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Prediction of greenhouse gas emissions for cities and local municipalities monitoring their advances to mitigate and adapt to climate change

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ABSTRACT

Under the Global Covenant of Mayors (GCoM) initiative, cities present their action plans committing to mitigate greenhouse gas (GHG) emissions and/or adapt to climate change. One concrete objective consists in setting a reduction target, by which cities commit to reduce their baseline GHG emissions for a chosen target year. In monitoring their emissions, cities report inventories for any arbitrary year(s), making available only discrete readings in what can be considered a very sparse yearly time series. Examining the performance of the cities for the target years of 2020 and 2030, the actual measurements are usually not available. Therefore, a machine learning methodology is proposed to predict the GHG emissions inventories for each city on their target year, enabling the assessment of the cities' performance inside a common reporting framework. Using the reported inventories, the methodology identifies a model for each city, minimizing the error for the last known reported value. As a result, the proposed method allows predicting GHG emissions for cities from their yearly inventories, controlling the uncertainty associated to the estimations and extracting reliable information that can be updated as soon as new emissions inventories become available.

1. Introduction

Greenhouse gas (GHG) emissions are the main driving force for climate change (Kona, Bertoldi, Monforti-Ferrario, Rivas, & Dallemand, 2018; Zhao & Du, 2015), being a world ambition to reduce the overall global emissions to the level of 2 metric tonnes of CO_2-equivalent per capita by 2050. As such, the forecasting of GHG emissions plays a key role for climate policy decision making. Not only to generate insights on the prospect for future global warming, but also on the expected impact and costs of implementing actions for mitigating and adapting to global warming. Furthermore, greater attention should be placed on the key actors generating GHG emissions, such as cities and largely populated areas (Bertoldi, 2018; Moran et al., 2022). In this sense, city-level emissions inventories are central for supporting mitigation goals and for monitoring the achievements of the cities along the green energy transition.

Through the Global Covenant of Mayors for Climate and Energy (GCoM) initiative (Melica et al., 2018; Palermo, Bertoldi, Apostolou, Kona, & Rivas, 2020), the European Commission endorses and supports the efforts of cities and local authorities to consolidate practices for reducing GHG emissions as well as acting on risks and vulnerabilities associated to climate change. Under this initiative, decision makers are encouraged to identify priority sectors, set emission reduction targets and adaptation goals, and plan relevant measures (Bertoldi, 2018; Melica et al., 2022).

The signatory cities present their action plans committing to mitigate GHG emissions and/or adapt to climate change at the My-Covenant reporting platform (https://www.covenantofmayors.eu/). After a cleaning process dedicated to harness the quality of the reported data, as described in Melica et al. (2022), a complete and up to date open data set has been published (Baldi et al., 2021), describing the *Covenant community*, along with the actions and measures taken, and the progress accomplished by its members. A key piece of information contained in the data set refers to the GHG emissions reduction target selected by each signatory, against which their progress can be evaluated. Therefore, it should be possible to assess the achievements of the cities for the target years of 2020 and 2030, in terms of the realized percentage reduction with respect to the reference baseline emission inventory.

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Nonetheless, a complete monitoring of the cities' performance is not available, as cities report follow-up emissions inventories for arbitrary years. In consequence, the open data set contains yearly inventories only for some years, being an open challenge to predict the cities' emissions on their target years of 2020 and 2030. Resolving such a challenge is necessary to properly assess the performance of the signatories for the corresponding target years.

Hence, this paper presents a robust statistical methodology for estimating and forecasting GHG emissions for cities holding at least one monitoring emissions inventory (besides their baseline emissions inventory). In this sense, addressing cities that in fact are monitoring their advances for mitigating and/or adapting to climate change.

The proposed methodology relies on a novel validation technique referred to as the *Leave Last Known Value Out-Validation* (LLKVO-V). For each city, the available information is treated as a uni-variate time series with its own trend and behaviour, identifying a model for each city to project their emissions on the corresponding target year. The behaviour of each city is modelled after minimizing the *Last Known Value* (LKV) prediction error, which is in fact the last known realization coming from the last submitted monitoring report (and which is left out of the sample to properly measure its prediction accuracy). Hence, the proposed statistical methodology uses all the available emissions inventories to identify the dominant trend and obtain a reliable estimate. The methodology is illustrated for a group of 1950 cities and local administrative units in the 27 European Union countries (EU-27), showing that the cities committed to a reduction target in 2030 are expected to achieve a mean 41% reduction with respect to their baseline GHG emissions.

Furthermore, the performance of the signatories is also examined with respect to their actions, and how moving towards a more integrated approach in climate change action planning, addressing both mitigation and adaptation (Grafakos, Trigg, Landauer, Chelleri, & Dhakal, 2019), may allow a higher success rate.

Different approaches can be found in literature dealing with the forecasting of emissions. There is an important body of research concentrating on structural-parametric models to forecast emissions at a global (McKibbin, Pearce, & Stegman, 2007; Zhao & Du, 2015), national (Chiu, Hu, Jiang, Xie, & Ken, 2020; Lin, Liou, & Huang, 2011; Pao & Tsai, 2011; Sahin, 2019), or national macro-sector (Javed & Cudjoe, 2022; Kazancoglu, Ozbiltekin-Pala, & Ozkan-Ozen, 2021) scales. Other approaches apply multi-variate regressions, studying the correlations between multiple socio-economic, urbanization and energy variables and national emissions (Antanasijević, Ristić, Perić-Grujić, & Pocajt, 2014; Azizalrahman & Hasyimi, 2019; Fang, Zhang, Yu, Jin, & Tian, 2018; Ghalandari, Fard, Birjandi, & Mahariq, 2021; Nguyen, Huyn, & Nasir, 2021), as well as panel regression for estimating province level emissions (Carson & Auffhammer, 2008). All of these approaches have in common the exploitation of the dependency existing between national or provincial carbon dioxide emissions, economic activity, energy consumption and the overall energy system. Meanwhile, a common difficulty consists in the limited availability of data, with the exception of the latter (Carson & Auffhammer, 2008), which uses a specific Chinese provincial-level panel data set.

It is here stressed the uniqueness of the GCoM data set, containing a high level of detail for every signatory unit (which can be a city on its own or for some cases, a group of cities). Thus, under the GCoM initiative and its common reporting framework, cities declare their energy activity and their associated emissions. Relying solely on the declared emissions, robust estimates can be obtained after characterizing the process explaining the cities' emissions, while controlling the error of prediction.

Related to this proposal, an example can be found for a uni-variate approach to forecast emissions for developed countries (Qiao et al., 2020), using advanced optimization techniques to improve the performance of support vector machines. On the other hand, city-level studies can be found based on spatial modelling (Moran et al., 2022), disaggregating emissions at city-level from national reported emissions, or for road transport, estimating emissions by using data from the urban traffic control and monitoring systems (Pla et al., 2021), or even from bicycle usage applications (Cao & Shen, 2019). In contrast, our approach focuses on the uniqueness of the GCoM open data set, which contains the city-declared emissions inventories for different years. Hence, our approach develops directly from the declared inventories, rather than distributing national emissions into smaller administrative units (Moran et al., 2022).

Under this line of research, a related example can be found (Hsu, Wang, Tan, Toh, & Goyal, 2022), which predicts the GHG emissions for EU local administrative units based on Covenant data (Kona et al., 2021). There, emissions are estimated for a given year between 2001 and 2018, taking all relevant predictors at the same year (or the latest available year) of the emissions estimation. Then, in order to evaluate if cities are on track to their declared target, the observed per capita trend is used to linearly extrapolate, or forecast, the emissions for the target years.

In this same line, another previous effort in forecasting the emissions of cities in the Covenant community has been developed in Kona et al. (2018), where the reported trajectory or linear trend between the baseline and the last monitoring inventories of each city is extrapolated up to the target year. As in the previous example, this last effort did not control for the performance of the statistical extrapolation, but it will be replicated here (which will be referred to as method M2) in order to assess and control the robustness of the present proposal.

In this way, firstly, by following the LLKVO-V statistical process, and secondly, by choosing the best model from a battery of linear time series and non-linear neural network models, this proposal contributes to the statistical validation, as well as the machine learning body of knowledge on predictive methods for GHG emissions, in particular for cities committing to climate change mitigation (Milojevic-Dupont & Creutzig, 2021) and adaptation (Rolnick et al., 2023). The method presented here is compared against the benchmark, consisting in linearly extrapolating the observed/estimated trend, as done in Hsu et al. (2022), Kona et al. (2018), while testing other simple and rather direct techniques, such as taking the last reported value or adjusting that value by the emissions per capita national trend, aiming at also improving the benchmark's performance. As it will be shown, all of the proposed models out-perform the above mentioned benchmark.

Furthermore, it should be noted that the GCoM initiative attaches an inherent intention or structure to the data time series for each city, as there is a commitment to mitigate or decrease the emissions counting from the declared base year, which should be continued by the following monitoring inventories. Hence, the GCoM data set holds a very specific structure regarding the expected trend of the time series holding the energy activity and its associated GHG emissions. In this sense, the proposed methodology is set out to identify the expected trend and behaviour based only on the reported GHG emissions inventories of the cities, where each city follows its own pattern, depending on the implementation of its own action plan. This is the standing point for the present research.

In order to present the proposed methodology, the paper is structured as follows. Firstly, in Section 2, the GCoM data set is described in detail, introducing the GCoM reporting framework and the key information that is used to build the models. In Section 3, the complete statistical, machine learning methodology is explained, including the forecasting of target year emissions and the measurement of the prediction error. The former allow assessing the achievements and trajectories of the cities following their proposed action plans, while the former enables the measurement of the performance of the proposed models. In Section 4, the results are presented, focusing on the performance of the models, and in Section 5, a discussion is given, examining the estimated accomplishments of the cities, based on the previous results. Finally, in Section 6, some conclusions are given together with future lines of research.

2. Global Covenant of Mayors (GCoM) open data set

This Section introduces the common reporting framework which cities follow under the GCoM initiative. It allows to properly understand the nature and contents of the GHG emissions inventories, included in the first release for the open data set *GCoM-MyCovenant, 2021* (Baldi et al., 2021), feeding the proposed methodology for GHG emissions forecasting.

2.1. The GCoM initiative

The Covenant of Mayors initiative was launched by the European Commission in 2008, supporting cities to reduce GHG emissions by at least 20% by 2020. Later on, in 2015, a new target was set aiming at a 40% GHG emission reduction by 2030, also integrating the adaptation to climate change.

Nowadays, since 2017, the GCoM stands as the world's largest coalition of cities and local governments voluntarily committed to fight climate change, committed to reducing GHG emissions by at least 55% by 2030 and becoming climate neutral by 2050, also addressing energy poverty. It gathers thousands of cities of all sizes across 6 continents and more than 120 countries, representing almost 10% of the world's population (Melica et al., 2022).

The GCoM initiative follows a common reporting framework,[1] developed by a team of multi-disciplinary experts, considering local governments' needs as well as national and regional contexts. Such a framework is coherent with the Intergovernmental Panel on Climate Change (IPCC), as well as with the United Nations Framework Convention on Climate Change (UNFCCC), aiming at ensuring compatible and comparable reporting approaches for signatory cities worldwide.

Therefore, the GHG emissions inventories reported by cities at MyCovenant, which are available in the GCoM open data set (Baldi et al., 2021), include all the significant categories of emission sources within a previously defined inventory boundary. These emissions are relevant to the cities' local and regional situations, reflecting their specific activities, capacity and regulatory context (Melica et al., 2022).

2.2. GHG emissions at city level

Inside the GCoM reporting framework, cities report their relevant energy consumption activity and related emissions factors following either an IPCC or a Life-Cycle Analysis approach, allowing the automatic computation of the corresponding GHG emissions. Cities should account for emissions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), reported in metric tonnes of CO_2-equivalent (tCO_2-eq).

Hence, the reporting framework requires cities to report consumption activity data and emission factors for all sources of emissions, disaggregated by activity sector and fuel type. The reported data includes at least three main sectors, namely stationary energy, transportation, and waste, but cities are encouraged to also report the activity from industrial processes and product use, and agriculture, forestry and other land use. Additionally, cities report energy generation activities, which include emissions from generation of grid-supplied energy within the city boundary or by facilities owned (full or partial) by the local government outside the city boundary.

Consequently, cities present their action plans, which include a baseline emission inventory (BEI) for the baseline year. This is the reference against which the targeted emissions can be measured. Following the plan submission, cities should report a monitoring emission inventory (MEI), ideally every two years (Bertoldi, 2018), enabling to follow the performance of their proposed actions according to their declared ambitions.

[1] https://www.globalcovenantofmayors.org/our-initiatives/data4cities/common-global-reporting-framework/

Table 1
Summary of signatory cities by commitment, with the proportion of cities taking only mitigation or both mitigation and adaptation actions along with their mean GHG emissions reduction targets.

Commitment	Only mitigation	Mitigation & adaptation	Mean absolute target
2020	90%	10%	28%
2030	14%	86%	50%

Although monitoring GHG emissions inventories are expected to be submitted every two years, as already noted, cities have shown difficulties in compiling GHG inventories on a regular basis. Thus, the monitoring history of emissions for the GCoM cities is not complete, making it necessary to fill in the gaps of their associated yearly time series of emissions, as well as estimating the emissions for their respective target years. Hence, a robust methodology is needed for completing the yearly performance of the cities up to their target years, allowing to assess their estimated achievements.

In order to present and illustrate such a methodology, a case study is developed on 1950 individual signatory cities belonging to the EU-27, accounting for (approximately) 511.4 million tCO_2-eq ($MtCO_2$-eq), which measured in per capita terms, amounts to 5.5 tCO_2-eq per inhabitant. Fig. 1 shows the yearly frequencies of monitoring inventories performed by the cities, along with the corresponding population and emissions per capita (tCO_2-eq). It can be seen that the majority (19%) of all MEIs are performed in 2012, approximately representing a population of 26 million inhabitants and emitting 4.6 tCO_2-eq per capita.

On the other hand, 80% of the action plans considered in this study have only 1 MEI, 15% have 2 MEIs and the remaining 5% have 3 or more MEIs. Hence, the available information is rather incomplete, and the methodology is designed to cope with such a challenge. Namely, a sparse data series with incomplete and heterogeneous observation frequency.

In total, as shown in Table 1, there are 1786 cities with a commitment for 2020, against 315 with a 2030 commitment. For the former, they have a mean emissions reduction target of 28%, while for the latter, their mean reduction target is of 50%. At the same time, it can be seen that 90% of the signatories for 2020 include actions for mitigation only, against 10% including also actions for adaptation. As for 2030 commitments, the proportion changes, being more important the adaptation actions, where 14% of the signatories present mitigation actions only, against 86% of the cities which also include adaptation measures.

Next, the methodology for forecasting the cities' emissions will be explained, making it possible to assess the estimated achievements for the different cities in their corresponding target years.

3. Methodology

In this Section, the complete methodology is presented for the forecasting of GHG emissions. Firstly, the sparse data series have to be properly handled, being here completed according to the reported trajectory of each city. Then, a machine learning methodology is proposed based on linear and non-linear modelling of the uni-variate time series, selecting the best model according to the prediction error for the last known emissions value.

3.1. Missing value imputation

Focusing on the 1950 cities and local units of this study, the statistical methodology for estimating and forecasting the cities' emissions was accommodated to make use of all of the available inventories for each

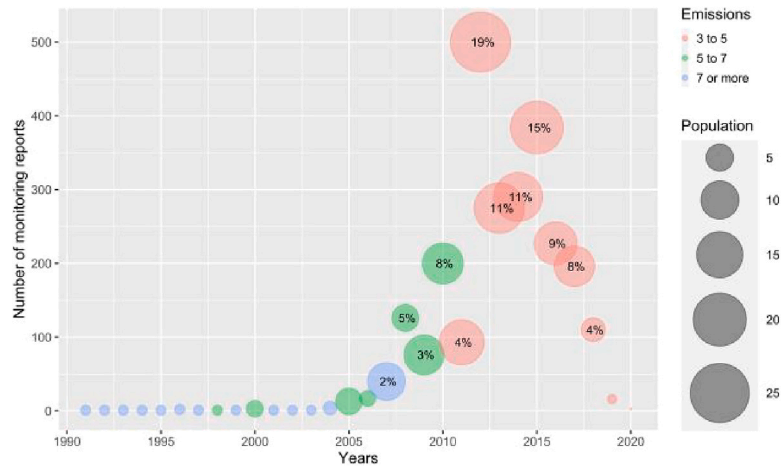


Fig. 1. Frequency of monitoring emissions inventories along with the population (millions) and emissions per capita (tCO2-eq) for every year.

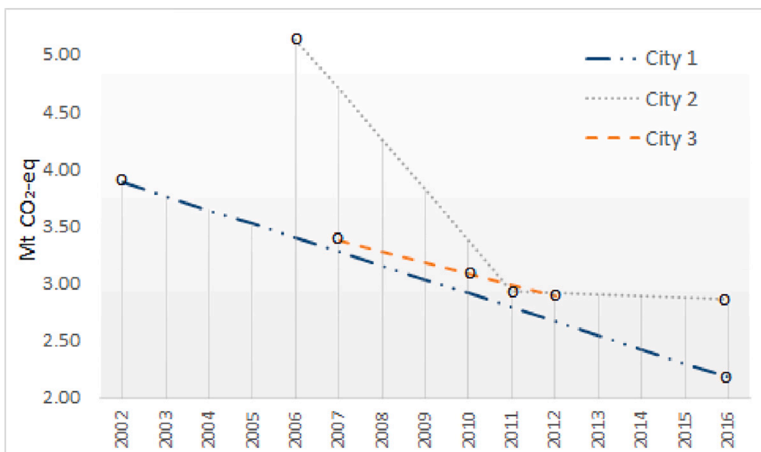


Fig. 2. Imputation of missing values following the linear trajectory in between the known-reported GHG emissions (o) values for three cities.

city. The methodology starts by building a yearly time series, which will then be modelled by statistical methods based on exponential smoothing, auto-regressive and moving average processes and artificial neural networks.

For each city, there is a *sparse* time series with a yearly frequency, being sparse because many years in between the base year and the last monitoring year have missing values. Besides, each city has its own series of an arbitrary length. In consequence, the missing observations in between the base and the last monitoring years will be imputed, building complete yearly time series on which the algorithms can learn the mechanism or function explaining their behaviour. This is done by continuing the linear trajectory between the years holding known emission values. See Fig. 2 for some examples on this data imputation task.

For each city, the base and monitoring years can be any year in between 1990 (1991 for monitoring) and 2020. For the base year the majority of cities chose 2005, and for the monitoring the majority chose 2012 (see again Fig. 1). In between those two specific references, cities reported their MEIs an arbitrary number of times (as already mentioned, 80% of cities considered in this study reported just 1 MEI), following their own trend in the generation of GHG emissions that should correspond with their efforts in their declared ambitions and the implementation of the action plan.

For the majority of cities having only one MEI, the result of the imputation is a line joining two points which may have a positive or negative trend (see City 1 in Fig. 2). For the rest of the cities having more than one MEI, some of them may have a smooth trajectory, confirmed by their MEIs (see City 3 in Fig. 2), while others may have a more complex behaviour (see City 2 in Fig. 2), depending on the year of implementation of the proposed actions and the context to which they belong.

Once a complete time series is obtained for every city, it can be modelled after different statistical methods. As a result, one model will be chosen according to the minimum error of prediction, computed for the last known emission value reported by each city.

3.2. Machine learning methodology

Following the imputation of the data, each city has a complete yearly uni-variate time series initiating and ending on any arbitrary years in between 1990 and 2020. This is the input for characterizing the series' behaviour, selecting the best model from three different approaches, namely Double Exponential Smoothing (DES), Auto-Regressive Integrated Moving Averages (ARIMA) and Auto-Regressive Artificial Neural Networks (AR-ANN).

Firstly, following a Double Exponential Smoothing (DES) (Box, Jenkins, Reinsel, & Ljung, 2016; Winters, 1960) approach, the level and the trend of the series is characterized according to

$$\hat{y}_{t+1} = L_t + T_t, \tag{1}$$

where $\hat{y}_{t+1}$ is the estimated emissions value for the year $t+1$, and L_t and T_t stand for the smoothed level and trend of the time series, respectively. In this way,

$$L_t = \hat{y}_t + \alpha(y_t - \hat{y}_t) \tag{2}$$

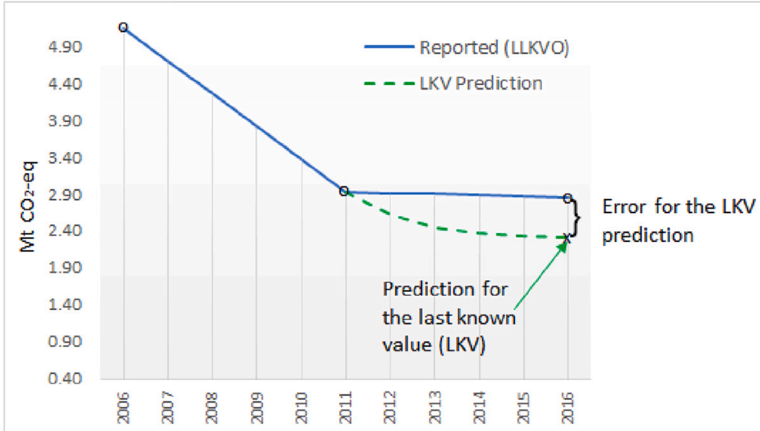


Fig. 3. Last known value (LKV) prediction error. Reported values are marked in (o) and the prediction in (x). This example corresponds to a neural network with 5 neurons and 3 lagged observations as input.

and

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)(T_{t-1}). \tag{3}$$

The best DES model, with optimal values for α and β, is chosen for each time series by minimizing the one period ahead squared prediction error.

Secondly, the Auto-Regressive Integrated Moving Average process (Box et al., 2016), commonly known as an ARIMA(p,d,q), allows implementing linear filters to characterize the series, in the form of

$$\hat{y}'_t = Z_t + \sum_{j=1}^{p} \phi_j y'_{t-j} + \sum_{j=1}^{q} \theta_j Z_{t-j}, \tag{4}$$

where y' stands for the differentiated series to the order of d, and p and q respectively stand for the number of lagged observations and the number of standard-normal innovations to include in the process. It should be noted that for the ARIMA models to be selected, they had to pass the validation against the Ljung–Box test (see again Box et al. 2016), checking that no significant correlation among the residuals was left unexplained.

The best ARIMA(p,d,q) model fitting the time series is selected after obtaining the maximum likelihood function value (L^*) and minimizing the Akaike Information Criterion (AIC), given by

$$AIC = L^* + 2k, \tag{5}$$

where k is the number of free parameters to estimate.

The third and last approach to modelling the yearly time series consisted in an auto-regressive feed-forward neural network with one hidden layer, allowing to estimate any non-linear function with a fair level of complexity (Hornik, Stinchcombe, & White, 1989). Here it should be noted that the predictive methods should not be, at first hand, very complex, due to the rather simple process that the cities' emissions describe throughout time, being non-cyclical but holding a smoothed trend and level. The resulting model can be expressed as

$$\hat{y}_t = f(\mathbf{y}_{t-1}) + \varepsilon_t, \tag{6}$$

where f is a non-linear function built from the neural network with h hidden units (or neurons) in its hidden layer, and $\mathbf{y}_{t-1} = (y_t, \ldots, y_{t-p}$ is a vector containing the lagged values of the time series. The activation function for each hidden unit consists in the sigmoid function, while the output unit is equipped with a linear activation.

The AR-ANN architecture is examined with a number of 3, 5, 7 or 10 hidden decision units in its single hidden layer, receiving as input from 1 to 5 lagged observations (depending on the available data). Meanwhile, its best configuration for weights and biases is chosen by minimizing the one period ahead squared prediction error.

3.3. Leave Last Known Value Out - Validation (LLKVO-V)

After identifying the best DES, ARIMA and ANN models for each city (i), a unique model is chosen according to the minimum error ($error_i$) for the predicted value ($\hat{y}_{it}$), computed over the last known emission value (y^*_{it}). The latter consists in the emission value coming from the city's last monitoring report. Thus, the *Last Known Value (LKV)* prediction error is computed for each city, as in

$$error_i = \frac{|\hat{y}_{it} - y^*_{it}|}{y^*_{it}} \tag{7}$$

The illustration for the measurement of Eq. (7) is shown in Fig. 3.

Therefore, a Leave Last Known Value Out-Validation (LLKVO-V) process is here developed, and the best model is selected according to the minimum prediction error. Finally, the complete time series is fitted again under the same functional form of the best model, obtaining the corresponding GHG emissions estimates for the committed target year (as shown in Fig. 4).

The proposed machine learning (ML) methodology is compared against other more direct methods, which allow extracting a concrete insight on the applied performance of the chosen models. A first method (M1) takes directly the last known value for the prediction. A second method (M2) continues the linear trend between the base and the last monitoring inventory (as done in Kona et al. 2018), and a third method (M3) adjusts the last known value according to the national per capita linear trend.

4. Results

4.1. Statistical methodology and predictive methods

The statistical methodology is applied over the cities included in the case study, computing the LKV prediction error over all the cities holding at least 2 MEIs, which is required to properly measure the LKV prediction error among the different methods, namely ML, M1, M2 and M3. The overall results are presented in Table 2, comparing the models' performance. As a result, the ML methodology outperforms in terms of the mean LKV-prediction error all other methods for 2020 commitments, while M3 obtains the best mean performance for 2030 commitments, showing that the national per capita trend proves to be a good indicator of the evolution of the cities' GHG emissions.

Overall, for 2020, ML accomplishes a minimum mean error of 0.196, followed by M3 with 0.199. Meanwhile, for 2030, M3 achieves 0.145, followed by ML with 0.152. Therefore, both ML and M3 methods are shown to achieve similar LKV prediction errors, showing that not only the cities' reported emissions history, but also the national per

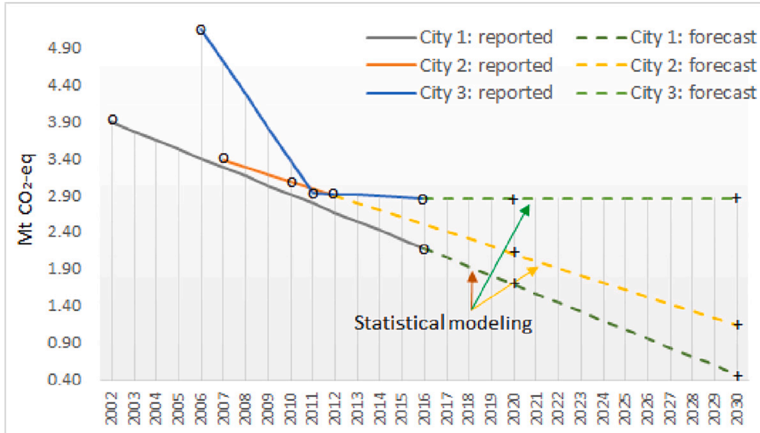


Fig. 4. Forecast for the GHG emissions values for three cities with 2020 and 2030 commitments. The forecasts (dotted lines) follow the models based on the known data (o), forecasting for 2020 and 2030 (+).

Table 2
The summary for the mean LKV prediction error for the statistical (ML), last known value (M1), linear trend (M2) and national adjustment (M3) methodologies.

Commitment	ML	M1	M2	M3
2020	0.196	0.222	0.339	0.199
2030	0.152	0.181	0.222	0.145

capita trend, offer relevant information to estimate the cities' GHG emissions for their target years.

On the other hand, the worst performing method consists in M2, which continues the signatory's linear trend between its base and last monitoring inventory. The evidence gathered in this case study discourages the use of M2, being there other techniques, like ML or M3 (or even M1, which is shown to be better than M2), which show higher reliability for predicting the cities' GHG emissions, also allowing a more robust assessment of the cities' GHG emissions reduction achievements.

4.2. Validation results by city size and by country

The behaviour of the predictive methods can be examined by country and by city size. Table 3 presents the summary of the cities' performance in terms of the average LKV prediction error by country, for the five most frequent countries and all the others. Likewise, Table 4 presents the summary by city size, classified as small, medium or big cities, depending if their population is lower than 50000, in between 50000 and 200000, or higher than 200000, respectively. The results confirm the previous claim, where in general, ML and M3 obtain better performances (lower LKV prediction errors), followed by M1, and in last place M2.

In particular, a very similar performance between ML and M1 or M3 can be observed for some countries, like e.g. 2020 commitments for Italy, Belgium or Germany. Or between ML and M3, for 2030 commitments in Spain or Italy. It is also interesting to see that M1 outperforms all other methods for 2020 commitments in Belgium or for 2030 commitments in Latvia. Examining the maximum error by country, ML and M3 achieve a maximum LKV prediction error of 0.32, followed by M1 with 0.46, and lastly by M2, with 2.78. This confirms that M2 does not seem to be a reliable technique to predict the expected performance of the cities' GHG emissions, and that ML and M3 are the most robust methods among the alternatives considered in this study. Such a conclusion is confirmed after the results by city size, where ML is the best method for all 2020 commitments (small, medium and big cities), and for small cities with 2030 commitments. On the contrary, M3 outperforms ML for both medium and big cities with 2030 commitments.

Table 3
Summary for the mean LKV prediction error for the four statistical methods, by commitment and country.

Commitment	Country (frequency %)	ML	M1	M2	M3
2020	Italy (42%)	0.184	0.199	0.245	0.19
	Spain (22%)	0.324	0.368	0.559	0.321
	Belgium (11%)	0.109	0.101	0.14	0.096
	Sweden (4%)	0.285	0.462	0.636	0.273
	Germany (3%)	0.122	0.132	0.118	0.114
	Other (18%)	0.104	0.126	0.366	0.107
2030	Spain (37%)	0.145	0.205	0.212	0.153
	Italy (27%)	0.166	0.204	0.21	0.147
	Belgium (10%)	0.136	0.177	0.234	0.165
	Finland (7%)	0.289	0.248	0.33	0.204
	Latvia (4%)	0.154	0.07	0.305	0.103
	Other (15%)	0.077	0.073	0.188	0.072

Table 4
Summary for the mean LKV prediction error for the four statistical methods, by commitment and size of the city.

Commitment	Size (frequency %)	ML	M1	M2	M3
2020	Small (73%)	0.222	0.245	0.355	0.224
	Medium (14%)	0.115	0.143	0.377	0.122
	Big (13%)	0.138	0.178	0.205	0.146
2030	Small (54%)	0.145	0.196	0.206	0.158
	Medium (25%)	0.174	0.177	0.247	0.160
	Big (21%)	0.145	0.151	0.231	0.094

It can be conjectured that, without implementing any actions on their own, medium and big cities are more likely to behave according to the national trend, following the predictions of the M3 method. But, more importantly, once the cities have enough time to successfully implement their proposed set of actions, then they are expected to find a path of their own, distancing from the national trajectory to achieve greater GHG emissions reductions. Hence, allowing more time for cities to implement their action plans, the ML models should be able to predict more accurately the performance of each individual city. This conjecture is supported by the fact that ML outperforms all other methods for 2020 commitments, once cities have already had enough time to implement their action plans.

4.3. Validation results per ML model

Examining in greater detail the ML results by commitment, for 2020 commitments, 51% of the cities emissions behaviour was characterized by a neural network using more than 2 lagged observations (NN_{345}), 23% was modelled by an ARIMA, 17% by a DES and the remaining 9%

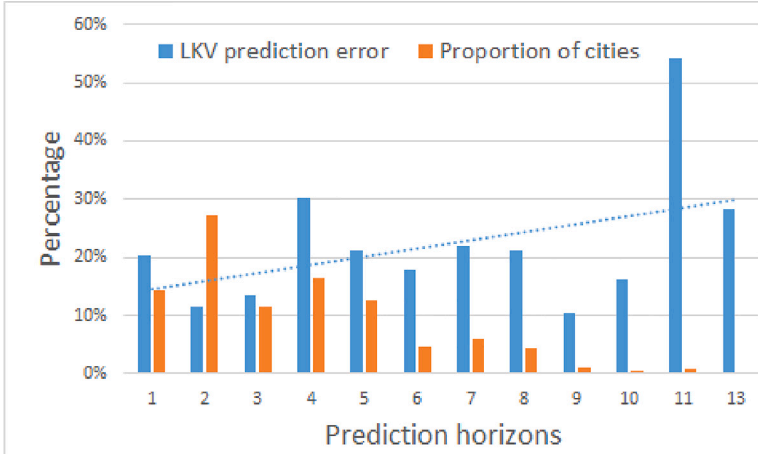


Fig. 5. For all the cities, the summary of the LKV prediction error by horizon and the proportion of cities with each horizon.

Table 5
The summary for the mean LKV prediction error for the ML methodology's modelling techniques.

Commitment	ARIMA	DES	NN_1	NN_2	NN_{345}
2020	0.137	0.158	0.055	0.038	0.262
2030	0.172	0.203	NA	0.053	0.139

Table 6
The summary for the mean LKV estimation error for the ML methodology's modelling techniques.

Commitment	ARIMA	DES	NN_1	NN_2	NN_{345}
2020	0.02	0.008	0.009	0.001	0.01
2030	0.04	6e−17	NA	2e−5	0.009

by a neural network using 1 (NN_1) or 2 (NN_2) lagged observations. On the other hand, for 2030 commitments, 58% was characterized by a neural network with more than 2 lags, 15% by an ARIMA, 21% by a DES, and the remaining 6% by a neural network using 2 (NN_2) lagged observations. The corresponding mean LKV prediction errors can be seen in Table 5, taking into account that the errors reported in Tables 2–5, in fact refer to heterogeneous forecasting horizons, depending on the number of years in between the next to last and the last monitoring years for each city (see Fig. 5 for a summary on the LKV prediction error for the different forecasting horizons).

Examining Fig. 5, it can be seen that the majority of cities (82%) have a forecasting horizon of 1 to 5 years, being the most frequent one the horizon of 2 years ahead (the case for 27% of the cities). Regarding the mean LKV prediction error, the highest error corresponds with the horizon of 11 years ahead (an error of 0.54, which amounts to a 54% deviation, according to Eq. (7), with respect to the known-observed value). Very few cities are in this situation (0.9%), and only one city has the greatest horizon of 13 years ahead, which achieves a 0.28 LKV prediction error. On the other hand, the horizons achieving better results are with 2, 3 and 9 years ahead, having a mean error of 0.11, 0.13, and 0.1, respectively, and in total, holding 40% of all the cities. In consequence, as expected, a general increasing trend (dotted line in Fig. 5) can be inferred between the size of the forecasting horizon and the LKV prediction error.

It should be noted that the some unusually high errors are due to very particular cases. For example, a city that has reported a last MEI with a very high emissions reduction with respect to the previous MEI, without any previous decreasing tendency. Then, the LKV prediction error of the ML method can only be very high. In fact, it would be relatively as high as the reduction accomplished by the city after successfully implementing its proposed action plan. Nonetheless, it can be claimed that the prediction error is expected to diminish after feeding the complete time series to the final forecasting model.

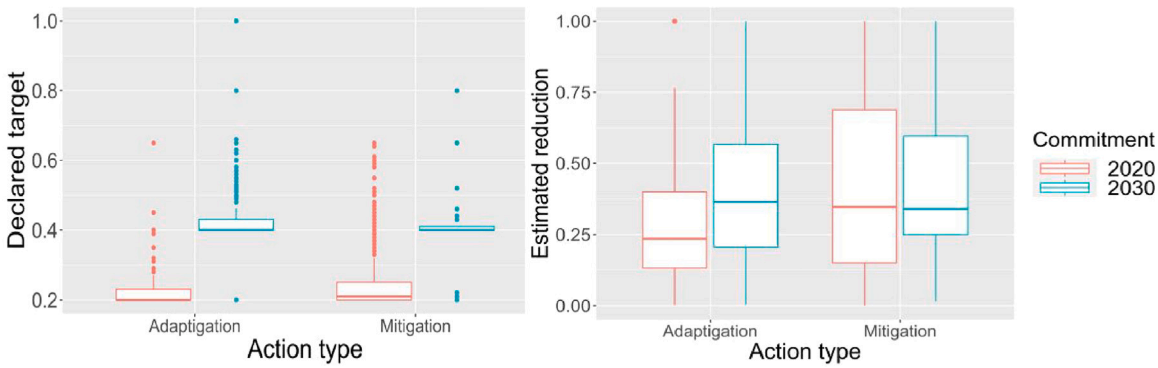
In this sense, supporting the above mentioned claim, it is possible to look at the estimation error once the complete time series is fitted with the best performing model according to the LLKVO-V process. This LKV estimation error is computed according to Eq. (7), taking y^*_{it} as the last known value of the complete series and $\hat{y}_{it}$ as its estimation (given the complete series up until y_{it-1}). Hence, the ML mean training error amounts to 0.0132 and 0.0128 for 2020 and 2030 commitments, respectively, supporting the claim that the estimation error should diminish after fitting the forecasting model with the complete series (see Table 6 for the complete summary of the mean LKV estimation error for each one of the ML modelling techniques).

5. Discussion

Based on the results presented in Section 4, the ML method is validated as the best alternative to evaluate the cities' expected achievements for their committed ambitions (see (Melica et al., 2022) for a detailed report with the key findings after the implementation of the proposed methodology on the GCoM data set). Table 7 presents the achieved reduction for the cities included in this case study, by commitment and type of actions (addressing mitigation and/or adaptation), and comparing them with their declared target together with the overall rate of success.

Considering 2020 commitments, cities implementing only actions for GHG emissions reduction achieved an overall reduction of 30% against a 26% for cities implementing both mitigation and adaptation to climate change actions (from now on referred to as *adaptigation*). In consequence, for the former (mitigation) there is a 50% rate of success to achieve their declared target, while for the latter (adaptigation), the rate decreases to 48%. On the contrary, such a rate increases from mitigation to adaptigation for 2030 commitments, where cities implementing only actions for mitigation have a 30% rate of success against a 32% rate for cities implementing adaptigation actions. Although, in this last case of 2030 commitments, the expected reduction for cities implementing mitigation actions is higher than the one for cities implementing adaptigation actions.

Taking a closer look over the cities which are expected to achieve a positive estimated reduction, Fig. 6 presents the distribution around the median of their targets and emissions reduction, by commitment and for mitigation and adaptigation types of actions. From a first standing point, for both types of actions, the median targets for 2020 and 2030 commitments are close to 20% and 40%, respectively (as shown in Fig. 6(a)). Thus, there is an important difference between the ambitions



(a) (b)

Fig. 6. Distribution over the median by 2020 and 2030 commitments and by type of action, mitigation or adaptigation, for (a) targeted reductions and (b) estimated/predicted reduction to be accomplished.

Table 7
Summary of signatory cities' target, expected reduction and rate of success by commitment and plan's approach to climate change.

Commitment	Declared target	Expected reduction	Rate of success
2020 — Mitigation	27.7%	30%	50%
2020 — Adaptigation	27.1%	26%	48%
2030 — Mitigation	49%	42%	30%
2030 — Adaptigation	50%	40%	32%

signed by the cities, being much more ambitious for 2030 than for 2020 commitments (in fact, this is a mandatory requirement for the Covenant community). Now, looking at the estimated reduction (see Fig. 6(b)), such a difference significantly diminishes, more so for cities taking only mitigation actions than for the ones taking adaptigation actions. For the former (mitigation), the median reduction is 34%. As for the latter (adaptigation), the median reduction for 2020 commitments is 24%, while for 2030 commitments is 36%. Having in mind that cities committed to 2030 still have to implement their actions until the upcoming deadline, and that only 10% of the cities take adaptigation actions in 2020 compared to the 86% of 2030, as presented in Table 1, it is an interesting insight to consider that cities undertaking adaptigation actions are taking the lead for accomplishing a significative reduction of their GHG emissions.

Lastly, it should be pointed out that adaptigation actions are more complex to implement as well as to measure in their final outcome. In this way, adaptigation to climate change aims not only at reducing GHG emissions. Rather, it considers a multi-dimensional strategy regarding vulnerabilities, exposure and hazards, where GHG emissions reduction should be an associated outcome of following the city's strategy to minimize the overall risk presented by climate change (Pour, Wahab, Shahid, Asaduzzaman, & Dewan, 2020).

6. Conclusions

A robust methodology, named LLKVO-V, has been proposed to estimate GHG emissions of cities committed to mitigation and adaptation of climate change. As a result, the proposed methodology allows controlling the uncertainty associated to the estimations, extracting reliable information pending the submission of the actual data from the signatory cities.

In this sense, it is stressed that the performance of the models is completely dependent on the data reported by the cities. Meanwhile, the LKV prediction error allows controlling for the uncertainty in the estimations, and once the cities monitor and report their advances, such an uncertainty is expected to be reduced under the ML approach.

In consequence, in the absence of monitoring reports, the national emissions per capita trend seems to be, by itself, a good predictor of the cities future achievements. On the contrary, once the cities report updated emissions inventories and advance in the implementation of their action plans, the ML methods present more competitive results and are expected to increase their accuracy as more data from the cities become available.

The reliable forecast of GHG emissions allows identifying which cities achieve the greatest achievements and which ones require close attention for timely support. Thus, it allows a timely feedback for them to act upon their specific needs to have a successful action plan that allows meeting the committed targets.

For future research, it remains to extend the proposed methodology to also cover cities with only one BEI (and no MEI). This could be accomplished by taking other information as input for regression models, more specific to their complete action plans, as well as their socio-economic and policy contexts.

Disclaimer

M.G.B. is a consultant for JRC-European Commission. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://data.jrc.ec.europa.eu/dataset/86ec3e42-f8e1-4cdb-a953-d396251d2029

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