Robust technological and emission trajectories for long-term stabilization targets with an energy-environment model

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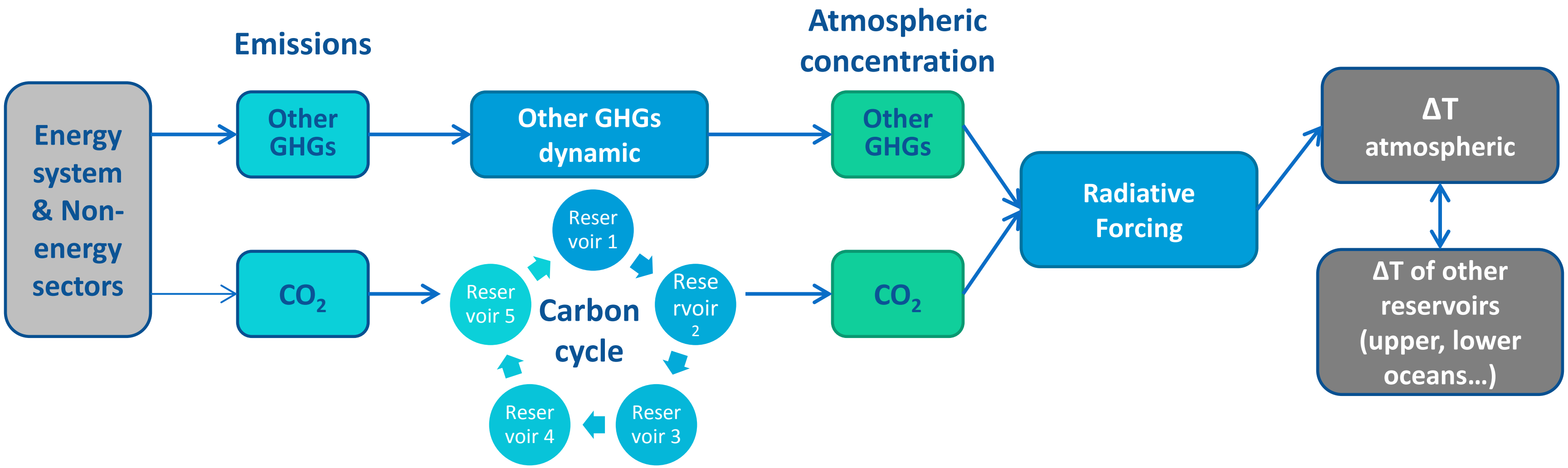
CONTEXT

- Widespread use of energy-economy-environment system models
  - Energy security and climate change: insights regarding the cost and benefit of policy objective and system effects
  - These models grow bigger and bigger
    - Sectoral and geographical coverages, coupling with other models, Higher level of details/complexity…
  - And are subject to criticisms (too complex, validation issue, hidden values issue)
  - The main criticism: uncertainty handling (Pindyck, 2013)
- Uncertainty treatment
  - Uncertainty not considered because of model size & complexity
  - A polymorphous uncertainty:
    - growth, technical parameters, backstop technology, climate system…
- Methods
  - Exogenous ways
    - Extensive scenario analysis (Babaee et al, 2014)
    - Sensitivity analysis (Hope, 2006)
    - Monte Carlo analysis (MIT 2011)
  - Endogenous ways
    - Stochastic programming (requires density functions)
    - Robust optimization : set-based uncertainty models, large cardinalities allowed (distributional robustness) (Babonneau et al, 2011)

Climate models in IAMs

- Small Climate models deriving from Global Circulation Models and/or Earth System Models of Intermediate Complexity (Van Vuuren et al, 2009)



- Lots of approximations / calibration methods which can impact the model results
- Idea: assess the robustness of the model to climate parameters uncertainty and understand which parameters or combination of parameters are the most sensitive
- Problem: a classic sensitivity study would take too long (with 10 parameters to study and only 2 values for each parameters, more than 1000 runs)
- Hence the use of robust optimization

ROBUST OPTIMIZATION: what is it?

- Principle
  - Immunize solutions of mathematical programs to adverse realizations of uncertain coefficients
- Initial approach
  - Soyster (1973): pessimistic « worst-case » solution
- Many improvements since the end of 90s
  - New formalisms (quadratic…) : El-Gahoui et al (1998); Ben-Tal and Nemirovski (2002)
  - Lots of efforts on linear formulations: Bertsimas and Sim (2004) – generalization of Soyster's approach
  - Ongoing extensions to general constraints (Ben-Tal et al, 2012)

➡ Very well established results for LP

ROBUST OPTIMIZATION: what is it?

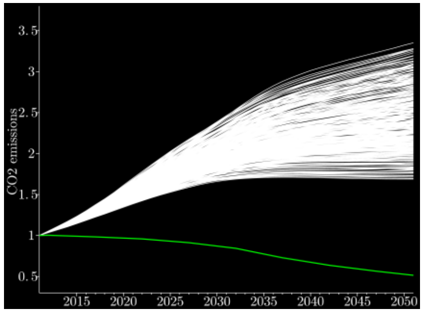
- Nominal LP problem
  - (P) $\begin{cases} \min C^T x \\ s.t.\ Ax \le b \\ x \in \mathbb{R}^n{}_+, b \in \mathbb{R}^m \end{cases}$
- Some parameters are uncertain, we assume they deviate in the "uncertainty set"
  - $a_{i,j} \in \left[\overline{a_{i,j}} - \widehat{a_{i,j}}, \overline{a_{i,j}} + \widehat{a_{i,j}}\right]$, $a_{i,j}$=$\overline{a_{i,j}}$+$z_{i,j}\ \widehat{a_{i,j}}$, $z_{i,j} \in [-1, 1]$
  - The "worst" case is unlikely hence: $\sum_j |z_{i,j}| \le \Gamma_i$, Γ: uncertainty budget
  - (P_{rob}) $\begin{cases} \min C^T x \\ s.t. \\ \sum_j \overline{a_{i,j}}\, x_j + \max\limits_{z\ i,j} \sum_j z_{\ i,j} \widehat{a_{i,j}}\, x_j \le b_i \\ z_{i,j} \in [-1, 1] \quad (\mu) \\ \sum_j |z_{i,j}| \le \Gamma_i \quad (\lambda) \\ x \in \mathbb{R}^n{}_+, b \in \mathbb{R}^m \end{cases}$
- Primal deviation problem
  - (P_2) $\begin{cases} \max\limits_{z\ i,j} \sum_j z_{\ i,j} \widehat{a_{i,j}}\, x_j \\ z_{i,j} \in [0, 1] \ \ (\mu) \\ \sum_j z_{i,j} \le \Gamma_i (\lambda) \\ x \in \mathbb{R}^n{}_+, b \in \mathbb{R}^m \end{cases}$
- Dual deviation problem
  - (D_2) $\begin{cases} \min \Gamma_i \lambda + \sum_j \mu_{i,j} \\ s.t.\ \lambda + \mu_{i,j} \ge \widehat{a_{i,j}} x_j \\ \mu_{i,j} \in \mathbb{R}_+, \lambda \in \mathbb{R}_+ \end{cases}$
- Using strong duality arguments
  - (P_{rob}) $\begin{cases} \min C^T x \\ s.t. \\ \sum_j \overline{a_{i,j}}\, x_j + \Gamma_i \lambda + \sum_j \mu_{i,j} \le b_i \\ \lambda + \mu_{i,j} \ge \widehat{a_{i,j}} x_j \\ \mu_{i,j} \in \mathbb{R}_+, \lambda \in \mathbb{R}_+ \\ x \in \mathbb{R}^n{}_+, b \in \mathbb{R}^m \end{cases}$

Why using this methodology?

- Input-based reasons
  - Tackling the computational burdens of large bottom-up IAMs

  - Being able to consider a lot of parameters at the same time

- Output based reasons
  - Proposing alternative model of uncertainty within IAMS

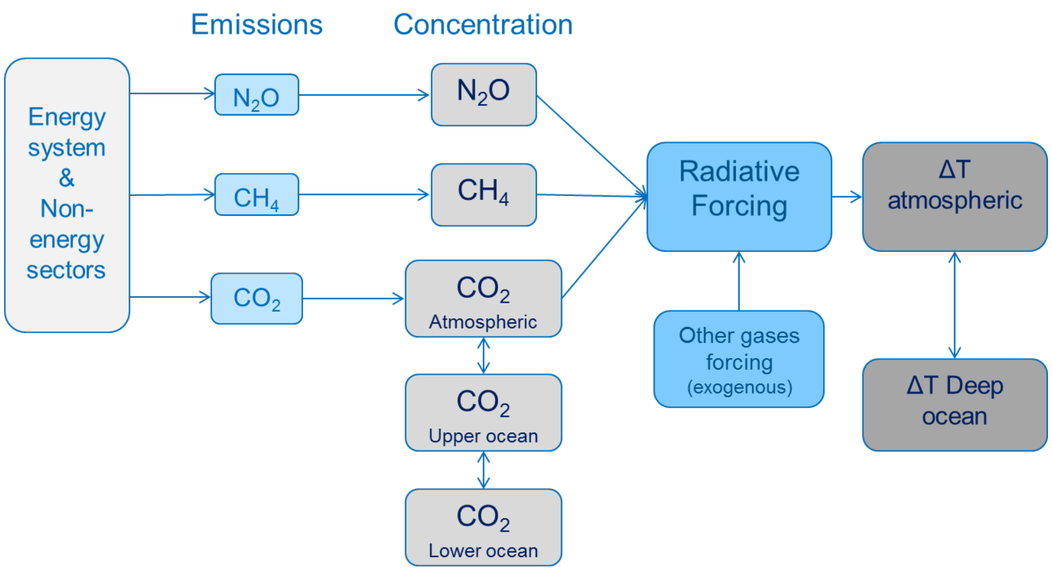


  - Obtaining trajectories robust to most parameter realizations

- Other potential applications
  - Cost uncertainty, technical parameter uncertainty, demand uncertainty

Application with the TIAM-World model

- The TIMES climate module is adapted from Nordhaus & Boyer (1999) (Loulou et al, 2010)



Parameters

- Carbon cycle: $\boldsymbol{\varphi_{au}}$, $\boldsymbol{\varphi_{ua}}$,$\boldsymbol{\varphi_{lu}}$, $\boldsymbol{\varphi_{ul}}$ annual CO2 flow coefficients between the three reservoirs
- Radiative forcing: $\boldsymbol{\gamma}$ is the radiative forcing sensitivity to a doubling of the atmospheric
- Temperature
  - $\boldsymbol{\sigma_1}$: speed of adjustment parameter for atmospheric temperature.
  - $\boldsymbol{\sigma_2}$: ratio of the thermal capacity of the deep oceans to the transfer rate from shallow to deep ocean
  - $\boldsymbol{\sigma_3}$: transfer rate (per year) from the upper level of the ocean to the deep ocean
  - **CS**: a feedback parameter, representing the equilibrium impact of CO_2 concentration doubling on climate.

- 9 parameters calibrated with more complex climate models (e.g. MAGICC)

Experimental setting

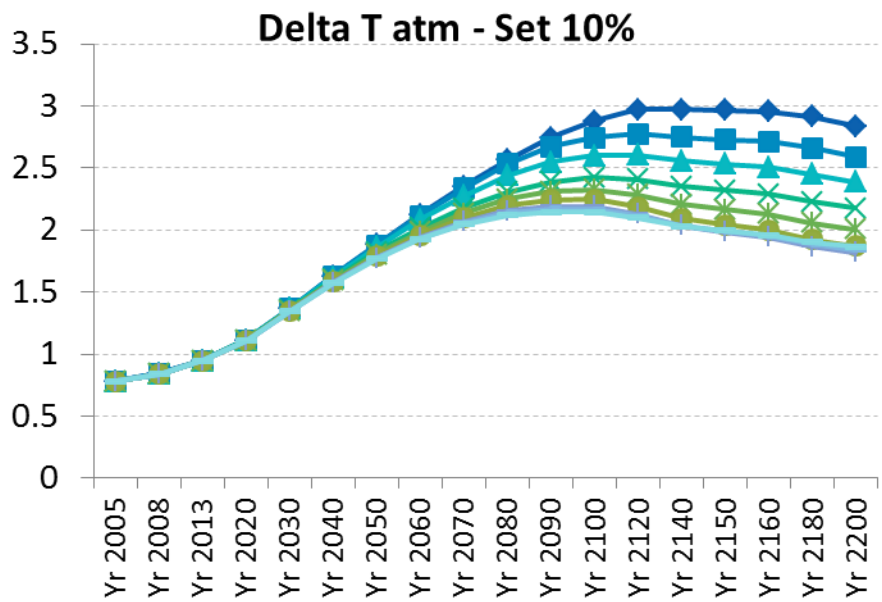
- Climate constraint: 3°C over the whole 2010-2200 horizon (no overshoot)
- 2 sets of climate parameter deviations

- Set 1: 10% set
  - Simple: Parameters can deviate of 10% of their nominal value
  - $a_{i,j} \in \left[\overline{a_{i,j}} - 0.1\overline{a_{i,j}}, \overline{a_{i,j}} + 0.1\overline{a_{i,j}}\right]$
- Set 2: literature set
  - Use deviation values found in literature
  - Difficulty to find homogenous data for all parameters

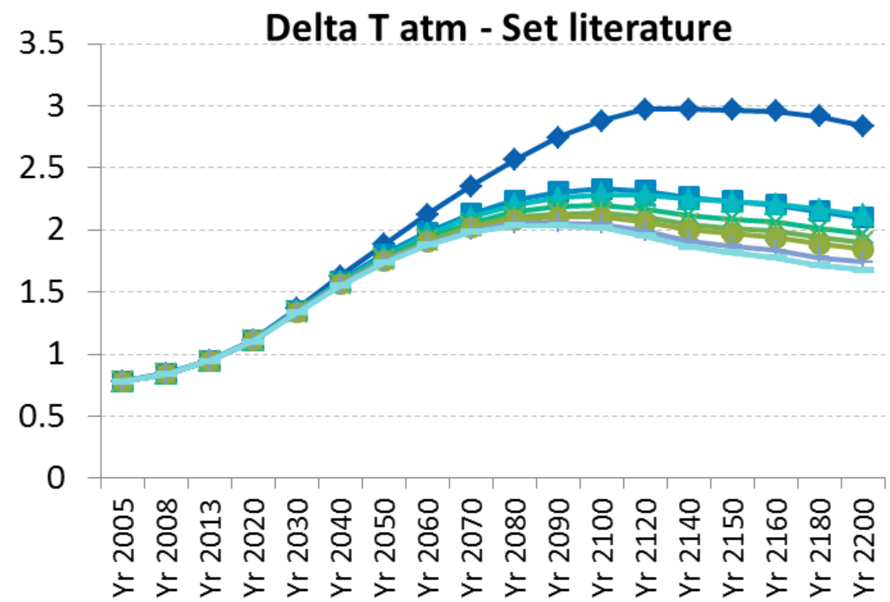
Parameters	Value	Deviation	
		10%	Literature
φ_{au}	0.046	10%	3.5%
φ_{ua}	0.0453	10%	3.5%
φ_{lu}	0.00053	10%	3.5%
φ_{ul}	0.0146	10%	3.5%
σ_1	0.024	10%	13%
σ_2	0.44	10%	10%
σ_3	0.002	10%	10%
CS	2.9	10%	50%
γ	3.71	10%	21%

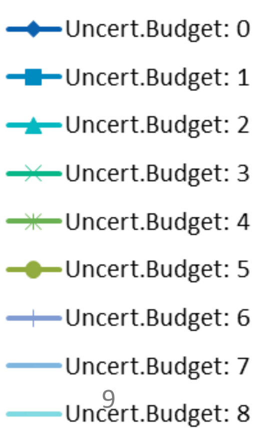
Most sensitive parameters

- Uncertainty set: 10%



- Uncertainty set: literature

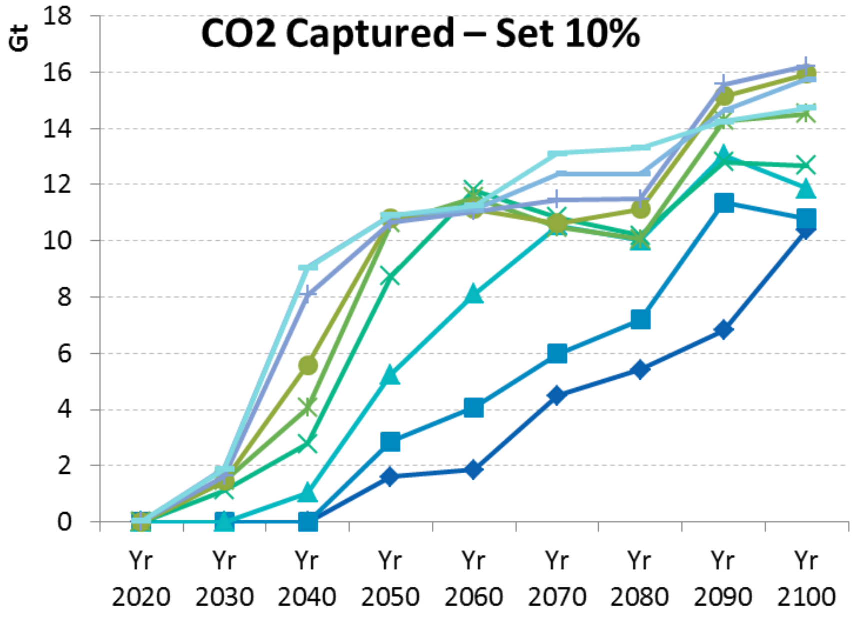


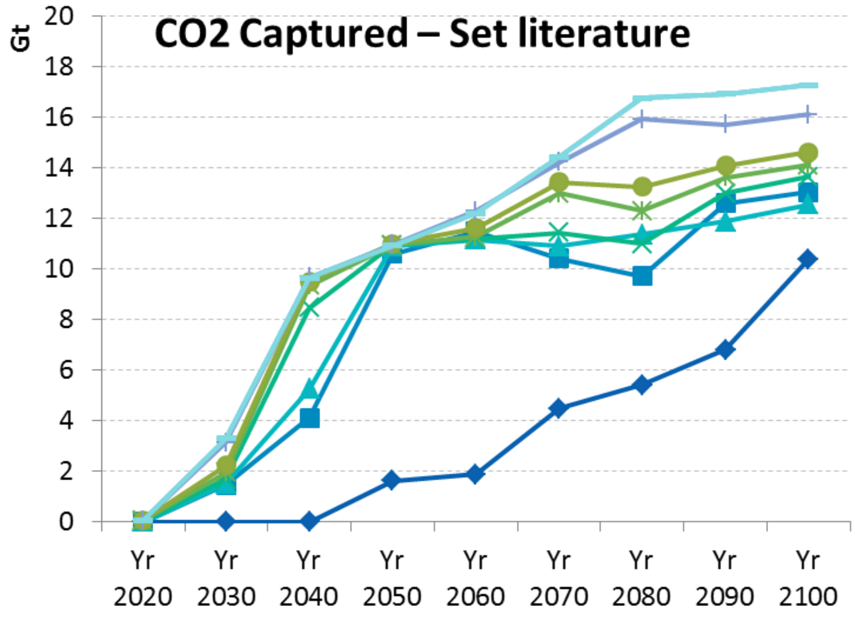


Deviation	φau	CS	φua	φlu	φul	σ1	σ2	σ3	γ
10%	1	2	3	5	4	7	6	9	6
Literature	3	1	4	7	5	2	3	9	8

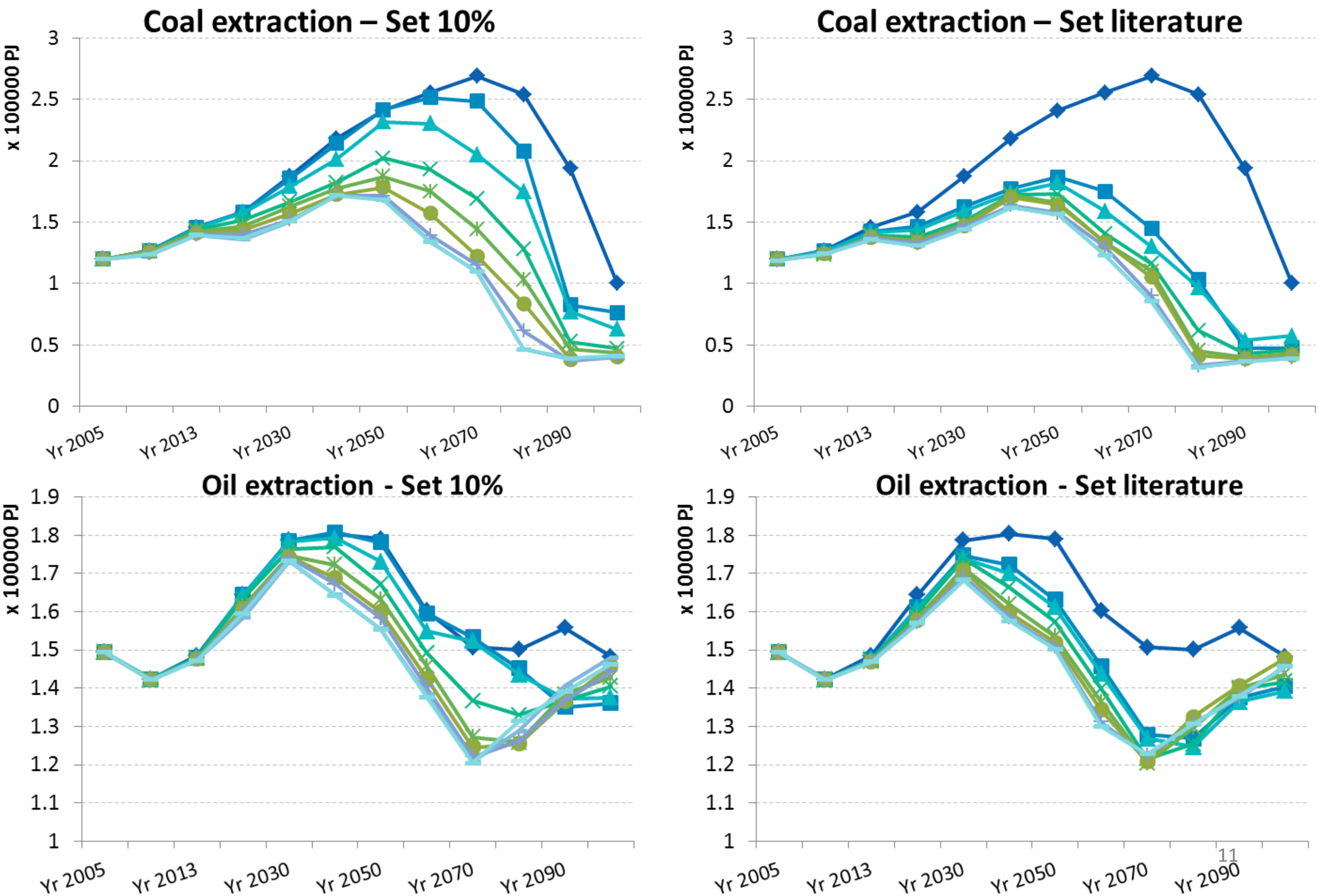
Parameter deviation order

CO_2 Captured





Primary energy



Conclusion

- Use of robust optimization for large bottom-up model with non-linear constraint
- Need to be careful with Small Climate Model results given the parameter diversity across models
- Adapt calibration? Generalize sensitivity study?

- Next step: going further with the robust optimization methodology. Trying to understand how we can interpret the robust trajectories (hedging, attitude towards risk…).

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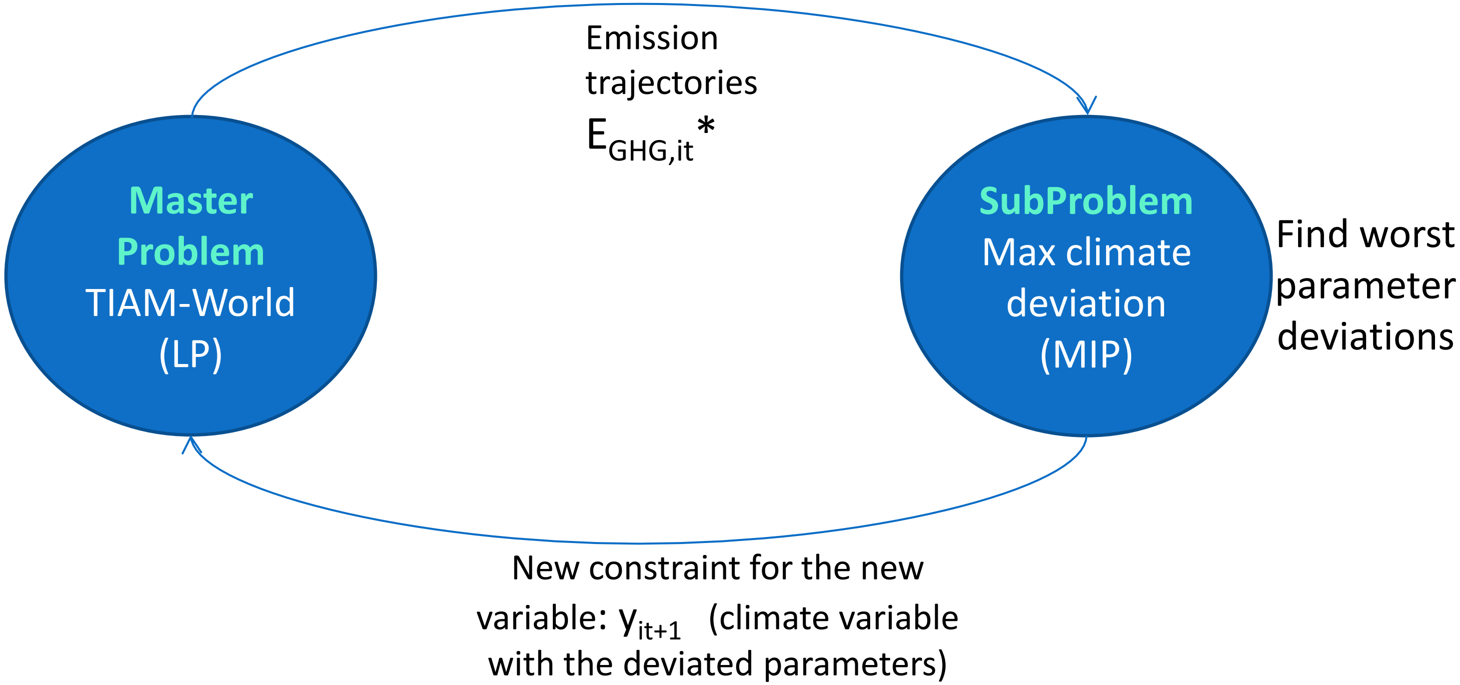
Thank you for your attention

Application with the TIAM-World model

- Implementation obstacle
  - The climate module is not linear in the parameters:
    - We linearized it using binary variables, the problem becomes a MIP
  - Implementation of a column and constraint generation algorithm using a MIP oracle



Times climate module

$$M_{atm}(y) = E(y) + (1 - \varphi_{atm\text{-}up})\, M_{atm}(y\text{-}1) + \varphi_{up\text{-}atm}\, M_{up}(y\text{-}1)$$
$$M_{up}(y) = (1 - \varphi_{up\text{-}atm} - \varphi_{up\text{-}lo})\, M_{up}(y\text{-}1) + \varphi_{atm\text{-}up}\, M_{atm}(y\text{-}1) + \varphi_{lo\text{-}up}\, M_{lo}(y\text{-}1)$$
$$M_{lo}(y) = (1 - \varphi_{lo\text{-}up})\, M_{lo}(y\text{-}1) + \varphi_{up\text{-}lo}\, M_{up}(y\text{-}1)$$

$$M_t = \mathrm{P} \cdot M_{t-1} + E_t,$$

$$\mathrm{P} = \begin{pmatrix} 1-\varphi_{a-u} & \varphi_{u-a} & 0 \\ \varphi_{a-u} & 1-\varphi_{u-a}-\varphi_{u-l} & \varphi_{l-u} \\ 0 & \varphi_{u-l} & 1-\varphi_{l-u} \end{pmatrix},$$

$$F_t = \gamma \left[f_1 + f_2 \left(m^T \mathrm{P}^t M_0 + \sum_{\tau=1}^{t} m^T \mathrm{P}^{t-\tau} E_\tau, \right) \right]$$

$$M_t = \mathrm{P}^t \cdot M_0 + \sum_{\tau=1}^{t} \mathrm{P}^{t-\tau} E_\tau,$$

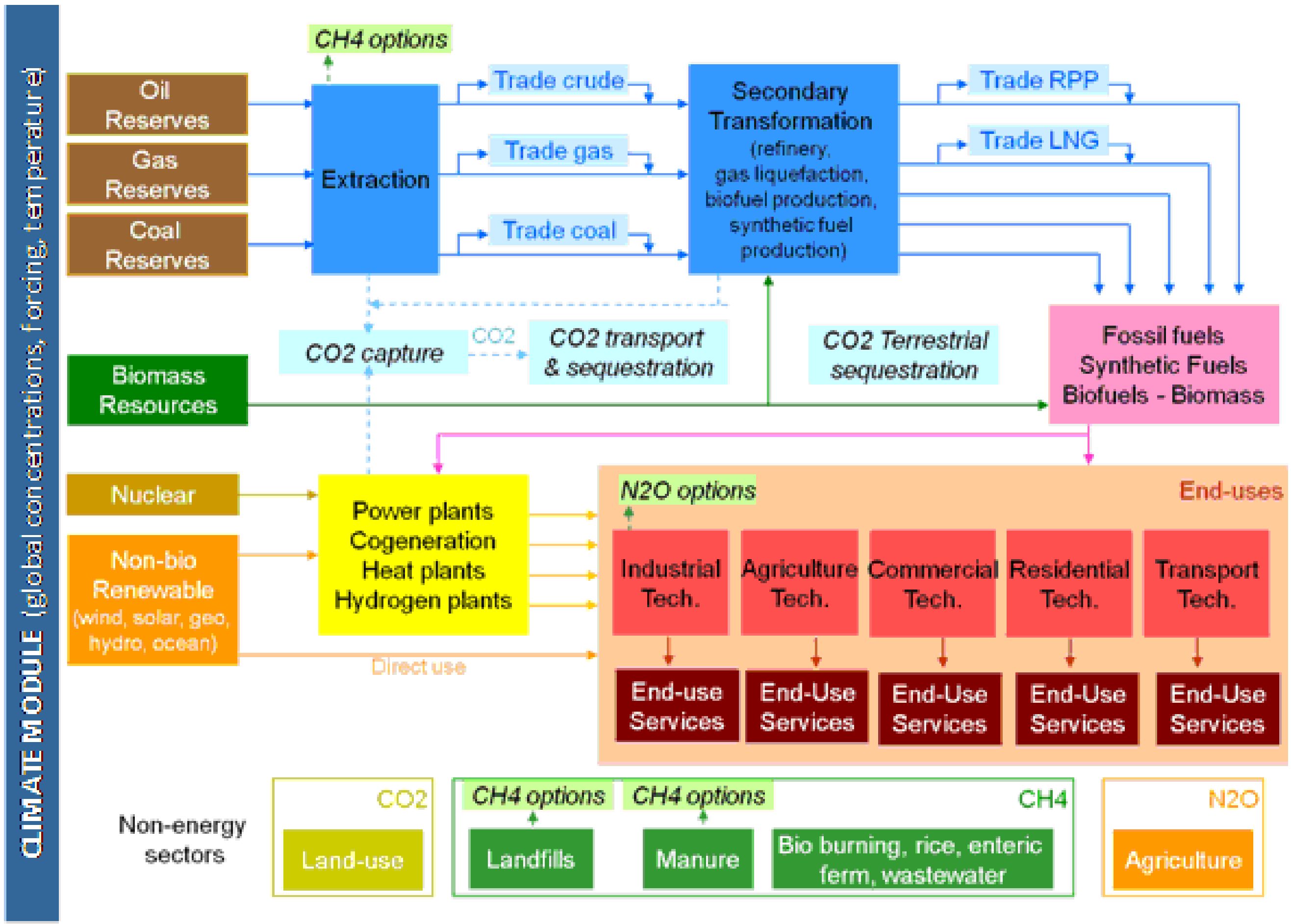
$$M_t^a = m^T M_t$$

$$\Delta T_t = S \Delta T_{t-1} + s F_t,$$

$$S = \begin{pmatrix} 1-\sigma_1(\lambda+\sigma_2) & \sigma_1\sigma_2 \\ \sigma_3 & 1-\sigma_3 \end{pmatrix}, s = \begin{pmatrix} \sigma_1 \\ 0 \end{pmatrix}$$

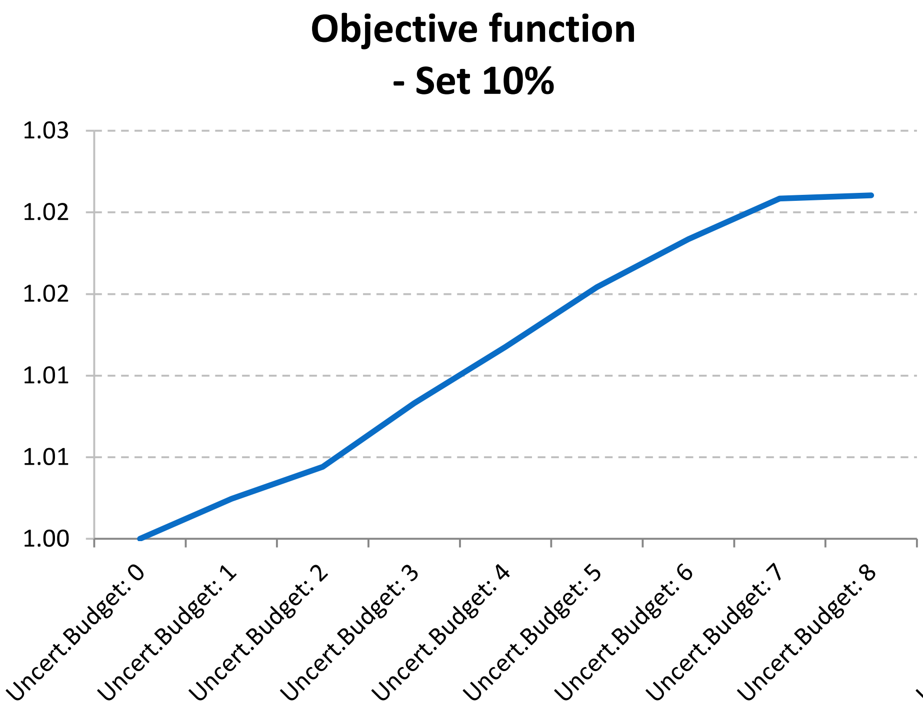
$$\Delta T_t = S^t \Delta T_0 + \sum_{\tau=1}^{t} S^{t-\tau} s F_\tau$$

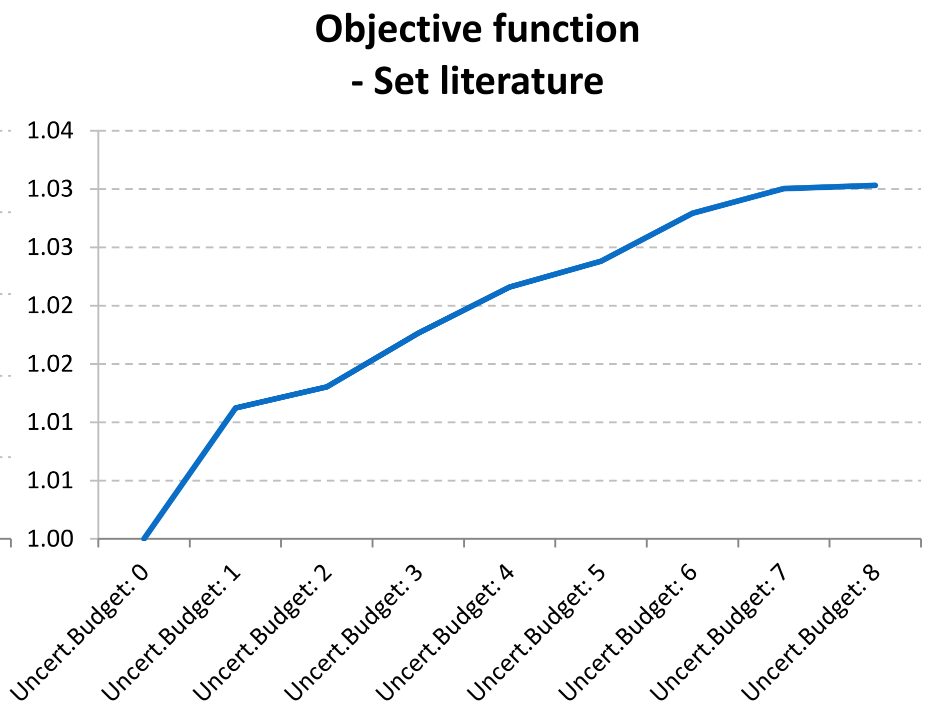
The TIAM Model



- A multi-regional and inter-temporal partial equilibrium model of the entire energy/emission system of the World
- 16 Regions
- Driven by a set of 42 demands for energy services in all sectors

Cost of robustness





Contributions

- Use of a recent technique developed in the operations research field: **robust optimization**. Application to tackle the climate module parameter uncertainty.
- This technique allows to derive robust trajectories
- And to highlight the most sensitive parameters or parameter combinations.