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Urban Carbon Mapping of Roads under The COVID-19 Situation: The Case of Tokyo 23 Wards

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ABSTRACT

Reduction in energy use and carbon emissions is essential for achieving resilient, green, and smart cities. Understanding the various patterns of energy changes in cities can serve as a foundation for planning the strategies related to mitigation of carbon emissions. It has been reported that carbon emissions were reduced during the global COVID-19 pandemic. However, this reduction pattern in cities has not been investigated using spatially-temporally fine-resolutions due to data unavailability. Therefore, this study aims to estimate reduction rates of carbon emissions, especially those that are related to transport activity, which is a key factor for building resilient, green, and smart cities. This was accomplished by using the urban carbon mapping approach with big data. Our target city was Tokyo 23 wards, Japan and the study was conducted for a time frame of January to June 2020. The results show that carbon emissions and transport activities in May decreased by approximately 40% when compared to those in January.

Keywords: carbon mapping, mobile GNSS/GPS data, electric vehicle, machine learning, COVID-19

NONMENCLATURE

Abbreviations	
COVID-19	coronavirus disease 2019
CO_2	carbon dioxide
GIS	geographical information system
GNSS	global navigation satellite system
GPS	global positioning system

1. INTRODUCTION

Due to rapid urbanization, it is understood that cities generate majority of the carbon emissions [1,2]. In order to mitigate different effects of climate change on earth, such as rising temperatures and sea levels, it is important to reduce carbon emissions globally by focusing primarily on cities.

During the COVID-19 pandemic, global carbon emissions declined. Le Quéré et al. showed that daily global carbon emissions decreased by approximately 17% by early April 2020 when compared to the mean global carbon emissions in 2019 [3]. Liu et al. reported an abrupt 8.8% decrease in global carbon emissions in the first half of 2020 when compared to those in the same period in 2019 [4]. However, more locally detailed reductions of carbon emissions have not yet been investigated. To understand spatial carbon emission dynamics and to promote mitigation strategies that would aid in the policy making process, it is necessary to acquire more spatially fine-scale data on carbon emissions.

As a powerful tool for visualizing spatially and temporally detailed carbon emissions, an urban carbon mapping approach has been proposed and applied to some major cities [5–9]. Recent development of the "big data" movement allows us to obtain high-resolution and detailed data on carbon emissions [10,11]. By using GNSS/GPS data, Yamagata and Yoshida discussed the smart lifestyles and urban forms after the COVID-19 pandemic era and evaluated the spatially-temporally detailed carbon emissions in Tokyo, Japan [12].

In this study, we have attempted to estimate reduction rates in transport activities and related carbon emissions of each road in Tokyo by using GNSS/GPS data

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during the months of January to June (2020). Since cities are required to develop plans based on urban energy resilience, this study will be useful in supporting future discussions on integrating transport systems and infrastructure post the COVID-19 situation.

2. MATERIALS AND METHODS

2.1 Study area and period

Tokyo 23 wards area forms the capital city of Japan. This area is known to be as one of the most populated cites in the world with over 9.6 million people as of 2020. As this area forms the core of Japan's economy and culture, it experiences massive issues with logistics and a plethora of tourists. Therefore, transportation problems including road congestion and carbon emissions are major issues that need to be tackled by the city.

We selected the last week of each month of the target time period and averaged the estimated carbon emissions for comparing the monthly change.

2.2 Data and sources

We used various GIS and statistical data in this study. (1) For road network data, we used Japan Digital Road Map, which comprises most amount of information regarding Japanese roads including road types (highway, national road, prefectural road, municipality road, minor street, etc.), number of lanes, and road regulations (one way, speed control, etc.) (2) For elucidating the road traffic patterns, we used GNSS/GPS data acquired by different mobile phones company, namely: Agoop, Corp. and Blogwatcher, Inc. Owing to the privacy protection policy, the data recorded include only timestamps, latitudes, longitudes, and user identifiers, which are unique only for that particular day. The recording followed the following rules: (i) if the mobile phone location did not change with time, the data was not stored; this resulted in the data obtained at homes and offices to be lost. (ii) The interval of the recording was approximately 15–30 min (time) or 500–1,000 m (distance); however, it was dependent on the operating system and status of the mobile phone. (3) For elucidating the traffic count, we used the 5-min interval monitoring data provided by "Japan Road Traffic Information Center." (4) For determining the total carbon emissions produced by various transport sectors in the study area, we used an official survey data published by the Bureau of Environment, Tokyo Metropolitan Government.

2.3 Carbon mapping estimation procedure

The estimation procedure of carbon emissions of each road has been summarized in Figure 1. At first, we detected car users using GNSS/GPS data; subsequently, we assigned the relevant data points to each road. Finally, we estimated carbon emissions of each road by using traffic patterns and statistical data.

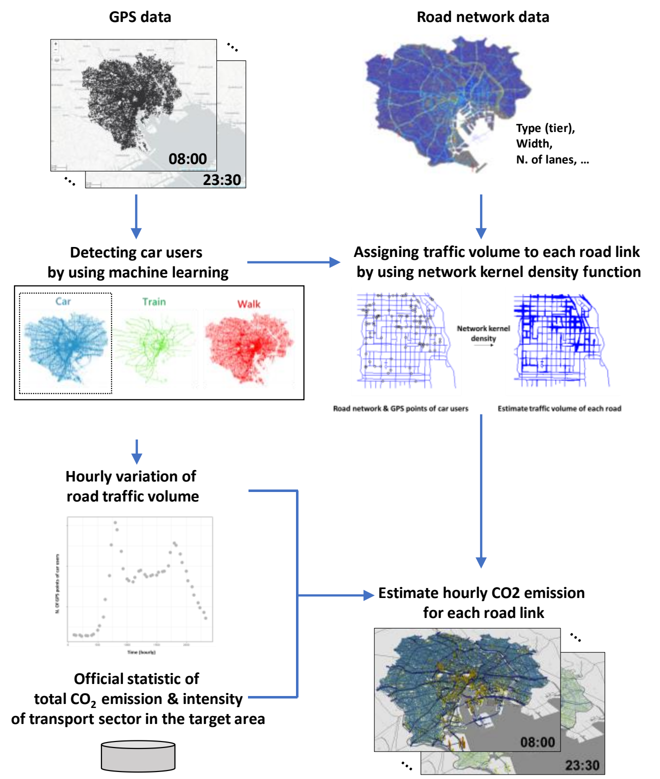

Fig 1 Schematic illustrating the procedure for estimating carbon emissions of each road

2.3.1 Detection of car users: extreme gradient boosting estimation

To estimate transportation modes in the GNSS/GPS data, we used an extreme gradient boosting method [13], which is known to be a highly efficient and flexible decision tree-based machine learning technique. As a training dataset, we manually detected three transportation modes, namely: cars, trains, and walking [14]. The training dataset comprised of over 18,000 records. To estimate the modes, we set two covariates, namely: the distance to the nearest train station and velocity of each GNSS/GPS point. The prediction accuracy obtained using cross-validation was 77.4%. Therefore, we used only the predicted GPS/GNSS points of car users for the next step of the process.

2.3.2 Assigning traffic volumes: network kernel density estimation

The kernel function reflects distance decay effects in the (network) space. To estimate traffic volumes of each road, we assigned the number of GPS/GNSS points to the road using a network kernel density function [15]. In this study, we have used the following function:

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{r} \cdot k\left(\frac{d_{is}}{r}\right),$$

where $\lambda(s)$ Is the kernel density at location s, r is bandwidth, k is the weight of a point $i \in (1, \ldots, n)$ at distance d_{is} to location s. Usually, k is modeled as a kernel function of the ratio between d_{is} and r. We used the Gaussian function, which is the most commonly used kernel function: When $0 < d_{is} \leq r$,

$$k\left(\frac{d_{is}}{r}\right) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d_{is}^2}{2r^2}\right).$$

Otherwise, the output would be 0. Then, by using the traffic count data, we adjusted the traffic volumes of each road.

2.3.3 Assigning CO_2 emissions: downscaling

To estimate carbon emissions in each road, we spatio-temporally downscaled the statistical data on carbon emissions of the study area. The carbon emissions, E_{jt} of the j-th road [$j \in (1, \ldots, N)$] at the t-th time period [$t \in (1, \ldots, T)$] were estimated by the following model:

$$E_{jt} = \frac{R_{jt}}{\sum_j^N \sum_t^T R_{jt}} E$$

where R_{jt} is the estimated traffic volume of the j-th road at the t-th time period and E is the total carbon emissions of the study area. The time period corresponds to a 30-min interval, so that $t = 1, 2\ldots.$, and T implies a time period of 0:00, 0:30, and 23:30, respectively.

3. RESULTS AND DISCUSSION

Figures 2 and 3 show that the transport activities and related carbon emissions in May 2020 decreased by approximately 40% when compared to those in January. In Japan, especially Tokyo, the COVID-19 confirmed cases were peaking during that period and the government promoted the stay at home campaign around middle of April. This has been reflected in our results.

Figure 4 shows the urban carbon mapping results of each road. The mapping on January can be viewed as the usual carbon emission patterns in Tokyo 23 wards, while the data suggests a gradual decrease till May before rising back again in June. Interestingly, carbon emissions from the highways decreased, which were the largest emission points. During the stay at home campaign, a lot of people used internet shopping, thereby bolstering delivery demands. However, because factories and large shopping malls, which are major delivery destinations, closed, transportation using heavy trucks decreased. Figure 4 reflects these effects to a certain extent.

These results show that the visualizing spatially-temporally changes would be useful to better understand and monitor current carbon emissions. Generally, local citizens and stakeholders are often unaware of carbon emissions from their activities; this is because the emissions are not immediately visible. The urban carbon mapping approach with big data would facilitate the implementation of urban carbon management strategies, thereby mitigating climate change.

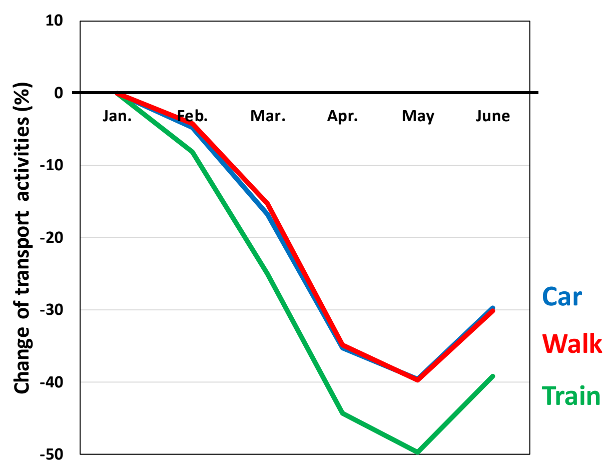

Fig 2 Rate of change in transport activities between January to June 2020 in Tokyo 23 wards

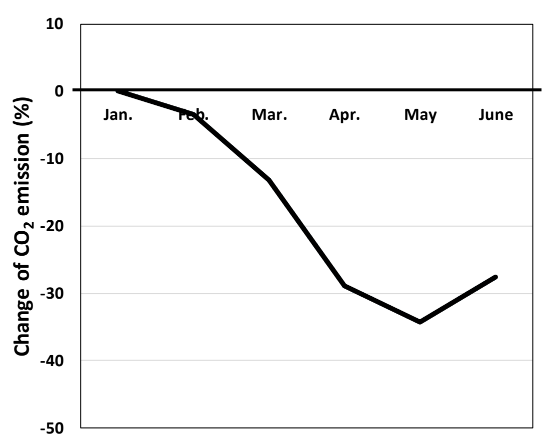

Fig 3 Rate of change in carbon emissions between January to June 2020 in Tokyo 23 wards

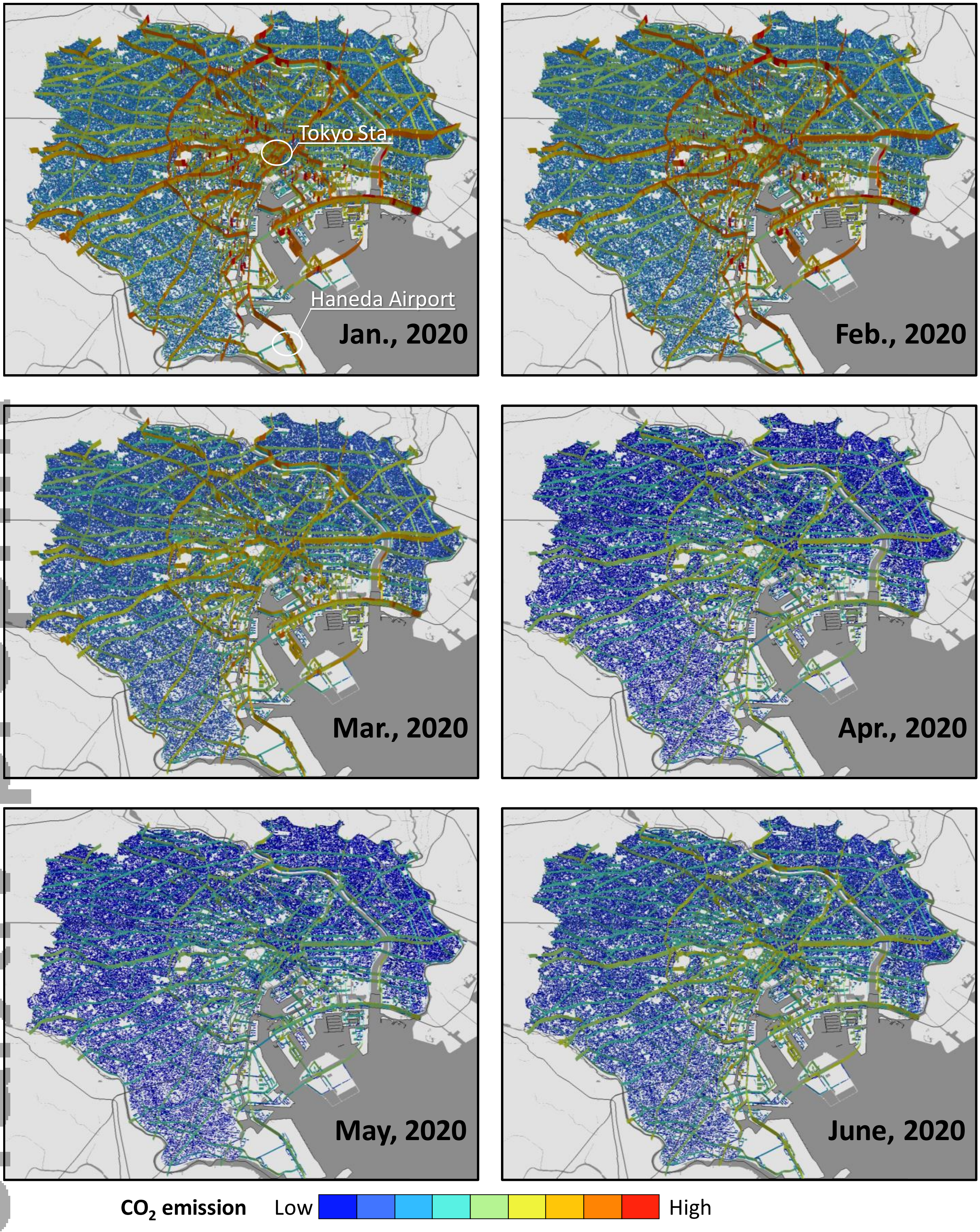

Fig 4 Urban carbon mapping of each road in Tokyo 23 wards during COVID-19

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