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Uncertainty in well-to-tank with combustion greenhouse gas emissions of transportation fuels derived from North American crudes

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A B S T R A C T

Many studies have calculated deterministic point estimates of well-to-combustion (WTC) emissions of transportation fuels from crude oil in an attempt to determine which crude oils have lower or higher emissions. However, there is considerable variation in the published results, resulting in uncertainty. The purpose of this study is to identify GHG emissions ranges for five conventional and two unconventional crudes by performing an uncertainty analysis using an improved version of the **FUN**damental E**N**gineering Principl**E**s-based Mode**L** for Estimation of **G**reen**H**ouse **G**ases (FUNNEL-GHG). Distributions for key inputs in the Monte Carlo simulation were determined based on values obtained from the literature. Eleven scenarios were developed, nine historical and two current, the former using life-long average production data from the oil fields studied and the latter using recent production data to illustrate how WTC emissions change as the fields age. The mean WTC emissions ranges for the eleven scenarios are 97.5–140 gCO_2eq/MJ. The uncertainty in the WTC emissions ranges from ±3% to ±11%. The largest source of uncertainty in the WTC emissions is from the venting, fugitive, and flaring volumes, fluid injection rates, and refinery yields.

1. Introduction

As climate change becomes a growing concern around the world, there is increased focus on the environmental impact of transportation fuel production. In 2014, the United States' greenhouse gas emissions (GHG) emissions for the petroleum and natural gas sector were 236 million tonnes CO_2eq with an additional 175 million tonnes CO_2eq from refineries [1,2]. Growing concern over climate change has led to environmental policies such as the California Low Carbon Fuel Standard, which requires a 10% reduction in California's transportation fuels' 2007 carbon intensity by 2020 [3], and the European Union Fuel Quality Directive, which requires a 6% reduction in transportation fuels' 2010 carbon intensity by 2020. One way to meet these reductions is to reduce the emissions generated during crude production and refining.

The well-to-combustion (WTC) emissions from different crudes vary widely depending on the production method used, the crude's properties, refining methods, regional regulations, and industry practices [4]. Additionally, as a crude reservoir ages, its pressure drops, and production decreases [5,6]. Enhanced oil recovery methods, such as water flooding, gas injection, artificial pump lift, gas lift and steam flooding, are implemented to improve production rates [6,7]. However, these methods increase the amount of energy required and emissions generated.

Well-to-wheel assessments, which are performed to compare gasoline vehicles to alternative drivetrain vehicles such as battery electric and hydrogen fuel cell, present their results in terms of gCO_2eq/km. However, well-to-wheel assessments that aim to

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Abbreviations: API, American Petroleum Institute gravity; API, American Petroleum Institute; FUNNEL-GHG-CCO, FUNdamental ENgineering PrinciplEs-based ModeL for Estimation of GreenHouse Gases in Conventional Crude Oils; FUNNEL-GHG-OS, FUNdamental ENgineering PrinciplEs-based ModeL for Estimation of GreenHouse Gases in Oil Sands; GHG, Greenhouse gas; GOR, Gas-to-oil ratio (m^3/m^3); GREET, Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation; GWP, Global warming potential; LHV, Lower heating value (MJ/kg); OPGEE, Oil Production Greenhouse gas Emissions Estimator; P5, 5th percentile; P95, 95th percentile; PRELIM, Petroleum Refinery Life Cycle Inventory Model; SAGD, Steam assisted gravity drainage; SCO, Synthetic crude oil; SOR, Steam-to-oil ratio (cold water equivalent m^3/m^3); VFF, Venting, flaring and fugitive; WOR, Water-to-oil ratio (m^3/m^3); WTR, Well-to-refinery gate; WTT, Well-to-tank; WTC, Well-to-wheel + combustion.

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compare the emissions from different crudes present their emissions in gCO_2eq/MJ. Here “MJ” refers to the lower heating value of the fuel that is released in the combustion chamber. The conversion from the fuel's lower heating value to km will depend on the efficiencies of the various components between the combustion chamber and the wheel, and the driving cycle, which will be the same for all crudes. Therefore, ignoring the vehicle's overall fuel efficiency removes unnecessary uncertainty. Technically excluding the vehicle efficiency would make these studies a well-to-combustion assessment.

Current transportation fuel WTC assessments consist of either a high-level top-down analysis to determine industry average emissions or a bottom-up analysis to determine pathway-specific emissions. Top-down models such as the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) and GHGenius use aggregated data, which makes it difficult to compare crudes and identify areas for improvement [8,9]. Bottom-up models such as the Jacobs, TIAX, Oil Production Greenhouse gas Emissions Estimator (OPGEE), Petroleum Refinery Life Cycle Inventory Model (PRELIM), **FUN**damental **EN**gineering Principl**E**s-based Mode**L** for Estimation of **G**reen**H**ouse **G**ases in the **O**il **S**ands (FUNNEL-GHG-OS), and **FUN**damental **EN**gineering Principl**E**s-based Mode**L** for Estimation of **G**reen**H**ouse **G**ases in **C**onventional **C**rude **O**ils (FUNNEL-GHG-CCO) use engineering first principles to calculate the amount of energy required and emissions produced at each stage [10–16]. Bottom-up models have uncertainties as they focus only on the large pieces of equipment and do not capture every source of emissions; however, the models provide details on the emissions from specific sub-processes.

The previous transportation fuel WTC assessments produce deterministic point estimates (versus Monte Carlo, which uses distributions to determine inputs), which vary significantly among models. The variations are due to inconsistent boundaries, assumptions among the models, and differences in the model inputs. The Carnegie Endowment for International Peace published a report titled “Know Your Oil” on the WTC emissions from thirty different crudes with consistent system boundaries using the OPGEE and PRELIM models [4]; however, the report does not include an uncertainty analysis, without which the confidence of the models is not determined. In order to compare crudes and determine which crudes have high and low emissions, a quantified uncertainty range is required. If the uncertainty in the emissions were larger than the difference in emissions between two crudes, it would not be possible to confidently state which crude has lower emissions.

Quantifying the effect each input uncertainty has on the total uncertainty will provide insight into how the model's accuracy can be improved. Furthermore, the assumptions made in WTC assessments are frequently questioned. Interested parties will ask how the results will change if certain parameters are varied and use the lack of information as justification to invalidate the work. By using ranges for the inputs we can show that with reasonable certainty, the emissions will be within the specified range. Input ranges also help reduce the effect of author bias (intentional or more often unintentional) as the ranges are generated from multiple data sources.

Uncertainty has been examined in top-down models such as GREET [17,18] and by Venkatesh et al. [17–19]; however, as mentioned earlier, the top-down models do not allow the examination of specific crude pathways. And although researchers like Spatari and MacLean performed a bottom-up uncertainty analysis, they focused on lignocellulose-based ethanol fuels and not conventional gasoline, diesel, and jet fuel [20].

Work by Vafi and Brandt [21] and Brandt et al. [22] assessed uncertainty in the regional well-to-refinery gate (WTR) emissions using smart defaults when crude-specific data are unknown. The goal of our work is to use crude-specific data as much as possible and focus on specific fields rather than regions. This will allow us to identify the high and low emission-intensive areas for comparison. The narrower scope will not only allow the examination of specific crude pathways but different technology pathways as well. Additionally, this work adds on the refinery-to-wheel stages to complete the WTC scope. Adding the refinery is important as the refinery yields will magnify the pre-refinery emissions and have a significant effect on the final WTC emissions.

In conclusion, a model that can accurately calculate the WTC emissions of various crudes with uncertainty is needed to fill the current gap in the literature. This work focuses on the uncertainty and variability along a specific crude production pathway. Uncertainty from using alternative technologies, such as different refinery configurations, is outside the scope of the current work.

The main goal of this study is to quantify the uncertainty of the WTC emission estimates; this will be accomplished through the following three stages. The first is to perform an uncertainty analysis and determine the GHG emissions ranges of the five selected conventional crude oils and two unconventional crudes. The second is to identify what additional data are required to improve the accuracy of the emission estimates of each crude oil. The third is to examine how emissions change as the condition of the crude field declines near the end of its useful life. The results of this study will enhance the understanding of the accuracy of the WTC emission estimates that are used in developing GHG reduction policies. The results showing how emissions increase as a field ages will also be useful to policy makers and industry leaders when assessing whether to keep producing from an aging field.

2. Methodology

This study uses the FUNNEL-GHG-CCO&OS modules, published in 2014 [12–16,23], as the basis for our uncertainty assessment. The goal of this study is to integrate the two previous models into a single universal model and enhance the model by adding an uncertainty analysis. The Excel-based models are flexible and transparent, making them ideal for this study. First, we modified the original model to improve the accuracy of the WTC estimates. Then we performed a sensitivity analysis to identify sensitive inputs and ran a Monte Carlo simulation to determine the uncertainty ranges in each crude's WTC emissions.

2.1. Base case model

Since our focus is an uncertainty analysis, this paper only gives a brief overview of the FUNNEL-GHG-CCO&OS modules, hereafter jointly referred to as the F-1 model. Readers are encouraged to refer to the previously published work for additional details [12–16,23].

The F-1 bottom-up model uses engineering first principles to calculate energy use and emissions generated at each stage from raw material production to product end use.

Fig. 1 shows the seven main sub-processes within the model boundary.

The production stage includes drilling the wells, injecting fluids to maintain reservoir pressure, and lifting the crude to the surface. Surface processing includes crude stabilization, gas treatment, and water treatment. Unconventional crudes need to be either upgraded or mixed with diluent prior to being transported to the refinery. Crude is transported by a combination of pipelines and marine vessels to refineries where it is processed into gasoline, diesel, and jet fuel. The finished products are distributed to bulk terminals by pipelines, trains, barges, and tankers and then distributed to fueling stations by truck. The final stage is combustion in a vehicle or aircraft.

This study uses a functional unit of gCO_2eq/MJ of gasoline produced unless specified otherwise. The paper focuses on gasoline production emissions, as the emissions from diesel and gasoline are relatively similar. All of the emissions generated before the refinery stage are the same for all three fuels. The only variation is in the refinery, distribution, and combustion stages, and is relatively small compared to the variation between crudes. Therefore, the diesel and jet fuel emissions are included in Section A6 of the appendix for interested readers.

The F-1 model analyzes five conventional and two unconventional crude oils with each crude oil using a unique production method (see Fig. 1). Maya oil is a Mexican heavy crude, 22° API, produced from the Cantrell field located 100 km off the coast of the Yucatan Peninsula [23]. Mars crude is a light, 31.5° API, sour crude produced from an offshore platform in the U.S. Gulf Coast [23]. Bow River oil is a heavy, 23° API, conventional oil produced in Alberta, Canada [23]. Alaska North Slope (Alaska) crude is primarily produced from the Prudhoe Bay field and is a medium, 29° API, oil [23]. California Kern County crude is a heavy, 13° API, crude produced primarily from the Midway-Sunset oil field [23]. Athabasca crude has an API of 8.2 and is produced primarily via steam assisted gravity drainage (SAGD) and surface mining [12,15,16]. The Athabasca crude is either shipped to the U.S. as dilbit or upgraded in Alberta and shipped as synthetic crude oil (SCO). Thus, there are four Athabasca scenarios: SAGD-Bitumen, SAGD-SCO, Mined-Bitumen, and Mined-SCO.

This study assumes all crudes are refined in the U.S. The refineries are located in Los Angeles, California for Alaska and Kern; Cushing, Oklahoma for Mars, Bow River, and Athabasca; and Houston, Texas for Maya [23].

The F-1 model focuses on assessing specific technology pathways; as a result, the model's uncertainty analysis does not capture variations from using different technology pathways such as different refinery configurations. The F-1 model assumes deep conversion refineries for all crudes as these are typical for North America, unlike “Know Your Oil,” which uses different refinery types for each oil [4,23]. Future work will examine the effect of different refinery configurations and crude blending.

2.1.1. Base case model modifications

In order to improve the accuracy of the F-1 model we made five modifications, including using detailed calculations for subprocesses that are large sources of emissions and integrating new sources that are more accurate. The modified model will be referred to as the F-2 model. The modifications are described below.

The F-1 model only examined single stage rather than multistage compressors. Using single stage compressors would overestimate the amount of energy required by the compressor when large compression ratios were required [13,14,23]. Compressors are used either to inject gas into the reservoir to maintain pressure or to aid in production using a gas lift system. The F-2 model calculations were modified using equations for multistage compressors from the OPGEE model described in the “Know Your Oil” report [4,24]. The number of compressor stages is chosen such that the compressor ratio of each stage is below 5, as higher compression ratios result in excessive outlet temperatures, thereby decreasing efficiency [24,25].

The original F-1 model assumed that 100% of California Kern and Athabasca steam is produced via cogeneration within the plant [23]. However, in reality the cogeneration capacity in the Midway-Sunset and Athabasca field can only provide approximately 30% and 18% of the field's steam requirement, respectively. A once-through steam generator is added to the model to account for the remaining steam [12]. Additionally, data from OPGEE were used to update the cogeneration calculations to include a range of cogeneration configurations [26].

Because there were limited data on venting, flaring, and fugitive (VFF) emissions, the F-1 model used a simplistic estimate. Research by Canter et al. determined a range of venting and fugitive emissions for crude oils by examining several pieces of literature [27]. Canter et al. integrated the VFF ranges into the F-1 model to improve the accuracy of the VFF emissions. We expanded on the work done by Canter et al. and added fugitive emissions for reinjected produced gas. For the F-1-OS module, Alberta-specific data were used to determine the VFF emissions.

Excess produced gas was not considered in the original F-1 model. This gas, however, can be used to offset natural gas consumption. The OPGEE model applies a credit for the production of produced gas equal to the natural gas upstream emissions with the transportation emissions excluded [24]. This credit method is integrated in the F-2 model to align the model boundaries with those in existing literature.

The F-1 model assumed all crudes have the same energy content. The new model calculates the lower heating value (LHV) using a correlation from Speight [28]. This correlation depends on the crude's specific gravity and has been used by the GREET and PRELIM models [8,29].

The F-1-OS module originally did not include land use emissions and now uses the F-1-CCO methodology to calculate land use emissions. Lastly, the F-2 model uses updated emission factors from GREET 2015, the F-1 model used GREET 2013. The crude transportation emissions have been updated to be consistent with work done by Di Lullo et al. which focused on non-North American crudes [30]. Detailed information on the modifications made to the original F-1 model is provided in Section A1.

2.2. Uncertainty analysis methodology

Output uncertainty in this study has two parts, input uncertainty and input sensitivity [31]. Inputs with high sensitivity and high uncertainty will have a large effect on the output distribution. Hence, a sensitivity analysis was first conducted to identify which key inputs should be further examined. Distributions for the key inputs were calculated from values obtained from the literature. ModelRisk, an Excel add-in software, was used to run a Monte Carlo simulation and determine the WTC emissions uncertainty [32]. Fig. 2 provides an overview of the methodology used.

2.2.1. Identify sensitive inputs

A ± 25% range of each input base case value was used in the sensitivity analysis on the WTT (well-to-tank) emissions, only one input is varied at a time. WTT emissions were analyzed instead of WTC emissions because combustion emissions, which represent 60%–90% of the total emissions and are constant for all of the scenarios, would minimize the input sensitivity [33]. Spider plots were used to identify any non-linear responses.

2.2.2. Determine distributions for key inputs

Due to the lack of publically available data, a conservative approach was used to determine the key input distributions. Triangle distributions require a most likely, minimum, and maximum estimates to generate and they favor extreme values [34], which results in a conservative output distribution. ModelRisk's copulas were used to link dependent inputs; for example, in the Alaska scenario, the produced gas volume is dependent on the injected gas volume. Fig. 3 provides a high-level overview of the identified key inputs; additional details are provided in Section A4. Tables A4 to A6 show a summary of the Monte Carlo input distributions and their sources.

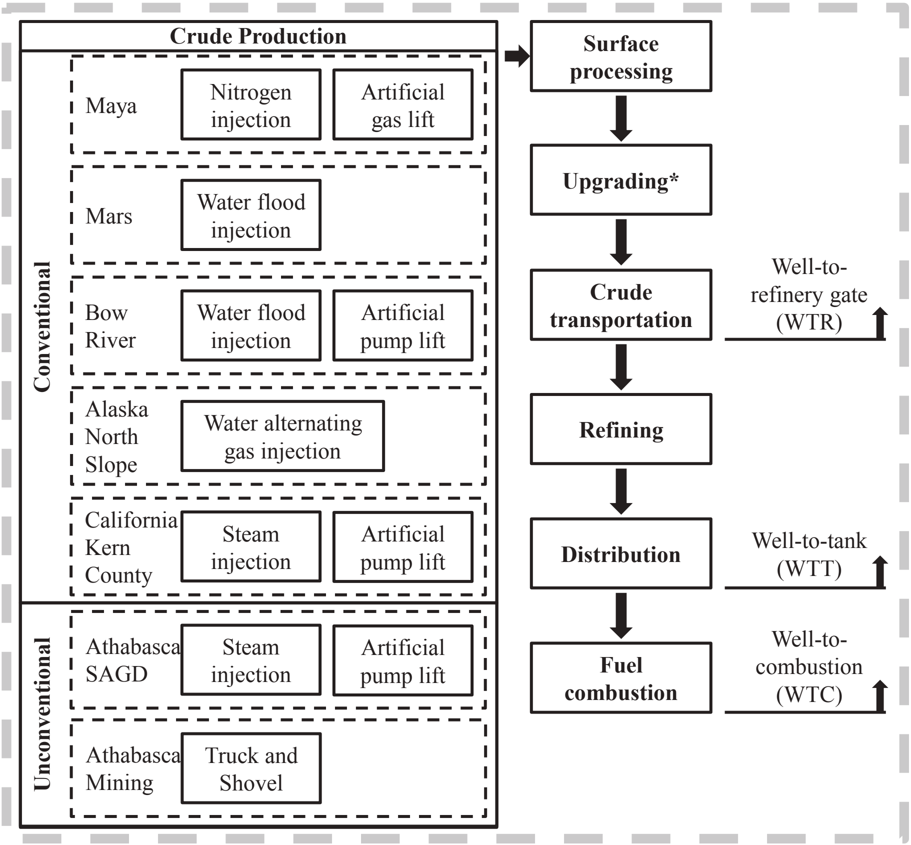

Fig. 1. The FUNNEL-GHG model stages from well to combustion (*upgrading applies to Alberta synthetic crude oils [SCO] only).

2.2.3. *Determine distributions for insensitive inputs*

The insensitive variables individually have little effect on the overall results but their combined effect could have a significant effect. As a result, all of the insensitive inputs are assigned an arbitrary triangle distribution wherein the maximum and minimum values are defined as ± 10% of the base case value. The output distributions with and without the insensitive input distributions are then compared to determine if ignoring the uncertainty in the insensitive values will have a significant effect on the results. Ideally, every input should have an uncertainty distribution but due to the large number of inputs, this is not practical.

3. Monte Carlo simulation

A Monte Carlo simulation allows us to examine how the resulting WTC emissions change as multiple key inputs are varied across a wide range of values. The Monte Carlo simulation ran with 50,000 samples, which ensures that the simulation sampling error has a 99% probability of being less than 0.1 gCO_2eq/MJ. The sampling error calculations and values for each crude are in Section A2 [35]. The results are reported using the 5th and 95th percentiles (P5, P95). An iterative approach was used wherein the ModelRisk-generated tornado plots were used to determine which inputs should receive more focus.

The tornado plots are generated by calculating the output mean from a subgroup of Monte Carlo samples. Each subgroup contains only the samples where the input value is within a given percentile range. This study used a 5% range (20 tranches); therefore, the subgroups would be split into ranges of P0-P5, P5-P10, et cetera. The subgroups with the largest and smallest output means are used as the tornado plot's maximum and minimum values [36]. Due to the number of inputs used and the accuracy of the tornado plots, only the key inputs are included. The tornado plots were further filtered to display only the significant inputs. An input was classified as significant if the input's tornado plot variance (maximum − minimum) was greater than 10% of the WTC variance (P95-P5).

Due to the complexity of the refinery portion of the model, an in-depth analysis was not performed for the refinery stage. The F-1 model uses Aspen HYSYS, an advanced refinery modeling software that is used globally by the oil and gas industry [37], to model the refinery. Aspen generates energy and mass balances for each process unit in the refinery [23], which are used by the F-1 model to allocate emissions to the transportation fuels. The Aspen model used was selected as it is based on a typical North American refinery. The uncertainty in the process units' mass and energy balances is not examined in this study due to the complexity of the refining process. However, boiler and heater efficiency as well as electricity emission factors are assigned Monte Carlo input distributions. The refinery yield is also assigned a range to reflect uncertainty from optimizing the refinery. Refinery emissions are determined using a Monte Carlo simulation that only examines the refinery portion of the model. Refinery output emissions are fed into the main model as Monte Carlo input distributions (Table A8). A second Monte Carlo simulation is run to find the WTC emissions.

3.1. *Monte Carlo simulation inputs*

The key inputs with their distributions and sources are listed in Table A5 and for general inputs that apply to all crudes and in Tables A6 and A7 for the crude-specific inputs. The Monte Carlo inputs include emission factors, efficiencies, specific heat capacities, process temperatures, VFF volumes, fluid injection and

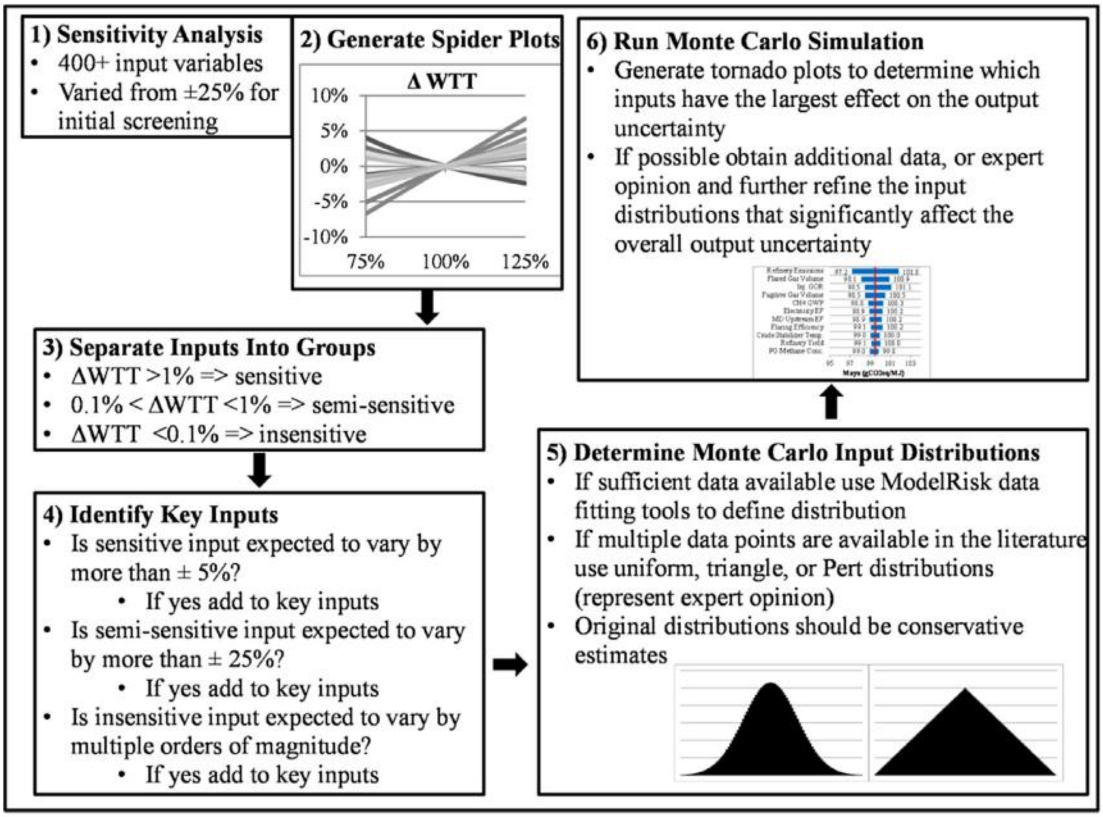

Fig. 2. Methodology overview (WTT = well-to-tank).

production ratios, well depths, process pressures, and other parameters (Fig. 3). Additional information on how the distributions are determined for each input is in Section A4.

3.2. Monte Carlo historical and current scenarios

Originally, one Monte Carlo scenario was run for each of the five crudes; however, for the Alaska and California Kern crudes the original results were 49 and 11% higher than the previous estimates from the F-1 model, respectively [23]. Additionally, the Kern scenario results were 25 and 41% higher than the Jacobs and TIAX results, respectively [10,11]. Further investigation found that the discrepancy was from the assumed water and gas injection and production ratios. The Alaska and Kern fields have been using enhanced oil recovery for over 20 years [33,38], and as the fields age the injection and production ratios have increased. Since the WTC emissions are sensitive to the injection and production ratios, two scenarios were developed for these fields, historical and current. The historical scenario uses cumulative ratios, which give an estimate of the average WTC emissions over the entire life of the field. The current scenario uses recent ratios to investigate how the WTC emissions rise as the field ages. Using two scenarios will provide more insight into how the WTC emissions can vary depending on the age of the data used.

Since we are interested in assessing how the WTC emissions change over time this analysis focuses specific oil fields. For Alaska this analysis focused on the Prudhoe Bay and Kuparuk fields as they represent 75% of Alaska current production and are adjacent [39]. The startup of the remaining fields in Alaska was not included. As a result of injecting lean gas the Prudhoe bay crude API has increased by 5° over the last 15 years [40]; hence, we used two crude assays to determine the refinery emissions for the historical case (see Section A3) [41,42]. For Alaska, all of the wells in the Prudhoe Bay area are included as the water and gas injection affects the entire field. For California Kern this analysis focused on the Midway-Sunset field. Unlike Alaska the crude composition has not changed significantly with time [43,44].

The only differences between the historical and current scenarios are the inputs for the injection WOR and GOR, and the production WOR and GOR, as well as the refinery crude assay for Alaska historical scenario only. Tables A3 and A4 show how the injection and production rates for Alaska and Kern have increased over time.

4. Results and discussion

The resulting WTC distributions show that the Alaska and Kern current scenarios have the highest emission intensity (Fig. 4A). Additionally, the Alaska and Kern current and historical scenarios show that emissions increased by 34% and 30%, respectively, as the fields aged. The Mars and Maya crudes have the lowest emission intensity due to their low energy intensive production methods (Fig. 4A).

When the error bars of two crudes overlap, it is not possible to confidently conclude that one crude oil has lower emissions than the other does. The results in Fig. 4A show an overlap between most of the crudes studied; this is because of the conservative approach taken in defining input distributions for the Monte Carlo simulation. However, the current Alaska and Kern scenarios clearly produce higher emissions than the other scenarios. Additionally, even with the conservative uncertainty, the Kern historical scenario does not overlap the Mars and Maya scenarios. While it is not possible to

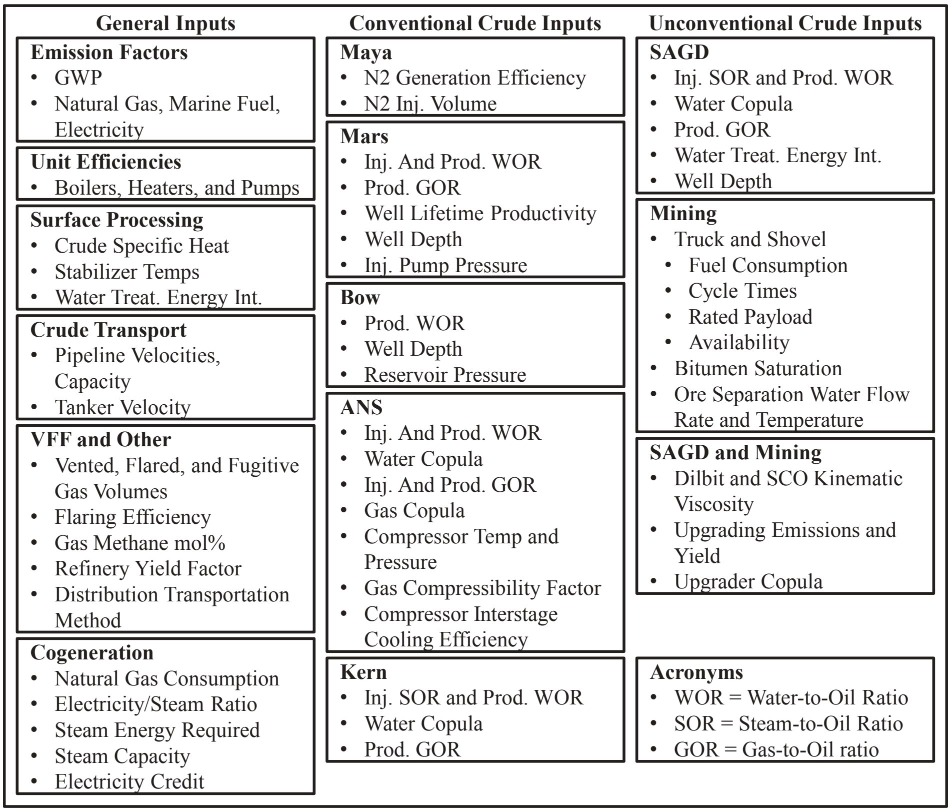

Fig. 3. Summary of key inputs identified by the sensitivity analysis and used in the Monte Carlo simulation; see Section A4 of the appendix for additional details.

definitively rank each crude based on its emission intensity, it is still possible to differentiate between high and low emission crudes.

Tornado plots (Figs. 5 and 6 and Figs A3–A6) are used to identify which inputs have the largest effect on the output uncertainty; inputs with a wider range have a larger effect on the output uncertainty. The refinery and VFF emissions are a significant source of uncertainty for all crudes and represent 12- 2%, and 1–8% of the WTC emissions, respectively. Additional production specific parameters such as the injection SOR, injection GOR, and ore separation temperatures significantly affected the uncertainty for crudes that used an energy-intensive production method. Some inputs result in larger uncertainties than others do due to either a lack of information or a wide range of data in the literature. Additionally, inputs with higher sensitivity will have a larger effect on the WTC uncertainty. Importantly, tornado plots cannot accurately display dependent inputs that are linked with a copula. For example, the produced WOR has a relatively small effect on the WTC emissions, but since it is linked to the injection WOR, which does have a significant effect on the WTC emissions, it appears to be significant on the tornado plot.

4.1. Refinery uncertainty

The uncertainty in the refinery stage has two main sources, the refinery yield factor and emissions. The refinery yield factor is the ratio of crude oil energy content to the finished product's energy content. The yield factor depends on the crude properties and refinery configuration. For example, the yield factor for Alaska from PRELIM varies from 1.07 to 1.53, depending on the refinery configuration [29]. A yield factor of 1.5 means that 1.5 bbls of crude are required to produce 1 bbl of transportation fuels; therefore, as the yield factor increases, the production emissions increase, because more crude is required per barrel of product. The WTC variance of the yield factor ranges from 6.9 to 7.4 gCO_2eq/MJ for the Kern current and Alaska current scenarios.

Five of the six inputs in the refinery tornado plots (Fig. 7 & Fig. A7) are related to the natural gas consumption, as natural gas is the primary energy source for the refinery. Therefore, efficiency improvements have the potential to significantly reduce the refinery emissions. The natural gas upstream emission factor is the first or second largest source of uncertainty for all eight crudes, therefore understanding where each refinery gets its natural gas from will have a significant effect on the results.

The large effect the refinery emissions have on the WTC emissions suggests that a more in-depth analysis is required to understand the emissions from the complex refinery processes. Additionally, it should be noted that the refinery yield factor can decrease by using additional conversion processes to further upgrade the bottom-of-the-barrel products, which results in higher emissions [29]. The current model does not include this correlation and provides a conservative range of WTC emissions.

4.2. Venting, fugitive, and flaring uncertainty

VFF emissions are one of the main sources of uncertainty. The VFF uncertainty is primarily due to fugitive volumes, flaring volumes, methane GWP, and produced gas methane concentrations (see Fig. 7 for an example).

Canter et al. studied venting and fugitive gas volumes for North American crudes by examining multiple sources for the oil and gas industry [27]. However, there is a wide range of values in these sources, which rely on approximation methods. There are limited publically available data on directly measured fugitive volumes from crude oil production and refinement [27]. To accurately

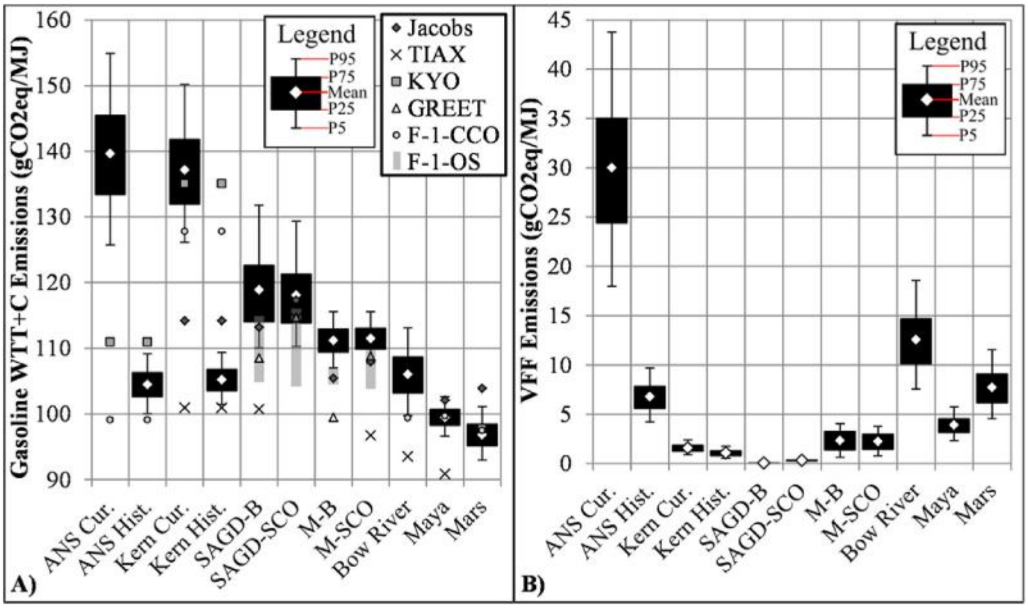

Fig. 4. A) Gasoline WTC emissions and B) Venting fugitive and flaring emissions. Synthetic crude oil (SCO) pathways include upgrading. The additional Alaska and Kern scenarios are included to show the effect of reservoir age on the WTC emissions. P95, P75, P25, and P5 represent the respective percentile values. Fig. 4A additional data from the literature:

- Jacobs produced a bottom-up model that examined 9 crudes (2009) [10].
- TIAX's WTC bottom-up model focused on creating a detailed refinery model (2009) [11].
- Know Your Oil (KYO) performed a detailed bottom-up WTC model examining 30 crudes (2015) [4].
- GREET is a top-down model focused on determining regional averages (2015) [45,46].
- F-1-CCO (2014) [13,14,23], and F-1-OS (2014) [12,15,16] are bottom-up models focusing on conventional crudes (CCO) and unconventional crudes (OS). The model developed in this study was built by combining and improving these two models.

determine the WTC emissions for the various crudes, more information is needed on the amount of fugitive gas released, especially for gassy oils, as in the Alaska current scenario. The injected gas fugitives are calculated specifically for the Alaska scenarios and are described in Section A4.5. As they are the largest source of uncertainty for the Alaska current scenario, more detailed data are required to reduce the uncertainty in the WTC emissions. Due to the unique process used for the Athabasca oil sands, crude-specific data were collected to model the VFF emissions (Section A4.9).

Methane GWP values also affect the uncertainty of the model results. Methane GWP values have a ±35% uncertainty range [47,48]. Usually a GWP of 34 is applied to the methane emissions to convert to GHG emissions (CO_2eq) [47,48]. However, in an uncertainty analysis of total GHG emissions, a higher methane GWP value will have a relatively larger impact on the total GHG emissions for crudes with large VFF volumes compared to crudes with small VFF volumes.

VFF emissions depend on the concentration of methane in the produced gas. The data analyzed for California showed that methane concentrations could vary from 50 to 100%, with a mean of 84%. OPGEE and the original F-1 model used 84% for all of the crudes analyzed [23,49]. Jacobs and TIAX use 75% and 80% methane for their produced gas, respectively [50,51]. Methane gas concentrations for each well should be reported to get a better understanding of the produced gas emissions.

Flared gas volumes also have a wide range of uncertainty due to the limited data and range from ±91% to ±382% [52]. Though a wide conservative range of 80%–99% flaring efficiency was assumed, it resulted in a relatively small variance of 0.4–1.2 gCO_2eq/MJ for five of the eleven scenarios (Fig. A8). However, for the Alaska historical and current scenarios the ranges were 3.4 and 3.3 gCO_2eq/MJ, respectively, as the larger flaring volumes amplified the effect of the flaring efficiency. Therefore, flaring efficiency should be closely monitored for gassy oil.

For the Alaska scenarios, the injection and production GOR values are significant since the venting and fugitive gas volumes are determined as a percentage of the produced gas volume. The produced gas volume also depends on the injected gas volume and is modelled using ModelRisk copulas.

The distribution of VFF emissions in Fig. 4B shows that a significant amount of the uncertainty in WTC emissions is due to VFF emissions. The VFF variance (P95-P5) is 57%–88% of the WTC variance for the Mars, Maya, Bow, and Alaska crudes. For Kern, the VFF variance is less than 15% of the total variance as it produces less gas than the other scenarios. For the mining scenarios, the VFF variance is 40% due to the high pond and mine surface fugitive emissions, while for SAGD it is less than 1% due to the low produced gas volumes. This shows that for crudes with a large production GOR, a better understanding of the VFF gas volumes is required to accurately estimate the WTC emissions.

4.3. *Effect of field age on WTC emissions*

Alaska and Kern current scenarios show emissions increases of 34% and 30%, respectively, from the historical scenarios (Fig. 4A). These increases are a result of increased water and gas injection and production rates as discussed in Section 3.2.

For the Kern scenario, the increase in emissions is primarily due to the production emissions, while VFF emissions are similar for the current and historical scenarios, as seen in Fig. 4B. Kern has high production emissions because it requires thermal enhanced oil recovery methods. The other crudes use mechanical enhanced oil recovery methods, which are less energy intensive. The injection SOR, production WOR, steam energy, and natural gas emission factors are the largest sources of uncertainty for the Kern scenarios. For the Alaska scenarios, the mean VFF emissions increased from 6.8 to 30.0 gCO_2eq/MJ, while the mean well-to-refinery (WTR) emissions, excluding the VFF emissions, increased from 7.5 to 20.9

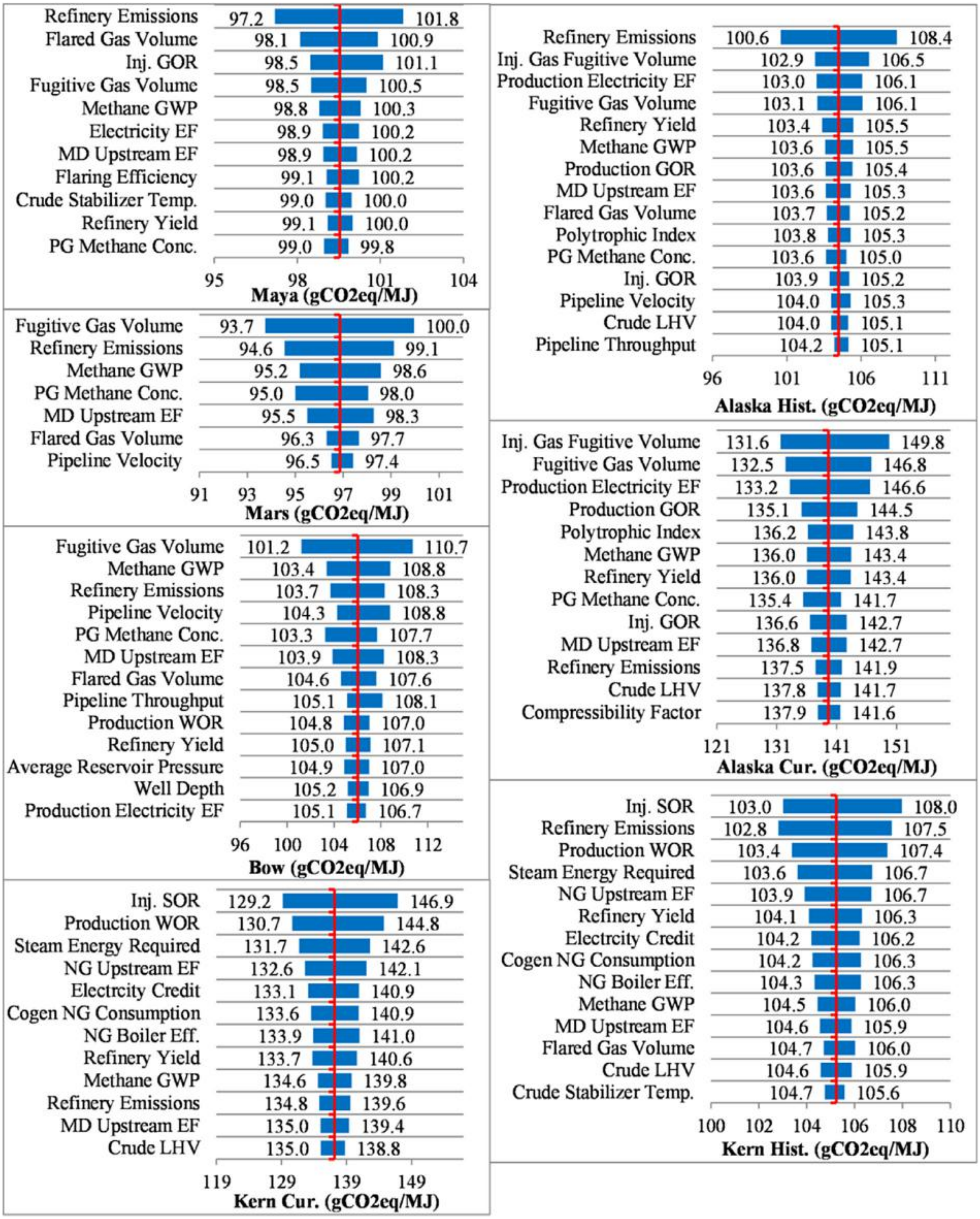

Fig. 5. Tornado plots of the gasoline WTC emissions for conventional crudes.
Inj.: injection, Eff: efficiency EF: emission factor, NG: natural fas, PG: produced gas, MD: marine diesel.

gCO$_2$eq/MJ. A better understanding of the VFF and production emissions will become increasingly important as Alaska gas and water volumes continue to increase.

4.4. Effect of insensitive inputs

The Monte Carlo gasoline WTC simulation results in Fig. 4 include the key inputs only. A comparison of the WTC emissions with and without the insensitive inputs found that the insensitive inputs had a negligible effect, the variance increased by less than 1%. This confirms the original assumption that detailed distributions are not required for the insensitive inputs as the effect will be negligible.

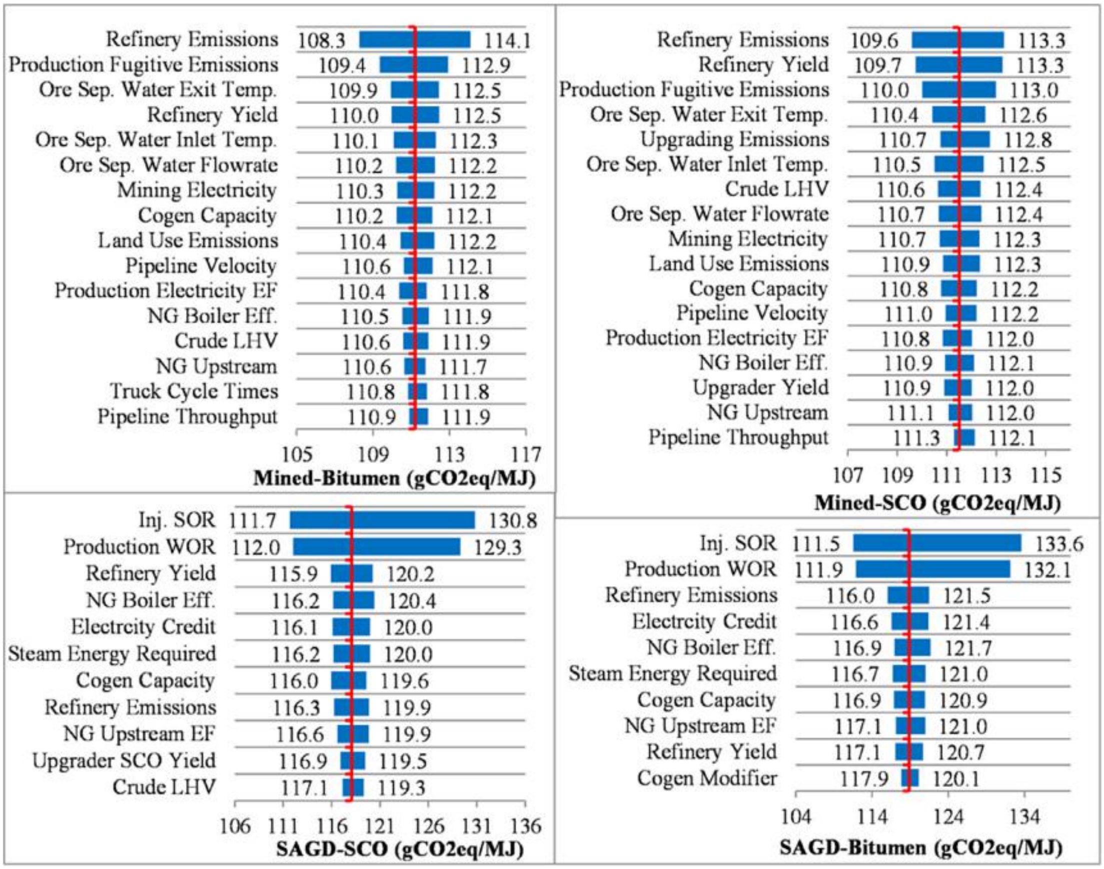

Fig. 6. Tornado plots of the gasoline WTC emissions for conventional crudes.
Inj.: injection, Eff: efficiency EF: emission factor, NG: natural gas, Sep: separation.

4.5. Model comparison with published literature

This study used an uncertainty analysis to determine the most likely range of emissions for each crude using a range of values for various inputs. If the input ranges used in this study cover all reasonable values, then the results from another model with the same model boundaries should be within the output ranges found in this study. Fig. 4A compares the WTC emissions for gasoline from this study, Jacobs, TIAX, “Know Your Oil” (KYO), and the original F-1 model. The models in Fig. 4A do not have the same boundaries, and as a result some of the WTC emissions are outside the range found in this study. The Jacobs and TIAX, F-1, and KYO models were developed in 2009, 2014, and 2015, respectively, and so did not use the same emission factors and methane GWP [4,23,50,51]. The F-2 model and the KYO model use 34 as the methane GWP and the others use 25 [4,10,11,23].

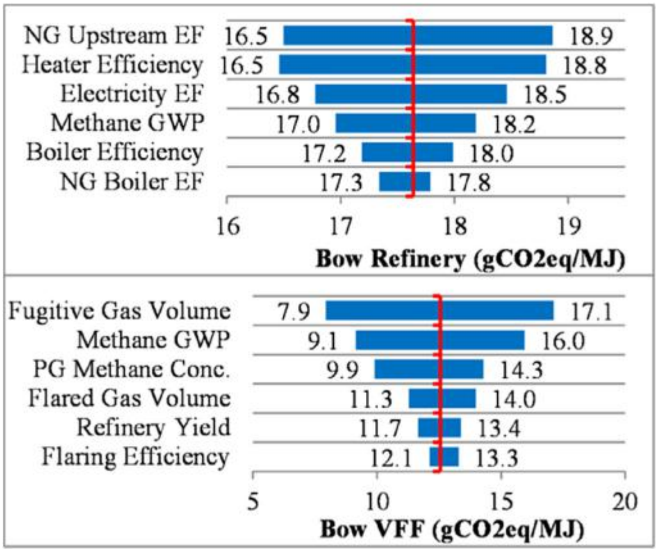

Fig. 7. Bow refinery and venting, fugitive, and flaring tornado plots.
EF: emission factor, NG: natural gas, PG: produced gas. Refinery emissions are for gasoline, VFF emissions are the same for gasoline, diesel, and jet fuel. Tornado plots for the remaining crudes, diesel, and jet fuel are in Section A6.

The TIAX emissions results are significantly lower than the other models'. This is because TIAX uses a simpler approach than the others when modeling well-to-refinery entrance emissions and focuses more on the refining emissions. TIAX uses medium conversion refineries; we used deep conversion, which results in lower refinery emissions.

The KYO and Jacobs results, except for the Jacobs Mars results, were within the range of values reported for all the crudes in this study. For Mars, the Jacobs results are higher than ours are due to the produced gas credit and the water injection ratio. This study calculated a 3.7 gCO_2eq/MJ gas credit. Jacobs does not use a gas credit for produced gas, and it used a water injection ratio of 5.5 m^3/m^3, which is the highest water production ratio in our study [10].

Interestingly, the KYO, F-1, and Jacobs model results line up with the lower end of our Kern current scenario. This makes for KYO and the F-1 model since they use SORs of 5.79 and 5.13 m^3/m^3 while our scenario uses a mean SOR of 5.74 m^3/m^3 with a minimum of 4.72 m^3/m^3. It was initially unclear why the Jacobs Kern scenario is 7% lower than our current scenario as it uses a SOR of 5 m^3/m^3.

Further investigation found that the variation was due to the refinery and electricity emissions. The Jacobs refinery emissions were lower due to differences in the refinery configurations used. The electricity emissions for the F-2 model were higher because the cogenerated electricity had a higher emission intensity than the grid electricity, which was used by Jacobs [10].

The original F-1 results differ from the F-2 results primarily due to the new VFF emissions. For example, the additional fugitive emissions for the reinjected gas increased the F-2 Alaska scenario emissions by 5 and 29% for the current and historical scenarios, respectively. This study's mining emissions tended to be higher than those from earlier studies due to the addition of land use and VFF emissions not included in the previous models and larger refinery emissions. The bitumen pathways also were found in this study to have high refinery yield factors, which magnified the upstream emissions. The F-1-OS emissions are shown as a range representing the cogen/no-cogen and coking/hydroconversion upgrading scenarios in the original F-1-OS model.

5. Policy implications

The uncertainty ranges determined by this study are important to policy makers and industry representatives as they show that even though these models have limitations, it is possible to differentiate between high and low emission crudes. Our results also showed that there is a large variation in the WTC emissions between crudes. The top-down GREET model found that the North American average WTC emissions for gasoline are 92 gCO_2eq/MJ, which is 32% lower than our results for Alaska [45]. While GREET's high-level analysis is appropriate for a country-wide analysis, it lacks the detail required to form specific regional policy. For example, when attempting to determine how stricter venting, fugitive, and flaring regulations will affect the WTC emissions of Alaska crude, a detailed bottom-up model is required.

Additionally, Alberta's recently introduced Climate Leadership Plan limits GHG emissions from the oil and gas industry to 100 Mt/y [53]. The current scenarios for Alaska and Kern show that as fields age their production emissions can grow significantly. As the Athabasca SAGD oil sands wells age, policy makers should monitor the SOR to ensure a similar emissions increase does not occur. Our model can be used to identify poor performance wells and areas for potential emissions reduction. To limit emissions, governments may want to implement limits on the injection fluid ratios.

Using distributions for key inputs allowed our results to include estimates from several data sources. For example, KYO, Jacobs and the F-1 model assumed that the Mars production WOR was 0.2, 5.5 and 5.5, respectively [4,13,50]. By using a range of 0.02–5.5, we are able to produce a WTC estimate that was not dependent on whether we used data source A or B, reducing the effect of unintentional bias.

The Alaska and Kern current and historical scenarios further highlighted the advantage of using multiple scenarios and distributions for key inputs. The wide range in WTC emissions estimates in the literature, from 85 to 111 gCO_2eq/MJ, and 101–135 gCO_2eq/MJ for Alaska and Kern, respectively, was a result of the assumed values used for the injection and production fluid ratios [4,11,13,50]. While all of the studies used similar data sources, variations in their assumed values resulted from the timeframe used. Since both crudes experienced periods of rapid decline, using an average over the last five years rather than the last ten years will provide significantly different values.

By determining the results as uncertainty distributions, rather than deterministic point estimates, we can reduce the severity the subjective assumption have on the WTC emissions. These ranges help policy makers understand how the assumed values affect the results and provide a more realistic overview of the differences in the crudes' WTC emissions. For example, the European Union's Fuel Quality Directive proposed grouping crudes in three categories (conventional crude, oil shale, and natural bitumen) and applying a default emission intensity for each group [54]. However, our analysis shows that due to the overlap in the WTC uncertainty ranges and the wide variation among crudes emissions, the use of generic defaults is unwise.

The VFF emissions were a large source of uncertainty in our model. While various government organizations provide high-level data on VFF gas volumes, the aggregated nature of the data makes it difficult to determine crude-specific VFF ratios. Additionally, some data sources such as the Alaska Oil and Gas Conservation Commission aggregate venting and flaring gas volumes [55]. Since the GHG emission intensity of venting is nearly 7 times higher than flaring, distinguishing between the two is essential to produce accurate WTC emission estimates. The VFF emissions, refinery natural gas consumption, refinery yield factors, natural gas upstream emission factors, and injection and production gas-to-oil ratios and water-to-oil ratios were found to have the largest effect on uncertainty. Policy makers interested in accurately determining the GHG emissions should focus on gathering additional data from industry related to these inputs.

When we compared our results to Di Lullo et al.'s, which examine the uncertainty in the WTC emissions for crudes extracted outside of North America [30], we found that there was no relation between crude WTC emissions and geographic location.

6. Conclusion

This study combined the FUNNEL-GHG-OS and FUNNEL-GHG-OS bottom-up life cycle assessment models into a single integrated Excel model, named F-2. This F-2 model was improved to expand its scope and updated to include current data. A sensitivity analysis was used to identify key inputs whose values have a significant effect on the WTC emissions. A Monte Carlo simulation using distributions for the key inputs was used to determine uncertainty ranges for the WTC emissions of eleven crude scenarios. Inputs that had a significant effect on the output uncertainty were determined using tornado plots. We found that while there is overlap between the WTC emission uncertainty ranges, it is still possible to differentiate between high and low emission crudes. The VFF emissions, refinery natural gas consumption, refinery yield factors, natural gas upstream emission factors, and injection and production gas-to-oil ratios and water-to-oil ratios were found to have the largest effect on uncertainty.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.energy.2017.04.040.

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