Energy Strategy Reviews 52 (2024) 101350

Contents lists available at ScienceDirect

Energy Strategy Reviews

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

Evaluating the impact of the COVID-19 pandemic on the geospatial distribution of buildings' carbon footprints associated with electricity consumption

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ARTICLE INFO

Handling Editor: Dr. Mark Howells

Keywords:
Carbon footprint
Buildings
Machine-learning models
Spatial analysis
COVID-19

ABSTRACT

The carbon footprint (CF) linked to electricity consumption in buildings has become a significant environmental issue because of its significant role in greenhouse gas emissions. This study seeks to assess and examine the CF of electricity consumption in buildings across various building types. Additionally, this paper aims to investigate the impact of the COVID-19 pandemic on the CF of buildings. The investigation involves a comparative analysis between the CF values observed and predicted during the years affected by the pandemic. Additionally, the study evaluates the influence of the pandemic on the accuracy of CF model predictions by employing three distinct machine-learning models. Spatial analyses were conducted to identify clustering patterns of CF and identify areas of both high and low CF concentrations within the study area. The findings demonstrate significant disparities in the CF of electricity consumption across distinct building types, with residential buildings emerging as the largest contributors to carbon emissions. Moreover, the pandemic has had a notable impact on CF patterns, leading to alterations in the areas identified as hotspots and cold spots during the pandemic years compared to the pre-pandemic period, based on building types.

1. Introduction

The carbon footprint (CF) of buildings is a crucial aspect of sustainability and environmental impact. As buildings consume energy and resources throughout their lifecycle, they contribute significantly to greenhouse gas emissions and climate change [1–4]. Furthermore, buildings play a pivotal role in global endeavors aimed at decreasing energy consumption, mitigating greenhouse gas emissions, and facilitating the transition to sustainable and clean energy sources [5]. With the challenges posed by climate change and national energy security concerns, international agreements, initiatives, and policies specific to the building sector are offering promising alternatives to the current situation. The concept of CF encompasses the total amount of greenhouse gases, particularly carbon dioxide (CO_2), emitted directly and indirectly from building-related activities, including construction, operation, and demolition [6–8]. Given the substantial energy consumption and emissions associated with buildings, understanding, and reducing their carbon footprints has become a priority in achieving global climate goals and promoting sustainable development.

The CF of buildings is gaining increasing attention as a crucial aspect of sustainability research. Mitigating the impact of buildings on the environment is critical in addressing the adverse effects of global warming. However, the methods for calculating CF in buildings vary widely, leading to inconsistencies in results. Despite this, the increasing demand for CF assessments driven by legal and business requirements has resulted in the widespread adoption of the Greenhouse Gas Protocol (GHG Protocol) [9]. The built environment, including buildings, transportation, and energy, is responsible for a significant proportion of global CF [7,10,11].

Electricity, though it only constitutes a small part of a country's GDP, is essential for human activities and plays a pivotal role in driving economic and social progress [12,13]. However, the production and consumption of electricity also have significant environmental impacts, including pollution and its contribution to climate change [13,14]. As

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https://doi.org/10.1016/j.esr.2024.101350
Received 28 August 2023; Received in revised form 11 February 2024; Accepted 23 February 2024
Available online 10 March 2024

such, reducing the CF associated with electricity consumption in buildings has become a priority in environmental policies worldwide. This is crucial for mitigating the harmful effects of climate change and promoting a more sustainable future [14–16].

The empirical literature on the CF of buildings contributes to understanding the environmental impact of the built environment. Studies have identified that residential and commercial buildings are among the largest consumers of energy worldwide, contributing significantly to global greenhouse gas emissions [17–21]. This consumption is primarily for space heating, cooling, lighting, and operating appliances, with most of the energy sourced from fossil fuels, thus exacerbating the CF. Furthermore, several studies have extensively investigated the role of building design and construction materials in energy efficiency [22–25]. Studies have shown that sustainable building materials and energy-efficient design can substantially reduce energy consumption and consequently, the CF of buildings. The incorporation of insulation, energy-efficient windows, and the use of passive solar design are among the methods that are effective. Trovato et al. [26] focused on the economic and environmental valuation of energy retrofit projects in public buildings. They integrated a life cycle analysis (LCA) into traditional economic-financial evaluation to assess the impact of sustainable low-–CO_2–emission technologies in building retrofit. They examined the effectiveness of retrofit strategies like wooden double-glazed windows, organic external wall insulation systems, and green roofs. These strategies show a significant reduction in energy needs for heating and cooling, with a decrease of 58.5% and 33.4% respectively. Additionally, the use of sustainable materials in the retrofit leads to a 54.1% reduction in the building's CF index. Li et al. [27] employed a hybrid systems analysis combining input-output analysis and process analysis to quantify the embodied energy consumption and greenhouse gas emissions of building construction. They highlighted the substantial role of the construction sector in driving energy consumption and greenhouse gas emissions across different scales and industries. Their study suggests the need for multi-entity responsibility and coordinated efforts for consumption and emission reduction, emphasizing the importance of considering the supply chain's full extent in environmental impact assessments of construction projects.

The COVID-19 pandemic has had a significant impact on electricity consumption, CF of buildings, and people's behavior [28–30]. During the pandemic, there was a notable shift in energy consumption patterns due to lockdowns and work-from-home policies. Several studies investigated the impact of the pandemic on the CF of buildings. For example, Rugani and Caro [31] investigated the environmental impact of COVID-19 lockdown measures in Italy, focusing on the CF associated with energy consumption across different economic activities and regions. The findings revealed a significant reduction (~20%) in CF during the lockdown, translating to an avoidance of approximately 5.6–10.6 $MtCO_2eqv$. The study observed greater impact savings in the more industrialized Northern regions of Italy, which were most affected by the pandemic. Huang and Gou [32] found that the restrictions had a greater impact on reducing electricity use in the first year of the pandemic compared to the second. The electricity use intensity significantly decreased across all public building types considered in the study except offices, with secondary schools experiencing the largest decrease and museums the smallest. Geneidy et al. [33] analyzed the CF of a multinational knowledge organization, highlighting the significant role of organizations in addressing the climate crisis. In response to COVID-19, three scenarios were developed to assess post-pandemic emissions. Results show that even with reduced business travel and increased remote working, Scope 3 and travel-related emissions continue to be the largest contributors to CF. Filimonau et al. [34] examined the CF of Bournemouth University during the lockdown period from April to June 2020, comparing it with the same period in previous years. The study found that although the overall CF of the university decreased by about 29%, the carbon intensity of online teaching and learning was substantial, almost equating to the CF of staff and student commutes before the lockdown. This suggests that online education, while reducing physical commute, still results in significant carbon emissions. The lockdown's effect on utility consumption in closed university campuses was also notable but less than expected, indicating that maintaining these facilities still requires substantial energy. Huang and Gou [35] employed the Gaussian Mixture Model (GMM) to analyze the electricity consumption patterns of public buildings in Scotland during the COVID-19 pandemic. The research found a sustained reduction in basic electricity consumption in public buildings post-pandemic, continuing the trend observed during the pandemic. Moreover, the peak electricity consumption in the post-pandemic period, although rebounding, did not reach pre-pandemic levels.

Studies of CF have uncovered substantial variations in consumption and emission patterns among households, communities, and regions, leading to a shift in the focus of analysis from a national to a local scale [15,36–39]. These findings indicate that reducing CF requires addressing differences in emissions produced by different socioeconomic sectors. However, these studies did not fully uncover the connection between electricity consumption and CF with disparities in building types within and between communities. A review of the literature highlights a shortage in the monitoring and assessment of CF of electricity consumption in buildings based on building occupancy. This is particularly relevant in emerging market economies like Qatar, which has a high electricity consumption and per capita carbon emission [21]. To tackle this, a thorough assessment of the CF is necessary. This aligns with Qatar's low-carbon city initiative, aimed at reducing its dependence on carbon-emitting activities and transitioning to a low-carbon economy [40]. The Qatari government is making strides towards a low-carbon economy through initiatives such as the development of Lusail and Msheireb Smart Cities, aimed at reducing electricity consumption.

During the COVID-19 pandemic, many buildings experienced reduced occupancy or temporary closures, leading to decreased energy consumption [41–43]. This resulted in lower carbon emissions associated with heating, cooling, and lighting. With fewer people using the buildings, energy demand decreased significantly. On the other hand, as more people worked remotely, residential energy consumption increased, particularly for heating, cooling, and electricity. This shift in energy demand patterns from the commercial and industrial sectors to the residential sector could have offset some of the environmental gains from reduced building occupancy.

Investigating the CF of buildings is crucial for reducing their environmental impact. Analyzing a building's CF based on its utilization offers an effective method for measuring emissions. By examining electricity consumption patterns, we seek to investigate the extent of CF from buildings in emerging economies like Qatar, which has been largely overlooked in previous studies, particularly during major health crises such as the pandemic. Therefore, this study aims to.

- Fill the knowledge gap by assessing the CF of six building categories in Doha, both spatially and temporally, using machine-learning and spatial statistical models.
- Assess the influence of electricity consumption in different building types during the pandemic on the emission pattern of CF in Qatar.
- Examine how the COVID-19 pandemic has influenced the predictive accuracy of machine-learning models in forecasting the CF of buildings based on building type.

Through the examination of variations in electricity consumption across different building types and their consequential impact on the CF, this study aims to provide valuable insights for policymakers and planners. The findings will contribute to a better understanding of the intricate relationship between electricity consumption and carbon emissions during health crises in Qatar, facilitating informed decision-making and strategic planning. This study aims to answer the following questions.

1 How do different building types contribute to the overall CF associated with electricity consumption spatially and temporally?
2 What is the impact of the COVID-19 pandemic on the CF of buildings associated with electricity consumption spatially and temporally?
3 How accurate are machine-learning models in predicting the carbon footprint of buildings during unpredictable events like pandemics?

This study addresses several gaps in understanding the CF of buildings, focusing on factors such as occupancy types, the impact of pandemics, and the effectiveness of predictive models. It significantly contributes to the field by offering a sector-specific analysis of CF in the context of a major health crisis, providing valuable insights for policymakers and planners. The contributions of this study to the literature are threefold: First, it conducts a detailed spatial and temporal analysis of the COVID-19 pandemic's impact on CF from electricity consumption across six different building categories in Doha, utilizing machine learning and spatial statistical models. Second, by covering data from 2017 to 2020, the study offers insights into how patterns of electricity consumption in buildings contribute to CF and how these patterns were affected by the pandemic. Third, it evaluates the performance of various machine-learning models in predicting CF during the pandemic, thereby advancing predictive analytics within sustainability research. By examining CF in residential, commercial, industrial, governmental, and hotel sectors, the study presents a comprehensive view of how different building types contribute to CF, especially during the pandemic.

While the pandemic itself may have passed, the findings of this study offer critical insights for future crisis management, energy policy, and environmental sustainability. The study provides a unique perspective on how sudden global events can drastically alter energy consumption patterns and the associated CF and highlights the need for adaptable and resilient energy systems.

2. Materials and methods

2.1. Study area

Situated in the eastern region of the Arabian Peninsula, the State of Qatar encompasses a land area totaling 11,437 square kilometers [29]. Qatar has undergone rapid economic and social development in recent years, driven in large part by its vast oil and gas reserves [44–46]. Studies have shown that this development has led to significant improvements in living standards and infrastructure but has also brought challenges such as a high population growth rate, labor issues, and environmental degradation [47–49]. The government of Qatar has implemented a number of efforts and development initiatives aimed at promoting sustainable economic and social development in the country [50]. Some of these initiatives include Qatar National Vision 2030; a long-term development plan that sets out the government's vision for the country's future, with a focus on economic diversification, human development, and environmental sustainability. The plan includes several specific targets, such as increasing the contribution of non-oil sectors to GDP and reducing the country's CF. Recently, the country hosted The FIFA World Cup 2022 which has had a significant impact on Qatar [51,52]. This includes the development of new infrastructure, such as stadiums, hotels, and transportation systems, alongside a surge in the population of expatriate workers within the country.

2.2. Database description

The present study utilized electricity consumption data obtained from the Qatar General Electricity and Water Corporation (KAHRAMAA) to examine CF within various socioeconomic buildings in Qatar. The spatial dataset consists of six distinct building types based on building usage, specifically residential (villas and flats), government, commercial, industrial, and hotels. For the examination of the CF of these buildings, the dataset includes daily recorded electricity consumption data from January to December, covering the years 2017–2020. The electricity consumption data used to investigate the impact of the pandemic on machine-learning model prediction spans from January to December during the years 2010–2020. The electricity consumption data were acquired at a highly precise and granular spatial resolution, specifically at the meter level, encompassing multiple periods and sectors. Additionally, rigorous quality control measures were implemented to ensure the integrity of the data. This involved thorough checks to eliminate any instances of missing or zero values within individual months throughout the entire study duration. The aim is to examine the alterations in the spatial arrangement of CF over time. Table 1 shows a detailed description of the data.

In a temporal context, this investigation centers around three distinct temporal levels. Firstly, the study focuses on the time intervals that demonstrate the progression of the COVID-19 pandemic's spread and the corresponding measures enacted at national and global scales to mitigate its transmission during the year 2020. This period is divided into three temporal phases. Initially, the pre-lockdown phase, comprising the months of January and February, represents the period before the dissemination of the pandemic. Subsequently, the lockdown period, spanning from March to May, indicates the timeframe when authorities implemented restrictive measures and enforced the stay-at-home policy. Lastly, the post-lockdown period, spanning from June to December, characterizes the phase when all restrictions were lifted, and daily life returned to its state prior to the pandemic. Secondly, the study investigates the changes in CF patterns on an annual basis between 2017 and 2020. Finally, to investigate the impact of the pandemic on the prediction accuracy of machine-learning models, monthly electricity data spanning from 2010 to 2020 was utilized.

2.3. Methodology

This study utilizes the Multi-Regional Input-Output (MRIO) method, spatial analysis tools, and three machine-learning models (Extreme Gradient Boosting (XGBoost), Support Vector Machines (SVM), and Random Forest (RF)) to analyze the CF resulting from electricity consumption in various building typologies, as illustrated in Fig. 1. The electricity consumption data was first converted into CF using the MRIO method, followed by a spatial analysis of CF at the zonal level. This analysis aimed to identify patterns of CF distribution across the study area and to determine whether these patterns are clustered or randomly dispersed. The primary objective of this approach was to graphically discern and illustrate the variations in CF across different zones within Doha, with a specific focus on the temporal aspect. This involved comparing CF in 2019 with the corresponding period in 2020, across the three phases of the COVID-19 pandemic's propagation. Three machine-learning models were used to investigate the impact of the pandemic on model prediction accuracy. The following subsections describe these models in detail.

2.3.1. Spatial analysis model

In this study, the investigation of carbon footprint's spatial distribution patterns and its clustering across different sectors and temporal variations was conducted using two renowned and established geospatial statistical tools in the GIS domain: the Getis-Ord G*i test and the Anselin Local Moran's I statistics tool. These tests serve as valuable resources for comprehending the spatial patterns of various geographical phenomena [53]. By employing these tools, it becomes possible to identify both hotspot and cold spot regions associated with CF, considering their spatial, temporal, and sector-specific characteristics.

The statistical analysis of the spatial distribution patterns of CF resulting from electricity consumption in six distinct building types was performed using the Getis-Ord Gi* statistic. This analysis aimed to identify specific zone-level areas exhibiting significantly high or low clustering of CF for each year within the study duration. The objective was to visually and statistically differentiate the CF across different

Table 1
Description of the building typology.

Building type	Description	Number of buildings (%)	Rational
Residential villa	Typically refers to a luxurious, detached and semi-detached house designed primarily for single-family living. It is often characterized by spacious interior and exterior designs, including multiple bedrooms, large living areas, and sometimes, personalized amenities like private gardens, swimming pools.	118,934 (41%)	Residential buildings are significant contributors to global greenhouse gas emissions, primarily through energy use for heating, cooling, lighting, and appliances.
Residential flats	Refers to housing units within a larger building where each unit is a separate living space. Flats are a common form of urban housing.	106,970 (36.9%)	Residential buildings are significant contributors to global greenhouse gas emissions, primarily through energy use for heating, cooling, lighting, and appliances.
Commercial buildings	Refers to structures that are primarily used for business activities. They encompass a wide range of building types, including office buildings, retail stores, shopping malls, restaurants, warehouses, and other facilities catering to commercial needs.	46,415 (16.67%)	Understanding and reducing the CF from commercial buildings can lead to more energy-efficient buildings, lowering operational costs.
Government buildings	Governmental buildings are structures used for various government functions and services.	15,551 (5.36%)	Government buildings, often numerous and sizeable, can set an example for sustainability practices in the community. Understanding their carbon footprint helps in shaping effective environmental policies and regulations.
Industrial buildings	Industrial buildings are structures designed primarily for manufacturing, processing, or storing goods. They include factories and workshops. These buildings are typically characterized by large, open floor plans to accommodate heavy machinery and production lines.	590 (0.2%)	Industrial buildings often consume large amounts of energy for manufacturing processes, heating, and cooling, leading to significant greenhouse gas emissions. Understanding their carbon footprint helps in devising strategies to control and reduce pollution.
Hotels	Hotel buildings are designed to provide accommodations, dining, and various amenities to travelers and guests.	1450 (0.5%)	Studying the CF of hotel buildings is important because they are significant energy consumers, often operating continuously throughout the year. This energy use, primarily for guest comfort and amenities, contributes considerably to greenhouse gas emissions.

regions within the study area during the three identified time phases, encompassing the pandemic year and the year preceding it. This step holds significance in determining areas with pronounced CF levels and assessing the potential temporal variations within the three designated periods, which were influenced by the spread of the COVID-19 pandemic and the associated measures. This crucial analysis helps elucidate the spatial, temporal, and sector-specific variability of CF.

The statistical significance of the identified clusters, specifically hotspots and cold spots, pertaining to CF emissions from diverse building types, was evaluated at three levels of confidence: 99%, 95%, and 90%. A higher positive Z-score indicates a stronger aggregation of high CF values. Consequently, hotspots are typically characterized by clusters exhibiting high positive Z-scores, while clusters with high negative Z-scores generally indicate cold spots. Utilizing the outcomes derived from the Getis-Ord Gi* values and their corresponding levels of significance, the city of Doha was subdivided into three primary sectors: hotspots, cold spots, and areas lacking significant clustering. The determined hot and cold areas were assessed for three distinct temporal intervals in both 2019 and 2020: pre-lockdown (January–February), during the lockdown (March–May), and post-lockdown (June–December). Mathematically, the calculation of the Getis-Ord Gi* is based on the following equation [42]:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{3}$$

Where n represents the total number of locations within the city. X_i denotes the attribute value at a specific location, while X_j represents the variable value at another location. X signifies the mean value of the variable across all locations. Additionally, W_{ij} represents the weight assigned to the comparison between location i and location j. The weight matrix used in this calculation is distance-based and relies on the inverse distance between locations i and j, expressed as $1/d_{ij}$.

Additionally, the Anselin Local Moran's I statistical tool was utilized to investigate the spatial pattern of CF within each block of the study area. The primary objective was to assess whether the CF levels in each block demonstrated statistically significant differences from neighboring blocks. This analysis aimed to identify significant clusters of high and low CF rates. Moreover, the tool facilitated the identification of outliers that exhibited values that were statistically distinct from their surrounding areas in terms of spatial and temporal characteristics.

2.3.2. *Multi-Regional Input-Output (MRIO)*

To accurately compute the CF arising from electrical power production in Qatar, it is imperative to calculate the Global Warming Potential (GWP100). This metric quantifies the amount of CO_2-equivalent emissions produced per kilowatt-hour (kWh) of electricity generated. The following methodological steps were adopted.

3. Data extraction

Essential data was meticulously extracted from the comprehensive EXIOBASE 3.8.2 database, a state-of-the-art multiregional input-output

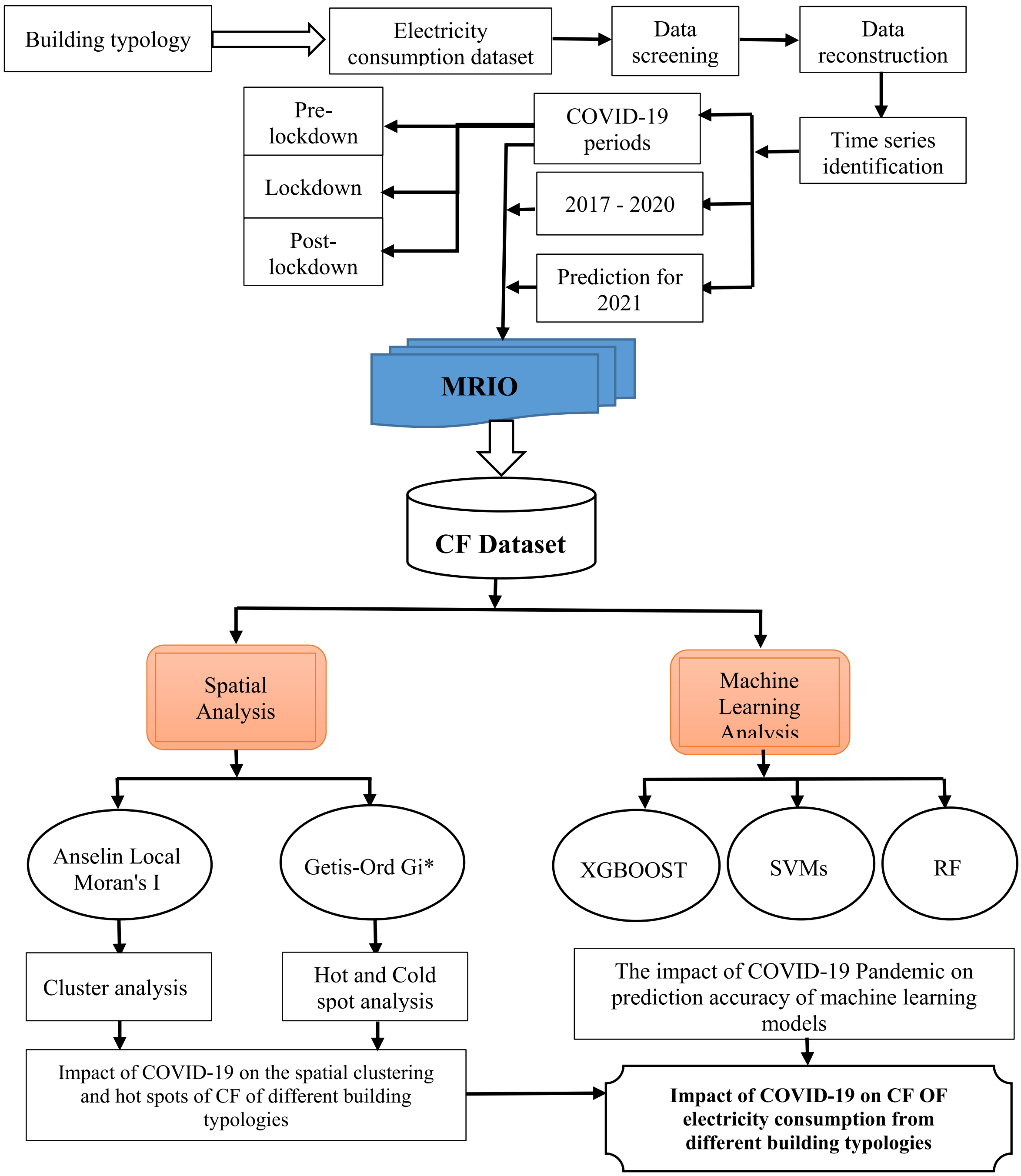

Fig. 1. The flow chart of the study.

database with high country and sector resolution, with a specific focus on the electricity consumption sector in Qatar and its associated greenhouse gas emissions. The selection of EXIOBASE 3.8.2 was predicated on its extensive coverage of various dimensions - social, economic, environmental, and sustainability aspects - pertaining to electricity generation. This database uniquely encapsulates the supply chain dynamics of electricity generation, stratified by source, country, and industrial sector. It encompasses a time series of symmetric multinational input-output tables, covering 43 countries and 5 rest of the world regions across 163 sectors, thereby representing nearly the global economy in its entirety. These input-output tables are constructed based on raw data sourced from authoritative databases such as Eurostat, Comtrade, the UN System of National Accounts, and various national statistical agencies. It is important to note that specific data for Qatar are not individually delineated in EXIOBASE. Consequently, Qatar is categorized under the 'Rest of the World - Middle East' (WM) segment within the EXIOBASE dataset.

3.1. Sector identification

The economic sectors in Qatar pertinent to electricity consumption are identified. These include both direct and indirect contributions, particularly from sectors generating electricity from gas and solar sources. The carbon footprint calculation was focused on the sectors "Electricity by gas" and "Electricity by solar photovoltaic."

3.2. Utilizing the MRIO model, an input-output analysis

This process traces the flow of electricity through various sectors, considering interdependencies. The MRIO model employs Leontief's inverse formula, shown in Equation (1):

$$X = (I - A) - 1 * y \tag{1}$$

Here, X denotes the total output vector (in Millions of Euros), Y represents the total demand vector, A is the input/output coefficient matrix, I is the identity matrix, and L=(I-A) - 1 is the Leontief inverse, symbolizing the total requirements matrix. The outcome of this analysis is a matrix that elucidates the impact of electricity generation in Qatar per Million Euros, providing a comprehensive understanding of the economic and environmental interplay.

Global Warming Potential Calculation:

Thereafter, the impact of electricity generation per Millions of Euro in Qatar is multiplied by the cost of electricity generation to calculate the footprint by equivalent carbon dioxide using the EXIOBASES's MRIO model through Eq. (2) as:

$$FEG = I_{me} \times CEG \times 10^{-6} \tag{2}$$

Where:

FEG is the footprint of electricity generation in Qatar per Kg/kWh. I_{me} is the impact of electricity generation per Millions of Euro, CEG is the cost generation of 1 kWh in Euro.

Subsequently, The GWP100 for "Electricity by gas" and "Electricity by solar photovoltaic" sectors are calculated by integrating the impact metrics of CO_2, CH4, and N_2O combustion with the Global Warming Potentials defined by UN Climate Change[1] and illustrated in Table 2 and shown in Equation (3):

$$GWP100_k = FEG\ [CO2] + FEG\ [CH4] \times 21 + FEG\ [N2O\ ] \times 310 \tag{3a}$$

Where:

$GWP100_k$ is the global warming potential of sector *k*.

$FEG\ [CO2], FEG\ [CH4]$ and $FEG\ [N2O]$ columns represent CO_2, CH_4 and N_2O emissions, respectively. All these columns are part of the FEG Matrix, which quantifies the footprint of electricity generation in Qatar in terms of Kg/kWh.

GWP100 Computation for Electrical Power Production: The GWP100 values for Qatar's electricity generation (over a 100-year horizon) are determined using Equation (4):

$$GWP100_e = \sum_{k=0}^{n} ID_k \times GWP100_k \tag{4}$$

Where:

$GWP100_e$ is GWP100 of electricity generation in Kg CO_2-eqv per kWh. ID_k is industrial designation or sector. $GWP100_k$ is the global warming potential of sector *k*.

In the context of Qatar, this calculation translates to a weighted sum of GWP100 values for gas and solar electricity generation, taking into account their respective contributions to the total electricity production. The global warming potential of Qatar's electricity generation (over a 100-year horizon) is shown in Table 3.

3.2.1. Machine-learning techniques

To assess the effect of the COVID-19 pandemic on the prediction accuracy of machine learning models, three commonly used supervised learning algorithms were employed in this study - XGBoost, SVMs, and RF. These models were selected due to their widespread use and effectiveness in handling complex, high-dimensional problems like those that the building CF prediction problem examined in this study. XGBoost is renowned for its efficiency and effectiveness in handling large and complex datasets [29,54], making it suitable for analyzing the multifaceted impacts of the pandemic. Its ability to manage missing data and process various types of features is crucial in COVID-19 research, where data can be incomplete or heterogeneous. SVMs are beneficial for their robustness and accuracy in classification problems [55]. They are particularly effective in discerning patterns and trends within the pandemic's data, which often involves high dimensional spaces. Lastly, RF is a versatile model known for its high accuracy and ability to run both classification and regression tasks [56]. It can handle large datasets with multiple variables, which is essential in COVID-19 research to account for the numerous factors influencing the pandemic's progression and impacts. The following subsections provide a detailed description of each of these models.

3.2.1.1. Extreme Gradient Boosting (XGBoost). XGBoost is a machine learning strategy founded on the gradient boosting framework [57]. This technique builds a predictive model via the combination of weak prediction models, typically decision trees [29]. The particular scalability and computational speed of XGBoost have facilitated its recognition, thus positioning it as an influential tool for handling large-scale data [58]. The employed methodology pivots around the objective function that XGBoost optimizes, expressed mathematically as:

$$L(\Phi) = \sum l(\widehat{y}_i, y_i) + \sum \Omega(f_k) \tag{5}$$

Wherein $l(\widehat{y}_i, y_i)$ signifies a differentiable convex loss function that quantifies the divergence between the prediction and the actual target, and $\Omega(f_k)$ represents a regularization term that limits the complexity of the model, thus averting overfitting [59]. Moreover, the regularization term $\Omega(f)$ plays a critical role in further smoothing the final learned weights to prevent overfitting, defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w\parallel^2 \tag{6}$$

Here, γT encapsulates the model's complexity in terms of leaf count, and $\lambda \parallel w\parallel^2$ implies the L2 regularization on the leaf weights.

3.2.1.2. Support vector machine (SVM). SVM is a fundamental tool in machine learning, renowned for its versatility and efficacy in classification tasks [60]. SVM excels in high-dimensional spaces and with limited data, addressing non-linear problems efficiently through kernel functions [61,62]. Its robustness and accuracy in various applications solidify its status as a key component of statistical learning and structural risk minimization within the machine-learning domain.

Table 2
Global warming potentials (IPCC second assessment report).

Industrial designation	Chemical formula	GWP values for X-year time horizon		
		20 years	100 years	500 years
Carbon dioxide	CO_2	1	1	1
Methane	CH_4	56	21	6.5
Nitrous oxide	N_2O	280	310	170

Table 3
GWP kWh of the Electricity generation sector for Qatar.

Year	GWP100 (gram CO2-eqv per kWh)
2020	400.560
2019	411.171
2018	440.709
2017	468.594

[1] https://unfccc.int/process/transparency-and-reporting/greenhouse-gas-data/greenhouse-gas-data-unfccc/global-warming-potentials.

Conceptually, SVM is a binary linear classifier that seeks to construct a hyperplane or a set of hyperplanes in a high-dimensional feature space. This hyperplane acts as a decision boundary and is optimized to segregate classes with maximal margin, thus minimizing the generalization error and ensuring optimal model performance. Mathematically, this involves solving a constrained optimization problem. Given a labeled training dataset $\{(x_i, y_i)\}$ (where $i = 1, 2, \ldots, n$), $x_i \in \mathbb{R}^d$, and $y_i \in \{-1, 1\}$, the primal form of the SVM problem can be formulated as:

$$\min_{w,b,\xi} 0.5 * w^T * w + C * \sum \xi_i \tag{7}$$

subject to:

$$y_i * \left(w^T * \varphi(x_i) + b\right) \geq 1 - \xi_i, \xi_i \geq 0 \; \forall i. \tag{8}$$

Here, w represents the weight vector perpendicular to the hyperplane, b is the bias, and ξ_i are the slack variables introduced to handle non-separable data and misclassifications. The function $\varphi(x)$ maps input vectors into a high-dimensional feature space, and $C > 0$ is a regularization parameter controlling the trade-off between maximizing the margin and minimizing classification errors [63].

To solve this problem efficiently, SVMs resort to the dual formulation of the problem using Lagrange multipliers ($\alpha_i \geq 0$), which enables the introduction of the kernel trick. This leads to the dual problem:

$$\max_{\alpha} \sum \alpha_i - 0.5 * \sum \sum y_i * y_j * \alpha_i * \alpha_j * K(x_i, x_j) \tag{9}$$

$$0 \leq \alpha_i \leq C \; \forall i, \text{and} \sum \alpha_i * y_i = 0 \tag{10}$$

where $K(x_i, x_j) = \varphi(x_i)^T * \varphi(x_j)$ is the kernel function which implicitly maps input vectors into a high-dimensional feature space without having to compute the map explicitly. It is important to note that the solution to the problem only depends on the inner product of the inputs, not on the inputs themselves. This is the fundamental property that allows the kernel trick to be possible [64,65]. While linear SVM is effective for linearly separable data, real-world data often exhibits non-linear patterns. This complexity necessitates the application of different kernel functions, such as polynomial kernels and Radial Basis Function (RBF) kernels, to capture these non-linear relationships. RBF kernels, in particular, have the advantage of transforming the data into an infinite-dimensional space, thus enhancing the model's flexibility [66].

3.2.1.3. Random Forest (RF). RF is an ensemble learning method that has gained significant popularity in the domain of machine learning for its interpretability, versatility, and robust performance across diverse tasks and data types [67]. Fundamentally, an RF model consists of a collection of decision tree classifiers $\{h(x, \Theta_k), k = 1, \ldots, K\}$, where Θ_k are independently identically distributed random vectors, and each tree casts a unit vote for the most popular class at input x. Unlike a single decision tree that may be prone to overfitting, an RF model leverages the power of 'majority votes' from numerous de-correlated trees to make the final prediction, which enhances generalization and robustness. Mathematically, the RF model can be expressed as:

$$h_{\text{rf}}(x) = \text{mode}(h(x, \Theta_1), \ldots, h(x, \Theta_K)) \tag{11}$$

where $h(x, \Theta_k)$ is the k-th decision tree in the ensemble, Θ_k are the parameters of the k-th tree learned during the training process, and mode($\bullet$) is the statistical mode, used to determine the most frequent prediction. Two key strategies contributing to RF's effectiveness are bagging (bootstrap aggregating) and random subspace method. In bagging, each decision tree is trained on a different bootstrap sample from the original data, adding an extra layer of randomness and reducing the variance without increasing the bias [68]. Mathematically, if the original dataset is denoted as D and the bootstrap sample as D_k, then:

$$D_k = \{d_1^k, \ldots, d_n^k\}, \tag{12}$$

where d_i^k is randomly picked from D with replacement.

The random subspace method involves selecting a random subset of features at each split point, thereby creating de-correlated trees and further enhancing the model's performance [69]. An advantage of RF is its natural ability to handle multiclass problems and estimate class probabilities. Given an input x, the estimated class probabilities can be obtained by averaging across the proportions of training samples in the leaf nodes of all trees:

$$P_{\text{rf}}(y|x) = \frac{1}{K} \sum_k I(h(x, \Theta_k) = y) \tag{13}$$

where $I(\bullet)$ is the indicator function, and y is the class label.

Finally, RF models provide a measure of feature importance by calculating the total reduction in the criterion brought by that feature. This offers not only a model with high predictive accuracy but also insights into the underlying structure of the data, making RF a powerful tool for both prediction and interpretation tasks [70].

4. Results

4.1. Carbon footprint of electricity consumption in buildings

In this study, our primary emphasis was on the carbon emissions linked to electricity consumption in the operational phase of buildings. Consequently, our analysis did not encompass other phases in the life cycle of buildings, such as construction and demolition. Following the calculation of buildings' overall electricity consumption, we employed MRIO analysis to estimate the total carbon footprints originating from the electricity generation sector, meeting the overall electricity demand. The monthly electricity consumption data in kilowatt-hours (kWh) from January 2017 to December 2020 were transformed into CF measurements. In this research, our primary approach involved employing MRIO analysis to calculate both the direct and indirect carbon footprints associated with the electricity production sector in Qatar. Rather than constructing a process-based environmental life cycle assessment model for estimating the carbon footprints of electricity, we opted for MRIO analysis as our primary method. This method effectively captured carbon emissions originating from both regional and global supply chain-related activities in Qatar's electricity production. The calculation of upstream impacts resulting from electricity production is accomplished by utilizing upstream impact factors derived from the MRIO model, using the EXIOBASE 3.8.2. This approach also enabled us to assess the global upstream supply chain-related carbon footprints associated with Qatar's electricity production.

This research utilizes data obtained from a total of 292,195 buildings, providing insights into the temporal dynamics of specific building categories within a defined timeframe (2017–2020) (Fig. 2a). The analysis of CF contributions over time and across sectors is depicted in Fig. 2b. The residential villas and flats category exhibits the largest number of buildings, displaying a progressive increase over the study period. However, when examining CF values, a contrasting pattern emerges. The residential villas contribute a significantly higher amount of CF compared to residential flats. In fact, the residential villa sector emerges as the primary contributor of CF when compared to other sectors, as illustrated in Fig. 2c. This discrepancy can be attributed to inherent characteristics of these residential villas, such as their size and the number of occupants, which contribute to higher CF emissions. The CF emanating from the residential sector, comprising both villas and flats, exhibits monthly variations in its magnitude throughout the year. Notably, the highest CF levels are observed during the summer season (Fig. 3). This surge in CF emissions can be attributed to the exceedingly high temperatures exceeding 40 °C, necessitating extensive utilization of

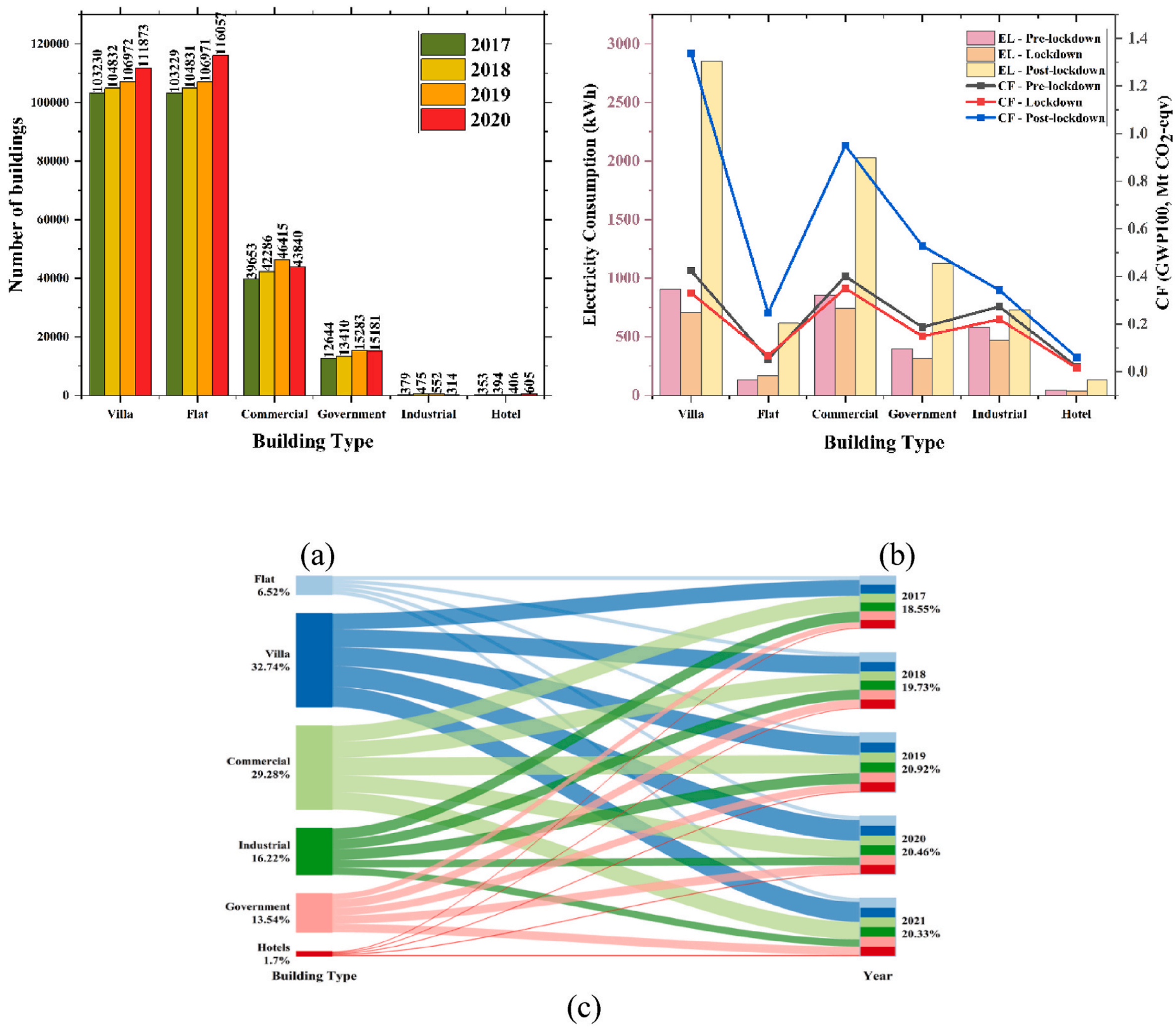

Fig. 2. (a) Total number of buildings during the study period, (b) Electricity consumption and the resultant CF of buildings, (c) Total shared CF by the different socioeconomic sectors between 2017 and 2020.

air conditioning systems by residents.

Within the six sectors examined, commercial buildings occupy the third position in terms of their numbers (Fig. 2a) but rank second in terms of CF emissions. Fig. 3c demonstrates that the commercial sector is accountable for around 30% of the overall CF emitted, exhibiting a consistent contribution over time. Interestingly, the commercial sector displays a similar CF emission pattern to the residential sector as shown in Fig. 3. Specifically, the monthly average CF emitted from commercial buildings shows an increase during the summer months and a decrease during the winter season. This pattern can be attributed to the extensive utilization of air conditioning systems within these buildings. Despite the relatively small number of industrial buildings compared to other sectors, their CF emissions are notably high, ranking third. This can be attributed to the substantial electricity consumption associated with industrial activities. Fig. 3 depicts that CF emissions from the industrial sector maintain consistent proportions throughout the studied timeframe. However, there is a divergence in the pattern of monthly average CF emitted from industrial buildings compared to other sectors. Fig. 3 illustrates that the variation in average monthly CF values within the industrial sector is comparatively lower, particularly during the summer season. This indicates a minimal impact of air conditioning usage in these industrial settings. The governmental sector, despite having a significantly larger number of buildings compared to the industrial sector, ranks fourth in terms of CF emissions. On the other hand, the hotel sector exhibits the lowest CF emissions resulting from electricity consumption, primarily due to the relatively smaller number of categorized hotel buildings and their specific characteristics. The average monthly CF emission patterns from the governmental and hotel buildings align with those observed in other sectors, except for the industrial sector. Notably, the highest CF emissions occur during the summer season due to increased electricity consumption across all sectors.

4.2. Temporal variation of CF of electricity consumption in buildings

Fig. 4 depicts the temporal fluctuations in CF of various building types on a monthly basis during the period spanning from 2017 to 2020. It presents the proportional variations in CF, expressed as a percentage, between consecutive years, thereby illustrating the observable trends of either augmentation or reduction in CF over time. Within the residential villa-building category, Fig. 4 illustrates fluctuating trends of increase or decrease of CF between 2017 and 2020. Notably, no discernible patterns emerge when comparing the same two months across different years. For instance, while CF experienced an increase in January between 2018 and 2019, it simultaneously decreased between 2018 and 2017, as well as between 2019 and 2020. However, February exhibits a distinct pattern, wherein CF demonstrates a higher percentage increase between 2017 and 2018, albeit maintaining an overall upward trend between 2017 and 2020. A similar pattern can be observed in June. It is worth noting that the most substantial decline in CF in this building type is observed in November, both between the years 2017 and 2018, as well

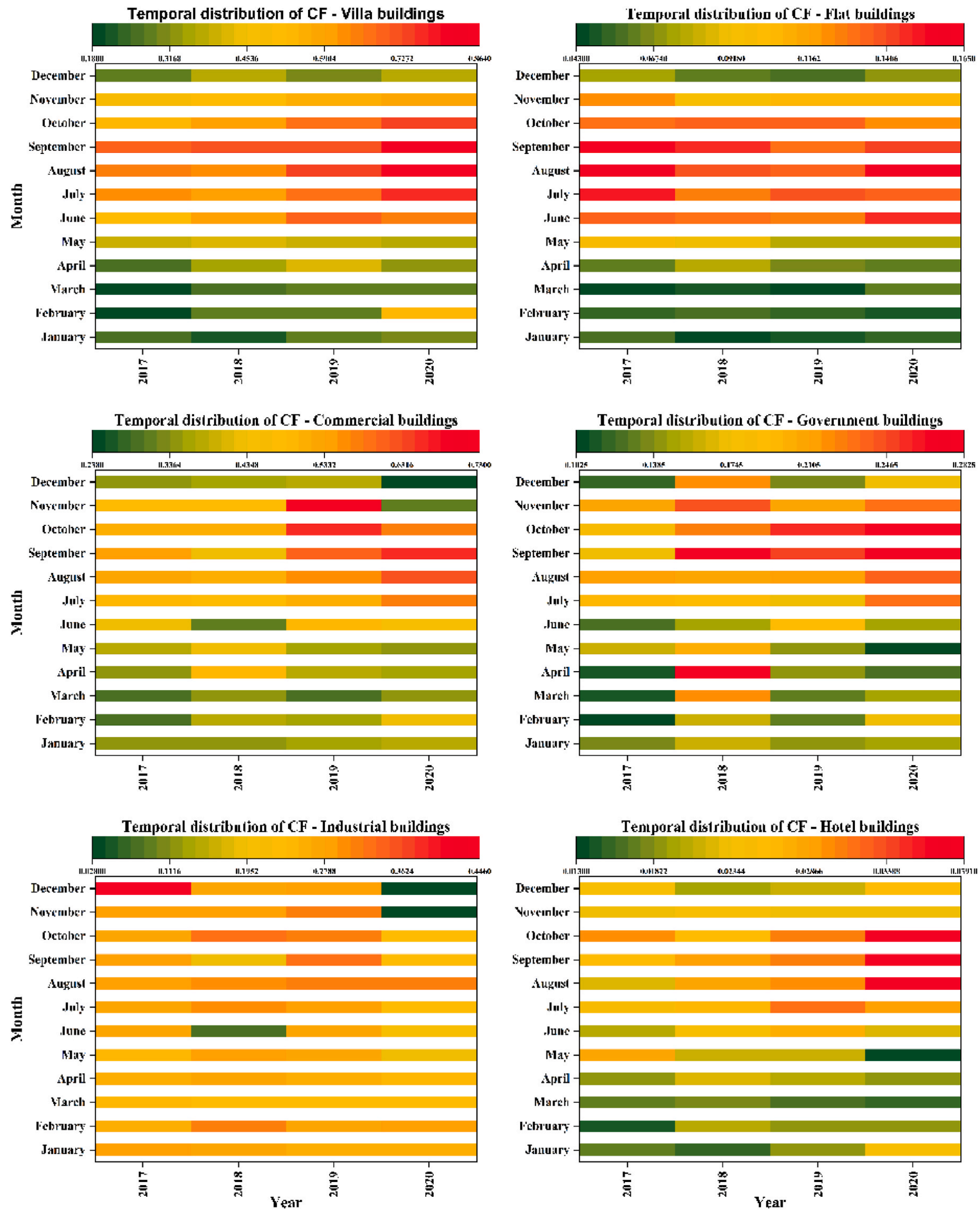

Fig. 3. The CF emitted from buildings over time and building type.

as between 2019 and 2020. The Figure does not present distinct patterns of monthly CF increase or decrease between the years 2017 and 2020 across all building types. Consequently, it is difficult to draw definitive conclusions regarding the significant impact of disease propagation on building CF. However, the figure does reveal noteworthy observations that all building types, except for residential sectors, experienced a significant decline in CF during March, April, and May between 2019 and 2020. These months align with the period of lockdown measures implemented during the first year of the COVID-19 pandemic.

4.3. *Spatiotemporal analysis of CF prior and during the pandemic*

This study comprises two sections that investigate the impact of the pandemic on the CF of buildings. The first section involves spatial analysis, aiming to identify the areas with significant changes in CF before and during the pandemic. The second section entails temporal analysis, aiming to assess the effects of the pandemic on CF and its subsequent impact on the accuracy of CF predictions for buildings.

The spatial distribution of CF among various building categories was examined through the use of clustering analysis, hotspot analysis, and

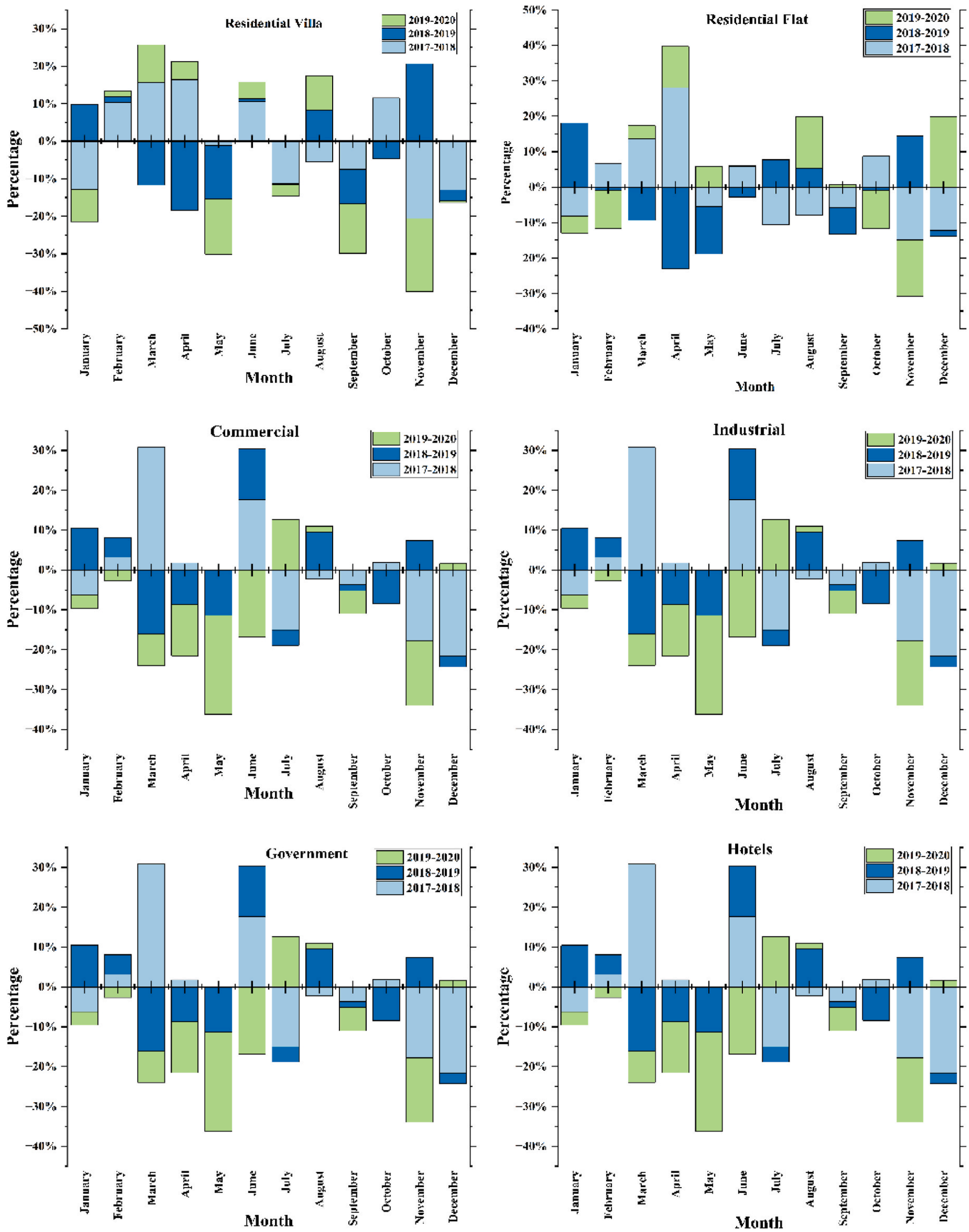

Fig. 4. The monthly changes in carbon footprint distribution among various sectors from 2017 to 2020.

cold spot analysis. This investigation specifically focused on the years 2019 and 2020 and explored three different temporal intervals: the pre-lockdown, lockdown, and post-lockdown phases as shown in Fig. 5. These stages depict the progressive phases of the COVID-19 pandemic in Qatar and the corresponding measures implemented for its containment in the first year of the pandemic. The aim was to assess the impact of the pandemic on CF by comparing the spatial distribution during the three time phases in 2020 with the distribution observed prior to the pandemic in 2019. Moreover, the spatial analysis was carried out within the Doha metropolitan area, which serves as the primary residence for the majority of the population and is a hub for economic activities.

4.3.1. Spatial analysis of CF prior to the pandemic

In order to examine the spatial clustering characteristics of CF, the statistical method of Anselin Local Moran's I was employed. The outcomes of the investigation indicate varying spatial clustering patterns of CF based on the type of buildings in year 2019. Notably, the predominant regions exhibiting high-high clustering of CF (i.e., statistically

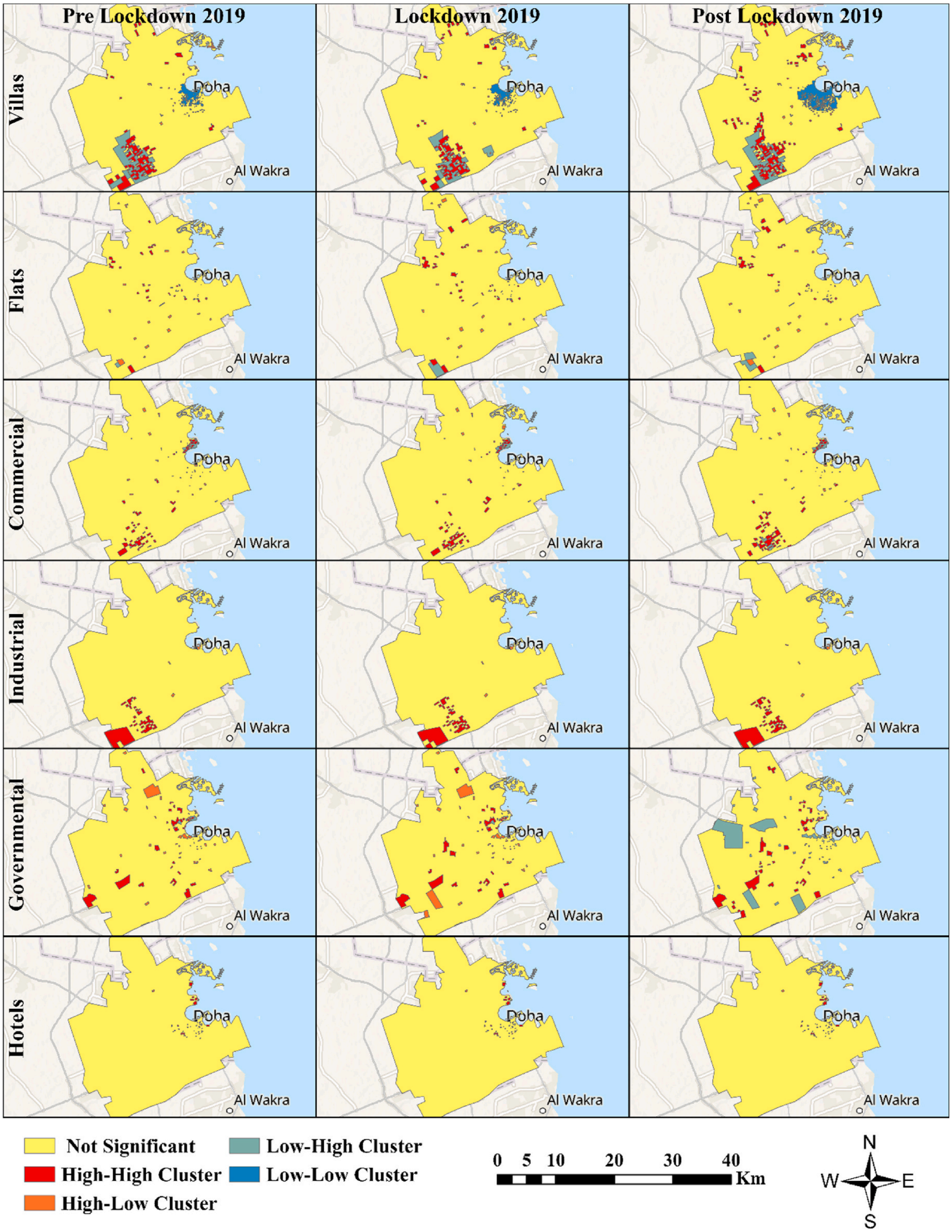

Fig. 5. The Anselin Local Moran's *I* statistics of CF across six types of building in 2019. Different areas are identified as high-high clustering in the residential (villa), industrial, and governmental buildings.

significant clusters with elevated values) are situated in the southwestern area, specifically associated with residential villas and flats, as well as the industrial and commercial sectors. Moreover, the CF exhibited a higher degree of clustering in villa buildings compared to other building types. The spatial distribution of CF within the residential villa sector demonstrated positive autocorrelation, primarily concentrated in the southern and southwestern regions of the Doha metropolitan area. These areas displayed a notable occurrence of high-high and low-high outliers in their neighboring regions. Importantly, this spatial pattern remained consistent across the three examined periods as shown in the figure.

This configuration diverges among residential flat buildings. The figure exhibits a stochastic arrangement of CF values pertaining to residential flat buildings within the studied vicinity, spanning across different time intervals. The aggregation tendencies of CF values, emanating from this specific building typology, predominantly manifest within the central sector of the City. The CF pattern observed in commercial buildings exhibits a strong positive correlation (high-high) primarily within the southwestern region, predominantly concentrated in the industrial zone, while demonstrating a comparatively weaker correlation in other areas of the city. This consistent pattern persisted throughout the year 2019. Industrial buildings exhibit a similar CF pattern to residential villas, as shown in the figure, with a high-high clustering observed in the southwestern part of the City, owing to the notable concentration of such buildings in that particular area. Governmental buildings, on the other hand, display a random high-high clustering pattern dispersed across various parts of the city, primarily concentrated in the central region. This pattern remained largely

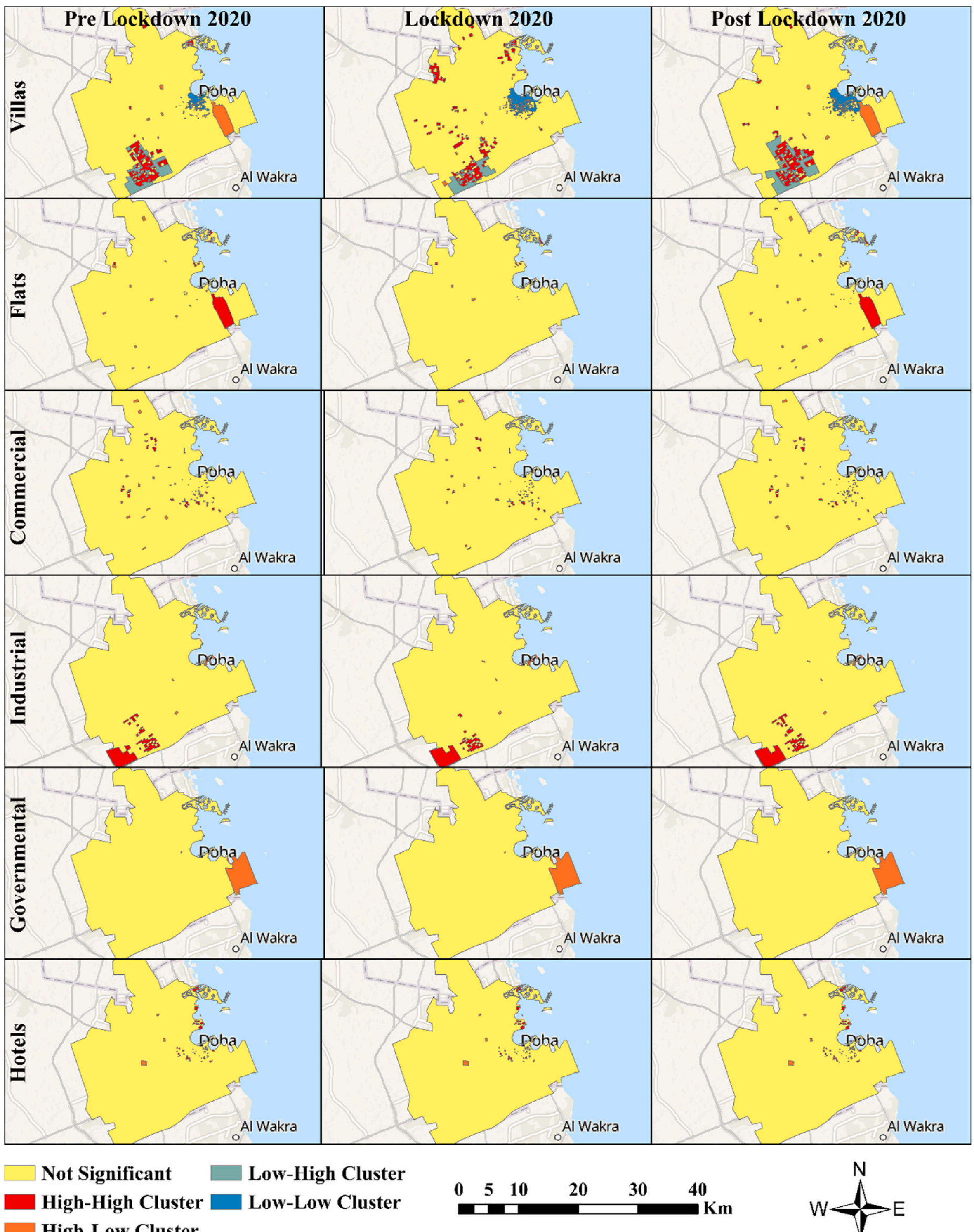

Fig. 6. The Anselin Local Moran's *I* statistics of CF across six types of building in 2020. Different areas are identified as high-high clustering in the residential (villa) and industrial buildings.

consistent throughout 2019, albeit with some instances of low-high clustering in the northern and southern regions of the city. Finally, the presented figure reveals an absence of discernible clustering patterns in the CF of hotel buildings.

4.3.2. Spatial analysis of CF during the first year of the pandemic

The CF patterns observed in 2020 exhibit both similarities and differences when compared to the CF patterns of various building types in 2019. In the residential villa sector, the spatial distribution pattern of CF remains largely consistent with that of 2019 (see Fig. 6). Prior to the implementation of lockdown measures, the southwestern region of the city demonstrates a high-high clustering pattern of CF, accompanied by a low-high clustering pattern. Conversely, the eastern part of the city exhibits a low-low clustering pattern. This distribution pattern aligns with the spatial pattern observed during the equivalent period in 2019. However, during the lockdown period, there are notable changes in the

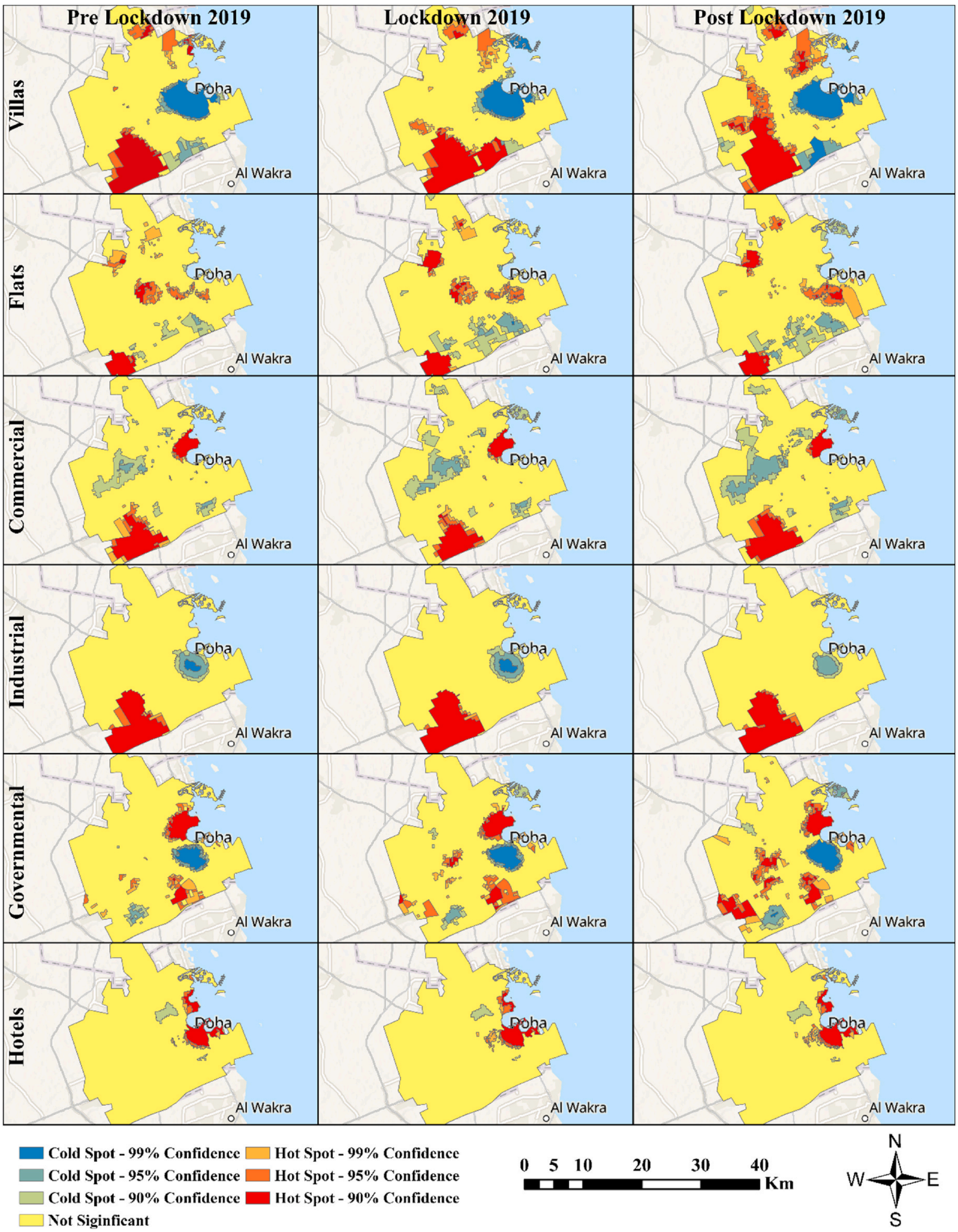

Fig. 7. The Getis-Ord G* i statistics of CF across different building types in 2019.

CF spatial patterns. The previously observed high-high and low-high clustering patterns in the southwestern area decline, while new instances of high-high clustering emerge in other areas of the city. In the post-lockdown period, the CF spatial distribution reverts to a pattern similar to the pre-lockdown period. However, the figure illustrates an increase in the area exhibiting high-high and low-high clustering in the southwestern region, along with an expansion of the low-low clustering pattern in the eastern part of the city.

4.4. Hotspot and cold spot analysis

For further spatial analysis of CF of buildings, hotspot and cold spot analysis was carried out in order to understand the spatial clustering of CF for each of the six types of buildings during the three distinctive periods of pre-lockdown, lockdown, and post-lockdown in 2020 in comparison to the year 2019. Fig. 7 reveals that the majority of areas depicting hotspot and cold spot CF of residential villas in 2019 have a

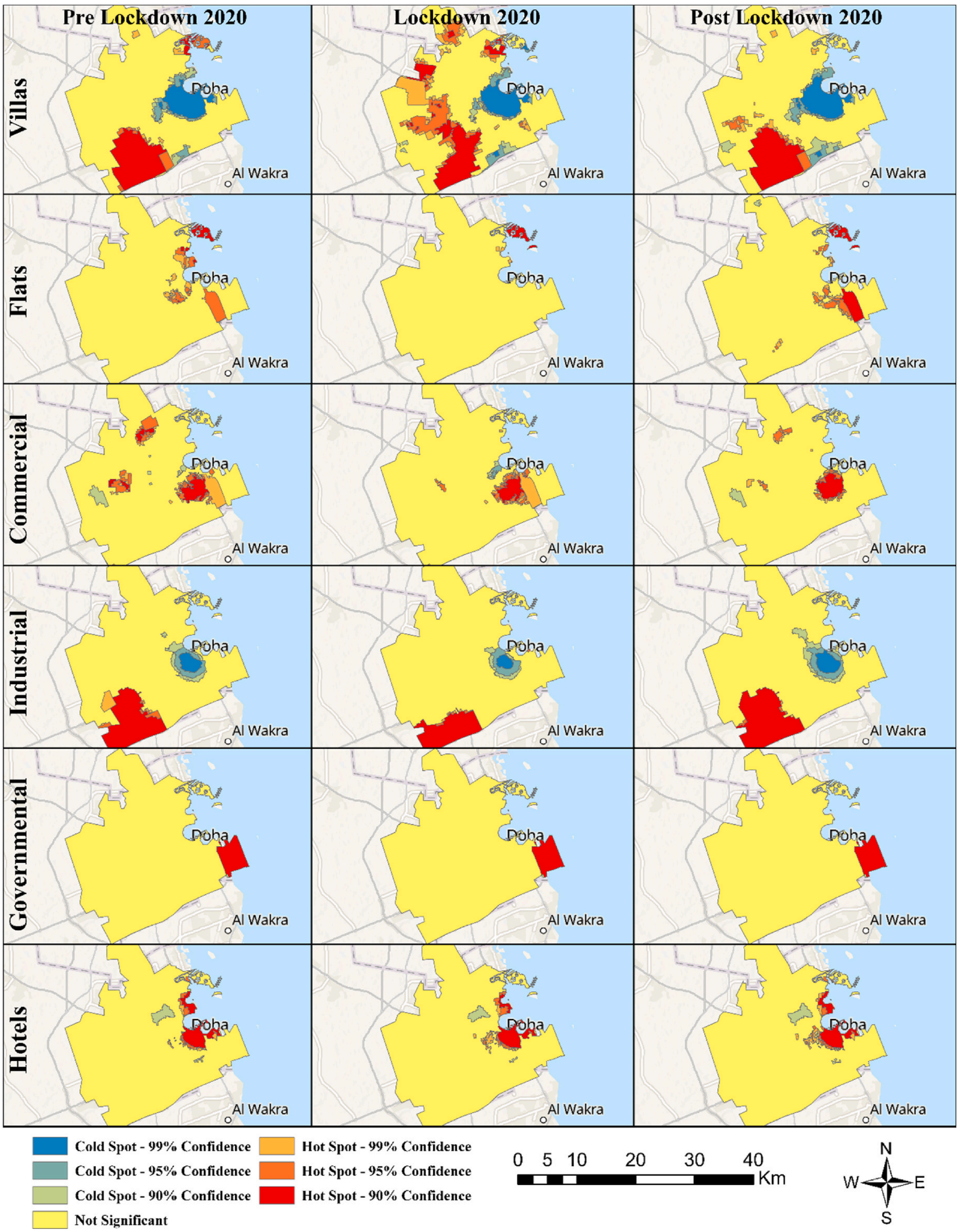

Fig. 8. The Getis-Ord G* i statistics of CF across different building types in 2020.

degree of similarity across the three time periods, with few exceptions of hotspot areas for the post-lockdown period. The spatial distribution of 2019 high CF from residential villas is manifested by hotspot areas that are concentrated in the southwest and in the north and northeast. On the other hand, the 2019 cold spot areas dominate the east side and have some noticeable presence in the south. The 2020 hotspots map reveals a significant difference of CF from residential villas during the lockdown in comparison the other two periods and to the same period of business-*as*-usual of 2019 as shown in Fig. 8. New hotspots appear in the north, northwest, and in the northeast in response to the stay-at-home/work-from-home policy imposed by the Qatari government during this period. The 2020 cold spots for the same sector do not exhibit noticeable differences across the three periods or against 2019 map. As for the residential flats buildings, the maps in Fig. 7 delineate 2019 hotspot areas of CF in the southwest and the center across the first and second periods; however, other hotspots appeared in the east for the post-lockdown period. The cold spots representing low CF are dominant in the southern part in the second and third periods at confidence levels of 90% and 95%.

Since the study area encompasses the capital city of Doha, a large proportion of the commercial buildings in the country can be found within this area. The 2019 map reveals hotspots concentration in the southwest and the east. These hotspots seem to be uniform across the three time periods which reflects the constant nature of commercial activities irrespective of seasonality before the pandemic. The 2020 map shows a completely different pattern of hotspots where they disappeared from the southwest area due to the pandemic, and where the effect of pandemic rippled through the rest of 2020 (even post-lockdown) where businesses struggled to regain in form of normality.

The other sector that has a sizable impact on CF in Qatar is the industrial sector which is mainly focused on oil and gas energy. Although the largest industrial areas are located outside the limits of study area, there is a sizeable industry within the study area, which is mainly located in the industrial area (southwest) and to a lesser extent in Doha downtown. The hotspots and cold spots of 2019 CF emissions show consistency across the three time periods, which reflects a stable and coherent sector within the study area. However, the maps show a different story during the 2020 lockdown period where the hotspot of CF emissions has contracted substantially, reflecting the effect of lockdown on the industrial sector and the CF produced by this sector. The cold spots have not shown any major changes across periods and between 2019 and 2020. The hotels sector also experienced a pattern of CF, which is quite similar to that of the industrial sector as a direct result of the lockdown on the international and national tourism in the State of Qatar.

4.5. Comparing the actual and predicted CF during the first two years of the pandemic

The examination of the spatial distribution of CF among the six distinct building types does not reveal any discernible pattern of CF variation across space, time, and sectors. While fluctuations in CF during the pandemic year have been previously observed over time and across sectors, the impact of the pandemic on CF remains unclear using this particular approach. Consequently, it becomes imperative to compare the actual CF derived from electricity consumption with the CF predicted based on historical electricity consumption data (2010–2019). To achieve this, three machine-learning models were employed to predict CF under pandemic-free conditions. Additionally, this process aims to ascertain which of the three models demonstrates superior performance and accuracy in predicting CF for the pandemic year. The evaluation of the three machine learning models was based on key metrics, such as mean squared log error (MSLE), mean absolute error (MAE), and the coefficient of determination (R^2). Table 4 presents the results, indicating that the XGBoost algorithm outperforms the other models with the highest coefficient of determination ($R^2 = 0.838$) and the lowest errors (MSLE = 0.185).

Table 4
Evaluation of the machine-learning models.

	XGBoost	RF	SVM
Coefficient of determination (R^2)	0.838	0.814	0.746
Mean squared log error (MSLE)	0.186	0.260	0.198
Mean absolute percentage error (MAPE)	0.219	0.198	0.310

The disparities in CF between the actual values observed during the first pandemic year and the pandemic-free scenario (referred to as the business-*as*-usual scenario), as derived from the outcomes of the three-machine learning models, are graphically presented in Fig. 9. By examining the discrepancies between the actual CF and the simulated CF, it becomes possible to discern the magnitude of CF gap over time and across sectors. This analysis sheds greater light on the impact of the pandemic on building CF, both in terms of temporal changes and sector-specific effects. The figure illustrates that the disparity between the actual and simulated CF notably increased during the post-lockdown period within the residential sector. While the CF experienced a surge during the lockdown phase, when residents were confined to their homes, the disparity between the actual and simulated CF was relatively less pronounced compared to the post-lockdown period. The latter period coincides with summer, during which residents heavily rely on air conditioning to combat the extremely hot weather. Additionally, with limited international travel within the first pandemic year, residents remained in the country, leading to extensive use of cooling systems and increased electricity consumption, consequently elevating the CF of residential buildings.

In the other building types (commercial, industrial, governmental, and hotels), the figure shows a reduction in CF of these buildings due to a reduction in electricity consumption. These economic activities were impacted significantly by the propagation of the pandemic due to the policies that were imposed to slow down the spread of the disease. Many non-essential commercial and industrial activities were closed down during the lockdown period and were gradually but slowly reached to full operation during the post-lockdown period due to the limited capacity restrictions during this period. The hotel buildings witnessed a reduction in CF during the lockdown period due to the lack of visitor or tourist activities during this period. However, during the post-lockdown period, many of these hotels were used as places for quarantine for 14 days for residents who returned to the country or international visitors resulting in increasing the CF of this building type.

In the case of other building types, including commercial, industrial, governmental, and hotels, the figure illustrates a notable reduction in CF for these buildings, primarily attributed to a decrease in electricity consumption. These economic activities experienced significant impacts resulting from the widespread transmission of the pandemic, brought about by various policy measures aimed at mitigating disease spread. During the lockdown period, numerous non-essential commercial and industrial operations were mandated to close temporarily, and their return to full operation occurred gradually and cautiously during the post-lockdown phase, subject to limited capacity restrictions. Regarding hotel buildings, the CF of these types of buildings witnessed a decline during the lockdown period due to the absence of visitor and tourist activities. However, in the post-lockdown period, several hotels were repurposed as quarantine facilities for residents returning to the country or international visitors, leading to an increase in CF for this particular building type. This shift in usage resulted in an elevated demand for energy and resources, thereby contributing to the observed rise in CF levels during this phase.

The CF of industrial buildings exhibited a decline during a significant portion of the pandemic year in 2020. Notably, during the lockdown period, there was an observed decrease in actual CF, primarily attributed to the temporary closure of most industrial activities. However, intriguingly, the three predictive models suggest that the CF of industrial

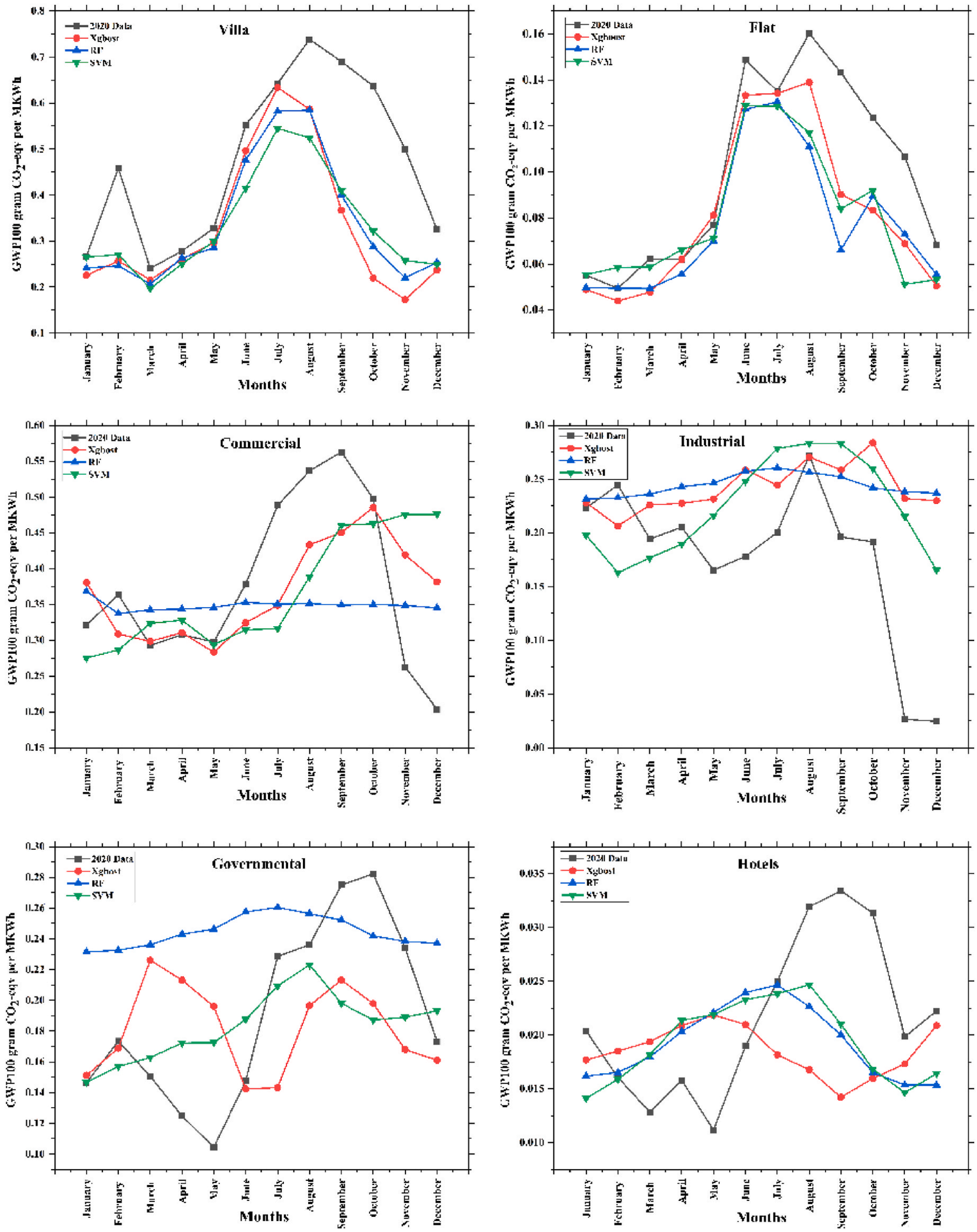

Fig. 9. Comparing the actual and predicted CF using machine learning models for year 2020.

buildings should have shown an increase during this period. Subsequently, as the post-lockdown phase commenced, the actual CF gradually increased, reaching its peak in August, followed by a subsequent decrease after September, only to peak down in November and December of 2020. Finally, the figure demonstrates fluctuations in the actual CF of governmental buildings during different phases of the pandemic. Notably, the CF reduced during the lockdown period owing to the implementation of work-from-home policies. Conversely, during the post-lockdown phase, the CF experienced a rapid increase, particularly in October, as in-person activities resumed in offices and educational institutions like schools and universities. However, as a new wave of the disease spread, the CF of governmental buildings declined in November and December due to the reinstatement of online working and learning. Despite efforts to predict the CF using three distinct models, none of the predictive models effectively simulate the actual CF of governmental buildings over time.

The study extended its investigation into the influence of the pandemic on the CF of buildings by exploring the relationship between the CF gap and the daily count of infected cases. Fig. 10 shows the findings for the first year of the pandemic (2020), while Fig. 11 illustrates the corresponding results for the second year (2021). The CF gap was determined as the disparity between the actual CF of buildings for each specific year and the outcomes generated by the three simulated machine-learning models. For any line of the three models, a positive value indicates that the simulated CF is lower than the actual value, whereas a negative value suggests the opposite scenario. The figures reveal diverse correlations over time and across sectors. Moreover, they provide insights into the pandemic's impact on the CF of buildings, specifically with regard to electricity consumption.

Fig. 10 provides compelling evidence of a significant increase in the CF disparity observed in residential buildings (Villas and Flats). This increase is strongly correlated with the rise in the number of COVID-19 cases, particularly following the initiation of the lockdown period in March, reaching its peak in August. This observed trend could be predominantly attributed to the enforcement of stay-at-home policies and restrictions on international travel, which resulted in individuals spending extended periods within their residences. In contrast, both the commercial and industrial sectors exhibited negative simulated CF

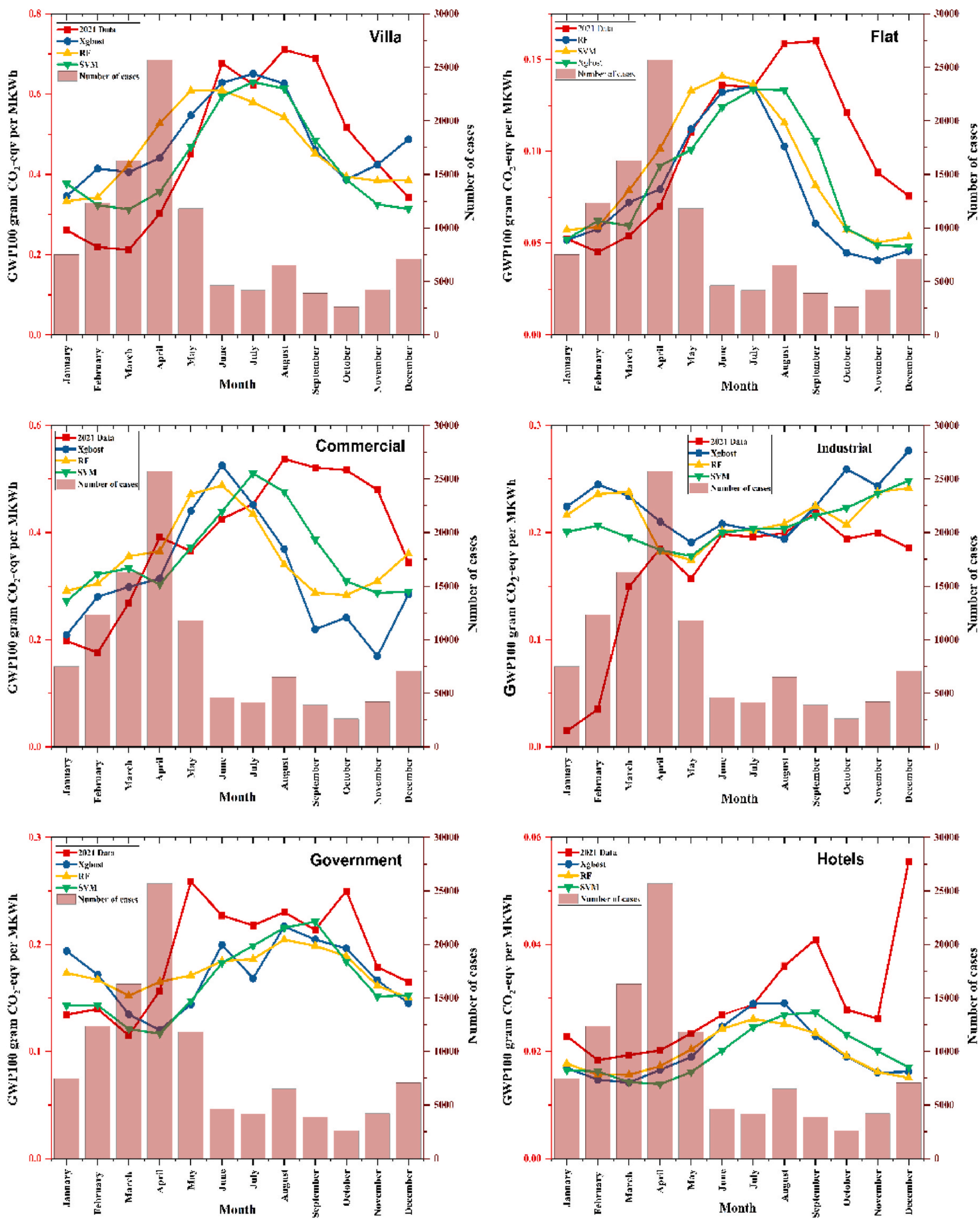

Fig. 10. the gap between the actual and simulated CF based on the three machine-learning models and building types in the first year of the pandemic.

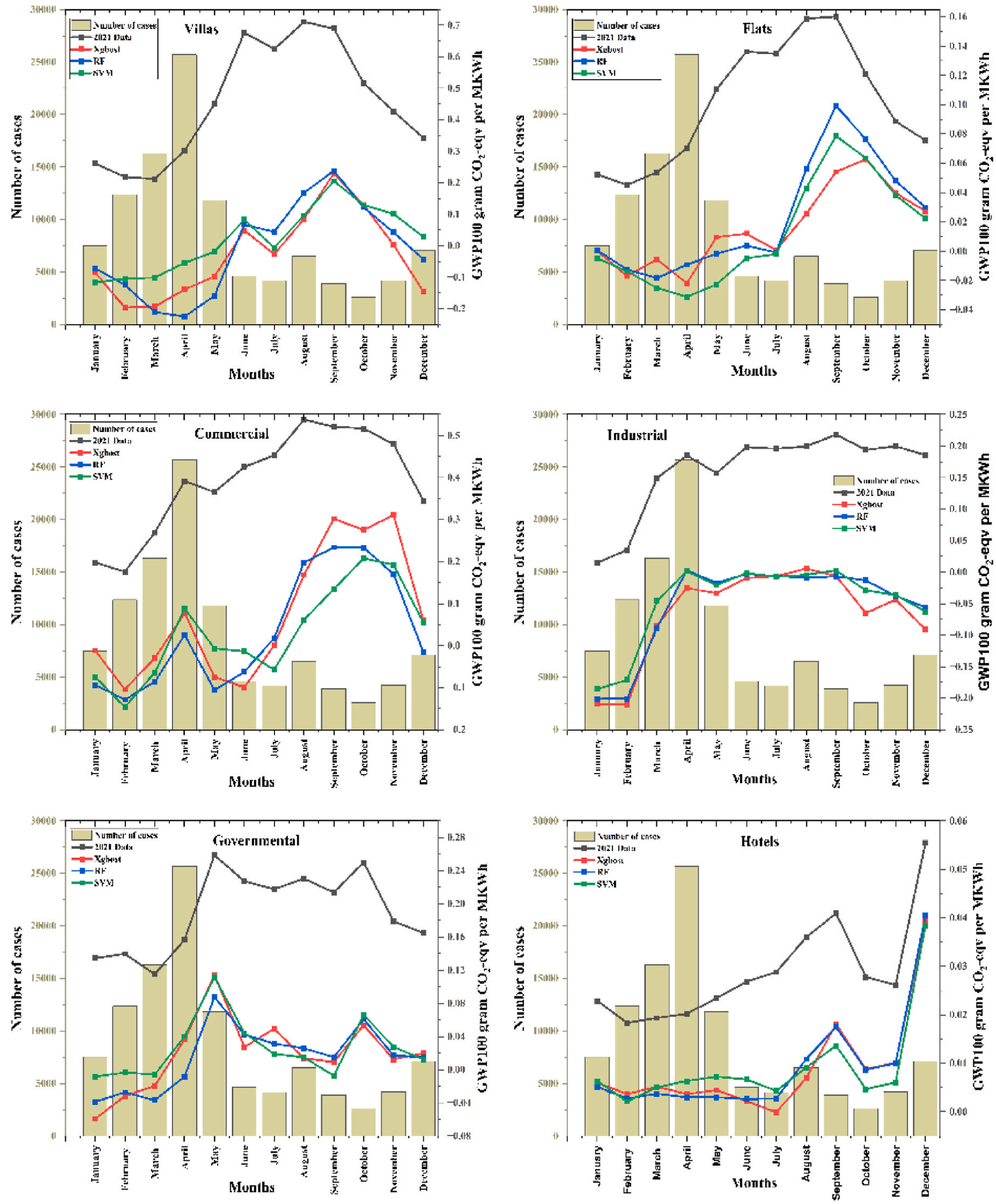

Fig. 11. the gap between the actual and simulated CF based on the three machine-learning models and building types in the second year of the pandemic.

values during the lockdown period and subsequent months of the post-lockdown phase, indicating that the actual CF of these buildings was considerably lower than the typical levels. This alignment with the number of COVID-19 cases and the implemented disease containment measures is evident. As the post-lockdown period progressed and the number of COVID-19 cases declined, the disparity between the actual and simulated CF diminished, reflecting the gradual resumption of in-person work activities.

In the prediction of the carbon footprint for various building types during the second year of the pandemic, we adhere to the same methodology employed in the first year. The sole distinction lies in the utilization of monthly CF data spanning the period between 2010 and 2020. This deliberate choice enables us to discern potential impacts of crises on the efficacy of the employed machine-learning models. In evaluating the pandemic's influence on the CF of buildings, a comparison is drawn between the actual CF and the simulated values for the year 2021, as depicted in Fig. 11. This analytical approach aims to ascertain the extent of the pandemic's effect on the CF across the different building types under consideration.

Fig. 11 reveals a distinct CF pattern in the residential sector during the initial months of year 2021, as opposed to the corresponding period in 2020. Notably, as the number of infected cases rose, the three models predicted higher CF values for these buildings compared to the actual measurements. Conversely, during the period between June and November of that year, the models projected lower CF values for residential buildings. The models projected higher CF values for commercial buildings than the actual measurements between January and June, except for April, presenting a distinct pattern compared to the corresponding period in 2020. Notably, the increase in infected cases coincides with this trend during these months. Conversely, for the remaining months, the figure demonstrates that the actual CF of these buildings exceeded the estimated values. Furthermore, in the second year of the pandemic, the predicted CF of industrial buildings surpassed the actual measurements. Notably, the CF gap exhibited a notable increase after the month of May, indicating that the country's economy had not fully recovered from the pandemic's impact, despite the absence of workplace restrictions and the commencement of vaccination efforts. Finally, we observe that the disparity between projected and observed CF values in the hotel sector exhibited notable fluctuations throughout the seasonal variations. Specifically, during the summer season, the gap was notably significant, attributed to a surge in domestic and international travel. This trend was exacerbated by the extreme hot weather conditions, where temperatures exceeding 40 °C, which negatively affected tourist interest in visiting the region. Conversely, during the winter season, a decline in the gap was observed. This reduction can be attributed to the hosting of the FIFA Arab Cup, which took place in late November and December. The event attracted a considerable number of football fans, who predominantly chose to stay in hotels during their visit. This phenomenon contributed to a decrease in the CF value discrepancy during the winter months.

5. Discussion

The COVID-19 pandemic has drastically altered CF patterns and electricity consumption trajectories, presenting unique challenges in Qatar. As the pandemic progressed, the government's dynamic mitigation measures significantly influenced the spatial and temporal aspects of CF from electricity consumption in buildings. This shift has necessitated a reevaluation of CF in various building types, highlighting the importance of electricity as a critical resource in economic and social sectors and having a great impact on the environment. The pandemic has catalyzed changes in socioeconomic practices, directly affecting electricity consumption and offering insights into potential climate change mitigation through altered consumption behaviors.

The analysis in this study is bifurcated into spatial and temporal assessments to assess the pandemic's impact on CF of electricity consumption in different building typologies during the period of the COVID-19 pandemic. This approach provides a holistic view of how pandemic-related measures have altered CF patterns spatially and temporally in Doha, reflecting the direct consequences of COVID-19 containment strategies on energy consumption and associated CF emissions in buildings. This analysis categorizes the pandemic into pre-lockdown, lockdown, and post-lockdown phases. The goal is to compare CF spatial distribution during these pandemic phases in 2020 with the pre-pandemic year of 2019 and to identify areas with significant CF changes attributable to the pandemic.

Spatiotemporal analysis across six sectors revealed distinct variations in CF of electricity consumption. A notable shift was observed from commercial and industrial sectors to residential sectors, influenced by lockdowns and disease spread. During lockdowns, residential electricity consumption spiked, and hence the CF, driven by increased home occupancy and remote work and learning practices. The absence of international travel further intensified this trend. Summer 2020 saw a significant rise in residential CF due to the increase in the electricity consumption, primarily due to increased air conditioning and appliance use. Conversely, the industrial and commercial sectors experienced a reduction in CF from electricity consumption, aligning with decreased economic activities and mobility restrictions. While residential and government sectors saw increased consumption, the overall electricity demand stabilized. The post-lockdown phase saw a gradual return to physical workplaces and resumed production, particularly in industrial and commercial sectors. However, these sectors faced challenges in returning to pre-pandemic consumption levels, potentially affecting the economy.

Geospatial analysis played a crucial role in understanding the distribution and dynamics of CF during the pandemic. Mapping hotspots and cold spots at the zonal level revealed significant spatial and temporal clustering and agglomeration in CF of different building typologies. This analysis provided valuable insights for policymakers to manage CF of buildings due to electricity demand during crises and identify high-CF areas. The spatial distribution of CF varied significantly across sectors and over time, underscoring the need for targeted interventions and an understanding of local demand dynamics.

The examination of CF among different building types during the pandemic reveals complex and multifaceted patterns. The lack of a discernible pattern in CF variation across space, time, and sectors, even during the pandemic year, underscores the complexity of the situation. This complexity is further highlighted by the need to compare actual CF from electricity consumption with predicted CF based on historical data (2010–2019). Employing three machine-learning models (XGBoost, RF, and SVM) to predict CF under pandemic-free conditions is a crucial step in understanding the pandemic's impact. The lockdown period led to an increase in residential CF, presumably due to heightened electricity usage as people stayed home. However, the post-lockdown phase exhibited an even greater disparity between actual and predicted CF, likely due to increased use of air conditioning during the summer months. In contrast, commercial, industrial, governmental, and hotel buildings experienced a CF reduction, reflecting the broader economic slowdown and policy responses to the pandemic. These findings illustrate the diverse ways in which different sectors responded to pandemic-related changes.

In contrast to residential buildings, other building types like commercial, industrial, governmental, and hotels saw a notable reduction in CF during the pandemic. This decrease was primarily due to reduced electricity consumption, a direct result of lockdown measures and the gradual, restricted reopening of these sectors. Hotel buildings, interestingly, had a varied CF pattern: a decrease during the lockdown due to reduced tourism, followed by an increase as they were repurposed for quarantine purposes. This scenario highlights the dynamic and sector-specific impacts of the pandemic on building CF. The industrial sector presented an interesting case, where the actual CF decreased during the lockdown, contradicting the predictions of the machine-learning models. This anomaly suggests the models' limitations in capturing unexpected shifts in industrial activity. The governmental buildings also displayed fluctuating CF levels, impacted by the transition between remote work and resumption of in-person activities, further complicated by subsequent waves of the pandemic. These variations underline the challenges in accurately predicting CF in dynamic and unprecedented scenarios like the pandemic.

The relationship between CF gap and daily COVID-19 cases offers intriguing insights. The significant increase in CF disparity in residential buildings during the pandemic's peak periods suggests a strong correlation with enforced stay-at-home measures and travel restrictions. Conversely, commercial and industrial sectors showed lower actual CF than predicted during the lockdown, aligning with reduced activities. The second year's analysis provides a different view, revealing how the models' predictions diverged from actual CF, particularly in the residential and hotel sectors. These findings underscore the pandemic's varied impact on different building types and the challenges in modeling such unprecedented events.

Thus, the findings of this research have both local and global environmental implications. While focusing on Qatar, the insights gained are applicable to other regions facing similar challenges, contributing to the broader understanding of environmental management and sustainability. This study is thus a valuable resource for policymakers, urban planners, and stakeholders in understanding and managing the environmental impact of buildings, particularly during global crises like the COVID-19 pandemic. Importantly, the findings contribute to a better understanding of the intricate relationship between electricity consumption and carbon emissions during health crises in Qatar. This understanding is crucial in facilitating informed decision-making and strategic planning, especially in times of public health emergencies. By providing this comprehensive analysis, the study aids in navigating the challenges posed by such crises, ensuring a more sustainable and resilient future in terms of energy consumption and environmental impact.

6. Study limitations

Although the study provides a comprehensive analysis of the impact of the COVID-19 pandemic on the CF from electricity consumption in various building types, there are several limitations that future research could address. Firstly, a comprehensive CF assessment of buildings should ideally include their entire lifecycle, from construction to demolition. However, due to data availability, this study focused mainly on CF resulting from electricity consumption. Another critical aspect for future studies is consumer behavior, which necessitates the creation and distribution of survey questionnaires among households. This approach would allow for the exploration of how socioeconomic factors influence building CF. While not the primary aim of this study, its findings can assist in identifying high CF (hotspots) and low CF (cold spots) areas. This localization is crucial for conducting targeted consumer behavior studies, comparing these areas to enhance the precision and complexity of machine learning model predictions. Additionally, acknowledging the influence of external elements like government policies, public behavioral shifts during the pandemic and economic activities on CF is important. Integrating these factors into predictive models remains challenging due to their complex and often intangible nature.

7. Conclusion and policy implications

The examination of the CF has revealed that there is no discernible temporal trend concerning the increase or decrease of CF across distinct building categories. However, an investigation of CF patterns between the years 2017 and 2020 has indicated a certain degree of similarity with seasonal variations. Notably, during the summer months, all building types exhibited elevated CF levels owing to prevailing weather conditions and the augmented demand for electricity, primarily for cooling systems. Conversely, the winter season, characterized by warmer weather, saw minimal reliance on cooling or heating systems throughout the country.

The COVID-19 pandemic has profoundly influenced Qatar's CF patterns and electricity consumption trajectories, particularly in the context of buildings. This situation necessitates a reevaluation of CF in different building types, emphasizing the critical role of electricity in economic and social sectors. The pandemic's alteration of socioeconomic practices has direct implications for electricity consumption, offering valuable insights into potential climate change mitigation through changed consumption behaviors as depicted from the spatial analysis in this study. Policymakers must consider these shifts when developing strategies for energy efficiency and environmental sustainability. The increased electricity consumption in homes during lockdowns, due to higher occupancy and remote work, underscores the necessity for policies that target energy efficiency in residential areas. Conversely, the reduced consumption in commercial and industrial buildings highlights the opportunity to reassess and potentially restructure energy use in these sectors for long-term sustainability.

The spatial examination of CF across various building types unveiled distinct spatial clustering and areas of high CF concentration within the study area. It is recommended that authorities prioritize these specific regions to effectively mitigate and reduce CF emissions associated with buildings in those areas. Authorities can implement policies targeting the CF of buildings that focus on promoting energy efficiency, encouraging the use of renewable energy, setting sustainability standards, and fostering public awareness. Furthermore, the study's spatial and temporal analysis during the COVID-19 pandemic reveals significant changes in CF due to electricity consumption across different building typologies in Doha. This highlights the importance of flexible and responsive energy policies that can adapt to rapidly changing scenarios. The government must recognize the dynamic nature of CF patterns and develop targeted interventions that address the unique energy needs and consumption behaviors of each sector. Policymakers should leverage the insights from this study to implement sector-specific energy policies and programs that not only mitigate the environmental impact but also enhance resilience to future crises.

According to the results of this research, it's clear that the COVID-19 pandemic has negatively affected the condition factor (CF) of certain types of buildings, especially residential ones. The actual CF levels increased during the pandemic years, primarily due to the implementation of stay-at-home policies and heightened public concerns surrounding the disease, especially in the initial year when vaccination or cure was not yet available. The stay-at-home policy resulted in increased indoor activities by residents and greater utilization of electronic devices within residential buildings. In contrast, there was a decrease in CF levels observed in other building types, primarily industrial and commercial, indicating a decline in economic activities during the first year of the pandemic. These factors have resulted in shifts in CF patterns among buildings. These variations in CF across building types have the potential to amplify energy demand, especially during prolonged periods of COVID-19 or any future extended crises. These findings emphasize the importance for authorities to implement distinct measures aimed at reducing CF during such crises.

CRediT authorship contribution statement

Esmat Zaidan: Conceptualization, Formal analysis, Data curation, Methodology, Writing – original draft, Funding acquisition. **Ammar Abulibdeh:** Conceptualization, Formal analysis, Supervision, Methodology, Funding acquisition, Data curation, Writing – original draft. **Rateb Jabbar:** Conceptualization, Methodology, Formal analysis, Validation, Data curation, Writing – original draft. **Nuri Cihat Onat:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Murat Kucukvar:** Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft.

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.

Data availability

The authors do not have permission to share data.

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).

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