IIASA's ASA Program is seeking to better handle uncertainty in prognostic scenarios:

This research aims at advanced learning from the past, namely

I. at treating uncertainty and its change seamlessly across time, **from the past to the immediate future** (near-term goal); and

II. at providing a **measure of reference for prognostic scenarios** (long-term goal).

It builds on two—**not yet interlinked**—approaches to study changes in uncertainty. We prefer explaining the two approaches in the context of global greenhouse gas (**GHG**) emissions, concentrations and/or global mean surface temperature change, each of which representing a **system with memory**:

1. retrospective learning (**RL**; also termed diagnostic learning): RL is based on the annual recalculation of previous estimates of GHG emissions (and removals); **RL allows identifying our knowledge increase**.
2. learning under controlled prognostic conditions (**CPL**): CPL aims at quantifying the explainable outreach (**EO**) of data that contain memory. Determining a series' EO requires evaluating its historical data by applying learning and testing and must **not** be confused with prediction. The EO can be visualized as a constrained uncertainty wedge of limited extent. It is in accordance with the system's past and can serve as **a measure of reference for prognostic scenarios**.

Retrospective Learning (RL):

We distinguish between changes in uncertainty due to **(i)** learning (one-sided, bottom-up) and **(ii)** structural changes in emitters, and speculate that the two processes are exponential and can be discriminated (Fig. 1; Jarnicka & Nahorski 2015; Żerbrowski *et al.* 2015).

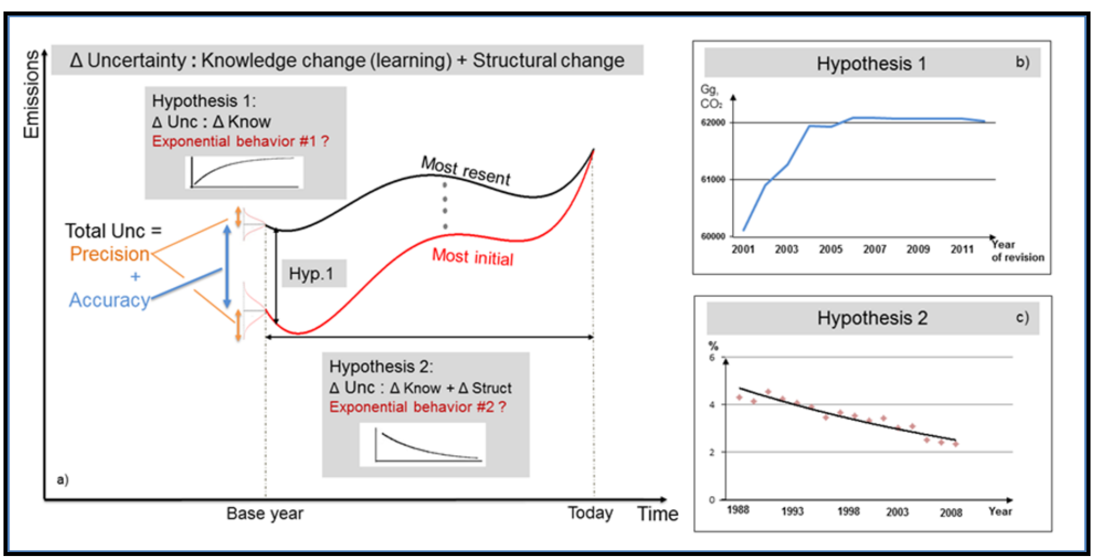

Fig. 1: Illustrating RL for uncertain (inaccurate and imprecise) emissions.

Emissions are updated by adding another year of data to the time series, while estimates for earlier years are revised (Fig. 1a). Uncertainty changes due to **(i)** learning (one-sided, bottom-up) and **(ii)** structural changes in emitters. We hypothesize that the two processes are exponential and can be discriminated (**i** as opposed to **i+ii**). Figure 1b reflects learning **(i)**. It shows the difference **[most recent – earlier estimates]** for Austria's CO_2 emissions (excluding emissions from land use) for the year 1990. **c)** The figure reflects learning and structural change in emitters **(i+ii)**. It shows the difference **[most recent – most initial estimates]** for Europe's (EU-15) CO_2 emissions (excluding emissions from land use) for 1990–2005 (Hamal 2010: Fig. 12; modified).

Learning under Controlled Prognostic Conditions (CPL):

The EO is derived for the historical part of the data series (past) and then shifted to "today" (assuming no "unknown" surprises), thus providing **a measure of reference for prognostic scenarios**. For a better understanding, Figure 2 reflects testing under the condition of the future being known (see black dots in the future part of the data series). Prognostic scenarios falling outside (above or below) the EO as well as scenarios falling within, but eventually extending beyond the EO are no longer in accordance with the series' past—allowing a decision-maker to inquire about the assumptions made in constructing a forward-looking scenario and to interpret these in terms of how effective planned measures (e.g., emissions reductions) need to be and/or how long the effectiveness of these measures remains uncertain.

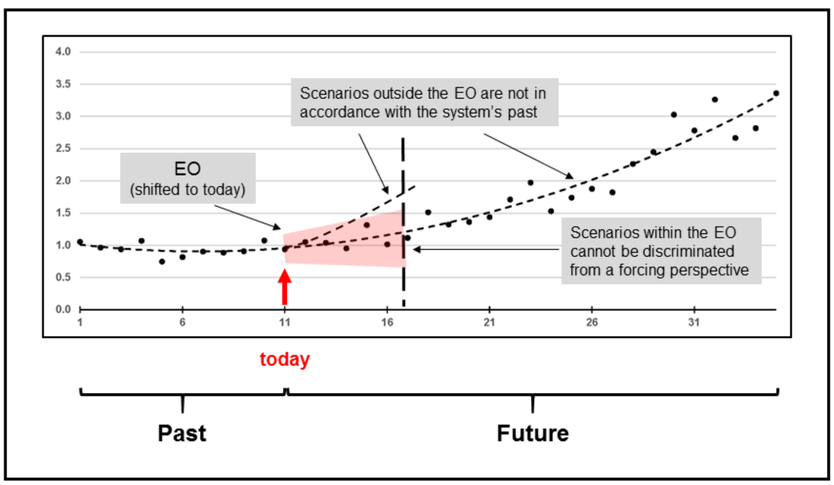

Fig. 2: Illustrating why knowing the EO of a data series is important.

The key question is how does RL influence the emissions' EO, in particular its direction; and thus its potential to serve as a reference for prognostic scenarios? **Based on the large revisions of historic emissions, we suspect that this influence will not be negligible.**

Hamal, K., 2010: Reporting GHG Emissions: Change in Uncertainty and its Relevance for the Detection of Emission Changes. Interim Report IR-10-003, International Institute for Applied Systems Analysis, Laxenburg, Austria, pp. 34, http://webarchive.iiasa.ac.at/Publications/Documents/IR-10-003.pdf.

Jarnicka, J. and Z. Nahorski, 2015: A method for estimating time evolution of precision and accuracy of greenhouse gases inventories from revised reports. In: *Proceedings*. 4th International Workshop on Uncertainty in Atmospheric Emissions, 7–9 October, Krakow, Poland [pp. 211, ISBN 83-894-7557-X], 97–102, http://www.ibspan.waw.pl/unws2015/index.php?go=presentations.

Żebrowski, P., M. Jonas and E. Rovenskaya, 2015: Assessing the improvement of greenhouse gases inventories: Can we capture diagnostic learning? In: *Proceedings*. 4th International Workshop on Uncertainty in Atmospheric Emissions, 7–9 October, Krakow, Poland [pp. 211, ISBN 83-894-7557-X], 90–96, http://www.ibspan.waw.pl/unws2015/index.php?go=presentations.