4th International Workshop
on Uncertainty in Atmospheric Emissions
7-9 October 2015, Krakow, Poland

PROCEEDINGS

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About the Workshop

The assessment of greenhouse gases and air pollutants (indirect GHGs) emitted to and removed from the atmosphere is high on the political and scientific agendas. Building on the UN climate process, the international community strives to address the long-term challenge of climate change collectively and comprehensively, and to take concrete and timely action that proves sustainable and robust in the future. Under the umbrella of the UN Framework Convention on Climate Change, mainly developed country parties to the Convention have, since the mid-1990s, published annual or periodic inventories of emissions and removals, and continued to do so after the Kyoto Protocol to the Convention ceased in 2012. Policymakers use these inventories to develop strategies and policies for emission reductions and to track the progress of those strategies and policies. Where formal commitments to limit emissions exist, regulatory agencies and corporations rely on emission inventories to establish compliance records.

However, as increasing international concern and cooperation aim at policy-oriented solutions to the climate change problem, a number of issues circulating around uncertainty have come to the fore, which were undervalued or left unmentioned at the time of the Kyoto Protocol but require adequate recognition under a workable and legislated successor agreement. Accounting and verification of emissions in space and time, compliance with emission reduction commitments, risk of exceeding future temperature targets, evaluating effects of mitigation versus adaptation versus intensity of induced impacts at home and elsewhere, and accounting of traded emission permits are to name but a few.

The *4th International Workshop on Uncertainty in Atmospheric Emissions* is jointly organized by the *Systems Research Institute of the Polish Academy of Sciences*, the Austrian-based *International Institute for Applied Systems Analysis*, and the *Lviv Polytechnic National University*. The 4th Uncertainty Workshop follows up and expands on the scope of the earlier Uncertainty Workshops – the *1st Workshop* in 2004 in Warsaw, Poland; the *2nd Workshop* in 2007 in Laxenburg, Austria; and the *3rd Workshop* in 2010 in Lviv, Ukraine.

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A metric for the prognostic outreach of scenarios: Learning from the past to establish a standard in applied systems analysis

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Abstract

Our study concerns retrospective learning, the characteristic feature of which is that prognostic uncertainty increases the more the further we look into the future. RL seeks to establish a metric for the outreach of prognostic scenarios. The purpose behind RL is to provide an easy-to-apply indicator, which informs non-experts about the time in the future at which a prognostic scenario ceases to be in accordance (for whatever reasons) with the system's past. Ideally, this indicator should be derived concomitantly with building a prognostic model. RL concerns the limitations of predictions and prognostic scenarios.

Keywords: Greenhouse gas emissions, emission inventories, emission scenarios, diagnostic uncertainty, prognostic uncertainty, learning

1. Introduction

Evaluating the performance of climate forecasts is becoming increasingly relevant [1]. At its heart this evaluation aims at judging the credibility of climate projections and quantifying the uncertainty in these projections [2–3]. In our study, which builds on (what we term) **retrospective learning** [RL], we take the opposite view.

RL seeks to establish a metric for the outreach of prognostic scenarios. The purpose behind RL is to provide an easy-to-apply indicator, which informs non-experts about the time in the future at which a prognostic scenario ceases to be in accordance (for whatever reasons) with the system's past. Ideally, this indicator should be derived concomitantly with building a prognostic model. In brief, RL concerns the limitations of predictions and prognostic scenarios.

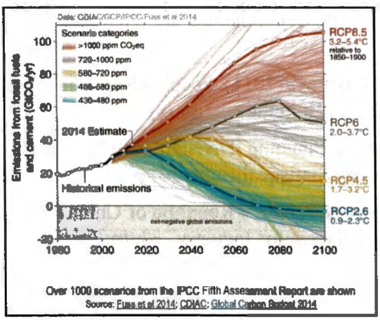


Figure 1. Historical and projected global fossil-fuel (CO_2) emissions, including emissions from cement production [4].

Figure 1 is a classical illustration of how quickly and strongly prognostic scenarios deviate from historical records. The figure shows historical and projected global CO_2 emissions resulting from fossil-fuel burning and cement production. From a purely intuitive perspective, only the highest emission scenarios appear to be in accordance with the historical record (until when?), but not the lower ones.

2. Motivation

From a theoretical point of view, we argue that the mathematical tools and techniques needed to quantify the outreach of prognostic scenarios based on learning from the past (that is, to apply RL) **are available**. However, the necessary epistemological insights to apply these tools and techniques properly, including outside their traditional context, are missing. The first statement (tools and techniques are available) is bold; while the second (knowledge to apply tools and techniques outside their traditional context is missing) is not new. Developing the first statement is subject to this paper. The second statement is at the core of empirical inference science, which is a maturing paradigm. Empirical inference science aims at complementing classical statistics in *Estimating dependencies on the basis of empirical data ... a central problem in applied analysis* [5: vii].

From a practical point of view, we argue that deriving the aforementioned indicator exhibits most interesting windfall profits: 1) We anticipate that generating the indicator while building a model will lead us onto new paths of constructing models and conducting systems analysis (i.e., towards a new standard of 'good modeling'). 2) Our insights in RL will allow the chance of complying with—or the risk of exceeding—agreed global warming targets to be corrected. We conjecture that the risk of exceeding 2050 global warming targets ranging between 2 to 4 °C and greater is underestimated. We will return to these two issues at the end of our paper.

3. Terminology

We explain the difference between diagnostic and prognostic uncertainty, the two terms at the core of our paper, in Section 5.1 below. Their definitions will provide the basis for understanding the difference between learning in a diagnostic and prognostic context and the other terms (e.g., 'prediction' and 'forecast') that we use.

4. Status quo

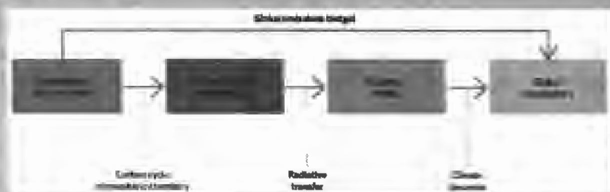
Since their inception, climate treaty negotiations have set out to stabilize Earth's climate by implementing mechanisms that reduce global greenhouse gas [GHG] emissions and lead to sustainable management of the atmosphere at a 'safe' steady-state level (assumed to hold for an increase in global average temperature of below 2 °C above preindustrial levels). In recent years, international climate policy has taken a step beyond achieving GHG concentration-related objectives by increasingly focusing on limiting temperature rise [6]. The idea of limiting cumulative global GHG emissions by adhering to a long-term global warming target was first discussed broadly and publicly by policymakers at the 2009 United Nations climate change conference in Copenhagen. It appears to be a promising and robust methodology [7–12] (cf. also Box 1). To comply with it, the emission reductions required from the fossil-fuel and land use/land-use change sector are daunting: 50%–85% below the 1990 global annual emissions, with even greater reductions for industrialized countries [13–15]. The underlying assumptions are equally daunting: terrestrial or oceanic sinks continuing to offset fossil-fuel and LUC emissions before achieving an emissions balance that goes beyond CO_2-C (i.e., CO_2-equivalents also including CH_4, N_2O, etc.), with no systemic surprises occurring during the transition process. In particular, the imperative followed for net emissions from LUC activities is that these will be reduced linearly to zero until 2050. That is, it is assumed that deforestation and other LU mismanagement will cease and that net emissions balance.

Box 1. Relationship between GHG emissions and global surface temperature [16: Fig. 3.2; 17].

The magnitude of an increase in global surface temperature is not determined by emissions in any one year, but by the concentration of GHGs in the atmosphere which, in turn, is the net outcome of total emissions and removals of GHGs to and from the atmosphere over an extended period.

Global emission budgets estimate the total amount of (net) GHG emissions that will result in a given temperature increase, within a probability range. This is why cumulative emissions (e.g., between today and 2050) are perceived as a good predictor for this temperature increase (e.g., in 2050 and beyond). That is, the emissions budget approach allows linking cumulative emissions of GHGs directly to temperature, without determining atmospheric concentrations of GHGs and their radiative forcing as intermediary observables (see figure below). The relationship between cumulative emissions and temperature is expressed as a probability, to reflect uncertainty of the climate response to a given amount of GHG emissions.

While global emission budgets identify the overall limit on global emissions, they do not prescribe the timing of peak emissions or the rate at which emissions must be reduced, so long as the overall budget is not breached. There will be a number of trajectories that could lead to the budgeted level of cumulative emissions and the related (but uncertain because trajectory-dependent) temperature increase over time. Because the emissions budget is ultimately fixed, however, delays in reducing emissions must be compensated with more rapid GHG emission reductions in future years.



In their study [15] Jonas *et al.* discuss diagnostic (retrospective: looking back in time) and prognostic (prospective: looking forward in time) uncertainty in an emissions-temperature-uncertainty [ETU] framework that allows any country to understand its national and near-term mitigation and adaptation efforts in a globally consistent and long-term context (worldwide coverage; warming range of 2–4 °C). To achieve this understanding, national linear emission target paths were established (from 1990 to 2050 or, alternatively, from 2000 to 2050) that are consistently embedded globally. In this systems context, cumulative emissions until 2050 are constrained and globally binding but are uncertain (i.e., they can be estimated only imprecisely); and whether or not compliance with an agreed temperature target in 2050 and beyond will be achieved is also uncertain. In a nutshell, the ETU framework can be used to monitor a country's performance—past as well as prospective achievements—in complying with a future warming target in a quantified uncertainty-risk context (cf. Box 2). The authors' objective, in particular, was to understand the relevance of diagnostic and prognostic uncertainty in this global emissions-temperature setting and across temporal scales. Although the mode of bridging uncertainty across temporal scales still relies on discrete points in time ('today' and 2050) and is not yet continuous, the authors' study provides a valuable first step toward that objective.

Box 2. Output features of the ETU framework [15; adapted].

The output of the ETU framework provides national linear target paths for emissions, which are consistently embedded globally,

- for two temporal (predictor) regimes: 1990–2050 and 2000–2050;
- for CO_2 and all six Kyoto GHGs (cumulative);
- for individual spheres: technosphere and land use land-use change;
- for three 2050 temperature targets: 2, 3 and 4 °C; and
- which allow monitoring Austria's performance—past (with and without embodied emissions) as well as projected achievements—in complying with these warming targets;

while accounting for both diagnostic uncertainty (which relates to the risk that true GHG emissions are greater than inventoried emission estimates reported in a specified year) and prognostic uncertainty (which relates to the risk that an agreed 2050 temperature target is exceeded)

5. Diagnostic versus prognostic uncertainty and learning in a diagnostic versus prognostic context

5.1 What is the difference between diagnostic and prognostic uncertainty and why do we consider them independent?

Jonas *et al.* [15] explain the difference between diagnostic and prognostic uncertainty in a temporal ('today'-versus-future) GHG emissions context:

Diagnostic uncertainty, our ability to estimate current emissions, stays with us also in the future. Assuming that compliance with an agreed emissions target is met in a target year allows prognostic uncertainty to be eliminated entirely. How this target was reached is irrelevant; only our real diagnostic capabilities of estimating emissions in the target year matter. This is how experts proceeded, e.g., when they evaluated ex ante the impact of uncertainty in the case of compliance with the Kyoto Protocol ... in 2008–2012, the Protocol's commitment period ...

Emissions accounting in a target year can involve constant, increased or decreased uncertainty compared with the start (reference) year, depending on whether or not our knowledge of emission-generating activities and emission factors becomes *more precise. The typical approach to date has been to assume that, in relative terms, our knowledge of uncertainty in the target year will be the same as it was in the start year.*

However, uncertainty under a prognostic scenario always increases with time [conservative systems view]. *The further we look into the future, the greater the uncertainty. This important difference suggests that diagnostic and prognostic uncertainty are independent. This differs from how prognostic modelers usually argue. A prevalent approach is to realize a number of scenarios and grasp prognostic uncertainty by means of the spread in these scenarios over time—which increases with increasing uncertainty in the starting conditions built into their models. However, this approach nullifies diagnostic uncertainty once a target (future) is reached.*

The notion of a conservative systems view is central to RL, meaning that a system cannot exhibit surprises in the future that it has not experienced during its 'one-reality' past.

This difference between diagnostic and prognostic uncertainty is not only theoretical. It becomes relevant in the next section.

5.2 What do we understand by learning in a diagnostic and prognostic context?

Learning under diagnostic conditions requires the 'measuring' of differences or deviations. Here we follow Marland *et al.* [18], who discuss this issue in the context of emissions accounting and uncertainty:

Estimates of uncertainty have traditionally been expert judgments based on the data input to the calculations. But for CO_2 emissions from fossil fuels, there are actually at least four approaches that one can take to gain some insight into the full uncertainty of emissions estimates: comparison of estimates made by independent methods, comparison of estimates from multiple sources, evolution over time of estimates from a single source, and, soon (we hope), modeling against remotely sensed data.

With respect to the evolution of estimates over time (3^{rd} approach), the authors state:

Many of the countries and organizations that make estimates of CO_2 emissions provide annual updates in which they add another year of data to the time series and revise the estimates for earlier years. Revisions may reflect revised or more complete energy data and more complete and detailed understanding of the emissions processes and emissions coefficients. In short, we expect revisions to reflect learning and a convergence toward more complete and accurate estimates.

Retrospective learning, in turn, is about the limitations of looking **(projecting)** into the future and may be best explained in contrast to retrospective forecasting. Retrospective forecasting strives for the most appropriate (best) forecast by minimizing the difference between forecast **(prediction)** and actual outcome, while the characteristics of the data record—here quantified by its dynamics and diagnostic uncertainty (random error)—are assumed **not** to change when inter- or extrapolating the historical data record. By way of contrast, retrospective learning seeks to capture the characteristic feature of prognostic uncertainty, namely, that **prognostic uncertainty increases the more the further we look into the future,**[1] while it is

[1] As a matter of fact, the confidence band of an (e.g.) linear regression also increases, but for mathematical rather than physical reasons, and it does so backward **and** forward in time.

assumed in the context of this proposal that the data record's memory is contained (as above) in its dynamics, not in its uncertainty.

Figure 2 attempts to visualize the fundamental difference between prediction and an advanced mode of learning from the past, the latter allowing the increase in prognostic uncertainty with time to be grasped. The mode of RL that we intend to explore builds on representation of the available data by way of two components: i) a Taylor (or equivalent) polynomial which captures the signal's predominant (lower-order) dynamics (**learning phase 1**); and ii) a linearly increasing 'uncertainty (learning) wedge',[2] which comprises the signal's higher-order dynamics and the uncertainty underlying the signal—or only the data record's higher-order dynamics if the data record is accurate and precise (**learning phase 2**). We expect this two-component split into lower-order dynamics and uncertainty wedge to be systems-dependent and unsharp, the latter resulting from uncertainty. In a nutshell, Figure 2 indicates that we seek to balance three things: the 'right' order of the dynamics and both the 'right' extension and the 'right' opening of the uncertainty wedge. It is this balance that must hold during the **testing phase**. The historical data held back for this phase have not been used before, that is, during learning phases 1 and 2, which is why we refer to this part of the data record as "historical future".

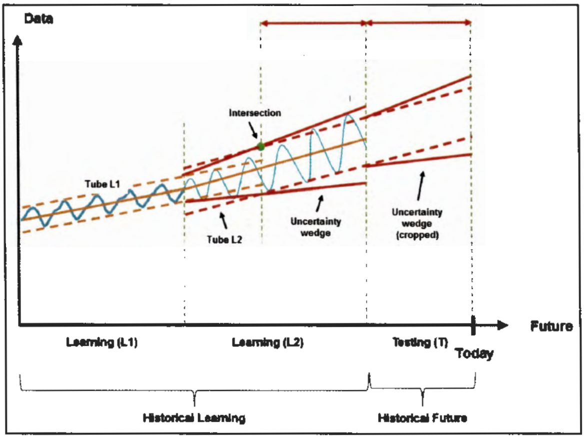


Figure 2. Illustrating the different steps of RL with the help of a simple (periodic, increasing, and periodically increasing) function.

6. Methodology—just one approach

Assume the following situation, namely, that we have more than one historical data record available, each **accurate and precise** (which can be easily relaxed to 'accurate and imprecise'), and that we have learned from the past (i.e., from an RL exercise):

- that each historical data record exhibits (but not necessarily) a linear dynamics;

[2] "Linear" meaning linear relative to the dynamics, which is why we also speak of **linear RL** (sufficient in the context of this study).

- that each data record's uncertainty (learning) wedge unfolds linearly into the future (up to what time in the future, however, is still unknown); and
- that our historical data records exhibit linear interdependencies. That is, in the case of an emissions-concentration-temperature [E-C-T] system, we mean linear interdependencies of a serial sort (fully sufficient in the context of this study): $T=T(C)$, $C=C(E)$, and $E=E(t)$; with T denoting global surface temperature, C atmospheric CO_2 concentration, E CO_2 emissions into the atmosphere, and t time. As a matter of fact, as individual time series these are exponential (posing no difficulties to treating their interdependencies in a similar way).

To facilitate understanding the philosophy behind the methodology, we consider two cases:

6.1 Serial interdependence E → C → T

Starting from $E=E(t)$, i.e.

$$E=m_{Et}t \qquad [E]=\frac{PgC}{y};\ [m_{Et}]=\frac{PgC}{y^2};\ [t]=y$$

with m denoting the signal's (here) linear dynamics and Et indicating that we are in the E-t plane; and

$$E_u=f_{Et,u}m_{Et}t \qquad [f_{Et,u}]=1$$

$$E_l=f_{Et,l}\,m_{Et}t \qquad [f_{Et,l}]=1$$

with the constants $f_{Et,u}$ and $f_{Et,l}$ indicating the upper [u] and lower [l] borders of the uncertainty wedge. The difference between upper and lower border at any time is given by $\Delta E=\Delta f_{Et}m_{Et}t$.

On the other hand, the difference between upper and lower border can be perceived as error in E, which suggests that use is made of the law of error propagation:

$$\sigma_E^2=\left(\frac{\partial E}{\partial m_{Et}}\right)^2\sigma_{m_{Et}}^2+\left(\frac{\partial E}{\partial t}\right)^2\sigma_t^2\ .$$

Assuming time to be known exactly (i.e., $\sigma_t=0$):

$$\sigma_E=\sigma_{m_{Et}}t\ ; \qquad [\sigma_E]=\frac{PgC}{y};\ \left[\sigma_{m_{Et}}\right]=\frac{PgC}{y^2}$$

that is, the error in E is given by the error in the slope m_{Et}, the signal's dynamics. Alternatively:

$$\frac{\sigma_E}{E}=\frac{\sigma_{m_{Et}}}{m_{Et}}\ .$$

Requesting $\Delta E:=2\sigma_E$, one finds via comparison

$$\Delta f_{Et} m_{Et} t = 2\sigma_{m_{Et}} t \quad \text{or} \quad \Delta f_{Et} = \frac{\Delta E}{E} = 2\frac{\sigma_E}{E} = 2\frac{\sigma_{m_{Et}}}{m_{Et}} \ .$$

In a nutshell, an accurate-precise system has been merged with classical statistics, meaning (here) that we grasp the historical future of our data record with the help of a straight line, the slope of which is uncertain. Another point warranting attention is that the law of error propagation is approximate and can only be applied under conditions that guarantee the validity of partial derivatives. In particular, if $\Delta f_{Et} = \Delta f_{Et}(t)$, these conditions could be violated quickly with increasing t.

One can proceed similarly for $C = C(t)$, i.e.,

$$C = m_{Ct} t \qquad [C] = \text{ppmv}; \ [m_{Ct}] = \frac{\text{ppmv}}{\text{y}}$$

... (here not repeated). Alternatively, instead of analyzing $E = E(t)$ and $C = C(t)$ individually, one can also look at the linearly interdependent case $C = C(E)$, i.e.,

$$C = m_{CE} E = m_{CE} m_{Et} t = m_{Ct} t \ ; \qquad m_{Ct} = m_{CE} m_{Et} ; \ [m_{CE}] = \text{ppmv} \frac{\text{y}}{\text{Pg C}}$$

or, to generalize further, at the linearly interdependent case $T = T(C) = T(C(E))$, i.e.,

$$\begin{aligned} T &= m_{TC} C = m_{TC} m_{CE} E \\ &= m_{TC} m_{CE} m_{Et} t = m_{Tt} t \end{aligned} \ . \qquad m_{Tt} = m_{TC} m_{CE} m_{Et} ; \ [m_{TC}] = \frac{{}^\circ\text{C}}{\text{ppmv}} ; \ [m_{Tt}] = \frac{{}^\circ\text{C}}{\text{y}}$$

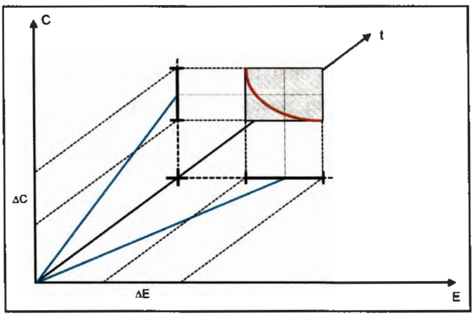


Figure 3. Graphical illustration of learning in the C-E space: independent versus linearly interdependent case. In the latter case, learning does **not** happen in a space which is spanned by a 2-dimensional square $(\Delta E \times \Delta C)$, but along a 1-dimensional space (red curve) belonging to a curved uncertainty wedge.

The above cases can be conveniently summarized:

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

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

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

... and so on. The interpretation is as follows: From analyzing (e.g.) the second equation, which allows $\Delta f_{Ct} = \sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2}$ to be extracted, it becomes obvious that the learning on the left side (Δf_{Ct}) is determined by the learning on the right side $\left(\sqrt{\Delta f_{CE}^2 + \Delta f_{Et}^2}\right)$. The resulting equation describes a second-order cone:

$\Delta f_{CE}^2 + \Delta f_{Et}^2 - \Delta f_{Ct}^2 = 0 \quad \leftrightarrow \quad \frac{x^2}{a^2} + \frac{y^2}{b^2} - \frac{z^2}{c^2} = 0$ (cf. also Fig. 3).

The basic idea behind the above procedure is to grasp the learning (Δf -terms) with the help of the error-propagation approach, the mathematics of which is well-established and easy to apply (even concomitantly with building a prognostic model). In the case of linearly interdependent variables (here $C = C(E)$), the learning does **not** happen in a space which is spanned by a (here) 2-dimensional square $(\Delta E \times \Delta C)$, but along a 1-dimensional curve belonging to a curved uncertainty wedge. It appears that this reduction to the 1-dimensional space is also preserved in the case of more than two linearly interdependent variables. But it would be premature to praise this as a major step forward in reducing uncertainty. We still do **not** have any knowledge on the outreach of the curved uncertainty wedge (which needs to be determined as indicated in Fig. 2).

6.2 Serial-parallel interdependence $\begin{matrix} \mathbf{E_1} & \rightarrow & \mathbf{C_1} \\ \mathbf{E_2} & \rightarrow & \mathbf{C_2} \end{matrix} \rightarrow \mathbf{T}$

Here, we do not derive the analytical expression for Δf_{Tt} which describes the learning. Deriving this expression is easy and straightforward. In contrast, another insight is much more important, namely, the analytical expression for Δf_{Tt} also holds for a system, where the second emissions source (E_2) has been replaced by a sink (R: removal): $\begin{matrix} \mathbf{E} & \rightarrow & \mathbf{C_1} \\ \mathbf{R} & \rightarrow & \mathbf{C_2} \end{matrix} \rightarrow \mathbf{T}$; meaning that the learning does not change while the two systems differ: $C = C_1 + C_2$ versus $C = C_1 - C_2$. That is, a sink reduces a source but their uncertainties still add up.

It is this game changer that has not so far been considered by prognostic modelers: a shortfall with far-reaching consequences, notably, when determining the risk of exceeding an agreed global temperature target in the future.

7. Summary and preliminary outlook

The purpose of our paper is to present a particular methodology to tackle retrospective learning, the characteristic feature of which is that prognostic uncertainty increases the more the further we look into the future. Alternative methodologies are conceivable. We currently consider the discussion of necessary assumptions and, if need be, simplifying assumptions (still) more important than immersing ourselves in numerical exercises.

So far, we see two important consequences emerging:

- The objective (i) to generate a metric / indicator to inform non-experts about the limitations of the predictive outreach of a prognostic scenario; and (ii) to demonstrate that this metric / indicator can be generated even concomitantly with building a prognostic model is within reach. We conjecture that the latter, in particular, will lead us, in the case of success, onto new paths of constructing models and conducting systems analysis—that is, towards a new standard of 'good modeling'.
- RL informs us that, from an uncertainty perspective, emission sources and sinks need to be separated—which is not done in estimating the risk of exceeding an agreed global warming target in 2050. This very risk can be determined by using multi-model emission scenarios like those in Figure 1 in connection with emission-climate change models (where "climate change" is quantified by changes in global surface temperature). The cumulative emissions of these scenarios are used as a predictor for the expected global temperature increase in the future (cf. Box 1). However, the crux of this exercise is that it starts—erroneously—from net emissions. (Take Fig. 1 above, for example: removals eventually outpace emissions and net emissions even become negative.) From an uncertainty perspective, preferring **net emissions** to **emissions minus removals** runs counter to the law of error propagation which informs us that **a sink reduces a source but their uncertainties still add up**. This shortfall has far-reaching consequences. 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.

This is why we argue that understanding and grasping RL is of fundamental and global relevance.

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Acronyms

C	concentrations
E	emissions
E-C-T	emissions-concentration-temperature
ETU	emissions-temperature-uncertainty
GHG	greenhouse gas
l	lower
RL	retrospective learning
T	temperature
u	upper