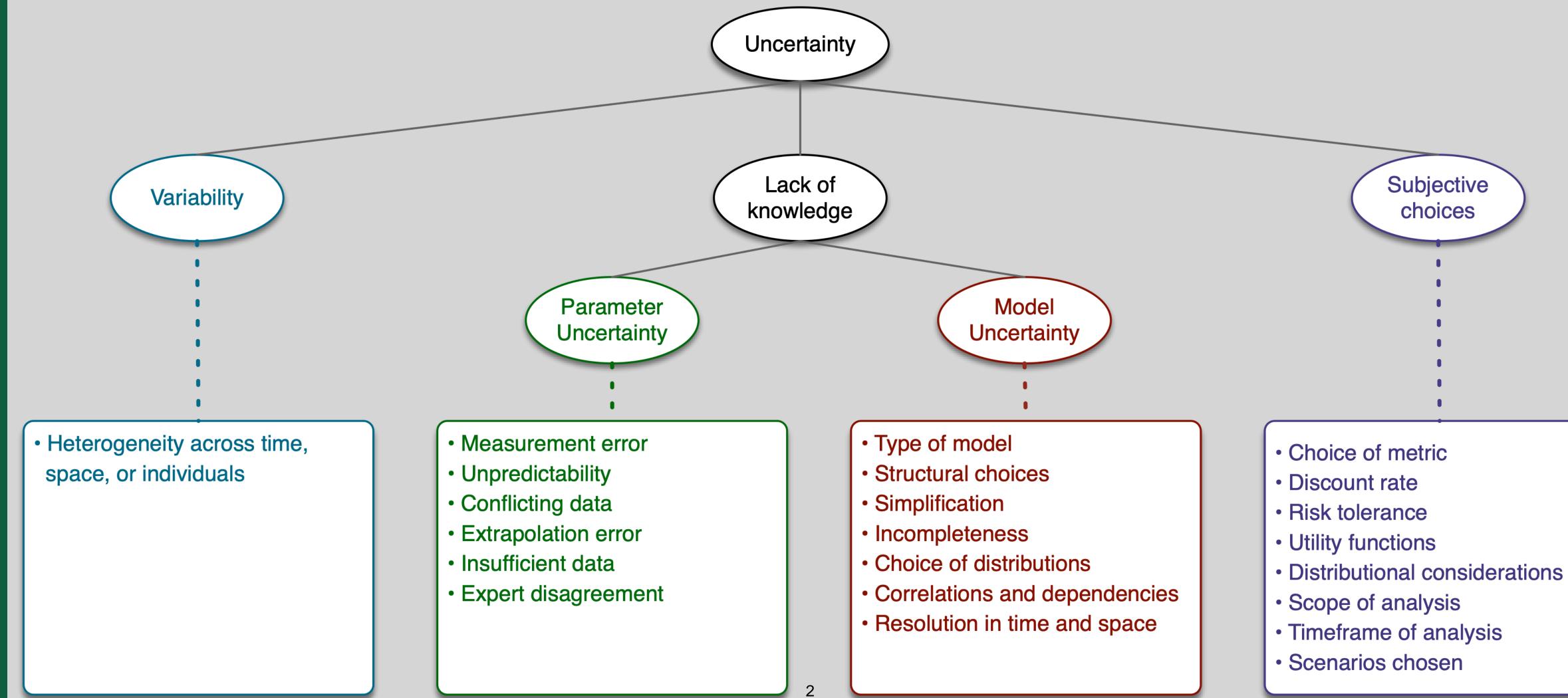
Uncertainty in estimating the climate effects of biofuels

EPA Workshop on Biofuel Greenhouse Gas Modeling

Richard Plevin, PhD March 1, 2022



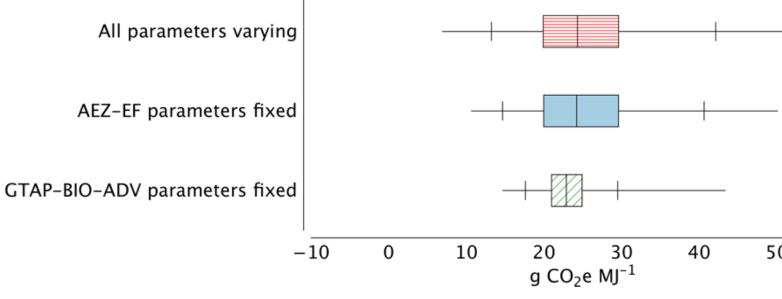
What do we mean by uncertainty?

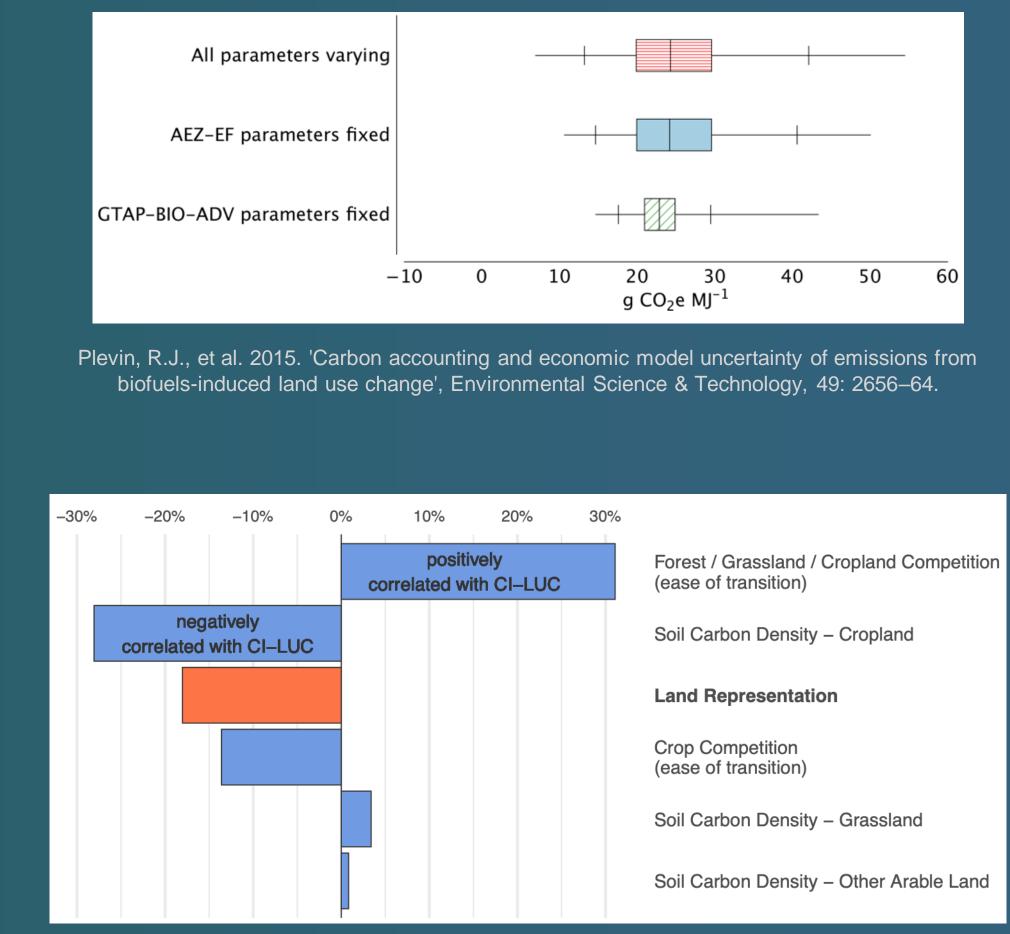




Uncertainty & sensitivity analysis

- Uncertainty quantification
 - Distribution of model results across alternative parameters & choices
 - Statistics describing distribution of model results
- Global sensitivity analysis (SA)
 - Shows relative influence of parameters & choices on model results
 - Global SA accounts for parameter interactions \bullet across their ranges
 - One-at-a-time SA fails to account for these
- Ensemble analyses (e.g., Monte Carlo simulation) can inform both of these





Plevin, R.J., et al. In review. 'Choices in land representation materially affect modeled biofuel carbon intensity estimates'

What uncertainty analysis doesn't do

- Global economic / ecosystem models are not truth machines
 - Many simplifications, deletions, and distortions
 - Can't predict non-stationary, complex, open systems

Therefore,

- Output distribution is not a (real world) probability distribution 0
 - It describes behavior of the model as constructed
- A range of model results may not bound real world outcomes

Oreskes, N. et al., 1994. 'Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences', Science, 263: 641-46.



Match methods to purpose

- What is the goal of our analysis and how will the result be used?
 - Choices: methods, scenarios, scope, resolution, timeframe, etc.
- Are we trying to:
 - 1. Estimate climate change mitigation from biofuel programs?
 - 2. Produce a CI value for use in a regulation?
- Models designed for (2) generally do not answer (1)
 - Different purposes require different analyses

Plevin, R.J., 2014. 'Using Attributional Life Cycle Assessment to Estimate Climate-Change Mitigation Benefits Misleads Policy Makers', Journal of Industrial Ecology, 18: 73-83.



Mitigation vs carbon intensity

To estimate climate change mitigation:

- Characterize effects on climate of an action compared to BAU
- Be comprehensive to avoid unintended consequences
- Improve model whenever data or scientific understanding allow

When estimating regulatory carbon intensity values:

- Methods may be prescribed in legislation
- Model updates causing large changes in results are politically fraught
- Avoid claims about mitigation not supported by this analysis

What is carbon intensity?

- CI has no well-established, concrete definition
- Every regulatory model of CI defines it differently
- Different methods, models, boundaries, assumptions, data, timeframes Implications:
 - Results using different definitions of CI are incommensurable

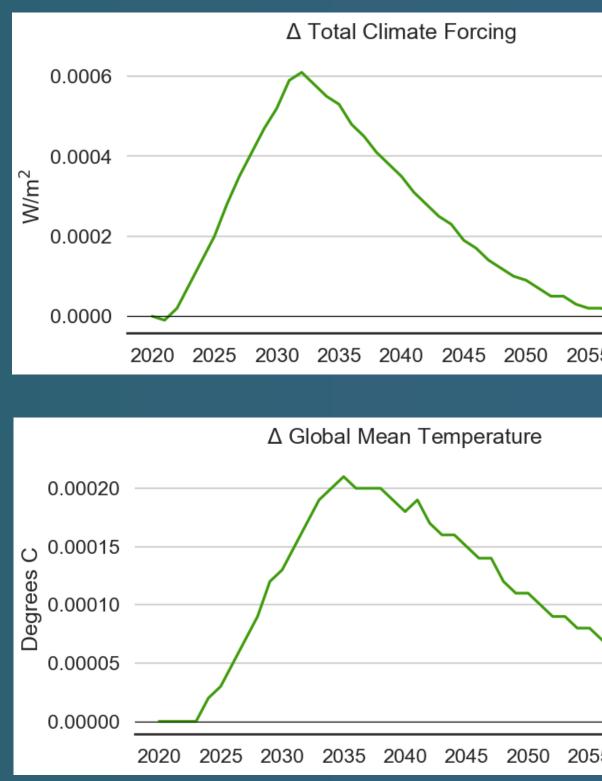
 - Cl is scenario & model dependent; it's not a concrete fuel property Range of CI results reflects disagreement more than uncertainty



Estimating climate change mitigation

- Include known climate forcings and their uncertainties
 - GHGs
 - GHG-precursors (e.g., CO, VOC)
 - aerosols (e.g., black carbon, organic carbon, SO_X)
 - albedo change (e.g., resulting from LUC)
- CO₂-equivalence of regional effects is not straightforward
- Better to aggregate as radiative forcing or temperature?
- Ignoring uncertain factors doesn't reduce uncertainty; it hides it

Biofuel shock results modeled in GCAM-



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Many subjective decisions are required

- Baseline scenario
- Analytic horizon or date of reckoning
- Size and shape of biofuel shock
- Climate effects to include \bullet
- Climate effects aggregation method (GWP, GTP, Δ RF, Δ T)
- Type of model (dynamic or static, myopic or foresight, partial or general equilibrium)
- Model resolution (sectors, regions, land types, technologies, time step)
- Focus of analysis (product vs policy)



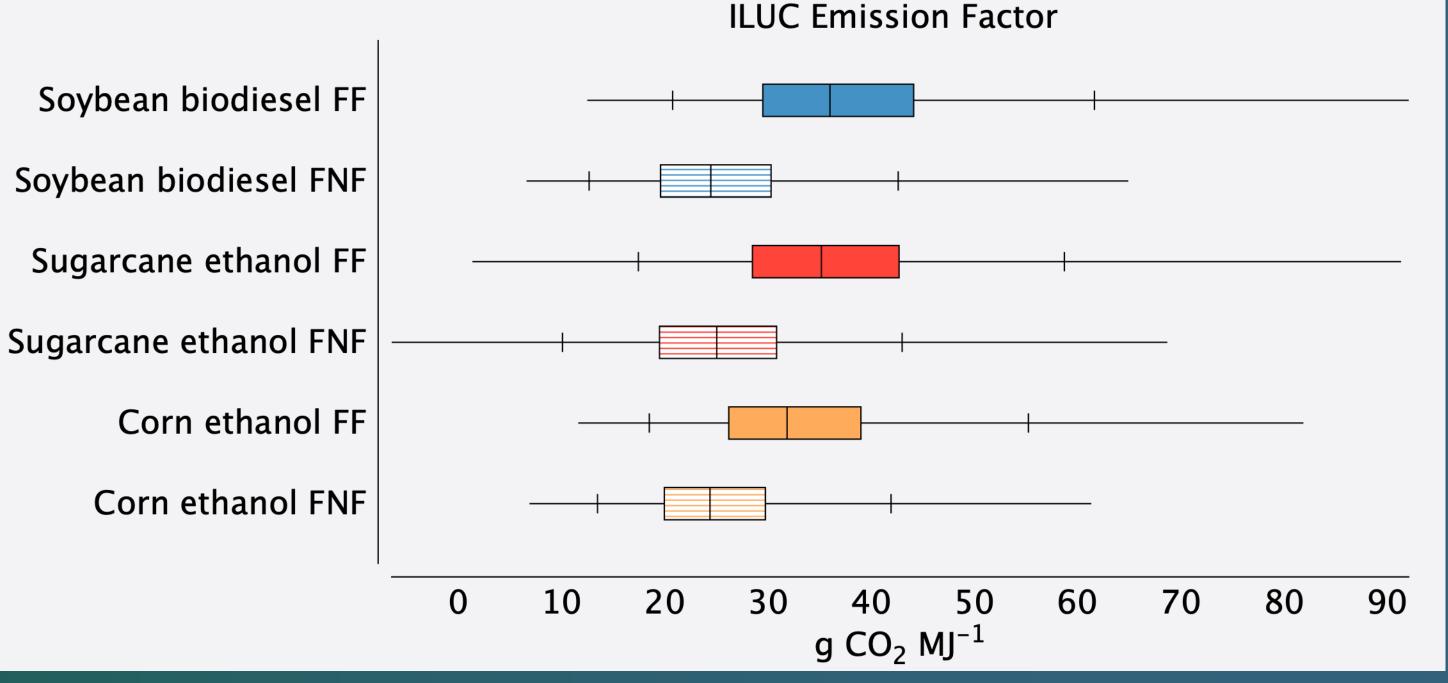
Best practices for modelers

- Sensitivity analysis is one of the "legitimate uses of a model" (Saltelli, et al. 2000)
 - Use global SA to capture parameter interactions
 - Use SA to interrogate your model, not "prove" it robust (Saltelli, 2010)
- Identify uncertainties strongly influencing variability in model results
- Demonstrate affects of subjective model choices on model results
- Avoid characterizing model results as predictions about real world
- Avoid unwarranted precision when presenting model results
- Document model limitations, assumptions, unquantified uncertainties

Saltelli, A., K. Chan, and E. Marian Scott. 2000. Sensitivity analysis (Wiley: Chichester ; New York). Saltelli, Andrea, and Paola Annoni. 2010. 'How to avoid a perfunctory sensitivity analysis', Environmental Modelling & Software, 25: 1508-17.

Example 1

- ILUC analysis with GTAP-**BIO** and **AEZ-EF** models
- Monte Carlo simulation
 - 3 biofuels
 - 2 model structures (food) consumption constraint)
- Results presented as distributions
- Model limitations explained

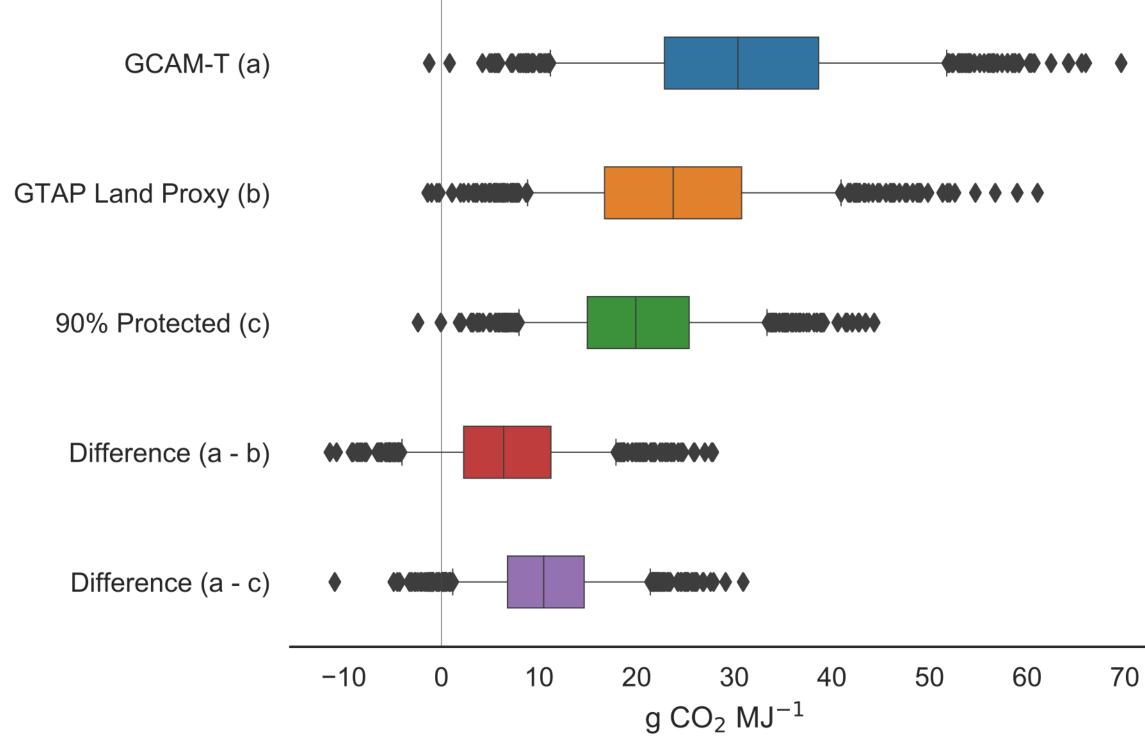


FF: food consumption fixed; FNF: food consumption not fixed

Plevin, R.J., et al. 2015. 'Carbon accounting and economic model uncertainty of emissions from biofuels-induced land use change', Environmental Science & Technology, 49: 2656-64.

Example 2

- Effect of land representation on LUC CI using GCAM
 - 3 different land representations
 - Monte Carlo simulation
- Presents distributions per model and for per-trial differences
- Avoids claims about real world outcomes

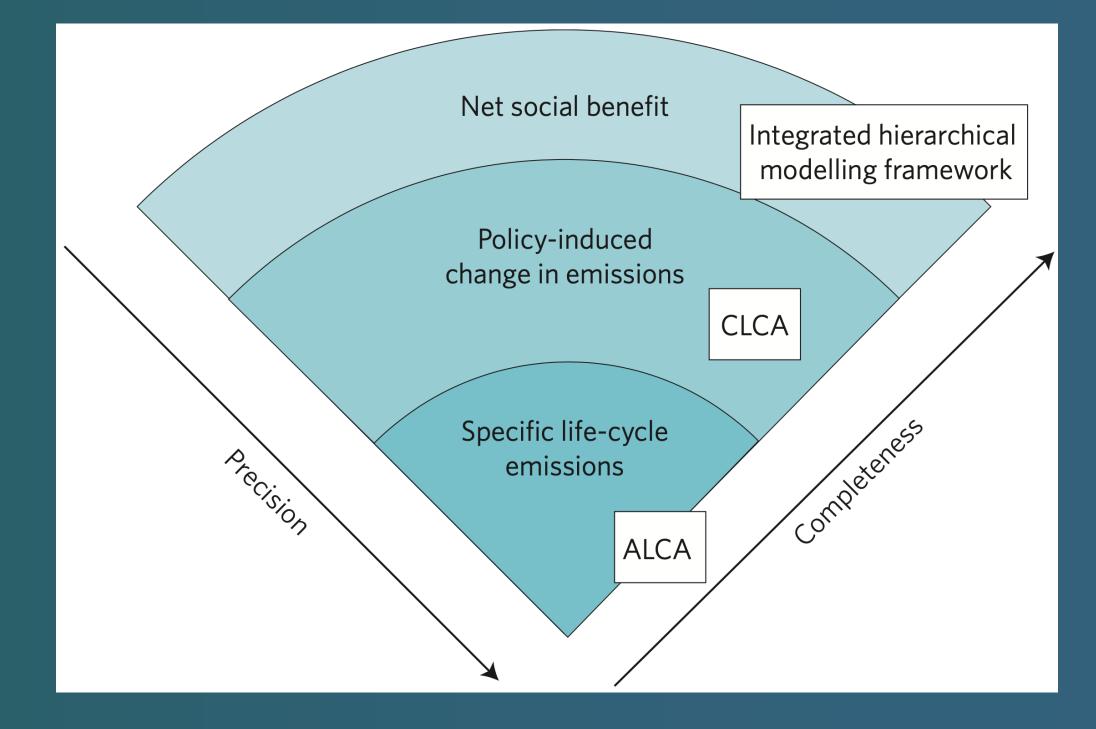


Plevin, R.J., et al. In review. 'Choices in land representation materially affect modeled biofuel carbon intensity estimates'.



Be forthright about model limitations

- The model is not the real world
- Subjective choices often drive results
- ILUC isn't the only market-mediated effect
- Actual net petroleum displacement is key determinant of mitigation (rebound effect)
- Cannot compare effects of biofuel with fossil fuel CI; oil displacement is one of these effects
- Models designed for one purpose may have blind spots when used for another purpose
- Excluding uncertain features doesn't reduce \bullet uncertainty
- Uncertainty increases with scope of model



Creutzig, F., et al. 2012. 'Reconciling top-down and bottom-up modeling on future bioenergy deployment', Nature Clim. Change, 2: 320-27.