Spatially detail urban carbon mapping: Integration of top-down and bottom-up approaches

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Abstract

The objective of this study is estimating carbon emissions in the building and transportation sectors in the Sumida ward, Tokyo. We combine top-down and bottom-up approaches, which use spatial big data, for the estimating. The estimated emissions from individual buildings and road links are visualized by a three-dimensional (3D) mapping. The results suggest the usefulness of our approach for visualizing urban carbon emissions for supporting community-level carbon monitoring and management.

Keywords: Urban carbon mapping, Spatial BigData; tower-monitoring

1. Introduction

Low carbon urban/regional management has attracted considerable attention from urban stakeholders, especially after the Paris Agreement adopted in December 2015. Already, 228 cities have pledged to reduce carbon dioxide emissions (carbon emissions, hereafter) by a combined total of 454 Giga-ton/year by 2020 (Gurney et al., 2015). Carbon emissions management is an important issue for not only government, which regularizes emissions, but also local municipalities to promote low carbonization on their own. Carbon mapping is an effective approach to encourage/support carbon management for policy makers. Carbon mapping allows us to compare the relative influences from each emission source (e.g., residences, offices, vehicles), make effective policies, quantify the impact of these policies, and identify hot spots and unexpected emissions, e.g., due to congestion, in a near real-time manner. Further, carbon mapping is useful in avoiding greenwashing. A term used to describe deceptive claims about the environmental benefits of a product, service or technology, which often inhibit cities from enacting real sustainable measures.

The recent development of sensor technologies allow for monitoring building conditions, human movements, market transactions, and other urban activities; they will offer useful insights for urban analysis (Batty, 2013). Despite that, these data are rarely used for carbon monitoring (Yamagata et al., 2017; 2018; Sharifi et al., 2018).

This study attempts to estimate and visualize carbon emissions from individual buildings and road links by combining the bottom-up and top-down approaches (Figure 1). We rely on the individual building and transportation data for the former whereas carbon intensity monitored at the Tokyo Skytree (Terada et al., 2017) is used for the latter.

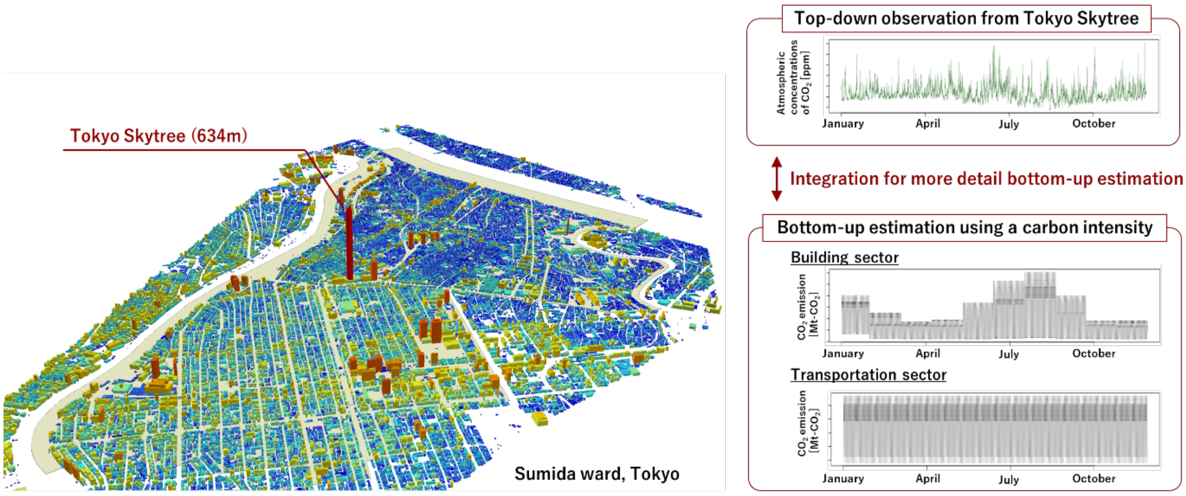

Figure 1: Study area (left) and an image of our carbon estimation approach (right)

2. Approach for carbon mapping

We have developed CO2 emission estimation models. It consists of the following submodels:
[Global Model]
We model the relationship between the concentration y_t^O observed at the Tokyo SkyTree at time *t* and the total carbon emission y_t^U in the Sumida ward, that estimated using unit consumptions, which we introduce later, using the following state space model:

$$\begin{bmatrix} y_t^O \\ y_t^U \end{bmatrix} = \begin{bmatrix} k \\ 1 \end{bmatrix} x_t + \begin{bmatrix} e_t^O \\ e_t^U \end{bmatrix}, \qquad \begin{bmatrix} e_t^O \\ e_t^U \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_O^2 & 0 \\ 0 & \sigma_U^2 \end{bmatrix} \right)$$

Equation 1

$$x_t = x_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_x^2)$$

Equation 2

where x_t is the true unknown emission from the entire Sumida ward. σ_O^2, σ_U^2, and σ_x^2 are variance parameters. This global-level state space model balances the tower-observations and the unit-consumption-based estimates to recover the true aggregated emission x_t.

The state-space model (equations 1 and 2) is estimated using the Expectation-Maximization (EM) algorithm, which repeats the model likelihood maximization to estimate the parameters and the updating the CO2 estimates x_t until the convergence.

[Local Model]
The local model downscales the estimated x_t into individual buildings and road links by proportionally distributing the estimated total emissions x_t at time *t* using the following model:

$$x_{t,i} = \frac{w_i}{\sum_{i=1}^{N} w_i} x_t$$

Equation 3

where w_i is the weight assigned for *i*-th building or road link. For buildings the weight is evaluated using the unit building per 1m^2 of total floor area. For road link, the weight is defined by multiplying (the number of cars at the time interval *t*) with (the unit emission per 1 ton/km). The number of cars is estimated using a mobile GPS data (provided by Agoop Co.Ltd.). Specifically, the GPS points are classified int pedestrians, car users, and train users. Then, the car users are allocated to their nearest road link for the counting. Note that y_t^U is defined by accumulating the unit emissions across the Sumida ward. In other words, x_t equals y_t^U after an adjustment so that the value is consistent with the tower observations.

3. Result and discussion

Comparative analysis of tower observations y_t^O and bottom-up estimates y_t^U. The results for the building sector and transportation sector are summarized in Figure 2. The daily CO2 emissions obtained from the state-space model were more intuitive, confirming the usefulness of the correction by tower observation. It might be because the tower observation flexibly estimates seasonal changes that could not be captured by the bottom-up estimation. From the results of the above correlation analysis, we confirmed the importance of utilizing tower observations as well as bottom-up observations.

The CO2 emissions estimated for October 11 and August 15 are plotted in Figure 3. Data assimilation with other real-time CO2 emissions can be an effective for estimating CO2 mapping at individual scale.

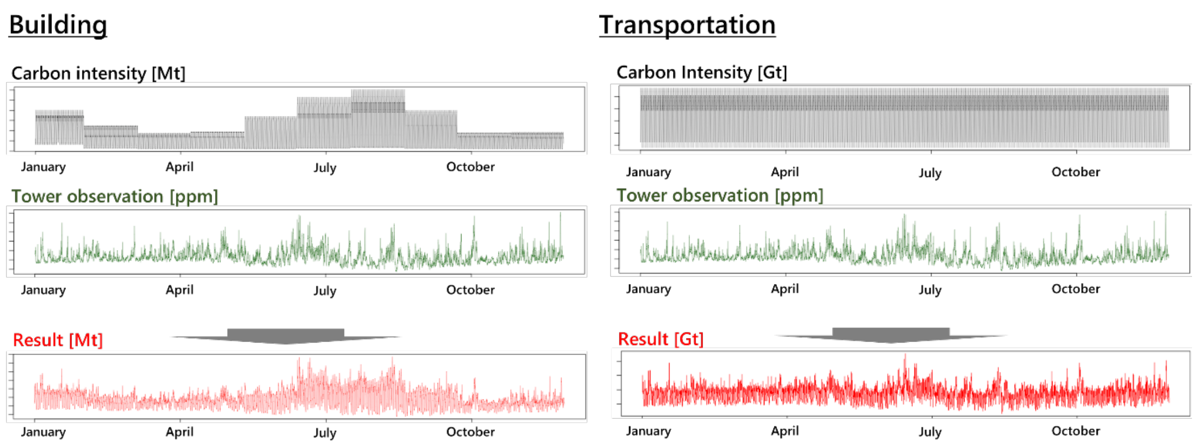

Figure 2. Estimation result of daily change of CO2 emission

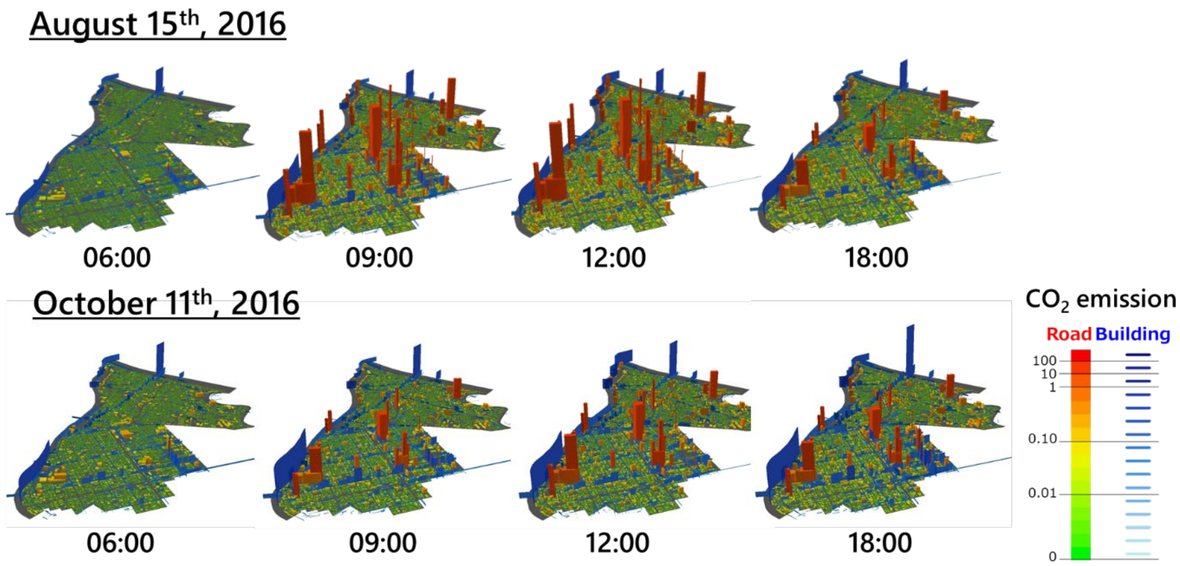

Figure 3. Urban carbon mapping estimation in Sumida ward, Tokyo.

4. Acknowledgements

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