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Hourly accounting of carbon emissions from electricity consumption

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Abstract

Carbon accounting is important for quantifying the sources of greenhouse gas (GHG) emissions that are driving climate change, and is increasingly being used to guide policy, investment, business, and regulatory decisions. The current practice for accounting emissions from consumed electricity, guided by standards like the GHG protocol, uses annual-average grid emission factors, although previous studies have shown that grid carbon intensity varies across seasons and hours of the day. Previous case studies have shown that annual-average carbon accounting can bias emission inventories, but none have shown that this bias is substantial or widespread. This study addresses this gap by calculating emission inventories for thousands of residential, commercial, industrial, and agricultural facilities across the US, and explores the magnitude and direction of this bias compared to hourly accounting of emissions. Our results show that annual-average accounting can over- or under-estimate carbon inventories as much as 35% in certain settings but result in effectively no bias in others. Bias will be greater in regions with high variation in carbon intensity, and for end-users with high variation in their electricity consumption across hours and seasons. As variation in carbon intensity continues to grow with growing shares of variable and intermittent renewable generation, these biases will only continue to worsen in the future. In most cases, using monthly-average emission factors does not substantially reduce bias compared to annual averages. Thus, the authors recommend that hourly accounting be adopted as the best practice for emissions inventories of consumed electricity.

1. Introduction

Greenhouse gas (GHG) emissions from electricity generation are a significant contributor to climate change and can comprise a large share of the carbon footprint of an individual activity, product, building, company, or city. Accounting and attributing these emissions to specific end-users of the electricity is a common practice and important tool to help understand the sources of climate-changing emissions and enable action to mitigate them. Once limited to academic life-cycle assessment studies and voluntary carbon disclosure initiatives, carbon accounting and disclosure is increasingly being used to guide financial investments, inform policymaking and business decisions, and measure compliance with regulations.

Current GHG accounting protocols account for 'scope 2' emissions (those associated with the consumption of grid electricity) by applying an annual-average, attributional grid carbon intensity factor to all electricity consumed by an entity each year. This annual-level accounting represents the carbon intensity of grid-supplied electricity as a single, static value throughout the year. However, because the mix of generators supplying electricity to the grid is constantly changing, grid carbon intensity also varies across seasons and the hours of each day [1–20]. While there are benefits to the simplicity of annual-level accounting, ignoring this hourly heterogeneity

may come at the cost of accuracy, which can have real effects both on academic analyses and the effectiveness of our policies in curbing climate change [16]. However, it is unclear from previous studies whether this potential bias is a substantial or widespread problem. Existing studies, primarily in the field of life-cycle assessment, focus on specific building GHG inventories as case studies, demonstrating that annual accounting may bias emission inventories anywhere between 0.2% and 26% when compared to hourly accounting, as summarized in table 1 [3, 5–8, 17, 21, 22][4].

To understand whether annual accounting leads to widespread bias in emission inventories, this study calculates scope 2 GHG emission inventories for approximately 113 000 simulated residential and commercial buildings in 52 grid balancing areas (BAs) across the United States, using annual-average, monthly-average, monthly time-of-day (TOD) average, and hourly grid emission factors. We also examine a specific case study of a high-renewable region in California, utilizing a dataset of actual metered load representing over 13 million residential, commercial, industrial, and agricultural facilities in the state. Our results suggest that the magnitude and direction of the bias introduced by annual accounting depend on when and how you consume electricity and where you are located: specifically, activities with more variable electric demand located in grids dominated by clean and renewable energy will see a larger relative bias from annual accounting than activities with flat demand in grids dominated by traditional fossil generation. We also find that these biases can only be meaningfully reduced by using emission factors that reflect both the seasonal and TOD variation in grid carbon intensity.

2. Background

The carbon intensity of the grid can vary continuously in response to changes in generation at the minute or second timescale. Thus, even hourly emission factors may not capture the full variability in grid carbon intensity. Indeed, some previous studies evaluating the variability of grid carbon intensity have utilized half-hourly or quarter-hourly emission factors [10–12, 22]. However, in this study, we use hourly-average carbon intensities as the baseline rather than sub-hourly values, first because hourly grid data is more widely available than sub-hourly data, and second due to the relatively low variation

in grid carbon intensity within a single hour. Previous studies note that the variability of wind and solar power, which contribute to the variability of grid carbon intensity, is much less at the hour or shorter timescale than it is across several hours or days [23]. We confirmed this by analyzing a dataset of 5 min resolution carbon emissions data published by the California independent system operator (ISO), finding that even in this renewable-heavy region, the mean coefficient of variation of grid carbon intensity within a single hour was only 2.4%, compared to 31% across the entire year.

Because we calculate actual carbon emissions as the product of hourly energy demand (D_h) and the hourly regional carbon intensity ($C_{r,h}$), the bias resulting from using an averaged carbon intensity value ($\bar{C}_{r,h,l}$) at some aggregation level l is the product of the hourly energy demand and the residual carbon intensity ($\mu_{r,h,l} = \bar{C}_{r,h,l} - C_{r,h}$). Thus, the expected bias introduced into an annual inventory by using an averaged carbon intensity value can also be expressed as the following equation (see the supplementary information [SI] for a full derivation available online at stacks.iop.org/ERL/17/044073/mmedia):

$$E[D_h \cdot \mu_{r,h,l}] = \text{Cov}(D_{b,h}, \mu_{r,h,l}) = \sigma_D \cdot \sigma_\mu \cdot \rho_{D,\mu}. \tag{1}$$
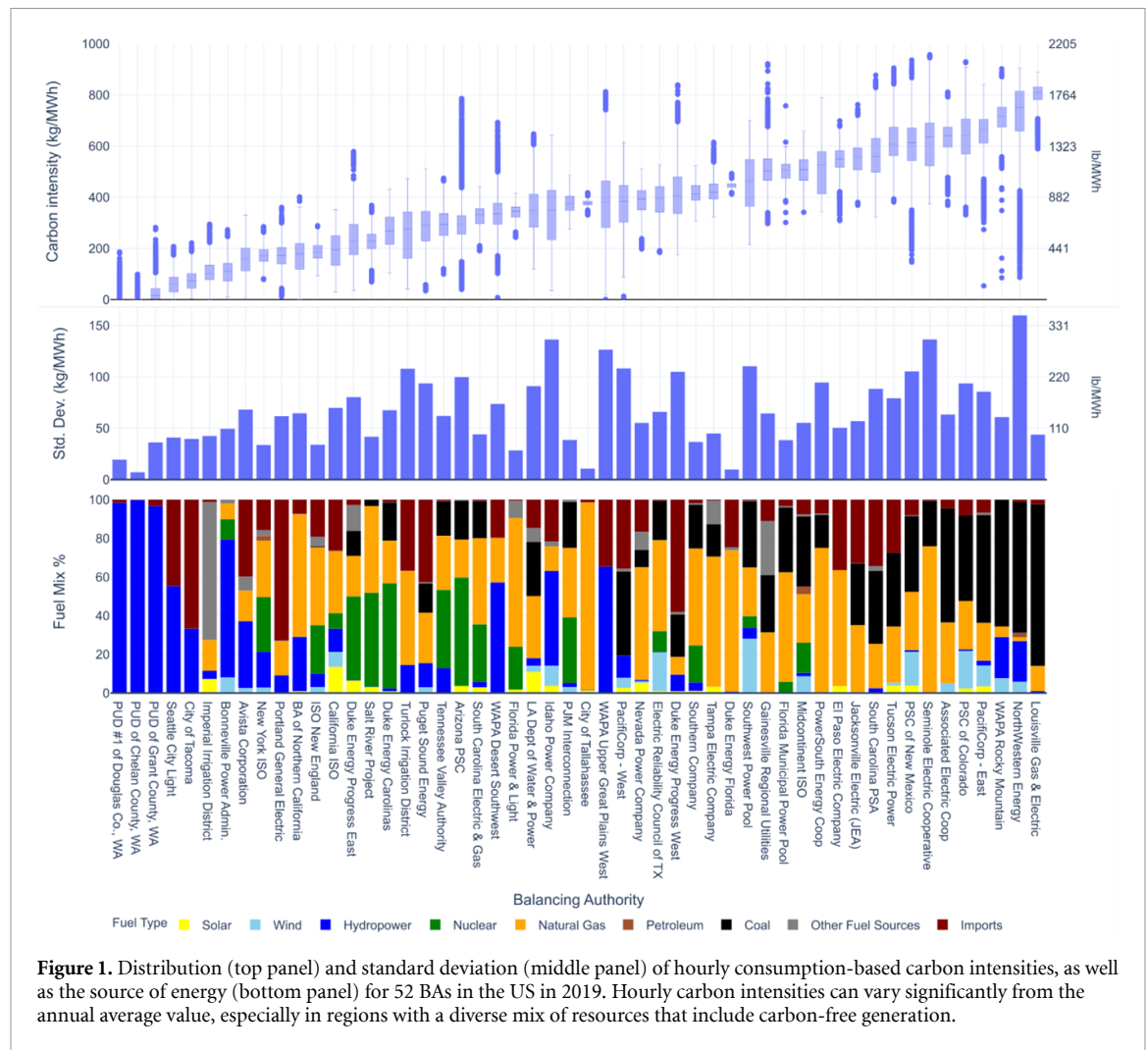
In this equation, σ_D is the standard deviation of hourly energy demand, σ_μ is the standard deviation of the residual hourly carbon intensity, and $\rho_{D,\mu}$ is the correlation coefficient between hourly energy demand and the residual hourly carbon intensity. This relationship suggests that the magnitude and direction of bias is driven by the variability in both carbon intensity and energy demand, as well as the correlation between demand and carbon intensity, and it has three important implications. First, in regions with substantial variation in hourly emissions rates (high σ_μ), there is a potential for larger bias, and vice versa. Second, end-uses of electricity with sizable hourly variation in energy demand (high σ_D) would expect to see larger biases than an end-use with flat energy demand. Finally, the sign of the bias (whether the inventory is over- or under-estimated) will depend on the sign of the correlation coefficient between demand and the residual carbon intensity ($\rho_{D,\mu}$). An end-use whose demand is correlated with times of high carbon intensity (and is thus negatively correlated with the residual carbon intensity), will have their emissions under-estimated by using an averaged carbon intensity value.

As shown in figure 1, hourly consumption-based carbon intensities in certain regions can be highly variable throughout the year, depending on the fuel mix of generated and imported electricity consumed in the region. While production-based carbon intensities only reflect emissions from generators that operate within each region, consumption-based carbon

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[4] A separate body of literature has focused on comparing the accuracy of using of average, attributional emission factors to marginal, consequential emission factors for quantifying the avoided emissions of grid interventions. However, it is important to note that marginal emission factors are not appropriate for use in attributional carbon footprinting and are thus not relevant to this paper.

Table 1. Summary of literature evaluating bias resulting from annual carbon accounting. Bias calculations have been standardized using [(annual − hourly)/hourly] for all papers. The carbon intensity types are defined as: produced: emissions per unit electricity generated, delivered: emissions per unit electricity consumed, not accounting for imports/exports of emissions, consumed: emissions per unit electricity consumed, accounting for imports/exports of emissions, direct: only considers combustion emissions from the generator, lifecycle: considers direct and indirect emissions (e.g. mining and transport of fuels) from the generator.

Paper	Geography	Data years	Temporal resolutions analyzed	Carbon intensity type	Case study	Electric demand data	Bias due to annual accounting
Bristow et al [3]	Ontario, Canada	2007	Annual hourly	Produced direct	Mid-rise residential building with 5 efficiency scenarios	Simulated, single building	−3.5% to +0.2%
Cubi et al [5]	Alberta and Ontario, Canada	2011, 2013	Hourly	Produced direct	Office and residential buildings with different efficiency variations	Simulated, two reference building types in two regions, with 6 efficiency variants (36 simulations)	−11% to +6% (one outlier at −44%)
Kopsakangas-Savolainen et al [21]	Finland	2011	Annual hourly	Produced lifecycle	Two residential buildings in Helsinki	Metered data, two buildings	+1% and +6%
Spork et al [6]	Spain	2012	Annual hourly	Delivered lifecycle	Generic commercial buildings with constant high load during operating hours and constant low load during non-operating hours	Synthetic data, 15 operating hour scenarios and different high to low demand ratios	−5% to +3% (special cases at −6% and −8%)
Roux et al [7]	France	2013	Annual hourly	Delivered lifecycle	Single family research house in Chambery, France	Metered data, single building	−26%
Vuarnoz and Jusselme [8]	Switzerland	2015	Annual hourly	Consumed lifecycle	Proposed mix-use building in Fribourg, Switzerland	Simulated, single building	+1.9%
Donti et al [17]	PJM Inter-connection, US	2017	Annual monthly monthly TOD hourly	Produced direct	Systemwide summer load in PJM	Measured data, aggregate region demand	Underestimated, numerical value not reported
Müller and Wörner [22]	Germany	2017, 2030, 2050	Annual quarter-hourly	Delivered lifecycle	Use phase of residential single-family home	Simulated, single building	−4.2% (2017) −7.7% (2030) −17.9% (2050)

Figure 1. Distribution (top panel) and standard deviation (middle panel) of hourly consumption-based carbon intensities, as well as the source of energy (bottom panel) for 52 BAs in the US in 2019. Hourly carbon intensities can vary significantly from the annual average value, especially in regions with a diverse mix of resources that include carbon-free generation.

intensities reflect emissions from electricity imported into a region as well. Because imported electricity represents a substantial portion of consumed electricity in many regions and can have a carbon intensity that differs from that of in-region generation, this paper focuses on consumption-based carbon intensity throughout.

3. Data and methods

This study examines carbon inventories for thousands of building load profiles across the United States at different temporal resolutions. To demonstrate the impact that the intra-regional variability in carbon intensity has on the magnitude and direction of the bias resulting from annual-average accounting, this study first examines annual and hourly inventories for approximately 113 000 simulated residential and commercial buildings across different climate zones in 52 different grid regions in the US. Then, to demonstrate the impact that variability in electricity demand profiles has on this bias, this study examines inventories for thousands of residential, commercial, industrial, and agricultural building profiles located within the California Independent System Operator (CAISO). Finally, we explore how well the use of

monthly and monthly TOD average carbon intensity values mitigates the inventory bias compared to using an annual average.

3.1. Hourly building demand data

Although as of 2019, over 60% of all electric meters nationwide included advanced metering infrastructure (AMI), which collect hourly or sub-hourly electricity demand data, wide-scale hourly demand datasets are not publicly available due to privacy concerns [24, 25].

However, the National Renewable Energy Laboratory (NREL) recently published a dataset of approximately 900 000 simulated end-use load profiles which have been calibrated and validated using actual meter data and statistically represent the US residential and commercial building stock [26, 27]. Each of the 14 unique commercial building types and nine unique residential building types (summarized in the SI) are represented by individual building variants with different combinations of physical and operational characteristics that affect the load profile. To keep the volume of data computationally manageable while representing the diversity of actual load profiles that would be found in each grid region, we select a stratified random sample of 10% of the buildings of

each type located in each climate zone in each grid region, resulting in a sample of 112 717 unique load profiles.

However, the NREL dataset does not include load profiles for agricultural, industrial, and certain common commercial (e.g. data center) end uses. Thus, for our California ISO case study that examines the impact of different building load profiles on bias, we utilize a dataset from Lawrence Berkeley National Lab (LBNL). This LBNL dataset contains actual hourly AMI data representing over 13.1 million individual residential, commercial, industrial, and agricultural electricity customers (aggregated into 2766 building profiles) across the three major investor-owned utility territories in the California ISO territory (see SI for details) [28]. The choice of CAISO as a case study is also useful because the region is on the vanguard of renewable energy deployment and may be more representative of the carbon intensity variability of more and more grids as the energy transition continues.

3.2. Grid carbon intensity data
We source hourly average, consumption-based emission factors for each grid BA in the US from Carbonara, a carbon analytics platform developed by Singularity Energy [29]. This study utilizes carbon intensity values for 53 of the 75 grid BAs in the United States, which represent a spatial resolution that reflect actual power system boundaries and operations [30, 31]. To calculate its production-based emission estimates, Singularity uses data on hourly net generation by fuel type for each BA from the U.S. Energy Information Administration's (EIA) Form 930, and multiplies it by the fuel-specific, annual-average, adjusted CO_2 output emission rate for that BA, from the U.S. Environmental Protection Agency's (EPA) eGRID2019 database [32]. To calculate consumption-based emissions, which account for imports and exports of electricity between BAs, they solve a multi-region input–output model which utilizes hourly BA-to-BA net interchange data from EIA-930 [16]. Using these hourly values, we then calculate annual, monthly, and monthly TOD averages.

3.3. Carbon inventory methodology
A carbon inventory I for each building b in each grid region r is calculated by summing the product of the building's hourly electricity demand D and the actual hourly grid carbon intensity C at each temporal aggregation level for each hour h in year:

$$I_{b,r} = \sum_{h=1}^{8760} D_{b,h} \cdot C_{r,h}. \tag{2}$$

An estimated carbon inventory $\bar{I}$ is then calculated in the same manner, but using an averaged grid carbon intensity $\bar{C}$, which can have one of three levels of temporal aggregation l (annual, monthly, or monthly TOD):

$$\bar{I}_{b,r,l} = \sum_{h=1}^{8760} D_{b,h} \cdot \bar{C}_{r,h,l}. \tag{3}$$

The relative carbon inventory bias from using averaged carbon intensity values is calculated as the percentage error compared to the hourly inventory:

$$\text{Relative bias}_{b,r,l} = \frac{\bar{I}_{b,r,l} - I_{b,r}}{I_{b,r}}. \tag{4}$$

4. Results

4.1. Regional differences in carbon inventory bias
The results of the 112 717 carbon inventories that we calculated for residential and commercial buildings around the country reveal that the use of annual-average carbon accounting can result in an overestimation up to 33% and underestimation up to 22% when compared to hourly-average accounting, although most bias falls in the range of ±5%. Importantly, as figure 2 demonstrates, the magnitude and direction of this bias depends on where you are located and who you are.

In certain regions, clustered near the center of figure 2, annual accounting introduces negligible bias for all inventories. Referring to figure 1, we can see that these low-bias regions tend to rely more heavily on fossil fuel generation and have low standard deviations in their hourly carbon intensity, which confirms what we would expect to see based on equation (1). In a region like Duke Energy Florida, which is supplied mostly by methane gas and has a small standard deviation in carbon intensity, we see a correspondingly low amount of bias, within the range of ±0.7%.

In contrast, in regions where the variability in hourly carbon intensity is higher, annual-average accounting results in higher inventory bias, although the magnitude and direction of the bias depends on the variability of the building load, and how highly correlated that load is with periods of high or low carbon intensity on the grid, both on a seasonal and daily basis. If building energy demand tends to peak during seasons or times of day that coincide with peaks in grid carbon intensity, annual accounting will tend to underestimate emissions. For example, in the New York ISO, where emissions peak seasonally in the summer and daily during daylight hours, annual accounting underestimates commercial building emissions because commercial building load follows a similar seasonal and daily pattern.

Because residential building demand profiles can peak at different times than commercial buildings, we see that in some regions annual-average accounting underestimates residential emissions while at the same time overestimating commercial building emissions. This can again be explained using equation (1), since we identified that the direction of the bias
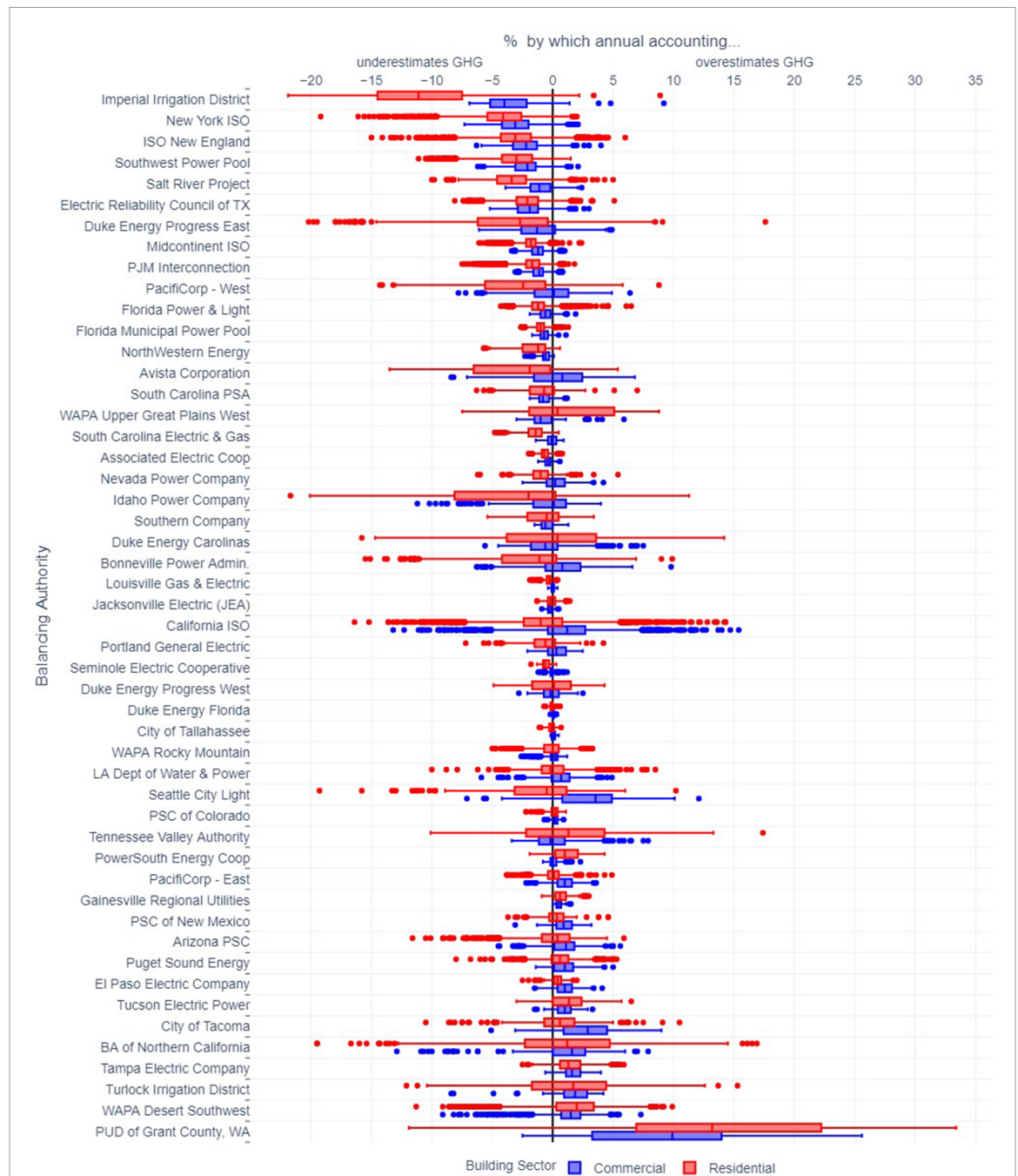
Figure 2. The relative bias that annual-average carbon accounting introduces compared to hourly accounting, for both residential and commercial buildings in each grid region. Each box plot shows the distribution of these biases for all building inventories in each region. The regions are ordered from lowest to highest median bias for all buildings in a region. The results for two regions were omitted from this figure (but can be found in the SI) for the readability of the results, as their relative biases ranged from −29% to +182%.

is driven by the sign of the correlation coefficient between demand and the residual carbon intensity.

Re-framing these results in terms of the regional energy supply mix, regions with higher bias tend to have higher shares of renewables, as renewables introduce more variability into the hourly carbon intensity. Additionally, emissions from buildings whose demand is positively correlated with the timing of generation from the predominant renewable energy source in the region will be over-estimated using annual-average accounting. For example, for

buildings that consume energy more heavily during the day, annual average accounting will over-estimate emissions in solar-dominated regions and under-estimate emissions in wind-heavy regions where wind tends to be stronger at night.

4.2. California ISO case study
While the national results primarily demonstrate how regional carbon intensity characteristics affect the bias introduced by annual-average carbon accounting, it also showed how the bias can differ
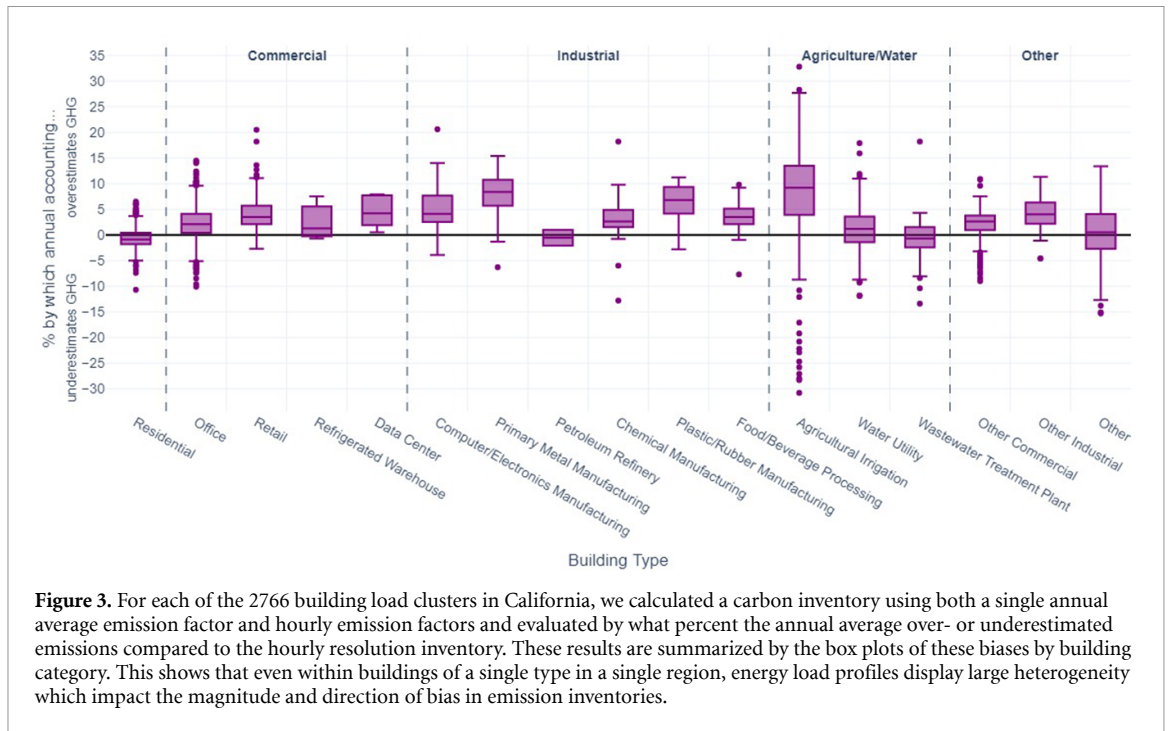
Figure 3. For each of the 2766 building load clusters in California, we calculated a carbon inventory using both a single annual average emission factor and hourly emission factors and evaluated by what percent the annual average over- or underestimated emissions compared to the hourly resolution inventory. These results are summarized by the box plots of these biases by building category. This shows that even within buildings of a single type in a single region, energy load profiles display large heterogeneity which impact the magnitude and direction of bias in emission inventories.

for different building types with different energy demand profiles. To further explore these demand-driven impacts for a more complete set of electricity end users (including industrial and agricultural loads), this section focuses on a case study located within the California ISO, using a demand dataset representing millions of actual buildings in the state.

From the results presented in figure 3, we can see that the heterogeneity in the energy demand profiles of individual buildings within a single category of buildings means that it is not always possible to generalize conclusions about the magnitude and direction of bias of annual-average accounting. Commercial office buildings, for example, may have their inventories overestimated as much as 15% or underestimated as much as 10%. For data centers in California, we could conclude that annual-average carbon accounting overestimates emissions, although the magnitude of this bias ranges anywhere from 0.5% to 8% for an individual data center.

In the California ISO, which has a high penetration of solar generation, the carbon intensity tends to dip during the mid-day, which shapes the bias trends that we see in figure 3. Most commercial buildings, whose energy demand also peaks during the day, will have their emissions overestimated by annual-average accounting.
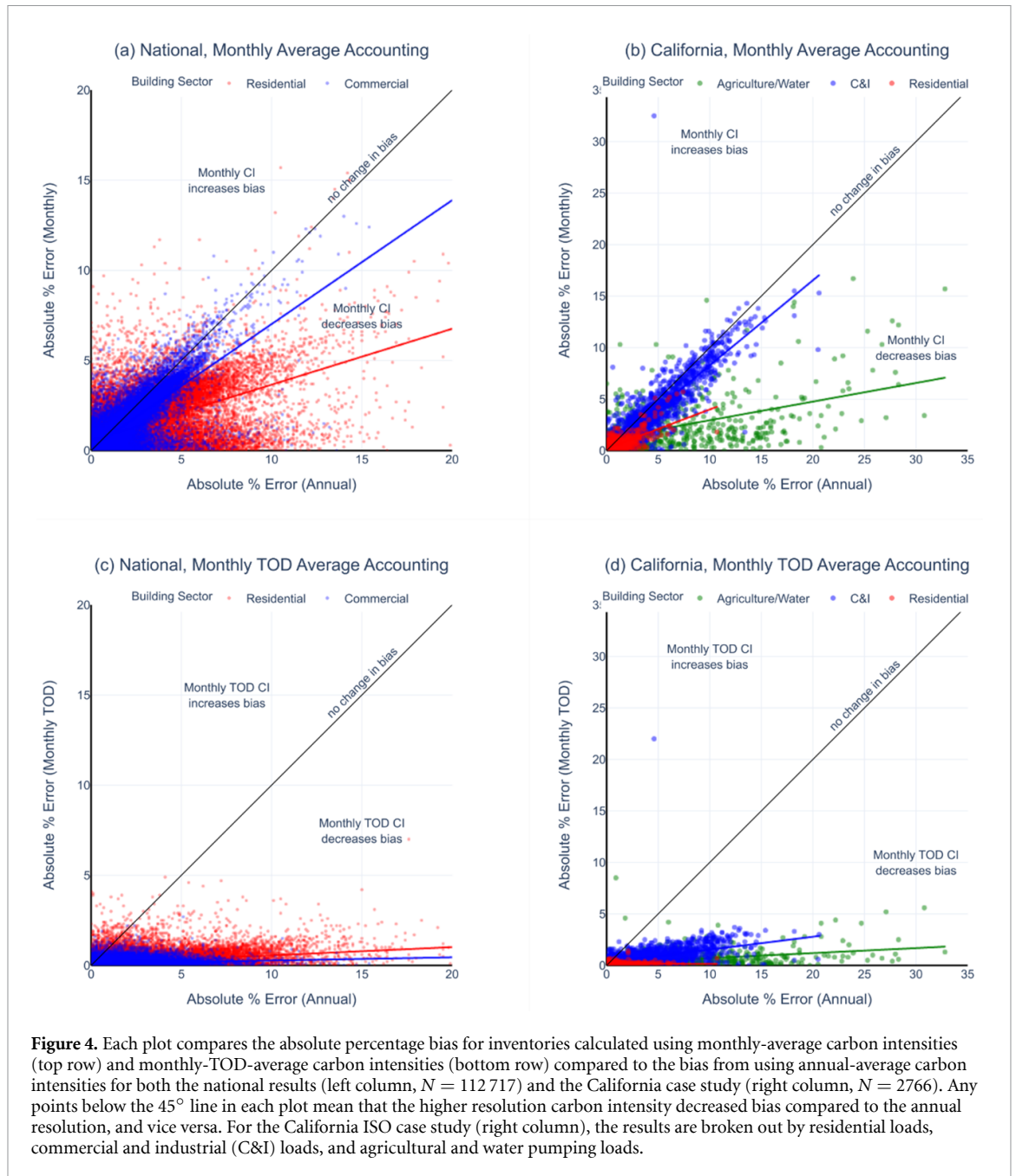
Industrial facilities, which can have larger swings in energy consumption between on-shift and off-shift times, and thus larger variability in energy demand (σ_D), tend to have higher emissions inventory bias resulting from annual-average accounting than commercial buildings. The exception is industrial processes which consume energy on a relatively continuous, 24/7 basis, like petroleum refining, for which

the inventory bias is much closer to zero. For energy demand that is more intermittent or seasonal in nature, like agricultural water pumping and irrigation, annual-average carbon accounting can introduce much larger biases, in the range of $\pm 30\%$, especially if the carbon intensity during the seasons or times of day when the pumping is occurring do not reflect the annual average, leading to a high correlation between demand and residual emissions ($\rho_{D,\mu}$).

4.3. Inventory bias at different temporal resolutions

While hourly accounting using 8760 unique emission factors for each hour of the year will more precisely quantify the emissions attributable to each end user, it also introduces greater data management complexity for accounting practitioners. Thus, this study also examines whether the use of 12 monthly average emissions factors, which reflect annual seasonality, or 288 monthly TOD average emission factors, which reflect both annual and daily seasonality, could improve accuracy while limiting complexity. From a practical standpoint, monthly-average carbon accounting would be convenient because most end-users of electricity are billed monthly and thus have easy access to monthly electricity consumption data.

Figure 4 plots the absolute percentage bias resulting from the use of annual average emission factors versus the absolute bias resulting from using 12 monthly average or 288 (12×24) month-by-hour-of-day average emission factors for each end-user in each grid region. Panel (a) shows that monthly-average accounting can reduce bias by over 50% on average for residential buildings, while having no substantial impact on the bias for commercial

Figure 4. Each plot compares the absolute percentage bias for inventories calculated using monthly-average carbon intensities (top row) and monthly-TOD-average carbon intensities (bottom row) compared to the bias from using annual-average carbon intensities for both the national results (left column, $N = 112\,717$) and the California case study (right column, $N = 2766$). Any points below the 45° line in each plot mean that the higher resolution carbon intensity decreased bias compared to the annual resolution, and vice versa. For the California ISO case study (right column), the results are broken out by residential loads, commercial and industrial (C&I) loads, and agricultural and water pumping loads.

buildings. Monthly-average accounting does not, however, lead to a systematic reduction in bias: approximately one-quarter of buildings showed no improvement or even an increase in bias when using monthly-average accounting. In panel (b), we can also see that for facilities with highly seasonal energy demands, such as water pumping and irrigation, monthly-average accounting may substantially reduce inventory bias compared to annual-average accounting, because these monthly averages reflect the predominant seasonality of the energy demand. These results suggest that monthly-average accounting could be beneficial for certain types of buildings in certain regions, but it does not represent a substantial improvement on a systematic basis.

The bottom panels of figure 4 demonstrate that monthly TOD average accounting substantially reduce, though do not eliminate, carbon inventory bias compared to annual-average accounting for all building types. This is because monthly TOD averages reflect both seasonal and daily patterns which are present in most energy demand profiles. These results suggest that the use of monthly TOD average emissions factors for accounting may strike a reasonable balance between simplicity and accuracy. However, in practice, monthly TOD average data may not be that much simpler to use than hourly emissions factors, because hourly energy demand data would still need to be collected and analyzed to use these emission factors.

5. Discussion

5.1. Recommendations

Accuracy is one of the fundamental GHG accounting and reporting principles described by *The GHG Protocol*. As noted in the Protocol's *Corporate Accounting and Reporting Standard*, 'data should be sufficiently precise to enable intended users to make decisions with reasonable assurance that the reported information is credible. GHG measurements, estimates, or calculations should be systemically neither over nor under the actual emissions value, as far as can be judged, and that uncertainties are reduced as far as practicable' [33].

As explained through equation (1), the results illustrate how the bias in carbon inventories is based on a combination of factors including the variability in hourly building demand, the variability in hourly carbon intensity, and the correlation between building demand and grid carbon intensity. If any one of these factors is small (close to zero), whether because building demand is relatively flat, grid carbon intensity is relatively flat, or the variation in either is mostly random and uncorrelated with the other, then the bias introduced by using annual accounting will be small.

However, the results of this study make clear that in today's electricity system, annual-average emissions accounting yields imprecise emission inventories in most regions and for most end-users. In addition, this study shows that monthly average emission factors do not reliably or substantially address this bias. Thus, we recommend that hourly or sub-hourly accounting be adopted as the best practice for attributional GHG accounting of grid-consumed electricity and for location-based scope 2 GHG inventories.

5.2. Implications and urgency

These results have broad implications for many fields including voluntary climate disclosure, building performance regulations, carbon pricing, community-scale climate action planning, climate-based investing, and general business decisions. As emissions accounting is increasingly incorporated into regulations, carbon pricing, and business decisions, the bias from annual-average carbon accounting could have real-world legal and financial implications. For example, New York City's Local Law 97 set a carbon emissions cap (enforced with a substantial fine of $268 ton^{-1} in exceedance) for 50 000 buildings in the city and will go into effect in 2024. If this law were to use annual-average grid emissions factors for accounting, the results of this study suggest that the emissions for commercial buildings located in the New York ISO could be underestimated by up to 7%, eroding the efficiency and effectiveness of this law.

These findings are also relevant to crafting effective transportation policies, especially those that require accurately quantifying air pollution related to charging electric vehicles (EVs) relative to pollution from internal combustion engines. For example, California's low carbon fuel standard, which is designed to decrease the carbon intensity of the state's transportation fuels, currently calculates its base EV charging credits based on annual-average grid carbon intensity, which may be eroding the efficiency of this credit market [34, 35].

This research has several important implications for the academic research community, especially in the fields of lifecycle assessment (LCA), energy and climate policy research, and transportation research. Due to the ubiquity of electricity as an input to the manufacturing and use phase of many products, our findings suggest that hourly emissions factors should be used whenever possible for conducting attributional LCAs, especially when evaluating emissions from individual plug loads or end uses whose demand profile can be more variable than those of entire buildings. Although this study focused on the bias introduced in *carbon* inventories, future research should evaluate whether these biases also translate to other criteria pollutants (such as NO$_x$, SO$_x$, and particulate matter), which are also relevant to many LCAs.

Beyond the implications of this bias on scope 2 emissions inventories, these results also have implications for the accuracy of an organization's scope 3 inventory, which focus on upstream sources of emissions, such as the emissions of raw materials or products. Especially for organizations who rely on energy-intensive raw materials such as aluminum, annual-average accounting could lead to inaccurate calculations of the lifecycle emissions associated with those inputs into their products.

Although this study focused on carbon inventories for individual buildings, and thus do not tell us about the annual accounting bias for community-scale or company-wide emissions inventories (which include buildings of many different types, possibly across many grid regions for a company with a national or international footprint), it nonetheless has important implications for how emissions are allocated within the inventory. For example, a community-scale inventory may seek to identify whether residential or commercial buildings represent a larger share of emissions, or a corporate-wide inventory may seek to identify which business region is responsible for the most emissions, so that funding and resources can be allocated to mitigate the largest sources of emissions. These results suggest that the bias introduced by annual accounting could potentially mis-allocate emissions between building sectors or regions, thus mis-informing these types of prioritization efforts.

Annual accounting can also limit effective decision-making about individual carbon-mitigation

efforts, such as energy efficiency investments. Using annual-average accounting would lead a decision-maker to believe that whichever project reduces the greatest number of kWh will reduce the organization's carbon footprint most effectively. However, using hourly accounting might reveal that if that project mostly reduces energy consumption when grid emissions are low, then the value proposition of that project would be undermined compared to a project that reduces consumption during hours of high carbon intensity.

The findings of this paper, and in particular the drivers of bias explained through equation (1), lead us to believe that these annual accounting biases will only get worse, based on current trends in building energy demand and grid carbon intensity. As grids continue to integrate more variable and intermittent renewable energy sources to meet state Renewable Portfolio Standards and other climate goals, the variability in hourly carbon intensity will likely increase, increasing σ_μ and inventory bias [12, 22, 36]. On the demand side, as more and more large end-use loads are electrified, such as vehicle charging, water heating, and space conditioning, building the total facility load profiles may become spikier and more variable, increasing σ_D and inventory bias [3]. Furthermore, efforts such as time-of-use rates, managed charging, and carbon-aware demand response, which seek to shape and shift load to better match the times when carbon-free resources are available, may strengthen the magnitude of the correlation between energy demand and grid carbon intensity ($\rho_{D,\mu}$), also increasing inventory bias. These three trends in combination, suggest that the continued use of annual carbon accounting will lead to inventories that become increasingly biased in the future.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://zenodo.org/badge/latestdoi/461343198.

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References

[1] Gordon C and Fung A 2009 Hourly emission factors from the electricity generation sector—a tool for analyzing the impact of renewable technologies in Ontario *Trans. Can. Soc. Mech. Eng.* **33** 105–18

[2] Fung A and Gordon C 2011 Analysis of time dependent valuation of emission factors from the electricity sector *Sustainable Growth and Applications in Renewable Energy Sources* (Croatia: IntechOpen) pp 295–312

[3] Bristow D, Richman R, Kirsh A, Kennedy C A and Pressnail K D 2011 Hour-by-hour analysis for increased accuracy of greenhouse gas emissions for a low-energy condominium design *J. Ind. Ecol.* **15** 381–93

[4] Stoll P, Brandt N and Nordström L 2014 Including dynamic CO_2 intensity with demand response *Energy Policy* **65** 490–500

[5] Cubi E, Doluweera G and Bergerson J 2015 Incorporation of electricity GHG emissions intensity variability into building environmental assessment *Appl. Energy* **159** 62–69

[6] Spork C C, Chavez A, Durany X G, Patel M K and Méndez G V 2015 Increasing precision in greenhouse gas accounting using real-time emission factors *J. Ind. Ecol.* **19** 380–90

[7] Roux C, Schalbart P and Peuportier B 2016 Accounting for temporal variation of electricity production and consumption in the LCA of an energy-efficient house *J. Clean. Prod.* **113** 532–40

[8] Vuarnoz D and Jusselme T 2018 Temporal variations in the primary energy use and greenhouse gas emissions of electricity provided by the Swiss grid *Energy* **161** 573–82

[9] Schivley G, Azevedo I and Samaras C 2018 Assessing the evolution of power sector carbon intensity in the United States *Environ. Res. Lett.* **13** 064018

[10] Khan I, Jack M W and Stephenson J 2018 Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity *J. Clean. Prod.* **184** 1091–101

[11] Khan I 2018 Importance of GHG emissions assessment in the electricity grid expansion towards a low-carbon future: a time-varying carbon intensity approach *J. Clean. Prod.* **196** 1587–99

[12] Khan I 2019 Temporal carbon intensity analysis: renewable versus fossil fuel dominated electricity systems *Energy Sources* A **41** 309–23

[13] Khan I 2019 Greenhouse gas emission accounting approaches in electricity generation systems: a review *Atmos. Environ.* **200** 131–41

[14] Marrasso E, Roselli C and Sasso M 2019 Electric efficiency indicators and carbon dioxide emission factors for power generation by fossil and renewable energy sources on hourly basis *Energy Convers. Manage.* **196** 1369–84

[15] Tranberg B, Corradi O, Lajoie B, Gibon T, Staffell I and Andresen G B 2019 Real-time carbon accounting method for the European electricity markets *Energy Strat. Rev.* **26** 100367

[16] de Chalendar J A, Taggart J and Benson S M 2019 Tracking emissions in the US electricity system *Proc. Natl Acad. Sci.* **116** 25497–502

[17] Donti P L, Kolter J Z and Azevedo I L 2019 How much are we saving after all? Characterizing the effects of commonly varying assumptions on emissions and damage estimates in PJM *Environ. Sci. Technol.* **53** 9905–14

[18] Pereira L and Posen I D 2020 Lifecycle greenhouse gas emissions from electricity in the province of Ontario at different temporal resolutions *J. Clean. Prod.* **270** 122514

[19] MacCracken M 2006 California's Title 24 & cool storage *ASHRAE J.* **48** 29–33

[20] Messagie M, Mertens J, Oliveira L, Rangaraju S, Sanfelix J, Coosemans T, van Mierlo J and Macharis C 2014 The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment *Appl. Energy* **134** 469–76

[21] Kopsakangas-Savolainen M, Mattinen M K, Manninen K and Nissinen A 2017 Hourly-based greenhouse gas emissions of electricity—cases demonstrating possibilities for households and companies to decrease their emissions *J. Clean. Prod.* **153** 384–96

[22] Müller A and Wörner P 2019 Impact of dynamic CO_2 emission factors for the public electricity supply on the life-cycle assessment of energy efficient residential buildings *IOP Conf. Ser.: Earth Environ. Sci.* **323** 012036

[23] Apt J 2015 Recent results on the integration of variable renewable electric power into the US grid *MRS Energy Sustain.* **2** 1–11

[24] US Energy Information Administration 2021 Annual electric power industry report, form EIA-861 detailed data files (Accessed 20 October 2021)

[25] Douris C 2017 *Balancing Smart Grid Data and Consumer Privacy* (Lexington Institute)

[26] Wilson E, Parker A and Frick N M 2021 End-use load profiles—a new public dataset for U.S. residential and commercial buildings *Webinar* (*28 October 2021*)

[27] Wilson E *et al* 2021 *End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification* NREL/TP-5500-80889 (National Renewable Energy Laboratory (NREL))

[28] Alstone P *et al* 2017 *2025 California Demand Response Potential Study – Charting California's Demand Response Future: Final Report on Phase 2 Results* LBNL-2001113 (Lawrence Berkeley National Laboratory)

[29] Singularity Energy Carbonara [API] (available at: https://carbonara.singularity.energy) (Accessed 11 June 2021)

[30] Colett J S, Kelly J C and Keoleian G A 2016 Using nested average electricity allocation protocols to characterize electrical grids in life cycle assessment *J. Ind. Ecol.* **20** 29–41

[31] Brander M, Gillenwater M and Ascui F 2018 Creative accounting: a critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions *Energy Policy* **112** 29–33

[32] U.S. Energy Information Administration *Hourly Electric Grid Monitor* (available at: https://www.eia.gov/electricity/gridmonitor) (Accessed 26 May 2021)

[33] WBCSD/WRI 2004 *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard* Revised edn (Washington, DC: WBCSD/WRI)

[34] California Air Resources Board LCFS Electricity and Hydrogen Provisions (available at: https://ww2.arb.ca.gov/resources/documents/lcfs-electricity-and-hydrogen-provisions) (Accessed 15 September 2020)

[35] California Air Resources Board 2020 Low carbon fuel standard annual updates to lookup table pathways *California Average Grid Electricity Used as a Transportation Fuel in California*

[36] Hamels S, Himpe E, Laverge J, Delghust M, van den Brande K, Janssens A and Albrecht J 2021 The use of primary energy factors and CO_2 intensities for electricity in the European context—a systematic methodological review and critical evaluation of the contemporary literature *Renew. Sustain. Energy Rev.* **146** 111182