Topic Paper #30

Data Variability and Uncertainty in Greenhouse Gas Life Cycle Assessment

On August 1, 2012, The National Petroleum Council (NPC) in approving its report, *Advancing Technology for America's Transportation Future*, also approved the making available of certain materials used in the study process, including detailed, specific subject matter papers prepared or used by the study's Task Groups and/or Subgroups. These Topic Papers were working documents that were part of the analyses that led to development of the summary results presented in the report's Executive Summary and Chapters.

These Topic Papers represent the views and conclusions of the authors. The National Petroleum Council has not endorsed or approved the statements and conclusions contained in these documents, but approved the publication of these materials as part of the study process.

The NPC believes that these papers will be of interest to the readers of the report and will help them better understand the results. These materials are being made available in the interest of transparency.

National Petroleum Council

Future Transportation Fuels Study

Topic Paper

Data Variability and Uncertainty in Greenhouse Gas Life Cycle Assessment

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How do you measure Carbon?

Life cycle analysis (LCA) is a computational approach based on models and available data. Like other models (e.g., economic, meteorological), these calculations are not perfect. The results from an LCA model can have considerable deviation from the 'true' or 'real' value, and this should be accounted for when comparing fuel/vehicle systems using life cycle principles and perhaps also included in policy design as discussed in Mullins et al. [ES&T 2010](1) . Recently published research (Stratton et al. 2011 (2), Brandt 2011(3)) advocates that relative comparisons of pathways should consider the variability that is inherent in LCAs and that comparisons of single value results (i.e., comparing one absolute value of g CO_2e/mile vs. another) can be misleading. Instead, these researchers suggest the use of uncertainty bars for each pathway, and argue that life cycle GHG inventories for transportation fuels be presented as ranges [Stratton et al. 2011 ES&T](2). The uncertainty bars represent both the 'variability' and 'uncertainty' associated with each pathway. If the uncertainty bars overlap between two pathways, it can be understood that there is not a significant difference between the two. This approach provides the researcher or policy maker with an indication of those areas or key variables in the model where additional data or new model approaches are required in order to make informed decisions. An example of model uncertainty was recently discussed at an LCA technical forum. At the Second CRC Workshop On Life Cycle Analysis of Biofuels, John DeCicco (4) pointed out that the lifecycle carbon content of a material cannot be determined by simply examining the chemical composition. For biofuel GHG calculations, one now needs several econometric models predicting world economic and agricultural activity over several future decades or even longer, plus many thousands of pieces of data, much of which is impossible to verify. And once this carbon intensity has been determined by an analyst, he is likely to have more parties that disagree with his results than agree with them. Although fuel carbon intensity may seem a simple concept, actually measuring it scientifically is an intractable problem.

Uncertainty and variability are philosophically very different. Variability stems from inherent variations in the real world [Huijbregts et al. 1998 IJLCA](5) and is a function of the system being evaluated. It is not reducible through either study or further measurement though it may be reduced through changes in the system. An example of variability might be two power plants of the same design, but having different GHG emissions because one plant may have a greater operating efficiency due to characteristics unique to the plant (down time, consistency of demand in the plant locations, etc). In comparison, uncertainty is the assessor's lack of knowledge about the parameters that characterize the physical system that is being modeled, and can arise from inaccurate measurements, lack of data, and model assumptions [Huijbregts et al. 1998 IJLCA](5). It is sometimes reducible through further measurement or study. An example of uncertainty might be a new fuel production process which only has pilot data by which to estimate its GHG emissions per unit energy produced. It is unknown if, when scaled up to full production, the process is as efficient and has the same GHG emissions profile as the pilot size.

Uncertainty is inherent in all GHG LCA modeling efforts. Some LCA studies break uncertainty into two broad categories: (A) systematic uncertainties, which result from LCA system boundary conditions, LCA approach (process-based vs. economic-based), and policy vs. technology evaluation, and (B) technical uncertainties, which result from data and model selection.

Technical uncertainties arise because GHG LCA values are estimated using both empirical (i.e. data-derived) and modeled data. A typical lifecycle analysis first breaks the process being analyzed into major lifecycle stages (e.g. fuel production and use on a vehicle), then breaks these stages into components (e.g. fuel production may be broken down into crude production and fuel refining), and finally develops estimates for each component. For existing fuel processes, such as gasoline production and corn-based ethanol production, historical, full-scale operational data may exist to aid with the analysis. While empirical data represents the most reliable input into the LCA process, it can still suffer from uncertainty due to sampling errors, measurement inaccuracies, inconsistent collection and faulty calculation processes. Technical uncertainties can usually be addressed by improving data availability and quality and by applying statistical analysis to LCAs.

When empirical data are unavailable, the analyst must resort to using engineering process models for the various steps in the production and distribution processes. Process models are best when calibrated with actual operational data For GHG LCA these data are rarely available. Modeling of processes almost always involves simplifying assumptions, which can result in a modeling outcome that is not representative of the actual process. Therefore, technical uncertainty is greater when analyzing processes which are not yet in full-scale production.

Monte Carlo analyses are often used to estimate technical uncertainty in life cycle analysis. A Monte Carlo analysis is a technique in which each variable in a calculation is described by its mean value and its statistical distribution to represent its uncertainty. Calculations are performed several hundred to several thousand times to determine the effect of variable uncertainty on the metric of interest (e.g., kg CO_2e/MMBtu of energy for fuel). By examining the impacts of input variability on the output of the analysis, Monte Carlo simulation can be helpful. However, the benefits of Monte Carlo techniques are dependent on assumptions about the type of statistical distribution of the input variables, and the amount and accuracy of the available data. For new and emerging technologies this information is largely unknown or there is little data. As a result, most Monte Carlo simulations are very dependent on the value judgment and the experience of the modeler.

A study by Venkatesh, Jaramillo, Griffin, and Matthews (6) found the technical uncertainty range around GHG emissions from gasoline production and use to be 13% with a mean value of 89 gCO_2e/ MJ (93,895 gCO_2e/MMBTU). Since gasoline and diesel fuel have years of historical data, the gasoline emissions value would be expected to have one of the smallest uncertainty ranges of most GHG LCA fuel pathways. The total GHG LCA emissions of corn ethanol have been found to range from 50 - 250 gCO_2e/MJ (52,750—263,750 gCO_2e/MMBTU) (7).

Examples of a systematic uncertainty in fuel GHG LCA include the allocation methodology that is chosen to “value” co-products and questions of whether or not, and how, to treat land-use related emissions. The land-use issue is discussed further below. The uncertainty associated with co-product allocation is highlighted in a recent study by Wang et al. [Energy Policy 2011](8). Wang et al. estimate that 57% to 92% of the total life cycle GHG emissions for the soybean to biodiesel pathway can be allocated to co-products (glycerin, soy meal), with the spread arising simply because of the allocation methodology that is used. Similarly, for the corn starch to ethanol pathway, values ranging from 19% to

46% are reported in the same study. Even if the co-product allocation approach is improved, there can be significant variability in the results, depending on factors such as co-product disposition and use. For example, Bremer et al. [Journal of Environmental Quality, 2010](9) report that the co-product GHG emissions credit for corn ethanol can vary by two-fold, from 11.5 to 28.3 gCO_2e per MJ (12,133 to 29,857 gCO_2e/MMBTU) of ethanol produced depending on the types of co-products produced, the proportion of this feed provided to beef cattle vs. dairy or swine, and the location of the corn production (10).

Figure 1 presents the ranges of GHG emissions reported by several studies. A list of the sources for the data represented in the ranges below can be found in Appendix 2 of the GHG chapter. The numbers in the boxes above the bars represent the number of data points for each pathway. Although these studies may not encompass all aspects of uncertainty and variability, the ranges are indicative of the uncertainty in these analyses. In some of the cases, the ranges appear to be very small. This can be an artifact resulting from a very limited number of studies for these pathways and/or a lack of knowledge about newer pathways, rather than due to significantly lower uncertainty in the pathways. This is quite often the case for new technologies that have not reached commercial scale and the range of operations is limited, as discussed earlier in this chapter. Better data and more studies that represent the full range of operations at large volume production are needed to reduce the uncertainties in all of the future pathways considered in this study. Future LCA studies could be more instructive if they were to quantify the range of uncertainties associated with the various inputs to the LCA model and deliver a range of results rather than a single point value for the pathway.

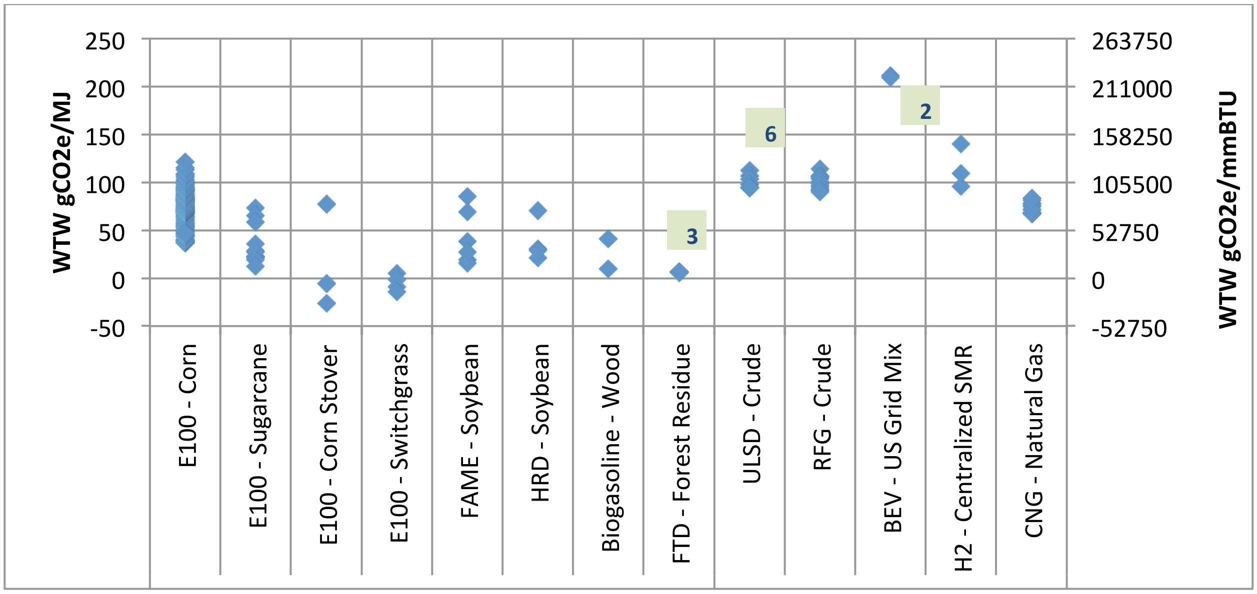

Figure 1. WTW GHG Emissions - *3rd Party Data Survey*

Indirect Land Use Change (ILUC)

The uncertainty for GHG LCA can increase dramatically when indirect impacts are considered, such as indirect land use change (ILUC). U.S. ILUC attempts to determine the worldwide impact of a change in U.S. cropland allocation. This requires models that merge U.S. and World agricultural and economic models. Modeling the world response to current and future U.S. biofuel use and land use changes is a daunting task.

The use of ILUC in LCA is relatively recent, and therefore studies to date have a wide variety of assumptions and a wide range of results. California and U.S. EPA have published ILUC values for some biofuels used in the California Low Carbon Fuel Standard and the U.S. Renewable Fuel Standard 2, respectively. Argonne National Labs has developed an ILUC value for corn fermentation ethanol and is in the process of evaluating ILUC for other biofuel pathways. Figure 2 and the table below compare the results of these three analyses for GHG LCA with and without ILUC. Note that the inclusion of ILUC significantly increases the GHG life-time emission estimates and that there is considerable variability and uncertainty between the ILUC values. California's estimate of corn ethanol ILUC GHG emissions ranges from 20 - 140 gCO_2e/MJ (21,100—147,700 $gCO_2e/MMBTU$) (11). In the CARB ILUC Uncertainty Report (12), there are many quotes dealing with non-trivial uncertainty. These thoughts can best be captured by Al-Riffai et al. (IFPRI) 2010(13): "…this modeling project has demonstrated how the current limits to data availability create significant uncertainty regarding outcomes predicted by these policy simulations."

It should be noted that some advanced biofuel feedstocks may have little or no iLUC effect since they are sourced from non-arable land (e.g., algae) or they do not involve disturbing or displacing plant life (e.g., forest residue). Similarly, improving crop yields can reduce iLUC effects for biofuel feedstocks that are sourced from arable land.

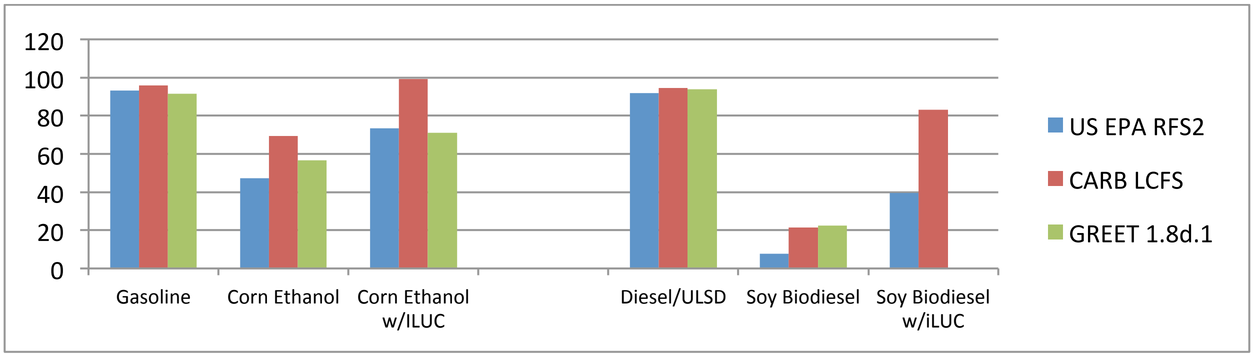

Figure 2. - Comparison of Selected GREET, US EPA and CARB GHG LCA values (gCO_2e/MJ)

Fuel	GREET 1.8d.1	US EPA RFS2	CARB LCFS
Gasoline	**91.4**[a]	**93.1**	**95.9**
Corn Ethanol	**56.8**[b]	**47.2**	**69.4**[c]
Corn Ethanol w/ILUC	**71.0**	**73.5**	**99.4**
Diesel/ULSD	**93.9**	**91.9**	**94.7**

Fuel	GREET 1.8d.1	US EPA RFS2	CARB LCFS
Soy Biodiesel	**22.5**	**7.6**	**21.3**
Soy Biodiesel w/ILUC	**N/A**	**39.5**	**83.3**

[a] Reflects GREET CY2010 default of 50% conventional gasoline and 50% RFG.

[b] Estimate reflects denatured ethanol with a 5% denaturant level.

[c] Reflects average Midwest corn ethanol.

GHG LCA Policy Implications

- Given the uncertainties involved with GHG LCA, policy makers need to be very certain before enacting policies that favor certain fuel/vehicle pathways over others. Alternatively, policy makers should pick alternatives that give significant and robust reductions under a wide range of scenarios.
- Policy makers should provide tools that appropriately differentiate between biofuels and their impacts to allow the marketplace to most efficiently select those offering sustainable values, while meeting the nation's needs to diversify energy supplies.
- Without appropriate safeguards, biofuels policies can significantly accelerate emissions in the agricultural sector. Protective policies within the transportation fuels sector must be complemented with appropriate safeguards in agriculture, trade and forest protection to effectively reduce emissions from biofuels.
- Transportation fuels policies need to ensure that policy driven demand for biofuels is commensurate with the capacity of the agricultural system to meet the demand.
- Policy makers may be able to reduce ILUC risk by pursuing feedstocks that are less reliant on land, encouraging investments that reduce the scope of ILUC and by reducing LUC risk for land-using feedstocks
- In making policy decisions for driving GHG reductions, policy makers need to consider the uncertainty range around each fuel/vehicle pathway LCA and not just the single mean value.

References

1. Mullins et al. [ES&T 2010]
2. Stratton et al. 2011
3. Brandt 2011
4. John DeCicco, Second CRC Workshop On Life Cycle Analysis of Biofuels , Argonne National Laboratory, Oct. 20, 2011
5. Huijbregts et al. 1998 IJLCA
6. Venkatesh, A.; Jaramillo, P.; Griffin, W. M.; and Matthews, H. S. **Uncertainty Analysis of Life Cycle Greenhouse Gas Emissions form Petroleum-Based Fuels and Impact on Low Carbon Fuel Policies.** *Environ. Sci. Technol.* **2011**, 45, 125-131.
7. W. Tyner, F. Taheripour, Q. Zhuang, D. Birur, U. Baldos **Land Use Changes and Consequent CO_2 Emissions due to US Corn Ethanol Production: A Comprehensive Analysis, Jul 2010**
8. Energy Policy 2011
9. Bremer et al. Journal of Environmental Quality, 2010
10. Bremer, V. R. : Liska, A. J.; Klopfenstein, T. J.; Erickson, G.E.; Yang, H.S.; Walters, D.T.; and Cassman, K. G**., Magnitude and Variability in Emissions Savings in the Corn-Ethanol Life Cycle from Feeding Co-Products to Livestock,** *CRC Workshop on Life Cycle Analysis,* Argonne National Laboratory*, Oct. 20-21, 2009*
11. Mullins, K. A.; Griffin, W. M.; and Matthews, H. S. **Policy Implications of Uncertainty in Modeled Life-Cycle Greenhouse Gas Emissions of Biofuels.** *Environ. Sci. Technol.* **2011**, 45, 132-138.
12. ARB Expert Workgroup on Indirect Land Use Change Uncertainty Final Report, 0105 2011.
13. CARB Expert Workgroup on Indirect Land Use Change Final Report,2011