High-resolution Global Building Emissions Estimation using Satellite Imagery

Paul J. Markakis[1,2] **Trey Gowdy**[2] **Jordan M. Malof**[3] **Leslie Collins**[1]
Aaron Davitt[4,5] **Gabriela Volpato**[4,5] **Kyle Bradbury**[1,2]

[1]Department of Electrical & Computer Engineering, Duke University
[2]Nicholas Institute for Energy, Environment & Sustainability, Duke University
[3]Department of Computer Science, University of Montana
[4]WattTime [5]Climate TRACE

{paul.markakis,trey.gowdy,leslie.collins,kyle.bradbury}@duke.edu
jordan.malof@mso.umt.edu
{aaron,gabriela}@watttime.org

Abstract

Globally, buildings account for 30% of end-use energy consumption and 27% of energy sector emissions, and yet the building sector is lacking in low-temporal-latency, high-spatial-resolution data on energy consumption and resulting emissions. Existing methods tend to either have low resolution, high latency (often a year or more), or rely on data typically unavailable at scale (such as self-reported energy consumption). We propose a machine learning based bottom-up model that combines satellite-imagery-derived features to compute Scope 1 global emissions estimates both for residential and commercial buildings at a 1km^2 resolution with monthly global updates.

1 Introduction

Direct (a.k.a. Scope 1[1]) emissions from residential and commercial buildings result from onsite fuel use such as natural gas, oil, and kerosene consumption. Residential buildings primarily use these fuels for thermal comfort (space and water heating), cooking, and other equipment and appliances; in commercial buildings, space and water heating generally remain the largest end-use. The magnitude of these end uses is correlated with, for example: building size, climate conditions, and the number of occupants [2]. However, timely and accessible high-spatial-resolution data on these are limited.

Existing bottom-up methods leverage data typically not accessible at scale, such as information on a building's insulation, appliances in a building, and information on occupant behavior [3]. These approaches may rely on building physics [4] or statistical approaches, but the data requirements for these approaches prevent them from being scaled globally.

Existing top-down approaches look to find broad criteria by which to disaggregate values of energy consumption and associated emissions. Existing estimates include the Open-source Data Inventory for Anthropogenic CO_2 [5], the Community Emissions Data System [6], the Emissions Database for Global Atmospheric Research (EDGAR) [7], the Global Carbon Grid [8], and the Global Gridded Daily CO2 Emissions Dataset (GRACED)[9]. While GRACED data is published near-monthly, most other key data are produced with a year or more of latency. Additionally, the highest resolution of

[1]"Scope 1 emissions are direct greenhouse (GHG) emissions that occur from sources that are controlled or owned by an organization (e.g., emissions associated with fuel combustion in boilers, furnaces, vehicles)." [1]

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these data is 0.1 decimal degrees or roughly 11 km near the equator. Lastly, few of these models break down emissions into residential and commercial subsectors as well as separate emissions estimates into individual greenhouse gasses.

2 Proposed Building Emissions Machine Learning Model

To address these challenges, we propose a high-resolution (1 km^2)[2], global machine learning (ML) model that is able to be updated monthly, separately provides estimates for both residential and commercial subsector Scope 1 building emissions, and provides estimates of the three primary greenhouse gasses (CO_2, CH_4, and NO_x). This will be accomplished by estimating the presence and growth in building area (A) from Sentinel-2 satellite imagery, predicting energy use intensity (EUI) from contributing factors including temperature fluctuations and economic indicators, and determining regional emissions factors (EF) based on regional fuel mixes used in buildings. We will estimate building emissions (GHG) as the product of these three quantities, $GHG = A \times EUI \times EF$.

First, to predict *building area*, we will build on the work of Liu et al. 2023 [10] to estimate building area from publicly-available satellite imagery and apply this at a global scale, providing monthly estimates of building coverage.[3] Second, we will estimate *energy use intensity* (energy consumed per unit area of building). We will fine-tune the NASA HLS Geospatial Foundation Model [11] to use as a convolutional neural network (CNN) for satellite image feature extraction across a global grid; each pair of grid index coordinates is denoted a, b. A combination of satellite imagery and building emissions proxy data will extract building-related features associated with emissions from globally-gridded satellite images $\mathbf{x}_{a,b}^{im}$ as part of our fine-tuning process, i.e., $\mathbf{h}_{a,b}^{im} = f^{cnn}(\mathbf{x}_{a,b}^{im})$. We will then combine the feature vector output from the CNN with emissions-related characteristics for buildings including population, temperature, and economic indicators ($\mathbf{x}^b, \mathbf{x}^p, \mathbf{x}^t, \mathbf{x}^e$), all geospatially aligned to match the same global grid as the satellite imagery, i.e., $\mathbf{h}_{a,b}^{ec} = f^{ga}(\mathbf{x}^b, \mathbf{x}^p, \mathbf{x}^t, \mathbf{x}^w)$. The aggregate embedding for each global grid cell is then $\mathbf{h}_{a,b}^{agg} = (\mathbf{h}_{a,b}^{im}, \mathbf{h}_{a,b}^{ec})$. We will train an ML regression model to predict building energy use intensity, i.e., $\hat{\mathbf{y}}_{a,b} = f_{a,b}^{agg}(\mathbf{h}_{a,b}^{agg}(\cdot))$. In addition to linear and tree-based regression models, we will explore graph neural network based regression models. We depict this proposed approach in Figure 1. Lastly, for each region, we will calculate an *emissions factor* by curating a collection of fuel mixes and fuel-specific emissions factors, as these characteristics typically do not vary as frequently as building area and energy use intensity.

We will combine these quantities to produce global emissions estimates, comparing our estimates to top-down models (e.g., GRACED, EDGAR, and ODIAC). While a lack of building emissions "ground truth" datasets makes validation difficult, we have identified several data sources to use. The International Energy Agency (IEA), the United Nations, and other bodies create national estimates of energy consumption including building emissions, but at the time of writing, no comprehensive dataset exists with *measured* building energy consumption or resulting emissions at a spatial scale below that of a nation. However, there are sparse estimates of building consumption at the municipal level via Data Portal for Cities (DPFC) [12], or ad-hoc disclosure by individual regions or buildings.

3 Preliminary Results

To explore our building-area-driven model for estimating building emissions, we use existing public data to create an early version of our approach. This preliminary effort predicts emissions for three distinct regions in the world: the United States states of Massachusetts and Michigan and the country of Mexico, selected as areas for which we have municipality-level ground truth data. Building area (A) we compute primarily using GHS-sourced global building areas, with some tuning based on higher-fidelity data from Microsoft building footprints. Energy use intensity (EUI) we compute using data from CURB [13], measured in Joules per square meter. Emissions intensity factors (EF) we compute primarily via IPCC data [14], measured in metric tonnes CO_2e/Joule. Although we are able to compute estimates at 1 km^2 resolution using GHS data, we compare aggregated estimates

[2]This is a 100-fold increase in information content of the estimates over the highest resolution data available, EDGAR and GRACED; a figure of this difference in resolution is included in the appendix

[3]Existing global building data such as the Global Human Settlements Layer latency of a year or more, so may not be able to provide monthly updates for this work.

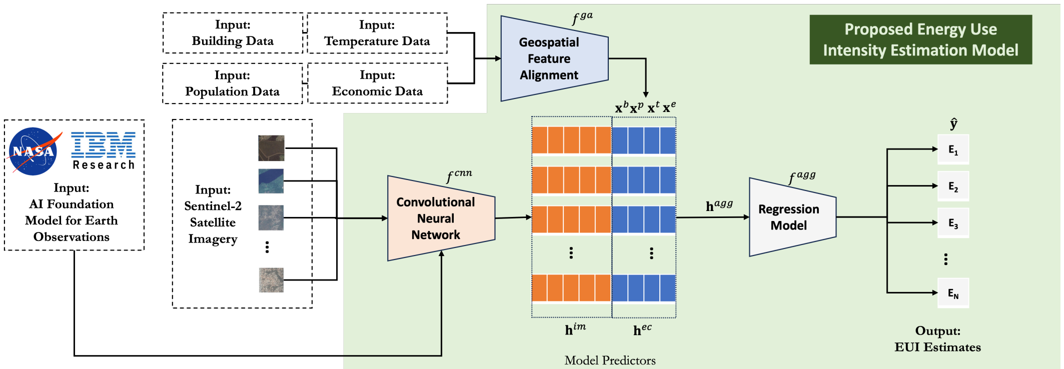

Figure 1: Proposed energy use intensity estimation machine learning model.

at the municipality level with the DPFC data for validation.[4] Table 1 shows the Weighted Absolute Percentage Error (WAPE) to show our model's performance as compared to GRACED and EDGAR, and Table 2 in the Appendix shows the Mean Absolute Percentage Error (MAPE) metric. We also show detailed plots of absolute percentage error per municipality in Figure 2 in the Appendix.

Table 1: Weighted Absolute Percentage Error (WAPE) metric to evaluate model performance.

	Weighted Absolute Percentage Error		
Model	Massachusetts	Mexico	Michigan
GRACED	86.9%	72.9%	86.7%
EDGAR	66.5%	**68.9%**	67.6%
Our Model	**38.6%**	306.3%	**50.8%**

*Best performing model shown in **bold**.*

4 Conclusions and Next Steps

These preliminary results suggest that even before adding in greater complexity through the proposed approach, our current building-area-driven model is competitive with existing methodologies for estimating direct residential and commercial building emissions for those municipalities that have larger total emissions. GRACED and EDGAR tend to perform better in municipalities with fewer GHG emissions. Since our model performs best in regions where there is high-fidelity building area data and a strong linear relationship between building area and emissions, we anticipate that improving our model by introducing additional characteristics related to buildings, population, temperature, and economics will improve the quality of our emissions estimates. In addition to introducing a regression-based model training approach for estimation, we also plan to expand the validation data to municipalities across twelve different countries within DPFC.

5 Pathways to Climate Impact

We expect that our modeling approach will enable high-quality global monthly independent estimates of residential and commercial building emissions at 1km^2 resolution. Independent estimates will guide policy decisions for local and national governments globally. For example, targeted energy efficiency retrofits require *high-resolution* information about the buildings that would benefit from increased energy efficiency and the communities in greatest need of assistance through subsidies or outreach. The growth of building energy emissions through new construction is a critical characteristic to monitor and incorporate into the process of sustainable development. This information can be used to track the impact on regions of new development and how strong the connection is between economic development, urbanization, and increased building energy consumption. Our model will

[4]GADM [15] Level 2 boundaries define geospatial boundaries for municipalities subdividing each region.

contribute building sector emissions data to Climate TRACE, to be the "world's first comprehensive accounting of GHG emissions based primarily on direct, independent observation." [16]

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A Data To Be Used for Prediction

We will utilize Sentinel-2 as our primary source of satellite imagery, which provides global imagery at 10m/pixel resolution with weekly global coverage. From this we will estimate building area globally, supplementing sources like the Global Human Settlements (GHS) data which contains building areas, volumes, and heights in select years at 1km^2 resolution, globally. Microsoft's Building Footprints Dataset [17] and Google Open Buildings [18] offer building footprint data; however, each covers select countries with varying degrees of completeness and both lack temporal detail. We will also consider high-fidelity building emissions datasets available for select cities around the world to use as model priors. [19] Population and wealth data are accessible through datasets such as the WorldPop gridded population dataset [20] and from the World Bank's World Development Indicators which will be inputs into the estimation process for energy use intensity. We will also use weather data as features, which are available globally at high spatial resolution including daily temperature [21].

B Additional Preliminary Results

The additional results shown here are for a simplified version of the model we are proposing that relies on existing public data sources. As shown previously in Table 1, the Weighted Absolute Percentage Error (WAPE) metric measures the absolute percentage error between actual and predicted emissions within a region weighted by the sum of the actual emissions. In this context, WAPE performance provides insight into a model's performance as compared to the magnitude of total emissions within the region; errors in municipalities with fewer total emissions would be penalized less using WAPE than errors in municipalities with greater total emissions. Because our goal is to prioritize emissions estimates in regions that have greater overall emissions, WAPE is our preferred choice of metric for quantifying model performance.

$$\text{WAPE}(R) = 100 \times \frac{\sum_{m=1}^{N} |A_m - P_m|}{\sum_{m=1}^{N} |A_m|}$$

The Mean Absolute Percentage Error (MAPE) metric measures the average value of the absolute percentage error between actual and predicted emissions within a region. In this context, MAPE performance provides insight into a model's performance agnostic of the total emissions within a region, weighting each region equally. Estimation errors in municipalities with fewer total emissions would be penalized just as heavily as estimation errors in municipalities with greater total emissions.

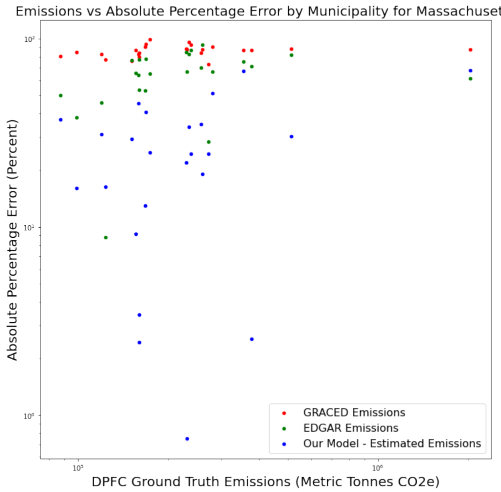
$$\text{MAPE}(R) = 100 \times \sum_{m=1}^{N} \left| \frac{A_m - P_m}{A_m} \right|$$

Table 2: Mean Absolute Percentage Error (MAPE) metric to evaluate model performance.

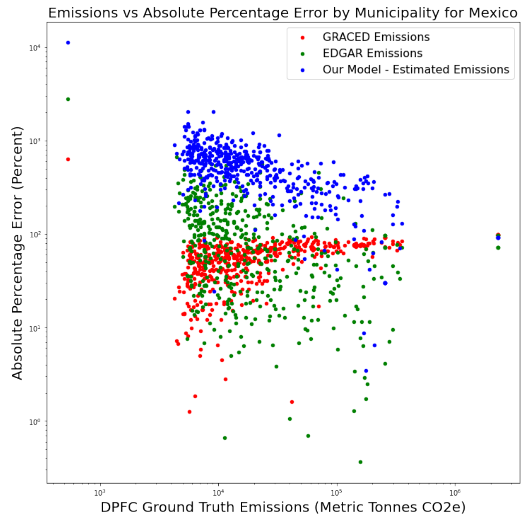
	Mean Absolute Percentage Error		
Model	Massachusetts	Mexico	Michigan
GRACED	86.2%	**56.0**%	**86.5**%
EDGAR	64.5%	114.4%	164.5%
Our Model	**27.0**%	578.5%	599.3%

*Best performing model shown in **bold**.*

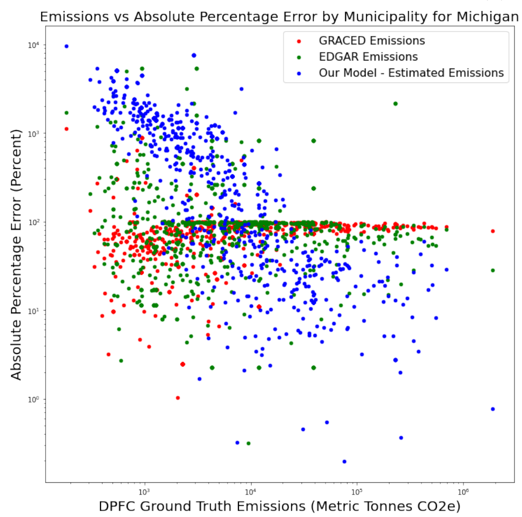
Figure 2 compares the ground truth emissions for each municipality (as reported in DPFC) with the absolute percentage error for each of the three models under consideration. In all three municipalities, our model tends to do best in municipalities with larger overall emissions. EDGAR shows a similar trend, whereas GRACED has far more consistent absolute percentage error independent of emissions magnitude.



(a) Massachusetts



(b) Mexico



(c) Michigan

Figure 2: Log-log scale plots comparing emissions and absolute percentage error for each municipality in each test region, shown for each of the three models under consideration.

C Spatial resolution comparison

A major difference between past approaches and what we are proposing here is the higher spatial resolution of the data the proposed method would be able to produce. GRACED and EDGAR provide estimates at a resolution of 0.1-by-0.1 decimal degrees, which at the equator is approximately 11-by-11 km. By utilizing satellite-derived data sources and a bottom-up approach to modeling, the proposed approach would be able to provide estimates at a 1-by-1 km, which provides nearly 100 times the number of estimates for the same area greatly increasing the level of detail that can be used to more accurately resolve emissions to individual municipalities and neighborhoods. This difference is shown in Figure 3.

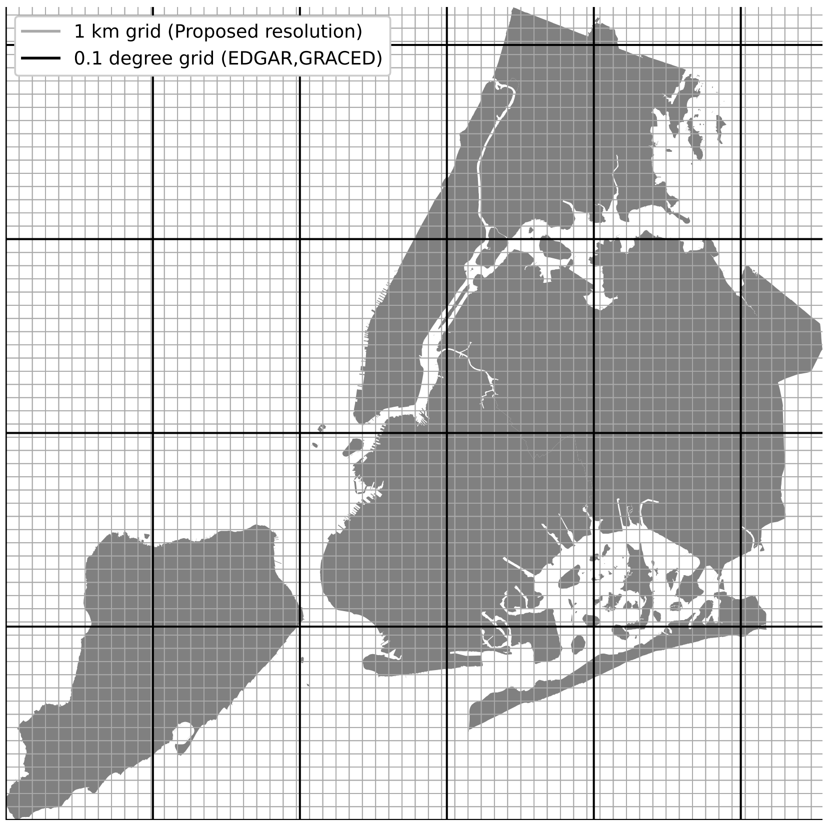


Figure 3: Comparison of spatial resolution of our proposed emissions estimation process (1 km × 1 km) and the EGDAR and GRACED estimates (0.1 degrees × 0.1 degrees, or approximately 11 km × 11 km at the equator) overlaid on top of the five boroughs of New York City (the island of Manhattan is in the center)