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- Accuracy vs. precision: how to quantify & propagate structural and parameteric uncertainties?

Extra Slides

JEFE (Sean P. Santos)

JEFE: Measuring Predictability

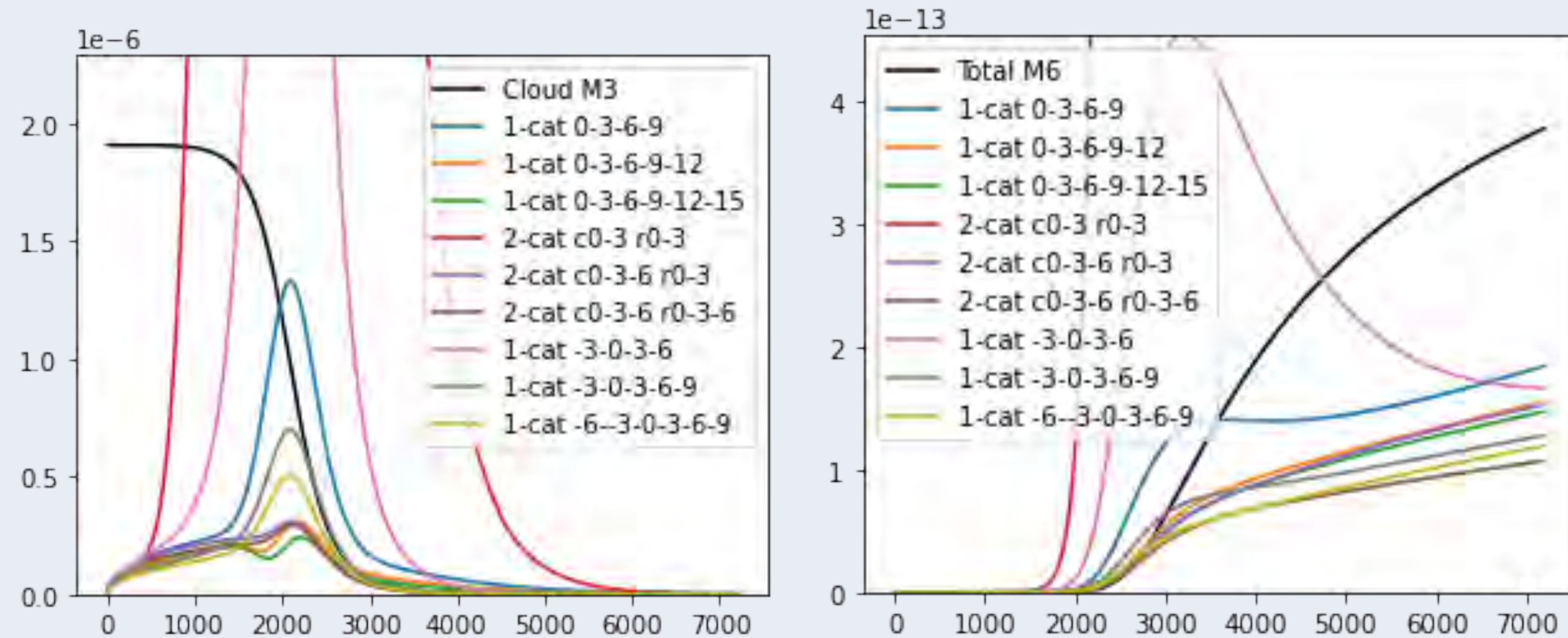### JEFE: Jacobian Evaluation of Functional Error

Figure 3:Adjoint-model-derived estimates of relative error of highly-accurate bulk schemes for cloud mass (left) and radar reflectivity (right).

A Challenge: inference complicated by state errors, initial & boundary condition uncertainty

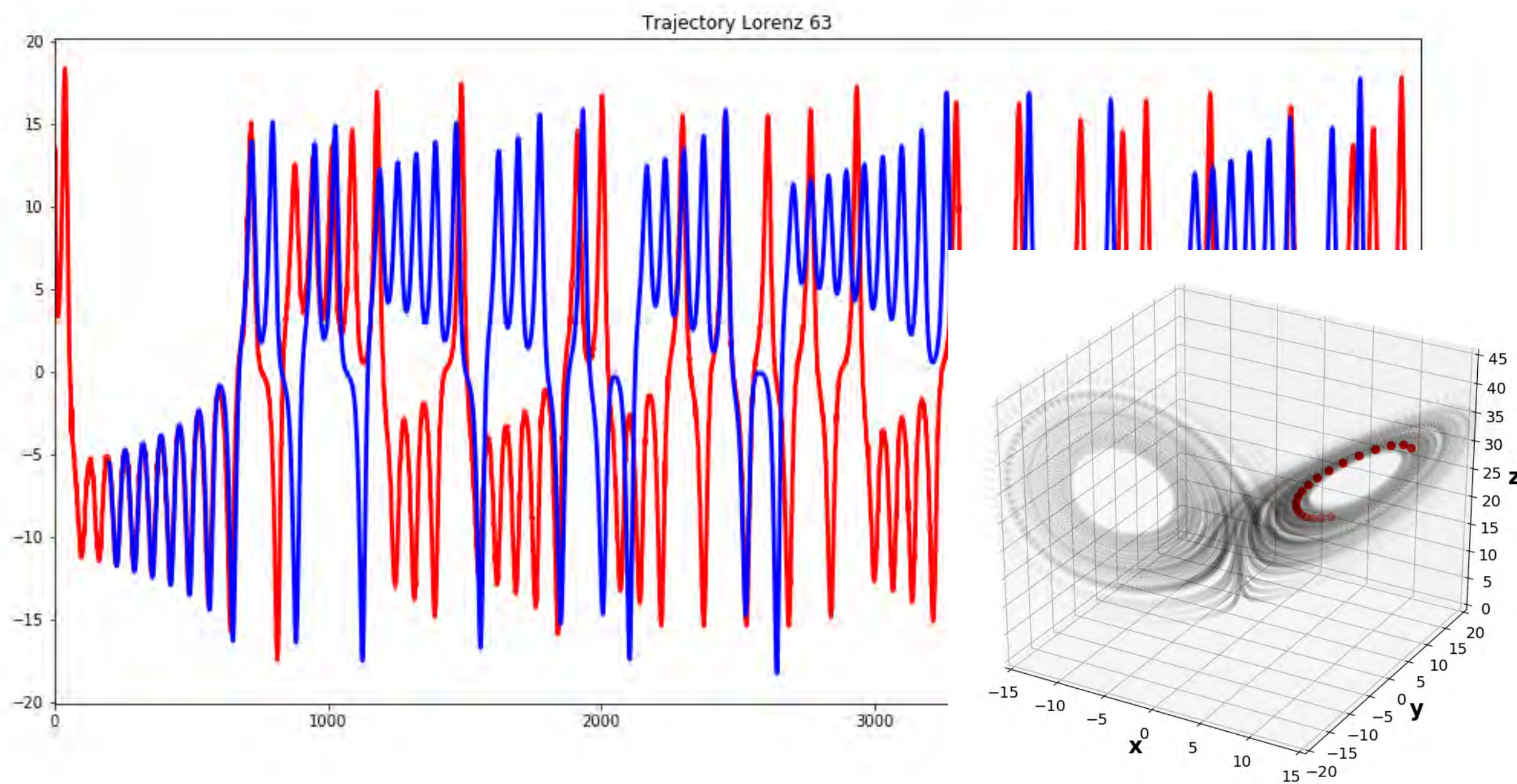# A Challenge: inference complicated by state errors, initial & boundary condition uncertainty

Some aspects of the atmosphere behave chaotically: errors grow nonlinearly from small perturbations, reducing predictability
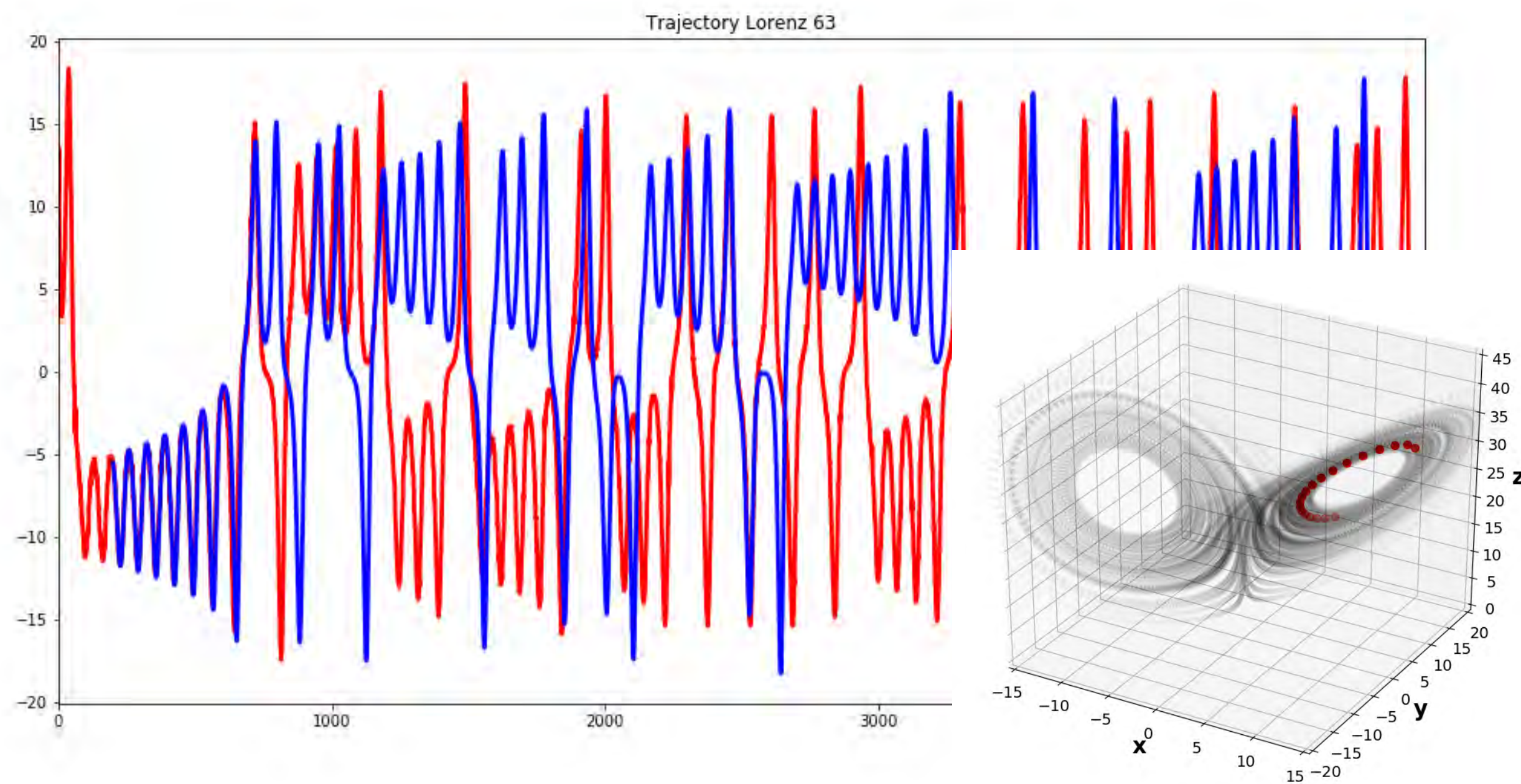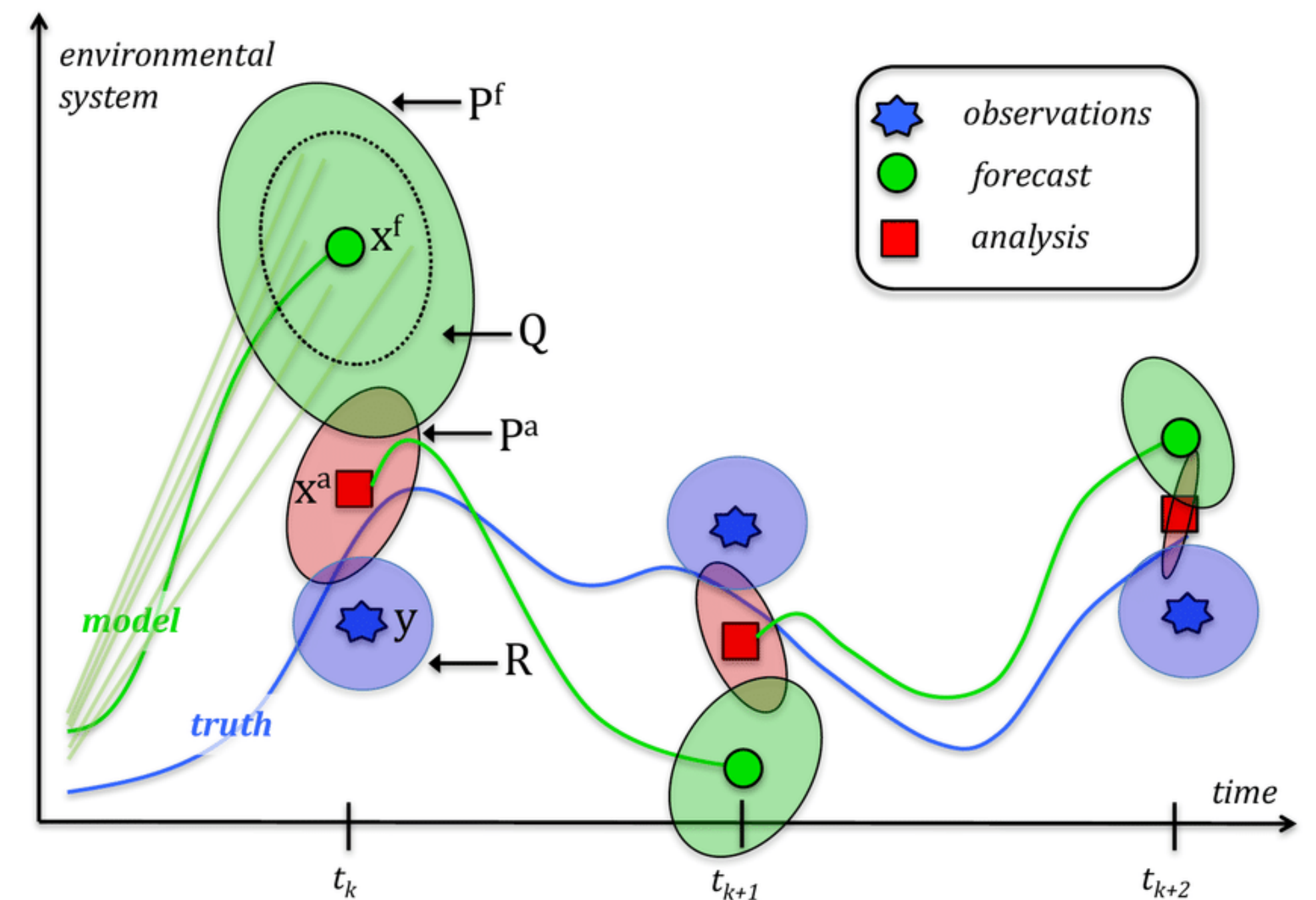

Lorenz (1963)

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"Data Assimilation" — correcting the state of a model forecast with observations
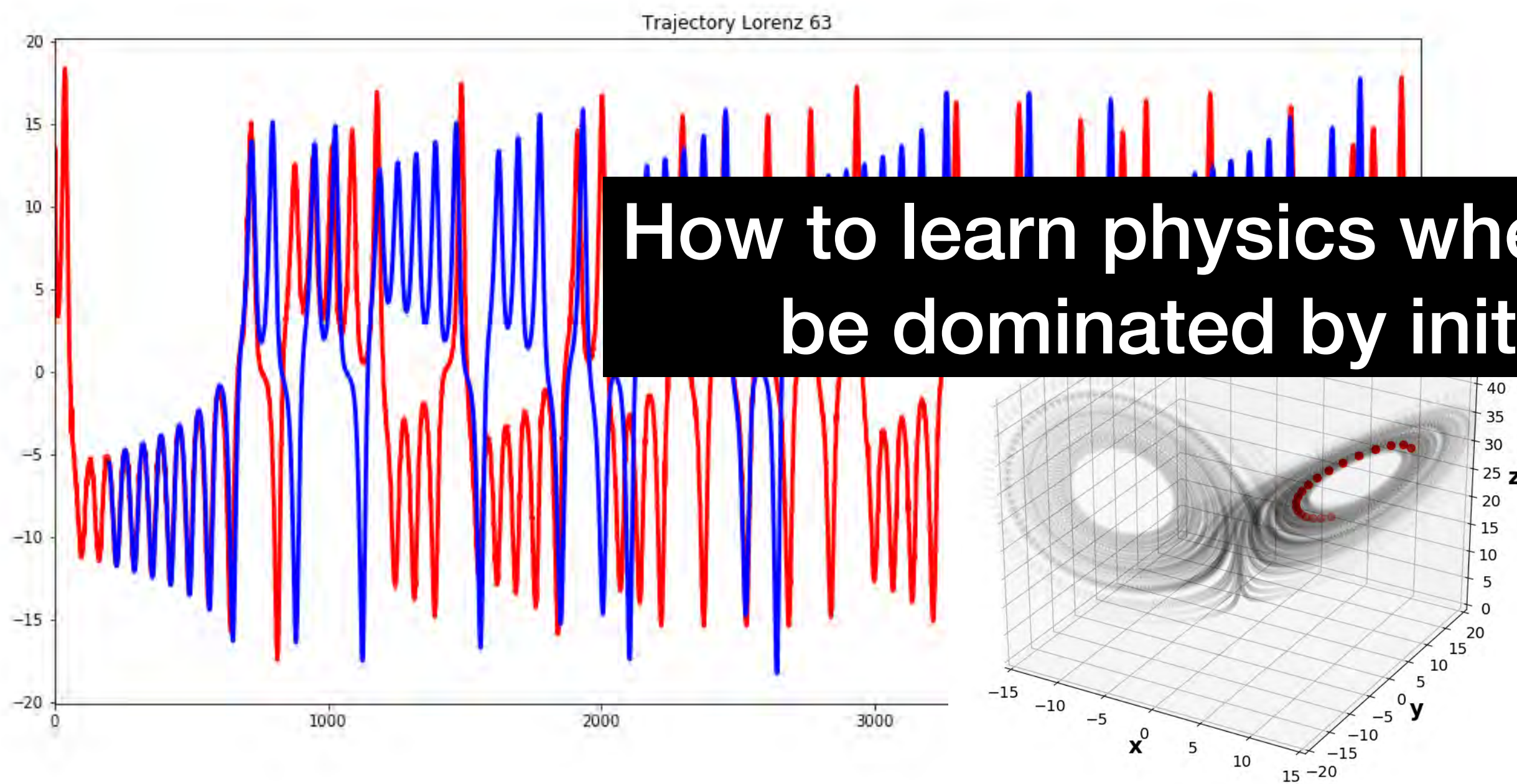

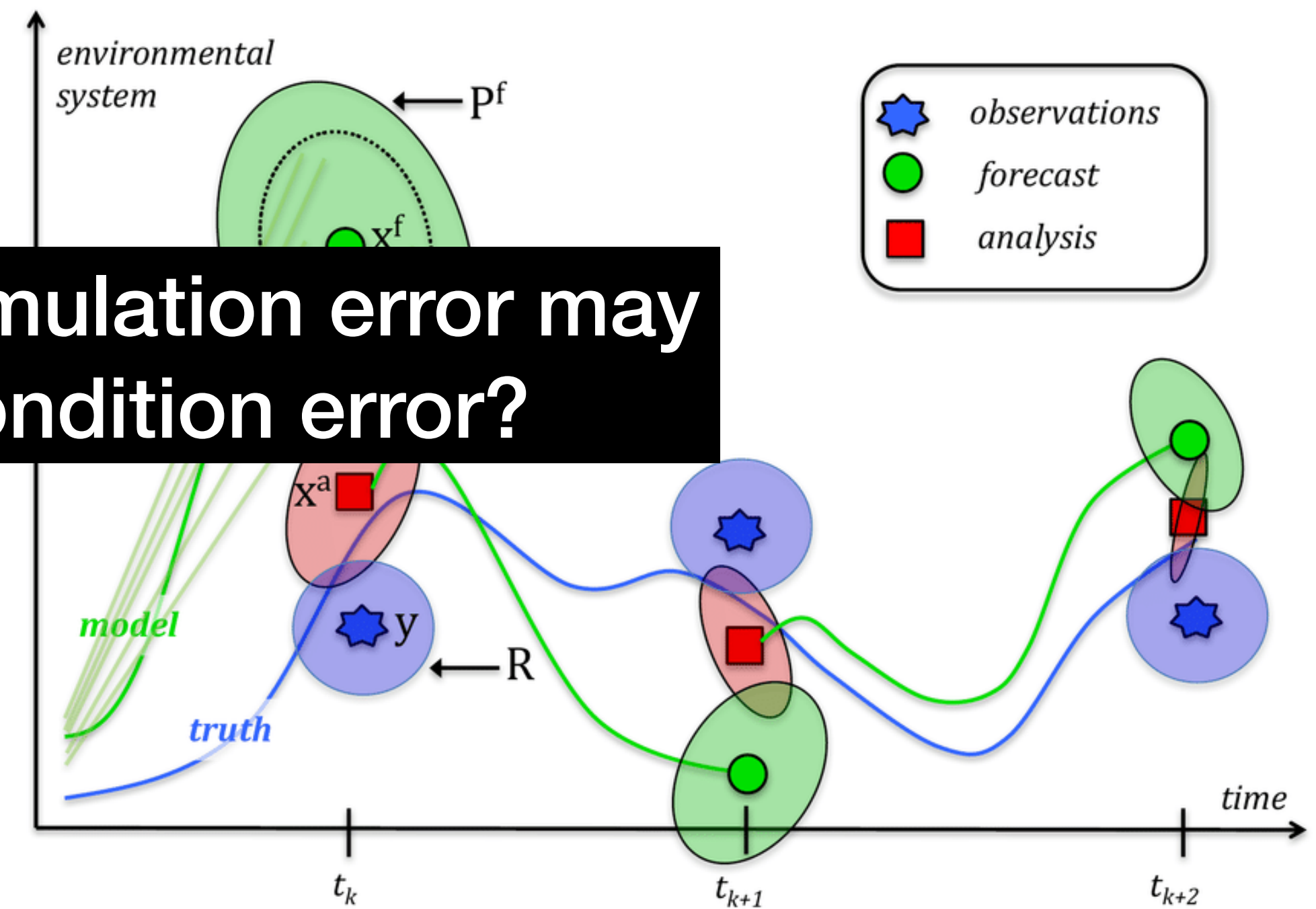*Lorenz (1963)*

Tandeo et al. (2018)

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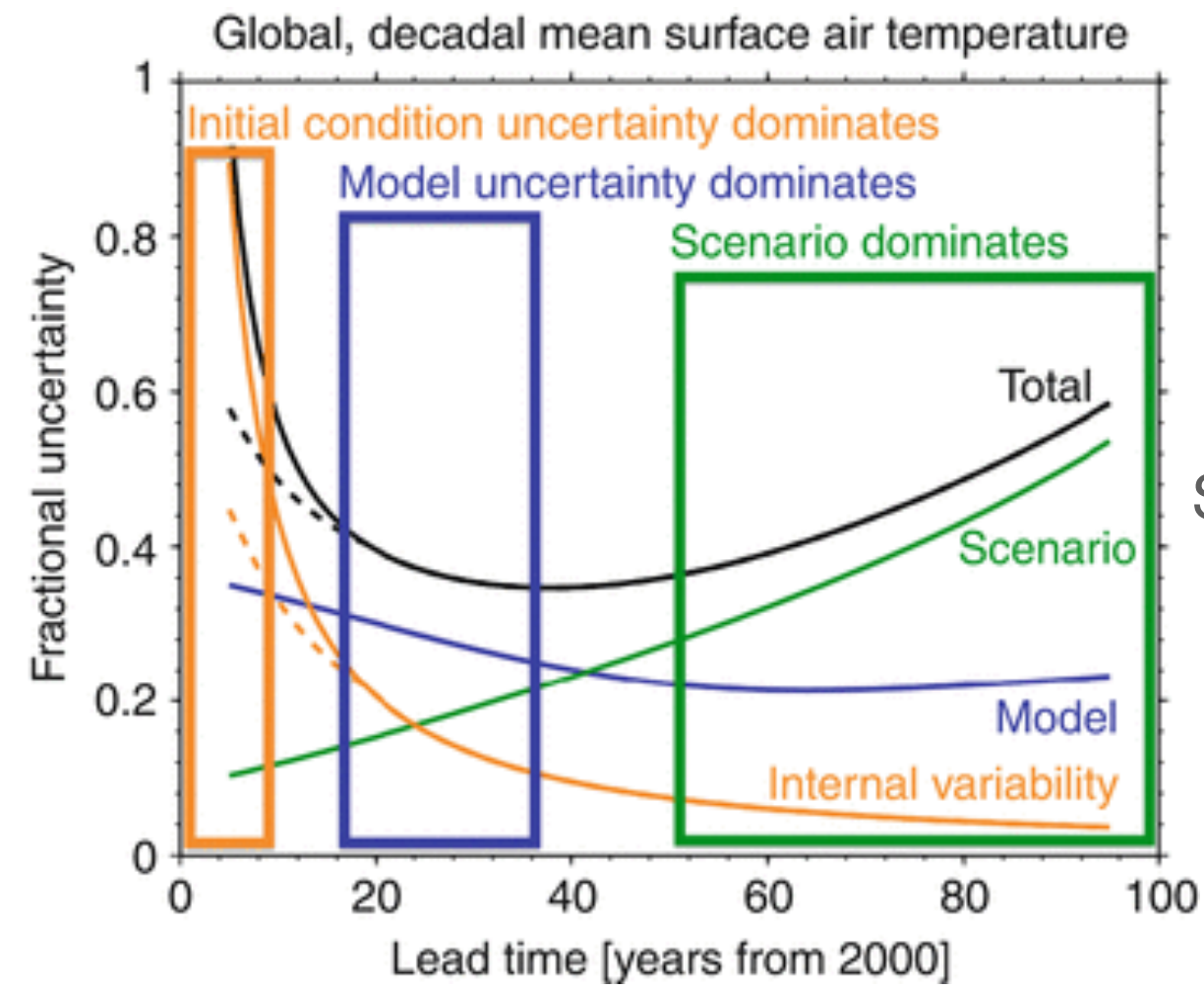**How to learn physics when simulation error may be dominated by initial condition error?**
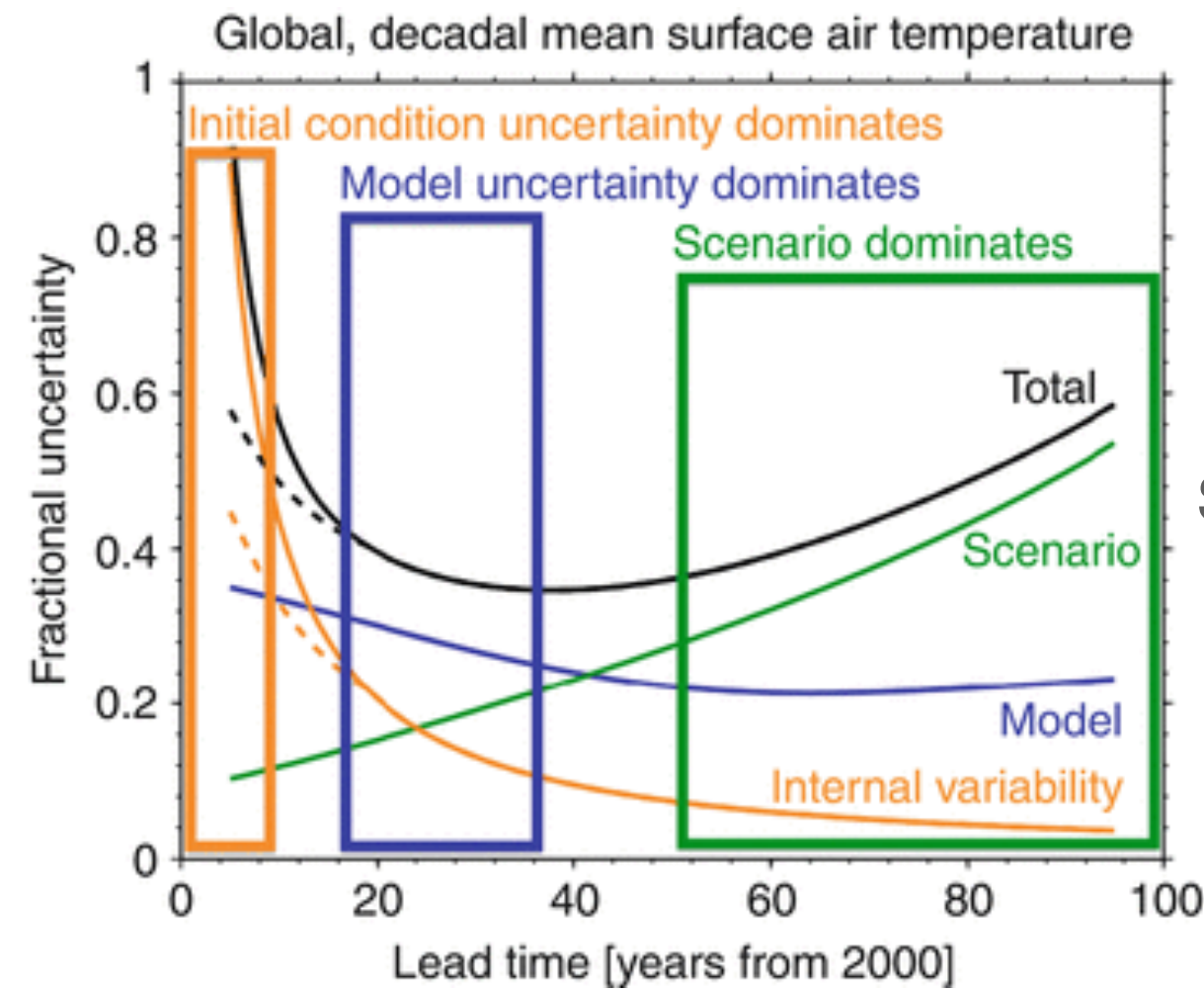
Tandeo et al. (2018)

Model error may be easier to tackle in climate simulations:

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Global, decadal mean surface air temperature

Initial condition uncertainty dominates
Model uncertainty dominates
Scenario dominates

Total
Scenario
Model
Internal variability

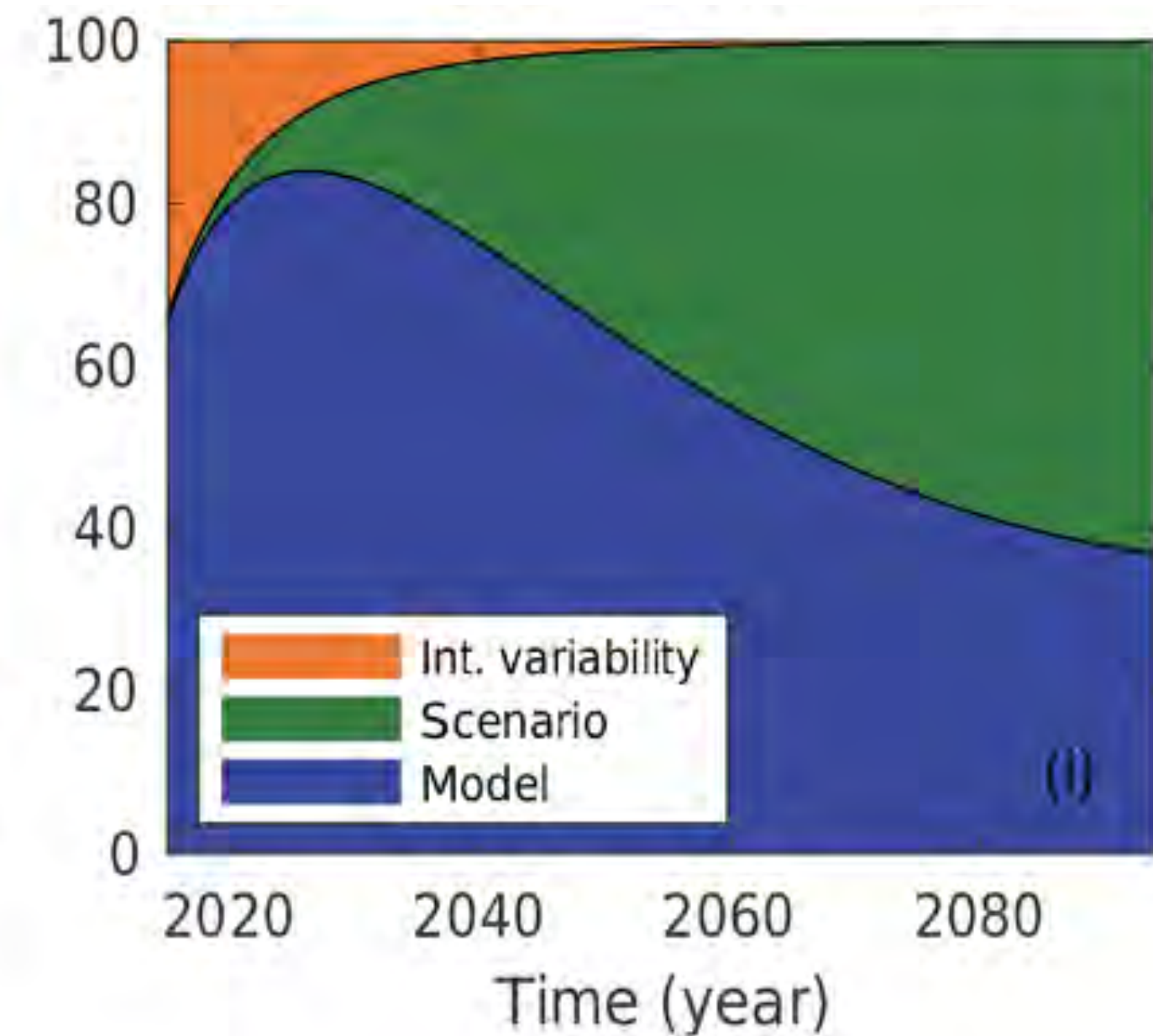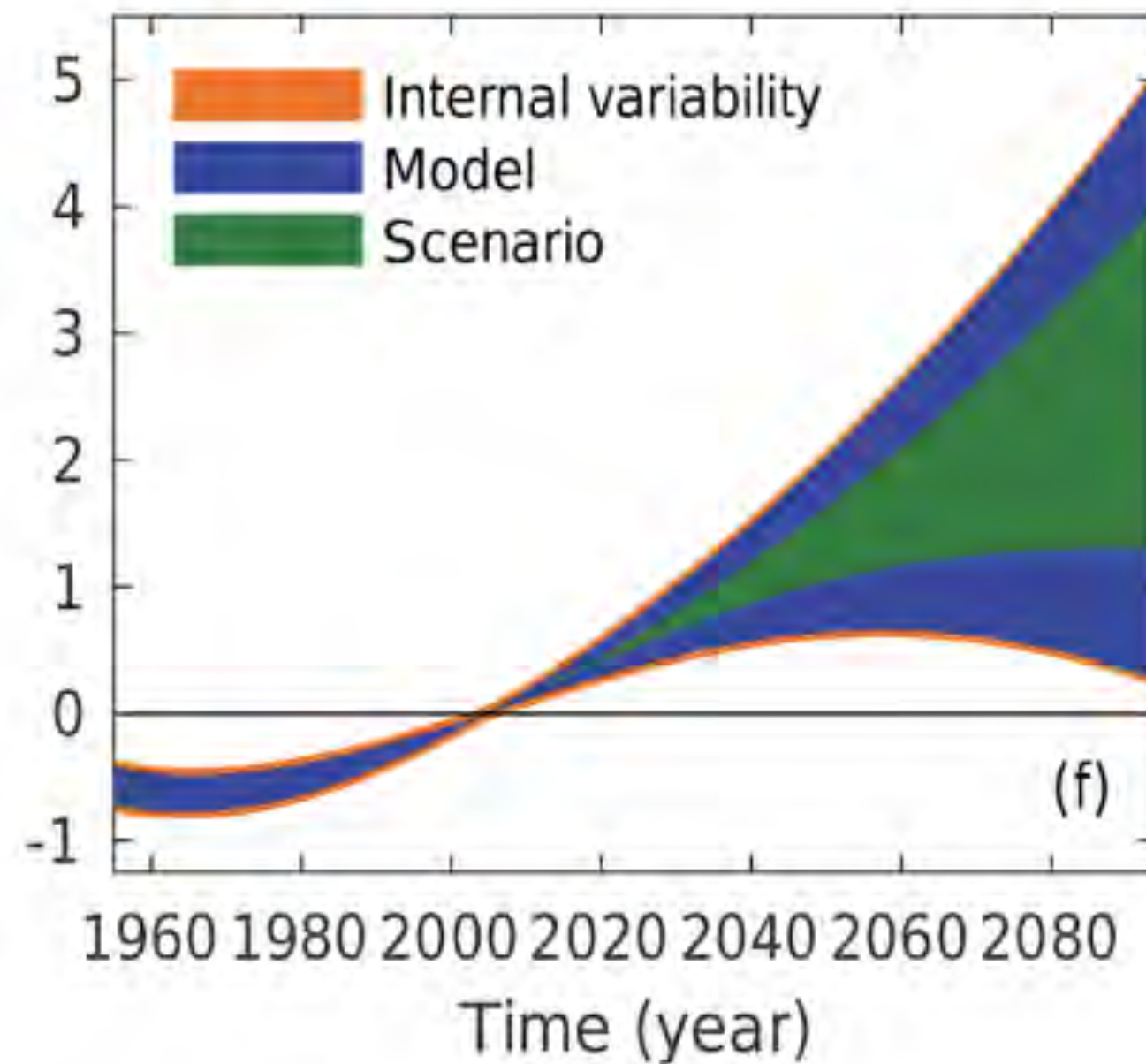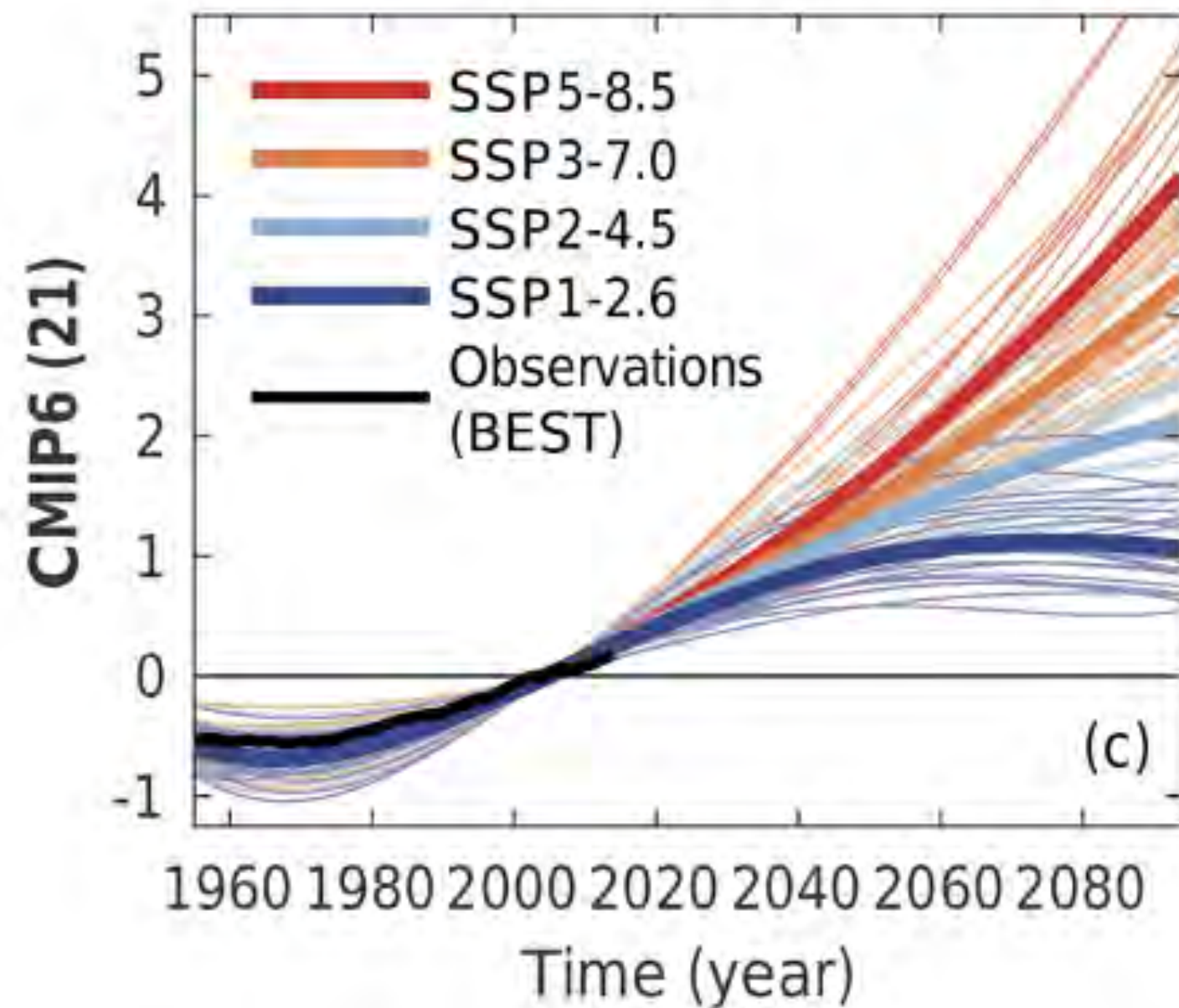Fractional uncertainty

Lead time [years from 2000]

Sanderson & Knutti (2012)
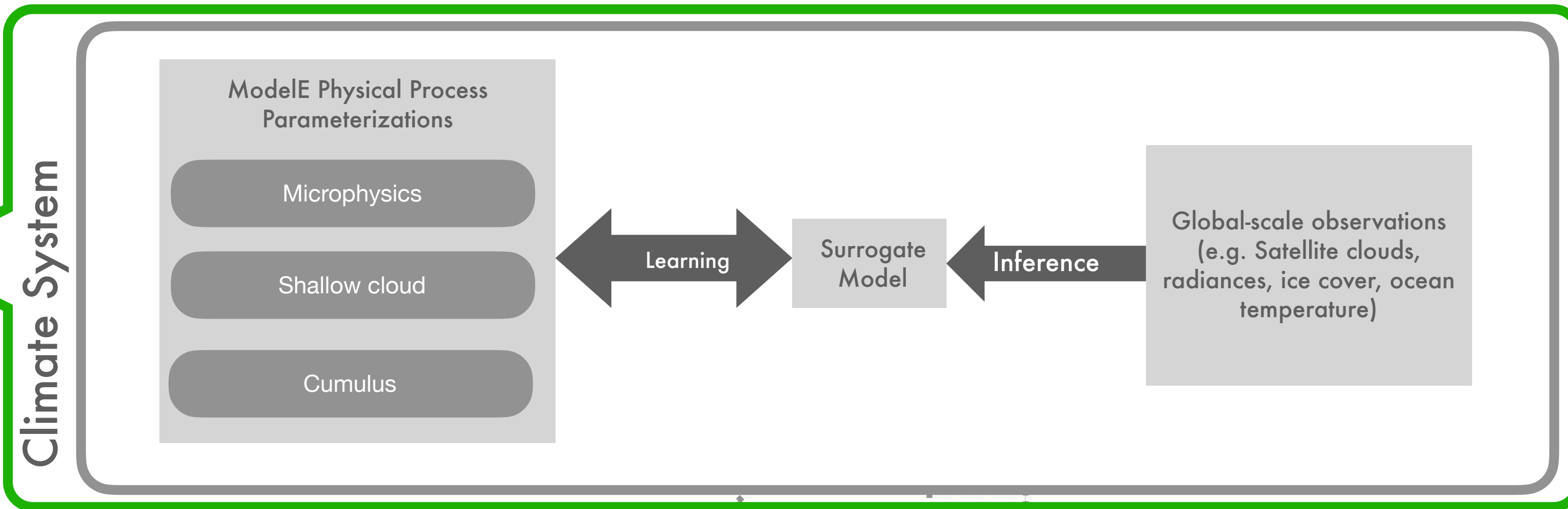
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Sanderson & Knutti (2012)

Lehner et al. (2020)

Top-down tuning of ModelE using MCMC and ML, informed by global satellite data

Climate System

ModelE Physical Process Parameterizations

Microphysics

Shallow cloud

Cumulus

Learning

Surrogate Model

Inference

Global-scale observations (e.g. Satellite clouds, radiances, ice cover, ocean temperature)

Future work uniting bottom-up and top-down approaches

"Bottom-up" inference using MCMC, informed by detailed schemes and theory

Microphysics Parameterization

Advances in cloud physics knowledge

Laboratory Studies

Theory

Cloud and Precipitation Observations

"Physically-based" parameterization

Bulk microphysics schemes e.g. BOSS (Morrison et al. 2020)

Inference

"Physically-based" parameterization

Detailed microphysics schemes (e.g. bin and Lagrangian schemes)

Inference

Cloud and precipitation observations (e.g. polarimetric radar, satellite radiance, in situ measurements)

Learning

Surrogate Model

Inference

Future work using observations to improve process-level understanding