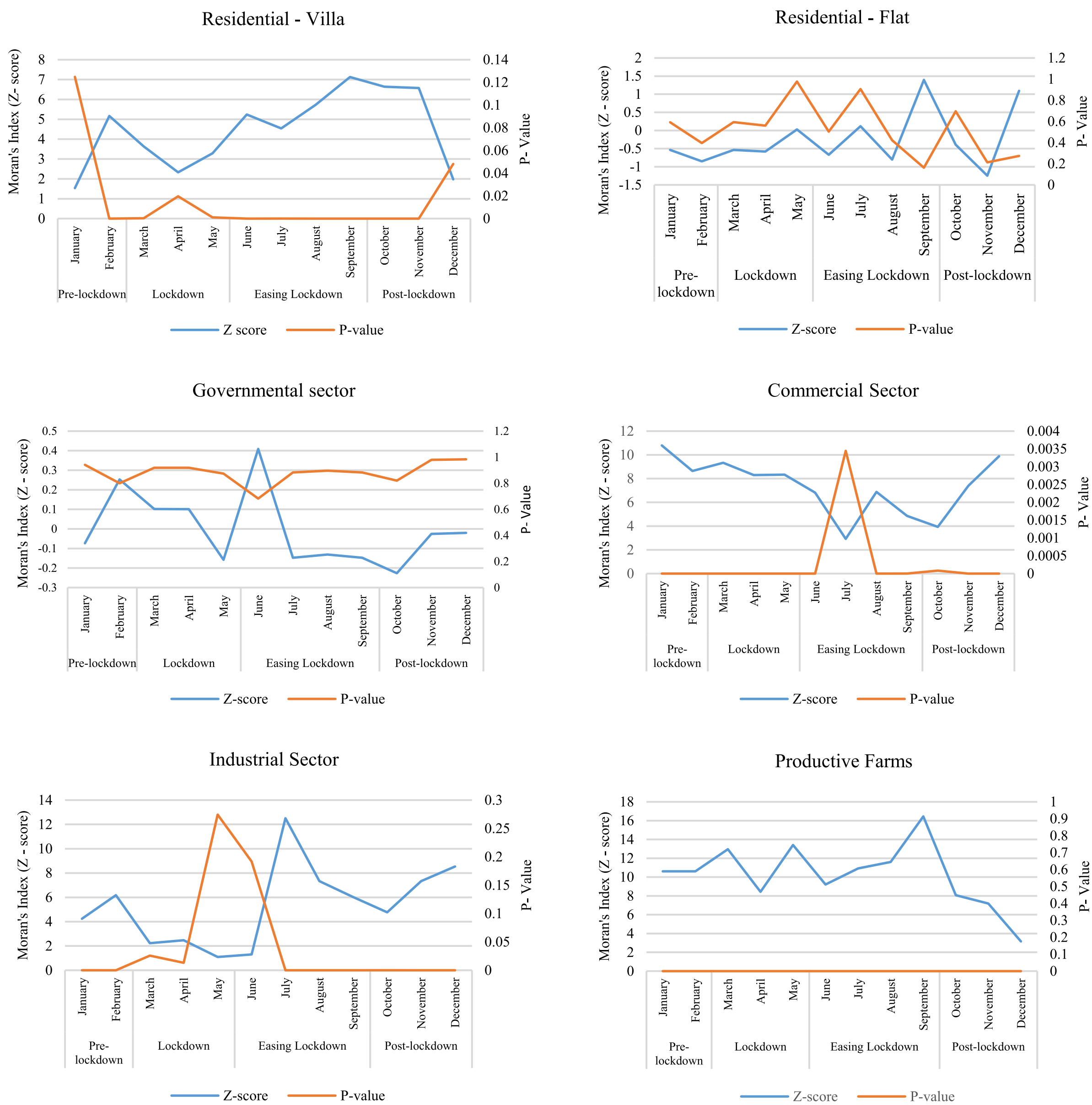


Fig. 14. Z- scores and P- values for the electricity consumption across six socioeconomic sectors.

clustered in the southern part of the city with some differences in the lockdown phase.

4.3. Hot spot analysis of water and electricity consumption

The analysis of the Anselin Local Moran's *I* statistic show different results for each socioeconomic sector based on the four phases time frame, as shown in Fig. 12 and Fig. 13. The figures show that some blocks are identified as high-high (statistically significant cluster of high values) water and electricity consumption levels. For example, the special pattern of electricity and water consumptions in the residential (villas and flats) sectors illustrate a hot spot and positive autocorrelation in the blocks located in the southern part of Doha city associated with low–high outliers in adjacent blocks, particularly concerning the electricity consumption during the four phases. The same pattern could be seen in the industrial sector, where the figures show a positive autocorrelation (high-high) pattern of water and electricity consumption in the southern part of the city. The productive farms sector also shows a positive autocorrelation (high-high) pattern of electricity consumption and to a less extent a positive autocorrelation (high-high) water consumption in different areas near Doha city.

The local Moran's *I* showed that the annual water and electricity consumption levels are clustered in some of the socioeconomic sectors and random in others, as shown in Table 4. Regarding the electricity consumption, the entries in the table show that residential (villas), industrial, productive farms, and commercial sectors are clustered, where Moran's Index indicates high positive values of Z- scores and was well above the 2.25 threshold (a confidence level above 95%), although the Moran's Index has a low positive value. This indicates that in blocks with high electricity consumption rate, the neighbouring blocks inclined to have analogous consumption rates. The results show a significant spatial autocorrelation, indicating that electricity consumption rates between the neighbouring blocks were positively and significantly spatially related in these sectors. On the other hand, the water consumption was found to be significant in the residential (villas), industrial, and government sectors, where Moran's Index indicate high positive values of Z-scores and were well above the 2.25 threshold.

Disaggregating these values to reflect the four phases during the pandemic year, the Z- scores and P-values are significant in some phases or at specific times of these phases, as shown in Fig. 14 and Fig. 15. In

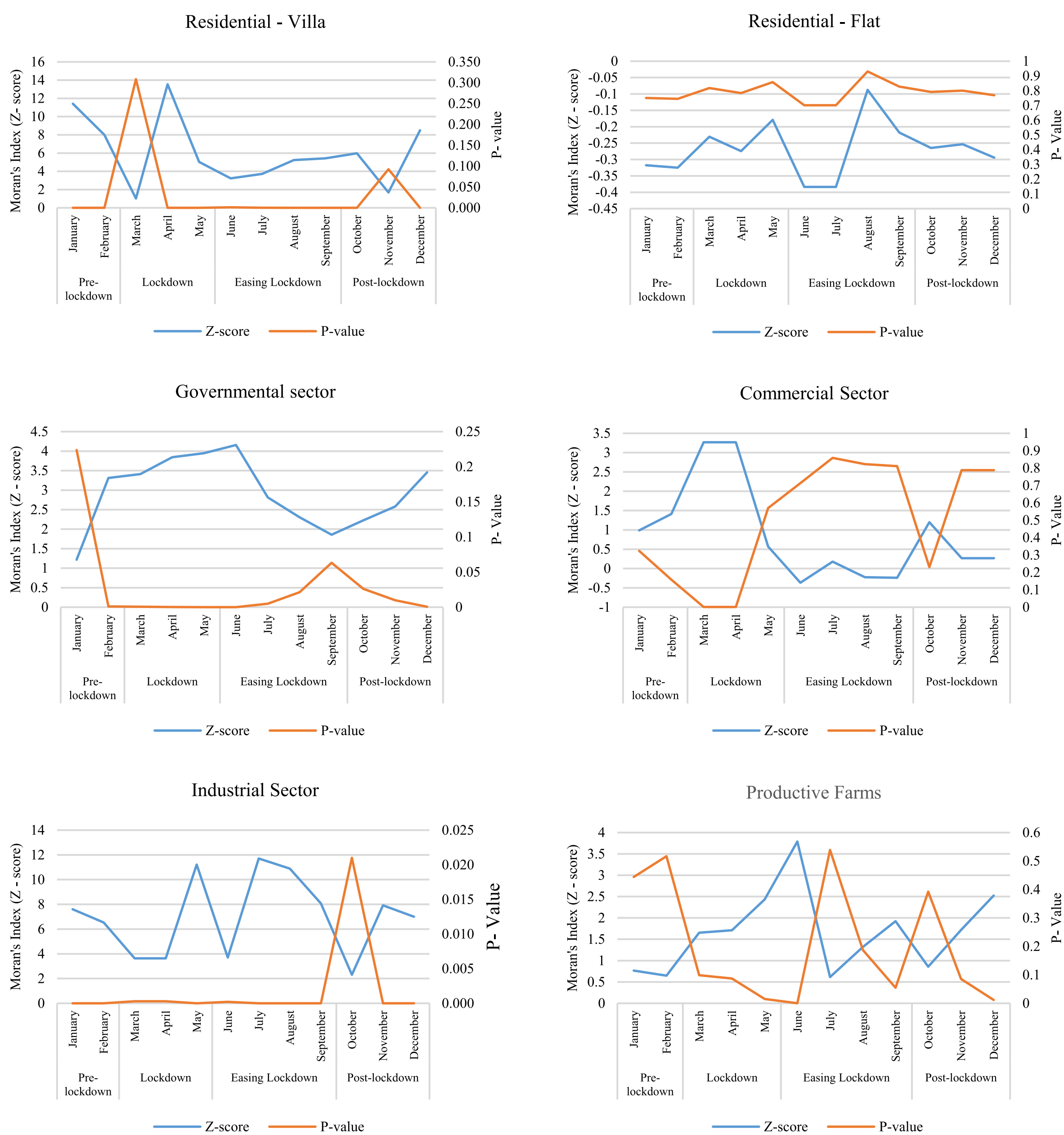


Fig. 15. Global Moran's test: Z- score and P- value for the water consumption.

terms of the electricity consumption (Fig. 14), the Z-score values in the residential (villas), commercial, industrial, and productive farms sectors show a value greater than 2.58 in most of the phases' periods, which gives a confidence level of 99% and indicates that there is less than 1% likelihood that the electricity consumption clustered pattern is a result of random chance. These values are associated with very low P-value (<0.005), which emphasises that the spatial pattern of electricity consumption is not random. However, the Z-scores in some periods of the four phases are low and associated with high P-values. For example, in the residential (villas) sector, the figure shows that the month of January has a low Z- score associated with high value of P-value. In the industrial sector, the figure shows that at the lockdown stages the Z-score value is very low and associated with high P-value. The Z-scores for the residential (flats) and the governmental sectors are not high during the year and are associated with high P-value as shown in the figure indicating that the electricity consumption is random in this sector.

The Z-scores and P-values of the water consumption during the four phases in the different socioeconomic sectors reveal different results from the electricity consumption in some of these sectors as shown in Fig. 15. The residential sector, for example, shows the same pattern as in electricity consumption pattern except at the beginning of the lockdown phase, where the Z-score value is low associated with high P-value. The Z-scores and the P-value of the water consumption in the government sector have different patterns than electricity consumption. The figure shows that the Z-score values across the four phases are high associated with low P-value. In the commercial sector, the Z-score values during the lockdown phase are high associated with low P-values.

Further analysis was done utilising Getis-Ord G_i^* to identify statistically significant hot spots and cold spots in the annual electricity and water consumptions across the six socioeconomic sectors, as shown in Fig. 16. This tool shows the same pattern in the spatial distribution of the positive correlation between blocks in the annual electricity and water consumptions. However, this tool shows more clustering of hot spots at the 99% confidence level with Z-score higher than 1.96 in the residential (villas and flats), commercial, industrial, and productive farms sectors in the annual electricity consumption. The figure shows that the high

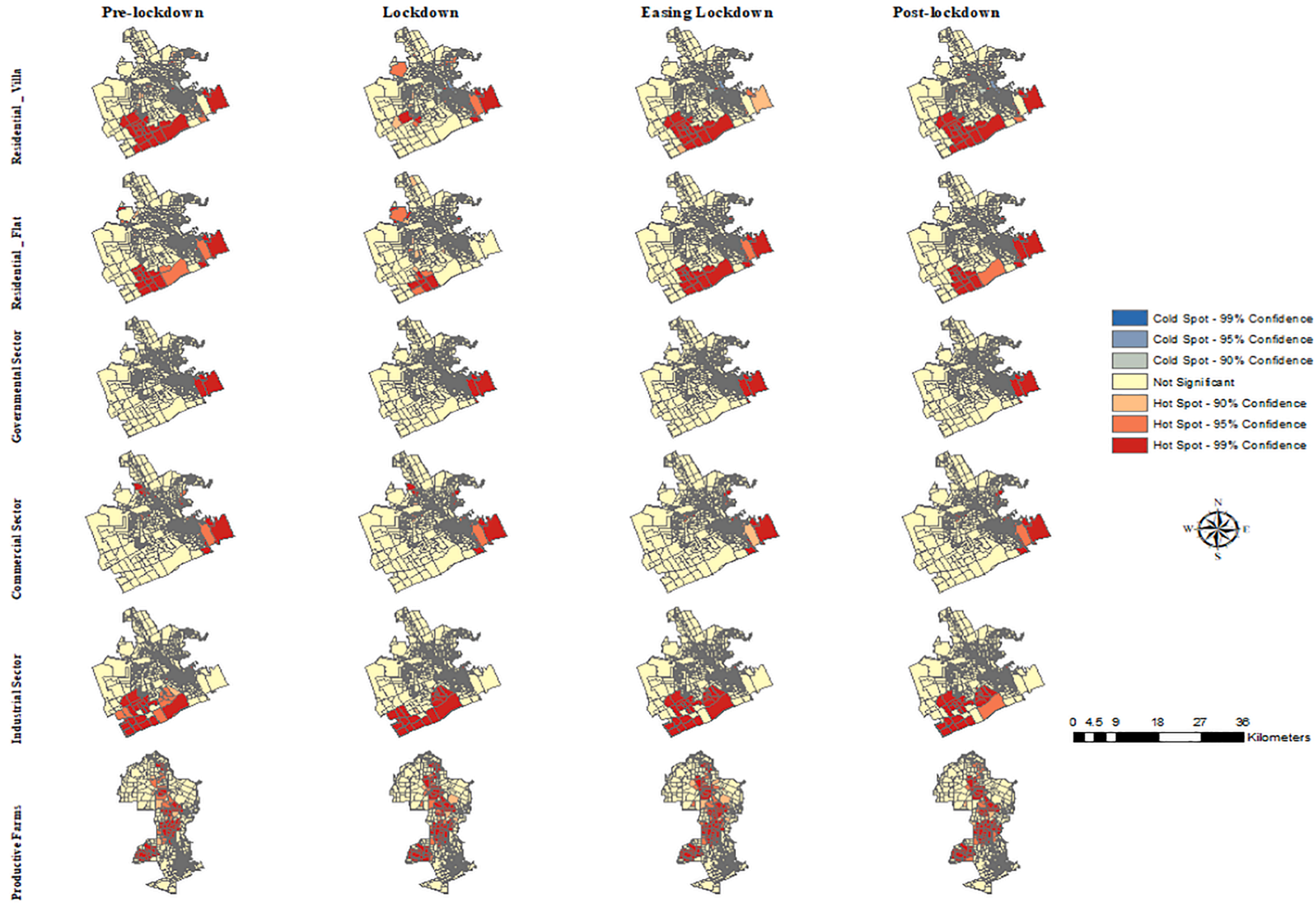


Fig. 16. The Getis-Ord G_i^* statistics of electricity consumption across six socioeconomic sectors.

consumption of electricity in the residential and industrial sectors are concentrated in the southern blocks of the city, while in the commercial sectors, the high annual consumption of electricity is concentrated in the eastern and northern parts of the city. The same pattern implies to the residential (villas) and the industrial sectors in terms of the annual water consumption, as Fig. 17 shows that the high annual water consumption is concentrated in the southern blocks of the city. However, the figure shows some high annual water consumption in the governmental sector in the northern blocks of the city.

4.4. Association between electricity and water consumption

4.4.1. Outcomes of the OLS global model

The OLS global model was applied to determine if there is an association between water and electricity consumption across the six sectors. For each sector, the electricity consumption is considered as the dependent variable, while water consumption is considered as the independent variable. The outcomes of the OLS model reveal that the Jarque-Bera P-value is not significant, and hence the model predictions are not biased. This indicates that the residuals are normally distributed (free from spatial autocorrelation). The spatial autocorrelation of regression residuals is expected in the model if underlying spatial relationships do exist. This illustrates the misspecification of the OLS model because of the non-stationary of the spatial process [34]. The results of the model reveal some significant clustering of the electricity and water consumptions in different socioeconomic sectors, as shown in Table 5. The coefficient estimates are highly significant with P-values less than 0.005 (except for the governmental sector) indicating a positive association between electricity and water consumption. Furthermore, the variables have free multi-collinearity since the VIFs values of the water and electricity consumption levels in all sectors are below the threshold of 5 [35,40]. However, the R^2 of the OLS model reveals very low adjusted value (0.259–0.426) suggesting that the model could not properly explain the spatial relation between water and electricity consumption levels and that the electricity consumption is associated and explained by other factors than water consumption and vice versa, and the OLS global model was not the best fit for this group of data. Spatially, Fig. 18 shows the blocks where electricity consumption is associated with water consumption, which are clearly shown in the residential (villas and flats), commercial, and productive farms sectors.

4.4.2. Outcomes of the geographically weighted regression

The GWR was employed to investigate the local spatial variation of the electricity and water consumption in each socioeconomic sector. The spatial differences are shown in Fig. 19. The maps show some blocks with high water and electricity consumption. These blocks are scattered in the residential (villas and flats) and commercial sectors throughout the city, while they are concentrated in the south-western part of the city in the industrial sector and the middle parts of the productive farms area. The values of the AICc and R^2 resulted from both OLS and GWR models vary across the socioeconomic sectors during the pandemic year. In general, the GWR model shows higher goodness-of-fit than the OLS model. The OLS model could account for 25.9%–42.6%, explaining the association between water and electricity consumptions, as shown in Table 6. Furthermore, the corresponding AICc values range between 7504.98 and 9283.58. On the other hand, the GWR model could explain between 53.1% and 63.7% of the association between the water and electricity consumptions in the six socioeconomic sectors, and the corresponding AICc values have dropped to the range between 5457.23 and 7498.23.

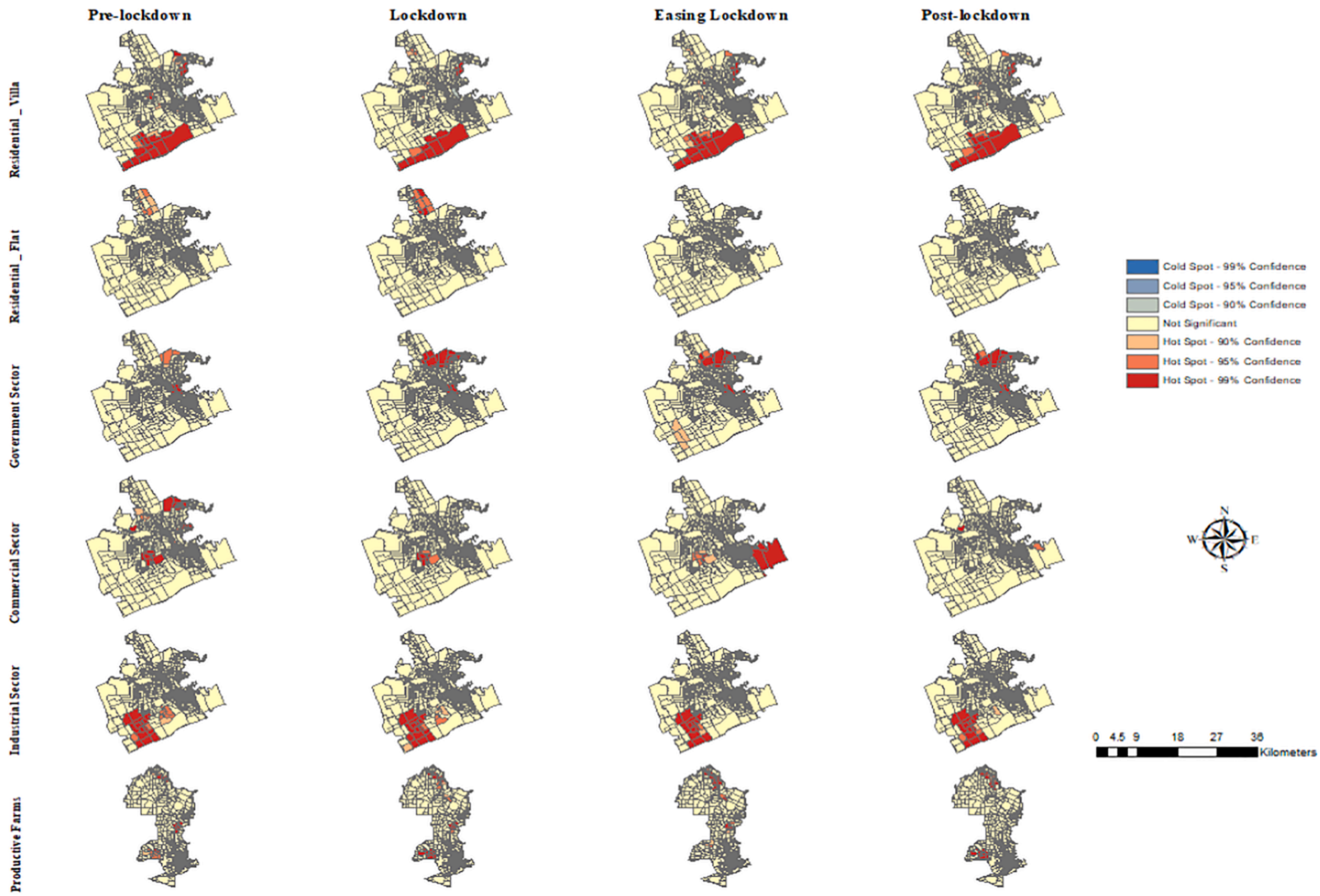


Fig. 17. The Getis-Ord G_i^* statistics of water consumption across six socioeconomic sector.

Table 5
Summary statistics of the OLS model in determining the association between electricity and water consumption in six socioeconomic sectors in Qatar.

Variable	Coefficient	St. Error	t- Statistic	Probability	VIF
Intercept	12690.845678	2516.874705	5.042303	0.000001	
Residential – Villa	7.003591	0.816526	8.577302	0.000000	1.475
Residential – Flat	6.923414	0.821227	8.430578	0.000000	1.487
Government	1.544196	7.335079	0.210522	0.833285	2.206
Commercial	2.269206	0.770241	2.946100	0.003275	1.836
industry	14.412368	0.563429	25.579736	0.000000	0.948
Productive Farms	25.228659	2.931446	8.606217	0.000000	1.422

To determine the spatial heterogeneity at the block level, the spatial distribution and variation of the local R^2 was mapped, as shown in Fig. 20. In the residential (villas) sector, the results show that there is a strong positive association between water and electricity consumption as well as a high spatial heterogeneity between the blocks that are located in the southern part of the city, where R^2 reaches the value of 0.9 and to a less extent in the western part ($0.36 > R^2 < 0.56$). This indicates that the GWR model explains accurately the local relationship between water and electricity consumption. The residential (flats) sector shows a different special pattern, where the high association between water and electricity consumption levels are shown in the central blocks of the city and more strongly in the western blocks. A weak relationship is predicted by the model between the water and electricity consumption levels in the government sector as the highest R^2 value is 0.38 in the northern blocks of the city, while the relationship is strong but less significant in the eastern blocks. In the commercial sector, the figure shows a strong positive relationship between water and electricity consumption in the western blocks of the city, where the highest value of R^2 is 0.75. Likewise, in the highest value of R^2 in the industrial sector is 0.75 and the strong association between water and electricity consumption is strong in the western blocks of the city. The pattern in the productive farms sector is different from the other socioeconomic sectors as the map shows no significant association between the water and electricity consumption levels in almost all the blocks except for few scattered areas in different parts outside Doha city.

5. Discussion

COVID-19 pandemic has created significant challenges concerning water and electricity industries and resources and profoundly changed the patterns and trajectory of water and electricity consumption. The mitigation measures imposed by the authorities in the country are characterised by its dynamics moving parallel with the dynamics of the pandemic; therefore, the spatial and temporal heterogeneities of the impacts of these measures on the water and electricity consumption levels in the country appeared gradual and changed over time. The pandemic has facilitated the transition to new practices in many socioeconomic sectors and this in turn reflects on the water and electricity

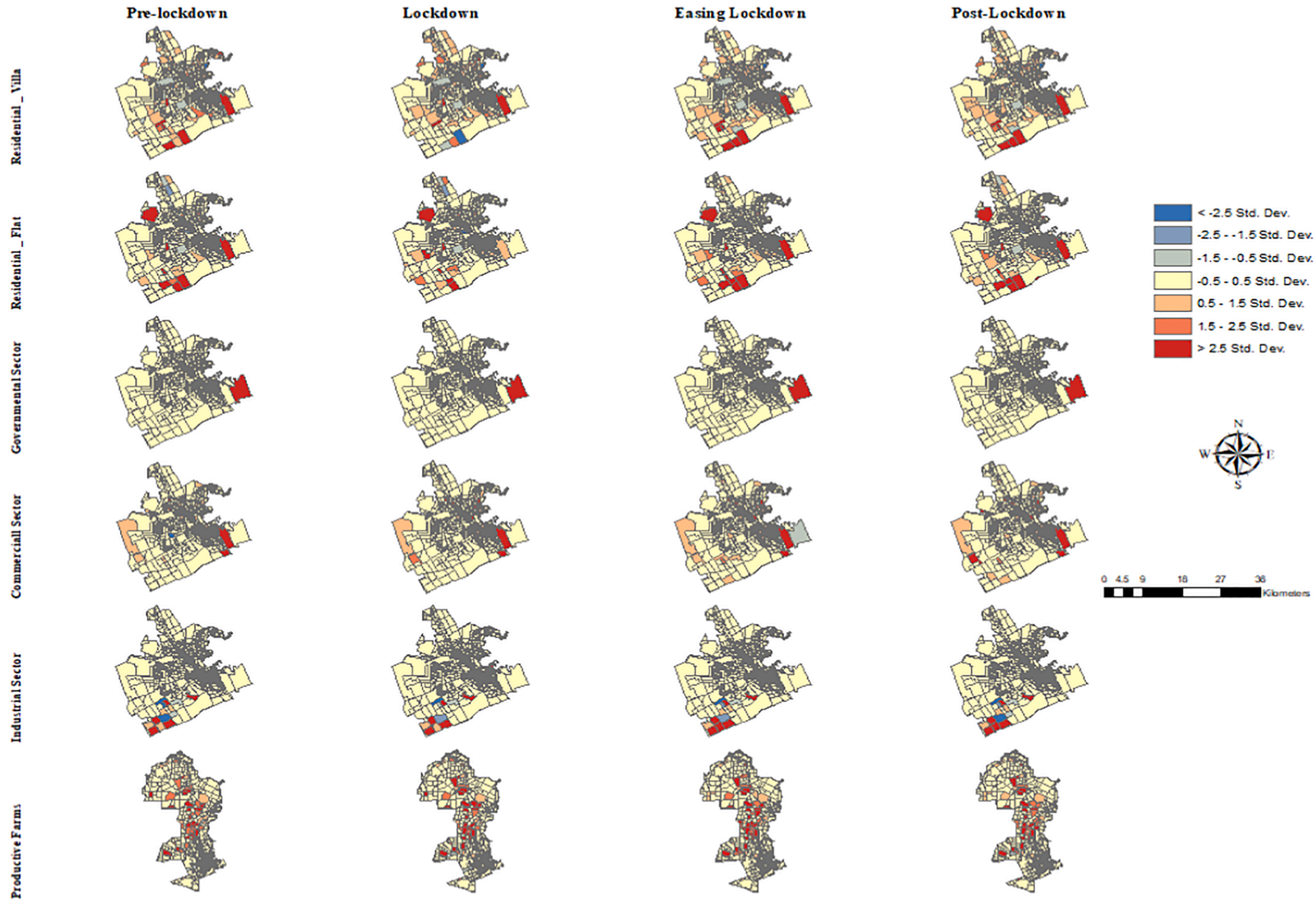


Fig. 18. The spatial association between electricity and water consumption based on OLS model.

demand and consumption. Overcoming these challenges requires intensive research and assessment of the impact of the COVID-19 pandemic on water-electricity consumption. Such assessment is important for different reasons. First, water and electricity are key resources in all aspects of the operation and production, and fundamental of economic prosperity and human wellbeing. Second, electricity is still dominating the consumption of energy resource in different socioeconomic sectors compared to other energy resources and types. Therefore, investigating the impact of the pandemic on the water-electricity consumption can reflect changes in the water and energy sectors under the context of the pandemic and could be considered as a reliable and vital indicator to assess the extent to which the society is negatively or positively (recovered) affected by the pandemic.

Analyzing the spatiotemporal correlation between the water and electricity consumption across the six sectors shows variation within and between these sectors over space and time. These spatial and temporal variations are complicated due to the decline of using these resources in the commercial and industrial sectors and the increase of the total consumption levels in the other sectors. This indicates the shift in water and electricity consumption from the commercial and industrial sectors to the residential sector. Disaggregating the consumption levels on monthly basis or during the four phases related to the propagation of the disease, the variations become more obvious and challenging. Most notably is the impact during the lockdown period, where the pandemic was severe and the number of mortality cases were high, this in turn reflects on the water and electricity consumption. During the lockdown phase, extra water and electricity footprints in the residential sector have exist because of the structural and pattern changes in water and electricity consumption. This extra consumption resulted due to the confinement measures that were imposed to slow down the propagation of the disease, which resulted in changing our ways of living. It was found that the highest consumption was in the residential sector in some blocks in the southern part of the city during the lockdown phase. These blocks are characterized by high population density and the concentration of workforce, particularly males. Many companies have allowed their employees to work remotely from home while students switched to e-learning, resulting in higher levels of water and electricity consumption in the residential sector. Furthermore, due to imposing restrictions on international travel, the majority of expats were unable to travel back to their home countries or for summer vacations, which imposed additional pressure on water and electricity resources. The analysis reveals that during the summer of 2020, the water and electricity consumptions have significantly increased compared to their levels in other phases of the pandemic year as well as to the prior years. This increase is mainly due to the high demand on the electricity because of the high temperatures of the summer as well as higher occupancy patterns in the residential buildings particularly during the daytime hours resulting in the use of energy-intensive systems such as appliances, air conditioning and lighting.

Conversely, the water and electricity consumption were positively correlated but declined in the industrial and commercial sector due to the curtailment in production, economic activities, and reduction in people's mobility. Many companies, businesses, factories, retails, and others were asked to shut down during this phase. Nevertheless, the extra consumption of these resources in the residential, government, and productive farms sectors may result in stabilising the water and energy demand. In the easing lockdown phase, the pandemic situation improved (the number of infected and mortality cases declined) but its impact on water and electricity consumption continued to be high, particularly in the industrial and commercial sectors. The reason behind

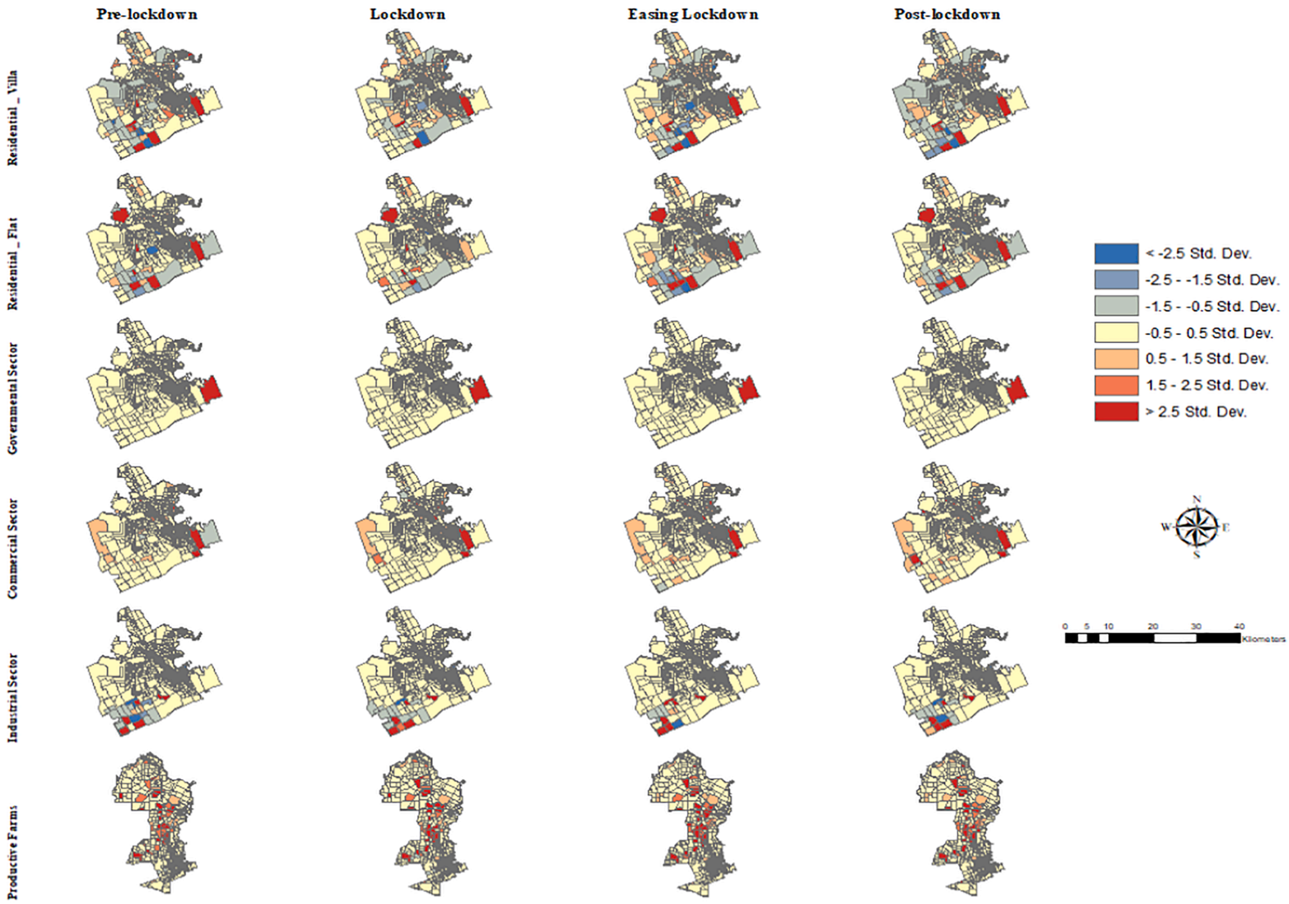


Fig. 19. The spatial association between electricity and water consumption based on GWR model.

Table 6
Comparison of OLS and WRG results in determining the association between electricity and water consumption levels.

Socioeconomic sector	OLS		WGR	
	AICc	R^2	AICc	R^2
Residential –Villa	7504.98	0.426	5457.23	0.637
Residential – Flat	8123.62	0.371	6389.45	0.531
Government	9023.71	0.302	7498.23	0.582
Commercial	8947.27	0.347	6634.61	0.601
Industrial	9283.58	0.259	7524.78	0.514
Farms	7959.37	0.324	6109.82	0.546

that is related to the gradual opening of none-essential services with limited capacity and the continued psychological panic and fear of people during this stage. The water and electricity consumption increased in the industrial and commercial sectors at later stages of the easing lockdown phase and during the post-lockdown phase as people returned physically to their workplaces and the resumption of production. However, the recovery in the commercial and industrial sectors after lifting the restrictions are challenging and present crucial differences than the other sectors. The water and electricity consumptions in these two sectors remained lower than previous years, which may have negative consequences on the economy of the country. From a macro-scale, although there was an overall drop of water and electricity consumption in the pandemic year, the elevation in residential and governmental water and electricity consumption should be considered to make a better conclusion on the water and electricity demand. From a micro-scale, the spatiotemporal distributions/patterns of water and electricity consumption have changed significantly in the short-term, particularly during the implementation of the lockdown measures. These results align, for example, with the results of other studies [41–47].

Mapping the hot spots and cold spots of water and electricity consumption over space, time, and sector shows how and where the consumption of these resources varies. The water and electricity consumption has notable local properties in term of geographical distribution among the block level with significant spatiotemporal agglomeration and clustering. The geospatial techniques used in the study enable us to recognize spatial areas showing high or low correlation between water and electricity consumption as well as the consumption of these resources and the spatial distribution of social variables at the block level with a higher certainty. In addition, mapping the statistically significant cluster of high values of water and electricity consumption illustrate where the hot spots and positive autocorrelations at the block level associated with low–high outliers in adjacent blocks. These geospatial techniques also showed that the annual water and electricity consumption levels are clustered in some of the socioeconomic sectors and random in others. Therefore, these maps and the outcomes of the analysis in this study can be considered as a spatial guideline for policy-makers to manage the water and electricity demand and consumption at the time of risk and to identify the factors that lead to high water and electricity consumption in certain areas. Furthermore, quantifying the water and electricity consumption on the block level can provide spatially explicit information about the demand of these resources, and to scale up intervention pathways to identify the local and sector demand dynamic due to imposing different mitigation and restriction measures to reduce the risk of the spread of the disease.

The spatial analysis of water-electricity consumption can give more insights into the dynamic changes in the water and electricity consumption over time during the pandemic year. Spatially, there were

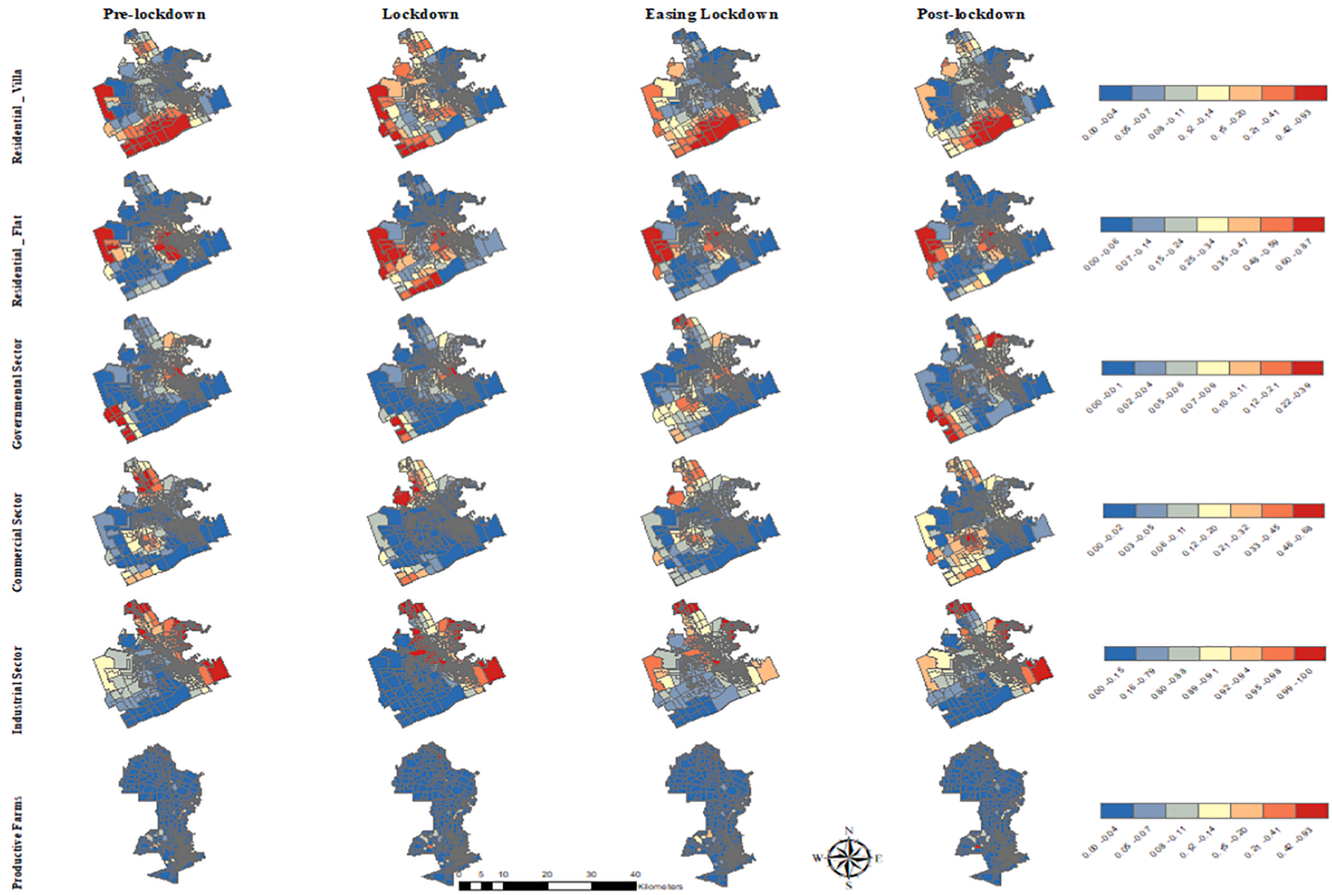


Fig. 20. Spatial distribution of local R2 of GWR for association between water and electricity consumption levels.

differences in the high and low consumption blocks prior and during the pandemic in all the socioeconomic sectors. This process is important to determine where and why hot spots and clusters of high water and electricity consumptions are located and changed due to the spread of the disease to provide clear and explicit perception of the spatial variation in water and electricity consumption levels. Furthermore, the correlation analysis highlight the spatial and temporal dynamic of the supply and demand trends of water and electricity consumption at the block level and in future emergencies. Although the total water and electricity consumption increased in some sectors and declined in others, the spatial and temporal variations at the block level are complicated. The intensity of water and electricity consumptions, represented by hot and cold spots, has presented apparent changes over space and time, and the recovery in different sectors demonstrates significant differences. The findings show that there is a distinction at the block level, across all sectors and over time. Hot spot and spatial regression analysis reveal spatial and temporal heterogeneities in the study area across the socioeconomic sectors. This heterogeneity is related to the characteristics of the land use and the distribution of these sectors over spaces. The intensity of hot spots of water and electricity consumption are found in the southern and western parts of the city due to high population density and the concentration of the commercial and industrial areas. These blocks are identified as statistically significant cluster of high values. On the other hand, other parts of the city that contain mainly residential areas with low population density and have few commercial services scattered in different blocks and with no industrial activities are not statistically significant cluster of high values. This distribution of the land use in the city affects the water and energy consumption at the block level.

6. Conclusion and policy implications

The aim of this study was to assess the spatiotemporal association between electricity and water consumption levels in the context of the propagation of the COVID-19 pandemic. The electricity and water consumption levels were spatially and statistically assessed across six socioeconomic sectors. Furthermore, the analysis was carried on through three temporal levels, which are the annual consumption, monthly consumptions, and through four different time phases related to the development of the disease, which are the pre-lockdown phase, lockdown phase, easing lockdown phase, and post-lockdown phase. The analysis is based on real data, which provides an accurate assessment of the water and electricity consumption and demand. The study employed a family of statistical and spatial models through the GIS environment to investigate the spatiotemporal differences in electricity and water consumption levels across each socioeconomic sector and the relationship between water and electricity consumptions in these sectors.

In general, the results of the water and electricity consumption levels and the relationship between them show a considerable spatial heterogeneity in the consumption rates across each socioeconomic sector and within the city boundary. The higher rates of consumptions are scattered in different parts in the city depending on the location of the presence of these sectors. However, it is important to study these locations and the associated factors for high consumption to allow for the authorities to develop a plan in times of risk to ensure the continuous supply of these resources if the demand increased in certain areas. Although the increase in consumption in some sectors and the decrease in others could achieve a balance between the supply and demand. However, this is not always the case at the time of risk.

The spatiotemporal assessment of the water-electricity consumption in different socioeconomic sectors under the context of the pandemic is needed to promote government's response in planning for water and electricity production and supply. This assessment is vital to recognize the interdependent relationship between increasing electricity demand and decreasing water resources in arid areas such as in the state of Qatar. In light of the pandemic, climate change, scarcity of water, and growing electricity/energy demand, analyzing the link between water and electricity consumption has crucial benefits for policymakers. These events and the depletion of resources can have negative impact on economic activities. Therefore, sustainable management of resources at time of risk is essential to avoid the weakening of country's economic development and fiscal situation. Therefore, policymakers should adopt different fiscal and non-fiscal instruments and financial incentives to manage the water and electricity resources in a coordinated manner. Furthermore, this study proposed the following policy implications and recommendations in response to the above findings. First, in the hot spot areas, where the water and electricity consumption is high, the authorities should assess transforming the power supply situation from using fossil energy to low-carbon green energy. Second, due to the positive relationship between water and electricity consumption in many blocks during the pandemic year, policies that encourages reduction in electricity consumption may result in reducing water consumption. Therefore, policymakers may consider developing water and electricity service policies considering this issue. Third, the authorities are encouraged to increase and promote policy support for the utilization of high-energy-efficiency equipment, particularly in the residential and governmental sectors, to make the economic development mode more resilience, dynamic, and healthier. Home office schemes (teleworking) practices are increasing due to the spread of the disease and these practices may become new patterns of performing work after the pandemic. Promoting energy efficiency enables authorities to achieve more environmentally friendly and sustainable management of water and electricity resources. Finally, policy measures should be considered to predict and anticipate the water and electricity supply and demand in the context of emergency, such as the COVID-19 pandemic.

This analysis is a first step in providing a greater understanding of the water and electricity consumption levels in the context of the COVID-19 pandemic. The water – electricity consumption is affected by many parameters such as the behaviour of the residents in consuming these resources. However, one limitation of this study is eliminating these parameters and focusing on the consumption rates of water and electricity. Nevertheless, this study is important to study the spatial distribution of the changes in water and electricity consumptions due to the spread of the pandemic and if there is a relationship between consuming these resources, which allows the authorities to take measures to maintain a balance between the supply and demand in each geographical block. Therefore, the outcomes of this study can serve as a spatial guideline for decision-makers to develop the future plans to manage these resources under risk situation such as the current pandemic.

CRediT authorship contribution statement

Ammar Abulibdeh: Conceptualization, Methodology, Formal analysis, Writing – original draft, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This publication was made possible by an NPRP award [NPRP13S-0206-200272] from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors. The open access publication of this article was funded by the Qatar National Library (QNL).

References

[1] Abulibdeh A. Can COVID -19 mitigation measures promote telework practices? J Labor Soc 2020;23(4):551–76. https://doi.org/10.1111/wusa.12498.
[2] Bruinen de Bruin Y, Lequarre A-S, McCourt J, Clevestig P, Pigazzani F, Zare Jeddi M, et al. Initial impacts of global risk mitigation measures taken during the combatting of the COVID-19 pandemic. Saf Sci 2020;128:104773. https://doi.org/10.1016/j.ssci.2020.104773.
[3] Son J-Y, Fong KC, Heo S, Kim H, Lim CC, Bell ML. Reductions in mortality resulting from reduced air pollution levels due to COVID-19 mitigation measures. Sci Total Environ 2020;744:141012. https://doi.org/10.1016/j.scitotenv.2020.141012.
[4] Vicentini C, Bordino V, Gardois P, Zotti CM. Early assessment of the impact of mitigation measures on the COVID-19 outbreak in Italy. Public Health Aug. 2020;185:99–101. https://doi.org/10.1016/j.puhe.2020.06.028.
[5] Jiang P, Fan YV, Klemeš JJ. Impacts of COVID-19 on energy demand and consumption: Challenges, lessons and emerging opportunities. Appl Energy 2021;285:116441. https://doi.org/10.1016/j.apenergy.2021.116441.
[6] 'Global Energy Review 2020 – Analysis - IEA'. https://www.iea.org/reports/global-energy-review-2020 (accessed Apr. 21, 2021).
[7] Mastropietro Paolo, Rodilla Pablo, Batlle Carlos. Emergency measures to protect energy consumers during the Covid-19 pandemic: A global review and critical analysis. Energy Res Soc Sci 2020;68:101678. https://doi.org/10.1016/j.erss.2020.101678.
[8] Perniola S, et al. Telemedicine will not keep us apart in COVID-19 pandemic. Ann Rheumatic Dis, 80(4). BMJ Publishing Group, pp. e48–e48, Apr. 01, 2021, doi: 10.1136/annrheumdis-2020-218022.
[9] Saadat S, Rawtani D, Hussain CM. Environmental perspective of COVID-19. Sci Total Environ, 728. Elsevier B.V., p. 138870, Aug. 01, 2020, doi: 10.1016/j.scitotenv.2020.138870.
[10] Madurai Elavarasan R, et al. 'COVID-19: Impact analysis and recommendations for power sector operation'. Appl Energy, 279, p. 115739, Dec. 2020, doi: 10.1016/j.apenergy.2020.115739.
[11] Abulibdeh A. 'water-energy nexus challenges and opportunities in Qatar'. In Qatar: Political, Economic and Social Issues, nova, 2019, pp. 209–227.
[12] Hamiche AM, Stambouli AB, Flazi S. A review of the water-energy nexus. Renew Sustain Energy Rev Nov. 2016;65:319–31. https://doi.org/10.1016/J.RSER.2016.07.020.
[13] Abulibdeh A, Zaidan E, Al-Saidi M. Development drivers of the water-energy-food nexus in the Gulf Cooperation Council region. Dev Pract Jul. 2019;29(5):582–93. https://doi.org/10.1080/09614524.2019.1602109.
[14] Mohtar RH, Lawford R. 'Present and future of the water-energy-food nexus and the role of the community of practice Human and environmental change, resource scarcity, and global risk', doi: 10.1007/s13412-016-0378-5.
[15] Wang Chunyan, Lin Lu, Olsson Gustaf, Liu Yi, Xu Ming. The scope and understanding of the water–electricity nexus. Resour Conserv Recycl 2019;150:104453. https://doi.org/10.1016/j.resconrec.2019.104453.
[16] Wolfe ML, Ting KC, Scott N, Sharpley A, Jones JW, Verma L. 'Engineering solutions for food-energy-water systems: it is more than engineering', doi: 10.1007/s13412-016-0363-z.
[17] Wang C, Wang R, Hertwich E, Liu Y, Tong F. Water scarcity risks mitigated or aggravated by the inter-regional electricity transmission across China. Appl Energy Mar. 2019;238:413–22. https://doi.org/10.1016/J.APENERGY.2019.01.120.
[18] Spang E S, Moomaw W R, Gallagher K S, Kirshen P H, Marks D H. The water consumption of energy production: an international comparison. Environ Res Lett 2014;9(10):105002. https://doi.org/10.1088/1748-9326/9/10/105002.
[19] Kiziltan Mustafa. Water-energy nexus of Turkey's municipalities: Evidence from spatial panel data analysis. Energy 2021;226:120347. https://doi.org/10.1016/j.energy.2021.120347.
[20] Abulibdeh Ammar, Zaidan Esmat. Managing the water-energy-food nexus on an integrated geographical scale. Environ Dev 2020;33:100498. https://doi.org/10.1016/j.envdev.2020.100498.
[21] Abulibdeh A. Analysis of urban heat island characteristics and mitigation strategies for eight arid and semi-arid gulf region cities. Environ Earth Sci Apr. 2021;80(7):259. https://doi.org/10.1007/s12665-021-09540-7.
[22] Abulibdeh A, Al-Awadhi T, Al-Barwani M. Comparative analysis of the driving forces and spatiotemporal patterns of urbanisation in Muscat, Doha, and Dubai. Dev Pract 2019;29(5):606–18. https://doi.org/10.1080/09614524.2019.1598335.
[23] Méndez C, Bicer Y. Towards a sustainable 2022 FIFA World Cup in Qatar: Evaluation of wind energy potential for three football stadiums. Energy Explor Exploit Sep. 2020;38(5):1893–913. https://doi.org/10.1177/0144598720948175.
[24] Zaidan E, Abulibdeh A. Modeling ground access mode choice behavior for Hamad International Airport in the 2022 FIFA World Cup city, Doha, Qatar. J Air Transp Manag 2018;73:32–45. https://doi.org/10.1016/j.jairtraman.2018.08.007.
[25] Bedeian AG, Mossholder KW. On the use of the coefficient of variation as a measure of diversity. Organ Res Methods Jun. 2000;3(3):285–97. https://doi.org/10.1177/109442810033005.
[26] Tran Kim Phuc, Heuchenne Cédric, Balakrishnan Narayanaswamy. On the performance of coefficient of variation charts in the presence of measurement errors. Qual Reliab Eng Int 2019;35(1):329–50. https://doi.org/10.1002/qre.v35.110.1002/qre.2402.
[27] Abbasi SA, Adegoke NA. Multivariate coefficient of variation control charts in phase I of SPC. Int J Adv Manuf Technol Nov. 2018;99(5–8):1903–16. https://doi.org/10.1007/s00170-018-2535-3.

[28] Ren Y, Allenmark F, Müller HJ, Shi Z. 'Variation in the "coefficient of variation": Rethinking the violation of the scalar property in time-duration judgments'. Acta Psychol (Amst), 214, p. 103263, Mar. 2021, doi: 10.1016/j.actpsy.2021.103263.
[29] Al-Kindi Khalifa M, Alkharusi Amira, Alshukaili Duhai, Al Nasiri Noura, Al-Awadhi Talal, Charabi Yassine, et al. Spatiotemporal assessment of COVID-19 spread over Oman using GIS techniques. Earth Syst Environ 2020;4(4):797–811. https://doi.org/10.1007/s41748-020-00194-2.
[30] Adegboye Oyelola A, Adekunle Adeshina I, Pak Anton, Gayawan Ezra, Leung Denis HY, Rojas Diana P, et al. Change in outbreak epicentre and its impact on the importation risks of COVID-19 progression: A modelling study. Travel Med Infect Dis 2021;40:101988. https://doi.org/10.1016/j.tmaid.2021.101988.
[31] Prasannakumar V, Vijith H, Charutha R, Geetha N. Spatio-temporal clustering of road accidents: GIS based analysis and assessment. Procedia - Social Behav Sci Jan. 2011;21:317–25. https://doi.org/10.1016/j.sbspro.2011.07.020.
[32] Li H, et al. 'Spatial statistical analysis of Coronavirus Disease 2019 (Covid-19) in China'. Geospat Health, 15(1), Jun. 2020, doi: 10.4081/gh.2020.867.
[33] Fotheringham AS, Charlton ME, Brunsdon C. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. Environ Plan A Econ Sp Nov. 1998;30(11):1905–27. https://doi.org/10.1068/a301905.
[34] Wu Decun. Spatially and temporally varying relationships between ecological footprint and influencing factors in China's provinces Using Geographically Weighted Regression (GWR). J Clean Prod 2020;261:121089. https://doi.org/10.1016/j.jclepro.2020.121089.
[35] Mollalo Abolfazl, Vahedi Behzad, Rivera Kiara M. GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Sci Total Environ 2020;728:138884. https://doi.org/10.1016/j.scitotenv.2020.138884.
[36] 'Spatial Regression Models - Michael D. Ward, Kristian Skrede Gleditsch - Google Books'. https://books.google.com.qa/books?hl=en&lr=&id=iyZaDwAAQBAJ&oi=fnd&pg=PT13&dq=Ward,+M.D.,+Gleditsch,+K.S.,+2018.+Spatial+regression+models.+155.+Sage+Publications.&ots=0nacVrMZUz&sig=XRmwtSUL-QtaQkDfQdtpJ9faXcA&redir_esc=y#v=onepage&q&f=false (accessed Apr. 22, 2021).
[37] Anselin L, Arribas-Bel D. Spatial fixed effects and spatial dependence in a single cross-section. Pap Reg Sci Mar. 2013;92(1):3–17. https://doi.org/10.1111/j.1435-5957.2012.00480.x.
[38] Fotheringham AS, Oshan TM. Geographically weighted regression and multicollinearity: dispelling the myth. J Geogr Syst Oct. 2016;18(4):303–29. https://doi.org/10.1007/s10109-016-0239-5.
[39] Koh Eun-Hee, Lee Eunhee, Lee Kang-Kun. Application of geographically weighted regression models to predict spatial characteristics of nitrate contamination: Implications for an effective groundwater management strategy. J Environ Manage 2020;268:110646. https://doi.org/10.1016/j.jenvman.2020.110646.
[40] O'Brien RM. A caution regarding rules of thumb for variance inflation factors. Qual Quant Oct. 2007;41(5):673–90. https://doi.org/10.1007/s11135-006-9018-6.
[41] Krarti M, Aldubyan M. 'Review analysis of COVID-19 impact on electricity demand for residential buildings'. Renewable and Sustainable Energy Reviews, vol. 143. Elsevier Ltd, p. 110888, Jun. 01, 2021, doi: 10.1016/j.rser.2021.110888.
[42] Abu-Rayash A, Dincer I. 'Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic'. Energy Research and Social Science, vol. 68. Elsevier Ltd, p. 101682, Oct. 01, 2020, doi: 10.1016/j.erss.2020.101682.
[43] Bahmanyar Alireza, Estebsari Abouzar, Ernst Damien. The impact of different COVID-19 containment measures on electricity consumption in Europe. Energy Res Soc Sci 2020;68:101683. https://doi.org/10.1016/j.erss.2020.101683.
[44] Norouzi Nima, Zarazua de Rubens Gerardo, Choupanpiesheh Saeed, Enevoldsen Peter. When pandemics impact economies and climate change: Exploring the impacts of COVID-19 on oil and electricity demand in China. Energy Res Soc Sci 2020;68:101654. https://doi.org/10.1016/j.erss.2020.101654.
[45] Agdas Duzgun, Barooah Prabir. Impact of the COVID-19 Pandemic on the U.S. Electricity Demand and Supply: An Early View from Data. IEEE Access 2020;8:151523–34. https://doi.org/10.1109/Access.628763910.1109/ACCESS.2020.3016912.
[46] Edomah N, Ndulue G. Energy transition in a lockdown: An analysis of the impact of COVID-19 on changes in electricity demand in Lagos Nigeria. Glob Transitions Jan. 2020;2:127–37. https://doi.org/10.1016/j.glt.2020.07.002.
[47] Santiago I, Moreno-Munoz A, Quintero-Jiménez P, Garcia-Torres F, Gonzalez-Redondo MJ. Electricity demand during pandemic times: The case of the COVID-19 in Spain. Energy Policy 2021;148:111964. https://doi.org/10.1016/j.enpol.2020.111964.