Predicting European Cities' Climate Mitigation Performance using Machine Learning

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Abstract

Although cities have risen to prominence as climate actors, emissions data scarcity has been the primary challenge to evaluating their performance. Here we develop a scalable, replicable machine learning methodology for evaluating the mitigation performance for nearly 50,000 local and municipal actors in the European Union from 2001–2018. We find that participation in one of the largest voluntary transnational climate initiatives is associated with a 1.6 percent reduction in annual emissions. Overall, these cities representing 301 million inhabitants have reduced nearly 186 million tons of carbon dioxide emissions. Compared to only 35 percent of external cities that have reduced emissions, 84 percent of cities participating in transnational climate governance have reduced emissions over the same time period. Participating cities reporting emissions data on average have higher annualized per capita reduction compared to cities without reported emissions. These findings provide quantitative evidence urban climate governance initiatives' effect on global climate mitigation.

Introduction

Cities have in recent years risen in prominence on the global sustainability policy agenda, as researchers and policy-makers have increasingly focused on urban jurisdictions as powerful policy actors in their own right. More than 10,000 of the world's cities are pledging various forms of climate mitigation, adaptation, and financing actions, and in many instances these municipalities participate in multiple voluntary transnational climate initiatives.[1] As part of these initiatives' requirements, in accordance with national government directives[2], or on their own volition, cities articulate strategies and policies to tackle climate change mitigation and, less frequently, adaptation. Cities predominantly put forth mitigation strategies centered on greenhouse gas emission reduction targets, often achieved through policies focused on increasing the use of sustainable transport, enhancing the efficiency of lighting in public and municipal buildings, adopting energy efficiency standards, promoting climate awareness to encourage citizen action, and other areas[3,4].

There are thousands of current strategies and policies detailing urban mitigation efforts, yet, as Milojevic-Dupont & Creutzig (2021)[5] point out, there is little understanding of these actions' effects. These knowledge gaps cause policymakers to be "disoriented on which measures are adequate and impactful" in urban areas and uncertain which "everyday decisions" regarding planning or infrastructure investments should be made to achieve mitigation targets. Little is known about the emission reductions from common urban climate policies and strategies, a missing block of vital information acknowledged in Chap. 12 on Human Settlements in the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC)[5,6].

Scholars have argued that cities' involvement in transnational climate governance "can accelerate their actions to curb GHG emissions under certain conditions"[7]. The evidence in support of this claim is scarce, making it hard to predict precisely what conditions would have this effect. Transnational climate initiatives typically require reporting of climate action plans and regular monitoring in the form of emissions inventories to assess whether mitigation goals are met, yet in practice only a small fraction of subnational actors meet these requirements[8,9]. Hsu et al. (2020)[10] found that out of more than 9,000 cities that were signatories to the EU Covenant of Mayors for Climate and Energy (EUCoM) initiative, only approximately 15 percent had reported any emissions data, and even fewer (around 11 percent) had reported both a baseline emissions inventory and an additional year of inventory emissions data needed to track progress towards voluntary reduction targets. When emissions data are available, they are frequently incomparable due to the limited availability of datapoints, a general lack of transparency regarding underlying methodologies, and the lack of standardized accounting approaches. Ibrahim et al. (2012)[11] evaluated seven distinct city-scale greenhouse gas emissions inventory protocols and methodologies and concluded that a common reporting standard or approach is needed for cities. Differences in the various standards' definitions – e.g. for emission scopes, particularly in Scope 3 supply chain emissions – must be addressed so that participants emissions' data can be appropriately compared.

Recent advances in machine learning (ML), the application of computational algorithms usually applied to large-scale datasets to simulate human learning, help us overcome these tricky emissions data challenges.[12] In this study, we employ a ML-driven approach to estimating and evaluating the performance for nearly 50,000 local and municipal actors in the European Union from 2001–2018. Our method develops a process for identifying spatial boundaries and geospatial predictors for each local and municipal government participating in the EUCoM, one of the largest voluntary transnational climate governance initiatives, and then utilizing the self-reported carbon emissions inventory data from 6,114 participating EUCoM cities as training data in an extreme gradient boosting model. To our knowledge, our resulting dataset is the most comprehensive time series dataset used to evaluate city-level carbon emissions and mitigation performance. We apply these data to evaluate the performance of three groups of European cities: "reporting" cities that have reported at least one year of emissions data; "participating" cities that have pledged voluntary climate action but have not reported any emissions data; and last, "external" cities representing local administrative units (LAUs) that are not participants.

Results

City-level predictors of climate emissions

Figure 1a shows the correlation between the city-level dependent (i.e., self-reported "emissions") and independent variables (i.e., heating degree days, fossil-fuel CO2, GDP per capita, etc.). We found a strong positive correlation between reported emissions inventory data and stationary fossil-fuel CO_2 emissions from the Open-Data Inventory for Anthropogenic Carbon dioxide (ODIAC)[13] ($r^2 = .81$), as well as between emissions and population ($r^2 = .89$). Population and stationary fossil-fuel CO_2 emissions were also highly correlated ($r^2 = .79$), confirming prior studies that demonstrate through the use of nighttime lights intensity the relationships between these data and energy consumption, economic activity, and fossil-fuel emissions.[14] Our analysis did not show strong relationships between self-reported emissions data and GDP per capita ($r^2 = 0.03$) or with fine particulate air pollution ($PM_{2.5}$; $r^2 = 0$). We determined that stationary fossil-fuel CO_2 emissions and population were the primary predictors of cities' self-reported emissions data with the highest contribution or importance to our emissions model (Fig. 1b). Figure 1b shows the gain value of the importance of each of the top six features we considered. The gain values are determined by the amount each attribute split improves the model's performance, weighted by the number of observations for the node. See Methods for more description about the grid search process and parameter tuning to determine the final model.

We predicted emissions for nearly 50,000 cities where we had underlying spatial data. Figure 2 presents scatterplots of cities' self-reported emissions data compared to our model's predicted emissions data. The resulting $r^2 = 0.94$ indicates our model is strongly predictive overall of cities' self-reported emissions inventories. We further validated our predicted emissions with other studies that report emissions data for European cities, including Moran et al. (2022)[15], who estimate 2018 direct (Scope 1) emissions for more than 100,000 European cities and Nangini et al. (2019)[16], who combine self-reported inventories with other data for 343 global cities. We found fair correlation ($r^2 = .50$ with Moran et al., 2022; $r^2 = .62$ with Nangini et al., 2019) between our predicted data and these other studies (Supplementary Fig. 7). Since most of the cities that report emissions data are small (mean population = 39,234; median population = 5,465), we find that our model tends to perform slightly better for larger cities ($r^2 = .98$), although this trend, and high correlation coefficient, appears to be largely driven by a few very large global cities like London and Berlin. For smaller cities, which comprise the majority of EUCoM cities and those reporting emissions inventories used to train our model, the model tends to underpredict self-reported emissions ($r^2 = .77$). As explained further in the Methods and Supplementary Information, we configured multiple models (e.g., separate models for large vs. small cities), but none performed as well in terms of minimizing error (i.e., RMSE) and achieving a high correlation (i.e., r-squared) between self-reported and predicted emissions. Figure 2b also shows the self-reported emissions data vs. predicted emissions data by country, which allows closer examination of potential eccentricities in our model or the predicted data. For instance, there are several cities in France where our model overpredicts their emissions. Further inspection of one of these outliers, Lyon, a city of 445,000 people in France, reports an emissions inventory of around 22,000 tons, resulting in per capita emissions of less than 0.05 tons, far below the national average of 5.4 tons per person.[17]

Predicting emissions 2001–2018

Our model provides annual emissions predictions for 2001 to 2018, the latest year for which we have fossil-fuel based CO_2 emissions. Figure 3 selects three illustrative time series plots for three cities of varying population size: Waimes in Belgium (population = 8,711), Tolosa in Spain (population = 17,349), and London in the United Kingdom (population = 8.6 million). In the case of Waimes, the city reported one baseline emissions inventory for the year 2006. Our model predicts slightly higher emissions (207 tons or 0.03 tons per capita) than its reported inventory. For Tolosa and London, both cities reported both a baseline and monitoring emissions inventory, and our predicted emissions show similar trends for both actors. Our model slightly underpredicts Tolosa's baseline emissions in 2007 (0.2 tons per capita) and inventory emissions in 2015 (0.01 tons per capita). For London, a similar trend emerges - our model slightly underpredicts the city's 2008 baseline emissions (0.05 tons per capita) and 2013 inventory emissions (0.01 tons per capita). On average, our model tends to slightly overpredict emissions (0.9 ± 2.23 tons per capita) compared to cities' self-reported emissions.

Trends in Performance

Utilizing the predicted emissions from our model, we analyzed trends in annual per capita emissions reduction over the time period from 2001 to 2018 for cities participating in the EUCoM that report emissions data (reporting cities), those that do not report (participating cities), and for all LAUs in Europe (external cities).

Overall, we find that EUCoM cities have reduced emissions from 2001 to 2018 compared to external cities in the European Union that are not signatories (-1.22 ± 2.00 vs. 5.21 ± 11.03 annual per capita emissions trend; Table 2). While 84 percent of EUCoM cities have reduced emissions during this time period, only 35 percent of external cities achieved a negative trend in emissions reductions. We interpret these emission trend differences between EUCoM cities and external LAUs with caution, however, noting the differences most notably in population between EUCoM (34,270 ± 199,844 inhabitants for reporting cities; 34,693 ± 161.567 for participating cities) and external LAUs, which tend to be on average must smaller (8,348 ± 22,851 inhabitants) (Table 1; Supplementary Fig. 6). Descriptive statistics (Table 1) and distributions (Supplementary Fig. 6) describing the three groups of cities in our analysis illustrate that EUCoM cities tend to have more sizeable stationary fossil-fuel carbon dioxide emissions and be larger in population and population density than external cities, which could explain differences in their emissions trends.

Within the EUCoM cities, we find that nearly 8,000 participating cities with 301 million inhabitants have reduced emissions 185.82 million tons between 2001–2018. Based on our quasi-experimental interrupted time series analysis, which models whether a policy intervention or program may have resulted in a measurable change in an outcome variable after its implementation,[18] we find that joining the EUCoM is associated with a -1.64 (se: 0.13) percent annual per capita reduction, when accounting for differences by country and holding GDP per capita, per capita emissions, and population density constant (Table 4). Thirty-eight percent of participating EUCoM cities achieved a greater annualized per capita emissions reduction after they joined the EUCoM, on average 3.67 ± 5.66 percent more than the year prior to their adhesion year.

Whether EUCoM cities self-report emissions data may be a predictor of mitigation performance. Seventy-five percent of EUCoM cities have reported at least one year of emissions data. At the country level, we observed large variation in the percentage of EUCoM cities reporting inventory data – e.g. 96 percent of Slovenia's 28 cities have reported at least one year of inventory data; while only 10 percent of nearby Slovakia's 29 cities evaluated have reported (Table 3). We observed a performance gap between reporting EUCoM cities and participating but not reporting cities (mean difference = 1.52; $p < 0.01$; Table 2). Despite being comparable in terms of population, population density, and GDP per capita (Table 1; Supplementary Fig. 6), reporting cities on average reduced per capita emissions 1.6 ± 2.0 from 2001 to 2018, while participating cities exhibited no or minimal reductions (-0.08 ± 1.5).

The EUCoM required cities to adopt at minimum a 20 percent reduction target by 2020 and at least a 40 percent reduction target by 2030, and we incorporated this information in two ways. First, we identified participating EUCoM cities as adopting "ambitious" (i.e., greater than 20 percent reduction by 2020 or beyond the EU's own 2020 target) or "unambitious" (i.e., adopting the minimum target). This classification allowed us to investigate whether participation in the EUCoM signals fundamental differences in participating cities compared to others (e.g., underlying structural differences that may predispose them to achieving certain outcomes). If our model is able to predict unambitious and ambitious reporting cities' equally well, this result would suggest that the model is valid for external cities that are equally "unambitious" (i.e., have not exceeded the EU's 20 percent reduction target). We did not find the designation of an "ambitious" (i.e., greater than 20 percent reduction by 2020 or beyond the EU's own 2020 target) emissions target a contributor to our predictive model (Fig. 1b), nor did we find differences in our model's predictions of ambitious or unambitious cities' emissions (Supplementary Fig. 5; see Methods:Limitations). Participating EUCoM cities that adopted "ambitious" 2020 emissions reduction targets that exceed the EU's, however, achieved higher annual per capita emissions reductions of -1.53 ± 2.7 (n = 3,570), compared to those that have adopted only the minimum (-0.47 ± 2.4; n = 3,964) (Table 2). Second, we used our predicted emissions data to determine whether participating cities were on track to achieving their targets, replicating the method we used in Hsu et al. (2020). Fifty-five percent of participating cities were on track to achieving their emissions reduction targets, with Scandinavian countries in the lead (87 percent in Denmark; 67 percent in Finland and Norway). Spain also boasts a large proportion of cities on track, with 74 percent. Twenty-nine percent of participating cities were not making sufficient progress towards their targets, while 16 percent have increasing emissions.

We observe differences in performance by country. Figures 4 and 5 compare the performance of participating EUCoM cities versus all other LAUs by country. In some countries, EUCoM cities, such as those in the Netherlands and Malta, on average have had higher annual per capita reduction trends than their non-EUCoM counterparts, although participating EUCoM cities in Netherlands tend to be larger than external cities (121,606 ± 177,804 for participating vs. 35,594 ± 26,906 for external cities). In others, such as Denmark and the United Kingdom, EUCoM cities appear to be underperforming compared to their counterparts (Fig. 4), as evidenced by comparing the distributions of annual per capita emissions reductions for both groups of cities. This result may reflect the fact that the national governments of Denmark and the United Kingdom require local climate action plans from municipalities (Reckien et al., 2018). Italy and Spain, where most of the EUCoM cities are located, appear to have relatively comparable performance for both groups, despite the significant percentage of emissions covered by EUCoM cities in both countries (Italy = 60 percent; Spain = 44 percent; Table 3). Countries where cities perform similarly are closer to the diagonal line in Supplementary Fig. 8, suggesting that the mean annual per capita emissions reduction trends are similar among EUCoM and external cities. Countries above the diagonal are those where EUCoM cities have achieved greater annual per capita emissions reductions than their non-EUCoM counterparts and include countries like Albania, Norway, Malta, Germany, Poland, among others. While acknowledging the limitations of our model in performing out of sample as well as the inherent differences and similarities between EUCoM cities and external cities, the findings point to the need for further data collection and research in this direction.

Discussion

Despite a measurable increase in urban climate governance scholarship over the past decade, gaps in understanding outcomes for transnational climate initiatives have persisted, particularly for smaller cities and on a systematic basis.[19] Part of this gap is due to data availability and comparability, which limit researchers' ability to trace causal impacts or linkages between the processes and institutions of transnational urban climate governance initiatives to outcomes.[19,20] To address this shortcoming, this study has developed a machine learning (ML)-based framework to predict nearly 50,000 European cities' emissions on an annual basis from 2001 to 2018 to evaluate cities adhering to one of the largest transnational climate governance initiatives. By utilizing globally gridded, spatially explicit predictor variables that are measured consistently and regularly and available self-reported emissions inventories, our ML-based model is able to explain 94 percent of the variation ($r^2 = 0.94$) between self-reported emissions inventory data from recording EUCoM cities and predicted emissions values, validated through comparisons with other studies that have produced city-level carbon emission estimates for a single year. We provide clear evidence that participating in the EUCoM is associated with a 1.6 percent reduction in annual per capita emissions. Compared to only 35 percent of external cities that have reduced emissions, 84 percent of cities participating in transnational climate governance have reduced emissions over the same time period. Participating cities that reported emissions inventory data on average have achieved higher annualized per capita reduction compared to participating cities without reported emissions data. Our method and resulting dataset allow for the largest-scale examination of municipal and local government climate emissions over time, shedding light on the impact of urban climate governance initiatives that was previously unattainable due to the lack of comparable, consistent data.

Our findings that participating EUCoM cities observe emissions reductions after they adhere to the initiative and compared to external counterparts provides, to our knowledge, the largest-scale evidence suggesting an association between participating in a transnational climate initiative and direct mitigation impacts, although we lack full understanding of the causal mechanisms driving these results. We observe cities a measurable decrease in annual per capita emissions changes around the year in which participating cities join the EUCoM, on average 1.6 percent when controlling GDP per capita, population density, and per capita emission levels constant. Since emissions reductions are generally easier to achieve at the outset when cities design climate action plans to tackle easier-to-achieve reductions through energy efficiency gains, conducting energy audits of buildings, and purchasing more fuel-efficient vehicles,[21,22] their transformations tend to follow an “S-shape,” where initial gains then slow down as incremental gains in reductions become more difficult to achieve or have already been met.[23] Fig. 5 illustrates similar trends in annual per capita emissions, where magnitudes reduce as time passes from the adhesion year, suggesting deeper transformational changes needed for cities adopting longer-term, decarbonization goals.[24]

Although the ITS design does not rule out the possibility that there could be some other unobservable or unmeasurable factor driving these results (see Methods), the finding that a majority (84 percent) of the EUCoM cities have reduced emissions in the observed time period echoes the results of our 2020 study of 1,066 EUCoM cities that have reported at least two emissions inventories. There, we found that 60 percent of cities were on track to achieve their 2020 emissions reduction targets, whereas this study found 55 percent to be on track. Our results provide support and clarity to previous studies evaluating the impact of transnational climate initiatives and cities’ mitigation performance. Kona et al. (2016), for example, estimated that 6,201 EUCoM cities, representing 213 million inhabitants, could reduce emissions by 254 million tons CO_2e in 2020 based on their pledged commitments, which were on average 7 percent higher than the 20 percent reduction target for the EU. The authors analyzed 315 reporting cities and found that they had reduced emissions by 23 percent on average. Since our analysis demonstrates reporting cities are driving most of the reductions compared to participating cities, the anticipated 254 million estimated tons in reductions in 2020 would largely hinge on reporting cities delivering these reductions. Yet at the time they made this report less than 5 percent of EUCoM cities had reported a baseline and monitoring emissions report. Our study, therefore, contributes the first wide-scale evidence of the scale and scope of cities’ mitigation contributions and the associated effect of participating in urban climate governance initiatives like the EUCoM.

While our study does not speak to causal mechanisms of the predicted emissions, nor whether there are endogenous conditions that may explain why EUCoM cities have experienced on average greater annual per capita reductions than their external non-EUCoM counterparts, it does suggest some insights relevant for urban climate governance and transnational climate initiatives. First, since emissions inventories and monitoring protocols are considered hallmarks of effective local governments’ climate mitigation plans,[8] the ability to monitor and report emissions are likely indicators of capacity and achievement. We measured significant differences between annualized per capita emissions reductions between reporting cities and participating cities that fail to report any emissions data. Second, while assessing emissions trends, as an outcome variable does not provide a “measure of effort”[25] nor describe the myriad inputs and factors that have led to a particular outcome, monitoring and reporting emissions inventories indicates a “means of implementation”[26] for evaluating an entity’s progress towards a climate policy outcome like climate mitigation. Data describing mitigation outcomes then allow for identification of “general conditions of successful implementation” and reverse engineering of causal pathways that led to the emissions reductions. Our dataset and replicable, scalable ML-framework can subsequently provide a first step towards disentangling which specific measures, or none at all, led to the observed emissions reductions. Since we were limited to data on cities’ population, GDP, and fossil-fuel CO_2 emissions, our analysis cannot account for other underlying structural differences (e.g., variation in governance institutions, etc.) that may further elucidate differences in emissions outcomes, since climate change action and policies are “deeply entwined with other policy agendas. ”[27]

Future Research

Since the availability of self-reported emissions inventory data at the subnational level is primarily constrained to Europe, future studies must broaden the search for relevant datasets and proxies that can fill this gap, particularly for capacity- and resource-constrained entities in the Global South.[28–31] Actors in these countries face limitations (e.g., expertise, lack of clearly designated roles in relevant government agencies for producing inventories, insufficient documentation and archival systems) and technical issues (e.g., incomplete or non-existent activity data or lack of experimental data for developing countries or technology-specific emission factors) for producing emissions inventories[10,32]. Our next step is to expand our approach to a set of subnational jurisdictions outside of Europe to produce a global dataset for cities participating in transnational climate initiatives, as recorded in Hsu et al.’s (2020)[10] dataset of more than 12,000 cities and regional governments. We have produced a scalable, reproducible framework and methodology for identifying spatial boundaries of cities and are able to match these boundaries to globally-gridded datasets, and then to utilize self-reported emissions and other data to predict and validate a machine-learning model. We find compelling evidence that large-scale, geospatial datasets can be applied to estimate city-level carbon dioxide emissions, even for small city actors that comprise the majority of participants in the EUCoM. Our method bridges the gap between these globally available, remote-sensing derived geospatial datasets to city-scale actors, a shortcoming Pan et al. (2021)[33] note in fossil-fuel CO2 datasets like the ODIAC inventory, which primarily distributes national fossil-fuel CO_2 emissions spatially based on satellite measurements of light-output intensity, and which may not correctly attribute emissions to subnational actors.

Conclusion

This research is a first step towards addressing the "lack of systematic knowledge on global contributions of cities to the Paris Agreement,"[34] which acknowledges the role of "all levels of government"[35] and seeks specific information regarding their impacts.[36] Few city actors participating in transnational climate initiatives report monitoring and inventory data, and even major cities claiming global climate leadership are absent from reporting.[9,10,34,37] Our study provides the most consistent approach and time series data to date, providing quantitative evidence of cities' participating in transnational climate governance mitigation performance, with potential for broadening the scope to areas outside of Europe.

Consistent, comparable, and widespread emissions data are essential to support the Paris Agreement's "facilitative and catalytic"[38] mode and its "pledge and review and ratchet" mechanism designed to continuously evaluate national and subnational actors' progress and contributions to global mitigation efforts.[39] For virtuous, catalytic cycles supporting this process to occur, emissions data are needed to assess which actions are effective in driving mitigation.

Methods

Dataset preparation

Self-reported emissions inventory and climate action policy data

Data for cities participating in the EUCoM were collected from two sources: Kona et al. (2021), which provides a "verified and harmonized version" of the EUCoM data for 6,200 member cities as of the end of 2019. The Kona et al. (2021) dataset for EUCoM cities includes self-reported emissions data (e.g., baseline or monitoring emissions inventories), as well as other characteristic data of the cities from the European Statistical Agency. We supplemented this dataset with more recent data for cities from the EUCoM website, which was scraped using the Beautiful Soup Python package (Richardson, 2007) in February 2021. We primarily collected information on each cities' adhesion date to the EUCoM initiative, baseline emissions year, baseline emissions (in tons of carbon dioxide emissions or tCO_2), emissions reduction target, target year, and any reported inventory emissions (i.e., emissions data reported at a later year than a defined baseline year, from each city's Progress page). We also derived information regarding the cities' population and geographic coordinates (latitude/longitude) from the EUCoM website if available. Since Kona et al. (2021) apply a series of statistical techniques to validate their dataset, we prioritized self-reported emissions data from this source if there were data available for a city both in Kona et al. (2021) and the EUCoM website. Supplementary Fig. 1 shows a scatterplot of the logged emissions data from both the EUCoM website and Kona et al. (2021), which illustrates a strong correlation ($r^2 = 0.986$). In total, our dataset contained names of 8,242 cities participating in the EUCoM initiative, with 6,309 reporting any emissions information. We also imputed a 20 percent emissions reduction target by 2020 if no specific emissions reduction target was reported in Kona et al. (2021) or on the EUCoM website for the purposes of the tracking progress analysis described in our previous study (Hsu et al., 2020).

Feature selection - Predictors of urban climate emissions

An important first step in building our predictive emissions model was determining a set of underlying predictors of city-level carbon emissions that would be universally available for all EUCoM cities and LAUs in Europe. We evaluated several predictors of urban greenhouse gas emissions to include as predictors in our model, based on existing literature regarding major sources and drivers of cities' emission profiles (Seto et al., 2014; Marcotullio et al., 2013; Dodman, 2009; Rosa and Dietz, 2012). In terms of emission sources, the energy sector, specifically conversion of energy to electricity, is the largest source of urban greenhouse gas emissions, comprising around half upwards to 65 percent of total urban emissions, followed by the transportation sector (15 to 20 percent) (Marcotullio et al., 2013). Since stationary sources do not explain city greenhouse gas emissions in their entirety, we also investigated other proxies for major emissions sources, including heating and cooling demand, and fine particulate air pollution, which in cities results primarily from transport (~ 25 percent; Karagulian et al., 2015). We also included population and gross domestic product (GDP) as relevant socioeconomic drivers of urban climate emissions (Seto et al., 2014), and evaluated a few country-level predictors, based on our previous study (Hsu et al., 2020) that found national-level emissions reductions were predictors of city-level climate change performance, including country-level CO_2 emissions trend (2000–2018) (WRI CAIT, 2020) and carbon intensity of electricity-generation for the European Union (EUROSTAT, 2021). Further details on the sources of these datasets and their processing are detailed in Methods.

Since high-resolution emissions data as a result of electricity production and consumption are not available for the vast majority of cities included in our analysis, we relied on the Open-Data Inventory for Anthropogenic Carbon Dioxide (ODIAC) database, which provides a globally-gridded, annual 1 km x 1 km spatial resolution data of carbon dioxide emissions from fossil fuel combustion, cement production, and gas flaring from 2000 to 2019.[13] We selected the ODIAC dataset based on prior evaluation of its relevance for urban-level carbon emissions analysis, as described in Hsu et al. (2020).[10]

As proxies for building energy consumption due to heating and cooling, we downloaded monthly-averaged, (0.5x0.625 degree or 55.5 x 69.375 km) spatial resolution land surface temperature data from the NASA MERRA-2 temperature product[40] and then calculated heating and cooling degree days (HDD and CDD, respectively) based on the number of monthly-averaged measurements that deviate from a baseline temperature, T_{base}, which were then multiplied according to the number of days in each respective month (i.e., assuming the same HDD or CDD for each day of the month) and then summed across a year, according to the Equations (1–2) below:

$$HDD = \Sigma_m \left(T_{base} - T_i\right) \times Days_m{}^{+} \text{ (Eq. 1)}$$

$$CDD = \Sigma_m \left(T_i - T_{base}\right) \times Days_m{}^{+} \text{ (Eq. 2)}$$

where $T_{base} =$ 15.5 degrees C for HDD and T_{base}= 22 degrees C for CDD[41] and $m$is the month. For the EU model, we excluded cooling degree days since 99 percent of European cities had 0 cdd.

We included an annual, gridded (~ 1 km) exposure to fine particulate matter pollution ($PM_{2.5}$) for years 2001 to 2015[42], since $PM_{2.5}$ pollution is generated from sources similar to carbon emissions in urban areas, mainly fossil fuel combustion from electricity generation and transportation.[43] We also evaluated a few country-level predictors, based on a previous study[10] that found national-level emissions reductions were predictors of city-level climate change performance, including country-level CO_2 emissions trend (2000–2018)[17] and carbon intensity of electricity-generation for the European Union,[44] although our final model did not include these variables, since they did not contribute significantly to the feature importance for our model (Fig. 1b).

We further accounted for population and gross domestic product (GDP) as relevant socioeconomic drivers of urban climate emissions.[6] For population, we used the Gridded Population of the World (GPW) dataset,[45] which provides population estimates at a 1-km spatial resolution for five-year increments from 2000 to 2020. We calculated annual population estimates by linearly interpolating between these five-year increments. For GDP, we used a globally, annually gridded GDP per capita data at a 1-km spatial resolution from Kummu et al., 2018,[46] which provides data from 1990 to 2015. We used a spline interpolation method using the na_interpolation function from the imputeTS package[47] in R to impute GDP per capita values for cities from 2016 to 2018 to match the time series of the other spatial predictors.

Spatially joining predictor variables with climate action participation dataset

Since the original format of these predictor variables (e.g., fossil-fuel CO_2 emissions) are all gridded spatial data, we merged these datasets to each EUCoM city through spatial joins. We first collected the latitude and longitude of each city's centroid as provided by the various data sources. When the city centroids were not available from Kona et al. (2021),[48] EU Covenant of Mayors' website, or we determined errors in the geographic coordinates from either of these sources, we extracted the city centroids through Wikipedia's GeoHack website (citation: https://www.mediawiki.org/wiki/GeoHack).

To determine each city's spatial boundaries, we used distinct approaches described below. For most of the cities, we collected data for local administrative units (LAUs), which are defined as "low-level administrative divisions of a country below that of a province, region or state," for all 28 European Union countries from the European Union's Statistical Agency.[49]The LAU data was spatially joined to our EUCoM city data frame in Python using the geopandas[50] package to associate each city with a LAU boundary for the purposes of matching additional predictor variables. We implemented a series of quality checks to ensure that the spatial joins were conducted correctly and to identify any issues in the geographic coordinates that may have been incorrectly specified on the EU Covenant website. These quality checks include 1) evaluating whether cities have the same geographic coordinates but are identified with distinct names; 2) comparing the reported population in the Kona et al. (2021)[48] or EUCoM website for an individual actor and the interpolated population after the spatial join; 3) examining any city with self-reported per capita emissions less than 0.2 tons per person or greater than 40 tons per person; 4) compound annual growth rate in emissions is greater than – 50 percent and less than 50 percent. These checks allowed us to determine whether there were any errors in the spatial join or underlying data collected for the EUCoM cities from either Kona et al. (2021)[48] or the EUCoM website.

Where manual corrections to LAUs also did not result in correct spatial joins, we utilized OpenStreet Map (OSM)[51] to get the correct boundary, particularly for large cities that may encompass more than one LAU. Supplementary Fig. 2 illustrates a few examples of the incorrect spatial join results and the fixed boundaries with OSM. After we verified the cities' boundaries, we then applied zonal statistics using the Python package rasterstats version 0.15.0,[52] where each predictor variable was summarized for each city using its spatial boundary. Based on the definition of the predictor variables, we calculated mean values, except population, where we calculated the sum of all pixels that intersect with each city or LAU boundary,

Model for predicting emissions and climate change performance

Cities participating in the EUCoM are required to submit a Sustainable Energy Action Plan that includes a baseline emissions monitoring inventory, and a monitoring inventory every two years after that. Yet, at the time of data collection in February 2021, out of the nearly 10,000 signatories listed on the website, only 6,114 actors had reported any emissions data, and only 1,400 had reported more than one year of emissions monitoring data. We only included cities' data with an interpolated population greater than the 5th percentile (374 inhabitants) of the cities' population distribution. In total, 329 cities had populations below this threshold and were not included in the training or the prediction datasets. Consistent with Hsu et al. (2020), we also filtered out datapoints that reported less than 0.2 tons CO_2 per person or greater than 40 tons CO_2 per person. The time period for self-reported emissions data ranged from 1990 to 2020, but we only used data greater than 2000 (5,621 unique actors with 7,007 emissions datapoints) for the model training since this is the time period available for the predictor variables.

We further split our data into three subsets: the first subset used as training data includes all EUCoM cities that have at least one year of emissions data reported, whether its baseline emissions or a later inventory-year of data reported (EUCoM, 2021); a second subset are cities participating in the EUCoM but have not reported any emissions data; the third subset are cities not participating in the EUCoM. The first subset of reported emissions data to the EUCoM are used as training data to predict emissions for the latter two subsets of data. We applied the model built with the first dataset to these cities and predict their likely emission of a given year. Supplementary Fig. 3 provides a flow diagram of the processing steps described above. Our training and test datasets were generated based on a standard 80/20 split of the data while preserving the underlying country representation (i.e., slightly over half of the available training data are from cities in Italy (52 percent), followed by Spain (26 percent).

Model selection - XGBoost

We evaluated several regression models including multilinear regression, random forest, SVM, and extreme gradient boosting (XGBoost). The multilinear model is from the R base library; random forest and SVM are from R package caret version 6.0-86[53] ; and XGBoost from XGBoost R package version 1.3.2.1. [54] We chose root mean square error (RMSE) and r^2 as the model comparison matrix to examine how each model performs on both the training and test datasets. For random forest, SVM, and XGBoost models that are controlled by a set of hyperparameters, we applied grid search with 5-folder cross validation to the models to get the best parameters that result in the lowest RMSE. Supplementary Table 3 shows the hyperparameters we used in these three models. Missing values in independent variables are a common issue in ML-based models, and the models we evaluated handle missing values in different ways. The XGBoost model is capable of handling missing values without any imputation. Therefore, after we trained an XGboost model with complete data in all independent variables (referred as XGBoost-w/o NA), we also trained the XGBoost model with the data may have NA values in the independent variables (referred as XGBoost-w/-NA in the following sections. Note that all NA values are dropped after we split the data into training and test sets, so that all train and test dataset are exactly the same for models besides XGBoost-w/ NA. Supplementary Table 4 shows the train and test RMSE and r^2 of the best tuned models. Both the random forest and XGBoost model are tree-based regression models, and our results suggest that the tree based models perform better than other models for our dataset (Supplementary Table 4). Additionally, the XGBoost-w/ NA model is trained with 357 more data points with NA values in the independent variables and achieved: train RMSE = 24202.05, test RMSE = 155865.63, train r^2 = 0.99, test r^2 = 0.90.

Based on the model training results and the capability of handling missing values, we decided to proceed with XGBoost. XGBoost stands for "extreme gradient boosting" and has gained popularity due to its high performance in machine-learning competitions such as Kaggle (Nielsen, 2016). Gradient boosting models like XGBoost perform supervised regression tasks through an iterative approach to predict a target variable (i.e., emissions), optimizing predictive performance by combining multiple "weak" trees to fit new models that are more accurate predictors of a response variable.[55,56] The XGBoost gradient-boosting model has XGBoost has been widely used in air quality monitoring[57–59] and greenhouse gas (GHG) emissions estimation[60] for its high efficiency, flexibility, and portability. Si and Du (2020)[56] further note additional advantages of XGBoost, which requires less data preprocessing and has fewer hyperparameters, parameters an ML model uses to control the learning process for tuning.[61]

Our implementation of the XGBoost is determined by a set of hyperparameters, which are parameters the machine learning model uses to control the learning process.[61] These included the maximum depth of the tree, the learning rate, the minimum sum of weight in a node, minimum loss reduction, and the percent of rows to use in each tree which are the standard hyperparameters included in the XGBoost implementation in R.[62] To obtain the best hyperparameters set for the model and evaluate how the model performs, we first split our dataset into a training dataset and testing dataset with a 80/20 split sampling across countries, meaning we used 80 percent of the data as training data to predict the other 20 percent of the dataset.[56] We then conducted a grid search (Supplementary Table 2) on the hyperparameters with 5-folder cross-validation to determine the model with the lowest mean root mean squared error. Supplementary Table 2 shows the hyperparameter ranges and the optimized values. Following the hyperparameter grid search, we trained the model with the training dataset with the best result from the hyperparameter grid search. We then tested the model using the test data.

The final model was built with the optimal parameter set from the grid search, which is the process of building models with all the possible parameter combinations and finding the best parameter set with which the model performs the best on training samples. As Supplementary Table 2 describes, the optimum result for the model is achieved when max depth = 5, minimum child weight = 1, eta (learning rate) = 0.1, gamma = 0.5, and trains the model with 999 rounds. The best model performance obtained was RMSE = 26859.36 tons emissions r2 = 0.99, MAE = 9173.89. Supplementary Fig. 4 shows scatter plots of the self-reported and predicted emissions for the training and test datasets. We used the XGBoost R package's built-in function *xgb.importance* to determine the final model's feature importance (i.e., which predictors have the greatest predictive or explanatory power).[54,62]

Predicting 'likely' emissions levels for all entities 2001–2018

After building the final model with optimal parameters and evaluation, we applied our model to 1) EUCoM cities that do not report emissions; and 2) all LAUs in Europe that do not participate in the EUCoM. We bootstrapped 1,000 predicted emissions intervals for each year for each actor to ensure robust median estimates. In addition to the optimum parameters from the grid search, we used the "subsample" parameter to introduce randomness into the model. This parameter determines the percent of rows in our dataset to use in each tree. We set this value to 0.90 and, so the model is built with 90% of the total dataset. We then calculated the 5th percentile, 95th percentile, mean, and median value for each predicted emissions estimates for each actor and year.

Performance metrics

We calculated several performance metrics (e.g., linear trend in predicted emissions between 2001 and 2018, annual percentage change in emissions, and annualized percentage reduction in per capita emissions) using the predicted emissions data for each actor and evaluated them before utilizing the annualized percentage reduction in per capita emissions (annual per capita emissions trend) as our main evaluation metric, consistent with Hsu et al. (2020),[10] as described in Eq. 3.

$$reduction_c = -100 \times \frac{predemissions_{\min(year)} - predemissions_{\max(year)}}{predemissions_{\min(year)}} \times \frac{1}{\max(year) - \min(year)} \text{ (Eq. 3)}$$

Consistent with Hsu et al. (2020), we determined whether a city is 'on track' to achieving their stated emission reduction goal or not, we calculated the ratio of actual (i.e., achieved) per capita emissions reduction in the inventory year to the targeted per capita emissions reduction in the inventory year, both in comparison to the baseline year, assuming that emissions reduction between the baseline year and the target year are pro-rated linearly (i.e., constant emissions reduction from one year to the next). More specifically, we define ρ through the following Equations (4–7):

$$Reduction_{achieved} = Predemissions_{min(year)} - Predemissions_{max(year)} \text{ (Eq. 4)}$$

where:

$Predemissions_{min(year)}$ is predicted emissions per capita of the city in the minimum year for which predictor data are available. For most cities this was the year 2001;

$Predemissions_{max(year)}$ is the predicted emissions per capita of the city in the maxmum year for which predictor data are available. For most cities this was the year 2018;

$$Timelapsed = \left(Year_{max} - Year_{min}\right) \div \left(Year_{target} - Year_{min}\right) \text{ (Eq. 5)}$$

Where:

$Year_{min}$ is the minimum year for which predicted emissions data are available

$Year_{max}$ is the maximum year for which predicted emissions are available

$Year_{target}$ is the year by which committed emissions reductions are to be achieved

$$Reduction_{required} = Predemissions_{\min(year)} \times Target \times Timelapsed \text{ (Eq. 6)}$$

where:

$Target$ is the committed emissions reduction of the city (percentage).

$\rho = \frac{Reduction_{achieved}}{Reduction_{required}}$ (Eq. 7)

Interrupted Time Series Analysis

To investigate whether participation in the EUCoM is associated with a change in a cities' emissions, we employed an interrupted time series (ITS) modeling approach[18] to compare trends in EUCoM cities' annual per capita emissions prior to and following their adhesion year. ITS designs evaluate an outcome for a population sample exposed to an intervention before and after, using repeated observations at regular intervals.[63,64] Although there is strong internal validity of an ITS design, there are limitations in terms of potential weak external validity in that the results may not be generalizable to other groups due to the fact that ITS cannot rule out the possibility of unmeasurable or uncontrolled factors leading to a change in the outcome variable.

We estimate annual percent changes in per capita emissions reductions ($pct.\ chg$)from 2001 to 2018 for each city (i) in country (c) for each year (t) with the following Eq. (8):

$$pct.\ chg_{i,c,t} = \alpha_i + \beta_1 Time + \beta_2 Joined + \beta_3 TSJ + \gamma_C + \log(GDP)_{i,c,t} + \log\left(popdensity_{i,t,c}\right) + predictedemissions_{i,t,c,} + \epsilon_{i,c,t}$$
(Eq. 8)

where $Time$ is a variable that indicates the number of years since a city adhered to the EUCoM initiative; $Joined$ is a dummy variable that indicates whether the observation refers to before (0) or after (1) the city adhered; TSJ is the time elapsed since a city joined the EUCoM in years. We also control for differences between cities' population density, GDP per capita, and emissions per capita predicted by our machine learning model. We also include country dummies (γ_C) to control for unobserved, time-invariant factors common to cities within a country.

Limitations

This study is certainly not without its limitations. There are a few areas of uncertainty that could affect the validity of our predictions and results. First, we assume that the self-reported emissions inventories from the EUCoM actors are a valid source of data to train our model and predict others' emissions. We used the "verified" dataset of self-reported emissions data for 6,200 cities that have reported emissions inventory data evaluated by the European Commission's Joint Research Centre.[48] Although Kona et al. (2021) applied a series of statistical checks to validate these reported emissions inventories, they note several limitations. Since the focus of the EUCoM is on greenhouse gas emissions relate to sectors where a local authority has power to influence through sectoral and policy measures, participating cities only report emissions from selected sources (e.g., energy consumption for buildings, transport and local energy generation, industrial sources not already covered by the EU Emissions Trading Scheme, and waste/wastewater) (EUCoM, 2016).[65] Kona et al. (2021)[48] acknowledge that the EUCoM inventories were "never meant to be a method to create exhaustive inventories of all emission sources in the territory or to deal with emissions already included in national-scale control initiatives, such as the EU Emissions Trading System (ETS) mechanisms." Therefore a second limitation is that there are emissions sources and sectors inherently missing from EUCoM cities' inventories, including supply chain or consumption-based emissions sources. Third, the use of different emissions factors, estimation methodologies, and reporting boundaries may add uncertainty. Fourth, we assume that the spatial boundaries of EUCoM cities and LAUs remained static over the time period, while these may have changed over time. Last, while we observed significant differences in EUCoM cities' emissions reduction trends compared to cities that do not participate, there may be some fundamental differences between these groups of cities. To evaluate our model's sensitivity to this potential factor, we included a dummy variable to designate whether an EUCoM city has committed to an ambitious emissions reduction target (greater than 20 percent) or if it has simply adopted the minimum EU target of 20 percent, which other non-EUCoM cities are presumably subject as part of national and regional climate targets. As shown in Supplementary Fig. 5, we found our model was able to predict emissions from both sets of actors with similar accuracy (r^2 = 0.94 for both groups). As Fig. 1b illustrates, the dummy variable 'ambitious 2020 target' did not contribute to the model's predictive gain values. Ideally we would be able to include self-reported emissions data from non-EUCoM cities in our training dataset, but these data are not available.

Software

Data scraping and geospatial data processing were conducted using python (version 3.68) and the R statistical programming environment (version 3.6.2). The machine learning model was developed and conducted in R using the XGBoost package.[54] Figures were made using ggplot2[66] data visualization package and maps were made in QGIS (version 3.16)

Declarations

Data Availability Statement

Data and code used to create figures are available at www.github.com/datadrivenenvirolab and on our UNC Dataverse Repository (https://doi.org/XXXX).

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Author contributions

AH conceived, co-designed study, collected data, conducted statistical analysis, made figures, and wrote the paper. XW collected data, conducted statistical modeling and validation, made figures, and contributed to the paper's writing. JT assisted with ML-model selection and implementation. WT assisted with data collection and merging.

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Tables

Table 1

Summary Statistics 1) Cities reporting emissions data in the European Covenant of Mayors for Climate and Energy (EUCoM); 2) Cities not reporting emissions data in the EUCoM; 3) All other European LAUs. Data correspond to year 2018.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
(1) EUCoM Cities reporting emissions data							
GDP per capita	5,472	34,270.330	10,500.000	2,898.161	24,907.560	42,653.010	65,779.700
Heating degree days	5,479	2,346.058	1,506.650	0.000	1,012.622	3,351.190	8,894.994
Population density	5,479	577.841	1,416.094	0.238	46.062	512.802	22,114.780
Population	5,479	33,775.060	199,844.500	35.308	1,683.855	15,272.490	8,965,276.000
Fossil-fuel CO2 emissions	5,479	41,870.170	222,138.600	0.000	2,345.647	17,175.120	5,957,429.000
Fossil-fuel CO2 emissions per capita	5,479	2.229	13.378	0.000	0.804	1.967	775.742
Fine particulate air pollution (PM2.5)	5,423	11.164	4.877	2.151	7.065	14.410	29.181
(2) EUCoM Cities not reporting emissions data							
GDP per capita	1,685	31,615.630	10,489.700	2,575.388	23,853.250	40,499.790	84,746.950
Heating degree days	1,685	2,589.232	1,630.994	0.000	1,142.226	3,557.862	7,956.604
Population density	1,685	512.940	1,707.357	2.344	45.674	352.777	45,852.780
Population	1,685	34,692.720	161,566.900	60.567	1,481.973	12,578.350	2,672,199.000
Fossil-fuel CO2 emissions	1,685	48,690.320	237,230.000	0.000	2,361.174	16,103.160	4,420,102.000
Fossil-fuel CO2 emissions per capita	1,685	2.037	4.678	0.000	0.901	2.207	120.650
Fine particulate air pollution (PM2.5)	1,641	10.508	4.053	2.924	7.318	13.390	30.334
(3) All other LAUS							
GDP per capita	39,742	33,670.690	12,293.380	4,552.309	25,150.820	40,107.690	100,726.400
Heating degree days	39,817	3,797.706	1,467.800	0.000	3,108.901	4,698.598	9,271.064
Population density	39,817	335.148	939.363	0.329	57.365	262.214	29,391.080
Population	39,817	8,348.308	22,851.110	1,000.194	1,663.810	6,567.054	866,314.800
Fossil-fuel CO2 emissions	39,817	12,973.500	70,225.040	202.095	2,338.124	9,386.230	4,706,230.000
Fossil-fuel CO2 emissions per capita	39,817	1.637	1.507	0.200	0.907	1.953	39.518
Fine particulate air pollution (PM2.5)	39,817	10.815	4.303	1.915	7.465	13.245	35.632

Table 2
Difference in annual per capita emissions reduction trend between different comparison groups.

	Mean ± sd trend (1)	**Mean ± sd trend (2)**	**Mean difference**	**Standard error**
(1) EUCoM cities vs. (2) All LAUs	-1.22 ± 2.00	5.21 ± 11.03	6.43***	0.0004
(1) EUCoM cities reporting inventories vs. (2) EUCoM cities not reporting inventories	-1.6 ± 2.0	-0.08 ± 1.5	1.52***	0.002
(1) Ambitious EUCoM cities versus (2) unambitious EUCoM cities	-1.53 ± 2.7	-0.47 ± 2.4	1.06****	0.001

Note

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3
Summary performance statistics of cities participating in the EUCoM.

country	Number of EUCoM cities evaluated	population	Share of national emissions (%)	Share of national population (%)	On track (%)	Reporting emissions (%)	Percentage of cities reducing emissions (%)
Austria	25	78952 ± 355736	10	22	8	36	32
Belarus	10	153961 ± 131148	7	16	0	30	30
Belgium	454	20615 ± 32880	49	81	37	65	92
Bulgaria	25	102572 ± 251793	35	37	20	88	44
Croatia	62	17771 ± 22203	29	27	13	89	56
Cyprus	21	23011 ± 27514	32	38	52	95	81
Czech Republic	16	144544 ± 331087	7.6	22	19	25	75
Denmark	38	81207 ± 106028	39	52	87	89	92
Estonia	5	100626 ± 159730	13	38	40	100	40
Finland	12	185181 ± 154967	18	40	67	67	92
France	107	113776 ± 275561	16	18	40	68	75
Germany	75	236089 ± 462209	15	21	43	57	79
Greece	150	39904 ± 110196	40	55	24	83	54
Hungary	146	40601 ± 211103	34	58	8	34	33
Ireland	13	135365 ± 184416	16	30	54	62	69
Italy	3854	13702 ± 82716	60	87	56	77	88
Latvia	20	65246 ± 161737	50	65	40	95	55
Lithuania	15	71618 ± 102545	24	39	27	80	33
Luxembourg	9	2943 ± 1427	2.1	4.3	44	11	89
Malta	23	5710 ± 4610	39	25	57	83	87
Netherlands	29	169151 ± 184105	19	28	31	52	79
Norway	6	190069 ± 231656	16	21	67	33	100
Poland	41	147621 ± 309957	8.3	16	17	80	68
Portugal	136	25919 ± 60168	35	34	46	78	79

Note: Table only includes countries with more than 5 city actors.

country	Number of EUCoM cities evaluated	population	Share of national emissions (%)	Share of national population (%)	On track (%)	Reporting emissions (%)	Percentage of cities reducing emissions (%)
Romania	97	163639 ± 447539	44	79	25	64	55
Slovakia	29	20169 ± 49424	8	11	7	10	69
Slovenia	28	27513 ± 59356	23	37	29	96	64
Spain	1885	19804 ± 111796	44	79	74	78	92
Sweden	59	82516 ± 144215	67	47	51	54	80
Switzerland	7	109682 ± 150017	8.4	7.7	57	86	100
Turkey	18	932090 ± 1167289	13.7	20	6	39	17
Ukraine	25	672451 ± 674177	17	36	32	76	48
United Kingdom	44	565707 ± 1366590	24	37	41	75	75
Note: Table only includes countries with more than 5 city actors.							

Table 4
Results of interrupted time series analysis.

	Dependent variable:
	Annual Percentage Change
Time	0.158***
	(0.012)
Joined	-1.638***
	(0.130)
Time Since Joining EUCoM	0.320***
	(0.024)
log(Population density)	1.033***
	(0.026)
log(GDP per capita)	3.484***
	(0.150)
Predicted emissions per capita	0.339***
	(0.010)
Constant	-52.116***
	(3.621)
Note: Standard errors are in parentheses. The regressions include country fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01	

Figures

Figure 1

a) Correlation matrices showing the relationship between various predictors of urban climate emissions. b) Importance of various predictor variables to the emissions' prediction model. The more an attribute is utilized in the grid search process to make decisions in the XGBoost classifier, the higher its feature importance is determined.

Figure 2

Scatterplot of self-reported emissions (n=7,007 self-reported emissions data-points from 5,621 cities reporting to the EUCoM used in the model training) compared to the predicted median emissions for each actor from the model on a log scale. a) shows all of the self-reported emissions inventories (in log tons CO2) of all actors versus the predicted emissions data (in log tons CO2); b) shows country-by-country facets of self-reported vs. predicted emissions where there were more than 1 datapoint.

Figure 3

Predicted, self-reported emissions, and primary predictor variables for three cities of varying population sizes.

Figure 4

Annual per capita emissions reduction trend from 2001-2018 for cities with a population larger than 375 inhabitants (the 10th percentile of the cities included in the training data) participating in the EUCoM (left) and all other local administrative units (LAUs; right).

Figure 5

Distributions of annual per capita emissions reductions between cities in the EUCoM and those not participating that have per capita fossil-fuel CO2 emissions greater than 0.2 tons per capita or less than 40 tons per capita. Negative numbers indicate emissions reductions and mean annual per capita emissions trends for each group are designated with vertical lines in each panel.

Figure 6

Annual percentage per capita change in emissions for EUCoM cities (plotted points) with predicted annual percentage per capita change in emissions determined by interrupted time series analysis (blue line). Panels include data for cities that joined the EUCoM in that specific year only, indicated by the red vertical lines.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation030822.docx