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science for global insight

4th International Workshop on Uncertainty in Atmospheric Emissions:

A Metric for the Prognostic Outreach of Scenarios

Learning from the Past to Establish a Standard in Applied Systems Analysis

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Krakow, Poland; 07–09 October 2015

This talk covers

1. Motivation
2. Framing conditions and definitions
3. Why diagnostic and prognostic uncertainty are different and independent
4. Learning in a prognostic context
5. Toward application: an accurate and precise system
6. Insights and outlook

1. Motivation

Our motivation is two-fold:

1. to expand Jonas *et al.* (2014) *Uncertainty in an emissions-constrained world* emerging from the 3rd (2010) Uncertainty Workshop;

2. and to contribute to the unresolved question of *How limited are prognostic scenarios?*

We are still moving at a theoretical level but we already encounter important insights and windfall profits!

1. Motivation (2)

An easy-to-apply metric or indicator is needed that informs non-experts about the time in the future at which a prognostic scenario ceases to be (for whatever reasons) in accordance with the system’s past.

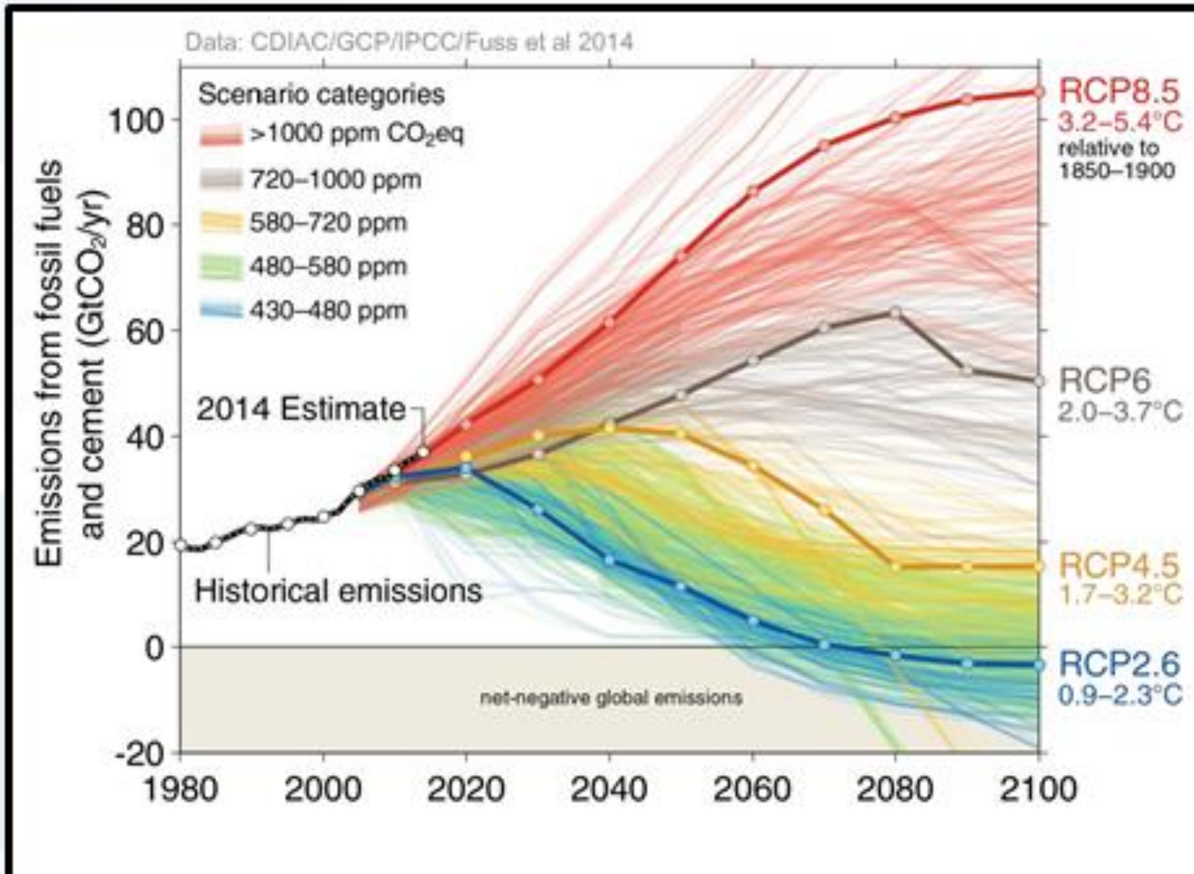
This indicator should be applicable in treating a system / model coherently (from beginning to end)!

1. Motivation (2)

An easy-to-apply metric or indicator is needed that informs n ... e at which a p ... whatever reasons) ... .

This indica ... em / model coh ...

Example:



Over 1000 scenarios from the IPCC Fifth Assessment Report are shown
Source: Fuss et al 2014; CDIAC; Global Carbon Budget 2014

1. Motivation (1)

Jonas *et al.* (2014):
The mode of bridging diagnostic and prognostic uncertainty across temporal scales relies on two discrete points in time: ‘today’ and 2050.

Now we want to become continuous ...

1. Motivation (1)

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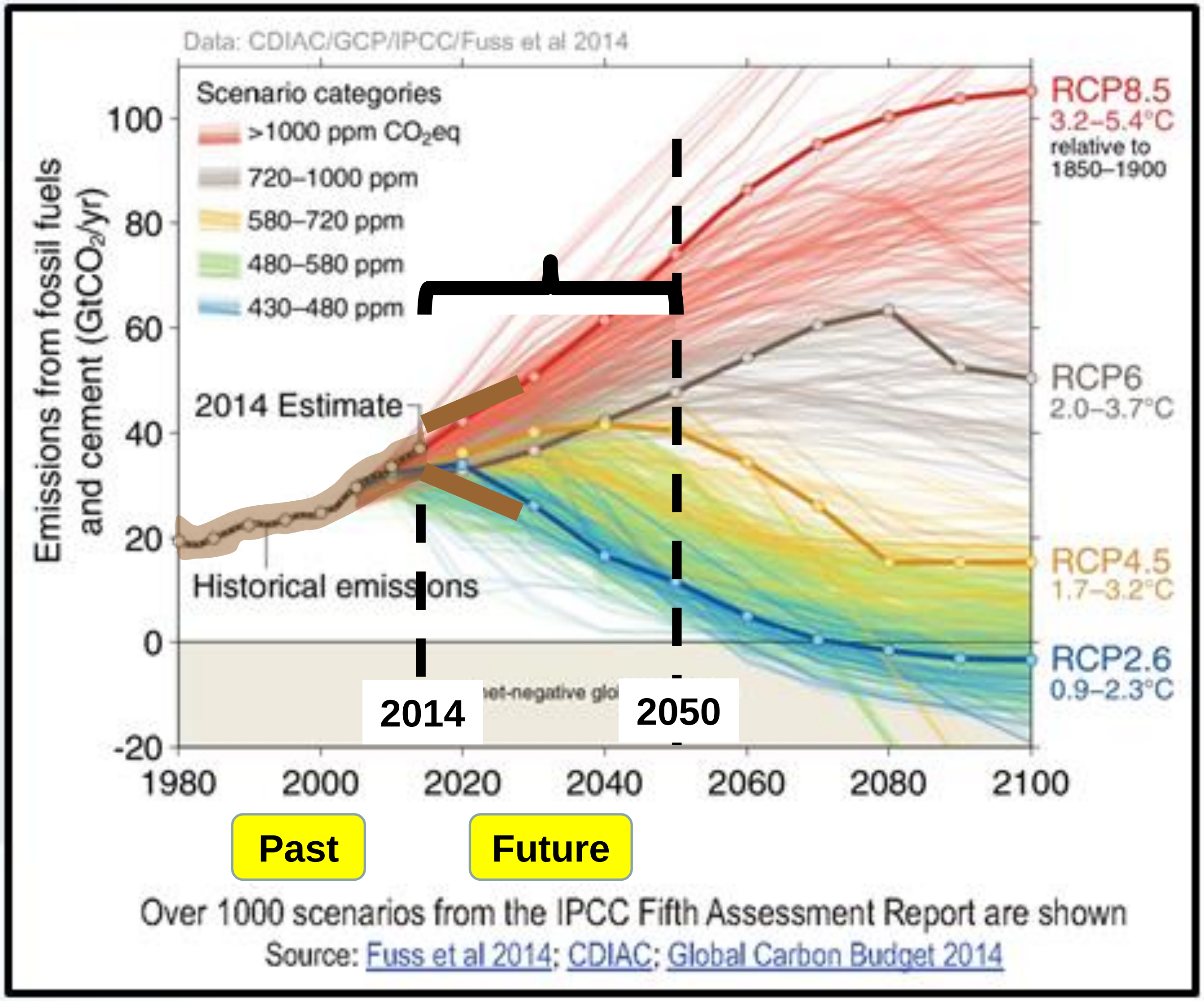
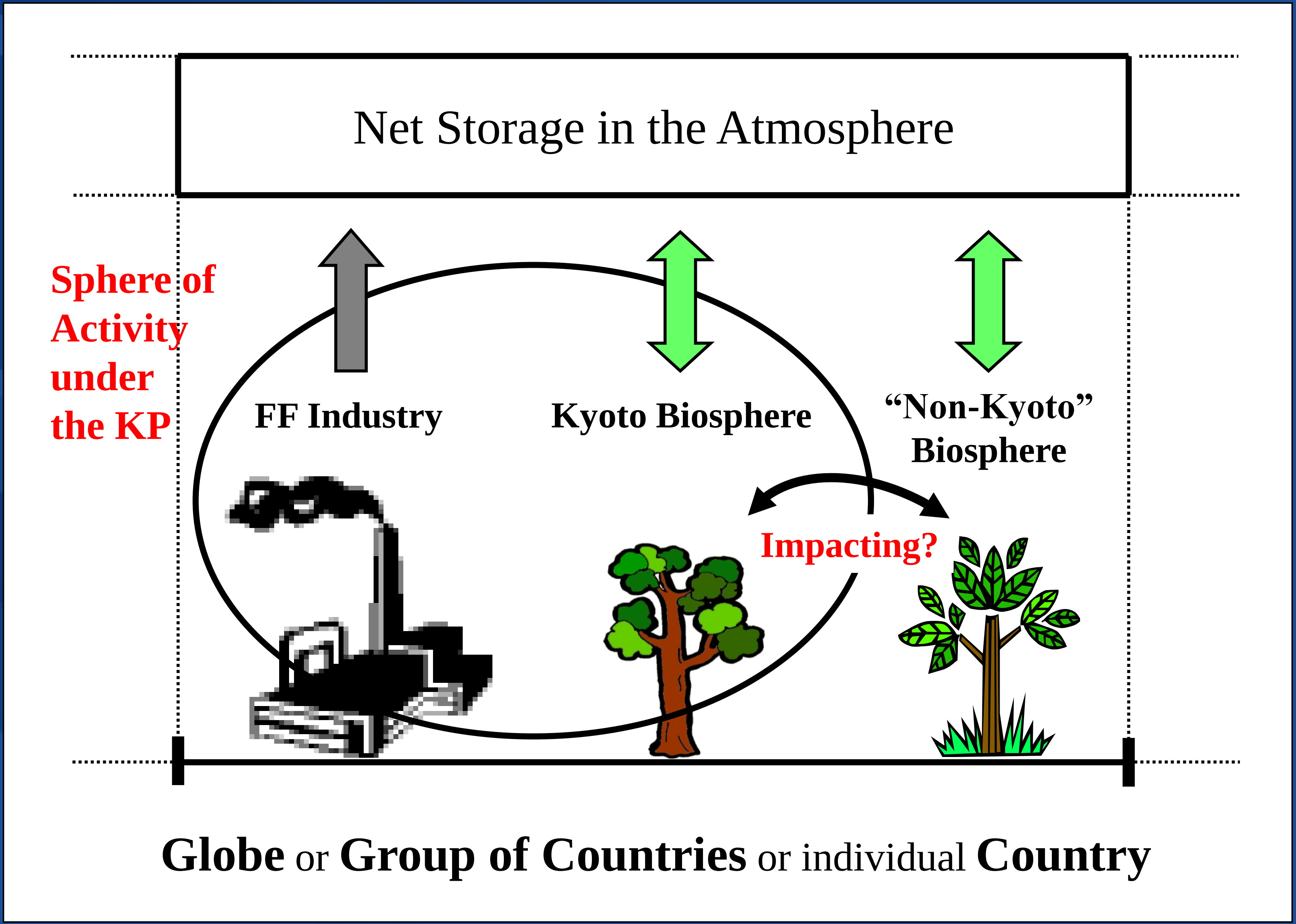
Now we

Example:

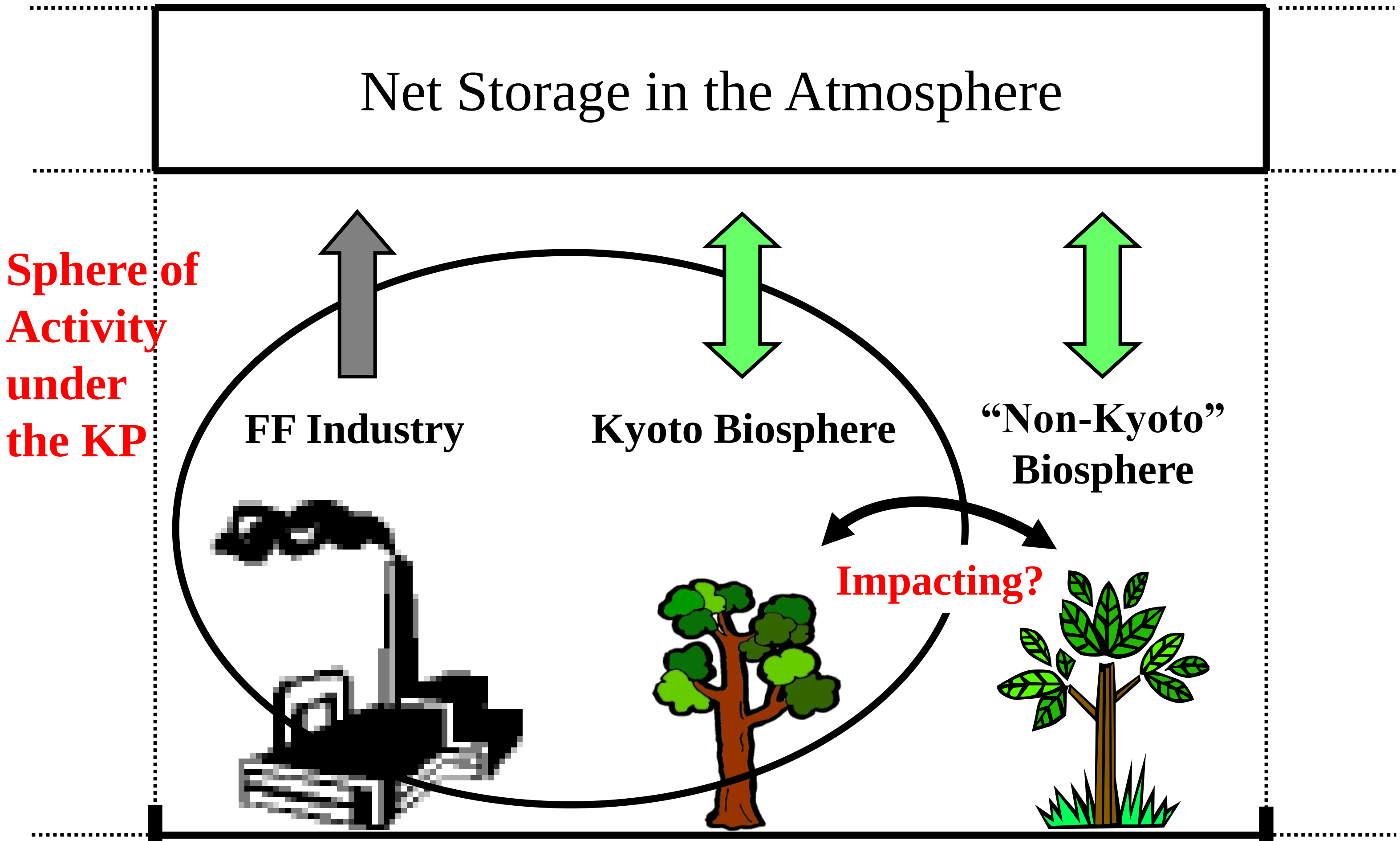


2. Framing conditions and definitions



Jonas and Nilsson (2007: Fig. 4); modified

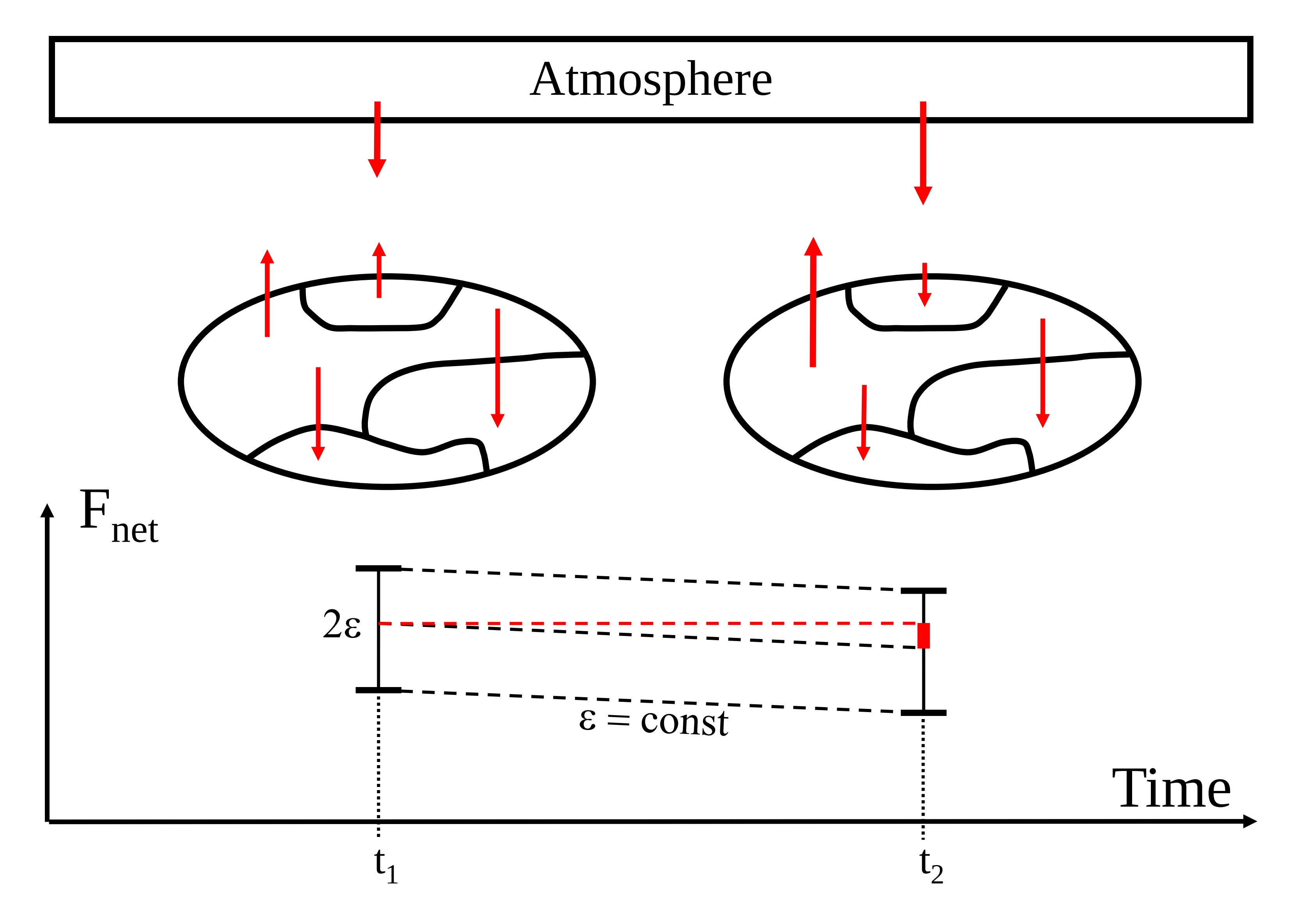
2. Framing conditions and definitions



Only F_{FF_C}, F_{terr_C} and F_{oc_C} can be discriminated top-down globally!

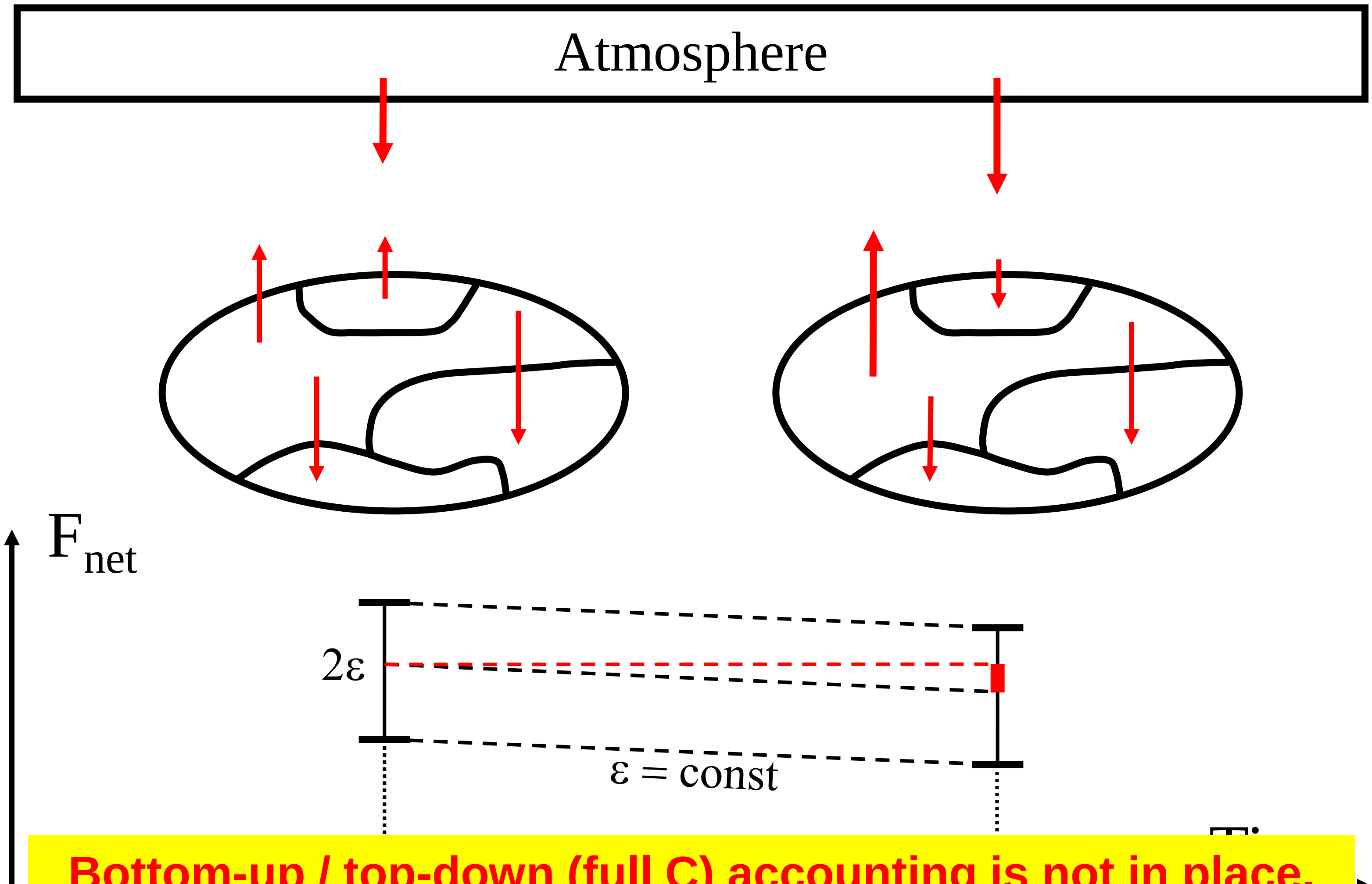
Jonas and Nilsson (2007: Fig. 4); modified

2. Framing conditions and definitions



Jonas and Nilsson (2007: Fig. 6); modified

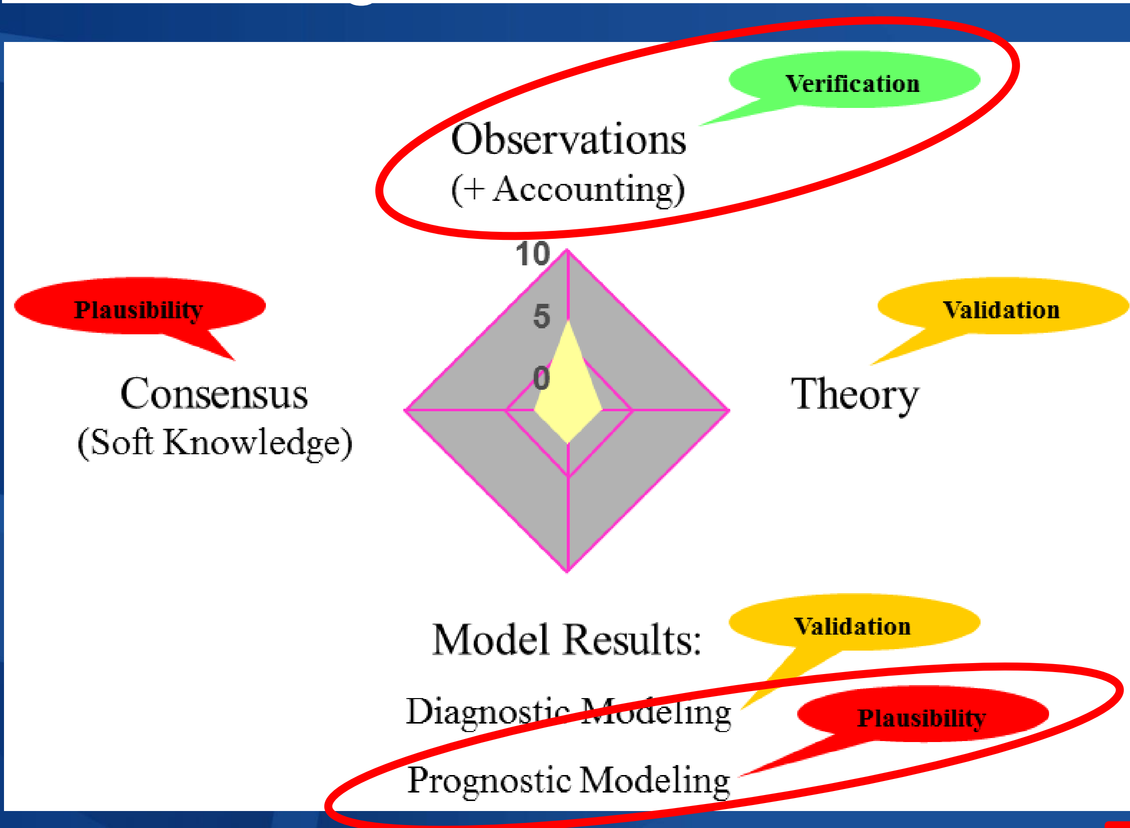
2. Framing conditions and definitions

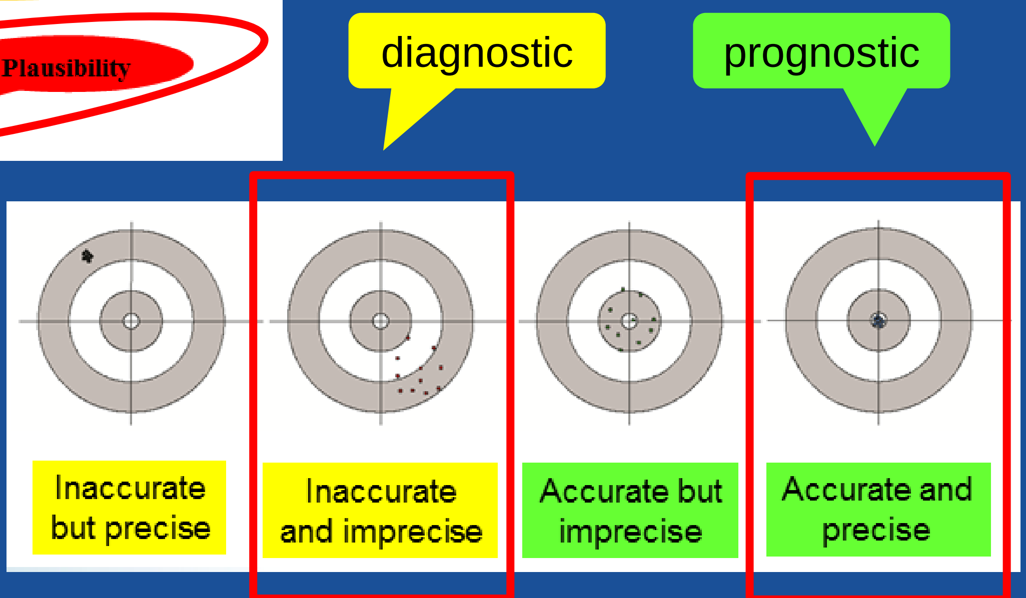


Bottom-up / top-down (full C) accounting is not in place.
We cannot yet verify ΔC fluxes at the country scale!

Jonas and Nilsson (2007: Fig. 6); modified

2. Framing conditions and definitions





Moss & Schneider (2000: Fig. 5; see also Giles, 2002); IPCC (2006: Vol. 1, Fig. 3.2)

3. Diagnostic vs prognostic uncertainty

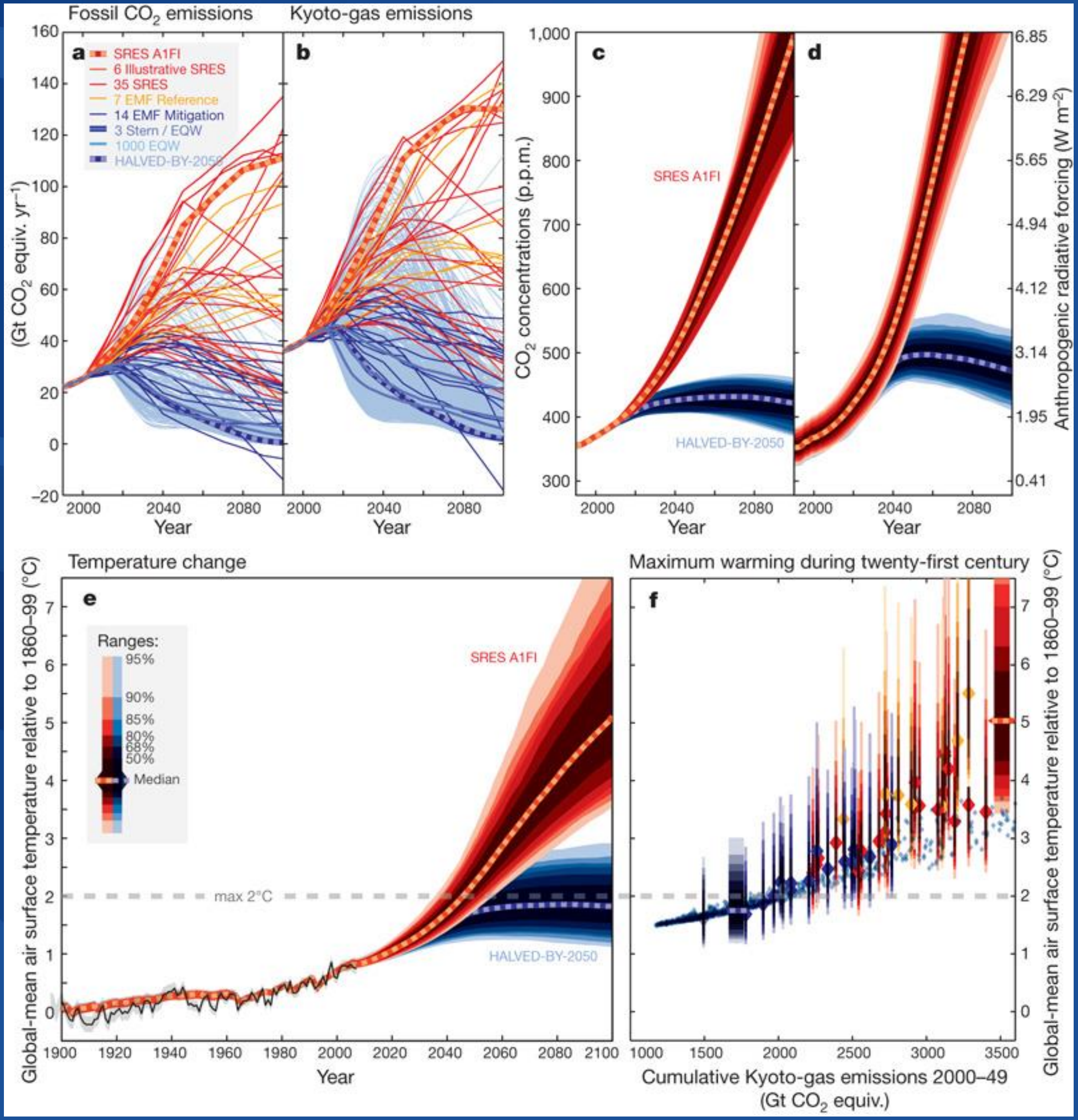
Diagnostic uncertainty

→ can **increase** or **decrease** depending on whether or not our knowledge of accounting emissions becomes more accurate and precise!

Prognostic uncertainty

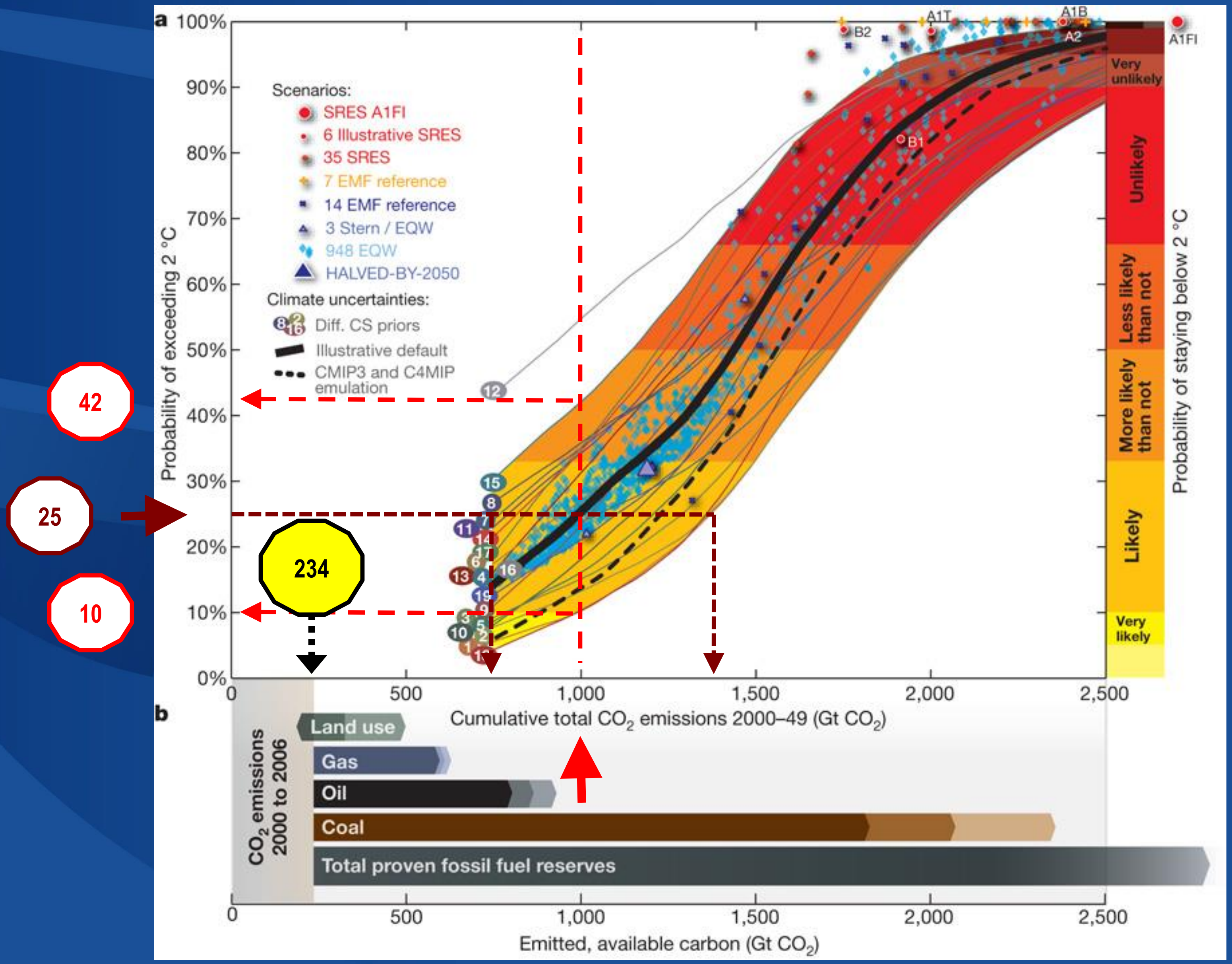
→ under a prognostic scenario **always increases** with time!

3. Diagnostic vs prognostic uncertainty



Meinshausen *et al.* (2009: Fig. 2)

3. Diagnostic vs prognostic uncertainty



Meinshausen *et al.* (2009: Fig. 3)

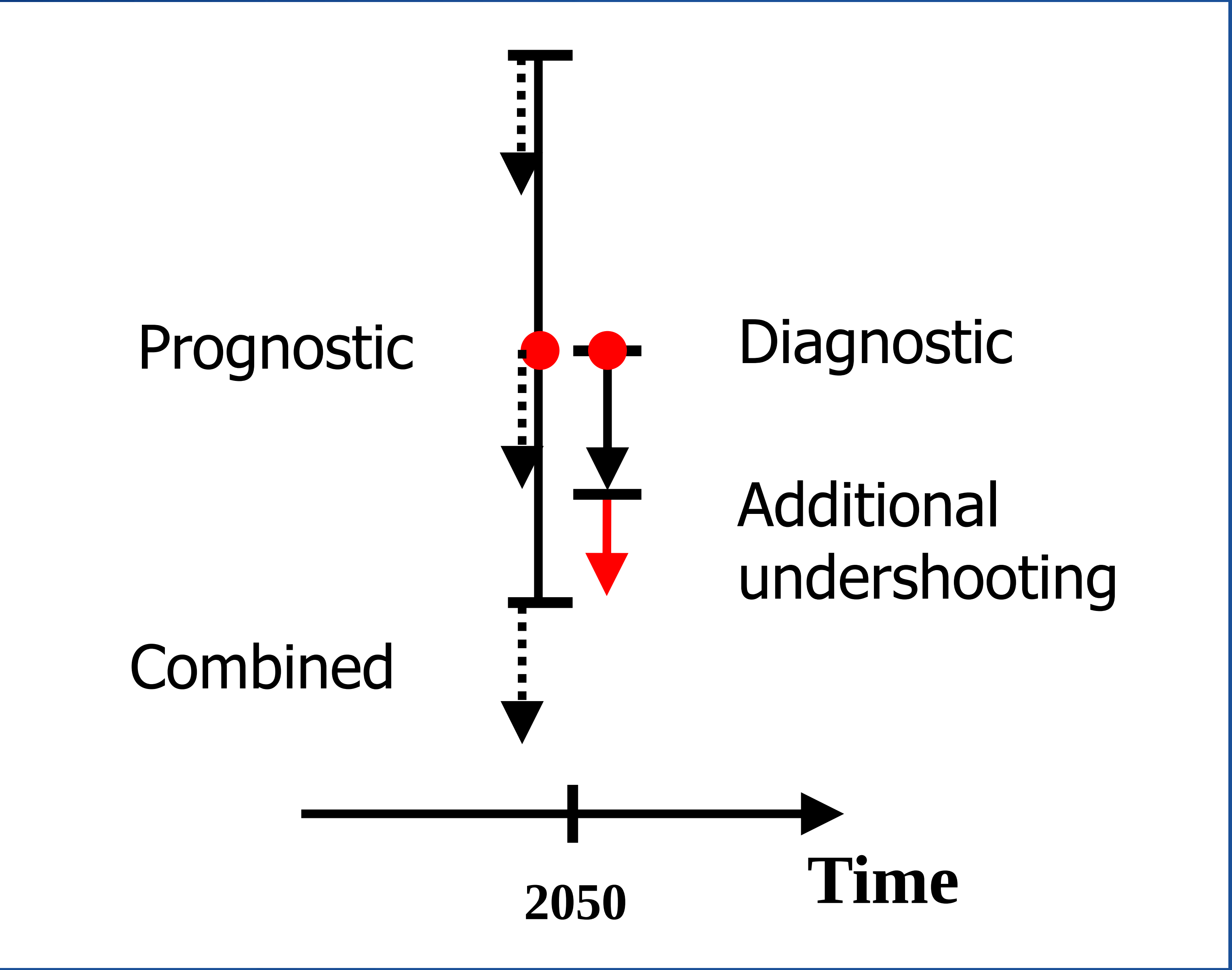
3. Diagnostic vs prognostic uncertainty

Probability of exceeding 2 °C:

Indicator	Emissions	Probability of exceeding 2 °C*	
		Range	Illustrative default case†
Cumulative total CO_2 emission 2000–49	886 Gt CO_2	8–37%	20%
	1,000 Gt CO_2	10–42%	25%
	1,158 Gt CO_2	16–51%	33%
	1,437 Gt CO_2	29–70%	50%
Cumulative Kyoto-gas emissions 2000–49	1,356 Gt CO_2 equiv.	8–37%	20%
	1,500 Gt CO_2 equiv.	10–43%	26%
	1,678 Gt CO_2 equiv.	15–51%	33%
	2,000 Gt CO_2 equiv.	29–70%	50%
2050 Kyoto-gas emissions	10 Gt CO_2 equiv. yr^{-1}	6–32%	16%
	(Halved 1990) 18 Gt CO_2 equiv. yr^{-1}	12–45%	29%
	(Halved 2000) 20 Gt CO_2 equiv. yr^{-1}	15–49%	32%
	36 Gt CO_2 equiv. yr^{-1}	39–82%	64%
2020 Kyoto-gas emissions	30 Gt CO_2 equiv. yr^{-1}	(8–38%)†	(21%)†
	35 Gt CO_2 equiv. yr^{-1}	(13–46%)†	(29%)†
	40 Gt CO_2 equiv. yr^{-1}	(19–56%)†	(37%)†
	50 Gt CO_2 equiv. yr^{-1}	(53–87%)†	(74%)†

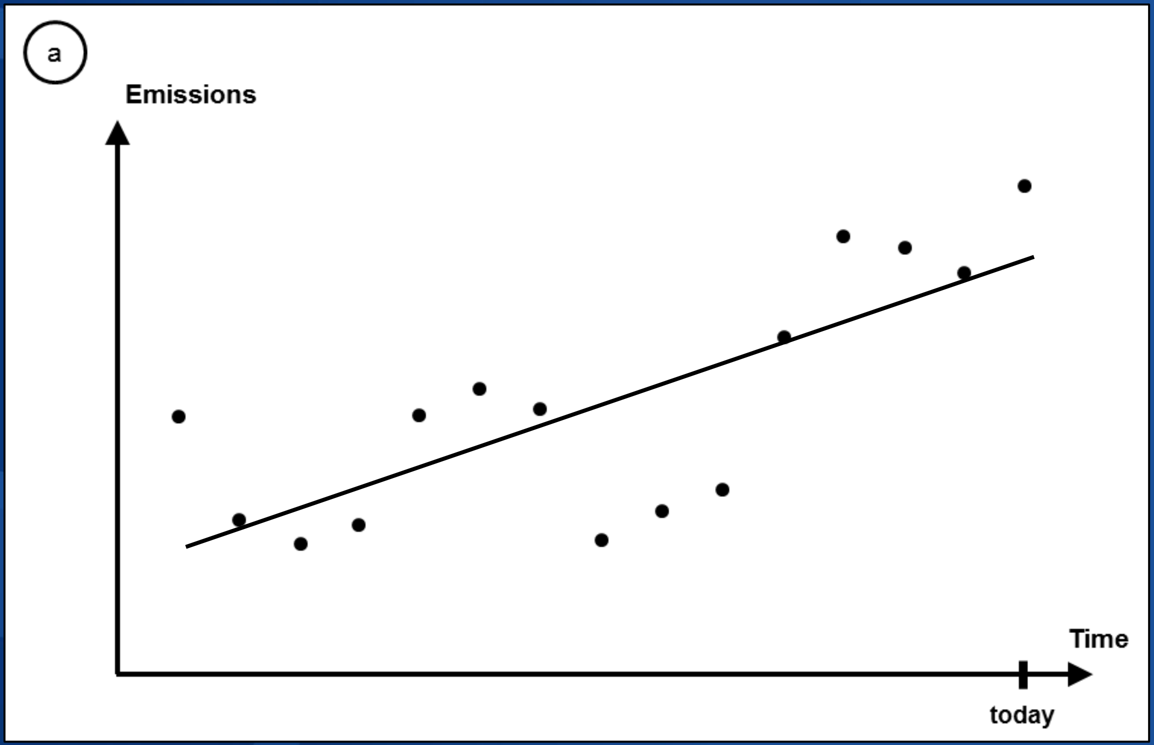
Meinshausen *et al.* (2009: Tab. 1)

3. Diagnostic and prognostic uncertainty

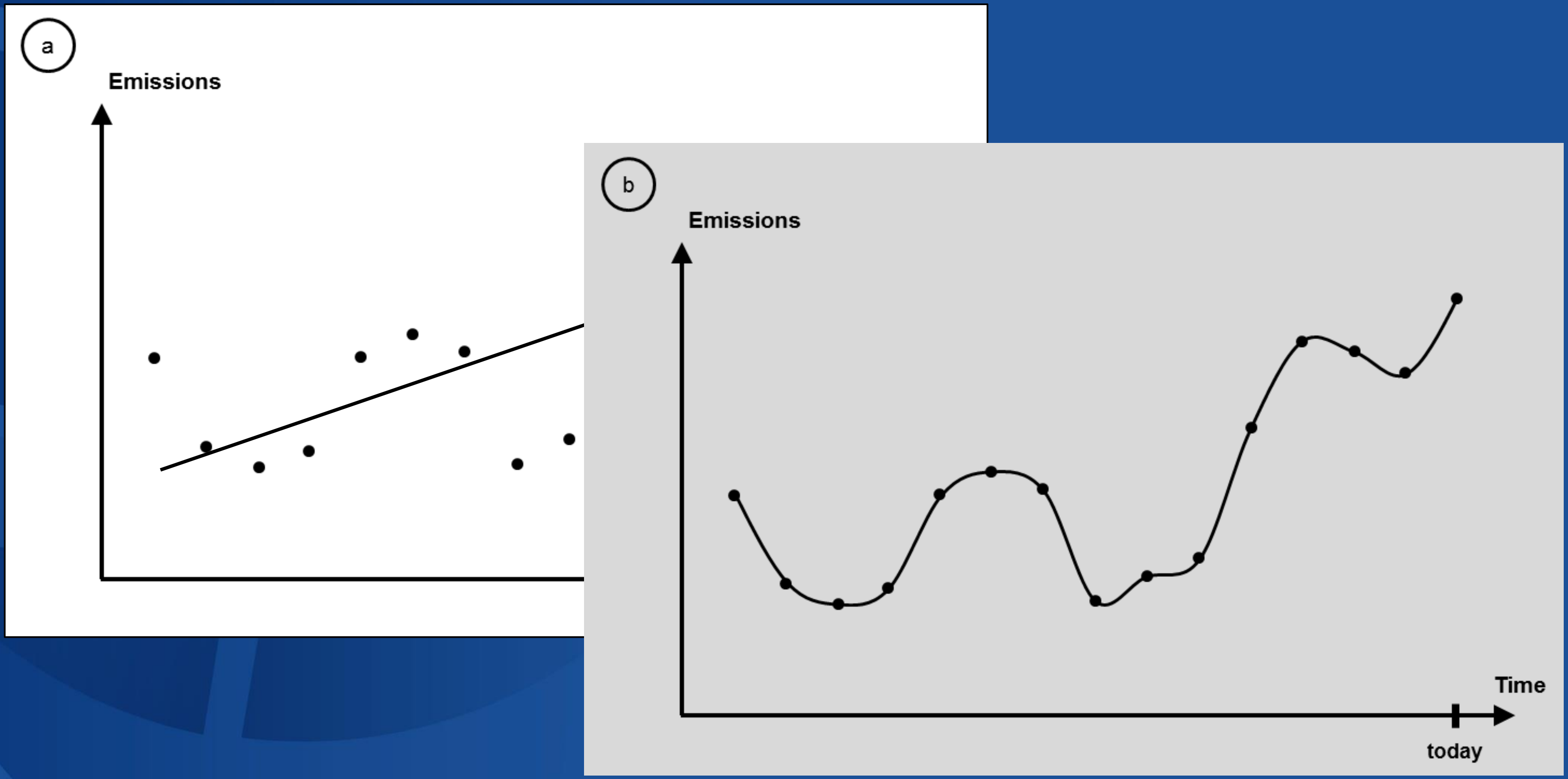


Massari Coelho *et al.* (2012: Fig. 10)

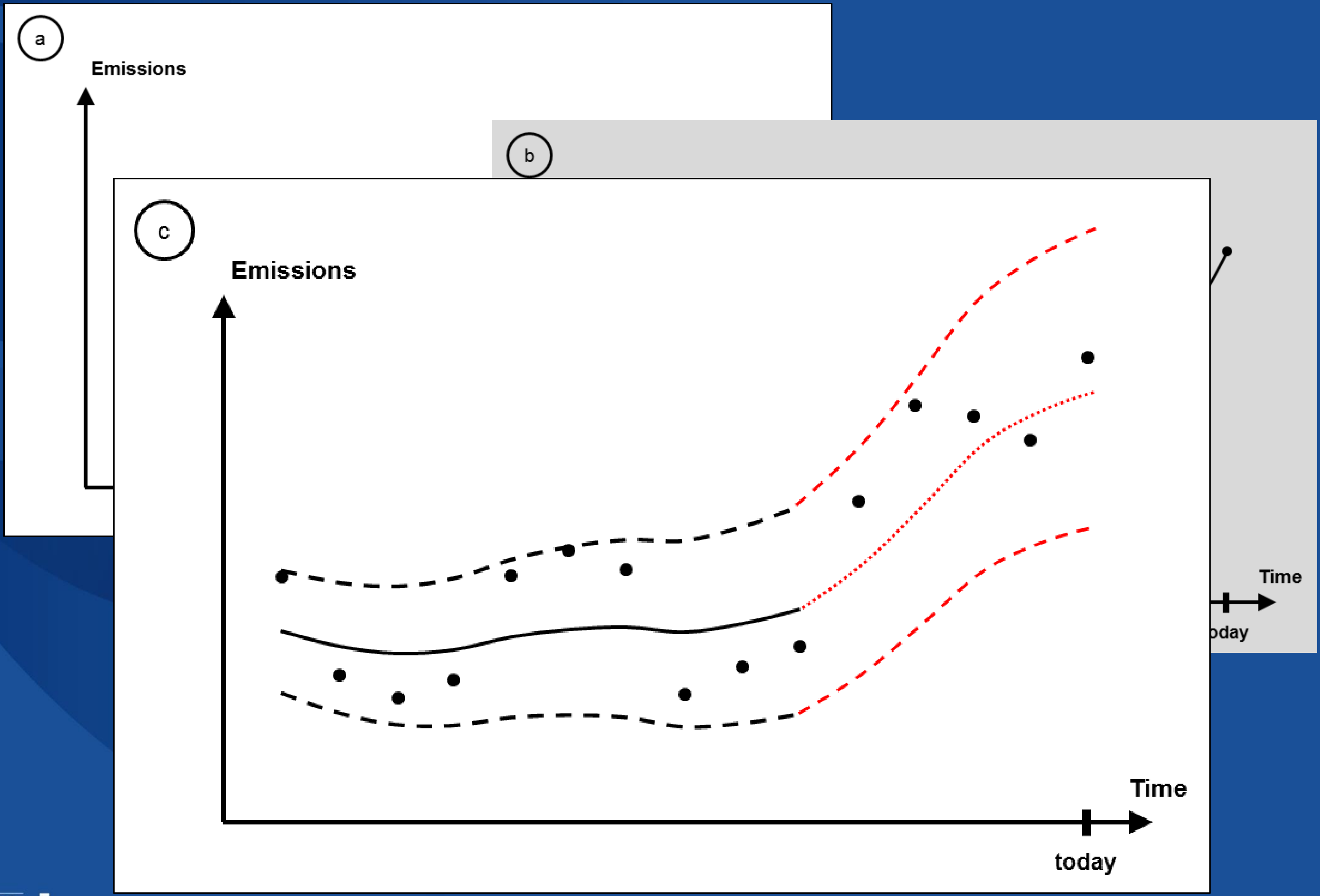
4. Learning in a prognostic context



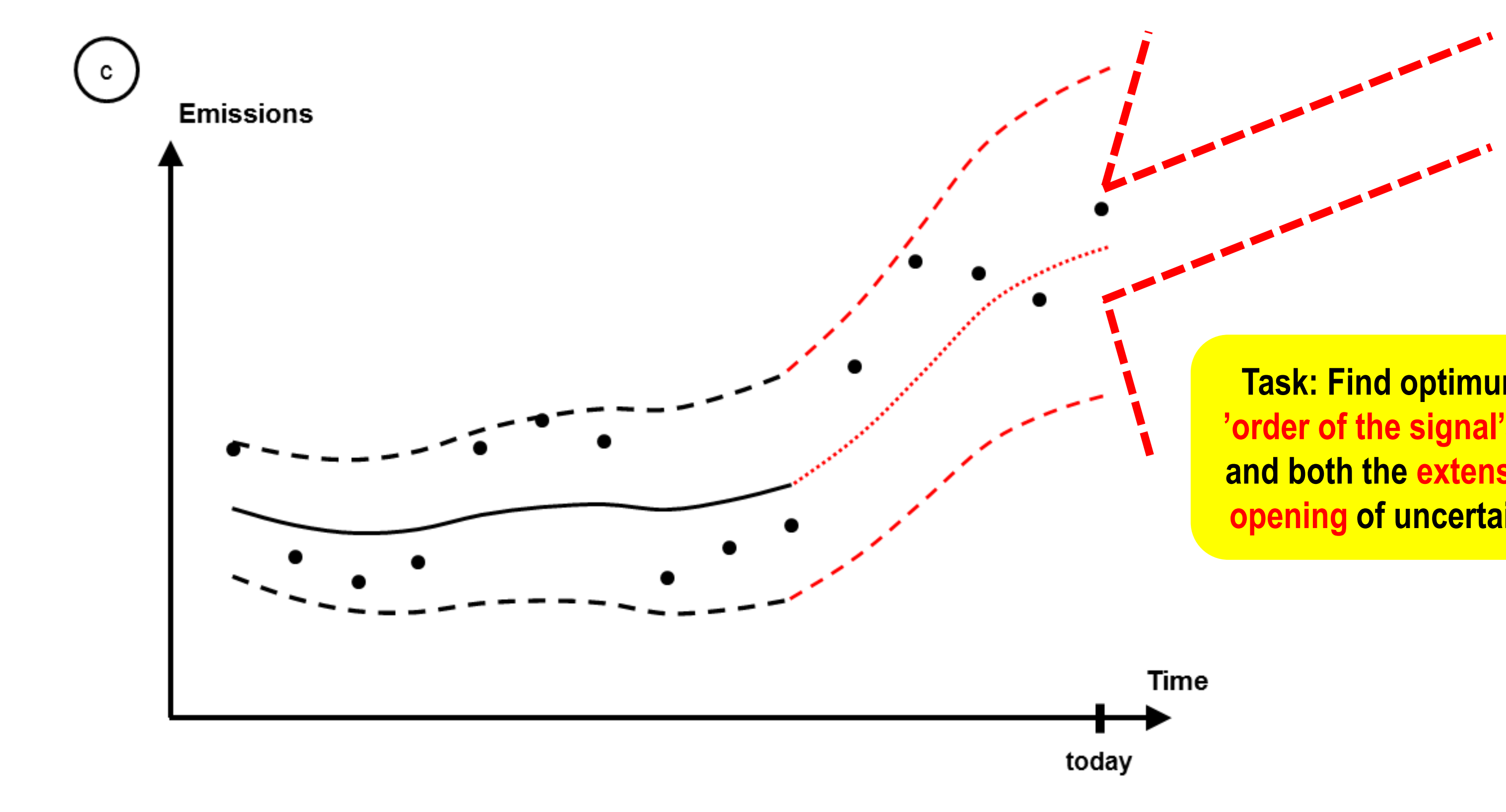
4. Learning in a prognostic context



4. Learning in a prognostic context

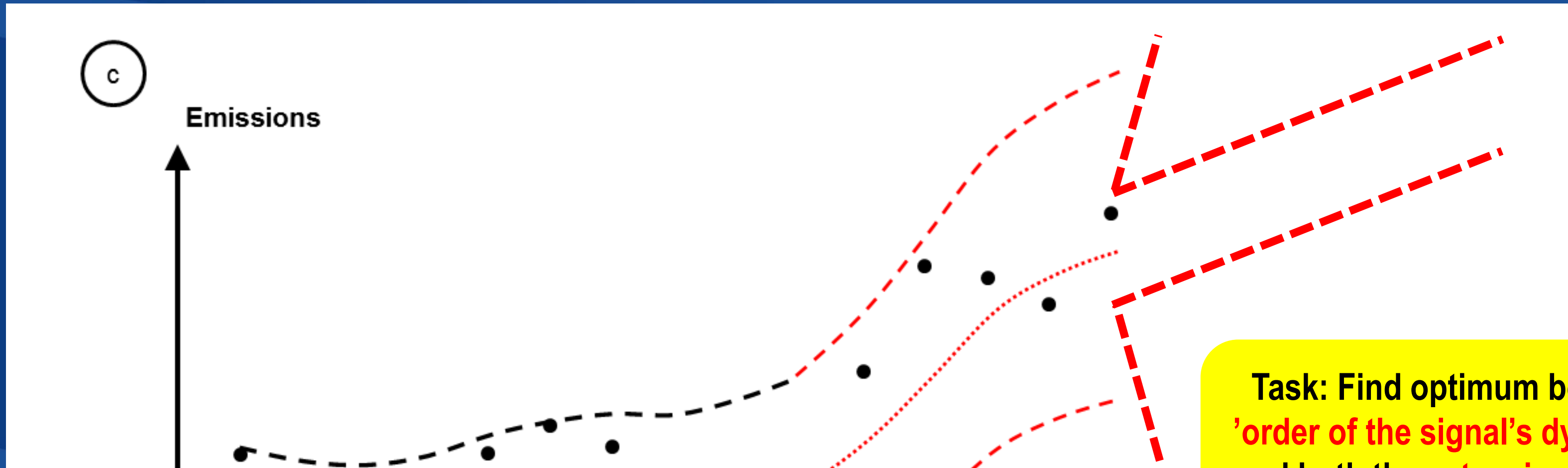


4. Learning in a prognostic context



Task: Find optimum between 'order of the signal's dynamics' and both the extension and the opening of uncertainty wedge!

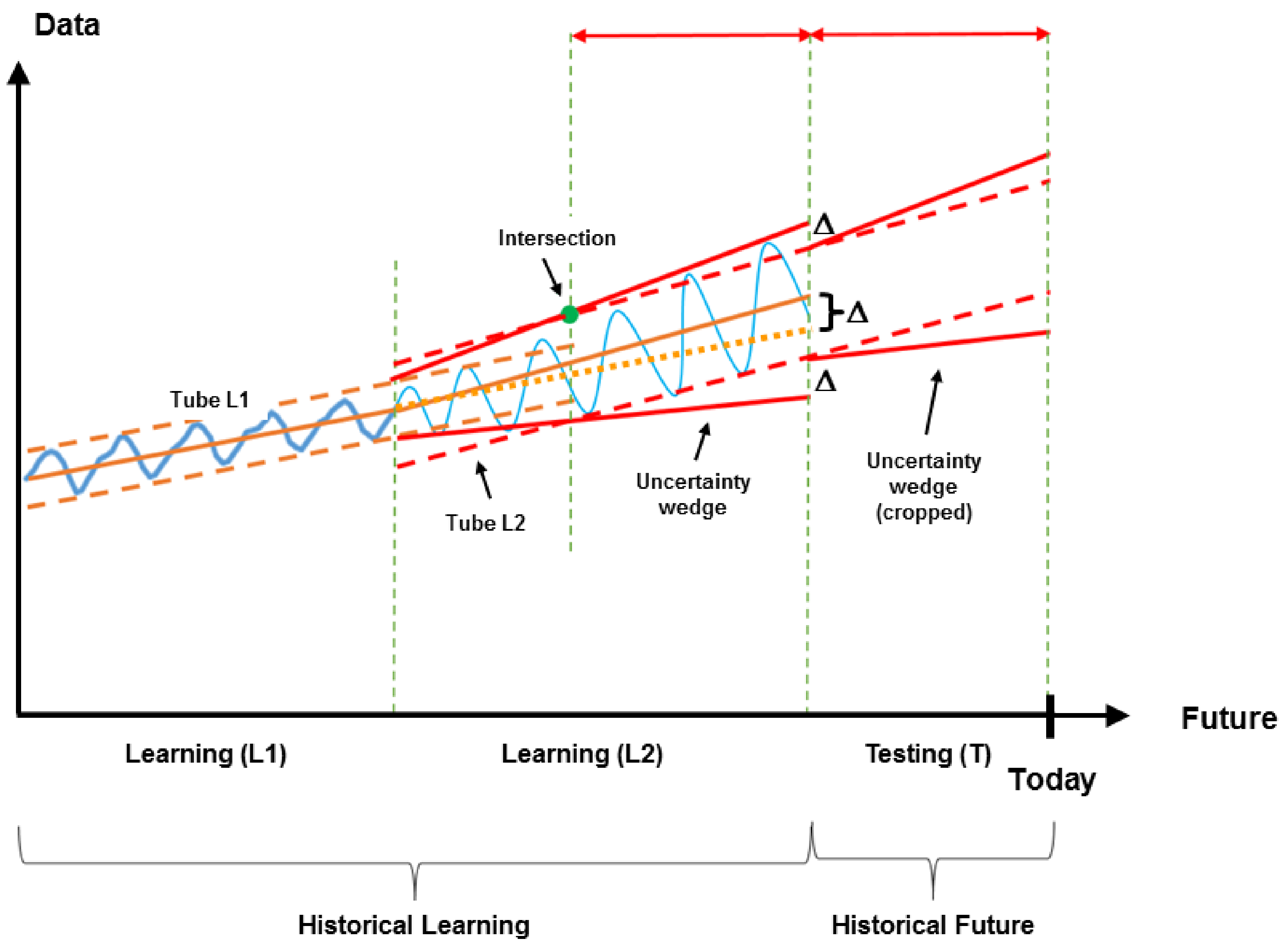
4. Learning in a prognostic context



Task: Find optimum between
’order of the signal’s dynamics’
... and the
... inty wedge!

		Uncertainty (Precision)	
		With	Without
Learning (L) / Forecasting (F)	No	✓ (F)	✓ (F)
	Yes	? (L)	? (L)

4. Learning in a prognostic context



Andriana (2015:Slide 15); modified

5. Toward application: accurate + precise system

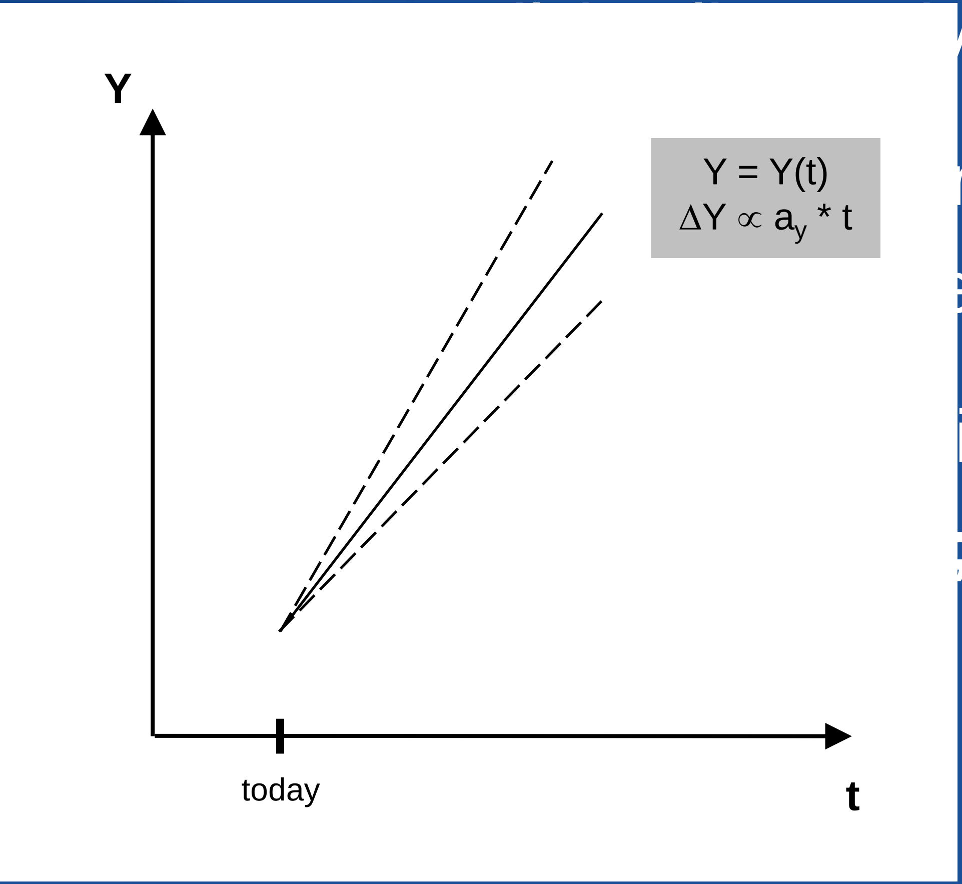
Assume that we have learned from a RL exercise

- that each historical data record has a memory and exhibits (but not necessarily) a linear dynamics;
- that each data record's uncertainty (learning) wedge unfolds linearly into the future (until when?);
- and that our data records exhibit linear inter-dependencies [eg: T = T(C) ; C = C(E) ; E = E(t)]

5. Toward application: accurate + precise system

Assume that we have learned from a RL exercise

- that each historical data record has a memory and exhibits (b… …ynamics;
- that each … …rning) wedge unfolds lin… …en?);
- and that ou… …inter-dependen… …; E = E(t)]



5. Toward application: accurate + precise system

$$E(t) \rightarrow C(t) \rightarrow T(t)$$

$$E = m_{Et}t\,; \quad C = m_{Ct}t\,; \quad T = m_{Tt}t$$

$$E_u = f_u m_{Et} t$$

$$E_l = f_l m_{Et} t$$

$$\Delta E = \Delta f_{Et} m_{Et} t = \Delta f_{Et} E$$

$$\sigma_E^2 = \left(\frac{\partial E}{\partial m_{Et}}\right)^2 \sigma_{m_{Et}}^2 + \left(\frac{\partial E}{\partial t}\right)^2 \underbrace{\sigma_t^2}_{=\,0} \Rightarrow \quad \sigma_E^2 = \sigma_{m_{Et}}^2 t^2$$

$$\Delta E = 2\sigma_E = 2\sigma_{m_{Et}} t = \Delta f_{Et} m_{Et} t = \Delta f_{Et} E$$

$$\Delta f_{Et} = \frac{\Delta E}{E} = 2\frac{\sigma_E}{E} = 2\frac{\sigma_{m_{Et}}}{m_{Et}}$$

We merge an accurate-precise system with classical statistics!

Δf_{Et} combines Unc (learn) + Dyn (mem) knowledge!

5. Toward application: accurate + precise system

Similarly for $C = C(t)$:

$$C = m_{Ct} t$$

$$T = m_{Tt} t$$

The linearly interdependent cases $C = C(E)$ and $T = T(C) = T(C(E))$:

$$C = m_{CE} E = m_{CE} m_{Et} t = m_{Ct} t;$$

$$T = m_{TC} C = m_{TC} m_{CE} E = m_{TC} m_{CE} m_{Et} t = m_{Tt} t$$

Find:

$$\Delta E = \Delta f_{Et} m_{Et} t = \Delta f_{Et} E$$

$$\Delta C = \Delta f_{Ct} m_{Ct} t = \Delta f_{CT} C = \sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2}\, C$$

$$\Delta T = \Delta f_{Tt} m_{Tt} t = \Delta f_{Tt} T = \sqrt{\Delta f_{TC}^2 + \Delta f_{CE}^2 + \Delta f_{Et}^2}\, T$$

...

That is:

$$\Delta f_{Ct} = \sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2},$$

$$\Delta f_{Tt} = \sqrt{\Delta f_{TC}^2 + \Delta f_{CE}^2 + \Delta f_{Et}^2}$$

...

5. Toward application: accurate + precise system

Similarly for $C = C(t)$:

Function	Variance	Standard Deviation
$f = aA$	$\sigma_f^2 = a^2\sigma_A^2$	$\sigma_f = a\sigma_A$
$f = aA + bB$	$\sigma_f^2 = a^2\sigma_A^2 + b^2\sigma_B^2 + 2ab\,\sigma_{AB}$	$\sigma_f = \sqrt{a^2\sigma_A^2 + b^2\sigma_B^2 + 2ab\,\sigma_{AB}}$
$f = aA - bB$	$\sigma_f^2 = a^2\sigma_A^2 + b^2\sigma_B^2 - 2ab\,\sigma_{AB}$	$\sigma_f = \sqrt{a^2\sigma_A^2 + b^2\sigma_B^2 - 2ab\,\sigma_{AB}}$
$f = AB$	$\sigma_f^2 \approx f^2\left[\left(\frac{\sigma_A}{A}\right)^2 + \left(\frac{\sigma_B}{B}\right)^2 + 2\frac{\sigma_{AB}}{AB}\right]$	$\sigma_f \approx \lvert f\rvert\sqrt{\left(\frac{\sigma_A}{A}\right)^2 + \left(\frac{\sigma_B}{B}\right)^2 + 2\frac{\sigma_{AB}}{AB}}$
$f = \frac{A}{B}$	$\sigma_f^2 \approx f^2\left[\left(\frac{\sigma_A}{A}\right)^2 + \left(\frac{\sigma_B}{B}\right)^2 - 2\frac{\sigma_{AB}}{AB}\right]$ [11]	$\sigma_f \approx \lvert f\rvert\sqrt{\left(\frac{\sigma_A}{A}\right)^2 + \left(\frac{\sigma_B}{B}\right)^2 - 2\frac{\sigma_{AB}}{AB}}$
$f = aA^b$	$\sigma_f^2 \approx \left(abA^{b-1}\sigma_A\right)^2 = \left(\frac{fb\sigma_A}{A}\right)^2$	$\sigma_f \approx \left\lvert abA^{b-1}\sigma_A\right\rvert = \left\lvert\frac{fb\sigma_A}{A}\right\rvert$
$f = a\ln(bA)$	$\sigma_f^2 \approx \left(a\frac{\sigma_A}{A}\right)^2$ [12]	$\sigma_f \approx \left\lvert a\frac{\sigma_A}{A}\right\rvert$
$f = a\log_{10}(A)$	$\sigma_f^2 \approx \left(a\frac{\sigma_A}{A\ln(10)}\right)^2$ [12]	$\sigma_f \approx \left\lvert a\frac{\sigma_A}{A\ln(10)}\right\rvert$
$f = ae^{bA}$	$\sigma_f^2 \approx f^2\left(b\sigma_A\right)^2$ [13]	$\sigma_f \approx \lvert f\left(b\sigma_A\right)\rvert$
$f = a^{bA}$	$\sigma_f^2 \approx f^2\left(b\ln(a)\sigma_A\right)^2$	$\sigma_f \approx \lvert f\left(b\ln(a)\sigma_A\right)\rvert$
$f = A^B$	$\sigma_f^2 \approx f^2\left[\left(\frac{B}{A}\sigma_A\right)^2 + \left(\ln(A)\sigma_B\right)^2 + 2\frac{B\ln(A)}{A}\sigma_{AB}\right]$	$\sigma_f \approx \lvert f\rvert\sqrt{\left(\frac{B}{A}\sigma_A\right)^2 + \left(\ln(A)\sigma_B\right)^2 + 2\frac{B\ln(A)}{A}\sigma_{AB}}$

$$\Delta f_{Ct} = \sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2}\,,$$

Source: http://en.wikipedia.org/wiki/Propagation_of_uncertainty

$$\Delta f_{Tt} = \sqrt{\Delta f_{TC}^2 + \Delta f_{CE}^2 + \Delta f_{Et}^2}$$

…

5. Toward application: accurate + precise system

To understand this result, look at $C = C(E)$, for which we found:

$$\Delta f_{Ct} = \sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2}$$

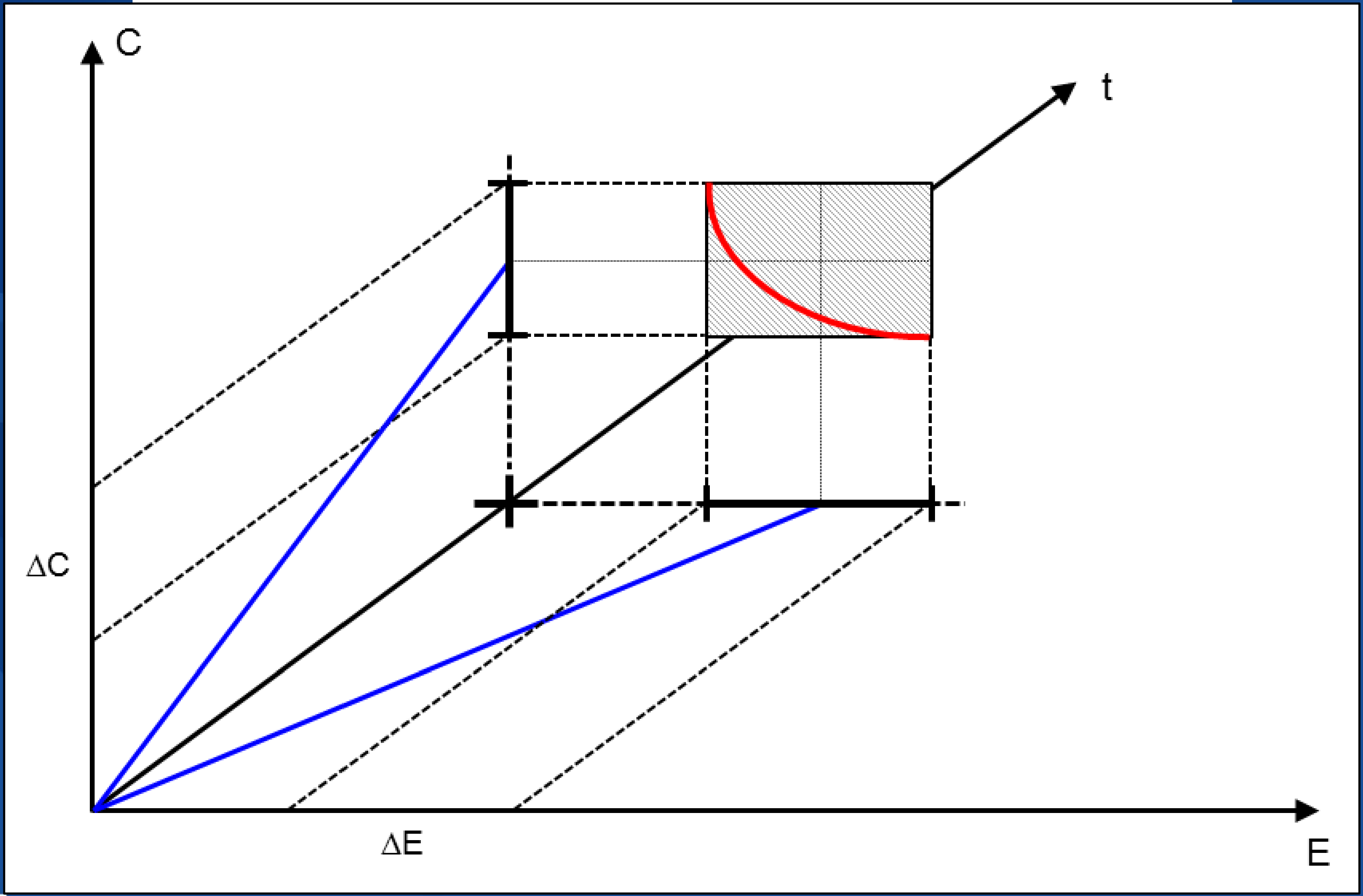
Rewrite as

$$\Delta f_{CE}^2 + \Delta f_{Et}^2 - \Delta f_{Ct}^2 = 0 \quad \leftrightarrow \quad \frac{x^2}{a^2} + \frac{y^2}{b^2} - \frac{z^2}{c^2} = 0$$

which describes a second-order cone:

5. Toward application: accurate + precise system

To understand this result, look at $C = C(E)$, for which we found:



5. Toward application: accurate + precise system

Serial-parallel interdependence:

$$\begin{matrix} E_1 & \rightarrow & C_1 \\ E_2 & \rightarrow & C_2 \end{matrix} \rightarrow T$$

Deriving Δf_{Tt} is easy and straightforward (particularly in the case of uncorrelated variables)!

The analytical expression for Δf_{Tt} also holds for a system, where the second emissions source (E_2) is replaced by a sink (R: removal):

$$\begin{matrix} E & \rightarrow & C_1 \\ R & \rightarrow & C_2 \end{matrix} \rightarrow T$$

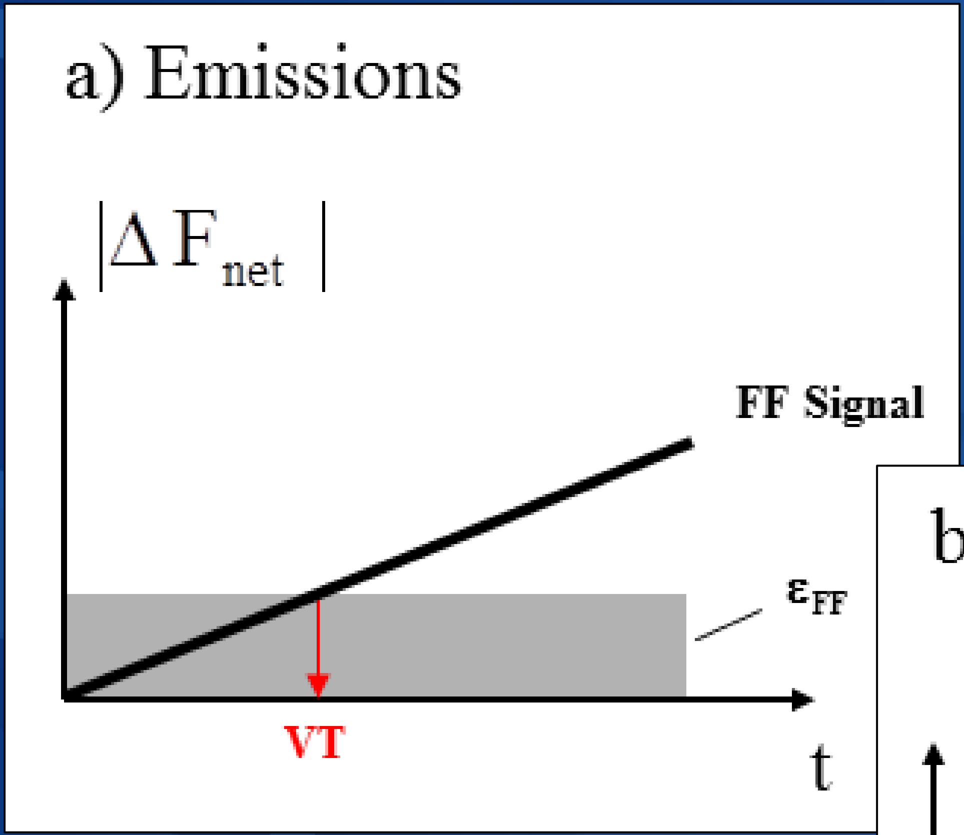
This is a game changer that has not so far been considered!

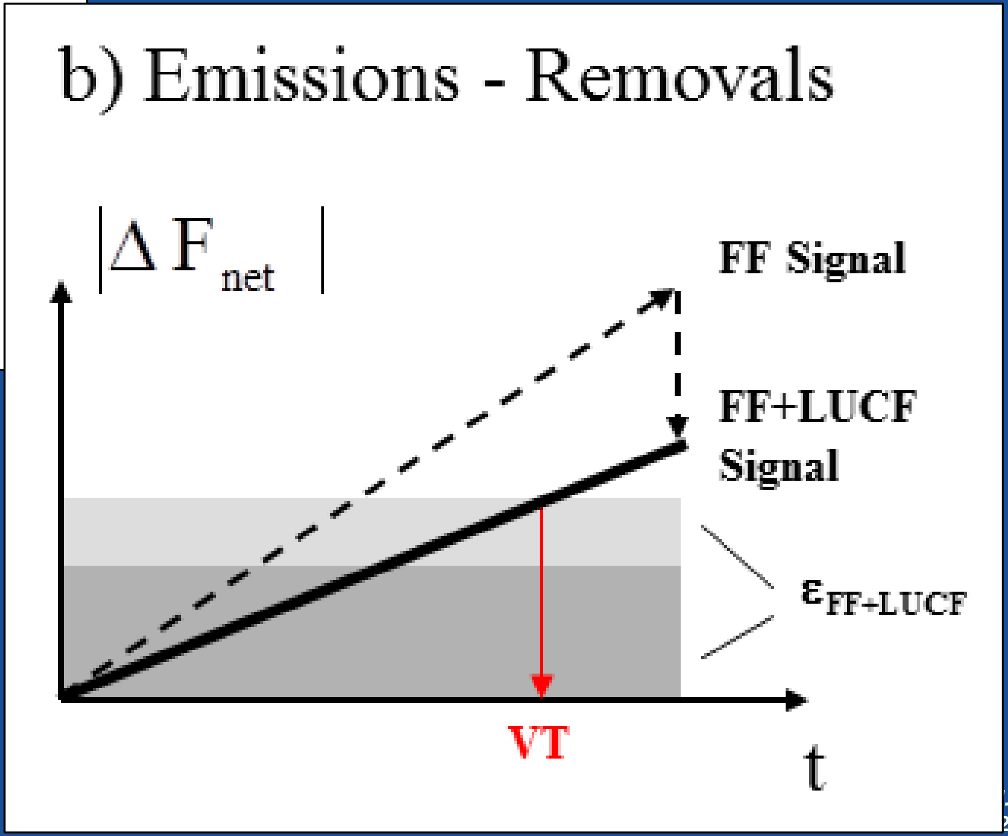
meaning that the learning does not change while the two systems differ:

$$C = C_1 + C_2 \quad \text{versus} \quad C = C_1 - C_2 \, .$$

That is, a sink reduces a source but their uncertainties still add up!

5. Toward application: accurate + precise system





Jonas &Nilsson (2007: Fig. 9); modified

6. Insights and outlook

1. The risk of exceeding a 2050 global temperature target (eg, 2 ^{o}C) appears to be greater than assessed by the IPCC!

The correct approach would have been to deal with cumulated emissions and removals individually to determine their combined risk of exceeding the agreed temperature target.

RL allows exactly this to be done: RL overcomes this shortfall and allows the effect of learning about emissions and removals individually to be grasped.

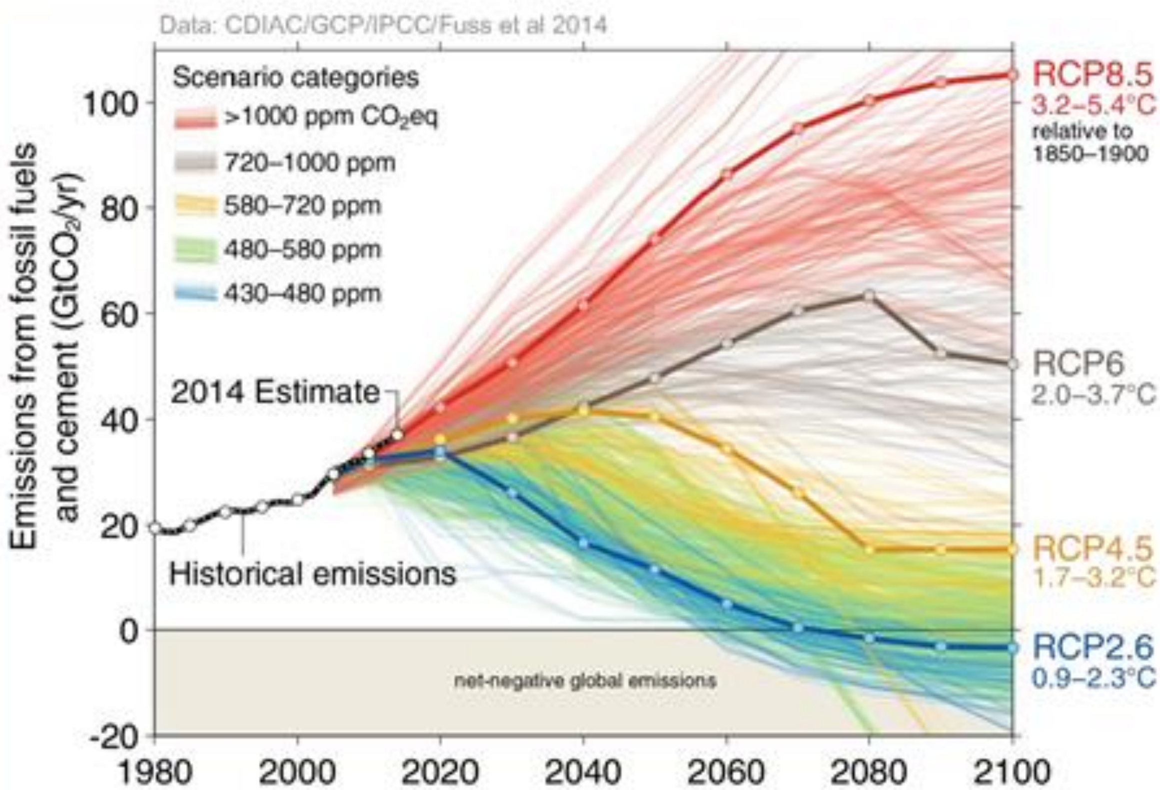
6. Insights and outlook

Example:

1. The risk … target (eg, 2 ºC) … the IPCC!

The correc… …mulated emissions … combined risk of exce…

RL allows … shortfall and allows … removals individually…



Over 1000 scenarios from the IPCC Fifth Assessment Report are shown
Source: Fuss et al 2014; CDIAC; Global Carbon Budget 2014

6. Insights and outlook

2. We anticipate that, in the case of success, the way of constructing prognostic models and conducting systems analysis will have to meet certain quality standards:

- Better diagnostic data handling (retrospective learning)!
- Specifying the models' outreach limits!
- Safe-guarding complex models by means of meta-models which fulfill the above!

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