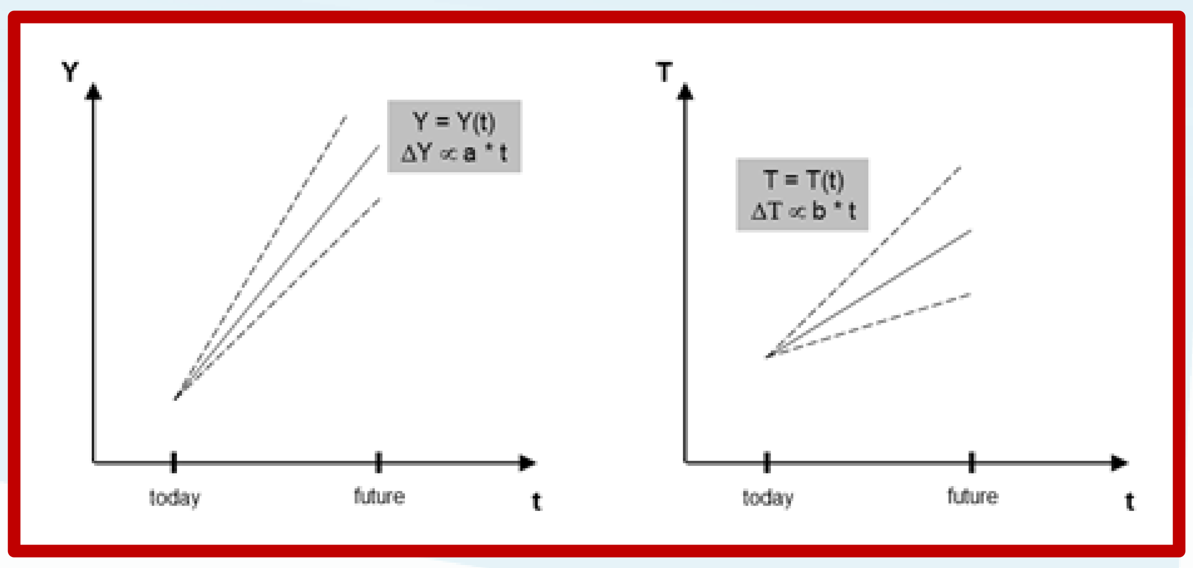
Why Prognostic Systems Analysis Has To Change – Learning from the Past Tells How

Arkady Kryazhimskiy (Advanced Systems Analysis Program, IIASA)
Matthias Jonas (Ecological Services and Management Program, IIASA)

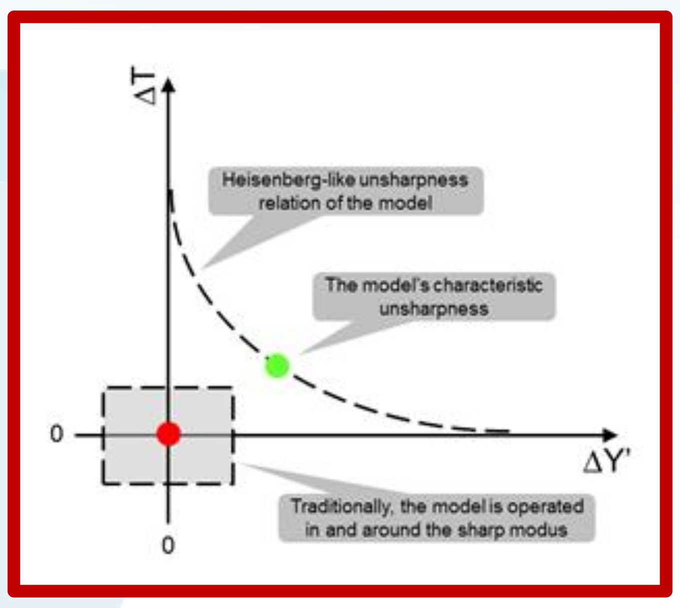
Challenge

Prognostic systems analysis is widely applied to generate 'sharp' projections into the future. However, prognostic scenarios and 'sharp' futures are a physical impossibility!



For illustration assume that our knowledge of the past suggests that global emissions, $Y = Y(t)$, and global temperature, $T = T(t)$, continue increasing linearly also in the future. Assume further that we also learned from the past that the unsharpness in projecting emissions and temperature forward in time increases linearly, that is $\Delta Y \approx a\,t$ and is $\Delta T \approx b\,t$.

This simplified example allows resolving for time and expressing ΔT as a function of ΔY, i.e., $\Delta T / \Delta Y$ = const, or, equivalently, $\Delta T \Delta Y'$ = const with $\Delta Y' = 1 / \Delta Y$. The combined equation informs us that the unsharpness in T and the unsharpness in Y are interdependent. We also speak of a 'Heisenberg-like unsharpness relation', which informs a model user that a prognostic parameter carries another parameter's unsharpness if the other parameter is resolved too sharply. By way of contrast, prognostic models are typically operated, and display their prognostic parameters, in a sharp modus. Their unsharpness regimes are out of bounds; they center at and around the zero-unsharpness origin in the figure.



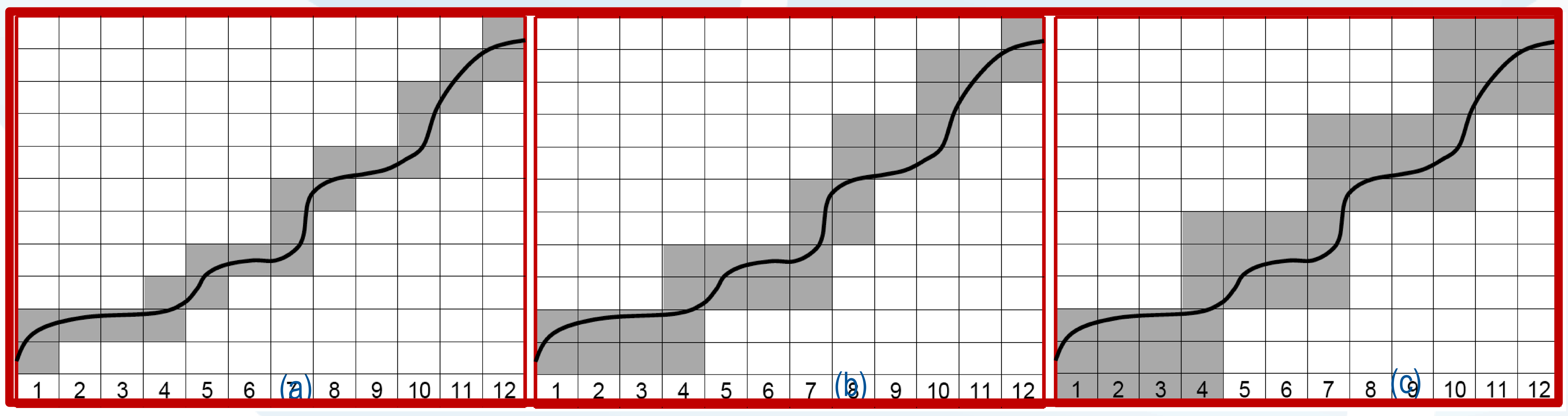
The key questions arising are (1) whether it is possible to determine the Heisenberg-like relation of a model; and (2) whether it is even possible to determine the model's characteristic unsharpness regime by learning from the past?

Approach

We grasp the dynamics of an emissions-temperature data series by finding the 'optimum' between two extremes:

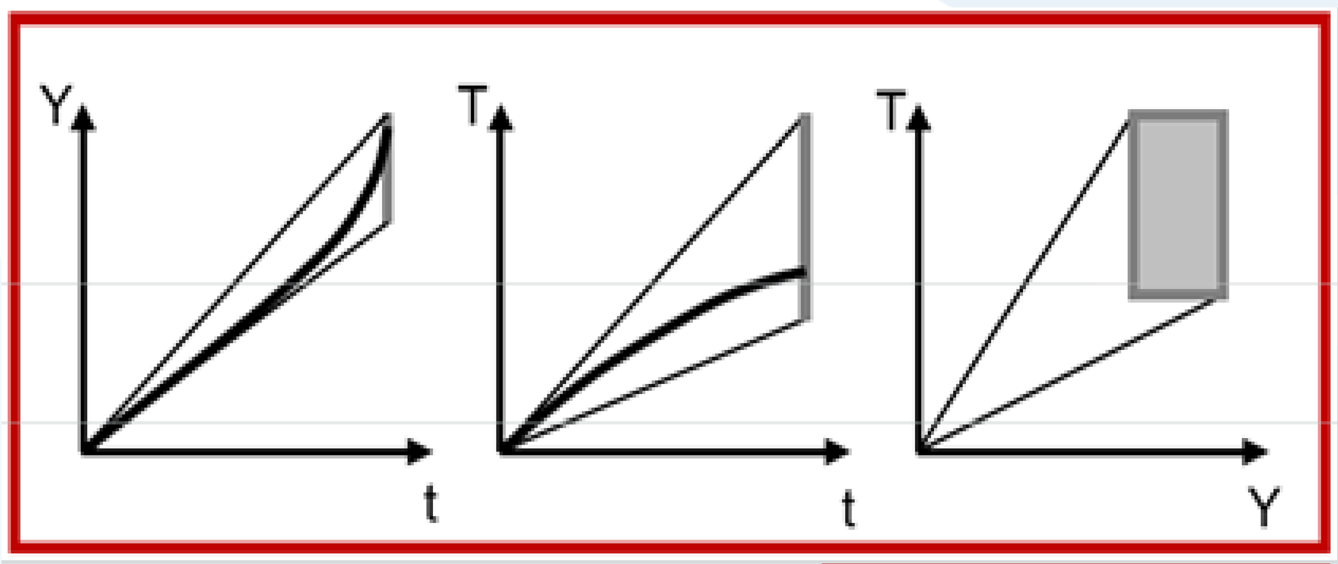
(i) the 'no learning needed' case under which the data series' dynamics has been nullified as, e.g., in the case of linear regression; and

(ii) the 'no learning possible' case under which the data series exhibits complete stochasticity and does not permit 'useful' learning in retrospect.

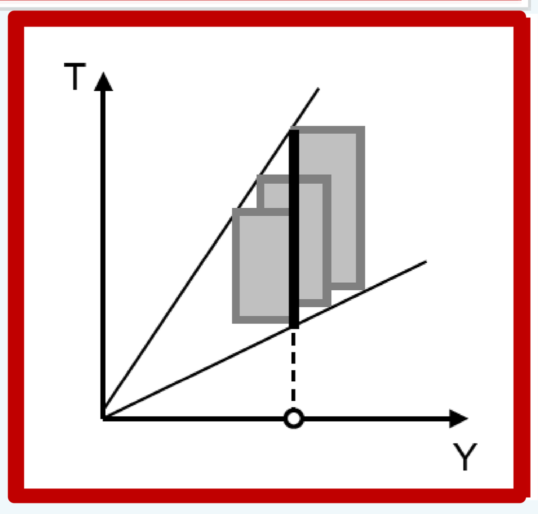


We learn about the historical emission-temperature path by plotting it on a grid and increasing the size of the grid's cells until the grid image of the historical path becomes tractable. In (a) and (b) the grids are too fine for successful learning. In (c) learning is successful – we see a regular ladder.

We extend the learning methodology from the 'data world' to the 'modelling world'; that is, from the emissions-temperature space to the parameter spaces of selected, simplified models which reproduce the emissions-temperature dynamics, and use the resulting 'optimal parametric learning' methodology to characterize the Heisenberg-like unsharpness relation inherent in the retrospective, model-based forecasts.



In retrospect, the simplest linear dynamical emission-temperature model is able to forecast precisely only intervals for emissions, Y, (left) and temperature, T, (middle). As a result, we get an unsharp emission-temperature forecast – the grey square in the (Y,T) plane (right).



Given an exact future emission value, the corresponding future temperature values lie in the union of the temperature projections of all unsharp emission-temperature forecasts (the grey squares in the (Y,T) plane) whose emission projections contain the given future emission value. A Heisenberg-like unsharpness relation arises.

Conclusion

Model- and data-based emission-temperature projections are necessarily unsharp. Retrospective analysis helps find the measure of unsharpness.