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Change of CO_2 Emissions in Tokyo under The COVID-19 Situation: Urban Carbon Mapping Approach

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ABSTRACT

Energy is vital for creating resilient and zero emission carbon cities. Over 70% of global carbon emission originate from urban activities. Urban carbon mapping is an effective approach for planning, managing, and monitoring energy consumption and carbon emission. However, this approach has not been exploited for evaluating the impact of the coronavirus on a city due to limited data. In this study, the carbon emission from buildings during the coronavirus pandemic is estimated and visualized using the three-dimensional fine-scale spatiotemporal urban carbon mapping approach through big data. We studied the 23 wards of Tokyo, Japan from January to June 2020, representing the COVID-19 first wave period in the area. The results reveal that the carbon emitted from commercial buildings decreased by approximately 40% compared to the January value. Conversely, residential buildings emission increased by at least 10% due to the increased stay at home lifestyle including working from home.

Keywords: Urban carbon mapping, CO_2 emissions, big data, COVID-19, residential sector, mitigation

1. INTRODUCTION

Government policies during the coronavirus (COVID-19) pandemic drastically changed the energy use patterns worldwide. In fact, human activities such as commuting, working, and shopping have been limited to avoid transmission of the virus. In addition, many people have been staying home or isolated elsewhere [1].

These changes, including reduced transportation and consumption patterns, significantly impacted carbon dioxide (CO_2) emission. Le Quéré et al. reported that daily global CO_2 emission decreased by 17% (11 to 25% at $\pm 1\sigma$) by early April 2020 compared with the mean 2019 level [2]. Using near real-time monitoring data, Liu et al. reported an abrupt 8.8% decrease in global CO_2 emission (1,551 Mt CO_2) during the first half of 2020 compared to the same period in 2019. The magnitude of this decrease surpasses those for periods of previous economic downturns including World War II [3].

To identify and recommend high priority CO_2 emission or energy use mitigation opportunities and locations in cities, producing actionable information maps accessible to city managers is important. However, current CO_2 emission accounting tools require the cities to aggregate and disparate the raw data. The urban carbon mapping is a powerful tool proposed for CO_2 emission accounting [4]. Urban carbon mapping has been employed for the investigations on Tokyo, Japan using big data [5–8]. To understand and manage the carbon footprint, the urban carbon mapping approach enables visualization at the street, building, and community levels.

This study involves an attempt to estimate the CO_2 emission of buildings through the three-dimensional urban carbon mapping approach using big data. We investigated the 23 wards of Tokyo, the capital of Japan and the most densely populated city in the world. The study period from January to June 2020 represents the first wave of the COVID-19 pandemic in Tokyo. The estimation of the impact of COVID-19 on CO_2 emission at the building scale is inexistent due to the lack of data. Owing to the need to develop plans for improving the post-COVID-19 energy resilience of cities around the world, this study is useful for supporting the discussion on new smart lifestyle scenarios [9, 10].

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2. MATERIALS AND METHODS

2.1 Study area and period

Tokyo, the capital of Japan comprises 23 wards. It is a densely populated city with over 9.6 million inhabitants, as of 2020. Owing to its core position in Japan for most aspects including the economy, culture, and government, many people are attracted to Tokyo. Therefore, the energy usage and CO_2 emission of buildings, especially in the commercial sector are major issues of the energy policy of the Tokyo Metropolitan Government.

The study period runs from January to June 2020, representing the first wave of the coronavirus pandemic. The CO_2 emission data for the last week of each month were averaged and compared.

2.2 Data and sources

In this study, we utilized geographical information system (GIS) and statistical data including the following: (1) Basic geospatial data such as the digital surface model (DSM) and digital elevation model (DEM) from the Geospatial Information Authority of Japan for the building footprint. The building attributes such as the buildings usage (e.g., commercial, residential, and factory), total floor area, and room vacancy rate were combined with the building point data provided by ZENRIN Co., Ltd. (2) A summary provided by the Japan Institute of Energy was used for the energy intensity data. This summary provides the typical hourly energy consumption per total floor area each month for various sectors such as the residential, commercial, and hospital estimated from surveys. (3) We used official survey data published by the Bureau of Environment of the Tokyo Metropolitan Government for the total CO_2 emission of buildings in the study area. (4) The global navigation satellite system (GNSS) data acquired by the mobile phones data management companies Agoop Corp and Blogwatcher Inc. were exploited for buildings activity data. Due to privacy protection policies, the data records are limited to the timestamp, latitude and longitude, and unique user identifier for the day. These records follow rules including (i) when a mobile phone location is unchanged within a certain period, the data are not stored to prevent detecting the home or work place and (ii) the record time interval is about 15–30 min or 500–1,000 m displacement, depending on the operating system and status of the mobile phone. The GPS records and confirmed COVID-19 cases for the 23 wards in Tokyo are displayed in Figure 1. As the confirmed cases increase, the GPS records decrease, suggesting that people and companies in Tokyo avoided the area.

2.3 Carbon mapping estimation procedure for buildings

The CO_2 emission estimation procedure for buildings is summarized in Figure 2, with detailed description in [6]. For calculating the CO_2 emission during the COVID-19 period, we compared the GPS records G between the same interval in 2018 and 2020 using the ratio $G_{2020,m}/G_{2018,m}$ ($m \in (1, 2, \ldots, 12)$) for each standard 500 m grid. We then estimated the CO_2 emission of buildings during the COVID-19 period by combining the results from the ratio and the urban carbon mapping [6].

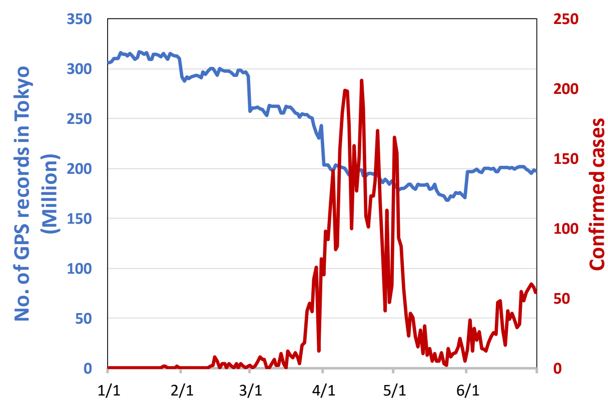

Fig 1 Plots showing confirmed COVID-19 cases and the GPS records for the 23 wards in Tokyo from January to June 2020

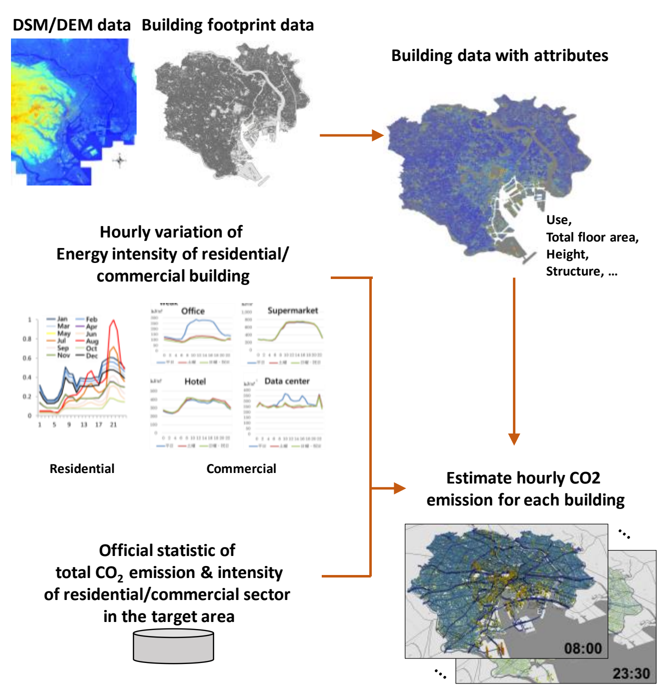

Fig 2 Procedure for estimating the CO_2 emission of buildings

3. RESULT AND DISCUSSION

Figure 3 shows that the CO_2 emission of commercial buildings in May decreases by almost 40% compared to January. Contrarily, the CO_2 emission of residential buildings increases by 10% due to more people staying at home including working from home. The rate of change for residential buildings may be underestimated due to the GNSS data limitation. As mentioned in section 2, the GNSS data excludes stationary mobile phones due to privacy security. Therefore, the actual rates of change likely surpass our estimates significantly.

The urban carbon mapping results for buildings are displayed in Figure 4. The mapping for January is considered as the regular CO_2 emission pattern for the

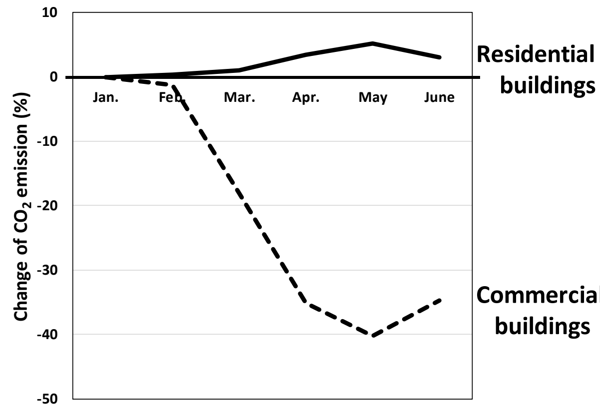

Fig 3 Changes in the total CO_2 emitted by buildings from January (used as the baseline) to June 2020

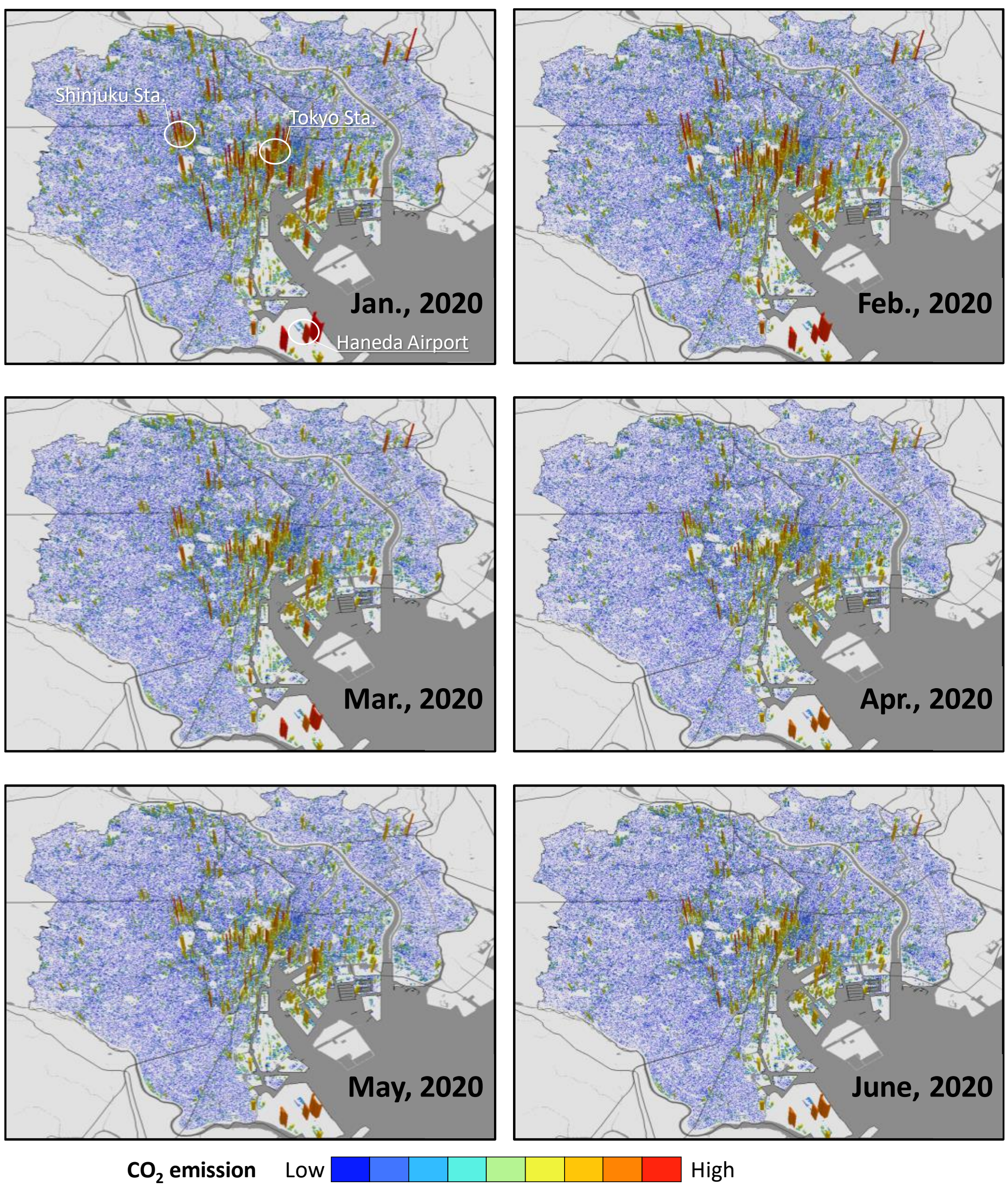

Fig 4 Building CO_2 emission in Tokyo 23 wards from January to June, 2020.

23 wards in Tokyo. The CO_2 emission of commercial buildings especially around the major business areas such as in front of the Tokyo and Shinjuku stations gradually decrease and then recovered in June compared to May. According to Figure 3, the CO_2 emission for residential buildings are visualized. Currently, many sensors connected to the internet (internet of things: IoT) are installed around cities. By combining the IoT technology, energy simulations, and human activities [11–14], the urban carbon mapping approach can provide near real-time information. This approach is more useful for understanding and monitoring current CO_2 emissions. Ideally, it can facilitate the implementation of climate change mitigation strategies.

4. CONCLUDING REMARKS

In this study, we estimated CO_2 emissions of buildings in Tokyo 23 wards between January to June 2020 through the three-dimensional urban carbon mapping approach using big data. The results can support to plan urban carbon emissions management and the discussion on new smart lifestyle scenarios in the post-COVID-19 era. One of the main limitations of this study is to validate the estimation results. We suggest further research to use energy measurement data for verifying our framework.

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