How to quantify uncertainty and variability in life cycle assessment: the case of greenhouse gas emissions of gas power generation in the United States

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Short title: Uncertainty and variability in carbon footprint of conventional natural gas power in the United States

Abstract. This study quantified the contributions of uncertainty and variability to the range of life cycle greenhouse gas (LCGHG) emissions associated with conventional gas-fired electricity generation in the U.S. Whereas uncertainty is defined as lack of knowledge and can potentially be reduced by additional research, variability is an inherent characteristic of supply chains and cannot be reduced without physically modifying the system. The life-cycle included four stages: production, processing, transmission and power generation, and utilized a functional unit of 1 kWh of electricity generated at plant. Technological variability requires analyses of life cycles of individual power plants, e.g. combined cycle plants or boilers. Parameter uncertainty was modeled via Monte Carlo simulation. Our approach reveals that technological differences are the predominant cause for the range of LCGHG emissions associated with gas power, primarily due to variability in plant efficiencies. Uncertainties in model parameters played a minor role for 100-year time horizon. Variability in LCGHG emissions was a factor of 1.4 for combined cycle plants, and a factor of 1.3 for simple cycle plants (95% CI, 100-year horizon). The results can be used to assist decision-makers in assessing factors that contribute to LCGHG emissions despite uncertainties in parameters employed to estimate those emissions.

1 Introduction

In recent years, the U.S. Energy Information Administration (EIA) has reported that natural gas fuelled power generation has been displacing coal-fired power generation (EIA, 2011a). If these trends continue, then the contribution of gas power to the environmental impact of electricity will increase accordingly. These impacts are not only generated at the power plant, but may occur at all stages of the life cycle from well to wire. Moreover, the nature of these impacts may vary by the composition of the gas and its method of extraction. The greenhouse gas (GHG) emissions of conventional

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gas power may be quantified via life cycle assessment (LCA) (ISO, 2006). LCA entails the aggregation of environmental impacts within a well-defined “system boundary”, normalizing them in terms of the function of the product, e.g. generated electricity. In recent years, several LCAs have been conducted to estimate life cycle GHG emissions from conventional gas from “well to wire” (e.g. Frischknecht *et al.*, 2007; Jaramillo *et al.*, 2007; Venkatesh *et al.*, 2012; Black, 2013; NETL, 2013). However, these estimates vary substantially, reflecting uncertainty and variability in the results (Faist Emmenegger *et al.*, 2007) . *Uncertainty* results from (1) the simplification of reality inherent in modeling (model uncertainty), (2) the introduction of arbitrary choices into models (decision rule uncertainty) or (3) lack of precision in estimates of parameters used in models (parameter uncertainty) (Morgan and Henrion, 1990). The importance of assessing these uncertainty types separately was also highlighted by a research working group on life cycles of aviation fuels (Allen *et al.*, 2009). By contrast, *variability* is due to real differences between alternative life cycles that yield a common product, due to the fact that those life cycles employ different technologies or processes. Although uncertainty may be reduced by additional research or data collection, variability is inherent and cannot be reduced unless one physically changes one or more systems under study.

It is important to properly account for both uncertainty and variability in LCA, (Huijbregts, 1998; Maurice *et al.*, 2000; Huijbregts *et al.*, 2003; Burnham *et al.*, 2011; NETL, 2013). If one can differentiate uncertainty from variability, then one may more clearly assess the sources of uncertainty in environmental impacts over a product life cycle. At the same time the separate quantification of variability allows one to identify key areas of research for technological improvements or practices.

In this paper we present a method for characterizing the relative contributions of uncertainty and variability to the range of life cycle impacts associated with power generated from natural gas obtained from conventional gas wells. We then apply this method to identify avenues for future emissions research that may yield the greatest impact upon the characterization of the life cycle GHG emissions of gas as a fuel for power generation, as well as key technological features of gas life cycles. The analysis is mainly based on 2011 data from the national greenhouse gas emission inventory, that refer to conventional wells, and from the Energy Information Administration (EPA/GRI, 1996a, b, c; EPA, 2013; EIA, 2011).

2 Materials and methods

2.1 System description

The life cycle of conventional natural gas from well to wire is illustrated in Figure 1. We divide the life cycle into four stages, following the convention of Jiang and co-workers (Jiang *et al.*, 2011). In the *extraction* and *production* phase (1), the gas well is drilled and completed. This phase also includes all activities associated with the transport of conventional gas from the pad to a processing and treatment facility, as well as water-gas separation and operation of gathering compressors. The *proc-*

essing stage (2) includes all activities associated with processing *and treatment* of gas, including removal of water, N_2, CO_2 and H_2S. The resulting “pipeline quality” gas then enters the *transmission* stage (3) of the life cycle. This stage includes all activities associated with the pipeline transportation of gas. The terminal phase (4) of the life cycle is a power plant, where gas is burned to generate electricity. We employ a functional unit of 1 kWh of electricity generated at the power plant. We distinguish between simple cycle (SC) and combined cycle (CC) power plants, because they are technologically different (Supplementary Information section S1).

2.2 Model approach

We conducted the life cycle GHG balance via a material balance on methane, accounting for all sources and sinks from “well to wire”. Methane is emitted to the atmosphere via leaks, blowdowns (intentional venting associated with maintenance or safety) and incomplete combustion. All of the remaining methane is consumed via combustion, yielding CO_2.

We estimate direct methane emissions via the activity factor/emissions factor (AF/EF) approach utilized by the U.S. EPA (EPA, 2013). Hereby, we exclude all data associated with unconventional wells and multiply the well equipment activity data by the percentage of conventional wells. Data refer to the latest year covered in the EPA 2013 published inventory, which is the year 2011. Non-combustive emissions of CO_2 are also calculated via the activity factor/emissions factor approach, utilizing the compositions of gas in each phase of the gas life cycle. We calculate combustive emissions using (a) the EPA combustion efficiencies for flaring and gas engines, and (b) calculated methane emissions associated with incomplete combustion. Each of these emissions estimates exhibits uncertainty, due to uncertainty in the activity factors, emission factors, and other parameters from which they are calculated. These particular uncertainties are discussed in SI section S3.

Life cycle emissions are then calculated as the sum of combustive and non-combustive emissions associated with a particular system boundary of power plants. We utilize GWPs from the most recent assessments of the IPCC (IPCC, 2007) to assess emissions of CO_2 and CH_4 on a common basis, and report the life cycle GHG balance in units of kg CO_2eq/kWh. We also include the uncertainty in the GWPs as described in the Supplementary Information.

The EIA 923 Data File (EIA, 2011b) provides an extensive amount of information about U.S. power plants, including the gas supplied to those plants, its heating value, and the net power output. The power generated at the end of gas life cycles defined by each of those plants is calculated by combining this information with the amount of gas leaving the transmission phase of the gas life cycle, as determined by the aforementioned material balance for methane.

The “Individual” power plant gas life cycle includes all operations and emissions associated with the delivery of gas to that particular power plant. Transmission quality gas used at the power plant cannot be identified by source. Thus, the boundary must include all wells that may contribute gas as power plant fuel (Figure 1). Processing and transmission steps are equal for all gas delivered to plants. GHG emissions of electricity generated at a plant differ due to differences between plants. Thus, variability can be calculated via comparison of these plant-specific life cycles.

By contrast, a “comprehensive” system defined by the dashed dark blue line in Figure 1 encompasses all of the “individual” life cycles and has a carbon footprint defined by the sum of all of their emissions and divided by the sum of their net power output. The life cycle impact of this system may be calculated via a sum of the “individual” power plant gas life cycle emissions, weighted by the net power generated from each plant (SI section S2). Insofar as it is composed of all other life cycles, it exhibits no variability per se. Thus any range of life cycle emissions associated with the “comprehensive system” is exclusively due to uncertainties in (a) parameters used in the LCA model or (b) estimates of emissions from particular sources.

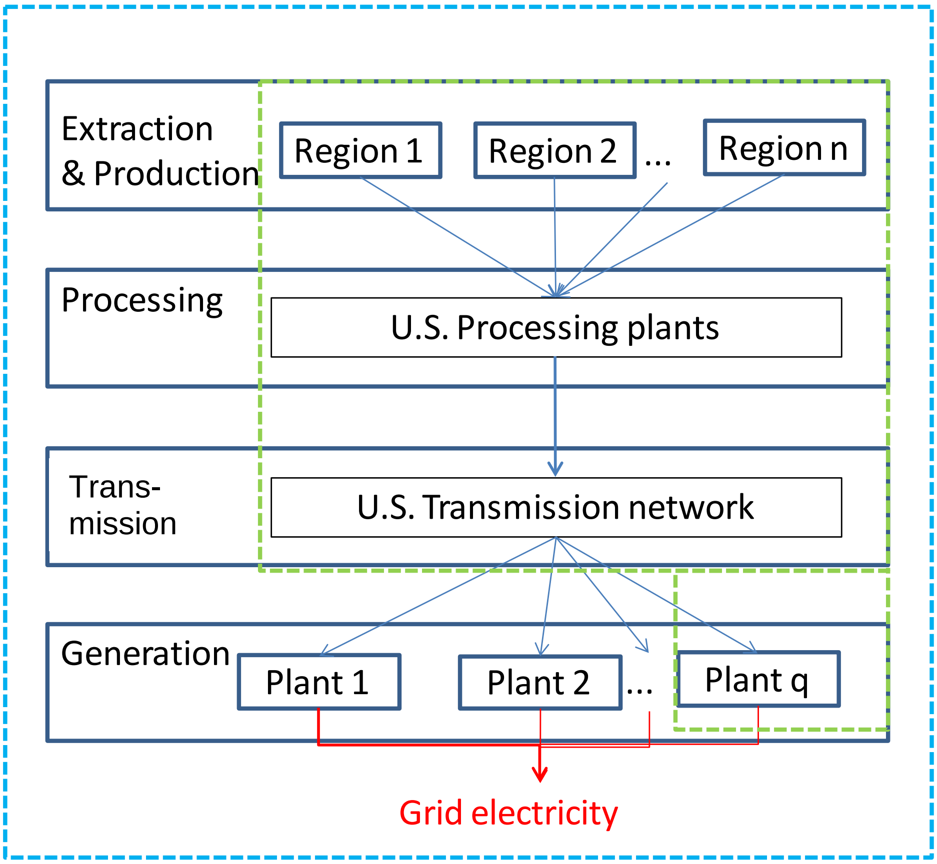

Figure 1. Life cycle model for electricity generation from natural gas in the U. S., including boundaries (dashed dark blue line for a “comprehensive” LCA; dashed green line for an LCA for an individual power plant), flows of material (light blue arrows) and electrical output at the power plant (red). Variability by drilling and completion methods, production practice, processing technology, operation of transmission pipelines and operation of power plants is represented by horizontal boxes at each stage of the life cycle.

2.3 Assessment of uncertainty and variability

2.3.1 Monte Carlo Simulation. To assess parameter uncertainty, carbon footprints for (a) each individual power plant life cycle $\pi = 1...p$ and (b) the comprehensive life cycle was calculated simultaneously via Monte Carlo (MC) (Huijbregts, 1998; Huijbregts *et al.*, 2003)). In each MC run, all uncertain parameters and emissions estimates are randomly selected in accordance with their distributions; the carbon footprints of the p "individual" life cycles as well as the comprehensive life cycle are then calculated using these values. After N runs, one has a set of N estimates of the comprehensive footprint $\{Y_n\}$, $n = 1...N$ as well as p sets of footprints for each individual power plant $\{y_{\pi n}\}$, $\pi = 1...p$; $n = 1...N$. The two classes of sets are distinct in their interpretations: Statistics calculated from $\{y\}$ are equivalent to those one would obtain from an analysis that considers variability as equivalent to uncertainty, e.g. analyses that consider power plant efficiency to be a random variable. Statistics calculated from $\{Y\}$ only capture the effects of uncertainty on the weighted average carbon footprint. Comparison of these statistics allows one to estimate the relative contributions of variability and uncertainty to the range of carbon footprints associated with gas power. We used a sample size of N = 50,000 runs to generate our results. Parameters previously discussed and their probability distributions sampled via Monte Carlo are provided in table S1.

2.3.2 Quantification of Variability. Variability was expressed in terms of a "variability ratio", which can be interpreted as a metric for inter-plant variation, i.e.

$$r = \frac{q_{0.975}(\{E(y)\})}{q_{0.025}(\{E(y)\})} \quad (2)$$

$\{E(y)\}$ is the set of p arithmetic means corresponding to each power plant. The numerator of Equation 2 is the 97.5th percentile of $\{E(y)\}$, and the denominator is the 2.5th percentile. We use the expectation values as estimators of the impacts of individual power plants.

The effect of power plant efficiency on the variance was also assessed. This was implemented by performing the calculations using a generation-weighted average efficiency for each power plant instead of that plant's actual efficiency.

2.3.3 Quantification of Parameter Uncertainty. Inasmuch as the "comprehensive" system integrates over all variability, differences among the MC-generated impacts ($\{Y\}$) result from parametric uncertainty. We quantified parametric uncertainty via an "uncertainty ratio"

$$\rho = \frac{q_{0.975}(\{Y\})}{q_{0.025}(\{Y\})} \quad (1)$$

where the numerator is the 97.5th percentile of the MC simulation results for the "comprehensive" system and the denominator is the 2.5th percentile of the same.

The contribution of uncertainties in individual parameters to the range in impacts associated with the life cycle GHG emissions of the comprehensive system (Y) was also assessed. This analysis consisted of a Monte Carlo simulation in combination with a Rank correlation (expressed as percentage of total variance) (Ragas *et al.*, 1999; Hauck *et al.*, 2011). The contribution to variance is a combination of the model's sensitivity to a parameter and the uncertainty range of the parameter. The resulting statistics may then be interpreted as the percentage of variance that may be explained by each uncertain input parameter. Details on the calculations can be found in the SI (section S4).

2.3.4 Quantification of Decision Rule Uncertainty. Uncertainty due to choice of a time horizon for GWP was taken into account by calculating the carbon footprint for three scenarios: 20, 100 and 500 years (IPCC, 2007).

2.3.5 Comparison of uncertainty and variability. The parameters r and ρ share certain features that assist in the interpretation of their values: If $r = 1$, then there is no effect of variability upon the results of the LCA. If $\rho = 1$, then there is no effect of uncertainty upon the results of the LCA. The relative contributions of uncertainty and variability to the range of life cycle emissions for gas power (SC or CC) may be discerned via the relative magnitudes of these quantities: If $r > \rho$, then variability is the primary cause of the range of life cycle emissions If $r < \rho$, then uncertainty is the primary cause of the range of life cycle emissions.

3 Results and discussion

3.1 Uncertainty vs. variability

The variation in life cycle GHG emissions of CC and SC power plants are reported in Figures 2, 3 and 4. Figure 2 gives an overview of ranges due to uncertainty and variability respectively. Figures 3 and 4 show variation due to uncertainty for individual power plants. For each time horizon, uncertainty includes uncertainty in life cycle parameters as well as uncertainty in GWP. Variability exceeded uncertainty for all time horizons, although uncertainty and variability were comparable for a 20 year time horizon. Variability was independent of choice of time horizon. Uncertainty is higher for a 20 year time horizon compared to the other time horizons.

Variability was a factor (r) of 1.4 (0.46 to 0.66 kg CO_2-eq/kWh for 100 years) for the life cycle GHG emissions of CC plants and 1.3 (0.66 to 0.89 kg CO_2-eq/kWh for 100 years) for that of SC plants. Parameter uncertainty (ρ) was 1.1 (100 year time horizon) for comprehensive life cycles of both CC plants (0.47 to 0.53 kg CO_2-eq/kWh) and SC plants (0.71 to 0.81 kg CO_2-eq/kWh); these ranges are comparable to the range reported by Venkatesh *et al*. (2011). If one employs GWPs with a 20 year time horizon, parameter uncertainty is 1.3; 500-year GWPs yield a factor of 1.1 for both CC and SC plants.

Table S8 shows that our median results and ranges are in good agreement with previous studies. If ranges are given in other studies, they are generally due to other reasons (for example differences between regions). Consistent with the large influence of the combustion phase, table S8 shows that studies with lower life cycle GHG emissions tend to have employed higher plant efficiencies, in line with the aim of the studies to assess future electricity generation possibilities (e.g. Jiang *et al.*, 2011; Venkatesh *et al.*, 2011) .

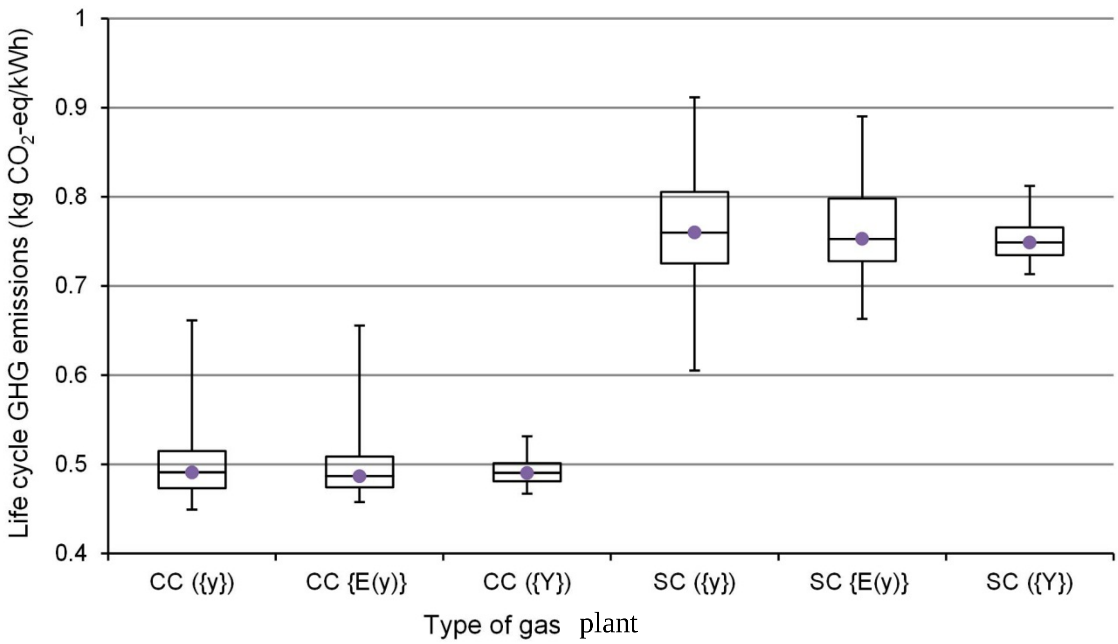

Figure 2. Life cycle GHG emissions associated with natural gas power generation (CC 239 plants, SC 69 plants) for a 100 year time horizon. Model results accounting for uncertainty and variability are denoted by y, for variability only by E(y), those accounting only for uncertainty (by way of the use of a national-level system boundary) are denoted by Y. Dots represent medians, boxes represents quartiles and whiskers, 2.5th and 97.5th percentiles.

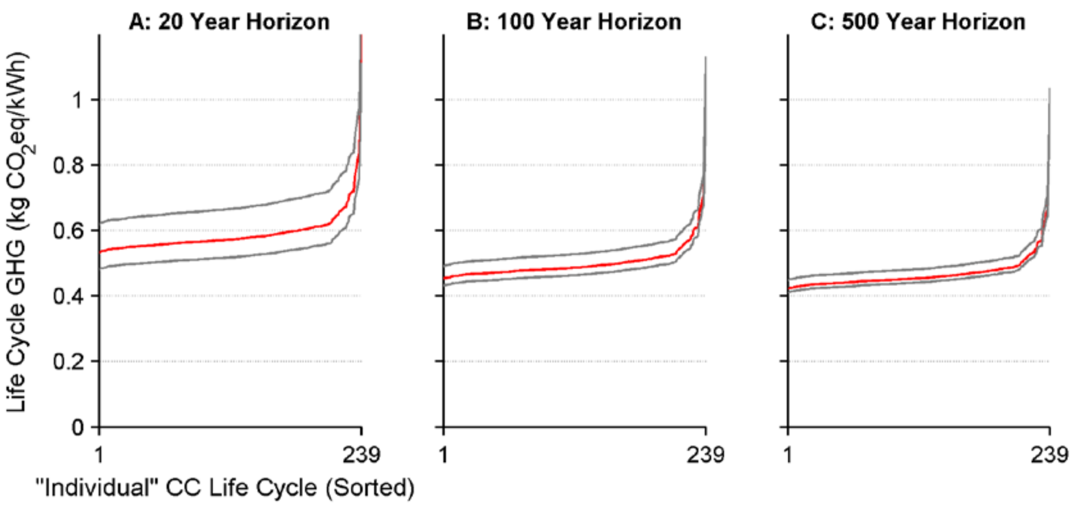

Figure 3. Variability and uncertainty in the life cycle of conventional natural gas used as fuel for combined cycle (CC) power generation for a) 20 year time horizon, b) a 100 year time horizon, c) 500 year time horizon**.** Red dots represent median estimates per plant and black dots the 95% confidence intervals.

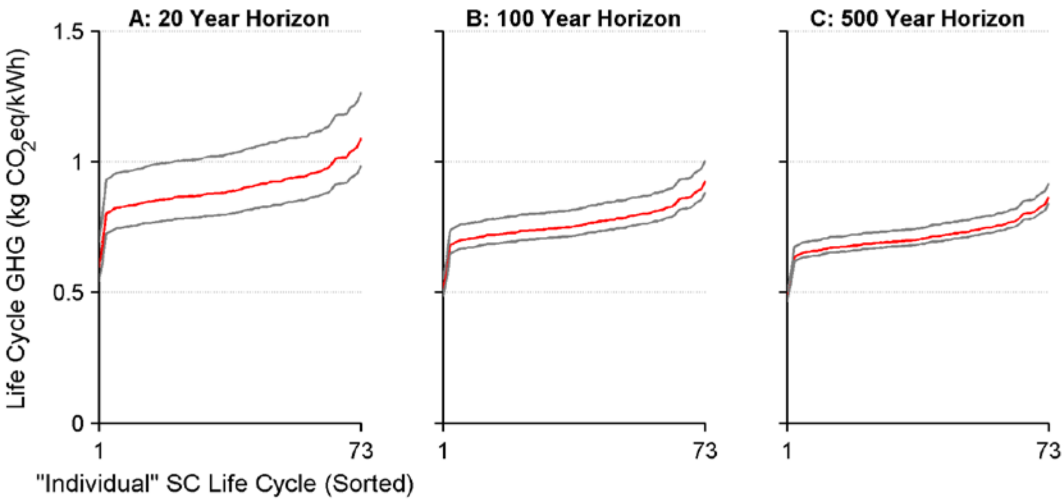

Figure 4. Variability and uncertainty in the life cycle of conventional natural gas used as fuel for simple cycle (SC) power generation, a) 20 year time horizon, b) 100 year time horizon, c) 500 year time horizon.

3.2 Contribution to variance

Technological differences between plants explained 99% of this variability: setting all plant efficiencies equal reduces the variability ratio to 1.01.

For variance due to uncertainty, Table 1 shows the parameters that contributed more than 5% to overall uncertainty for at least one time horizon. Together, these parameters accounted for 87% of the variance in outcomes. The results reported in Table 1 also convey the effect of the GWP of CH_4 upon the relative importance of CH_4 and CO_2 emissions. These results are based on GWPs from the 4th Assessment Report of the IPCC (IPCC, 2007). In the recently published 5th Assessment Report, these GWPs have been updated (Myhre *et al.*, 2013), accounting for indirect effects such as aerosols as reported by Shindell et al. (2009). An analysis including these updated values is included in the Supplementary Information. The contribution of uncertainty in the GWP of methane was around 55% to overall uncertainty for a 100-year time horizon.

Uncertainties associated with emissions from gas engines and turbines as well as reciprocating compressors were strong contributors to overall uncertainty due to a combination of (a) a relatively large contribution (>5%, results not shown) to upstream emissions and (b) a relatively high uncertainty in activity data and emissions factors respectively (see Table S1 (EPA/GRI, 1996a, b)). These results conflict with two previous studies: Venkatesh *et al*. (2011) identified uncertainties associated with lease fuel consumption (gathering system gas engines) as the greatest contributor to life cycle uncertainty. Furthermore, Burnham *et al*. (2011) and Littlefield *et al*. (2012) identified CH_4 venting associated with “liquids unloading” as the largest source of overall uncertainty, due to the large emission factor employed for this fugitive emission in both studies. However, these conclusions are difficult to compare: Burnham *et al*. (2011) did not consider combustion emissions as uncertain, and did not characterize uncertainty associated with liquids unloading as we did. Littlefield et al. (2012) assessed sensitivities with a constant change in parameter values. Venkatesh *et al.* (2011) by contrast, used a different method for the calculation of CO_2 emissions from gathering system gas engines (lease fuel).

Table 1. Contribution to uncertainty in life cycle GHG emissions for the national system boundary by uncertain parameters that contributed more than 5% for at least one time horizon. Results are shown for CC plants. Results for SC plants are shown in Table S10.

	20 year time horizon	100 year time horizon	500 year time horizon
Absolute GWP CH_4 (W m^{-2}yr/kg)	59%	41%	12%
Activity factor, Gas turbines, processing (Millions of HPhr/yr)	5%	19%	45%
Activity factor, Gas engine, processing (Millions of HPhr/yr)	6%	14%	26%
Absolute GWP CO_2 (W m^{-2}yr /kg)	11%	8%	2%
Emission Factor, Reciprocating compressor for compressor station, transmission (scf/d/comp)	6%	4%	1%

3.3 Upstream contribution

The upstream emissions were 0.012 kg CO_2eq/MJ delivered to each plant, with a 95% uncertainty range of 0.009-0.017 kg CO_2eq/MJ HHV (100 year GWP). Using a 100 year time horizon, emissions from production, processing and transmission accounted for 19% of the total life cycle GHG balance (95% CI: 15% - 25%). Life cycle GHG emissions and upstream emissions for the 20 and 500 year time horizon are reported in Table S8 along with values from recently published studies on GHG emissions from gas life cycles.

3.4 Reduction potential

Based on the finding that differences in efficiencies are decisive for life cycle GHG emissions of the type of natural gas plants we considered, and to illustrate potential uses of our results, we set a benchmark for gas power plants, where plants were assumed to have the median efficiency if their original efficiency was lower. This led to a reduction in GHG emissions of $7.9\cdot10^{9}$ kg CO_2-eq for CC power plants, which equals 2.4% of the total fleet emissions estimated in our study (100 year time horizon). For SC plants, savings amounted to and $1.8\cdot10^{9}$ kg CO_2-eq (2.6% of our total estimated fleet emissions). Another requirement, all plants have at least the 95th percentile efficiency, led to a reduction in GHG emissions of $1.9\cdot10^{10}$ kg CO_2-eq (5.8%) for CC plants and $5.7\cdot10^{9}$ kg CO_2-eq (8.4%) for SC plants. Differences in these reduction potentials are related to contribution to total electricity generation.

We successfully separated uncertainty and variability in life cycle GHG emissions of gas fuelled electricity based in the GHG emissions of United States domestic conventional non-associated gas. Separation of uncertainty and variability showed that variability in efficiencies between plants is more important than uncertainty in upstream stages of the life cycle for a 100-year time horizon.

Acknowledgments

This study was part of a collaboration between ExxonMobil Research and Engineering (NJ, USA) and the Department of Environmental Science of the Radboud University Nijmegen (The Netherlands).

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