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Uncertainties in the EDGAR emission inventory of greenhouse gases

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Abstract

The Emissions Database for Global Atmospheric Research (EDGAR) estimates the human-induced emission rates on Earth collaborating with atmospheric modelling activities as well as aiding policy in the design of mitigation strategies and in evaluating their effectiveness. In these applications, the uncertainty estimate is an essential component as it quantifies the accuracy and qualifies the level of confidence in the emission.

This study complements the EDGAR's emissions inventory with estimation of the structural uncertainty stemming from its base components (activity data statistics (AD) and emission factors (EF)) by *i)* associating uncertainty to each AD and EF characterizing the emissions of the three main greenhouse gases (GHG) CO_2, CH_4 and N_2O; *ii)* combining them, and *iii)* making assumptions for the cross-country uncertainty aggregation of source categories.

It was deemed a natural choice to obtain the uncertainties in EFs and AD from the Intergovernmental Panel on Climate Change (IPCC) guidelines issued in 2006 (with a few exceptions), since the EF and AD sources and methodological aspects used by EDGAR have been built over the years based on the IPCC recommendations, which assured consistency in time and comparability across countries. While on one side the homogeneity of the method is one of the key strengths of EDGAR, on the other side it facilitates the propagation of uncertainties when similar emission sources are aggregated. For this reason, this study aims primarily at addressing the aggregation of uncertainties sectorial emissions across GHGs and countries.

On global average we find that the anthropogenic emissions of the combined three main GHGs for the year 2015 are accurate within an interval of -15% to +20% (defining the 95% confidence of a log-normal distribution). The most uncertain emissions are those related to N_2O from agriculture, while CO_2 emissions, although responsible for 74% of total GHG emissions, accounts for and for approximately 11% of global uncertainty share. Sensitivity to methodological choices is also discussed.

Introduction

According to the latest release of the Emissions Database of Global Atmospheric Research (EDGAR version 5, *Crippa et al., 2019*; *Crippa et al., 2020a*), in the year 2015 the global greenhouse gas (GHG) emissions of CO_2, CH_4 and N_2O due to anthropogenic activities totaled 48.1 Gt CO_2eq[1]. In the same year, the share of global CO_2-equivalent (CO_2eq) of non-CO_2 GHG emissions (CH_4 and N_2O) was approximately of 1/4. Significant efforts expanded to promote measures to attenuate temperature rising and mitigate long-term change to climate dynamics have contributed to uphold the role of non-CO_2 gases, such as CH_4 and N_2O. Their high warming potential compared to CO_2 (25 for CH_4 and 298 for

[1] CO_2 equivalent emissions (CO_2eq) are computed using the Global Warming Potential values from the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC). These emissions include the fossil CO_2 component and the contribution of CH_4, N_2O.

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N_2O, over a time horizon of 100 years (*IPCC, 2007*)) and relatively shorter life-time (on average CH_4 persists in the atmosphere for approximately a decade, N_2O for over a century and CO_2 for even more than 1000 years (*NCR, 2010; Ciais et al., 2013*)) allow to design mitigation strategies focusing on shifting emission control measures from energy-related CO_2 to other less controversial and more responsive sources (*Janssens-Maenhout et al., 2019; United Nations Environment Programme, 2019*). At the same time, while for fossil fuel CO_2 emissions the uncertainty is relatively small and, overall, well defined, for the other gases the emission estimates are significantly more uncertain. In turn, emission reduction measures issued by national plans highly depend on the degree of uncertainty of sectors that are supposed to factor to the reduction targets. As depicted in the example by *Olivier (1998)* a sector contributing by 10% to the national reduction target may contribute to 5% or 15% if that sector's emission factor is ±50% uncertain.

EDGAR aims at consolidating its position in support to scientific research and application to modelling as well as independent tool in support of monitoring and mitigation policies. Therefore, a reliable quantification of the uncertainties assumes the same degree of importance as the consistency and comparability of the emissions. This study moves in this direction, by adding the uncertainty dimension to the EDGAR database, thus enhancing its value with much needed information on reliability and promote comparability with other datasets. Reporting of uncertainty is of relevance, among other applications, for:

- scientific/assessment/impact purposes, as for example assessing robustness of long-term emission trends, provide a-priori state to and a-posteriori comparison with independent top-down estimates (*Bergamaschi et al., 2018*), aid in network design (*Super et al., 2020*).
- Inter-comparison studies (*Choulga et al., 2020*; *Petrescu et al., 2020*)
- Assessing the feasible potential of mitigation strategies (e.g. *Van Dingenen et al., 2017*)

This study adds the uncertainty component to the EDGAR data by devising methods to propagate the uncertainty introduced by AD and EF to any combination/aggregation of sources, countries, and GHGs. Methods, aggregation strategies and dependencies are presented and investigated. Analyses are conducted for the emission year 2015 for CO_2, CH_4 and N_2O. Sensitivity to methodological choices is also discussed. The methodology presented here has been already applied to EDGAR and discussed in the scientific literature in comparison to other methods (*Choulga et al., 2020*), to other inventories (*Petrescu et al., 2020*), for assessing the uncertainty of the EDGAR-FOOD inventory (*Crippa et al., 2020b*), application to specific sectors (*Muntean et al., 2020*), trend analysis of global GHG emissions and for communication to policy and the public (*Crippa et al., 2019, 2020c*).

2. Methodology

EDGAR is a 'bottom-up' model for estimating emissions, relaying on a large spectrum of activity statistics (or activity data, AD) covering human activities with a high degree of detail. AD are combined with emission factors (EF) to yield the emission, per source, and country. For example, for combustion sources AD consist of fossil fuel consumption while the EF is the amount of emission produced per unit of activity. In this case the emission is typically obtained simply by multiplying AD by EF, while other sources (e.g. waste) require more sophisticated models.

AD are primarily retrieved from international statistics, complemented, when necessary with information (e.g. trends) from other sources, such as scientific literature and national data. The quality, consistency, comparability of AD through time and space is an essential component of the overall 'goodness' of an emission database.

Default EFs compiled by IPCC Guidelines *(IPCC Guidelines, 2006,* hereafter referred to as IPCC-06) are adopted by EDGAR for most sources and countries, supplemented by information from scientific literature, and other sources for specific process and countries. *Janssens-Maenhout et al. (2019)* produced a detailed description of data providers and methodological choices for the GHGs emissions of EDGAR. Further information on methodological aspects of data collection and sources is given by *Crippa et al. (2020a)*.

2.1 Emissions and uncertainty

The uncertainty of AD (u_{AD}) collected by international agencies or organisations (e.g. the Food and Agriculture Organization (FAO), International Energy Agency (IEA)) is of statistical nature, stemming from incompleteness, representativeness of sampling, imputation of missing data, extrapolation (e.g. projecting to future years) (*Rypdal and Winiwarter, 2001*; *Olivier and Peters, 2002*; *IPCC-06*). Other aspects to take into considerations when compiling a global inventory are the degree of wealth of a country as well as the year under study. Less developed countries and countries whose economy has fully developed in recent years, are more probable to have not yet developed a reliable statistical system. Similarly, AD of countries with transitional economies for past decades are expectedly less accurate than for recent years (*Janssens-Maenhout et al., 2019*).

Uncertainty in EF (u_{EF}) has many sources, as for instance: inexactness of assumptions and/or of source aggregation (e.g. assumption of constancy in time); bias, variability and/or random errors (e.g. due to measurement errors); under-representativity of operating conditions. Due to the non-statistical nature of u_{EF}, its quantification eludes a general methodological approach. IPCC adopts a tiered approach for estimating uncertainty, accounting for different levels of sophistication (*IPCC-06*). Tier 1 uncertainties on default EFs are based on expert judgements, which often offers a range of uncertainties for a given process, source, and/or fuel. Higher tiers (up to Tier 3) offer more elaborate estimates, based on localized measurements/ad-hoc experiments on specific emission factors and for specific processes. Accuracy of the uncertainty estimate increases with tier. Further, the model used to build emission inventories based on activity statistics may be too simplified (e.g. based on linearization and/or linear regression due to, e.g., poor understanding, lack of data), and may not fully capture the complexity of a given emission process. These 'model' errors are difficult to assess in isolation from other source of uncertainty and are generally attributed to uncertainties in EFs (*Rypdal and Winiwarter 2001*; *Cullen and Frey, 1999*).

This study reflects the methodological approach of EDGAR adopting default EF factors, thus associated with Tier1 uncertainty estimates. The term 'uncertainty', in this study as in similar ones (*Rypdal and Winiwarter, 2001*; *Olivier and Peters, 2002*; *Janssens-Maenhout et al., 2019*), is used in a rather broad sense, lumping together all mentioned sources of errors due to current limited knowledge to distinguish among them. After IPCC introduced quantitative uncertainty in GHG inventories, the inventory uncertainty is usually expressed as two standard deviations, approximately corresponding to 95% confidence for a variable with a normal distribution (i.e. the uncertainty reflects the square root of the variance of the variable, multiplied by a coverage factor of 2 to provide a confidence interval of 95%).

Finally, the uncertainty tackled here shall not be confused with the variability stemming from a range (or ensemble) of estimates. The variability is used as proxy of structural uncertainty in the faith that a range of models using diverse underlying assumptions would span the true uncertainty space. However, the estimates are seldom 'diverse' as they build up from same data/assumptions (sometimes different versions of the same model are used) leading to overconfident estimates (*Solazzo et al., 2018*).

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2.1.1 Uncertainty in Activity Data

Table 1 summarizes the uncertainty for AD. When two values are listed (e.g. ±5; ±10%), the lower uncertainty value is assigned to countries with developed economy, while the larger values to countries with less developed economy or with economy in transition.

TABLE 1.

According to IPCC-06, u_{AD} for fuel combustion activities (mostly derived from IEA statistics) are estimated with high confidence (5 to 10% uncertainty). The same uncertainty range is estimated for fugitive emissions (referring to venting and flaring during oil and gas production). u_{AD} in the residential (10 to 20%) and aviation and navigation (5 to 25%) sectors are assumed more conservative to account for the under-representativeness of the sample and for the difficulty of distinguishing between domestic and international fuel consumption (IPCC-06). For combustion processes using biofuels, the statistics is however less robust. *Olivier et al (2002)* suggests u_{AD} of 30% for industrialised countries and 80% for less developed ones (based on IPCC-06 recommendations). Recent updates (*Andreae, 2019*) confirm these estimates.

Uncertainty for some chemistry production processes and waste is calculated on the total emission rather than on AD and EF separately, and is discussed later. The waste sector also utilizes a slightly more elaborated model for estimating emissions than the simple multiplication of AD and EF. It assumes that emissions are not instantly released into the atmosphere, but they accumulate and continue to also emit several years after their disposal. The model for the waste sector depends on several parameters and assumptions, detailed in section 3.1.5).

2.1.2 Uncertainty on Emissions factors

Tables 2 and 3 define the uncertainties of EFs for CO_2, and for CH_4 and N_2O, respectively. Uncertainty of EFs for CO_2 is determined by the carbon content of the fuel and is relatively smaller and determined with higher level of accuracy than uncertainty of EFs for CH_4 and N_2O. Moreover, uncertainty of EFs for CH_4 and N_2O lumps several sources of uncertainties, as mentioned earlier.

TABLE 2.

TABLE 3.

As mentioned earlier, u_{EF} are based on Tier 1 estimates provided by IPCC-06, based on expert judgments and as such vary over wide ranges to account for a variety of conditions, e.g. u_{EF} for N_2O (agriculture and energy sources in particular) clearly reflects the large temporal variability and spatial heterogeneity of these processes.

2.2 Emission aggregation and uncertainty propagation

The vast majority of EFs in EDGAR are based on IPCC Tier 1 estimates (especially so for combustion sources) to ensure comparability, consistency, and transparency, allowing:

- *completeness* accomplished through the inclusion of all relevant sources for a given year;
- *consistency* implying that the same methodology is applied through years for a given source;
- *comparability*, assuring that emissions are comparable across countries, e.g. source definitions, emission calculations and emissions factors are the same across countries.

The adoption of comparable methods for source emission and consistency implies that the uncertainties of the final emission estimates are inter-dependent as they stem from the same methodology. When

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emissions are combined/aggregated this lack of independence factors in, and the following assumptions are made:

a) emissions uncertainty (u_{EMI}) is the sum of the squares of the uncertainty of AD (u_{AD}) and the uncertainty of EF (u_{EF}) (Eq. 1);
b) Uncertainties of different source categories are uncorrelated (e.g waste and agriculture);
c) Subsectors of a given emission category for CH_4 and N_2O are fully correlated, thus the uncertainty of the sum is the sum of the uncertainties;
d) When dealing with CO_2, full correlation is assumed for energy combustion sources sharing the same emission factor (fuel-dependent);
e) Aggregated emissions from same categories but different countries are assumed to be fully correlated, unless the emission factor is country-specific, or derived from higher tiers (i.e. emissions are not derived from default EF defined by IPCC but are retrieved by other sources and are specific to that country/process);
f) When uncertainty is provided as a range (e.g. for the energy sector, IPCC-06 recommend that the methane emission factors are treated with an uncertainty ranging from 50% to 150%), the upper bound of the range is assigned to countries with less developed statistical infrastructure and the upper one to countries with more robust statistical infrastructure.

Conditions a) and b) match the suggestion of the uncertainty chapter of the IPCC guidelines (IPCC-06, Chapter 3), whilst the latter two conditions are more cautious formulations of the error propagation to account for covariances. More explicitly the uncertainty of the emission, u_{EMI}, due to multiplying AD by EF is calculated as:

$$u_{EMI} = \sqrt{(u_{EF}^2 + u_{AD}^2)} \qquad \textbf{EQ. 1}$$

The uncertainty on the emission, u_{Emi}, due to adding emissions is calculated as;

$$u_{EMI} = \frac{\sqrt{\sum_i (EMI, i * u_{EMI,i})^2}}{\sum_i |EMI, i|} \qquad \textbf{EQ. 2}$$

That is, basically, the squared sum of the uncertainty of each emission process normalised by the sum of emissions, which assumes that all emission sources are uncorrelated (IPCC-06). However, in general, the variance of the sum of any two terms x_1 and x_2 having variances of σ_1 and σ_2 is $\sigma_{sum}^2 = \sigma_1^2 + \sigma_2^2 + 2cov(x_1, x_2)$. Since the covariance can be expressed as $2cov(x_1, x_2) = 2r\sigma_1\ \sigma_2$, where r is the coefficient of correlation, when $r = 1$ (full correlation), the variance of the sum becomes the linear sum of the two variances:

$$\sigma_{sum} = \underbrace{\sigma_1 + \sigma_2}_{correlated\ r=1} \geq \underbrace{\sqrt{\sigma_1^2 + \sigma_2^2}}_{uncorrelated\ r=0} \qquad \textbf{EQ. 3}$$

Therefore, for fully correlated variables, the uncertainty of their sum is simply the sum of their uncertainties.

When uncertainties are larger than 100%, Eq. 2 tends to underestimate the uncertainty and a correction factor F_C is recommended (IPCC-06), so that the uncertainty on the emission is:

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$$u_{EMI,C} = u_{EMI} \times F_C$$

$$F_C = \left[\frac{(-0.72 + 1.0921 u_{EMI} - 1.63x10^{-3} u_{EMI}^2 + 1.11x10^{-5} u_{EMI}^3)}{u_{EMI}}\right]^2 \qquad \textbf{EQ. 4}$$

Where $u_{EMI,C}$ is the correction to be applied to the uncertainty estimated from error propagation. Eq. 4 is used for multiplicative or quotient terms in the range $u_{EMI} \in [100\%, 230\%]$ (Equation 3.3, IPCC-06 Volume 1 Chapter 3). The effect of *Fc* is to return larger uncertainties (see e.g. *Choulga et al., 2020*). The use of F_C is based on the work by *Frey (2003)* to account for the error introduced in the approximation of the analytical method compared to a fully numerical one (based on Monte Carlo analysis). The error in the approximation increases with the uncertainty and thus the correction factor F_C is needed, according to *Frey (2003)*, for large uncertainties. The analysis presented in this study takes into account for the correction factor F_C (unless specifically indicted) and for simplicity the 'C' is dropped in $u_{EMI,C}$ to yield u_{EMI}.

To avoid that the emissions take negative, unphysical values when uncertainty is large, the probability distribution function (PDF) is transformed to lognormal with the upper and lower uncertainty range defined according to IPCC-06:

$$u_{EMI} = \frac{1}{EMI}\left(\exp\left(\ln(\mu_g) \pm 1.96 \ln(\sigma_g)\right)\right) - 1 \qquad \textbf{Eq. 5}$$

where μ_g and σ_g are the geometric mean and geometric standard deviation about the mean (emission) *EMI*.

The contribution to variance *var share* of a specific emission process *s* emitting EMI_s to the uncertainty of the total emissions EMI_{tot} is calculated as:

$$var\ share_s = \frac{u_{EMI,s}^2 * EMI_s^2}{EMI_{tot}^2} \qquad \textbf{EQ. 6}$$

according to IPCC-06.

2.2.1 Additional remarks

The assumption of correlation between subcategories (or fuel for energy sector emitting CO_2) and between countries for the same category (or fuel for energy-CO_2) is introduced to ensure that the uncertainty of sources sharing the same methodology for estimating the EF is propagate in case of aggregation. If the same methodology is applied to estimate the emission for that category for a group of countries, then the correlation is kept when calculating the total emission of that group of countries for that category. These same assumptions were adopted by e.g., *Bond et al. (2004)* and *Bergamaschi et al. (2015)* (though for different inventories). This is a direct implication of the consistency and cross-country comparability of EDGAR, that adopts Tier 1 emission factors defined by IPCC-06 for most of the inventory. By contrast, if each country follows diverse methods to estimate the EFs for a given source category, the uncertainty u_{EF} stemming from that methodology does not co-vary when calculating the total of that category, and thus Eq. 2 holds. Some further considerations:

- The assumption of source/country correlation is the main difference between the uncertainty estimated in this study and the uncertainty reported by, e.g., *Petrescu et al. (2020)* for

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EU27+UK, where no correlation was assumed although not all countries developed independent methods to estimate EFs.

- The choice of assuming 'full' correlation (i.e. correlation coefficient of one) is conservative in the sense that it will yield the upper bound of u_{EMI} and is motivated by two main reasons: it simplifies the calculation (Eq. 3) and there are no indications as to better estimate *r*;
- EDGAR does include country-specific EFs for some processes and countries derived from the literature or through technical collaborations and continuous updates in over two decades (e.g. EFs for cement production are computed including information on country-specific clinker fractions, EFs for landfills consider the country specific waste composition and recovery, EFs for enteric fermentation of cattle which include country/region specific information on milk yield, carcass weight and many other parameters, etc.). These instances are flagged in our methodology and the u_{EF} is not propagated when aggregating these sources.

3. Uncertainty in emission sectors

3.1 Emissions from CO_2, CH_4 and N_2O

3.1.1 Power industry Sector

IPCC sector 1.A includes the EDGAR categories related to combustion of fossil and biofuels for energy production (ENE), manufacturing (IND), energy for buildings (RCO), oil refineries and transformation industry (REF, TRF), aviation (TNR aviation), shipping (TNR ship), and road transport (TRO). Emissions from biofuel burning (e.g. wood) in sector 1.A are considered carbon neutral and are calculated for CH_4 and N_2O only.

EDGAR adopts AD statistics of fossil fuel combustion compiled by the IEA (IEA, 2017) for developed and developing countries, integrated with data from EIA (2018) for biofuels.

TABLE 4.

The share of GHGs emissions from industrialised and developing countries is reported in Table 4 to aid later interpretation of the uncertainty shares. In fact, in countries with developed economy (Table 5) energy statistics is considered having lower uncertainty than for countries in development (*Olivier and Peters 2002*). IPCC suggests u_{AD} for the power industry ranging between 5 to 10%. We have assigned 5% to industrialised countries and 10% uncertainty to developing countries to account for less robust census capability. IPCC-06 provides fuel-dependent u_{EF} for CO_2 (Table), which have been mapped to match the fuels in each EDGAR emission category. u_{EF} for CO_2 are relatively small as reflected by the (well known) carbon content of the fuel.

TABLE 5.

For CH_4 and N_2O, EFs are more uncertain than for CO_2. IPCC-06 suggests a wide range of u_{EF} for the whole energy sector, ranging between 50% and 150% for CH_4 and between one tenth and ten times the mean emission value for N_2O. These estimates are provided by expert judgement based on the reliability of current estimates. The reasons for such high uncertainty are those mentioned before, that is lack of understanding of emission processes and of relevant measurements, uncertainty in measurements, lack of representativity of operational conditions. EFs for biofuels combustion are highly uncertain, estimated in the range 30% (*Andeae and Merlet, 2001*) to 80% (Olivier et al., 2002). Recently, *Andreae (2019)* has reviewed u_{EF} to less than 20% (6-18% for CH_4 from the major burning categories savanna, forests, and biofuel). The uncertainty of processes using biofuels is calculated separately and then combined with the fossil fuel uncertainty assuming uncorrelation (Eq. 2).

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FIGURE 1.

Emissions of CO_2 account for over 90% of world's total GHG emissions from fuel combustion, and are assessed with high degree of confidence (Figure 1a,b,c) due to the accuracy of u_{EF} reflecting the carbon content of the fuel. Thus, the share of emission for each subcategory (manufacturing, transformation and power industry, oil refinery, residential heating, road and non-road transport) is mirrored by the share each category contributes to the sector uncertainty (Figure 2), although with some notable exceptions for non-road transport in Brazil (large share of highly uncertain domestic aviation and inland water shipping), and transformation industry in Russia (share of emission and uncertainty of ~10% and ~37%, respectively).

FIGURE 2.

The very low confidence in N_2O emissions is responsible for almost 50% of world's total uncertainty (Fig 1f) although N_2O only accounts for a minor portion of total emissions in this sector (less than 1%). An alternative u_{EF} estimation for N_2O in the fossil fuel combustion sector is set in the range ±50% (developed countries) to 150% (countries with economy in development). This choice also reflects previous uncertainty estimation by *Olivier et al. (2002)*. The N_2O emission uncertainty and the N_2O contribution to uncertainty in sector 1.A become as shown in Figure 3:

FIGURE 3.

The uncertainty distribution (Figure 3) and relative contribution reflects the weight of the component GHGs and the world's total uncertainty (10%) is only slightly larger than the uncertainty of CO_2 (7%, Figure 1a,b,c). Adopting the u_{EF} of 50-150% for N_2O in sector 1.A reflects the large uncertainty associated with this sector and allow comparability/aggregation with other gases (Figure 3b).

3.1.2 Fugitive emissions from coal, oil and natural gas

Fugitive emissions from solid fuels (mainly coal, 1.B.1) and from oil and natural gas (1.B.2) are covered by the EDGAR's categories REF, TRF and by fuel exploitation PRO. As pointed out in *IPCC-06*, uncertainty in the fugitive emissions sector arises from applying the same EF to all countries (Tier 1 approach) and from uncertainty in the emission factors themselves.

AD for coal statistics is a collection of products (full details are provided by *Janssens-Maenhout et al. (2019)* and references therein): the *World Coal Association (2016)*; IEA (2017) *for* exploration of gas and oil; *UNFCCC (2018)* and *CIA (2016)* for transmission and distribution; IEA (2017) for venting and flaring, complemented with data from GGFR/NOAA data (2019) and *Andres et al. (2014)*. According to *Olivier at al. (2002)*, u_{AD} for sector 1.B lies within the range ±5 to ±10%, which is aligned with the estimates provided by *IPCC-06*.

Fugitive emissions from solid fuels (1B1) in EDGAR are dealt with by considering emission factors from IPCC (2006) Guidelines, supplemented with *EMEP/EEA (2013) Guidebook* for coal and *UNFCCC (2018)*. For oil and natural gas (1B2), we use information from UNFCCC as well as from the IPCC (2006) guidelines, supplemented with data of *UNFCCC (2014)*. While gas transmission through large pipelines is characterised with relatively small country-specific emission factors of *Lelieveld et al. (2005)*, much larger and material dependent leakage rates of IPCC (2006) guidelines were assumed for gas distribution. For venting processes EFs for CH_4 are based on country-specific *UNFCCC (2014)* data for reporting countries (and the average value as default for all other countries) (*Janssens-Maenhout et al., 2019*).

IPCC-06 provides a detailed synthesis of uncertainty associated with EFs for sectors 1.B.1 and 1.B.2, distinguishing between developing and developed countries (Tables 4.2.4 and 4.2.5 of IPCC-06, chapter

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4). u_{EF} is the same for CO_2 and CH_4, while is larger for N_2O. A summary of uncertainty ranges is provided in Table 3.

Uncertainties in the 1.B.1 sector depend on the type of mining activity: 'surface' (surf), 'underground' (und) and 'abandoned' (abandon). u_{EF} for these sectors can be rather large (>100%), as detailed in Table 3, according to IPCC-06 and in line with Olivier et al. (2002). For 1.B.2, the distinction is made between leakage in production (prod), transmission and distribution (trans), and venting/flaring (vent). The uncertainty is estimated as large as three times the average emission value for some instances (Table 3) for CH_4 and CO_2 and up to 1000% for flaring N_2O emission. We note that while some AD are known or retrievable through various governmental agencies (e.g. number of gas production wells, miles of pipelines, number of gas processing plants), other activity data (e.g., storage tank throughput, number of various types of pneumatic controllers, and reciprocating engines), are more uncertain. As reported by EPA, '*petroleum and gas infrastructure consist of millions of distinct emission sources, making measurement of emissions from every source and component practically unfeasible*' (EPA 2017).

FIGURE 4.

The sector is dominated by CH_4 emissions and this is reflected in the contribution to the total uncertainty of GHG emission from sector 1.B (Figure 4e). The upper world uncertainty estimate exceeds 110%, almost entirely due to CH_4 emissions. For the US, upper uncertainty estimate for oil and natural gas (Figure 4c) of 23% is in slightly less than the EPA's upper estimate of 30% for the natural gas system (*EPA, 2017*) and that of *Littlefield et al. (2017)* of 29%, while for the petroleum system the EPA's uncertainty is much larger (149%), possibly due to higher u_{AD}.

The country's uncertainty mirrors the distinction made in this study between developed and developing countries, mostly visible for fugitive emissions from oil and natural gas (Figure 4c) but also in the detailed u_{EF} provided by IPCC-06 for the various emitting stages of extraction, distribution, transport, storage. The composition of emissions for the five top emitters in sector 1.B.2.b can be used to illustrate this aspect.

TABLE 6.

The US and Russia have country-specific EFs, which are defined for all stages of the fugitive emissions from natural gas, and therefore the accuracy is higher. Iran, Saudi Arabia, China have a very large share of emissions due to the production stage of natural gas (approximately 85%, 97%, 76%, respectively), to which u_{EF} = ±75% applies, and a much lower share of emissions apportioned to the other stages (transmission and distribution) approximately 10% due to gas distribution with an uncertainty of -40% to +500% including the correction factor (Eq. 4), contributing to the very low confidence in the emission estimate shown in Figure 4e, compared with the medium confidence for USA and Russia, to which country-specific u_{EF} are applied (±25%) (Table 3). The high uncertainty in the transmission/distribution sectors is the main responsible for the difference in uncertainty apportionment.

Variability of bottom-up estimates of CH_4 emissions from coal mining (-29%, +43%) and natural gas and oil systems (-16%, +15%), as recently reported by *Saunois et al. (2020)*, stems from methodologies and parameters used, including emission factors, '*which are country- or even site-specific, and the few field measurements available often combine oil and gas activities and remain largely unknown*' (*Saunois et al., 2020*). The authors reported examples of very large variability of EFs between inventories, even of 2 orders of magnitude for oil production and by one order of magnitude for gas production. Moreover, large uncertainties in emissions of CH4 from venting and flaring at oil and gas extraction facilities were reported by e.g. *Peischl et al. (2015)*. Gas distribution stage is a further large source of uncertainty, in particular in countries with old gas distribution city networks using steel pipes

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now distributing dry rather than wet gas, with potentially more leakages (*Janssens-Maenhout et al., 2019*). Analysis based on inversion modelling by *Turner et al (2015)* found, for the North America region an error variability of -43% to 106% (with respect to the prior estimate based on EDGAR v4.2) attributed to emissions from oil and gas. Hence, the uncertainty in Figure 4c might be too low for industrialised countries. A more realistic application of uncertainty ranges for sector 1.B.2 (oil and gas), as suggest e.g. by *Olivier et al. (2002)* could be to assign u_{AD} = ±5 and ±15% (industrialised and developing countries, respectively) and u_{EF} = ±100% to all countries and u_{EF} of 50% to countries for which EF are specifically estimated (Tier 3).

FIGURE 5.

The resulting distribution (Figure 5) reflects the comparable uncertainty of these emissions across countries. Global u_{EMI} is of approximately 100%, thus slightly less than the uncertainty obtained by applying the IPCC-06 recommendations (122%, Figure 4e).

3.1.3 Industrial Processes and Product Use (IPPU)

IPCC category 2 covers non-combustion emissions from industrial production of cement, iron and steel, lime, soda ash, carbides, ammonia, methanol, ethylene, methanol, adipic and nitric acid and other chemicals and the non-energy use of lubricants and waxes (*Janssens-Maenhout et al., 2019*). The EDGAR sectors FOO (food production), PAP (paper and pulp production), IRO (iron and steel), non-energy use of fuels (NEU), non-ferrous metal production (NFE) and non-metallic minerals production (NMM) cover the industrial process emissions.

Activity statistics for industrial processes are retrieved from several reporting providers, as detailed by *Janssens-Maenhout et al., 2019*; Crippa et al, 2019). For this class of processes u_{AD} are higher than u_{EF} due to the deficiency or incompleteness of country specific data and reluctance by companies to disclose production data. CO_2 emissions in EDGAR are based on tier 1 EF for clinker production, whereas cement clinker production is calculated from cement production reported by USGS (2014). The fraction of clinker is based on data reported to UNFCCC for European countries, to the China Cement Research Institute (www.ccement.com; yjy.ccement.com/) and the National Bureau Statistics of China (for historic years) for China and to the 'getting the numbers right' for non-Annex I countries (https://gccassociation.org/gnr/). According to IPCC-06, the uncertainty for cement production stems prevalently from u_{AD}, and to a lesser extent from u_{EF} for clinker (IPCC-06, chapter 2). For Tier 1, the major uncertainty component is the clinker fraction of the cement(s) produced and u_{AD} can be as high as 35%. We assume u_{emi} of 11 to 60% depending on the accuracy of clinker data.

As for cement, the u_{AD} for lime outweighs u_{EF} due to lack of country specific data. We assume u_{AD} of ±35% and u_{EF} = ±3%. For glass, glass production data are typically measured accurately as reflected by u_{AD} = ±5% suggested by IPCC-06, while for Tier 1 the suggested u_{EF} is of ±60%. u_{EF} for other carbonates (e.g. limestone) is due to the variability in composition and is very low (~1 to 5%), while u_{AD} can be much larger due to poor quality statistics and is assumed of ±35%.

Production of ammonia, nitric and adipic acid as well as caprolactam, glyoxylic and glyoxylic acid is known with high degree of accuracy and u_{AD} for these processes can be estimated as ±2%. The corresponding u_{EF} is reported in Table and Table 3 and is derived from expert judgment elicitation and reported in IPCC-06 ($u_{EF}^{ammonia}$= ±7%; $u_{EF}^{Nitric\ Acid}$= ±20%; $u_{EF}^{Carbide}$ = ±10%). For petrochemical and carbon black production (methanol, ethylene, ethylene dichloride, vinyl, acrylonitrile, carbon black), IPCC-06 provides reference values for u_{EMI} associated to these processes (IPCC-06, Volume 3, Chapter

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3, Table 3.27), based on expert judgments. The values are reported in Table 3, ranging from ±10% for CH_4 emission for ethylene production to ±85% for CH_4 emission from carbon black production.

As summarised in Table 1, the AD for iron and steel (including furnace technologies) production are considered very accurate, with u_{AD} = ±10%, and for ferroalloys u_{AD} is set to ±10% for industrialised countries and u_{AD} = ±20% for developing countries, based on own judgment (IPCC-06 suggests u_{AD} = ±5%). The data for iron production are updated monthly using data from the World Steel Association (*WSA, 2019*), while for ferroalloys data are extrapolated using trends from USGS commodity statistics (*USGS, 2016*). u_{EF} is equal to ±25%.

Production data for aluminium, magnesium, zinc, and lead are deemed accurate within 2% to 10% (Table 1). For aluminium, the reactions leading to CO_2 emissions are well understood and the emissions are very directly connected to the quantity of aluminium produced (IPCC-06), and u_{EF} is assumed within 10%. The u_{EF} associated with CO_2 emitted from magnesium production is also well understood and is assumed within 5%. Lead and zinc production have higher u_{EF} (50%) associated with default emission factors (Tier 1), and of 15% if country specific data are adopted (Tier 2). CO_2 emissions for non-energy use of lubricants/waxes (like petroleum jelly, paraffin waxes and other waxes, classified under IPCC sector 2.D.2 and corresponding to EDGAR sector NEU) are assumed highly uncertain (u_{EF} of 100%; u_{AD} of 5 to 15%) due to the lack of accurate information and to country specific operating conditions.

FIGURE 6.

CO_2 emissions in sector 2 are one and two orders of magnitude higher than N_2O and CH_4 emissions respectively (Figure 6). Nearly 50% of CO_2 emissions in this sector originate from cement production. The accuracy ranges from medium-high to high for all top emitters and the global uncertainty is of 12%. For N_2O, the main source (~85%) is the production of nitric and adipic acid, which results in medium-high accuracy both country wise and globally. Finally, CH_4 is more uncertain due to the large u_{EF} of carbon black and methanol production, which account for ~52 % of global CH_4 emissions in the IPPU sector.

3.1.4 Agriculture

Agriculture related activities in EDGAR cover partially the IPCC category 3 (Agriculture, forestry and land use), including enteric fermentation (ENF, corresponding to 3.A.1), manure management (MNM, 3.A.2), waste burning of agricultural residues (AWB.CRP, corresponding to 3.C.1.b – biomass burning of cropland), direct N_2O emissions from soil due to natural and synthetic fertiliser use (corresponding to 3.C.4), indirect N_2O emissions from manure and soils (corresponding to 3.C.5 and 3.C.6), urea and agricultural lime (AGS.LMN and AGS.URE, corresponding to IPCC codes 3.C.2 and 3.C.3), and rice cultivation (AGS.RIC corresponding to 3.C.7). Forestry and land use are not covered. Derivation of AD for the agriculture sector are compiled by *Janssens-Maenhout et al., (2019*).

For sectors ENF and MNM, EDGAR follows *IPCC-06* for estimating emissions, with animal counting data from *FAOSTAT (2018)*. For ENF, uncertainty in AD is due to cattle numbers, feed intake, and feed composition, while for MNM the distribution of manure (volatile solids) in different manure management systems is also a source of uncertainty. u_{AD} for these sectors is estimated of ~±20% to account for uncertainty of the manure management system usage, lack of detailed characteristics of each country's livestock industry and how information on manure management is collected, and lack of homogeneity in the animal counting systems (IPCC-06; Olivier et al., 2002). The estimate slightly higher than u_{AD} from other US studies for ENF (*EPA, 2017, Hristov et al., 2017*), whilst for MNM u_{AD} of ±20% might be underestimated according to e.g. Hristov et al. (2017). EFs are calculated following IPCC (2006) methodology, using country specific data of milk yield and carcass weight integrated with trends from *FAOSTAT (2018)* for cattle, and using regional EFs for livestock. Tier 1 u_{EF} for ENF and MNM is estimated to be larger than ±50%, with a minimum of 30%) unless livestock characterisation is known with great accuracy, in which case Tier 2 uncertainty can be ~±20% (*IPCC-06).*

AD for burning of agriculture waste (AWB.CRP) can be highly uncertain, especially in developing countries, due to several factors including the estimates of the area planted under each crop type for which residues are normally burnt and the fraction of the agricultural residue that is burnt in the field. EDGAR estimates the fraction of crop residues removed and/or burned using data from *Yevich and Logan (2003)* and from official country reporting. Uncertainty is deemed very high, in the range $u_{AD}^{AWB.CRP} \approx 50\ to\ 100\%$ (*Olivier and Peters, 2002*; *Olivier et al., 1999*). EFs for this sector are obtained from the mass of fuel combusted, provided by IPCC-06 as default (Tier 1) EFs for stationary combustion in the agricultural categories, and are estimated with an uncertainty of ~-60% to +275% for N_2O, and ~±50% to ±150% for CH_4 , according to the uncertainty for combustion processes.

Emissions from rice cultivation are relevant to CH_4. According to the last release of EDGAR, in 2015 almost 10% of total emissions were due to rice cultivation. Default, baseline EF for rice cultivation has an uncertainty in the range -40% to +70%, which has been substantially reviewed in the refinement (2019), both in terms of EF value and of uncertainty. The refinement also gives regional-dependent EF and uncertainty ranges, but those have not been implanted yet in EDGAR, therefore we refer to the *IPCC-06* guidelines. In EDGAR the baseline EF is multiplied by a set of scaling factors that account for the water regimes before and during the cultivation period: upland (never irrigated), irrigated (IRR), rain fed (RNF) and deep water (DWP), which are assigned the following uncertainty (derived from *IPCC, 2006*): IRR: -20% to +26%; UPL: 0%; RNF and DWE: -22% to +26%. Organic amendments and soil type are not included. The AD consist of cultivation period and annual harvested area for each water regime and are derived from FAO (2011) and complemented with data from *IRRI (2007)* and *IIASA (2007)*. We assume u_{AD} of 5% to 10% (*Olivier 2002*). All the conditions together yield an uncertainty range of -0.45% to +75% for RNF,DWE and IRR, and of -0.41% to +70% for UPL.

FIGURE 7.

AD for sectors 3.C.2 (CO_2 emissions from liming), 3.C.3 (CO_2 emissions from urea application), are derived from *FAOSTAT (2016)*, and from official country reporting. Uncertainty of emissions of CO_2 from lime (urea) fertilization stems from uncertainties in the amount of urea applied to soils and from the uncertainties in the quantity of carbonate applications that is emitted as CO_2. u_{AD} is assumed of 20% (Olivier et al.,1998) to account for uncertainty in sales, import export and usage data adopted to derive the AD. EFs are derived from IPCC-06 Tier 1, assuming that all C in urea is lost as CO_2 in the atmosphere, which might give rise to systematic bias. u_{EF} is assumed ranging between ±50% and ±100%.

Sectors 3.C.4, 3.C.5, 3.C.6 cover direct and indirect N_2O emissions from managed soils and manure management. AD data are taken from *FAOSTAT (2016), UNFCCC (2018).* Nitrogen from livestock for developed countries is derived from the CAPRI model (*Leip et al., 2011*) and can be considered as Tier 3 level accuracy. Indirect N_2O emissions are due to leaching and runoff of nitrate and are subject to various sources of uncertainty (both AD and EFs) due to natural variability and to the volatilization and leaching factors, poor measurement coverage and under-sampling as well as due to incomplete/inaccurate/missing information on observance of laws and regulations related to handling and application of fertiliser and manure, and changing management practices in farming (IPCC-06). For these sectors, u_{AD} is estimated ±20% and u_{EF} in the range ±65% to ±200% according to IPCC-06).

The large variation of N_2O emissions in time and space is well recognised (e.g. *Stehfest and Bouwman, 2006*). Spatial heterogeneity, in particular, is largely driven by soil properties, and the influence of soil

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properties changes with scale and is responsible for the large confidence intervals given for the IPCC emission factors (*Milne et al., 2014*).

With a few exceptions the confidence in emission estimates from agriculture sector varies between medium and low for CO_2 and CH_4 (Figure 7a,b) depending on the composition of the agricultural sources and on the accuracy assigned to the specific country (developing vs industrialised). N_2O (Figure c) emissions are very uncertain (in excess of 300%), which is reflected in the global share of uncertainty (over 90%, though the share of global N_2O emissions does not exceed 30%, Figure d).

For the UK, *Milne et al. (2014)* estimated a 95% CI of −56% to +139%, *Brown et al. (2012)* of −93% to +253%, whereas *Monni et al. (2007)* of −52% to +70% for Finland (but based on older and more conservative IPCC guidelines). Our uncertainty estimates for the UK for sectors 3.C.4, 3.C.5, 3.C.6 combined is of -74% to 305% (as effect of assuming full correlation, if the three sectors are considered uncorrelated the 95% CI interval for the UK is -59% to +259%, which is in line with the other estimates).

FIGURE 8.

Uncertainties due to rice cultivation and enteric fermentation outweigh the uncertainty from other sources due to being the dominant emission shares over the emissions from burning of crop residues (which has higher uncertainty but low impact on overall emission) (Figure 8). Agricultural uncertainties in China are attributable to rice cultivation for ~80%, whilst rice emission accounts for less than 60% of the agriculture total. Similarly, the uncertainty due to enteric fermentation dominates the USA agriculture uncertainty (75% share).

3.1.5 Waste

The waste-related emissions in EDGAR correspond to IPCC category 4 (Waste), including emissions from managed and non-managed landfills (SWD: solid waste disposal on land and incineration, categories 4.A, 4.B and 4.C), wastewater handling (domestic WWT.DOM and industrial WWT.IND, categories 4.D.1 and 4.D.2, emitting CH_4 and N_2O), and waste incineration (emitting CH_4 and N_2O and also CO_2). Globally, the waste sector accounts for 4.4% of total GHG anthropogenic emission in 2015 and 21.5% of total anthropogenic CH_4 emissions (*Crippa et al., 2019*).

In EDGAR, emissions are based on a combination of population and solid and liquid waste product statistic. CH_4 emissions from landfills are calculated following the first order decay model proposed by IPCC-06, which assumes that emissions do not occur instantaneously but are spread over several years. The model depends on several parameters (Table 1 and Table 3), and the main factor in determining the CH_4 generation potential is the amount of degradable organic carbon (DOC) (IPCC-06; Olivier et al., 2002; *Janssens-Maenhout et al. 2019*). The average weight fraction DOC under aerobic conditions is provided by the IPCC Waste Model for 19 regions, which has been used as the default for all countries. Moreover, the default parameters for the methane correction factor (MCF), constant (k) and the oxidation factor (OX) are adopted (full details in Table 1 of *Janssens-Maenhout et al. 2019*). Each component of the waste model has been assigned a normal distribution using the 95% CI defined in Table 1 and Table 3 and combined using a sample population of 10000 elements. The range of overall uncertainty is between 35% and 134% for CH_4 and between 10% and 490% for N_2O.

For the incineration of waste, AD are derived from *UNFCCC NIR and IPCC-06*, country reports and scientific literature, extrapolated using population trends (e.g. for countries with scarce data on municipal solid waste) , while for composting (category 'other'), data are obtained from UNFCCC NIR

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for Annex I countries and scientific literature for developing countries and for India (Table 1 of *Janssens-Maenhout et al., 2019* and references therein).

As detailed in *Janssens-Maenhout et al. (2019)*, the IPCC-06 default values for wastewater generation and chemical oxygen demand (CODs) are used to derive the total organically degradable material (TOWs), differentiating by type of industry (meat, sugar, pulp, organic chemicals, ethyl alcohol). Population from UNHABITAT statistics (UNHABITAT, 2016) is used to derive country-specific percentages of population at mid-year residing in urban and rural areas, with low and high income, for calculating domestic wastewater. Different wastewater treatments are specified with technology-specific CH_4 emission factors. For domestic wastewater, the sewer to wastewater treatment plants (WWTP), sewer to raw discharge, bucket latrine, improved latrine, public or open pit and septic tank are distinguished. Uncertainty of domestic wastewater depends on the technology (sewer to raw discharge, bucket latrine, improved latrine) as specified in Table 1 and Table 3, and is composed of uncertainty in AD (population data ~36%) and uncertainty on EF (33% to 78%).

Uncertainty on AD for industrial wastewater data ranges between -56% to 103%, estimated using the IPCC-06 suggested values, which are in line with those provided by Olivier et al (2002) (-50% to 100%). Uncertainty on EF includes 30% uncertainty for the maximum CH_4 producing capacity (parameter B_0) and uncertainty on the CH_4 correction fraction of 50% to 100% (based on the range of default values for MCF provided by IPCC-06 in table 6.8 of Volume 5).

Emissions of CH_4 from the waste sector is one order of magnitude higher than N_2O and two orders higher than CO_2 (Figure a,b,c) and although N_2O emissions are more uncertain, the share of uncertainty still reflects the share of emissions (Figure d). The confidence in the emission estimates varies from medium to medium low for CO_2 (depending on the status of development of the country), from medium to very low for CH_4 (depending on the status of development of the country and on the composition of the waste sector, discussed next) and is very low for N_2O (due to high u_{EF} in waste water).

FIGURE 9.

The composition of the waste sector for CH_4 (Figure) shows that there is a strong correspondence between the emissions share and the uncertainty share. For the USA, landfills emissions accounts for ~73% of waste emissions, and the uncertainty due to landfills is ~90%. In India, domestic wastewater accounts for over 85% of waste emissions, driving the overall uncertainty with 97%.

FIGURE 10.

Worldwide, the CH_4 emission share from landfills and domestic wastewater is approximately equivalent (~44% and ~41%, respectively), whilst landfills have a relatively larger weight in the global uncertainty share (~55% and ~41%, respectively).

3.2 The Global and European picture

The values in Table 7 summarise the global uncertainty ranges by gas and categories, including the global totals.

TABLE 7.

Globally, while CO_2 is by far the largest emitted GHG gas (in excess of 75%) followed by CH_4 (19%), the main source of uncertainty (~50%) is N_2O (Figure a), followed by CH4 (~29%). Agriculture alone accounts for 39% of the global uncertainty (Figure b) and almost entirely due to N_2O as discussed earlier

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(Figure 8d) and energy accounts for 44% (almost half of the uncertainty for energy is due to N_2O, Figure 1f) and waste (11%, driven by CH_4 emissions, Figure 9d).

FIGURE 11.

The picture is quite similar for EU27+UK (Figure 12) with the main difference being the larger uncertainty share of N_2O (~70%) due to the higher level of accuracy associated with CO_2 and CH_4.

FIGURE 12.

4 Uncertainty due to methodology

The considerable number of 'degrees of freedom' influencing the uncertainty of an emission inventory such as EDGAR is *itself* a source of uncertainty originating from different methodological assumptions. As such, the structural uncertainty of emissions tackled in the previous section is subject to variability due to the sets of assumptions, methods, choices adopted for its quantification. It originates from lack of agreement/incomplete knowledge on the processes governing the emission sources and their representativeness. Such a *methodological uncertainty* reflects the judgment of the uncertainty emission compiler and can give rise to a significant share of the overall uncertainty estimate. For instance, two experts could suggest two different probabilistic models for the value of a certain source, leading to a certain degree of variability in the PDFs of the source. Methodological uncertainty, thus, may arises from the assumptions adopted assessment, particularly when there are no clear guidelines or reference cases about methodological choices that allow comparability between evaluations.

One of the most impactful assumptions of this study is the correlation between subcategories/fuels and, for the same category/fuel, between countries. This has a profound impact on the uncertainty estimate, for example in inter-comparison studies where EDGAR's uncertainties are shown next to other inventories whose uncertainty estimates do not account for correlation (e.g. *Petrescu et al., 2020*).

FIGURE 13.

The global weight of the correlation is reflected in the total of Figure 13, where the uncertainty ranges from 4% (no correlation) to above 20% for the correlated cases. The impact of assuming correlation of the uncertainties when aggregating the emissions of several countries outweighs any other assumptions. For instance, the assumption to constrain the N_2O uncertainty for energy to ±50% and ±100 has, globally, much lower impact over the total uncertainty (23% rather than 20%).

FIGURE 14.

As shown in Figure 14 for EU27+UK, the effect of correlation on the variability of the uncertainty is considerable. Emissions from the energy sector are estimated as accurate as the 95% CI lies within 2% of mean value when no correlation is assumed across countries and of 7% when the correlation is set to one. The uncertainty of 13% for the Tier1 'default case' reflects the high share of uncertainty due to N_2O since the only difference between the 'T1 default' and 'T1+OJ N_2O' for energy is the upper limit of N_2O uncertainty to ±50% and ±100. The same arguments apply to the other sectors, most notably to agriculture (130% vs 36%, with or without correlation), and is reflected in the total GHG emissions (15% vs 4%).

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This simple reasoning suggests that if EU27+UK reported its emissions as a single party, even Tier 1 propagation methods would return an accuracy comparable to the combination of independent estimates (i.e. as if all EU parties used independent, Tier 2 or 3 estimates of their emissions).

The comparison between the 'default' uncertainty ranges and 'EDGAR in-house expert judgment' for N_2O shows the impact of choices on the quantification of the uncertainty, contributing to enhance the uncertainty variability. The case of energy in Figure 14 is an example: the default uncertainty of 13% can vary as much as 46% (down to 7%) due to different judgments in estimating u_{EF}.

5. Conclusions

This study quantifies the structural uncertainty of the EDGAR inventory of GHGs. Given the wide-spread applications of EDGAR in many areas – modelling, policy, evaluation, planning – the qualification of its accuracy and quantification of its uncertainty are essential added values.

EDGAR is a consistent database based, predominantly, on Tier 1 methods to quantify emission from anthropogenic sources (on a three-level of sophistication, Tier 1 is the simplest). As such, the uncertainty analysis presented here follows the corresponding Tier 1 approach for uncertainties, also suggested by IPCC (2006; 2019) to assist in country reporting. Some additional assumptions have been put forward to allow for the simple Tier 1 uncertainty method to integrate with the EDGAR global database.

The global, comparable nature of EDGAR is one of its main attractiveness. Zooming in individual countries, the accuracy of EDGAR cannot, in general terms, match that of the country's inventory reporting panel who might adopt higher tiers for estimating emissions and uncertainties. Hence, it is when looking at cross-sector, gases and countries aggregation that the analysis presented in this study shows its benefits.

When sources sharing the same underlying methodology are aggregated, we have assumed that the uncertainty is amplified and therefore the aggregation must account for their correlation. The correlation is kept when aggregating the same sectors across countries and when aggregating subcategories, with some exceptions and caveats detailed in the main text.

To summarise:

- Global CO_2 emitted from the energy sector alone (IPCC sector 1) accounts for 96% of global GHG emission, and is accurate within 7% (generally, high confidence levels for top emitters);
- When adding CH_4 and N2O, the accuracy of the energy sector decreases to an uncertainty of -12.8; +15.9%;
- The uncertainty of N_2O for the power industry sector (factor of 10 suggested by IPCC guidelines) indicates a very poor accuracy. The value is however too high to be used in a comparative analysis and aggregation, as it masks the results and contribution of other sources/gas. Therefore, expert judgement for N_2O in sector 1.A is to use u_{EF} = ± 50 to 150% (industrialized and developing countries, respectively), to yield a global uncertainty of ~112%;
- CH_4 emitted by the oil and gas extraction facilities is highly uncertain although the guidelines provide detailed uncertainties for all stages (extraction, storage, distribution, transmission) and differentiated by the level of development of the country. Due to the discrepancies with scientific literature and the number of parameters and components of this sector we suggest to apply a conservative estimate of u_{AD} = ±5 and ±15% (industrialised and developing countries, respectively) and u_{EF} = ±100% to all countries (u_{EF} of 50% for country specific EF) when

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considering aggregation of sectors/countries which produce uncertainty ranges more in line with the scientific literature to yield a global CH_4 uncertainty of -55%; +93%;
- Agriculture emissions are dominated by CH_4 and N_2O, with the uncertainty of the latter (over 300% on a global average) outweighing that of CH_4 due to large uncertainty in emission factors. At the global scale, CH_4 uncertainty is driven by rice cultivation and enteric fermentation;
- Waste is also a sector dominated by CH_4 emissions, followed by N_2O. The uncertainty of the latter are very high (often exceeding 400%), while for CH_4 emissions, the share from landfills and domestic wastewater is approximately equivalent (~44% and ~41%, respectively), whilst landfills have a relatively larger weight in the global uncertainty share (~55% and ~41%, respectively).

The strongest assumption, already used in previous studies, is the full correlation of subcategories and countries which introduces a further source of uncertainty – methodological uncertainty – that is very impactful. Uncertainty around methodological choices arises when there are different views about what constitutes the ‘‘correct’’ approach for optimum decision making. This form of uncertainty might be dealt with by agreeing on a ‘‘reference case’’ or on a list of methodological choices to allow comparability between different inventories.

The choice of methods can have a profound impact on the overall uncertainty assessment and needs to be take into consideration when comparing inventories. For EU27+UK, for example, the choice to assume or not correlation among countries can result in a ~4-fold variability of the uncertainty (4% vs 15%).

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Data availability

The database underlying the analysis is EDGARv5.0 available at https://edgar.jrc.ec.europa.eu/overview.php?v=50_GHG

Author contribution

E.Solazzo: design of the study, analysis, writing; M.Crippa, D.Guizzardi, M.Muntean: emission database; M-Choulga: support in the uncertainty analysis of CO2; G. Janssens-Maenhout: design of the study.

Competing interests

No competing interests

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FIGURES

FIGURE 1. GHG EMISSIONS FROM TOP EMITTERS AND WORLD FOR SECTOR 1.A (ENERGY FROM FUEL COMBUSTION). A) CO2 FROM ENERGY INDUSTRIES; B) CO2 FROM MANUFACTURING INDUSTRIES; C) CO2 FROM TRANSPORT; D) CH4 FROM FUEL COMBUSTION; E) N2O FROM FUEL COMBUSTION; F) WORLD TOTAL: TOTAL UNCERTAINTY; EMISSION AND UNCERTAINTY SHARES. COUNTRY'S NAMES ARE COLOR-CODED ACCORDING TO THEIR CLASSIFICATION (CYAN: INDUSTRIALISED; RED: DEVELOPING). CONFIDENCE LEVELS ARE GIVEN IN THE RANGES: HIGH (0,10%]; MEDIUM-HIGH (10,20%], MEDIUM (20,40%]; MEDIUM-LOW (40,60%], LOW (60,100%], VERY LOW > 100% (COUNTRY CODES ARE EXPLICITATED IN TABLE 5).

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FIGURE 10. CH_4 UNCERTAINTY AND EMISSIONS SHARES FOR EDGAR'S EMISSION SECTORS UNDER IPCC CATEGORY 4 FOR BRAZIL, CHINA, INODONESIA, INDIA, MEXICO, RUSSIA, UNITED STATES OF AMERICA, AND THE WORLD.

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Tables of Solazzo et al., Uncertainties in the EDGAR emission inventory of greenhouse gases

TABLE 1 AD UNCERTAINTY (UPPER AND LOWER LIMITS DEFINE THE 95% CI OF A NORMAL DISTRIBUTION). WHEN TWO VALUES ARE LISTED, THE SMALLER RANGE APPLIES TO INDUSTRIALISED COUNTRIES, THE LARGER RANGE TO DEVELOPING COUNTRIES

IPCC categories (IPCC 2006)	u_{AD} (%)	
	Industrialised	Developing
1A – Fuel Combustion	±5	±10
1A4- Fuel combustion in residential sector	±10	±20
1A3a – Aviation (domestic)	±5	±100
1A3a – Aviation (international)	±5	±5
1A3d - Navigation	±25	±25
1A – Fuel Combustion (Biofuels)*	±30	±80
1B1 - Fugitive emissions (solid fuel)	±5	±10
1B2 - Fugitive emissions (gas and oil)	±10	±20
2B5 Carbide, 2B6 Titanium dioxide 2B7 Soda ashes production	±5	±5
2B1 Ammonia, 2B2 Nitric Acid, 2B3 Adipic acid, 2B4 Caprolactam; Glyoxylic and glyoxylic acid	±2	±2
2C1 Iron and steel 2C2 Ferroalloy 2C3 Aluminium 2C4 Magnesium 2C5 Lead 2C6 Zinc	±10 ±10 ±2 ±5 ±10 ±10	±10 ±20 ±2 ±5 ±10 ±10
2A1 Cement	Included in u_{EF}	
2A2/2A4 Lime/Limestone	±35	±35
2A3 Glass	±5	±5
2D2 Non-energy use of fuels, lubricants/waxes	±5	±15
3A1 - Enteric fermentation	±20	±20
3A2 - Manure management	±20	±20
3C1 Biomass burning of crops	±50	±100
3C2 CO_2 emission from liming	±20	±20
3C3 CO_2 emission from Urea fertilization	±20	±20
3C4 Synthetic Fertilizers; Animal Manure Applied to Soils; Crop Residue; Pasture	±20	±20
3C5 Indirect N_2O from managed soils	[±50]	[±50]
3C6 Indirect N_2O from manure management	[±50]	[±50]
3C7 - Rice cultivation	±5	±10
4D1 - Domestic wastewater	For CH_4: Population: ±5; Per-capita biochemical oxygen demand (BOD): ±30%; Degree of utilisation of treatment for income group: ±5; ±50; Income group: ±15; Correction factor for collected industrial BOD into sewers: ±20 For N_2O: Population: ±5; Annual per capita protein consumption: ±10; Fraction of nitrogen in protein: ±6; utilization of large WWT plants: ±20; Adjustment for non-consumed protein: ±15; Adjustment for co-discharge of industrial nitrogen into sewers: ±20	
4D2 - Industrial wastewater	For CH4:	

	± 25% on industrial production; -50% to 100% on the weight of degradable organics concentration per unit of product. For N2O: ±34% (as for WWT.DOM)	
4C Solid waste	Municipal solid waste: - Country specific= ±30%; - Developed = ±10%; - Developing= -50% to 100% Fraction of solid waste disposed - Country specific= ±10%; - Developed = ±30 %; - Developing= -50% to 100%	
5A Indirect emission from NOx and NH3	± 20	± 20
5B Other (includes burning…)	± 50	± 50

Source: IPCC (2000; 2006) and elaborations by Olivier et al (2002);
Figures in square brackets are own expert judgments (OJ).

TABLE 2 CO_2 UNCERTAINTY ON EF BY FUEL-TYPE (FROM TABLE 3.2.1 OF IPCC 2006)

Fuel Type	Category	description	Industrialised/ Country Specific	Developing	
			Min(%) Max (%)	min (%)	Max (%)
Combustion sectors					
Motor Gasoline	1A	fuel combustion	-2.6; 5.3	-5.3; 5.3	
Aviation gasoline	1A	fuel combustion	-3.6; 4.3	-4.3	4.3
Gas/ Diesel Oil	1A	fuel combustion	-2.0; 0.95	-2.0	2.0
Liquefied Petroleum Gases (LPG)	1A	fuel combustion	-2.3; 4.0	-4.0	4.0
Kerosene	1A	fuel combustion	-2.0; 3.0	-3.0	3.0
Lubricants , naphta, white spirit, non-specified petroleum products, other hydrocarbon, paraffin waxes, refinery feedstocks' soda	1A	fuel combustion	-1.9; 2.6	-1.9; 2.6	
	1A	fuel combustion	-1.5; 1.5	-1.5; 1.5	
	1A	fuel combustion	-3; 3	-3; 3	
Natural Gas	1A	fuel combustion	-3.2; 3.9	-3.9; 3.9	
Natural Gas Liquids	1A	fuel combustion	-9.2; 9.6	-9.2; 9.6	
Anthracite	1A	fuel combustion	-3.8; 2.7	-3.8; 2.7	
Biodiesel and biogasoline	1A	fuel combustion	-15.5; 19.1	-15.5; 19.1	
Blast furnace gas	1A	fuel combustion	-15.8; 18.5	-15.8; 18.5	
Additives/blending components	1A	fuel combustion	-1.5; 1.5	-1.5; 1.5	
	1A	fuel combustion	-3.0; 3.0	-3.0; 3.0	
Crude oil	1A	fuel combustion	-1.5; 1.5	-1.5; 1.5	
bitumen	1A	fuel combustion	-15.5; 18.1	-15.5; 18.1	

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Sub-Bituminous Coal	1A	fuel combustion	-3.4; 4.0	-3.4; 4.0
BKB/Peat Briquettes	1A	fuel combustion	-14.5; 18	-14.5; 18
Brown coal	1A	fuel combustion	-10; 14	-10; 14
Other bituminous coal	1A	fuel combustion	-7.7; 6.8	-7.7; 6.8
charcoal	1A	fuel combustion	-25; 25	-25; 25
ethane	1A	fuel combustion	-8.3; 11.3	-8.3; 11.3
biogas	1A	fuel combustion	-50; 50	-50; 50
Gas coke	1A	fuel combustion	-16; 17	-16; 17
Gas Works Gas	1A	fuel combustion	-16; 22	-16; 22
Residual Fuel Oil	1A	fuel combustion	-2.4; 1.8	-2.4; 1.8
Municipal Waste (Renew) in Fuel combustion petrole	1A	fuel combustion	-7; 7	-7; 7
Bagasse in Pumped storage of electricity	1A	fuel combustion	-7; 7	-7; 7
Heat Output from Non-spec. Manuf. Gases	1A	fuel combustion	-7; 7	-7; 7
Primary Solid Biomass in Fuel combustion petroleum	1A	fuel combustion	-16; 17	-16; 17
Oil shale	1A	fuel combustion	-16; 17	-16; 17
Petroleum Coke	1A	fuel combustion	-15; 18	-15; 18
Coke Oven Coke	1A	fuel combustion	-10.5; 11.2	-10.5; 11.2
Coke oven gas	1A	fuel combustion	-16; 22	-16; 22
Coking and hard Coal	1A	fuel combustion	-7.7; 7	-7.7; 7
Coal Tar	1A	fuel combustion	-0.14; 11.4	-0.14; 11.4
Crude/NGL/Feedstocks	1A	fuel combustion	-3; 3	-3; 3
Gasoline jet fuel	1A	fuel combustion	-2.6; 4.3	-2.6; 4.3
Kerosene jet fuel	1A	fuel combustion	-2.5; 4.0	-2.5; 4.0
Industrial waste	1A	fuel combustion	-20; 32	-20; 32
Municipal waste	1A	fuel combustion	-20; 32	-20; 32
Oxygen Steel Furnace Gas	1A	fuel combustion	-15; 18	-15; 18
Patent Fuel	1A	fuel combustion	-15; 18	-15; 18
peat	1A	fuel combustion	-5.7; 1.9	-5.7; 1.9
Refinery gas	1A	fuel combustion	-16.3; 20	-16.3; 20
Non combustion sectors				
PRO	1B2aii	Venting and flaring during oil and gas production, Oil transmission, Transport by oil trucks	-50; 50	-75; 75
Gasoline, Diesel, LPG, naphta, white spirit, natural gas, anthracite, biodiesel, blast furnace gas, crude oil, bitumen, BKB/Peat Briquettes, other bituminous coal, ethane, gas coke, Gas Works Gas,	1B1c	Fuel transformation coke ovens	-50; 50	-50; 50
	1B2b	Fuel transformation of gaseous fuels: Non-specified transformation	-100; 100	-100; 250
	2D2	Other Non-energy use of fuels in industry	-100; 100	-100; 100
	2C1	Blast furnaces	-25; 25	-25; 25

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Residual Fuel Oil, Renewables Wastes (1B1c only, Coke ovens I NPUT: Non-specified Combust),				
Industrial Processes	2A1	cement	-11; 11	-61 61
	2A2	lime	-2; 2	-2; 2
	2A4d	limestone	-3; 3	-3; 3
	2B1	ammonia	-7; 7	-7; 7
	2B2	titanium	-7; 7	-7; 7
	2B5	Silicon, calcium	-10; 10	-10; 10
	2B4	Ethylene, methanol	-30; 30	-30; 30
	2B4	Vinyl	-50; 20	-50; 20
	2B4	carbon black, urea	-15; 15	-15; 15
	2C1 2C2	Steel, ferroalloys	-25; 25	-25; 25
	2C3	aluminium	-10; 10	-10; 10
	2C3	magnesium	-50; 50	-50; 50
	2C5, 2C6	lead, zinc	-50; 50	-50; 50
	2A3	glass	-60; 60	-60; 60
Solvents	2D3		-25; 25	-25; 25
CO2 from urea, dolomite and limestone application	3C2 3C3	C in urea fertilizer applied	-50; 50	-100; 100
	5B	Oil/coal fires	-100; 100	-100; 100
	4C1	Waste incineration without energy recovery	-40; 40	-40; 40
Non-energy use of lubricants/waxes	2D2	petroleum jelly, paraffin waxes and other waxes	-100;100	-100;100

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TABLE 3 UNCERTAINTY OF EF FOR CH_4 AND N_2O DEFINED BY IPCC SECTORS AND CORRESPONDING EDGAR SECTORS (SEE TEXT FOR ABBREVIATIONS). OJ: OWN EXPERT JUDGEMNT

IPCC 2006	Uncertainty CH_4 (%)				Uncertainty N_2O (%)	
1A	±50; ±150				-10 to 1000 uncertainty range from one-tenth of the mean value to ten times the mean value (IPCC, 2006)	OJ ±50 (Industrialised) ±150 (Developing) ±50 (country-specific)
Aviation	-57 to 100				-10 to 1000 uncertainty range from one-tenth of the mean value to ten times the mean value (IPCC, 2006)	OJ ±50 (Industrialised) ±150 (Developing) ±50 (country-specific)
Navigation	±50				-10 to 1000 uncertainty range from one-tenth of the mean value to ten times the mean value (IPCC, 2006)	OJ ±50 (Industrialised) ±150 (Developing) ±50 (country-specific)
Raod Transport	±40				-10 to 1000 uncertainty range from one-tenth of the mean value to ten times the mean value (IPCC, 2006)	OJ ±50 (Industrialised) ±150 (Developing) ±50 (country-specific)
Fuel Combustion (Biofuels)*	±30; ±80				-10 to 1000 uncertainty range from one-tenth of the mean value to ten times the mean value (IPCC, 2006)	OJ ±50 (Industrialised) ±150 (Developing) ±50 (country-specific)
1B1 Fugitive emissions from solid fuels	Surf ±66.7 ±200 ±50	Und ±50 ±100 ±50	Abandon -50 to 100 -66 to 200 -50 to 50	OJ :±100	-10 to 1000	
1B2a Fugitive emissions from oil	Prod ±75 -67 to 150 ±50	Trans ±100 -50 to 200 ±100	Tank ±50 -50 to 200 ±50	OJ :±100	-10 to 1000	
1B2b Fugitive emissions from natural gas	Prod ±25 ±75 ±25		Trans ±100 -40 to 500 ±100	OJ :±100	-10 to 1000	
2. Nitric acid Caprolactam Glyoxylic Anaesthesia/aerosol spray Carbide	±10				±20 ±40 ±10 ±10	
Methanol	-80% to +30%					
Carbon black:	±85%					
Ethylene oxide Ethylene	±60% ±10					
3A1 Enteric Fermentation	±30; ±50					
3A2 manure management	±30				±50; ±100	
3C7 Rice cultivation	-40 to +70 on default emission factors plus uncertainty on water regimes: irrigated: -20 to +26 UPL: 0% Rainfed and Deep water: -22 to +26					
3C1 Non-CO2 Burning cropland	OJ: ±50; ±150 according to uncertainty in combustion sector					OJ: ±50; ±150 according to uncertainty in combustion sector
3C4 Synthetic Fertilizers; Animal Manure Applied to Soils; Crop Residue; Pasture					±70 (±65 for pasture); ±200	
Indirect N2O from managed soils					±70; ±200	
3C6 Indirect N2O from manure management					±50; ±150	

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4C	DOC and DOCf: 20% (CS:10); CH_4 Correction factor: ±30 F: ±0.5 R: ±10; ±50 Half-life: ±50 (depends on type of waste and climate zone)	N_2O emissions from incineration and composting No indications from IPCC. Same as for CH_4
4D1 - Domestic wastewater	±30% on B_o plus uncertainty on MCF technology (within the range 0-1): Latrines (BLA; ILA; LAT): ±50% Septic (SEP): 0%; Lagoons: ±30% S2R, S2W -> 30%;	±90; ±4900
4D2 - Industrial wastewater	±30% on B_o plus uncertainty on MCF technology (within the range 0-1): Untreated: 100; Treated: ±30	Same as 4D1
5A Indirect emission from NOx and NH3		±100

TABLE 4. SHARE OF GHG EMISSIONS (DERIVED FROM CO2, CH4 AND N2O EXPRESSED IN CO2EQ) OF DEVELOPING AND INDUSTRIALISED COUNTRIES FOR SECTOR 1.A BASED ON EDGAR EMISSIONS FOR THE YEAR 2015

Sector 1.A	Developing	Industrialised
CO_2	44.0%	53.9%
N2O	0.4%	0.3%
CH4	1.11%	0.2%

TABLE 5. COUNTRY CODES, NAMES AND DEVELOPMENT STATUS (DEVELOPING AND INDUSTRIALISED).

Country ISO code	**Country name**	**Country class**
ABW	Aruba	Developing
AFG	Afghanistan	Developing
AGO	Angola	Developing
AIA	Anguilla	Developing
AIR	Int. Aviation	0
ALB	Albania	Industrialised
ANT	Netherlands Antilles	Developing
ARE	United Arab Emirates	Developing
ARG	Argentina	Developing
ARM	Armenia	Industrialised

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ASM	American Samoa	Developing
ATG	Antigua and Barbuda	Developing
AUS	Australia	Industrialised
AUT	Austria	Industrialised
AZE	Azerbaijan	Industrialised
BDI	Burundi	Developing
BEL	Belgium	Industrialised
BEN	Benin	Developing
BFA	Burkina Faso	Developing
BGD	Bangladesh	Developing
BGR	Bulgaria	Industrialised
BHR	Bahrain	Developing
BHS	Bahamas	Developing
BIH	Bosnia and Herzegovina	Industrialised
BLR	Belarus	Industrialised
BLZ	Belize	Developing
BMU	Bermuda	Developing
BOL	Bolivia	Developing
BRA	Brazil	Developing
BRB	Barbados	Developing
BRN	Brunei Darussalam	Developing
BTN	Bhutan	Developing
BWA	Botswana	Developing
CAF	Central African Republic	Developing
CAN	Canada	Industrialised
CHE	Switzerland	Industrialised
CHL	Chile	Developing
CHN	China	Developing
CIV	Cote d'Ivoire	Developing
CMR	Cameroon	Developing
COD	Congo_the Democratic Republic of the	Developing
COG	Congo	Developing
COK	Cook Islands	Developing
COL	Colombia	Developing
COM	Comoros	Developing
CPV	Cape Verde	Developing
CRI	Costa Rica	Developing
CUB	Cuba	Developing
CYM	Cayman Islands	Developing
CYP	Cyprus	Industrialised
CZE	Czech Republic	Industrialised
DEU	Germany	Industrialised
DJI	Djibouti	Developing
DMA	Dominica	Developing
DNK	Denmark	Industrialised
DOM	Dominican Republic	Developing

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DZA	Algeria	Developing
ECU	Ecuador	Developing
EGY	Egypt	Developing
ERI	Eritrea	Developing
ESH	Western Sahara	Developing
ESP	Spain	Industrialised
EST	Estonia	Industrialised
ETH	Ethiopia	Developing
FIN	Finland	Industrialised
FJI	Fiji	Developing
FLK	Falkland Islands (Malvinas)	Developing
FRA	France	Industrialised
FRO	Faroe Islands	Industrialised
FSM	Micronesia, Federated States of	Developing
GAB	Gabon	Developing
GBR	United Kingdom	Industrialised
GEO	Georgia	Industrialised
GHA	Ghana	Developing
GIB	Gibraltar	Industrialised
GIN	Guinea	Developing
GLP	Guadeloupe	Developing
GMB	Gambia	Developing
GNB	Guinea-Bissau	Developing
GNQ	Equatorial Guinea	Developing
GRC	Greece	Industrialised
GRD	Grenada	Developing
GRL	Greenland	Industrialised
GTM	Guatemala	Developing
GUF	French Guiana	Developing
GUM	Guam	Developing
GUY	Guyana	Developing
HKG	Hong Kong	Developing
HND	Honduras	Developing
HRV	Croatia	Industrialised
HTI	Haiti	Developing
HUN	Hungary	Industrialised
IDN	Indonesia	Developing
IND	India	Developing
IRL	Ireland	Industrialised
IRN	Iran, Islamic Republic of	Developing
IRQ	Iraq	Developing
ISL	Iceland	Industrialised
ISR	Israel	Developing
ITA	Italy	Industrialised
JAM	Jamaica	Developing
JOR	Jordan	Developing

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JPN	Japan	Industrialised
KAZ	Kazakhstan	Industrialised
KEN	Kenya	Developing
KGZ	Kyrgyzstan	Industrialised
KHM	Cambodia	Developing
KIR	Kiribati	Developing
KNA	Saint Kitts and Nevis	Developing
KOR	Korea, Republic of	Industrialised
KWT	Kuwait	Developing
LAO	Lao People's Democratic Republic	Developing
LBN	Lebanon	Developing
LBR	Liberia	Developing
LBY	Libyan Arab Jamahiriya	Developing
LCA	Saint Lucia	Developing
LKA	Sri Lanka	Developing
LSO	Lesotho	Developing
LTU	Lithuania	Industrialised
LUX	Luxembourg	Industrialised
LVA	Latvia	Industrialised
MAC	Macao	Developing
MAR	Morocco	Developing
MDA	Moldova, Republic of	Industrialised
MDG	Madagascar	Developing
MDV	Maldives	Developing
MEX	Mexico	Industrialised
MHL	Marshall Islands	Developing
MKD	Macedonia, the former Yugoslav Republic of	Industrialised
MLI	Mali	Developing
MLT	Malta	Industrialised
MMR	Myanmar	Developing
MNG	Mongolia	Developing
MNP	Northern Mariana Islands	Developing
MOZ	Mozambique	Developing
MRT	Mauritania	Developing
MSR	Montserrat	Developing
MTQ	Martinique	Developing
MUS	Mauritius	Developing
MWI	Malawi	Developing
MYS	Malaysia	Developing
MYT	Mayotte	Developing
NAM	Namibia	Developing
NCL	New Caledonia	Developing
NER	Niger	Developing
NFK	Norfolk Island	Developing
NGA	Nigeria	Developing
NIC	Nicaragua	Developing

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NIU	Niue	Developing
NLD	Netherlands	Industrialised
NOR	Norway	Industrialised
NPL	Nepal	Developing
NRU	Nauru	Developing
NZL	New Zealand	Industrialised
OMN	Oman	Developing
PAK	Pakistan	Developing
PAN	Panama	Developing
PER	Peru	Developing
PHL	Philippines	Developing
PLW	Palau	Developing
PNG	Papua New Guinea	Developing
POL	Poland	Industrialised
PRI	Puerto Rico	Developing
PRK	Korea, Democratic People's Republic of	Developing
PRT	Portugal	Industrialised
PRY	Paraguay	Developing
PYF	French Polynesia	Developing
QAT	Qatar	Developing
REU	Reunion	Developing
ROU	Romania	Industrialised
RUS	Russian Federation	Industrialised
RWA	Rwanda	Developing
SAU	Saudi Arabia	Developing
SCG	Serbia and Montenegro	Industrialised
SDN	Sudan	Developing
SEA	Int. Shipping	0
SEN	Senegal	Developing
SGP	Singapore	Developing
SHN	Saint Helena	Developing
SLB	Solomon Islands	Developing
SLE	Sierra Leone	Developing
SLV	El Salvador	Developing
SOM	Somalia	Developing
SPM	Saint Pierre and Miquelon	Industrialised
STP	Sao Tome and Principe	Developing
SUR	Suriname	Developing
SVK	Slovakia	Industrialised
SVN	Slovenia	Industrialised
SWE	Sweden	Industrialised
SWZ	Swaziland	Developing
SYC	Seychelles	Developing
SYR	Syrian Arab Republic	Developing
TCA	Turks and Caicos Islands	Developing
TCD	Chad	Developing

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TGO	Togo	Developing
THA	Thailand	Developing
TJK	Tajikistan	Industrialised
TKL	Tokelau	Developing
TKM	Turkmenistan	Industrialised
TLS	Timor-Leste	Developing
TON	Tonga	Developing
TTO	Trinidad and Tobago	Developing
TUN	Tunisia	Developing
TUR	Turkey	Industrialised
TUV	Tuvalu	Developing
TWN	Taiwan_Province of China	Developing
TZA	Tanzania_United Republic of	Developing
UGA	Uganda	Developing
UKR	Ukraine	Industrialised
URY	Uruguay	Developing
USA	United States	Industrialised
UZB	Uzbekistan	Industrialised
VCT	Saint Vincent and the Grenadines	Developing
VEN	Venezuela	Developing
VGB	Virgin Islands_British	Developing
VIR	Virgin Islands_USA	Developing
VNM	Viet Nam	Developing
VUT	Vanuatu	Developing
WLF	Wallis and Futuna	Developing
WSM	Samoa	Developing
YEM	Yemen	Developing
ZAF	South Africa	Developing
ZMB	Zambia	Developing
ZWE	Zimbabwe	Developing

The EU27 comprises: Austria, Italy, Belgium, Latvia, Bulgaria, Lithuania, Croatia, Luxembourg, Cyprus, Malta, Czechia, The Netherlands, Denmark, Poland, Estonia, Portugal, Finland, Romania, France, Slovakia, Germany, Slovenia, Greece, Spain, Hungary, Sweden, Ireland.

OECD comprises: Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

TABLE 6. SHARE OF CH4 EMISSION IN SECTOR 1B2B (FUGITIVE EMISSIONS FROM NATURAL GAS) FOR THE FIVE TOP EMITTING COUNTIES

	USA	RUSSIA	IRAN	SAUDI ARABIA	CHINA
Natural gas production	50.3%	47%	84.7%	97.5%	76%
Natural gas transmission	30.3%	21.5%	5.7%	2.5%	15%
Natural gas distribution	19.4%	31.5%	9.6%	0%	9%

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TABLE 7. GLOBAL UNCERTAINTY RANGES DEFINING THE 95% CI OF A LOGNORMAL DISTRIBUTION

IPCC sector	GHG	upper uncertainty (%)	lower uncertainty (%)
1 Energy	CH4	94.2%	60.4%
1 Energy	CO2	7.1%	7.1%
1 Energy	N2O	113.3%	113.3%
2 IPPU	CH4	35.4%	53.4%
2 IPPU	CO2	22.5%	22.5%
2 IPPU	N2O	15.7%	12.4%
3 Agriculture	CH4	37.5%	30.6%
3 Agriculture	CO2	73.2%	73.2%
3 Agriculture	N2O	301.7%	224.9%
4 Waste	CH4	78.8%	77.7%
4 Waste	CO2	38.1%	38.1%
4 Waste	N2O	202.6%	159.0%
5 Other	CH4	117.3%	117.3%
5 Other	CO2	125.0%	125.0%
5 Other	N2O	111.8%	111.8%
1 Energy	total GHG	15.9%	12.8%
2 IPPU	total GHG	22.1%	21.9%
3 Agriculture	total GHG	118.1%	90.2%
4 Waste	total GHG	86.2%	82.4%
5 Other	total GHG	114.4%	114.4%
Total	Total GHG	19.6%	15.4%

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Figures of Solazzo et al., Uncertainties in the EDGAR emission inventory of greenhouse gases

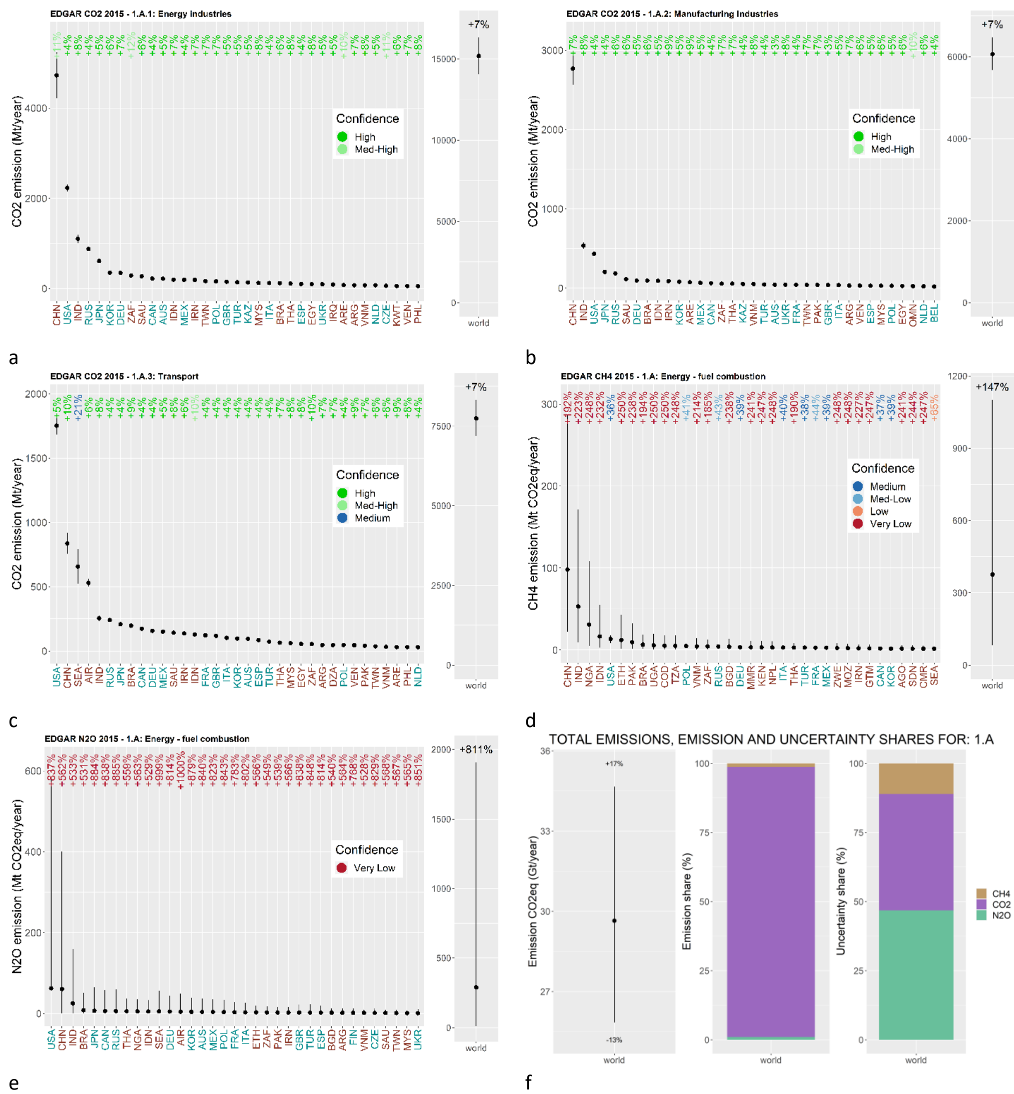

Figure 1. GHG emissions from top emitters and world for sector 1.A (energy from fuel combustion). a) CO2 from Energy industries; b) CO2 from manufacturing industries; c) CO2 from transport; d) CH4 from fuel combustion; e) N2O from fuel combustion; f) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

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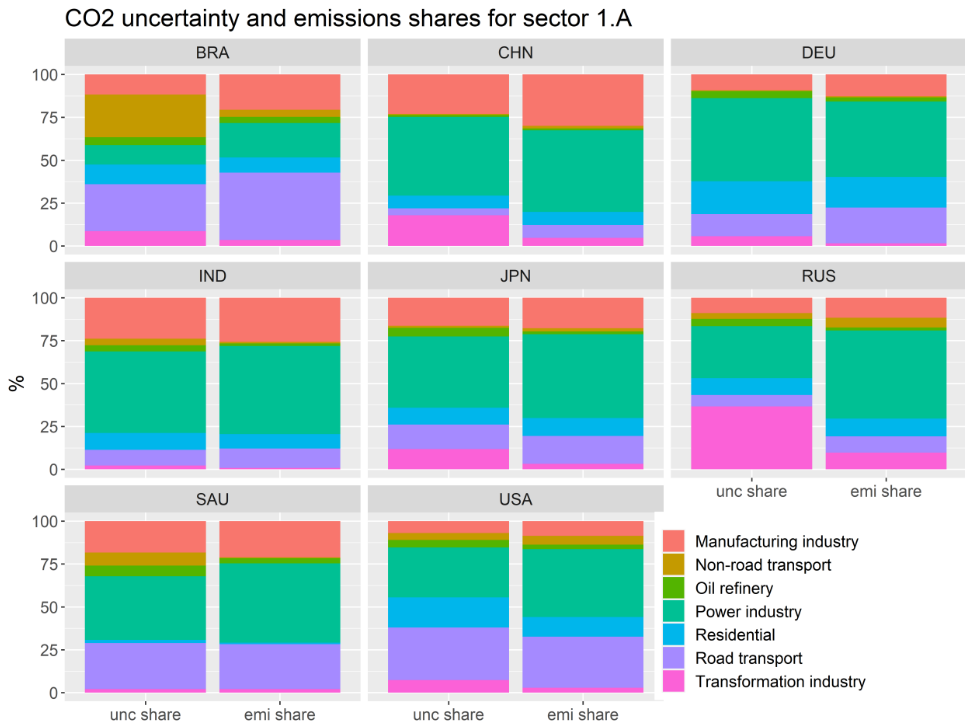

Figure 2. CO2 uncertainty and emissions shares for EDGAR emission sectors under IPCC category 1A for Brazil, China, Germany, India, Japan, Russia, Saudi Arabia, United States of America.

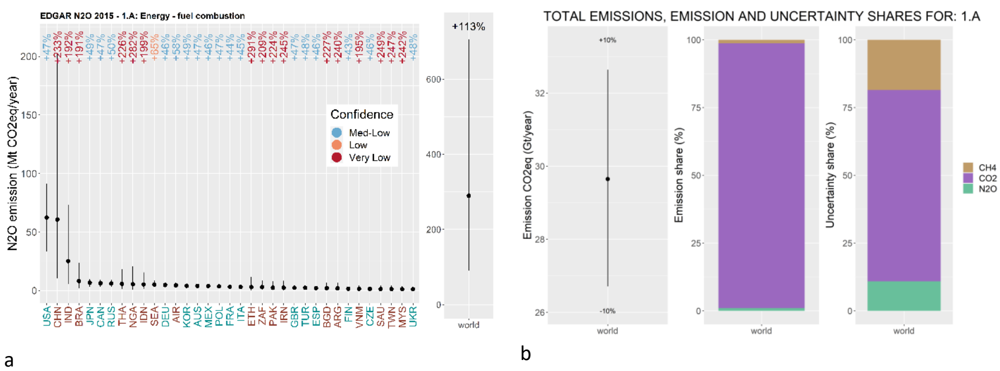

Figure 3. a) N2O emissions from top emitters and world for sector 1.A (energy from fuel combustion) when uncertainties are set in the range ±50% (industrialised countries) to 150% (developing countries) b) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

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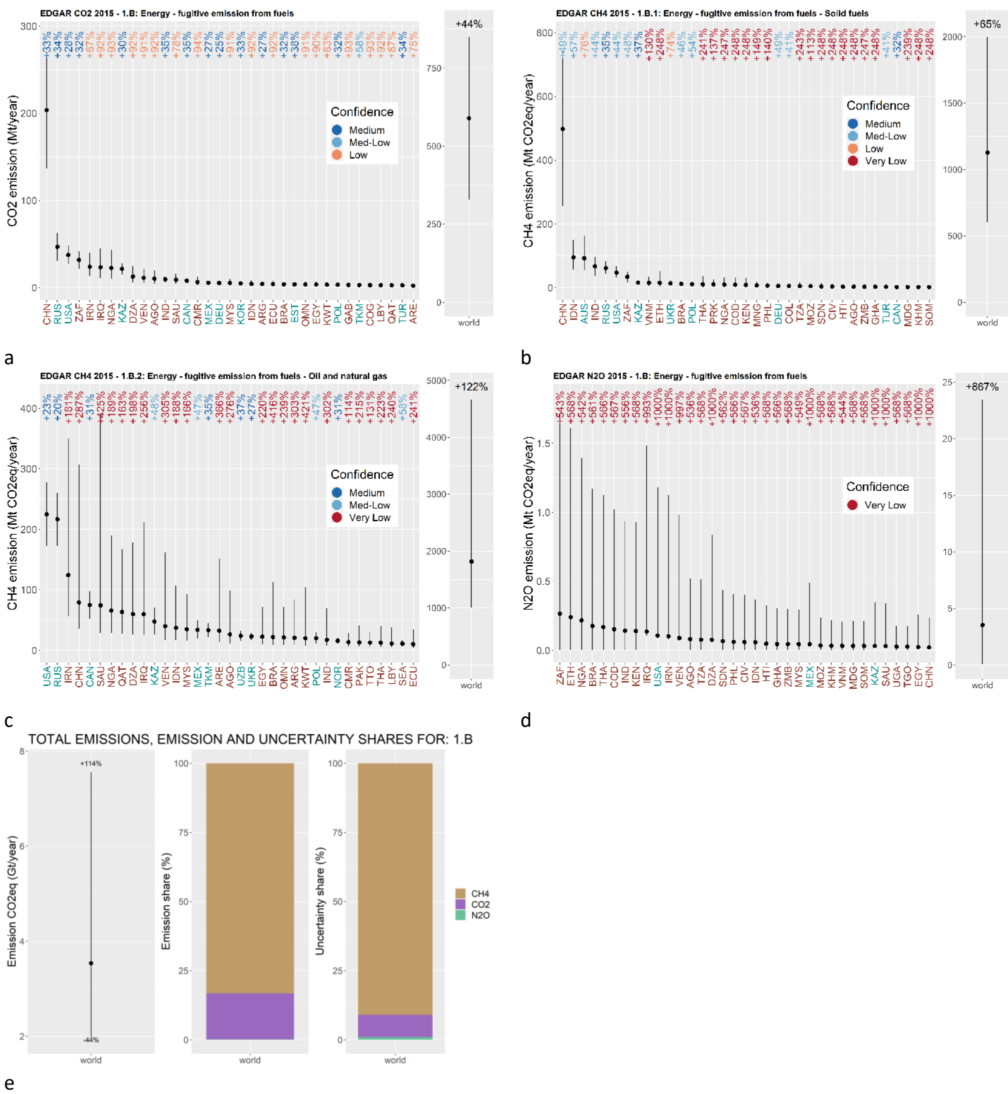

Figure 4. GHG emissions from top emitters and world for sector 1.B (ENERGY - Fugitive emissions). a) CO2 from Fugitive emissions from fuels; b) CH4 from Fugitive emissions from solid fuels; c) CH4 from Fugitive emissions from oil and natural gas; d) N2O from Fugitive emissions from fuels; e) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

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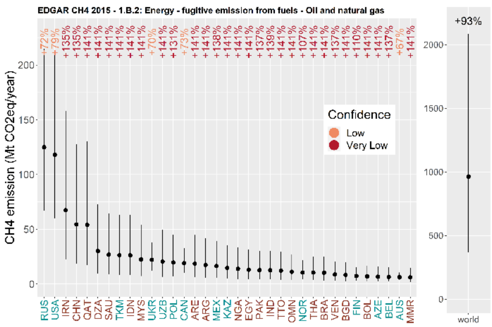

Figure 5. Methane emissions from top emitters and world for sector 1.B.2 (ENERGY - Fugitive emissions from oil and natural gas) with revised u_{EF} and u_{AD} (see text). Colour codes as in the caption of Figure 4.

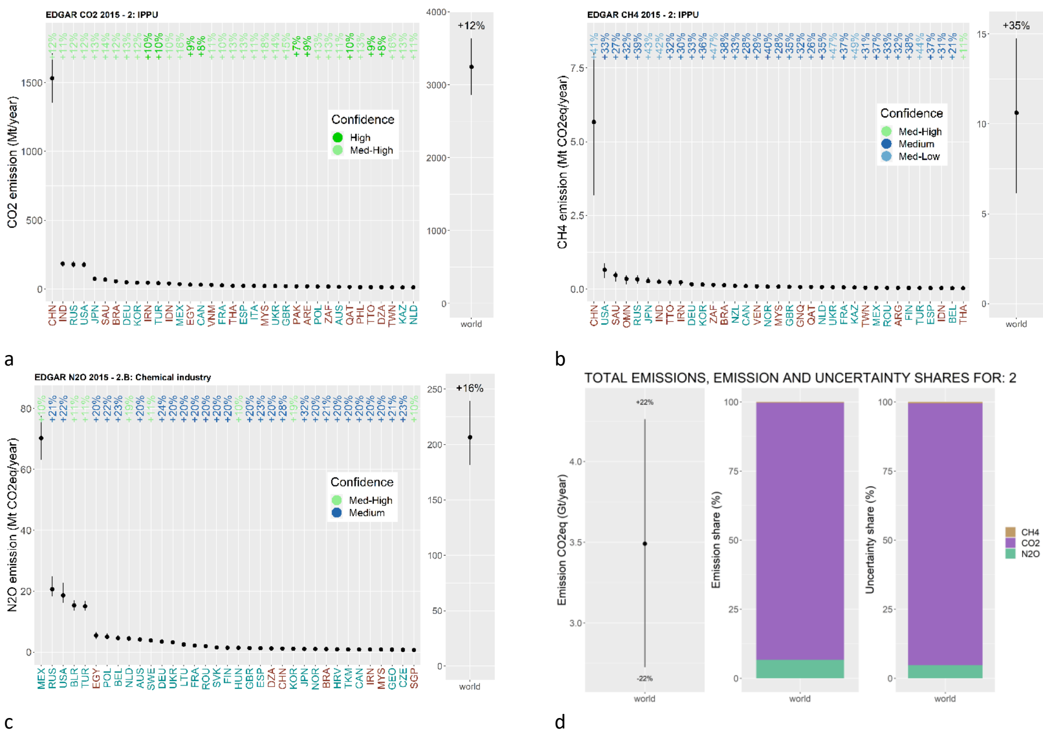

Figure 6. GHG emissions from top emitters and world for sector 2 (Industrial processes and product use). a) CO2; b) CH4; c) N2O; D) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

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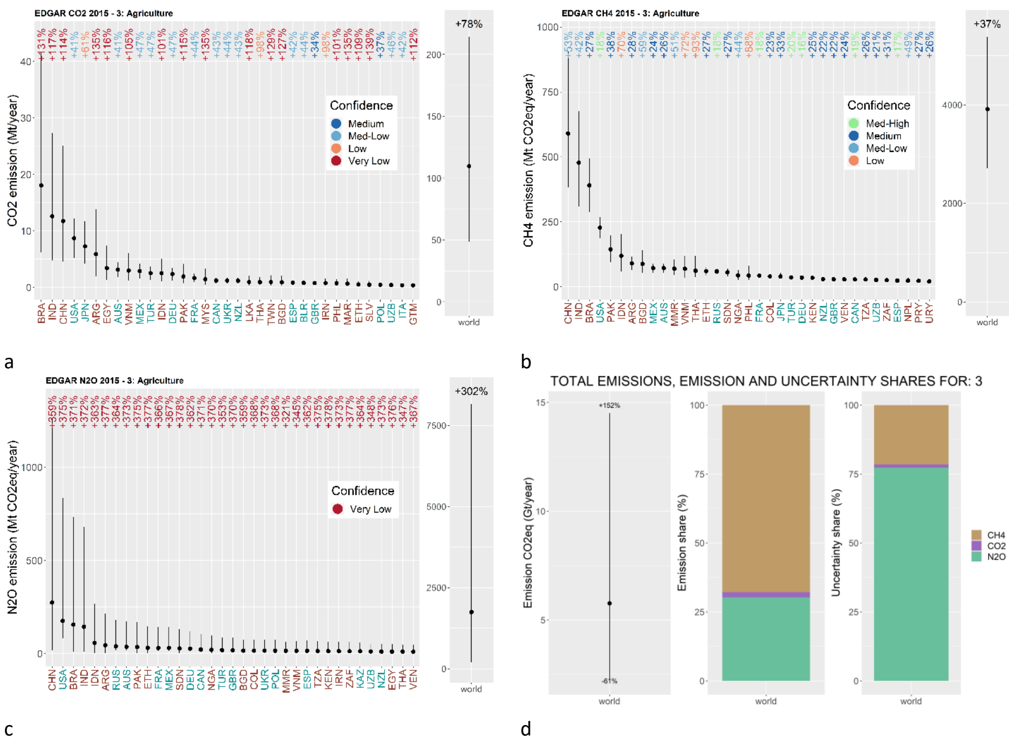

Figure 7. GHG emissions from top emitters and world for sector 3 (Agriculture) in CO_2 Eq (Tg/year). a) CO2; b) CH4; c) N2O; D) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

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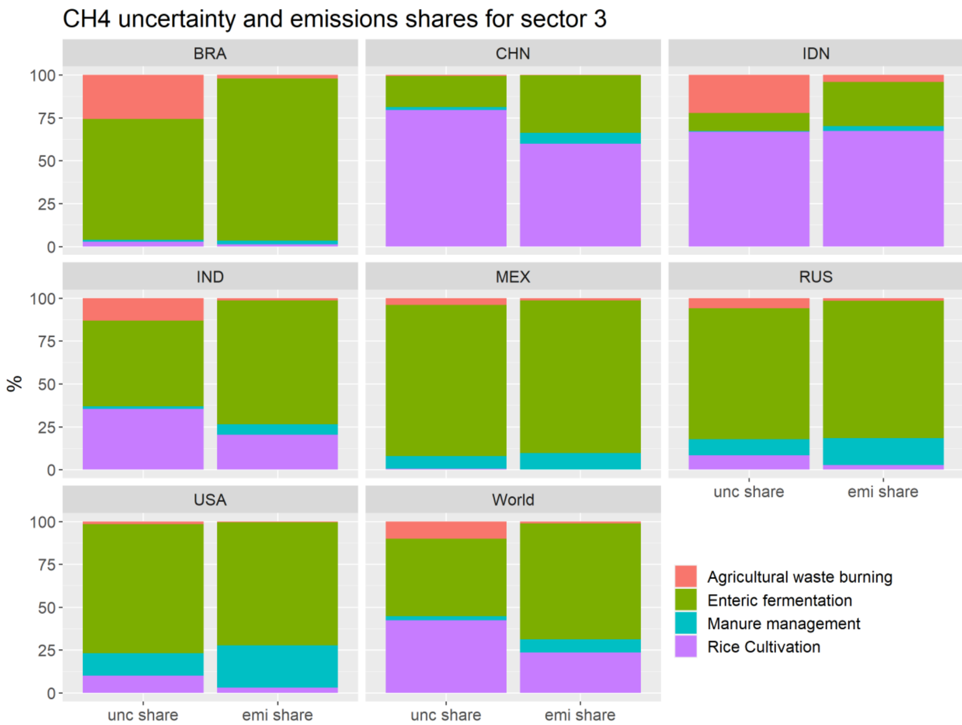
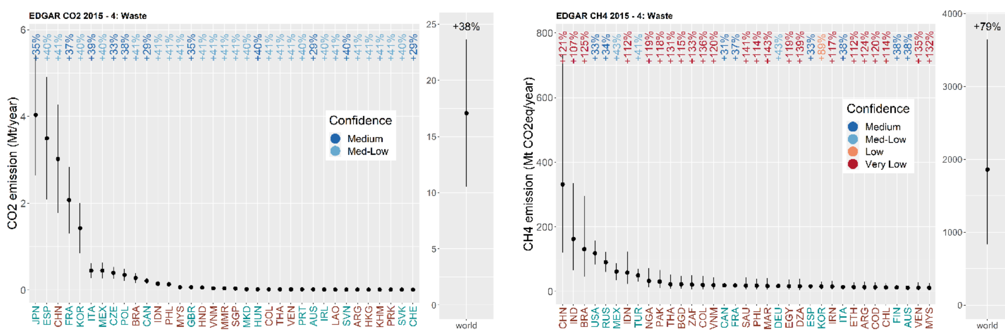


Figure 8. CH4 uncertainty and emissions shares for EDGAR's emission sectors under IPCC category 3 for Brazil, China, Indonesia, India, Mexico, Russia, United States of America, and the world.



a

b

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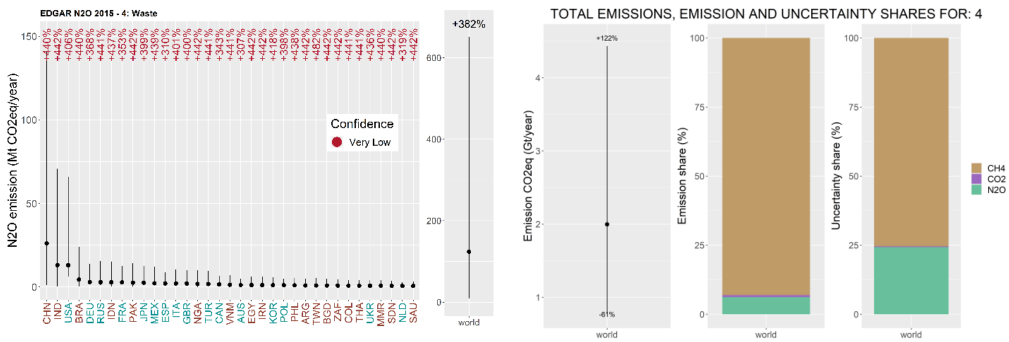

c d

Figure 9. GHG emissions from top emitters and world for sector 4 (WASTE). a) CO2; b) CH4; c) N2O; D) world total: total uncertainty; emission and uncertainty shares. Country's names are color-coded according to their classification (cyan: Industrialised; red: Developing). Confidence levels are given in the ranges: High (0,10%]; Medium-High (10,20%], Medium (20,40%]; Medium-Low (40,60%], Low (60,100%], Very Low > 100% (country codes are explicated in Table 5).

Figure 10. CH_4 uncertainty and emissions shares for EDGAR's emission sectors under IPCC category 4 for Brazil, China, Indonesia, India, Mexico, Russia, United States of America, and the world.

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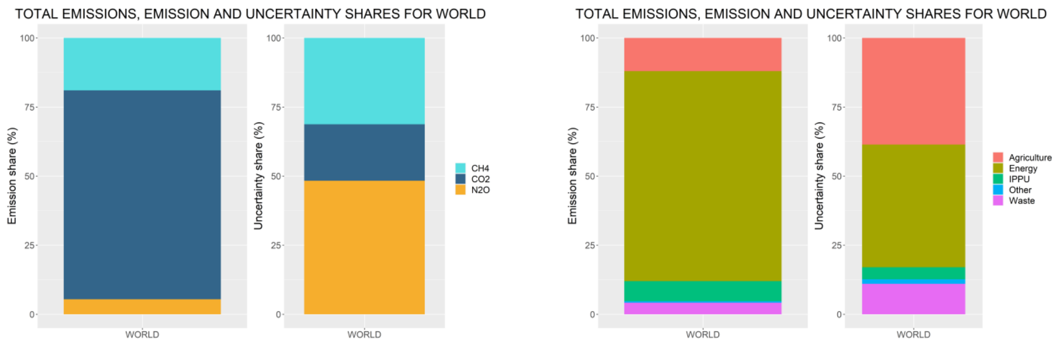
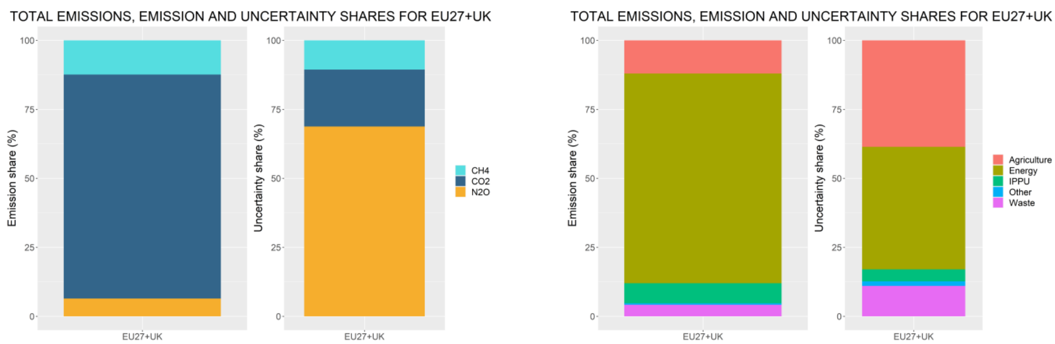


a) b)

Figure 11. Global share of emissions and uncertianty by a) gas and b) category



a) b)

Figure 12. EU27+UK share of emissions and uncertainty by a) gas and b) category

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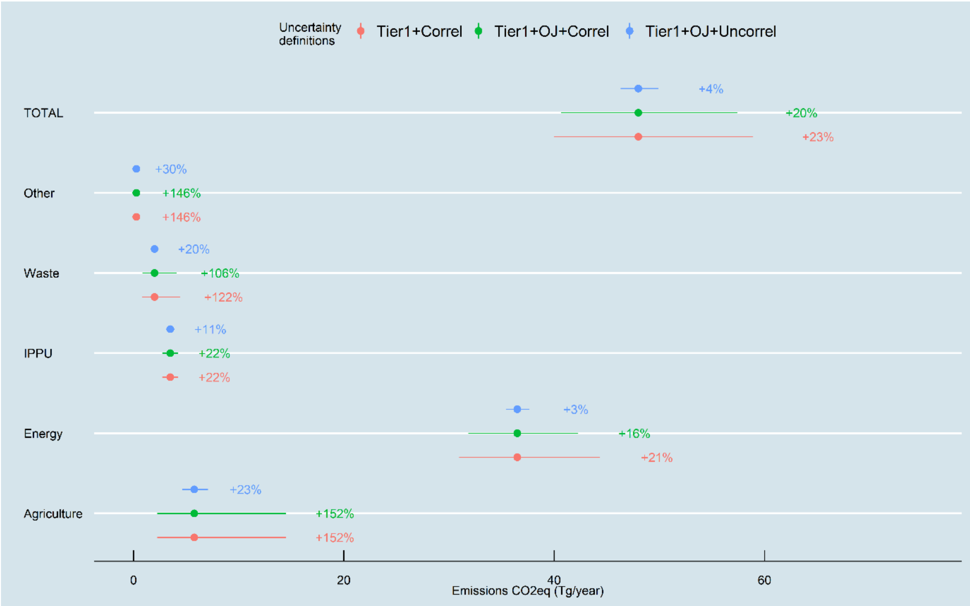

Figure 13. Variability of World emissions uncertainty introduced by methodological choices: correlation and default uncertainty (red); correlation and default uncertainty and own expert judgment for N_2O in sector 1A (±100% to ±150%) and upper uncertainty set to 250% to all N_2O sectors (green); uncorrelation and default uncertainty and own judgment for N_2O in sector 1A (±50% to ±100%) and upper uncertainty set to 250% to all N_2O sectors (Blue).

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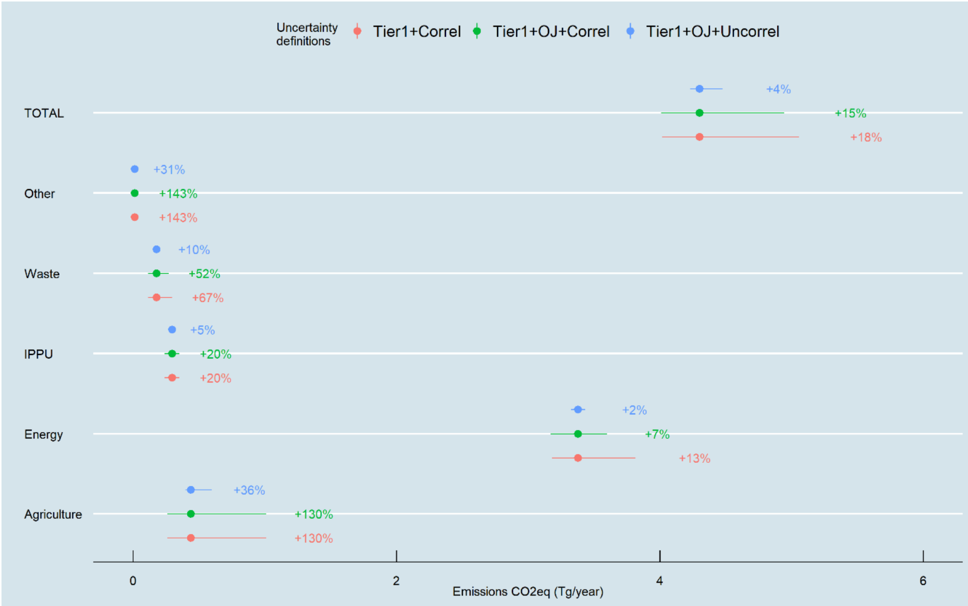

Figure 14. Variability of EU27+UK emissions uncertainty introduced by methodological choices: correlation and default uncertainty (red); correlation and default uncertainty and own expert judgment for N_2O in sector 1A (±100% to ±150%) and upper uncertainty set to 250% to all N_2O sectors (green); uncorrelation and default uncertainty and own judgment for N_2O in sector 1A (±50% to ±100%) and upper uncertainty set to 250% to all N_2O sectors (Blue).