



POTSDAM INSTITUTE FOR
CLIMATE IMPACT RESEARCH

How can economic impact and integrated assessment models account for the full scope of complex climate risks?

Franziska Piontek

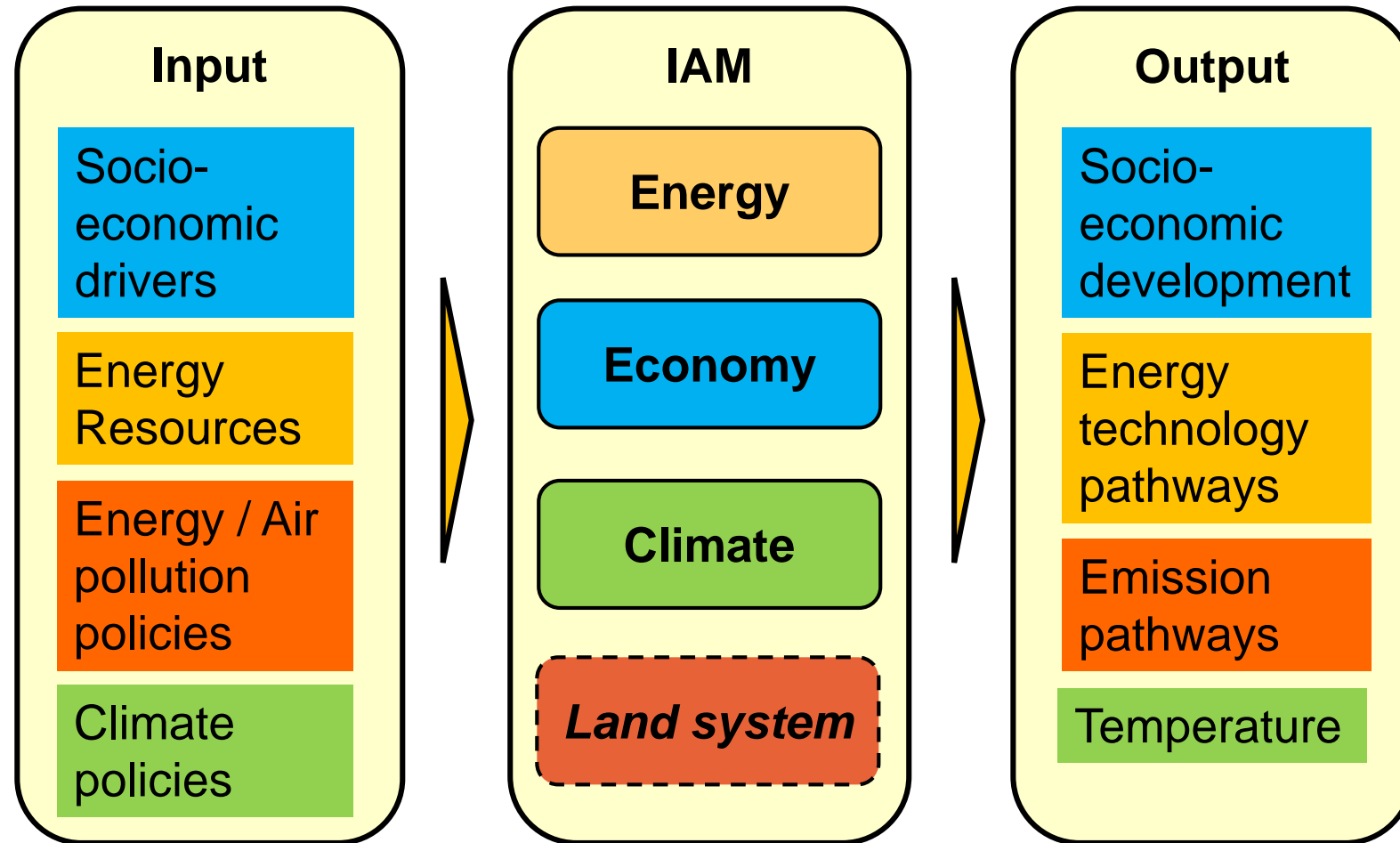
Outline

- › Different types of integrated assessment models (IAMs)
- › How do they represent different types of uncertainty?
- › Uncertainty about climate impacts
- › How can we improve for better policy advise?

Scope of integrated assessment

Inform policy decision making through assessing future scenarios under given assumptions/constraints

Interaction of economy, society and environment



Types of IAMs

Cost-benefit IAMs

- › Focus:
 - › costs and benefits of avoided warming
 - › SCC
- › Scope: fast, transparent, manageable number of parameters and equations
- › Examples:
 - › Classic: DICE, FUND, PAGE
 - › Recent: RICE50+, MIMOSA, NICE

Process-based IAMs

- › Optimizing growth models (e.g. REMIND, WITCH, MESSAGE): detailed analysis of mitigation pathways → cost-effectiveness analysis
- › CGEs (e.g. AIM, GEM-E3, IMACLIM, ICES): Focus on sectoral and macroeconomic interactions along mitigation pathways
- › Represent detailed processes in energy/land sectors
- › Increasingly represent damages (aggregate and process-based)

Types of IAMs & uncertainty analysis

CBA-type IAMs

well suited for
uncertainty analysis
requiring large
number of runs and
many variations

BUT

unrealistic mitigation
pathways



Process-based IAMs

used for detailed policy
analysis and advice (e.g.
IPCC, EU climate policy)

BUT

too computationally
demanding for large
numbers of runs and too
complex for detailed
uncertainty analysis

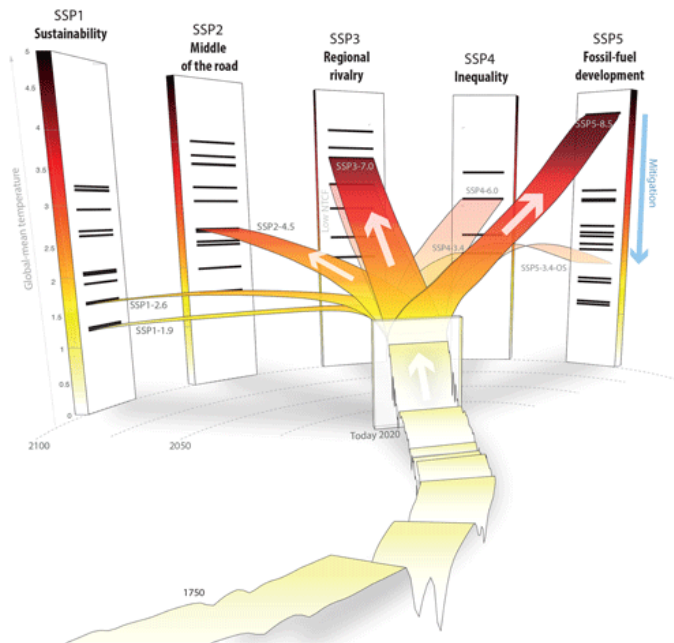
Types of within-process uncertainty (Rising et al. 2022)

Source of uncertainty	Common representation	Example	CBA-IAMs	PB-IAMs
Scenario uncertainty			X	X

Examples for representation of uncertainties in IAMs

(1) Scenario uncertainty – narratives

Socioeconomic: Shared Socioeconomic Pathways (SSPs) (O'Neill et al. 2017)



Meinshausen et al. (2020)

Climate: Representative concentration pathways

(a) Global surface temperature change
Increase relative to the period 1850–1900

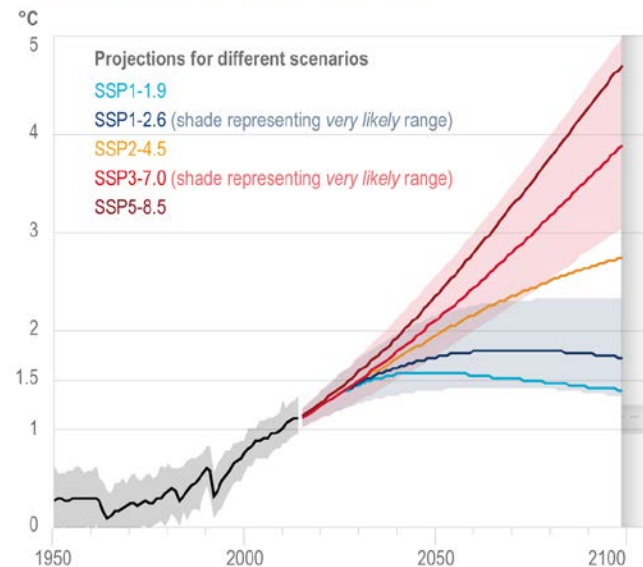
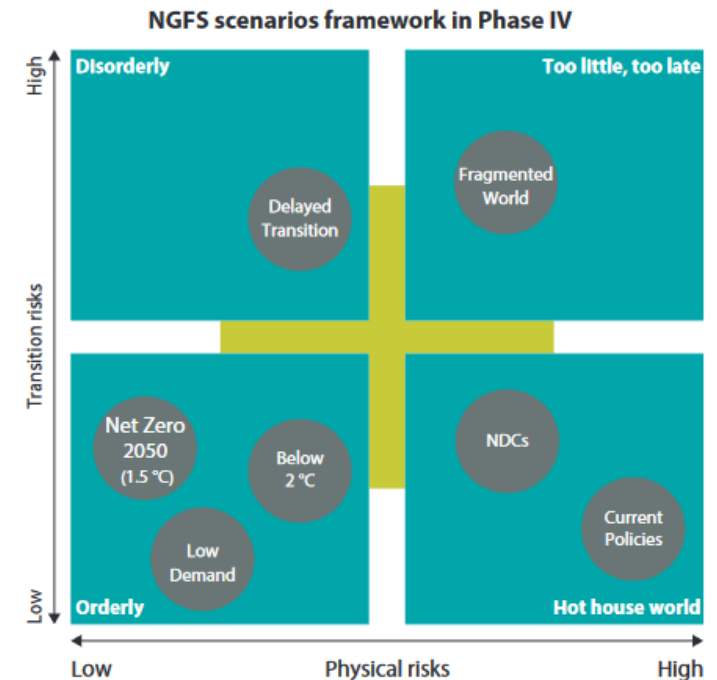


Figure 16.5 in O'Neill et al. (2022): Key Risks Across Sectors and Regions. IPCC AR6 WG2 Chapter 16

Policy/technology scenarios



Positioning of scenarios is approximate, based on an assessment of physical and transition risks out to 2100.

Types of within-process uncertainty (Rising et al. 2022)

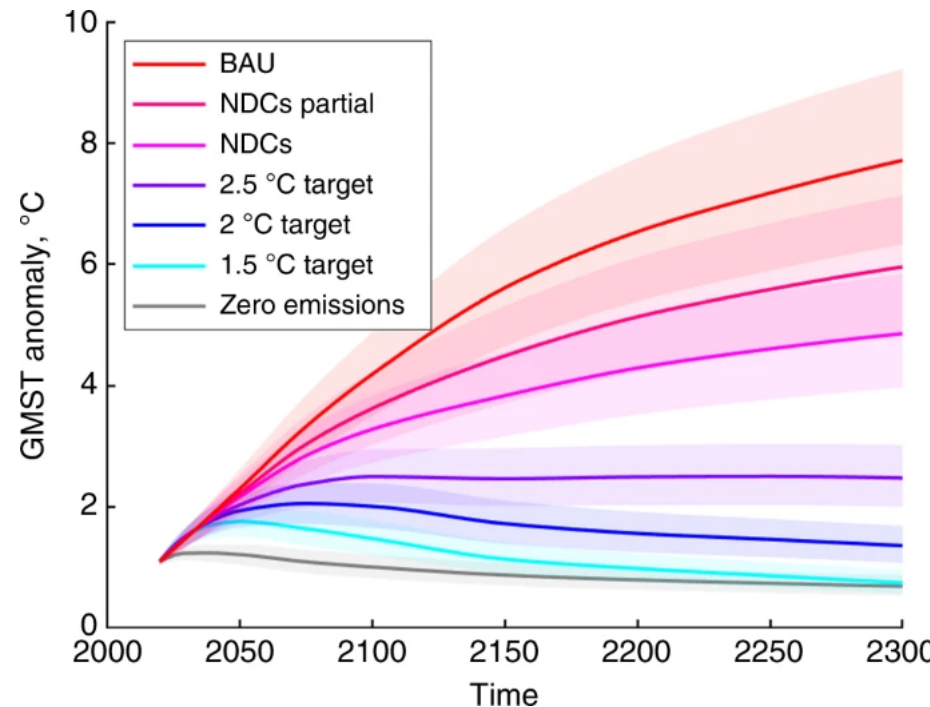
Source of uncertainty	Common representation	Example	CBA-IAMs	PB-IAMs
Scenario uncertainty	<ul style="list-style-type: none"> (1) Representative sets of scenarios for emission or socioeconomics (2) sets of policy targets or technological constraints 	<ul style="list-style-type: none"> (1) RCPs & SSPs (2) climate targets like 1.5° with/without overshoot 	X	X
Process parameter uncertainty			X	(X)

Examples for representation of uncertainties in IAMs

(2) Process parameter uncertainty – CBA IAMs

- › Uncertain parameters
 - › Most important: discount rate, climate sensitivity, damage function parameters
 - › Furthermore: economic growth, intertemporal elasticity of substitution, risk aversion
 - › Addressed e.g. through Monte Carlo approaches

Yumashev et al. (2019):
PAGE-ICE with Monte Carlo
approach to sample climate
uncertainty from
permafrost carbon feedback
and surface albedo
feedback



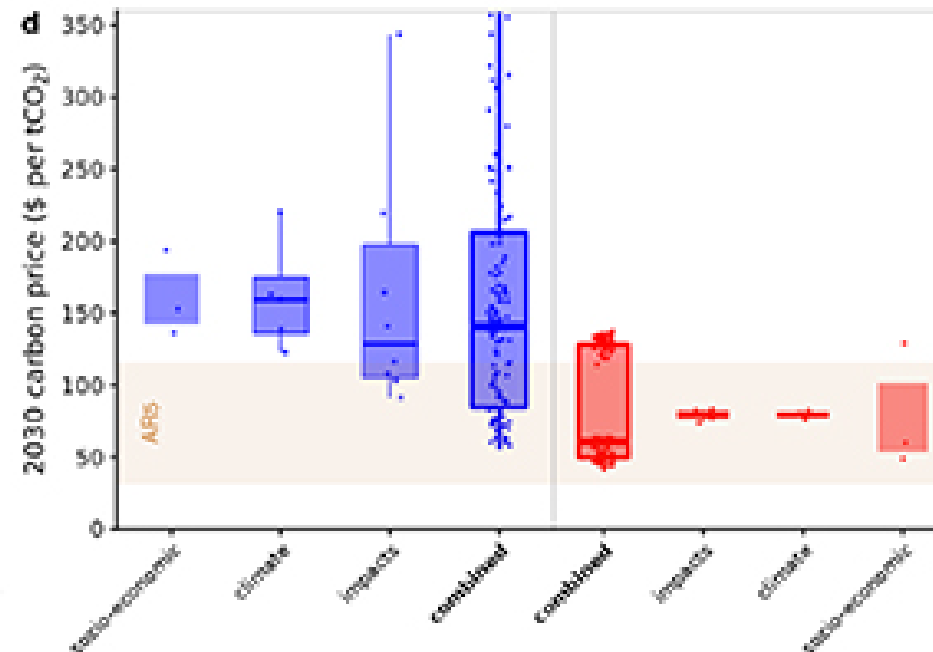
Examples for representation of uncertainties in IAMs

(2) Process parameter uncertainty - process-based IAMs

- › Uncertain parameters:
 - › As in CBA-IAMs + many more parameters in the detailed technology and resource representation
- › Addressed through sensitivity analysis → global sensitivity analysis almost impossible in a process-based IAM

Schultes et al. (2021):

- › Analysis of least total cost scenarios using the process-based IAM REMIND
- › Varies climate sensitivity, damage function specification, SSP



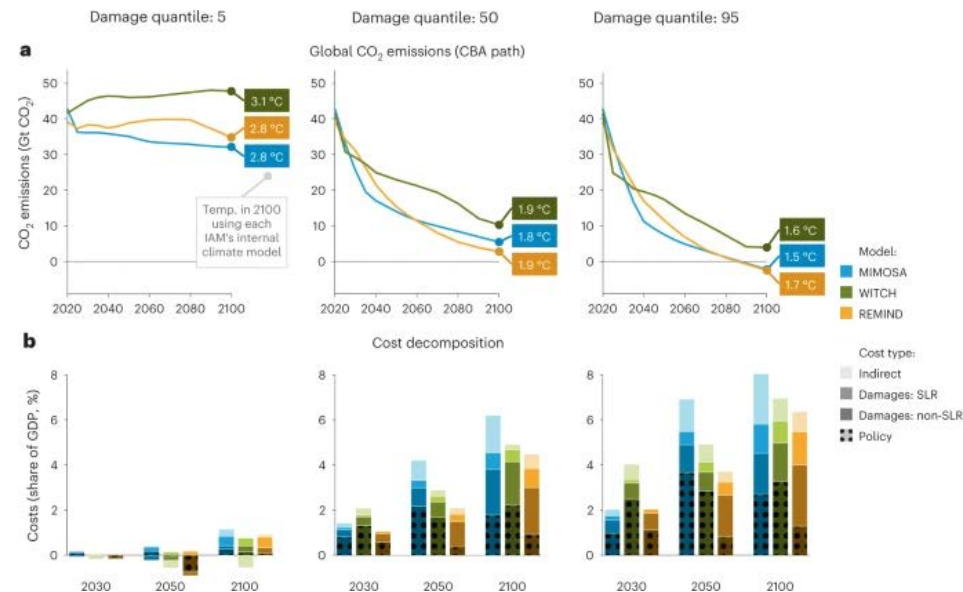
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Process parameter uncertainty	<p>Probability density functions across process parameter values</p> <p>Sensitivity studies for parameter values</p>	<p>Equilibrium climate sensitivity distribution used in an IAM</p> <p>Welfare parameters</p>	X	(X)
Model uncertainty			X	X

Examples for representation of uncertainties in IAMs

(3) Model uncertainty

- › Model intercomparisons “bread and butter” of process-based IAMs
- › EMF studies 1-37 focused on mitigation questions
- › Van der Wijst et al. (2023): impacts (PB & CBA-IAMs)
- › Emmerling et al. (under review): inequality



Examples for representation of uncertainties in IAMs

(3) Model uncertainty

Gillingham et al. (2018):

- › Compare process-based and CBA IAMs
- › Two-track approach to differentiate parameter and model uncertainty:
 - › Emulators of IAMs
 - › PDFs for key input variables: population, TFP, climate sensitivity
 - › Combine for Monte Carlo simulations
- › Results:
 - › Generally parameter uncertainty larger than structural uncertainty – except for SCC!
 - › TFP uncertainty more important than the others

Table 7. Fraction of Uncertainty (Variance) Explained by Model Differences

Variable	Fraction Explained by Model Differences*
Output (2100)	.14
Radiative forcing (2100)	.15
CO ₂ concentrations (2100)	.24
Temperature (2100)	.26
Population (2100)	.28
Emissions (2100)	.38
Damages (2100)	.45
Social cost of carbon (2020)	.80

Note. Note that the estimates for damages and the social cost of carbon are only for three models.

* Ratio of standard deviation of model means to total standard deviation.

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Model uncertainty	Results from multiple models or perturbed physics explorations	CMIP, ISIMIP, IAM model intercomparisons	X	X
Trajectory uncertainty			X	

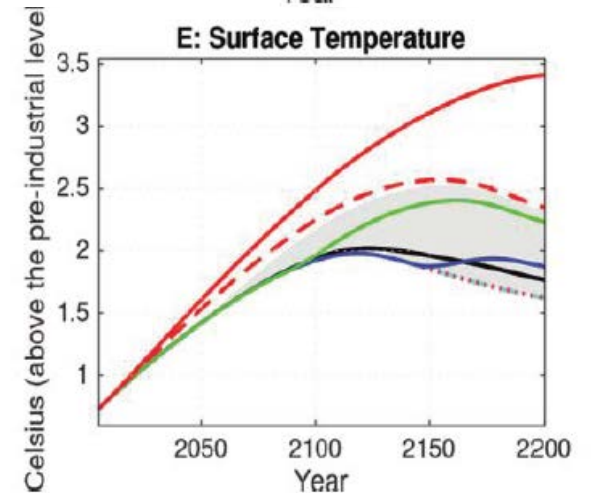
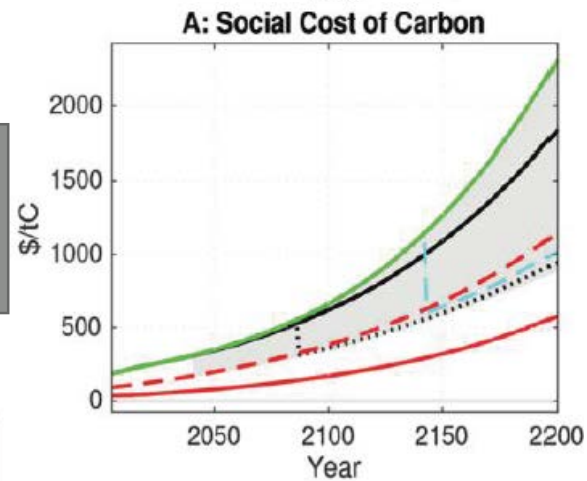
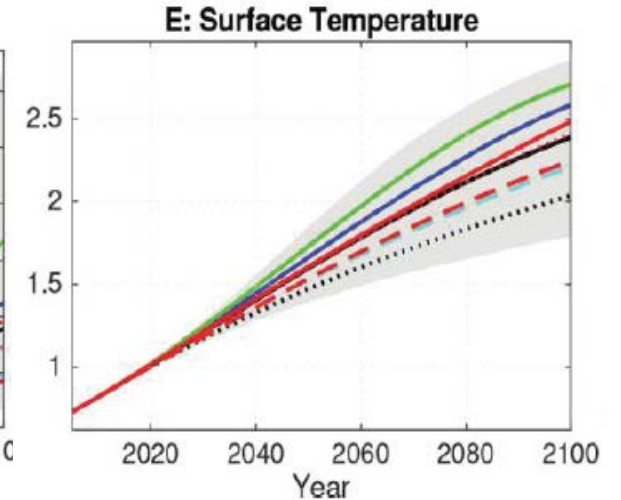
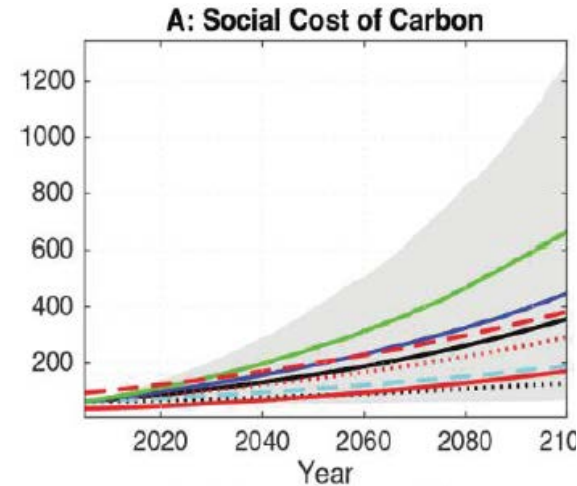
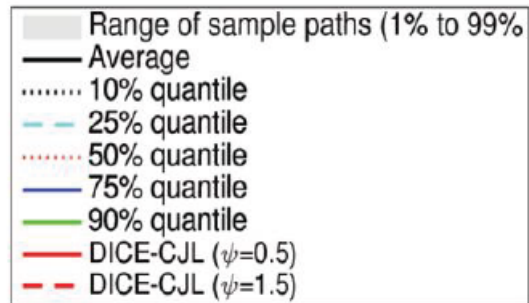
Examples for representation of uncertainties in IAMs

(4) Trajectory uncertainty

- › DSICE (Cai & Lontzek 2019) with tipping points: increases SCC in 2005 from 94\$/t C to 188 despite 75% probability of tipping not before 2150

Stochastic growth benchmark

Climate tipping benchmark



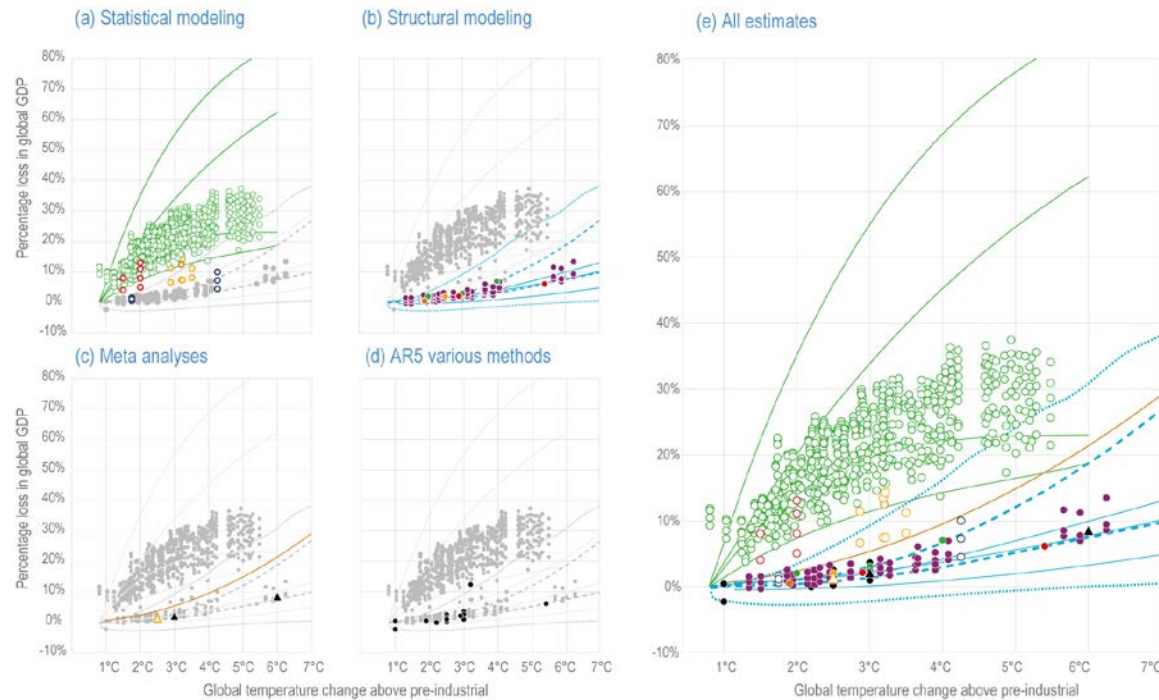
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Model uncertainty	Results from multiple models or perturbed physics explorations	CMIP, ISIMIP, IAM model intercomparisons	X	X
Trajectory uncertainty	<p>(1) Multiple realizations from a model with perturbed initial conditions</p> <p>(2) Probabilistic internally consistent distributions for population/GDP/emissions</p>	<p>(1) “initial-condition uncertainty” in GCMs</p> <p>(2) RFF-SPs, stochastic IAMs, climate variability in IAMs</p>	X	
Model inadequacy (structural limitations)	Descriptions and discussion of model limitations	Lack of spatial/temporal resolution or types of impacts in IAMs		

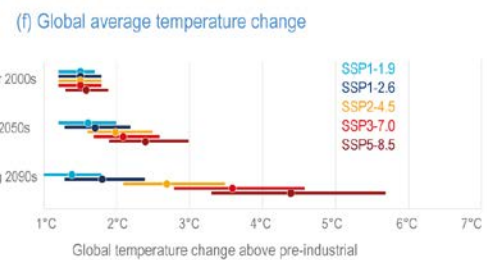
Examples for representation of uncertainties in IAMs

(5) Model inadequacy - impact representation

Global aggregate economic impact estimates by global warming level



- (a) Statistical modeling
 - Kahn et al. (2019)
 - Kalkuhl & Wenz (2020)
 - Burke et al. (2018) - SR
 - Pretis et al. (2018)
 - Maddison & Rehdanz (2011)
 - Burke et al. (2015)
- (b) Structural modeling
 - Takakura et al. (2019)
 - Dellink, Lanzi & Chateau (2019)
 - Kompas et al. (2018)
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 - Bosello et al. (2012)
 - Rose et al. (2017)
 - Rose et al. (2017) - FUND 5th & 95th
 - Rose et al. (2017) - PAGE 5th & 95th
- (c) Meta analyses
 - ▲ Nordhaus & Moffat (2017)/Nordhaus (2016)
 - ▲ Tol (2018)
 - Howard & Sterner (2017)
- (d) AR5 various methods
 - AR5

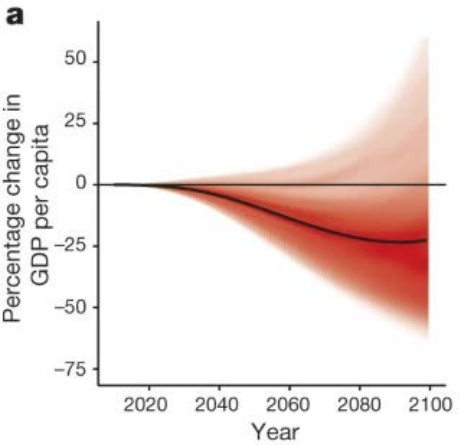


“The wide range of estimates, and the lack of comparability between methodologies, does not allow for identification of a robust range of estimates with confidence (high confidence).”

Figure Cross-Working Group Box ECONOMIC.1 in O'Neill et al. (2022): Key Risks Across Sectors and Regions. IPCC AR6 WG2 Chapter 16

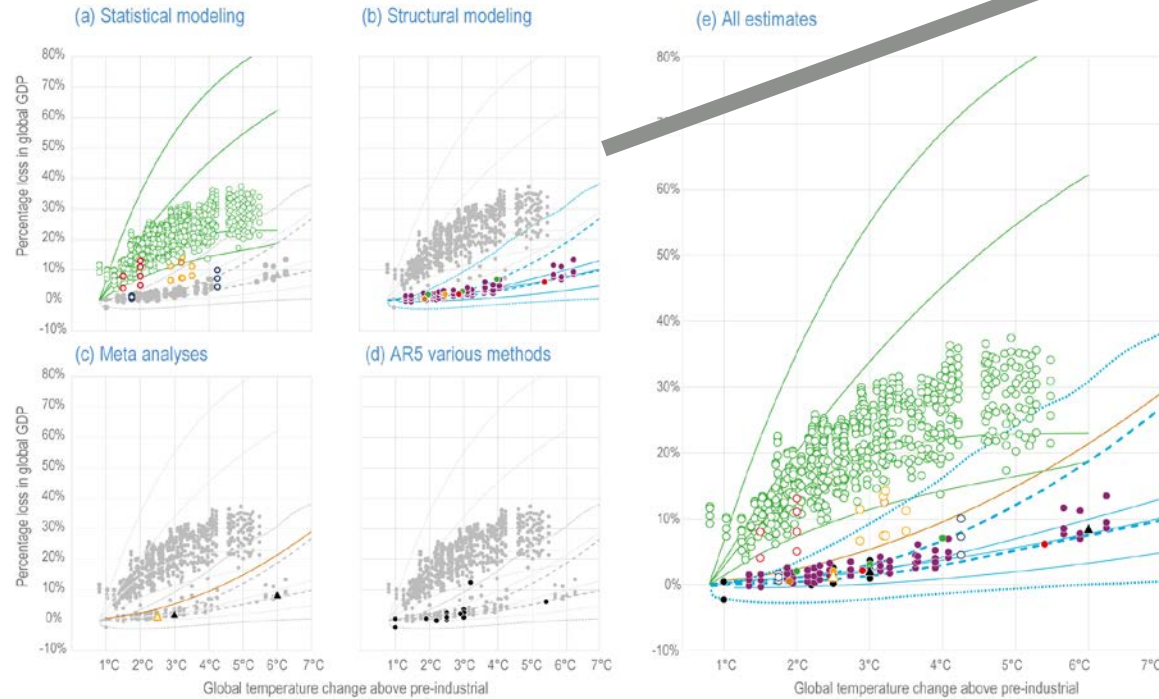
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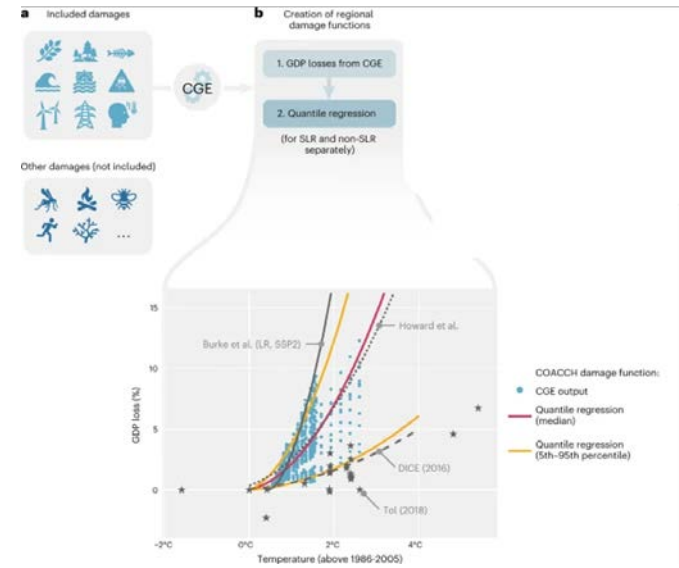


Burke et al. (2015)

Global aggregate economic impact estimates by global warming level

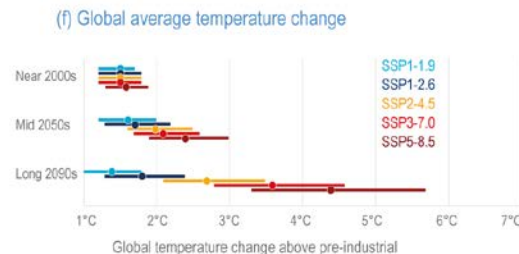


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Van der Wijst et al. (2023)

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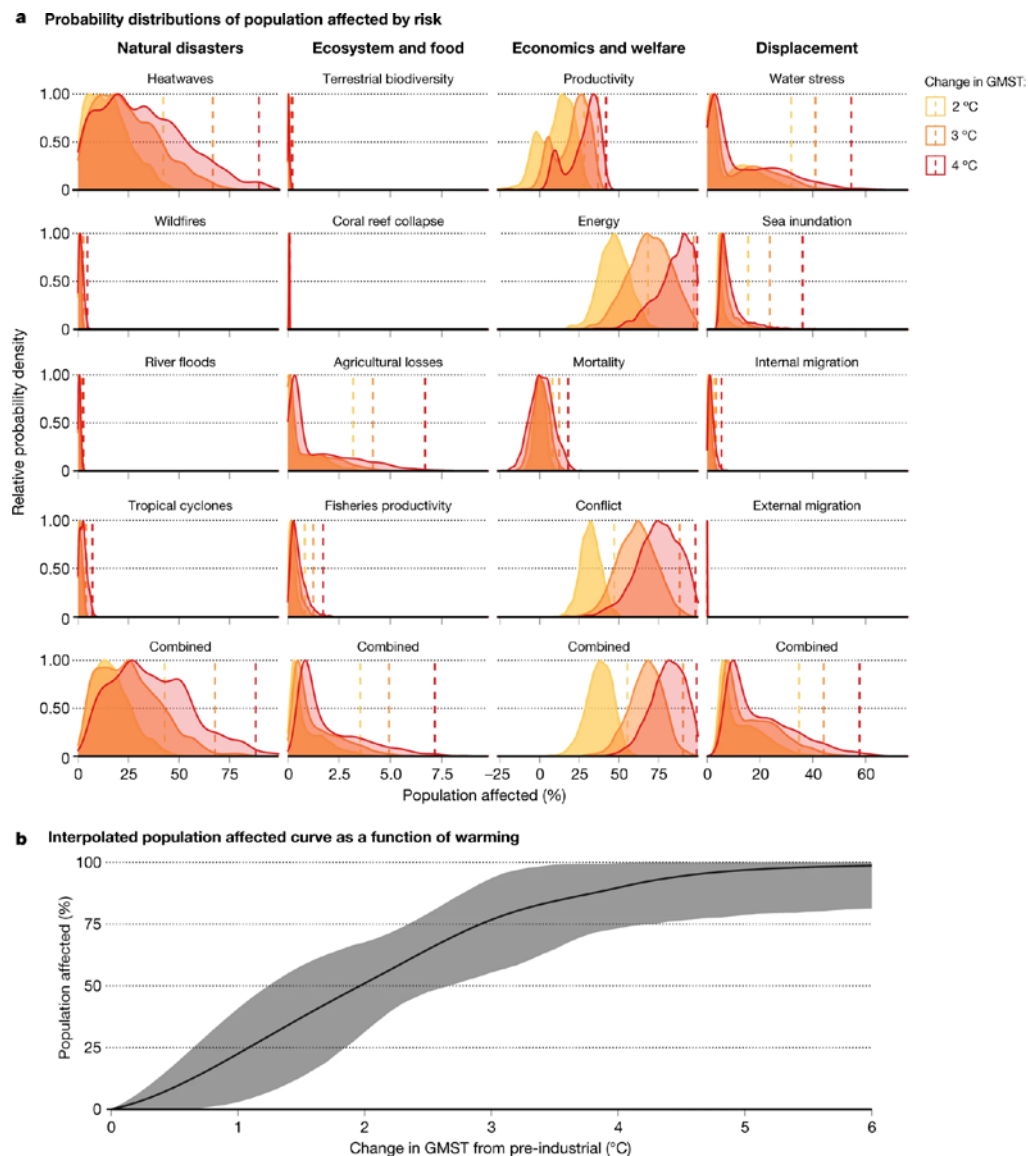
Impacts in IAMs: missing risks in economic impact assessments

- › Missing biophysical impacts (e.g. health, biodiversity, human capital)
- › Spatial and temporal extremes (challenge in impact and integrated assessment modeling)
- › Feedback risks and interactions (e.g. compounding and cascading events, tipping points)
- › Deep uncertainty, i.e. no robust probability distribution is possible (e.g. disruptions of ecosystems or social systems, black swan events)
- › Unidentified risks

➔ Interdisciplinary research agenda to identify most crucial gaps and funding to fill them

Integrating uncertainty into policy-relevant scenario analysis from process-based IAMs

Rapidly quantifying missing risks



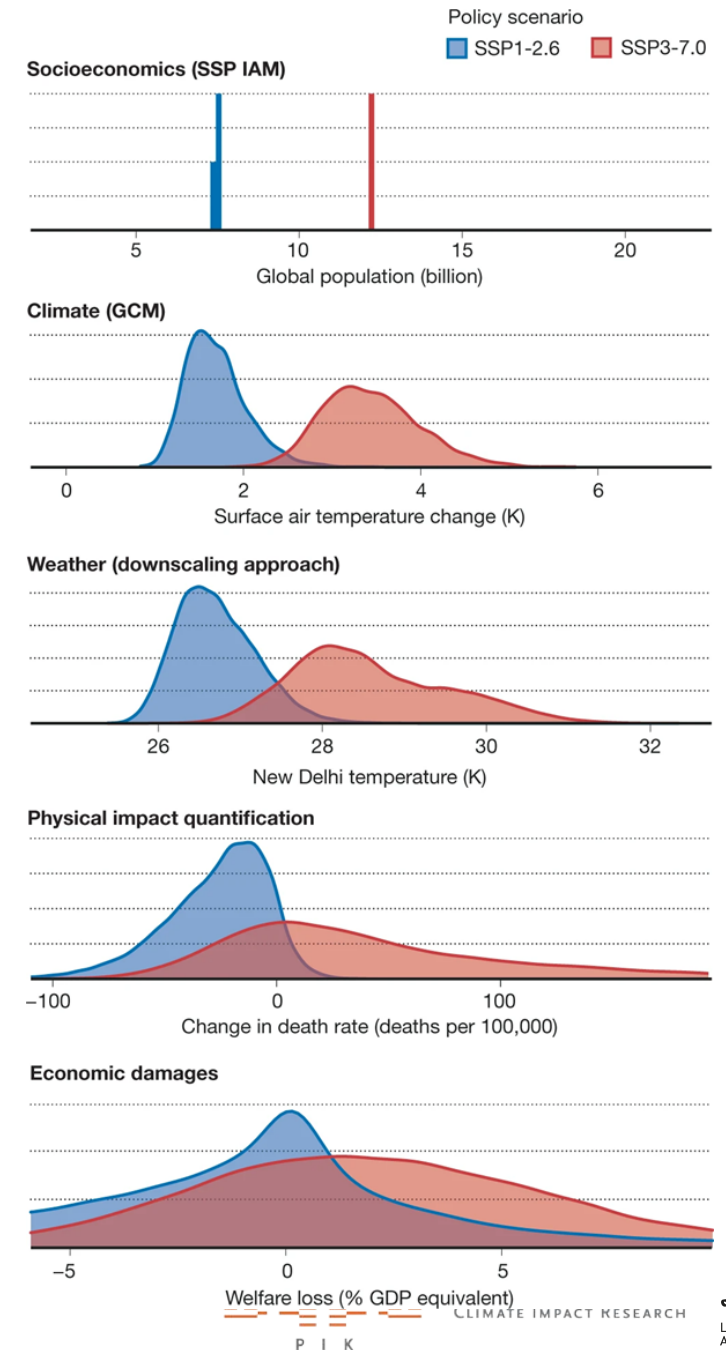
Combining uncertainty and qualitative information about missing risks:

1. Define a consistent metric across risks
 2. Describe each risk as a distribution of possible consequences dependent on temperature
 3. Determine correlation of uncertainty between pairs of risks
 4. Determine degree of double counting between pairs of risks
 5. Apply copula approach to combine risks
- Easy to add risks later without repeating the whole analysis
- Note: no economic valuation!

Assessing uncertainty of economic damages

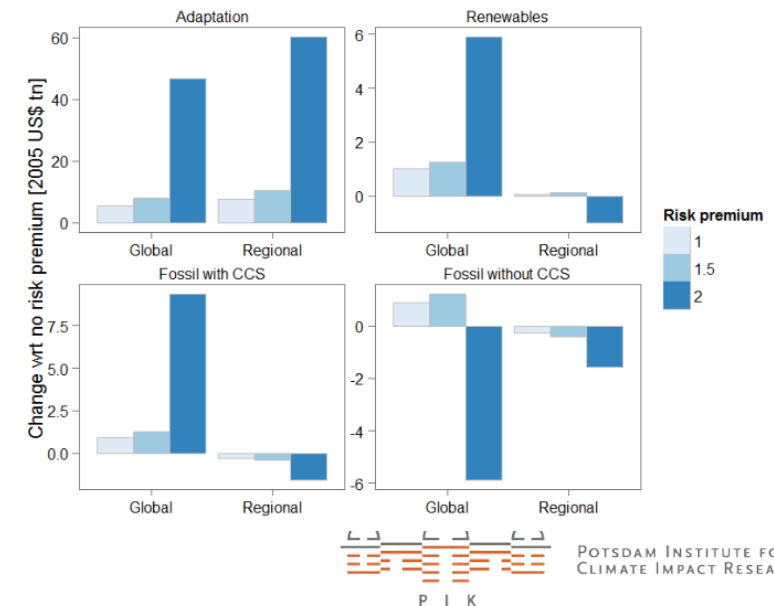
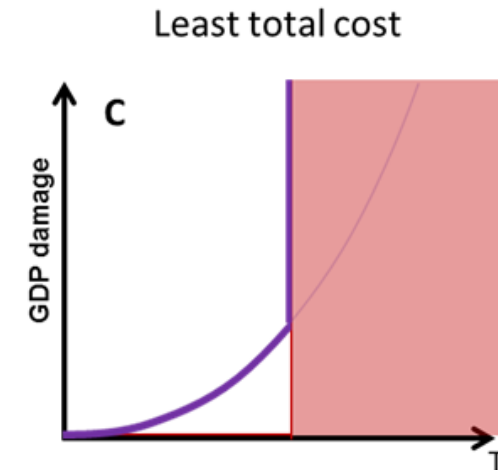
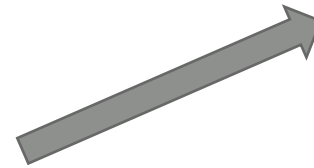
- › Compounding uncertainty across modeling chain
- › Combine model & trajectory uncertainty by using high resolution climate inputs and assessing parameter uncertainty by using Monte Carlos from multiple GCMs and multiple impact models
- › link to optimizing IAM not always necessary!

Rising et al. (2022): bottom-up example of changes in temperature-related mortality in New Delhi



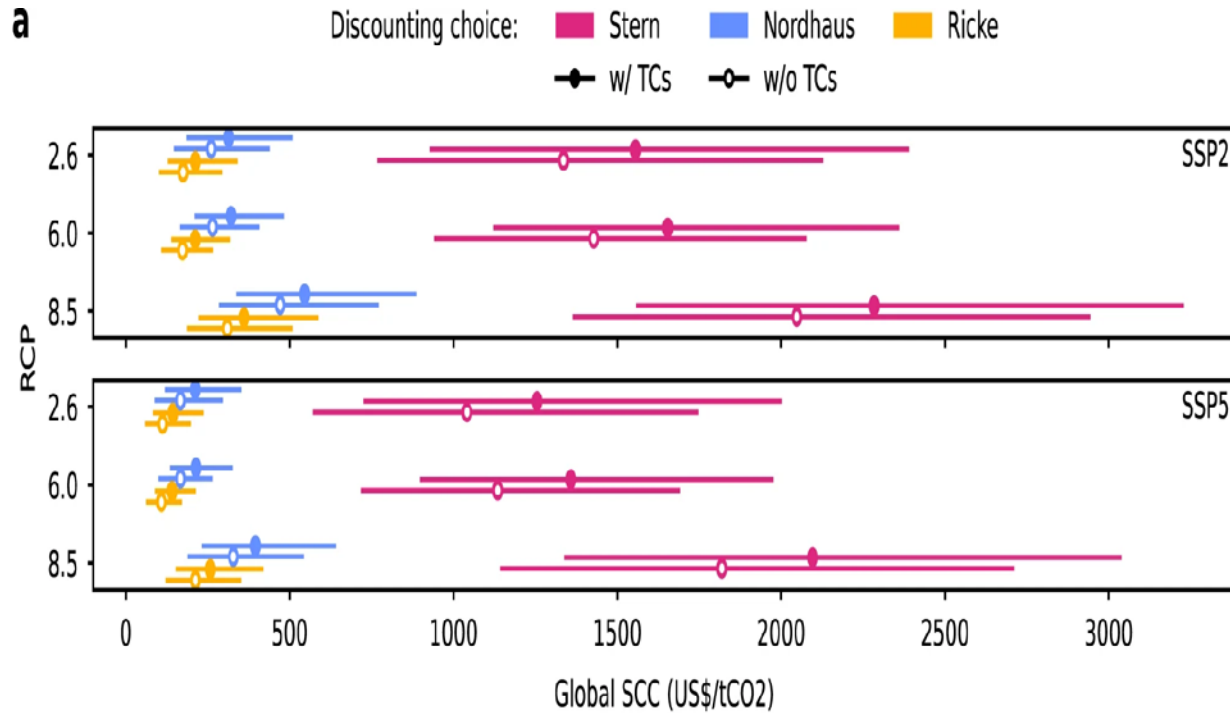
Precautionary principle – inform damage estimates used in IAMs

- › Including uncertainty seems to increase mitigation ambition – warrants precautionary principle
- › Combine guardrail target with impacts to hedge against impacts not included (“least total cost” analysis) (Schultes et al. 2021)
- › Include risk premia to account for uncertainty of damages (Markandya et al. 2016) or other results from CBA-IAMs

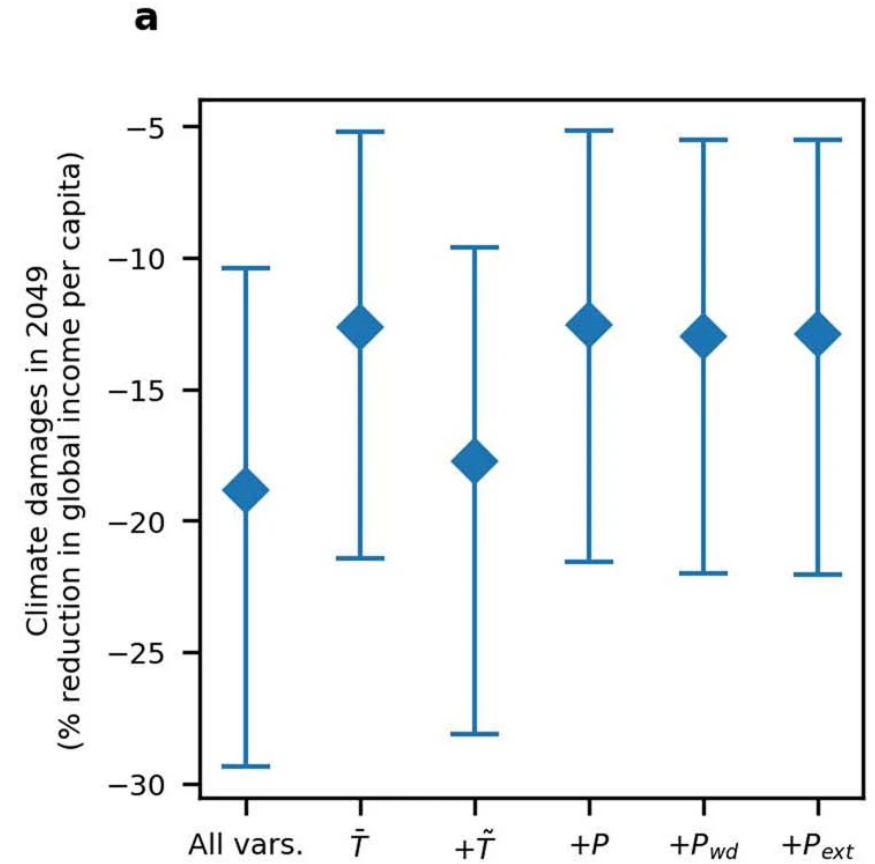


Include extremes in econometric damage estimations

› Note: lacks risk component



Krichene et al. (2023): mean temperature change + tropical cyclones



Kotz et al. (2024): mean temperature + temperature variability + precipitation effects

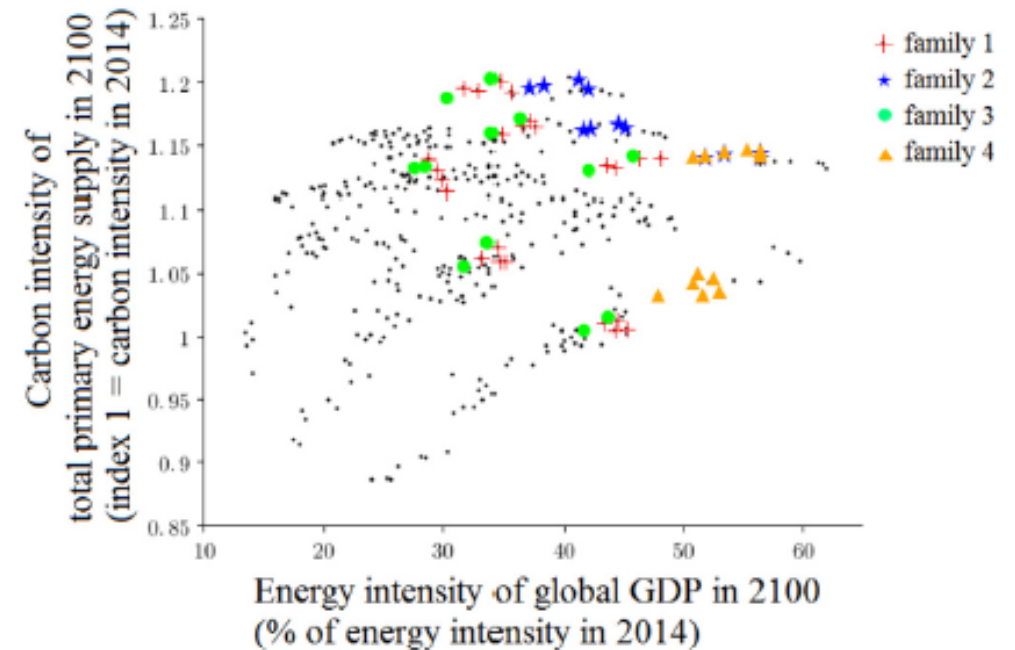
Sensitivity analysis

- › Challenging for computationally intensive models
- › As a minimum, provide sensitivity analysis for selected parameters relevant for your results
- › Design as real robustness test for the policy conclusion
- › Model emulators
 - › Of IAMs for Monte Carlo analysis (Gillingham et al. (2016))
 - › New climate and impact model emulators allow for easier and faster application in IAMs (e.g. MESMER, RIMES)

Scenario exploration/storyline approach

- › Model intercomparison surrounding disruptive scenarios (“storyline approach”)
- › Scenario discovery to assess diversity & robustness → to explore different or prevailing pathways towards given outcomes

Guivarch et al. (2016): scenarios with high cumulative emissions → 4 families, all with high availability of fossil fuels and energy-intensive demand, but other drivers vary → e.g. high emission is not necessarily related to high GDP growth

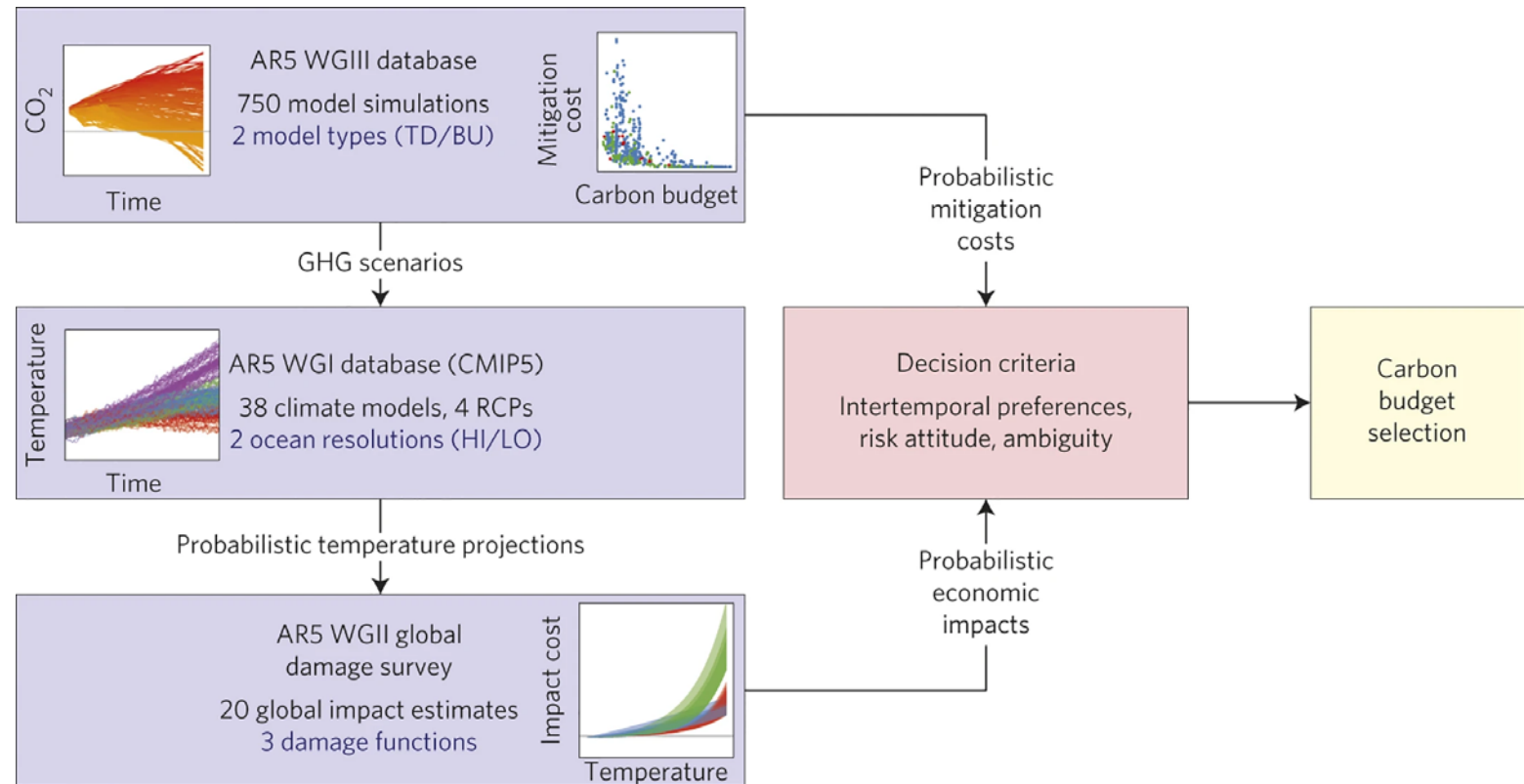


Assessment of uncertainty through post-processing evaluation of a set of IAM scenarios

› Use set of scenarios combining models and policies, e.g. IPCC database, to identify robust policies through different decision-making criteria

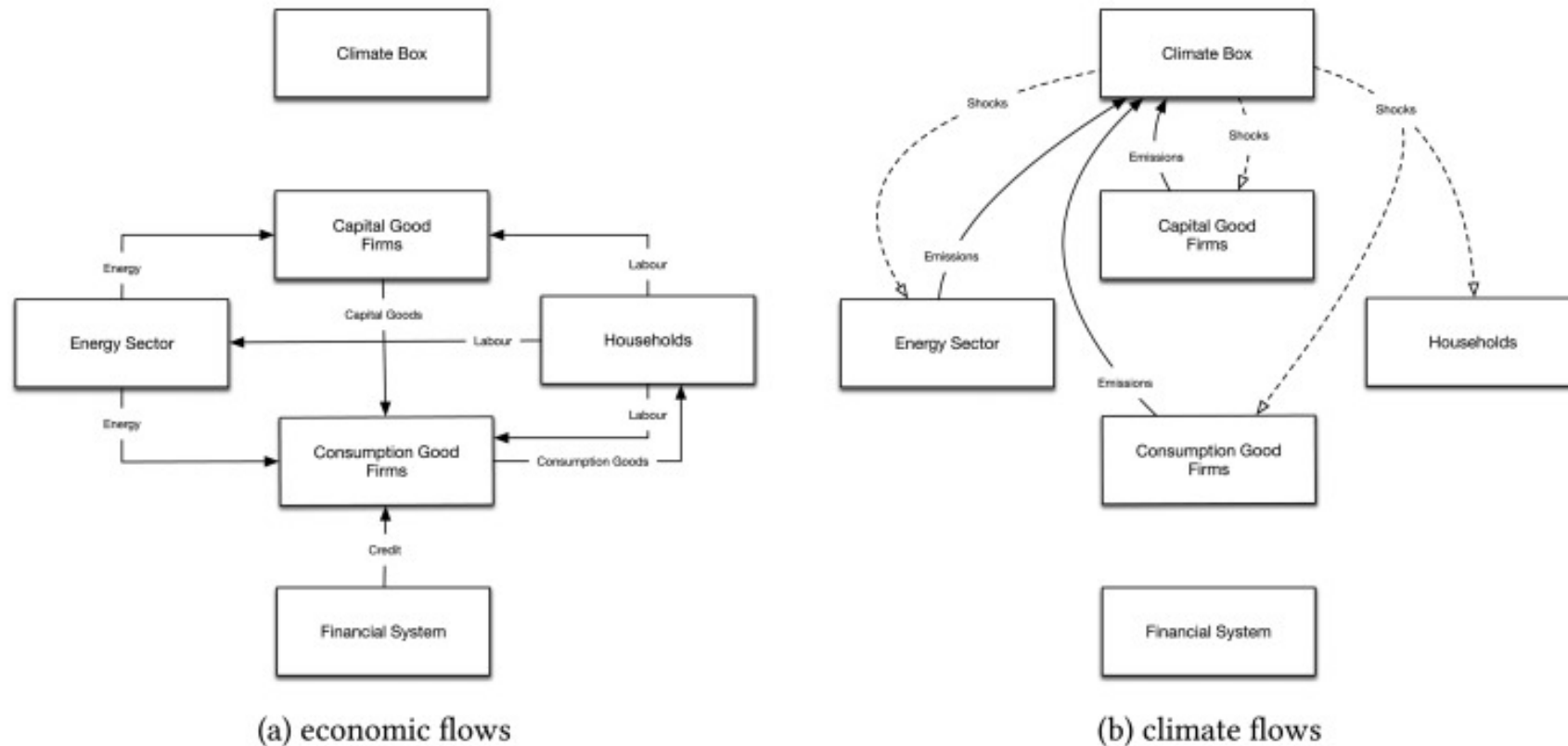
› Drouet et al. (2015): different decision-making criteria to find optimal carbon budget based on AR5 scenarios (different models & states of the world)

→ choice of decision criteria has large influence on results



Leave behind the general equilibrium approach: agent-based models to link climate, macro-financial and policy dynamics (Monasterolo et al. 2018)

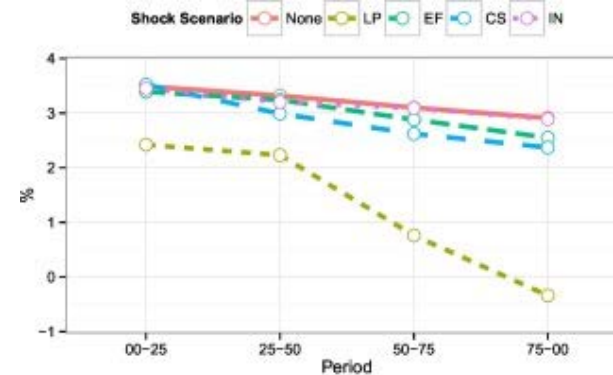
Lamperti et al. (2018): Dystopian Schumpeter meeting Keynes (DSK) model – first agent-based IAM



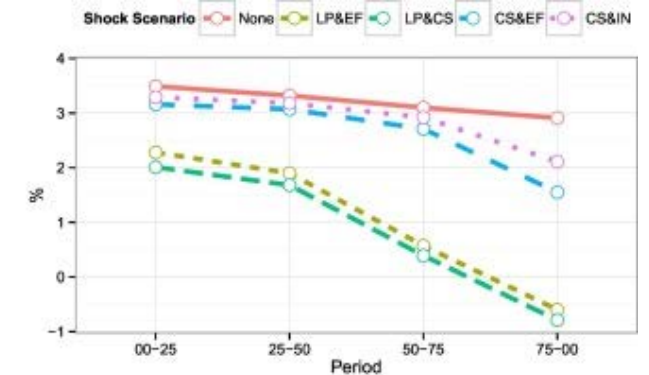
Agent-based models to capture uncertainty related to macro-financial and policy dynamics (Monasterolo et al. 2018)

Lamperti et al. (2018): Dystopian Schumpeter meeting Keynes (DSK) model – first agent-based IAM

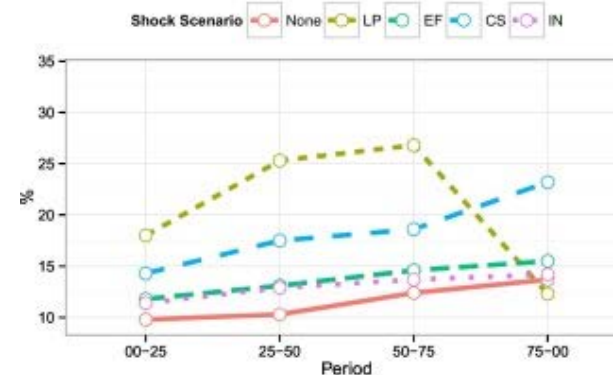
- › Analysis of climate shocks on: labour productivity, energy efficiency, capital stock, inventories
- › Non-linear growth processes lead from self-sustained growth to stagnation (coupled labor productivity and capital stock shocks)



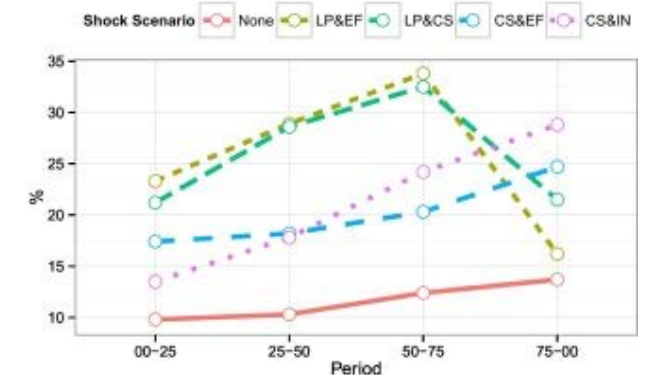
(a) Output growth; un-combined shocks.



(b) Output growth; combined shocks.



(c) Likelihood of crises; un-combined shocks.



(d) Likelihood of crises; combined shocks.

Conclusions

- › Uncertainty analysis is under-represented in policy-relevant IAM applications
- › Extensive work with CBA-IAMs but no realistic mitigation pathways VS limited work with process-based IAMs which inform policy processes
- › Economic impacts and their uncertainty of highest relevance for policy advise, but lots of gaps – in particular ambiguity about impacts often largest driver of uncertainty
- inclusion of uncertainty should be standard, level depending on the question at hand
- more interaction between disciplines (impact modelers, economists, complexity science, social science)
- multi-model exercises for testing scenario outcomes including alternative modeling approaches – use comparative advantage of each modeling type
- model intercomparison with focus on identifying gaps
- methodological advances open new options (especially for including impacts)
- larger emphasis on robust decision making methods for scenario sets and story telling approaches for disruptive events

Thank you



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