Air Resources Board Expert Workgroup on Indirect Land Use Change

Subgroup: Uncertainty

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Consensus Recommendations

1.1 Immediate

1. Estimates of ILUC by all methodologies should incorporate complete and systematic characterization of their inherent uncertainties.
2. For existing models, characterize the uncertainty in each model component to allow (in the medium-term) the propagation of uncertainty through an integrated model of indirect effects.
3. ARB should analyze and clarify the objectives it proposes to seek through the LCFS and those it thinks inappropriate.
4. Improvements in modeling and data (see other subgroup reports) will probably reduce uncertainty ranges for specific fuel *g* values; this will make accounting for uncertainty in LCFS implementation easier, but will not avoid explicit decision analysis of the types we describe.
5. Establish a formal multi-disciplinary expert elicitation process to improve the analysis of uncertainty, compare expected outcomes with expert opinions, and produce probability distributions for ILUC emissions or for parameters to models of ILUC emissions (Morgan et al 2009).

1.2 Medium-term

1. Propagate uncertainty through at least one integrated model of indirect effects. Use this model to perform a global sensitivity analysis, which will quantify the relative contribution to variance of each uncertain model parameter in the context of the full model. These results will be useful for focusing further research efforts on those uncertainties that substantively affect model results. We note, however, that this approach does not account for model uncertainty, which is also substantial.

2. Formally recognize the difference between γ – the actual changes in global warming caused by using a fuel, and g – the value selected to represent this in the LCFS. No model can estimate γ perfectly; CARB must select the value for g that best achieves its goals.
3. Examine and characterize the cost of error at least for important possible asymmetries such as:
    a. climate (ΔT) cost
    b. future evolution of biofuel technology, especially advanced (high-yield, cellulosic, non-land based, etc) biofuels
    c. non-climate costs (e.g., food, economic impacts, biodiversity, sustainability)
    d. system response (e.g., petroleum rebound effect)

1.3 Long-term

1. Explore a meta-model that combines results from several models of ILUC emissions. If available, include alternative models that are not based on economic equilibrium alone, such as system dynamics and agent-based models. This analysis would help understand whether the intra-model uncertainty overwhelms the infra-model uncertainty.
2. In lieu of focusing only on quantitative values for iLUC, establish an expert elicitation process to recommend adaptive decision rules and guidance for categorizing feedstocks and fuel pathways according to relative iLUC risk, based on an assessment of all available information.
3. Moreover, include in the expert elicitation process consideration of measurable, performance-based incentives to improve land use management in ways that could reduce the risk of land use change. Such a system of incentives, if properly implemented, could provide a stronger empirical basis and greater certainty of the GHG impacts of crop-based biofuels than further investments in modeling.

Consensus Observations

Uncertainty in regulatory environmental modeling

All models are simplifications and approximations of reality (NRC 2007). Best practice for regulatory decision making based on models includes quantification and communication of uncertainty. For example, the draft guidance from US EPA's Council for Regulatory Environmental Modeling (CREM) recommends performing sensitivity and uncertainty analyses to inform users of the confidence that can be placed in model results (Pascual, Stiber et al. 2003). A report (NRC 2007) by the National Research Council's Committee on Models in the Regulatory Decision Process, convened at the request of the CREM, says:

> In some cases, presenting results from a small number of model scenarios will provide an adequate uncertainty analysis (for example, cases in which the stakes are low, modeling resources are limited, or insufficient information is available). In many instances, however, probabilistic methods will be necessary to characterize properly at least some uncertainties and to communicate clearly the overall uncertainties.

The NRC report notes that a full probabilistic analysis is frequently infeasible for large models, but rather than using this as justification for avoiding uncertainty analysis, the NRC suggests combining sensitivity analysis, probabilistic methods, and scenario analysis to characterize uncertainty as well as possible under time and data constraints. In a study by Resources for the Future—commissioned by EPA—Krupnick et al (2006, p. 7) concur, writing:

> Overall, there is a tendency to avoid formal uncertainty analyses unless the uncertainties can be included comprehensively and quantified precisely. An alternative—arguably, preferred approach—would be to conduct uncertainty analysis as well as possible, even if abilities are limited; almost any uncertainty analysis is better than none at all.

How much should be invested to reduce uncertainty?

--LUC is a complex phenomenon with significant variation across space and time.

--Validating the role of any one factor/driver of LUC is difficult, at best, and very information-intensive.

--So, even with substantial additional investments in models, some uncertainties surrounding current iLUC estimates are irreducible.

What might be done to constructively address this uncertainty?

"...in many situations, limitations of data, scientific understanding, and the predictive capacity of models will make (uncertainty) estimates unavailable, with the result that they must be supplemented with other sources of information."

--Morgan et al. (2010), "Best Practices for Characterizing, Communicating, and Incorporating Scientific Uncertainty in Climate Decision making."

"Expert elicitation" is a formal assessment by individual experts, based on the full range of scientific evidence, of their best judgment of a subjective probability distribution for the value in question. Expert elicitations have been used to address many questions of climate science (e.g., role of aerosols). While not a substitute for further research, expert elicitation can allow for a formal expression of diversity of opinion not fully reflected in the literature. Subject matter experts could help review a wider suite of information defining the influence of biofuels on land use, not only from economic models (GTAP, FASOM/FAPRI, etc.) but also the supporting databases, as well as studies from other disciplines.

Additional Recommendations from Two Perspectives

The Uncertainty Subgroup developed additional recommendations based on two different perspectives. Not all subgroup members were in full agreement with the perspectives.

Perspective 1 Recommendations

Scientific approaches to document and improve the representations of the current and potential relationships between the LCFS policy and land use will do far more to reduce uncertainty, than further research focusing on economic modeling alone. CARB should reduce uncertainty surrounding the conceptual model framework now being used to estimate ILUC.

The relationships between policy and land-use changes need to be supported by empirical data and analytical approaches that are verifiable, replicable and meet scientific standards. Some specific suggestions for ARB along these lines include:

a. Develop and verify analyses of recent empirical evidence to guide the adaptation of regulations to better fulfill defined goals for an effective, efficient, performance-based, LCFS.
b. Establish a system to regularly update the analysis of policy effects with respect to targets:
    1. Assess factors affecting progress toward meeting goals for reduced emissions
    2. Focus on manageable time horizons for targets and assessments (4-6 years)
    3. Consider regulatory options that reduce uncertainty and transaction costs, and facilitate evaluation of performance
c. Support research to clarify interactions among policy, shifting production, and domestic and global markets. For example, to:
    1. Better reflect trends and production capacities in baselines
    2. Distinguish how the economy actually responded to an "advance notice" of expected biofuel targets over time, versus how it has been treated in models (an imposed "demand shock" on a static economy)
    3. Assess how an expanding production base interacts with cyclic markets, volatility and inherent risks to disruption from weather and external policies
    4. Evaluate the use of performance contracts to incentivize/penalize entities/fuels based on data from practices that effect the GWP due to indirect emissions e.g. ILUC.

d. Define regulations to provide incentives for improved efficiency and more sustainable land management practices that are measurable and integrate feedstock production with emission goals, such as (Jansson et al. 2010; Lal 2010):
    1. Increasing carbon storage in long-term above and below ground sinks
    2. Increasing photo-sequestration
    3. Increasing stable soil carbon pools

Perspective 2 Recommendations

1. Where g_i is the operative, published global warming index for fuel *i*, and g_{ij}* is an estimate thereof from model *j*, ARB can model uncertainty by using the central, most likely, or single reported value of g_{ij}* for a chosen model estimate as the operational g_i. In turn, this chosen model may be specified by a prespecified rule such as "most recent peer-reviewed published value", or by staff analysis of competing estimates. ARB can average different estimates, with or without weights representing some measure of confidence in each.
2. In situations of poorly structured uncertainty like ILUC, where variability in estimates is rooted not only in sampling from well-behaved stochastic processes but also in differences in model structure and assumptions, ARB can develop a structured expert elicitation of opinion to construct an operative probability density function.
3. Choose an action that is robust across a wide range of possible values of an uncertain quantity, or to invoke some version of the "precautionary principle" and avoid actions that might cause especially great and/or irreversible damage. What these would look like within the constraints of the LCFS as currently structured, which requires a precise operational value of *g* for each fuel (as opposed to designing a completely different policy to reduce vehicle GHG) is not clear at present. If we regard assignment of a GWI to a fuel as an action, choosing the optimal value on some systematic grounds from many possible values, we can frame the policy challenge as a problem in decision theory.

Discussion

Not all subgroup members were in full agreement with the following perspectives.

Perspective 1

Much of the discussion of uncertainty has revolved around different "scores" from a set of similar economic models, but the validity and relevance of these scores remains unsubstantiated. The models use common land ***cover*** data which has been shown to be unreliable for estimating land ***use*** (see discussion in white papers from other CARB work groups and Reference: CBES 2009). Given the inherent uncertainty of data, assumptions and relationships underpinning those models, we may later discover that they were not useful tools for estimating ILUC. Indeed, economic models driven by differential prices are unlikely to enlighten estimates of "hollow frontiers" yet, that is precisely what they attempt to do when simulating first-time conversion of land areas (Rueda 2010, Turner 2010). Turner states, "Land change research, by definition, must establish the land-use and -cover changes in question, commonly reported by the full area of the study." These steps have not been taken to support modeling that has been applied to generate CARB estimates of ILUC. There is no scientific consensus on the conceptual framework showing a chain of causality between the proposed LCFS policy and new land clearing (See Appendix B). While prices affect decisions about what to plant, other factors predominated in the processes that by necessity occurred previously and determined what land was cleared.

Furthermore, the current models do a very poor job of depicting direct land use in the USA - something that needs to be improved as a prerequisite if we hope to eventually get better estimates of indirect effects. For example, data need to be analyzed to verify the degree of impact that bioenergy policy may have on keeping US land in production, and what emission profile changes occur with and without bioenergy policy.

However, even with substantial additional investments in data and analysis, there seem to be real limits to the degree to which quantitative estimates of the role of any one factor influencing LUC can be improved. Land use change (LUC) is a highly complex social and biophysical phenomenon that exhibits significant variation across space and time. Turner *et al.* (2007) observe that "…no facet of land change research has been more contested than cause," and describe how results of LUC evaluations differ depending on the discipline of the investigator, the methods applied, the spatial scale and timeframe of evaluation, and the quality of underlying data. And while economic factors and market conditions have captured demand for land reasonably well at a macro scale, these relationships are often observed to break down when analyzed with finer resolution. Finally, they note that the role of biophysical factors in LUC has, in general, received less attention than economic and institutional ones.

Estimating the incremental influence of biofuel demand on land use and corresponding GHG impacts through the use of an international trade model coupled with incomplete land cover data is likely too reductive an approach for a policy instrument such as the LCFS. This leaves policymakers facing uncertainties that are, at their core, irreducible.

It has been argued that good biofuel policy can (and should) have positive impacts on deforestation and land use (Kline et al. 2009). Policy can best address potential negative effects when it sets goals that are performance-based and measurable. Could the bar be raised to create stronger incentives to maintain or increase the carbon stocks on all land used for bioenergy production? Could policy more effectively reinforce efforts (such as those by Brazil) to develop and apply land use planning, transparent monitoring and carbon stock accounting, to reduce emissions from forest degradation and loss? These questions can only be addressed if policy makers are informed with data, scientific research and multi-disciplinary analysis of policy effects – all important tools that will be required to generate more robust estimates of LCFS effects on land-use related emissions.

Given the uncertainty surrounding the basic conceptual model framework for ILUC, efforts for reducing uncertainty should begin by developing better representations of the current and potential relationships between the LCFS policy and land use; ones that are grounded on empirical data and scientific analytical approaches (verifiable, replicable, based on evidence). Some specific suggestions for CARB along these lines were presented as Perspective 1 Recommendations (above).

Regarding current published ILUC estimates, first we must recognize that this is a new and emerging field. We could be just one new paper away from a new paradigm in an early stage of understanding. Also, while peer review is generally a good standard, it cannot guarantee quality or validate the ILUC estimates being modeled. In addition, expert judgment is valuable and may be superior to a set of published conclusions from similar modeling approaches. Expert judgment is often used as a basis for parameter estimation and decision making. Based on their analytical approach, Bauen et al (2010) suggest that at least one crop-based biofuel has ILUC values bordering on 0. To reduce the risk to terrestrial carbon stocks and large additions of C to the atmosphere from their loss, Bauen et al., recommend measures to directly protect high carbon stock land, the use of land with low soil organic matter levels or the production of crops and use of management practices which conserver or increase soil carbon, the use of advanced, high yielding agricultural methods that increase yields at a greater rate than inputs used for production, better supply chain efficiency, complete use of co-products and associated integration of crop and livestock systems to optimize resource use and minimize the landscape footprint of these systems. They call these approaches action-based and contrast them with the use of ILUC factors generated by models like GTAP. Their analysis leads to a preference for specific actions over the use of inferential values generated by models.

While these measures are not part of the current AB32 framework, that may be more a matter of omission than intent. It might be more productive for the state to enter into performance contracts with willing partners to directly protect significant areas rather than to continue a costly conflict over ILUC scores that can never be resolved. And by taking a more proactive approach, the State could provide valuable leadership and develop a larger partnership of willing collaborators and jurisdictions. A tax on fuel could provide revenue and would likely be more cost effective in reducing emissions than the current policy (but this may be impractical for other reasons). Thus the recommendation is for CARB to extend policy scope to address the greatest uncertainty and largest GHG effects which are associated with a few landscape types and areas. CARB should consider a separate policy restricting use of such landscapes for economic purposes may reduce uncertainty and the risk of policy failure more effectively than by continued analysis and ILUC modeling.

Perspective 2

Uncertainty about the size of indirect land use change GHG discharge (ILUC) triggered by biofuel cultivation has been a salient theme in biofuel policy debate since ILUC was first estimated. The Low Carbon Fuel Standard (LCFS) requires the Air Resources Board to assign a global warming index to each fuel in the California vehicle fuel system, an index that includes so-called “direct” emissions of GHG per energy unit of the fuel and also its attributed ILUC (which some advocate should be taken as zero). This discussion attends to uncertainty about ILUC[1], a quantity estimated by different models and methods to have a wide range of values that will probably shrink with further research but not to zero in the time the LCFS must operate.

[1] But note discussion in Appendix A regarding uncertainty in “direct” emission estimates.

In the following discussion, we distinguish three quantities:

- g^*_{ij} = estimate of "physical" GWI of fuel *i* from model *j*
- γ_i = real "physical" GWI: if fuel *i* is substituted for fuel *k* on a MJ/MJ basis, additional GHG release is (γ_i - γ_k).
- g_i = operational GWI of fuel *i* used in LCFS implementation.

γ_i cannot be observed directly, and uncertainty about its real value leads to analytic questions regarding how the ARB should best implement its task of assigning g_i values to fuels.

The sources of uncertainty about ILUC include

- Errors in assumed conceptual frameworks: relationships between biofuel policy and land use change
- Errors and variety in model structures
- Errors in model parameters estimated from data
- Intrinsic variation in real-world variables over time and space
- Variation in judgment on the part of different stakeholders and experts
- Concern that existing models rely on a narrow land use data base
- Uncertainty about the correct metric used to compare fuels and represent policy effects

Other subgroups are attending to better modeling and prediction practice that can reduce these sources; our discussion begins with a refractory remaining non-trivial uncertainty, uncertainty on whose importance ILUC modelers agree:

> The lesson for policymakers is that results from economic models depend heavily on assumptions, and because we are trying to predict long-run human behavior, there can be legitimate differences in these assumptions."– Dumortier et al. 2009
>
> …this modeling project has demonstrated how the current limits to data availability create significant uncertainty regarding outcomes predicted by these policy simulations. – Al-Riffai et al. (IFPRI) 2010
>
> … one cannot escape the conclusion that modeling land use change is quite uncertain. Of course, all economic modeling is uncertain, but it is important to point out that we are dealing with a relatively wide range of estimation differences. – Tyner et al. 2010

Unfortunately, the research base on which the present analysis rests is currently quite thin, and important elements remain to be filled in. Estimates of ILUC from different analysts report uncertainty incompletely and inconsistently, sometimes varying a few key parameters or model features and reporting the range, sometimes presenting a Monte Carlo analysis including variation of only a partial set of parameters or inputs. We are not aware of published research linking uncertainty in ILUC estimation to the specific assignment of GWI values, nor of other jurisdictions engaged with biofuels policy having adopted a systematic approach to ILUC uncertainty.

Although the number of estimates of ILUC emissions is growing, virtually all the studies to date have relied exclusively on local sensitivity analyses to generate a range of values from their models. These alternative model runs do not illuminate the overall uncertainty in the estimates, nor do they identify the model parameters that contribute the bulk of the variance in the result. A more systematic analysis of uncertainty will be extremely useful.

Key assumptions and spatial relationships, including causality analysis and more detailed analysis of where LUC and ILUC occur and the corresponding GHG emission implications, remain untested .

Figure 1 shows the ranges of results reported in several studies of ILUC emissions induced by expanding corn ethanol production in the US. These values are discussed in more detail in Plevin, O'Hare et al. (2010b). The range shown for Tyner, Taheripour et al. (2010) results only from different base years and different treatment of demand growth and the relative productivity of converted cropland. The range for Hertel, Golub et al. (2010a) is based on a combination of high and low values for various uncertain economic model parameters. The range in Dumortier, Hayes et al. (2009) is based on evaluating alternative versions of the FAPRI model. Values for USEPA (2010) reflect the 95% confidence interval around mean, considering only the uncertainty in satellite data analysis and carbon accounting. Al-Riffai, Dimaranan et al. (2010) estimated the range of results of an additional 10^6 GJ of biofuel beyond meeting the 5.6% mandate and for greater trade liberalization.

The fact that there is such high variability in these reported results is noteworthy given that these results are limited to a few computational equilibrium economic models using common sources of data for key emission factors. Specifically, the results were all based on economic equilibrium modeling that "shocked" an assumed static production case with increased biofuel demand for feedstock. Some experts doubt that such an approach is an appropriate representation of LCFS policy. Secondly, the models used a common data set for estimated average carbon stocks on the land assumed to be converted. This controlled for another area of large recognized uncertainty – e.g. the assumed values are not supported by analysis of areas where new land is being brought into production in response to markets.

Figure 2 portrays possible probability distributions for ILUC of US corn ethanol as generated in Plevin et al 2010, emphasizing that while different aggregations of different model results and ranges may give different results, these distributions are all asymmetric to the right. No model of which we are aware has shown zero ILUC for any current biofuel, but possible combinations of plausible parameter values can generate very high values at least within the types of model reviewed here, which are CGE estimates based on an exogenous shock to biofuel consumption of the general type currently adopted by ARB.

Figure 1. Ranges of results from models of ILUC emissions. This figure is derived from the data presented in Plevin, O'Hare et al. (2010b), with the addition of the entry for Tyner et al. (2010).

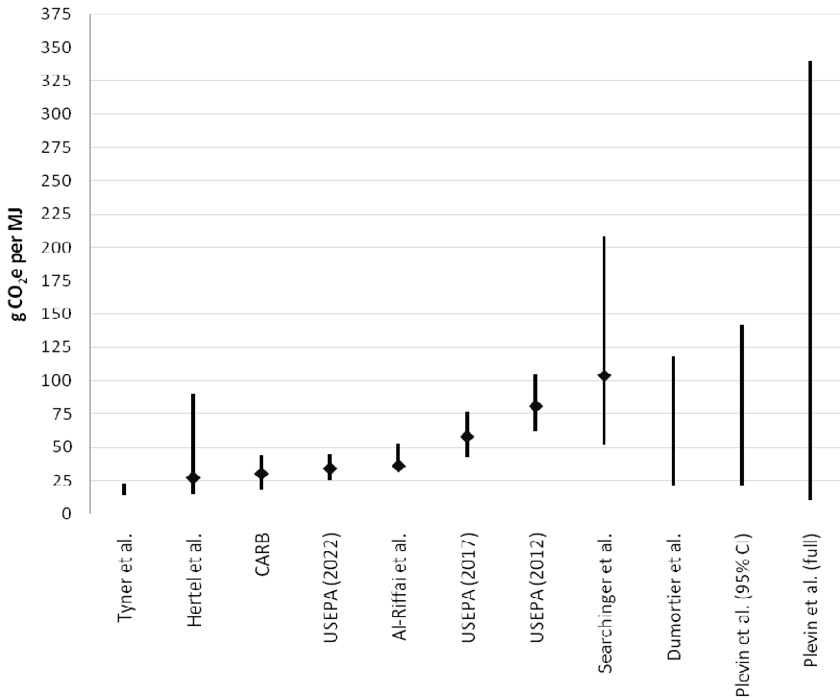
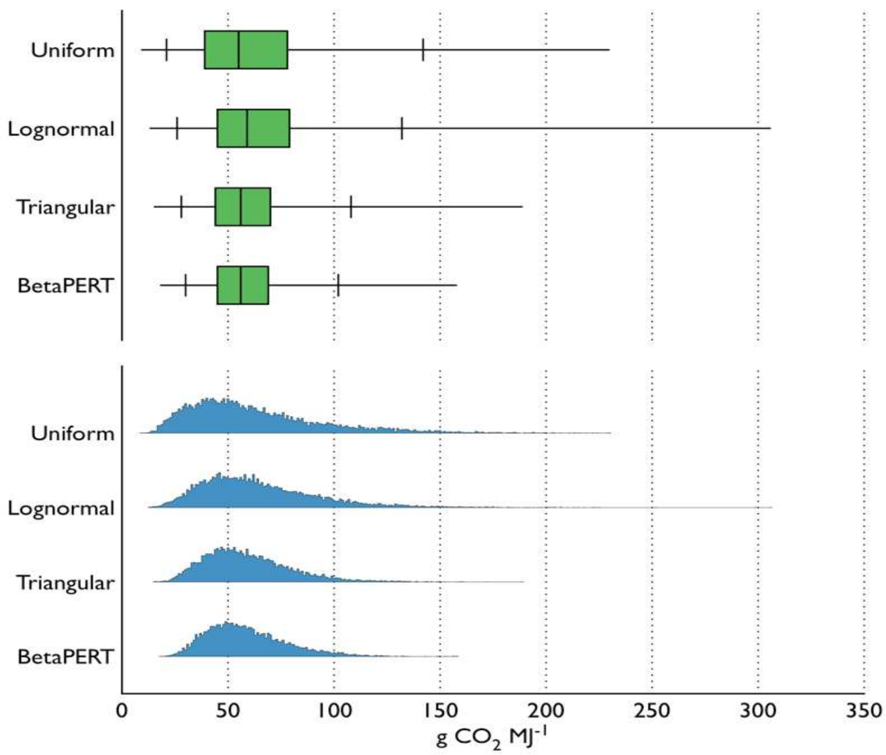


Figure 2. Probability distributions for ILUC for US corn ethanol, from models of ILUC emissions using each of four forms of distribution for elements of the reduced-form model. This figure is derived from the data presented in Plevin, O'Hare et al. (2010b), with the addition of the entry for Tyner et al. (2010). Whiskers are total range, ticks are 95% HDRs.



Incorporation of uncertainty in ARB LCFS implementation

Against the background described above, we now examine the specific task confronting the ARB, which is to move from the variety of estimates and sketchy uncertainty portrayals for each to a single value of each fuel's GWI.

Options:

- ARB can use the central, most likely, or single reported value of g_{ij}* for a chosen model estimate as the operational g_i. In turn, this chosen model may be specified by a prespecified rule such as "most recent peer-reviewed published value", or by staff analysis of competing estimates.
- ARB can average different estimates, with or without weights representing some measure of confidence in each.

Both of the foregoing treat uncertainty especially heavy-handedly or ignore it. In situations of poorly structured uncertainty like ILUC, where variability in estimates is rooted not only in sampling from well-behaved stochastic processes but also in differences in model structure and assumptions, heuristic practices may have a useful role.

- ARB can develop a structured expert elicitation of opinion to construct an operative probability density function

This may be useful, particularly if ARB convokes a multi-disciplinary panel with expertise in dealing with global data on land cover and land-use change, and those experienced in addressing land-use change challenges – e.g. people who are working in the field to address land-use change and therefore have practical understanding of the relationships between LUC drivers and policies at various levels. It is important to get feedback from field-based experts concerning which policy and regulatory options are most likely to be helpful (or harmful) to efforts to improve land management and curb destructive land-use change.

Sometimes it is possible to choose an action that is robust across a wide range of possible values of an uncertain quantity, or to invoke some version of the "precautionary principle" and avoid actions that might cause especially great and/or irreversible damage. What these would look like within the constraints of the LCFS as currently structured, which requires a precise operational value of *g* for each fuel (as opposed to designing a completely different policy to reduce vehicle GHG) is not clear at present.

If we regard assignment of a GWI to a fuel as an action, choosing the optimal value on some systematic grounds from many possible values, we can frame the policy challenge as solving a problem in decision theory.

Even if ARB cannot implement this framing with complete formality, the description will highlight the importance of objectives and the cost of error, neither of which has received sufficient attention in the biofuels context to date. The elements of this framing are as follows (O'Hare et al 2010):

A probability distribution *f* for $\gamma_{i,}$ the physical GWI of fuel *i* in the sense described above. The distributions in Figure 2 are illustrative of the asymmetry that may apply.

Because of this asymmetry, choosing the 'best' value for g_i is not simply a matter of choosing the mode (most likely value) of the distribution, and the **cost of being wrong** also matters. Regulation commonly chooses values "on the safe side", that may be far from the most likely or central values, when the cost of being wrong is greater in one direction than the other. For example, structural materials like steel are used as though they are weaker than we know they 'really' are, because the cost of overestimating their strength (collapse of structures and lost lives) is much greater than the cost of underestimating them (more expensive structures).

Furthermore, the fuel market and related systems will respond to a choice of g_i in ways more complicated than direct substitution of fuels (the fossil fuel "rebound" effect is one such potential response). Representing this response as **R**$\{g_i\}$, a vector of variables with probability distribution *h,* the value of the outcome of this system as *V*, a general formulation of the regulatory choice is to choose a set of values g_i so as to **maximize the expected value of *V*** over distributions *f* and *h*

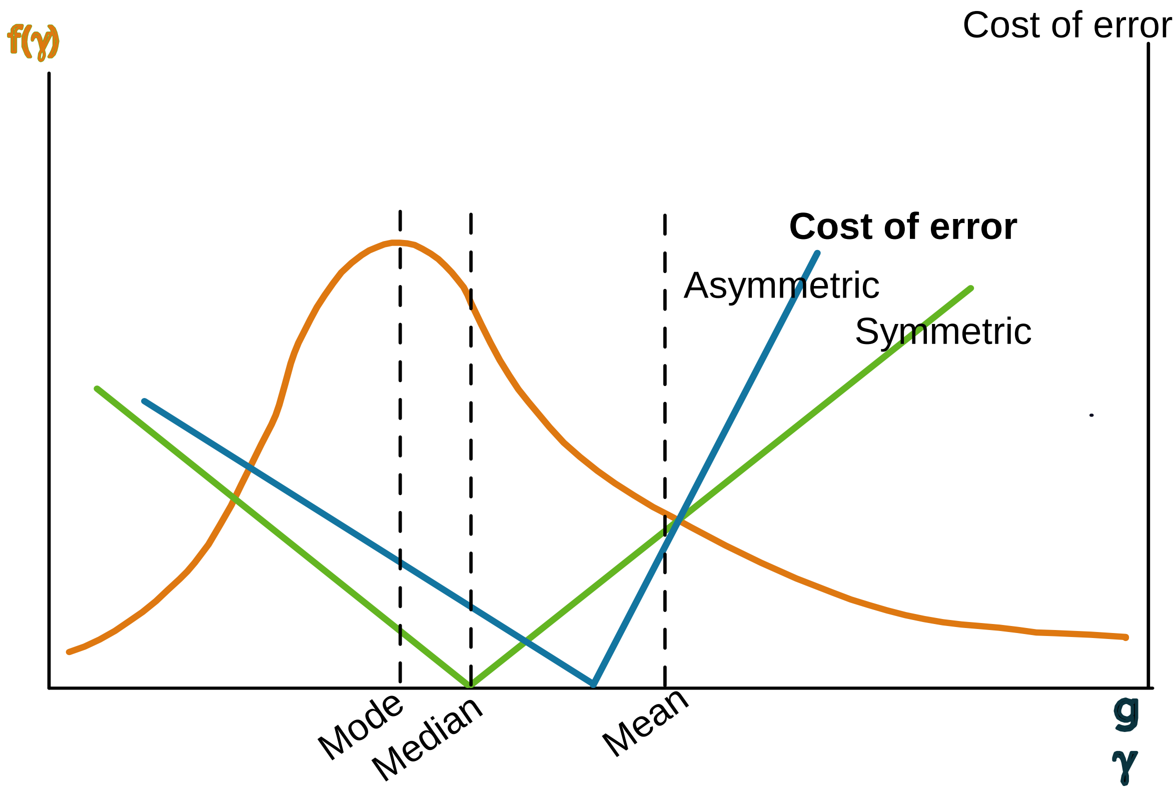
$$= E_{f,h}\left[V\left(\{g_i\},\{\gamma_i\},\mathbf{R}\{g_i\}\right)\right]$$

Note that it is the probable asymmetry of a reasonable probability distribution for γ that forces our attention to the cost of error, a concept that in turn forces attention to ARB's objectives for the LCFS. These are not unambiguously inferable from the regulations or the executive order itself. For example, any of the following different goals might be the right ones for ARB to pursue (characterizing *V* in the expression above):

- **Climate**
  - Minimize difference $g_i - \gamma_i$?
  - Minimize ΔT at a date (end of LCFS?)
  - Minimize additional GHG in atmosphere at a date (end of LCFS?)
  - Minimize total forcing up to a date?
  - Minimize probability of an undesired outcome (LCFS increases one of the above)?
- **Other**
  - Minimize social cost (including cost of ΔT, food effects, socioeconomic/welfare effects…?)
  - As of when (discounted how?)

Figure 3 illustrates the importance of the shape of the cost of error function (the value lost if *g* differs from γ by some amount), simplifying by omitting consideration of **R**. If the cost is linear and symmetric, the optimal value of *g* is the median of the distribution of γ; if it is asymmetric like the blue example, the optimal value is higher.

Figure 3. Illustration of the relationship between uncertainty about γ, the cost of g being different from γ, and the optimal value of g



Little is known about the cost of error in *g* nor has the ARB explicitly explored the implications of different objective frameworks on the best value to assign to fuel GWI. A variety of considerations affect the symmetry, the functional form of missing the “true” value of γ by some degree in either direction, including the effect on the advanced biofuels industry, effects on food consumption and cost, irreversibility or very slow reversibility of at least some land use change (which vary significantly by fuel type and location), and the uncertainty surrounding which choices could trigger catastrophic events like the Gulf Stream stopping or peat decomposition feedback, and land use change that may reduce deforestation.

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Appendix A (Perspective Two): Uncertainties in estimates of fuel global warming intensity

Although our primary focus here is indirect land use change, it's important to recognize that fuel life cycle assessment (and LCA more generally) is always uncertain, and that LCAs of natural systems are more uncertain than those of engineered systems. In particular, the global warming intensity of biofuels is much more uncertain than that of fossil fuels, owing to variability and uncertainty in yield, soil carbon fluxes, co-product credits, and N_2O emissions (Edwards, Szekeres et al. 2008). In contrast, approximately 80% of the climate effects of refined fossil fuels results from CO_2 released during combustion, about which there is relatively little uncertainty.

In the CARB model, which adds GREET fuel cycle results to ILUC estimates, the uncertainty in ILUC emissions, which we believe has a right tail (Plevin, O'Hare et al. 2010a) must be combined with the uncertainty in the GREET model result, which for many biofuels also has a right tail.

In principle, the best way to understand how these uncertainties affect the estimate of ILUC would be to combine the economic, landcover change detection, emissions, and time handling in a single model that could be run stochastically, e.g., using Monte Carlo simulation. This would allow us to understand (i) the contribution to uncertainty of different components, and (ii) estimate the uncertainty in the estimate of ILUC emissions produced by the combined model. It would also allow us to use an estimator such as mean or median rather than a point estimate for use in the LCFS. Importantly, the mean or median will differ from a point estimate produced using average inputs when the output distribution is skewed. Analysis using a reduced-form model of ILUC emissions suggests that the distribution for these emissions may have a long right tail (Plevin, O'Hare et al. 2010a).

However, a stochastic simulation of an integrated model poses some challenges:

- As used by CARB, GTAP requires about 10 minutes per solution on a typical desktop computer. A simulation with a relatively small number of trials (say, 1000) would take about a week of continuous (24/7) run time. This time could be reduced by splitting the analysis over a number of computers, assuming each was able run GTAP. (This may be more a licensing issue than a technical one.)
- Many of the economic model parameters are poorly characterized. However, given this ignorance, it may be more appropriate to define poorly-characterized parameters using a uniform distribution over a plausible range rather than choosing a single point estimate as is currently done.
- Correlation among model parameters is frequently difficult to characterize.

- Differences in results across economic models used to estimate ILUC indicate much model uncertainty. Propagating uncertainty through the CARB modeling system would not capture this model uncertainty.

Hertel et al. used a version of GTAP with per-region emission factors built into the model to examine uncertainty using GTAP's Systematic Sensitivity Analysis (SSA) feature (Hertel, Golub et al. 2010a; Hertel, Golub et al. 2010b). A significant limitation of this approach is that it permits only symmetric distributions, and produces only symmetric distributions as output. The SSA is therefore unable to inform us about skewness. Nor can it inform us about the contribution to variance of individual parameters. However, if Monte Carlo analysis is deemed too difficult, the SSA at least offers some indication of overall uncertainty.

USEPA performed a Monte Carlo analysis to propagate uncertainties in their estimates of ILUC for the RFS2 program. Their analysis, however, treated as uncertain only those parameters related to remote sensing of changes in land cover types and to emission factors for land conversion: economic model output was treated as though known with certainty. However, uncertainties in the output of the economic model—namely, the magnitude and location of ILUC—appear to contributes more to the variance in ILUC emissions than do the remote sensing or emission factor uncertainties (Plevin, O'Hare et al. 2010a). Therefore, EPA's frequency distributions cannot be used reliably to test compliance with RFS2. However, the underlying analysis will be useful for developing a more complete analysis of uncertainty, especially if CARB transitions to using the Winrock emission factor model.

Appendix B (Perspective 1)

There was ongoing debate in the subgroup over the assertion that, "we know ILUC values must be greater than zero" and similarly, that we know their probability function will have a given shape and tail. These assertions are acceptable if qualified by acknowledging that they only describe modeled estimates (not knowledge) of ILUC and that the estimates are based on a single econometric approach that simulates a biofuel demand shock to a static production system. Such models will always give a positive ILUC estimate – and that is entirely reasonable. The ILUC estimates illustrated in a Figure above are based on such partial and general equilibrium economic models. These estimates of ILUC represent one approach and just one aspect of a policy. But the ILUC results: (a) lack validation; (b) do not simulate LCFS policy; (c) defy empirical evidence for direct land use; and (d) fail to represent behavior on frontiers of deforestation (first-time conversion) which are isolated from the assumed price-induced effects.

Is it possible that such economic models are inappropriate to estimate bioenergy policy effects on first-time land conversion? The models assume rational, profit-making behavior, compliance with laws, private ownership of property etc. First time conversion is generally characterized by public lands (FAO 2010: nearly all remaining tropical forests are public property), illegal behavior, extensive unmanaged but previously disturbed areas (far more land has already been cleared than what is actively used or needed for cultivation), insecurity, and other factors that are explicitly excluded from the economic models and the assumptions employed thus far to estimate ILUC. Given the difference between these assumptions and the places where first time conversion occurs, the models can provide little reliable information about the effects of LCFS policy on phenomena in the frontier zones of primary concern.

After analyzing deforestation in the Yucatan, Rueda (2010) concluded that "This analysis illustrates the spatio-temporal heterogeneity of much tropical forest change and caution that it should bring to simple formulations of modeling this change and prescribing policies to control it."

To improve modeling, it will be necessary to distinguish: (a) how policy affects behavior in different landscapes from how models are representing and simulating policy; and (b) how the variability of emission profiles in a dynamic baseline will differ as a result of policy. This can determine whether policy induces changes that produce positive or negative values in terms of GHG emissions. Actual emission values will always "depend" on many interacting local variables. If a link between behavioral changes and policy can be made, and the change in behavior changes emissions in a measurable way, then we should attribute the changes to the policy. There is evidence of cases where the effects of bioenergy policies appear to lead to improved environmental compliance and reduced emissions. We should learn from these cases and strive to reinforce such incentives.

The history of deforestation in Brazil is documented, as is the history of its sugar industry. In the past seven years, deforestation has decreased dramatically and the sugar industry has taken noteworthy and measurable steps to improve environmental compliance, expand riparian protection zones, increase forest reserves and reduce the use of fire for harvests. Many of these changes can be plausibly linked – at least partially and indirectly if not directly – to external biofuel policies. And these changes in behavior can produce verifiable, measurable changes in emission profiles.

Researchers and economists in the US quickly developed agreement on assumptions and methods, but it is important for parties directly involved in researching LUC in the field to help test the plausibility of those assumptions and methods and such experts should be identified and included in future elicitation.

In the US, Nelson et al. (2009) noted, "There exist areas throughout the United States with negative net carbon fluxes or where accumulation of soil carbon is greater than agricultural fossil fuel emissions (Fig. 10). Carbon sources and sinks can change annually based on changes in cropland management." Thus, if bioenergy policy provided effective incentives to maintain or increase carbon stored in agricultural lands, this could generate net GHG benefits. And such policy could indirectly affect other agricultural practices (promoting ground covers, double crops and other mechanisms that offer multiple benefits in terms of carbon storage, economics and conservation).

If bioenergy policy is designed to accelerate, incentivize and reinforce the positive behaviors (e.g. to develop and apply land use planning, transparent monitoring and carbon stock accounting; and to reduce emissions from forest degradation and loss or other land use change), and to bar unacceptable behavior, the policy would be better positioned to achieve CARB goals than one based on an irreconcilable ILUC estimate. Results that can be measured by performance based metrics are preferable to ones that can never be measured and will fester as costly points of contention.

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