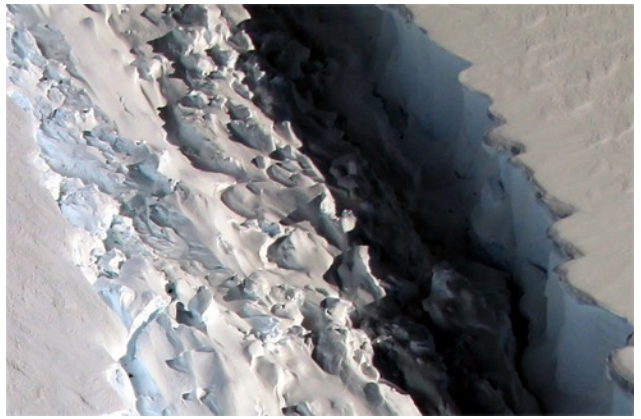
SCIENCE



Evapotranspiration Uncertainty Quantification

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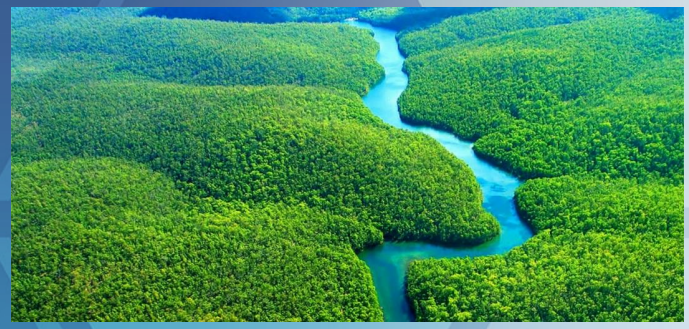
Summary of UQ activities

- With all the data that has been gathered over the past decades enhancing our knowledge of Earth and the universe, three new classes of high-stake decision making processes have emerged:
  - What to observe next that we don't already know?
  - How do we make sure that the observation solves the science question?
  - How robust are decisions based on the new data?
- Solution: Better quantitative characterization of these complex systems through the application of system engineering and uncertainty quantification methods would enable:
  - Improved science analysis and applications results
  - Improved science traceability for optimizing measurement system (mission and instruments) design
  - Improved prioritization of missions and instruments



Summary of JPL activities

- Observing System Simulator Capabilities (building on existing ‘models’ of the state of knowledge)
- Training in UQ for STMs/proposal
- Team of UQ experts that helps teams with traceability (e.g. FINESSE, InSight, …)
- Guidelines in Playbook
- (Science) CML entry/exit criteria (Foundry)

Example: UQ in evapotranspiration

- ECOSTRESS produces a standard L3 product for Evapotranspiration (ET).
- Two ET models are used – here we focus on disALEXI (developed by USDA)
  - Takes 14 inputs, including meteorological data, vegetation information, and LST from ECOSTRESS
- Currently, uncertainty is estimated as a standard deviation of model runs (PT-JPL), or scaled LST uncertainty (disALEXI)

$$\left(X_1(s_i), X_2(s_i), \dots, X_p(s_i), E(s_i)\right)$$

Spatial-statistical model

ET model

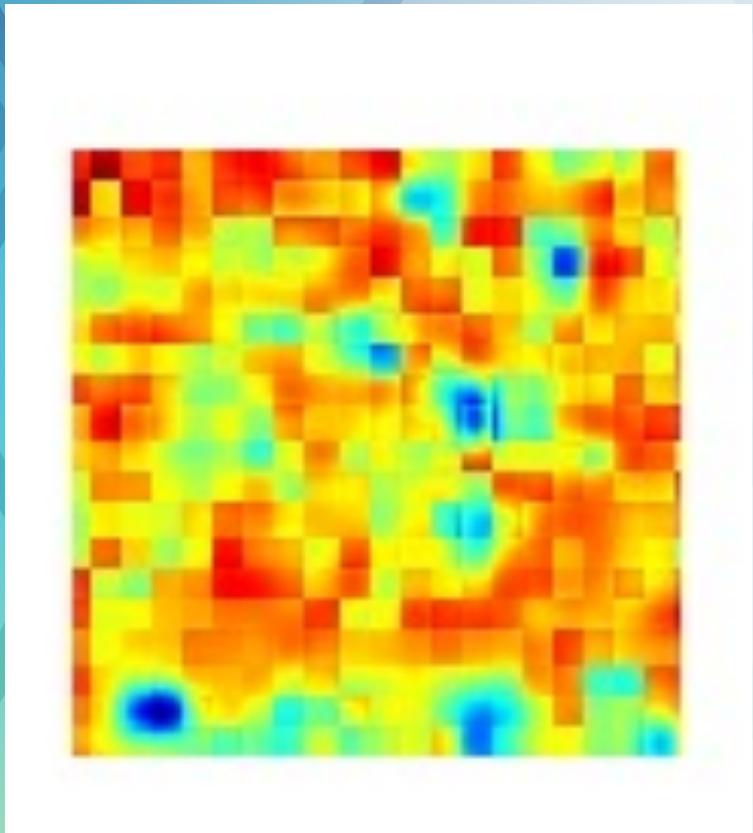
$$\{X_1^{sim}(s_i), X_2^{sim}(s_i), \dots, X_p^{sim}(s_i)\}$$

$$\{\hat{E}_m^{sim}(s_i)\}$$

$$\{\hat{E}_m^{sim} - \boldsymbol{E}\}_{m=1}^{M}$$

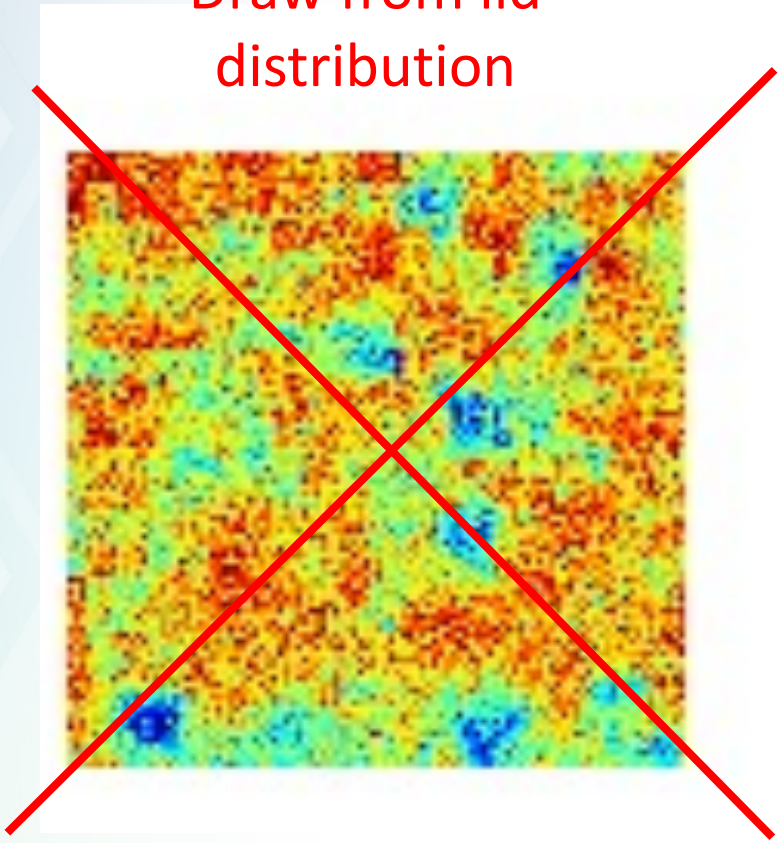
By treating the entire field at once, spatial and between-variable dependence structures are maintained in the

Input comparison



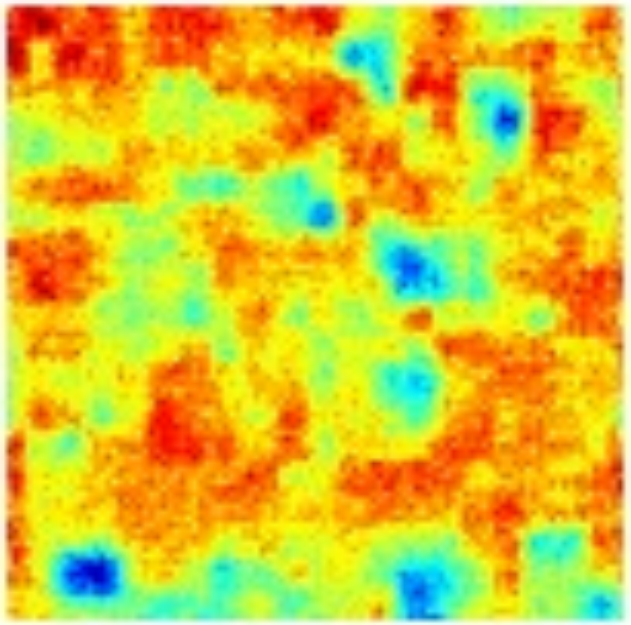
Original LST

Draw from iid distribution



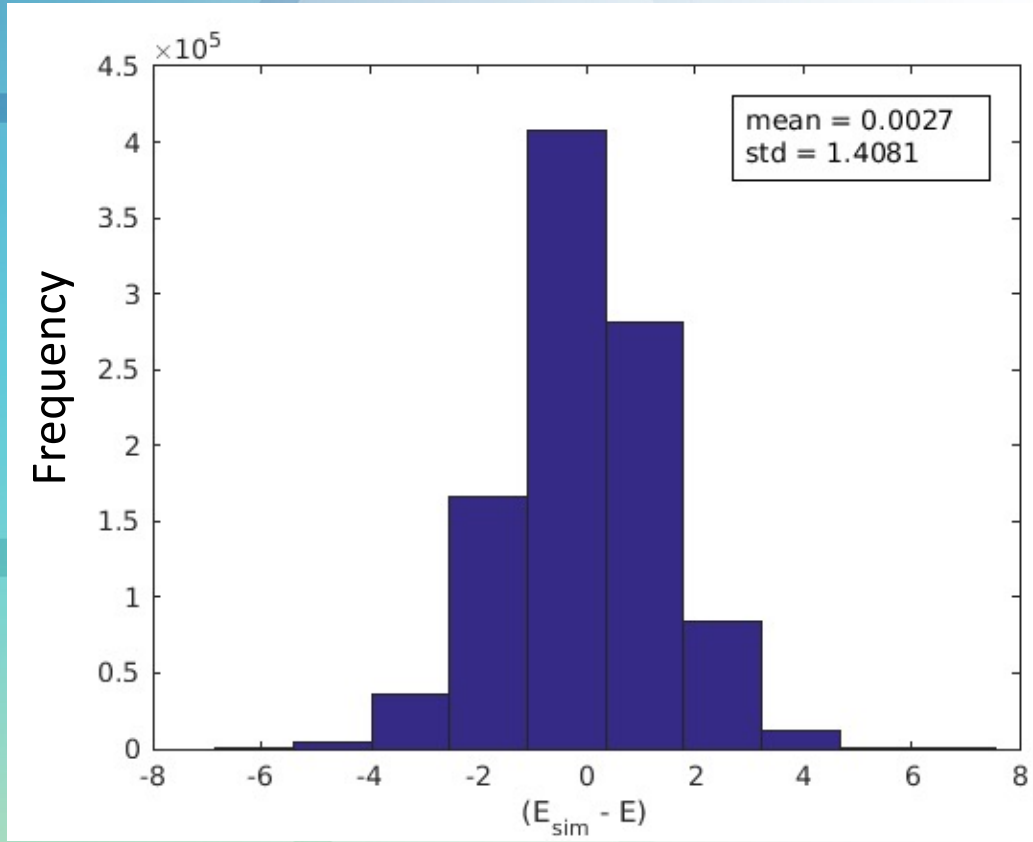
Noisy LST

Draw from fused Gaussian process model

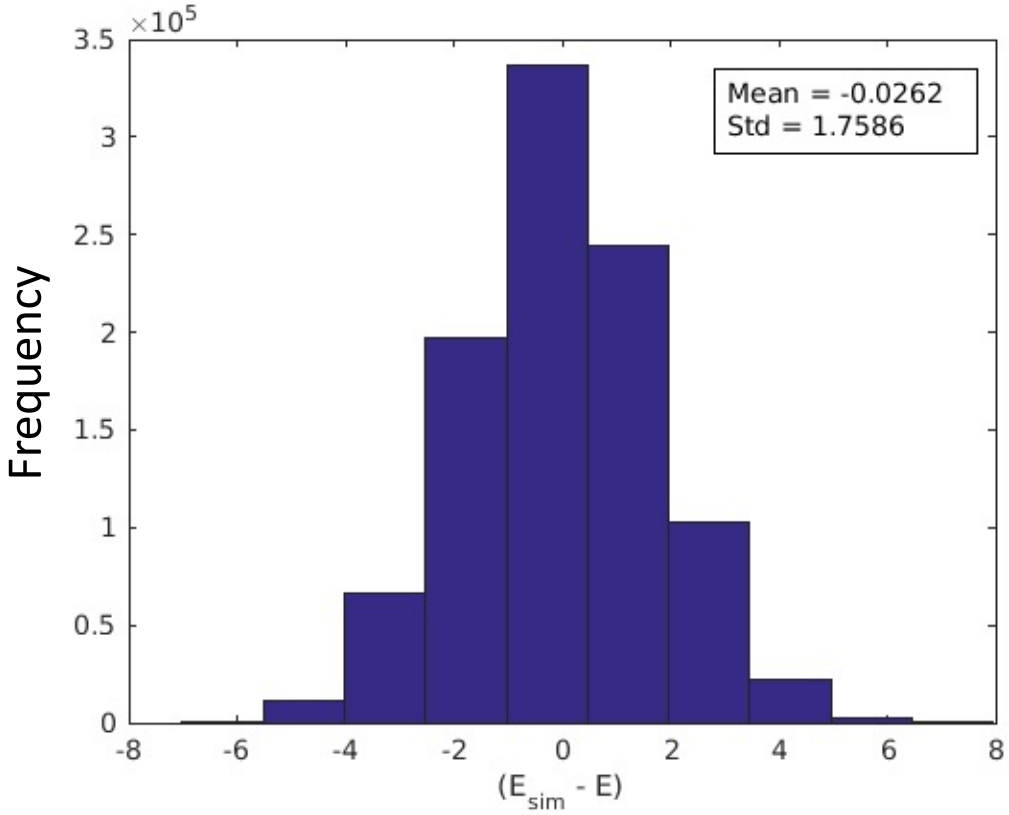


Simulated LST

Sensitivity illustration

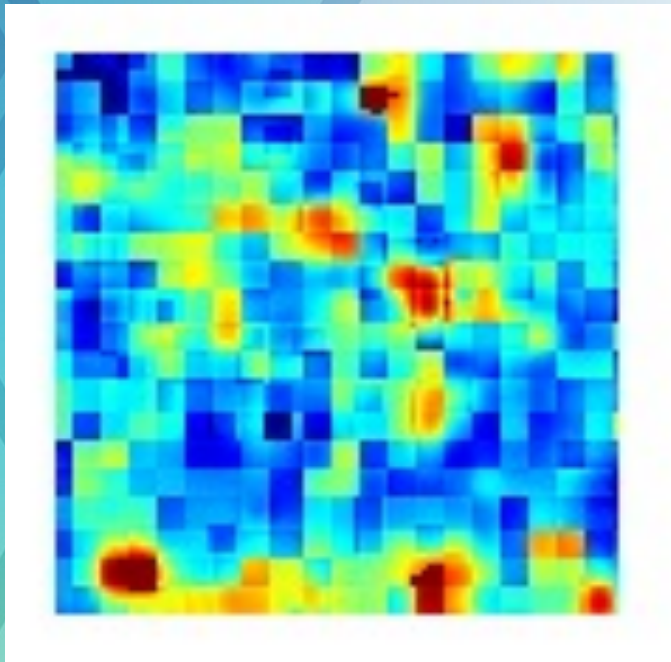


With simulated LST as input

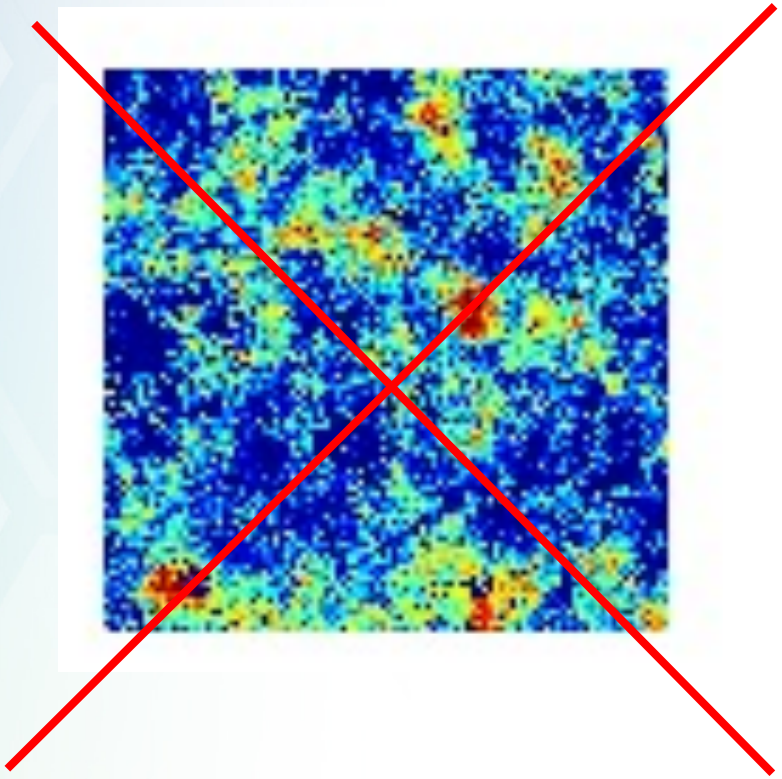


With i.i.d. noisy LST as input

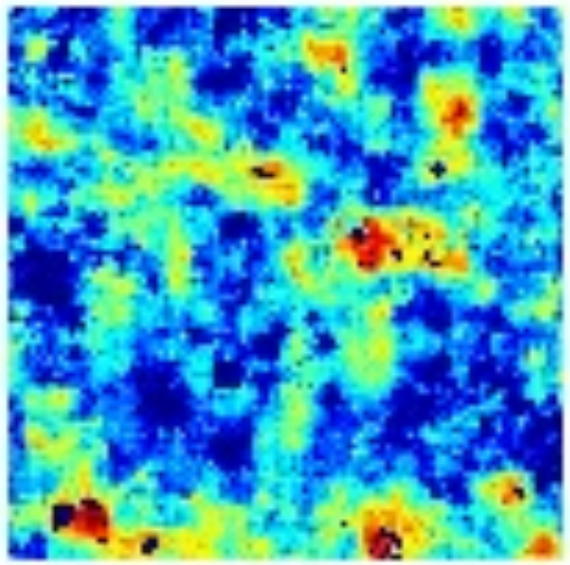
Output comparison



Original ET

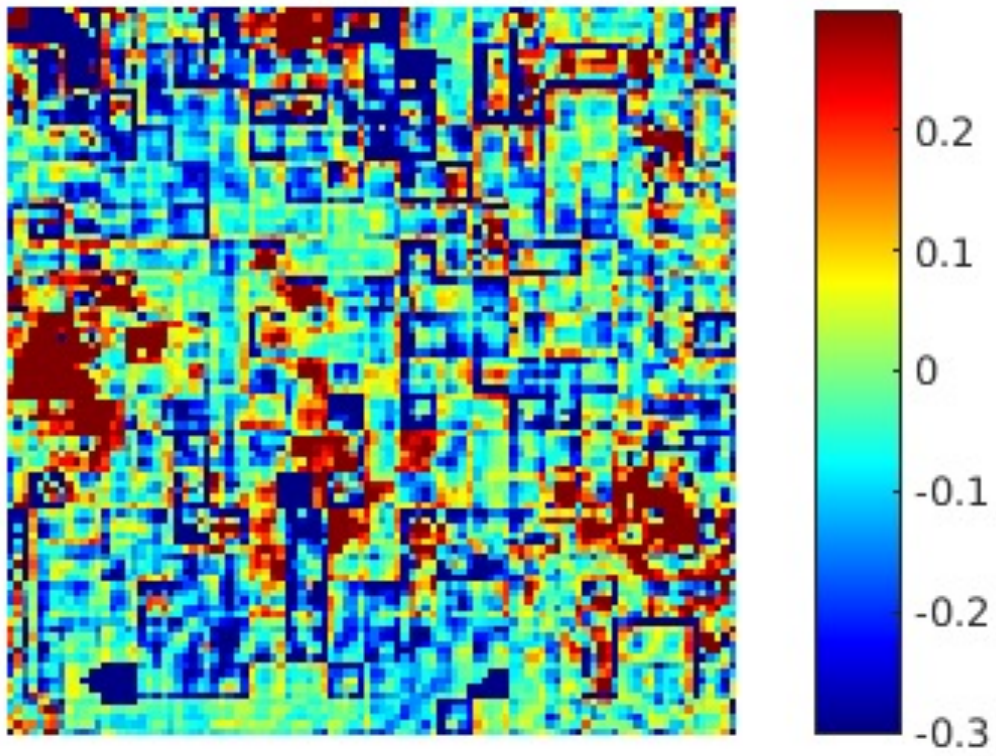


ET model with noisy input

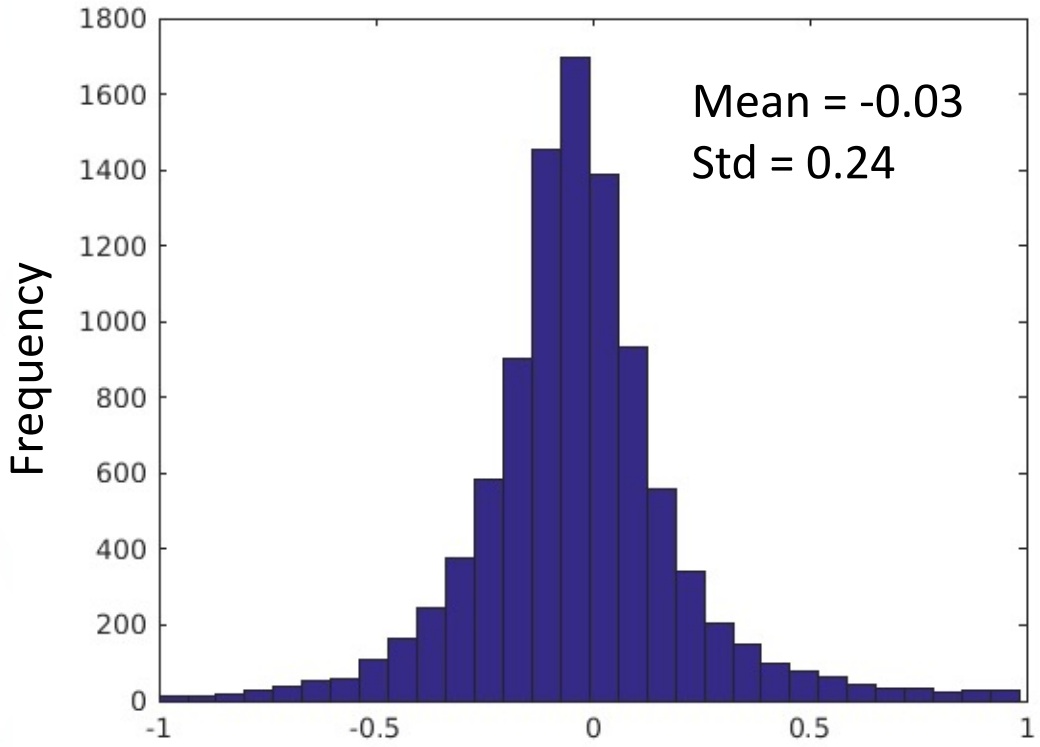


ET model output 2

Results

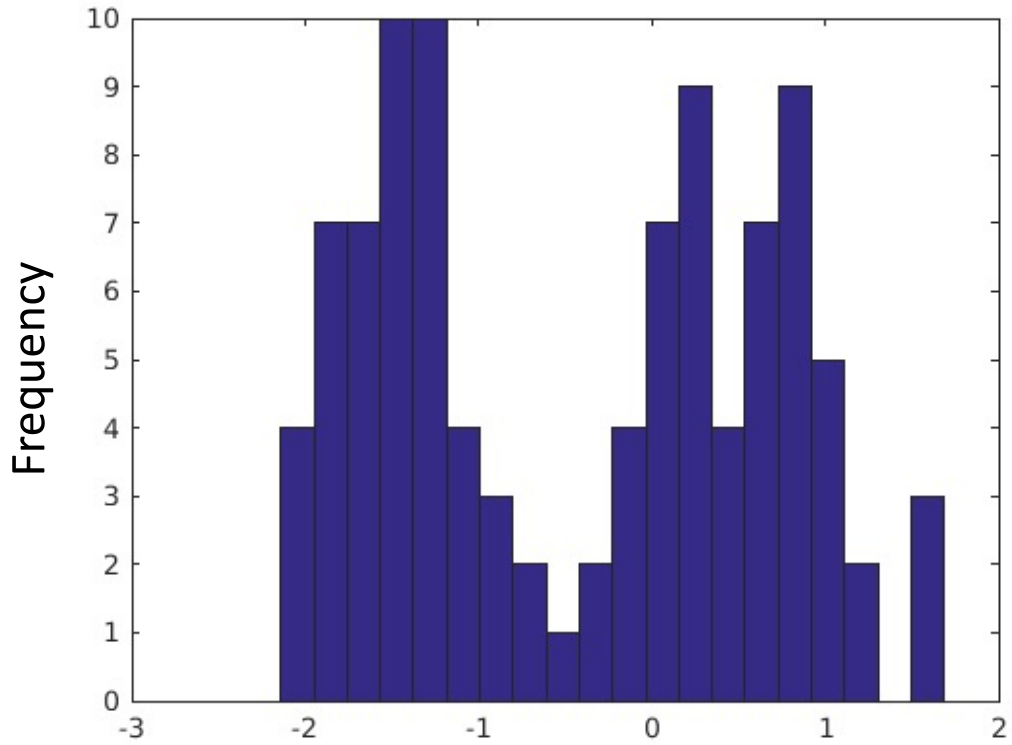


Predicted – Observed as proportion

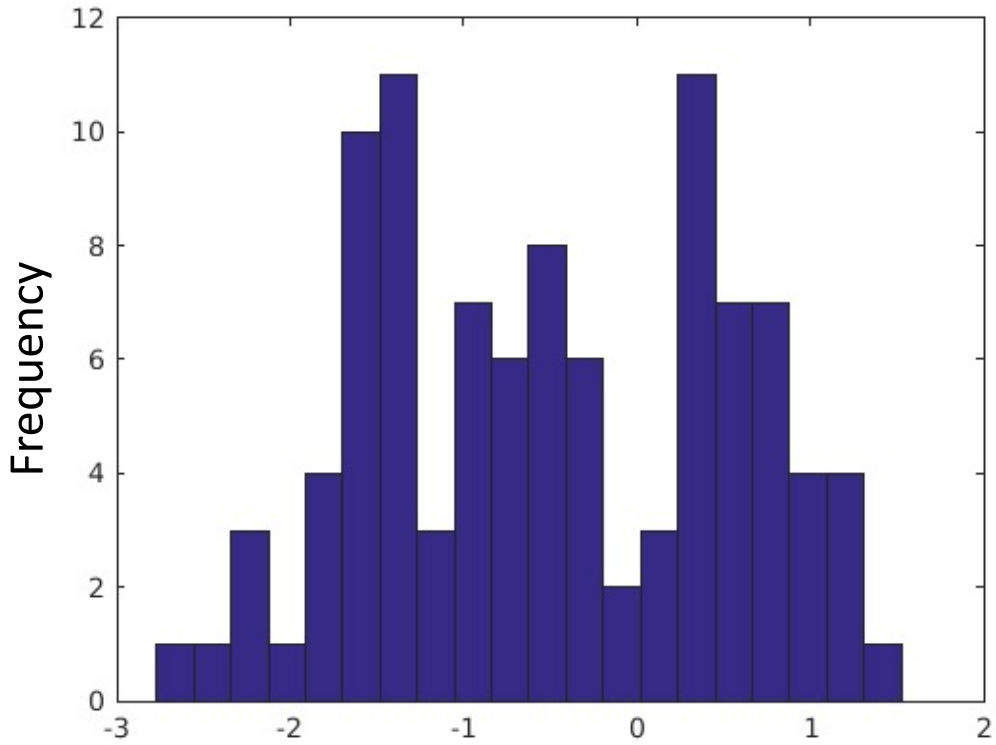


Predicted – Observed as proportion

Accuracy per pixel



(ET_0 – ET_out)



(ET_0 – ET_out)

Summary

- Accuracy and precision are not useful concepts for ET!
- What is the proper metric for ET uncertainty?
- What should we be reporting, and to whom?
- How should we formulate requirements for future missions (e.g. SBG) if “accuracy” isn’t a useful concept?

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