QGP parameter extraction via a global analysis of event-by-event flow coefficient distributions

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Model to data comparison

Input parameters

η/s, τ_0, α, ...

↓

Model

initial conditions

viscous hydro

sampler

UrQMD

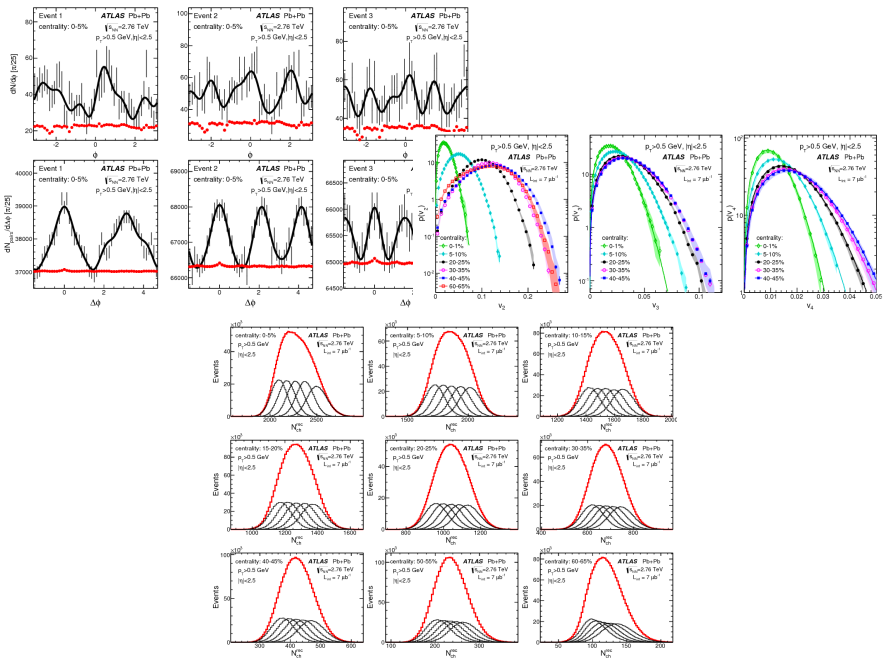
↓

Output (observables)

flow, multiplicity, ...

?

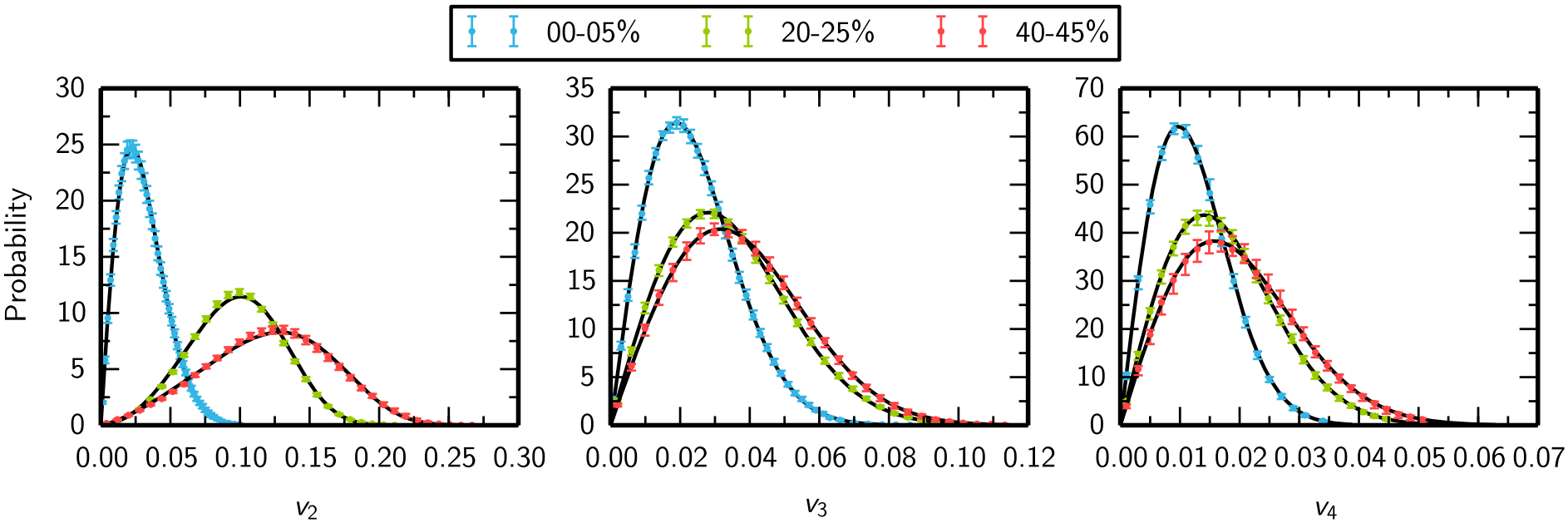
Experimental data



The data

- ATLAS event-by-event flow distributions for v_2, v_3, v_4.
- Shapes of distributions could provide a more sensitive probe of QGP properties than average flows.
- Reduce to three parameters by fitting to generalized gamma distribution

$$f(x; s, a, c) = \frac{c}{s\,\Gamma(a)} \left(\frac{x}{s}\right)^{ac-1} \exp\left[-\left(\frac{x}{s}\right)^{c}\right]$$



ATLAS collaboration, hep-ex/1305.2942

The model

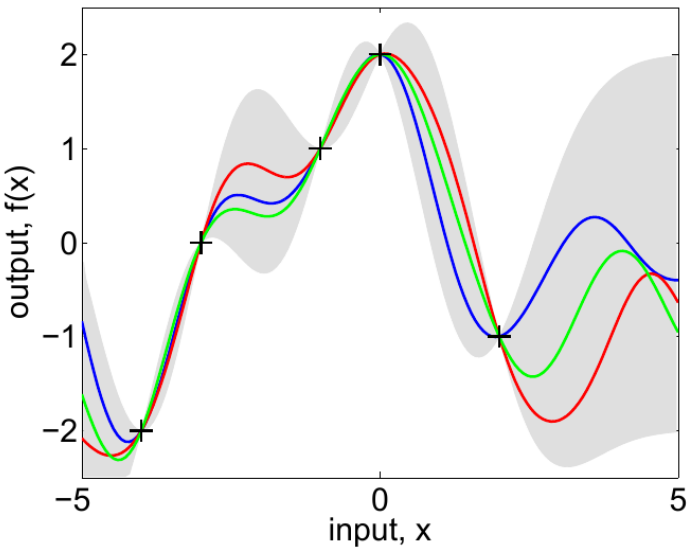
Modern version of the OSU+Duke hybrid model VISHNU (Viscous Hydro and UrQMD):

- MC-Glauber initial conditions [H.-J. Drescher and Y. Nara, nucl-th/060512]
- 2+1 viscous hydro [H. Song and U. Heinz, nucl-th/0712.3715]
- Cooper-Frye hypersurface sampler [Z. Qiu and C. Shen]
- UrQMD [S. Bass *et. al.*, nucl-th/9803035; M. Bleicher *et. al.*, hep-ph/9909407]

Input parameters	Observables
Normalization	
WN/BC α	v_n distributions
Thermalization time τ_0	Multiplicities
Viscosity η/s	...
Shear stress relaxation time τ_Π	

Computer experiments with slow models

- Run model at predetermined set of input-parameter points.
  - Each parameter influences multiple observables.
  - Must vary all parameters simultaneously.
- Interpolate between points to complete parameter space.
- Calibrate the model: determine parameters that optimally describe reality.



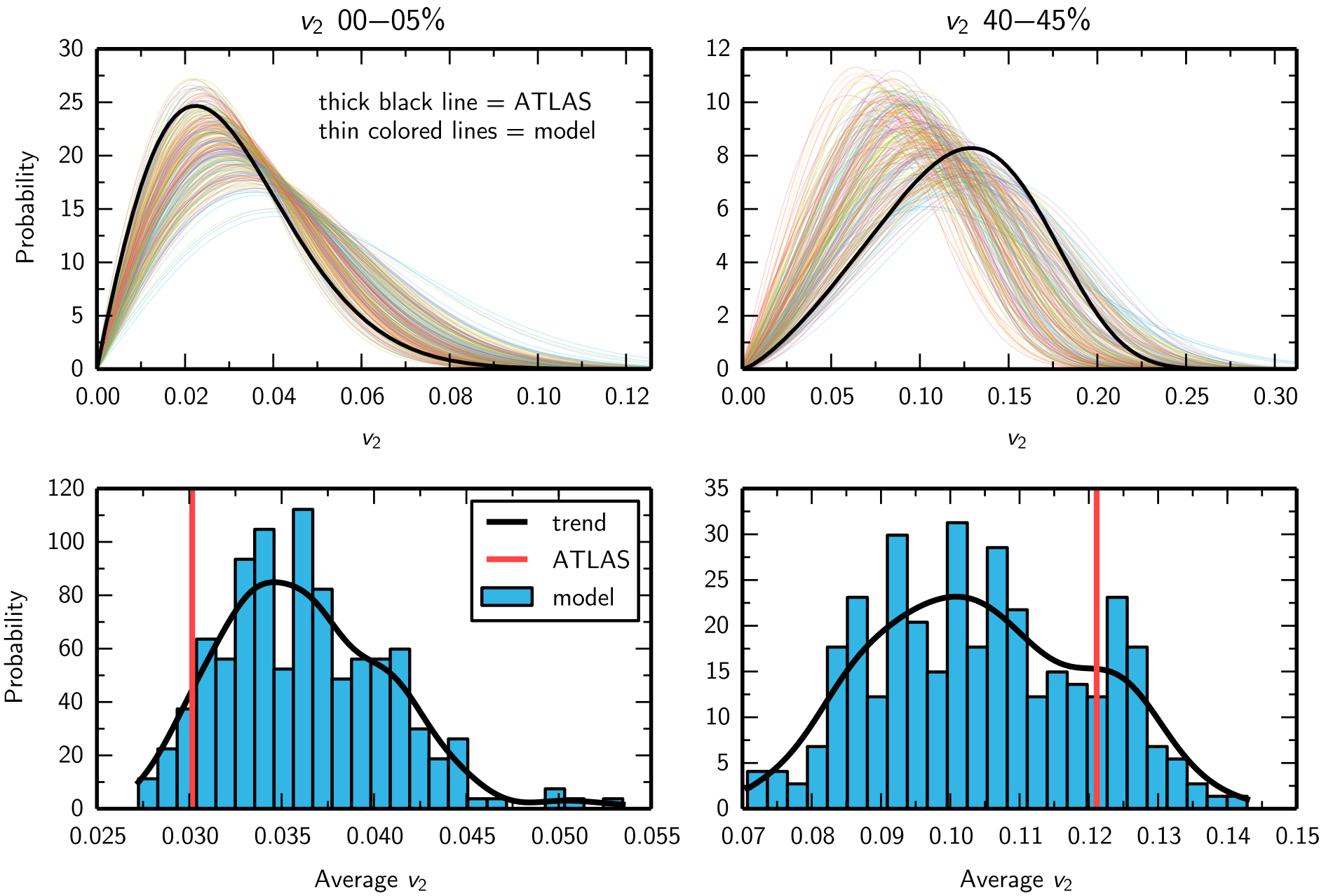
Gaussian Processes for Machine Learning, Rasmussen and Williams, 2006.

Computer experiment design

- Five centrality bins from 0–5% to 40–45%.
- 256 Latin-hypercube points across five input parameters.
- Running on Open Science Grid.
- Completed 1000-2000 events per centrality bin and input-parameter point.
  - $\sim$1.9 million total
  - $\sim$0.25 μb^{-1} (ATLAS results based on 7 μb^{-1})

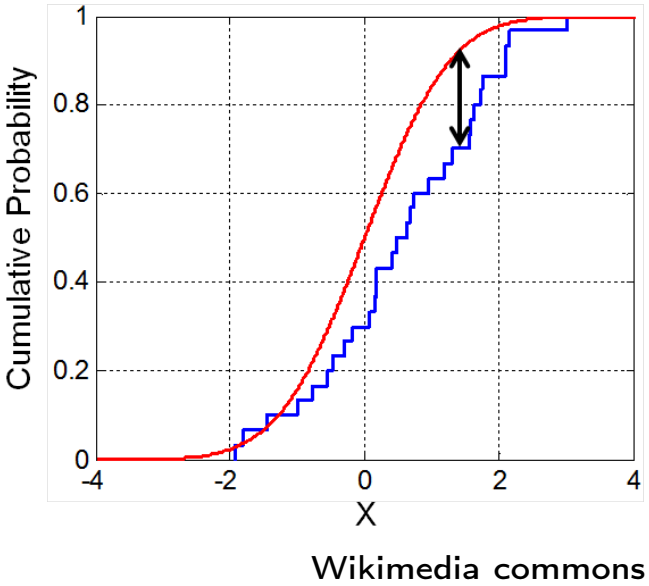
- (5 centrality bins) $\times$ (3 flow coefficients) = 15 flow "categories"
- v_2 0–5% and v_2 40–45% are representative.

Model flow distributions

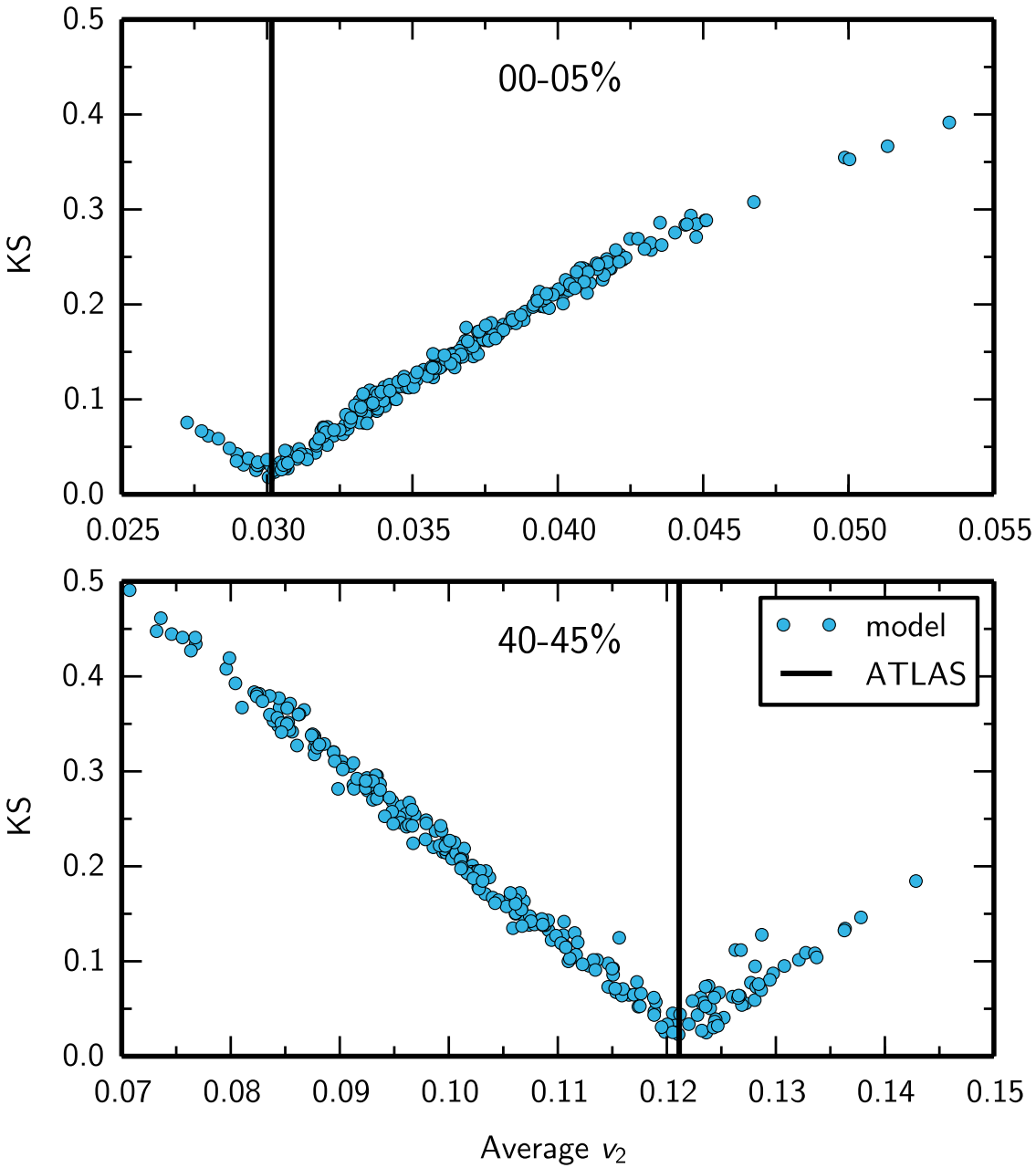


Comparing model and experimental distributions

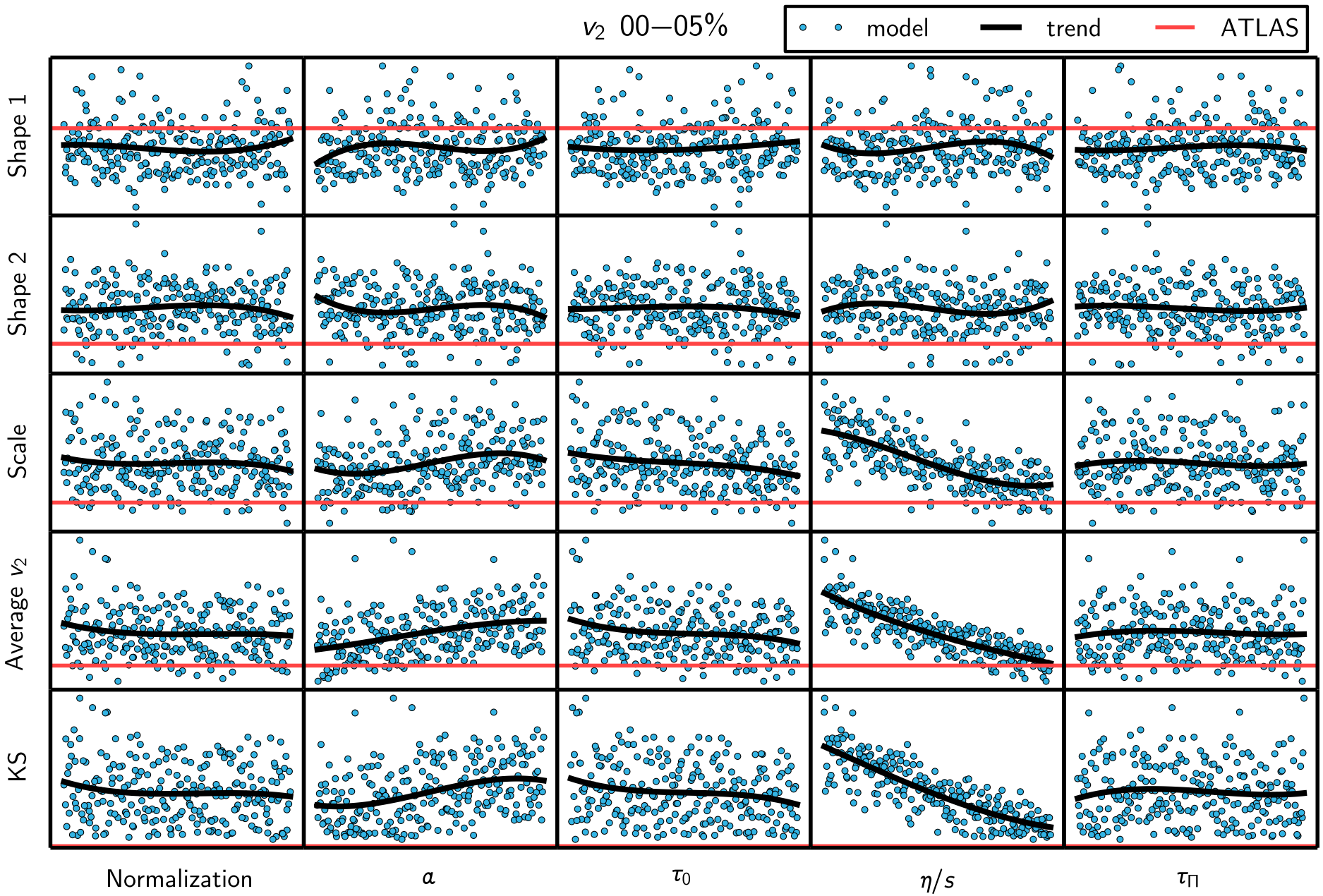
Kolmogorov-Smirnov test



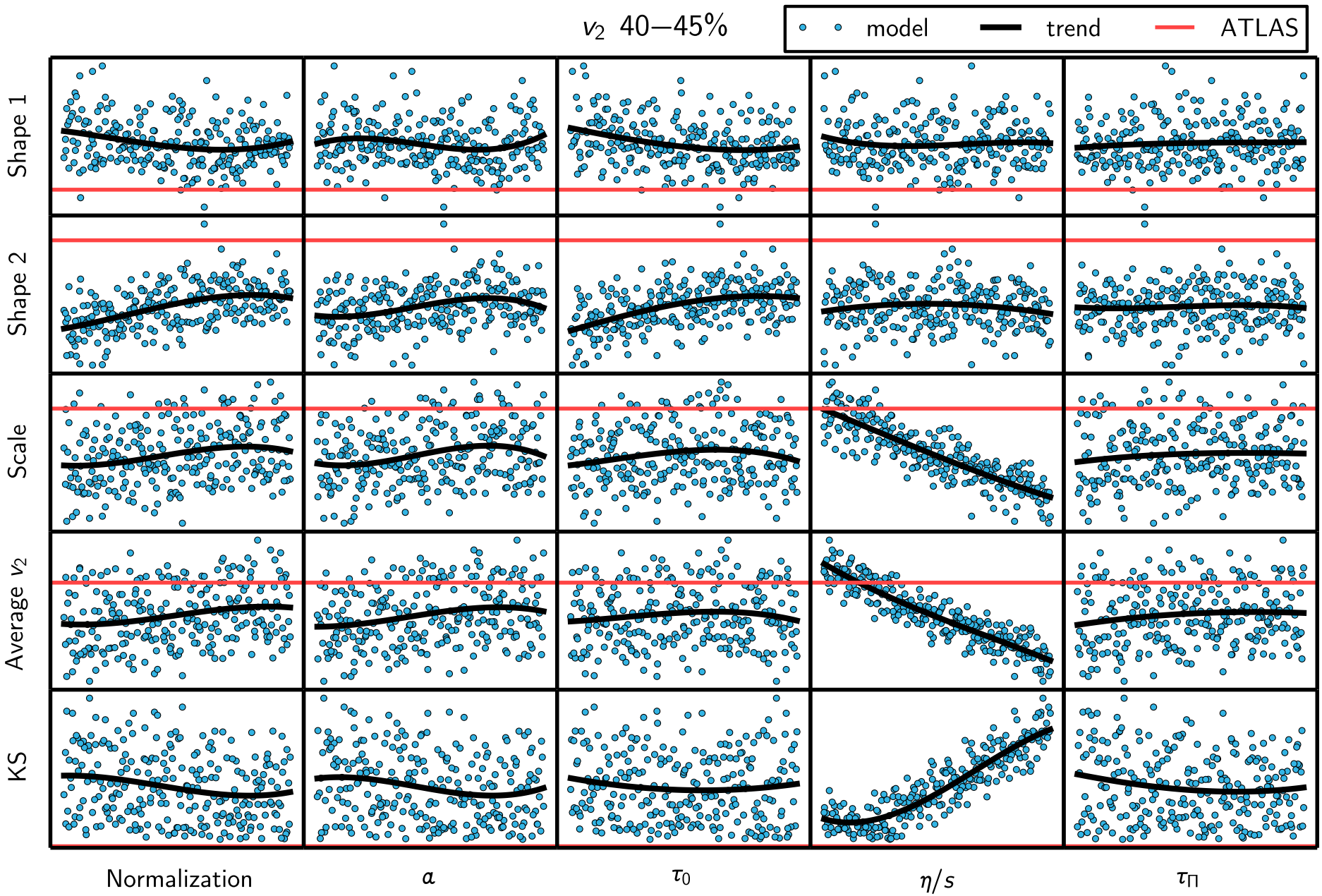
smaller KS $\Longrightarrow$ better fit



Input-output summary



Input-output summary



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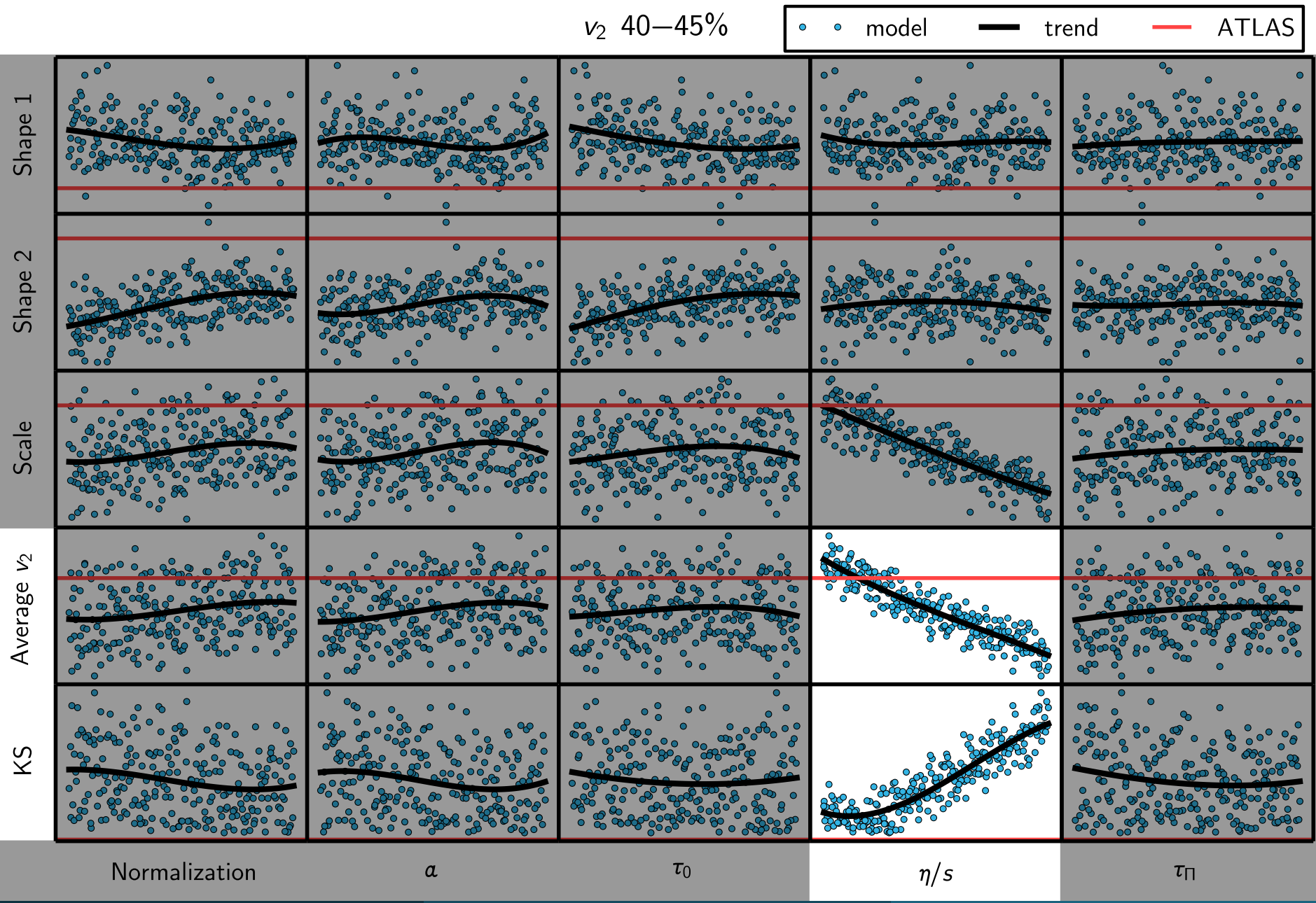
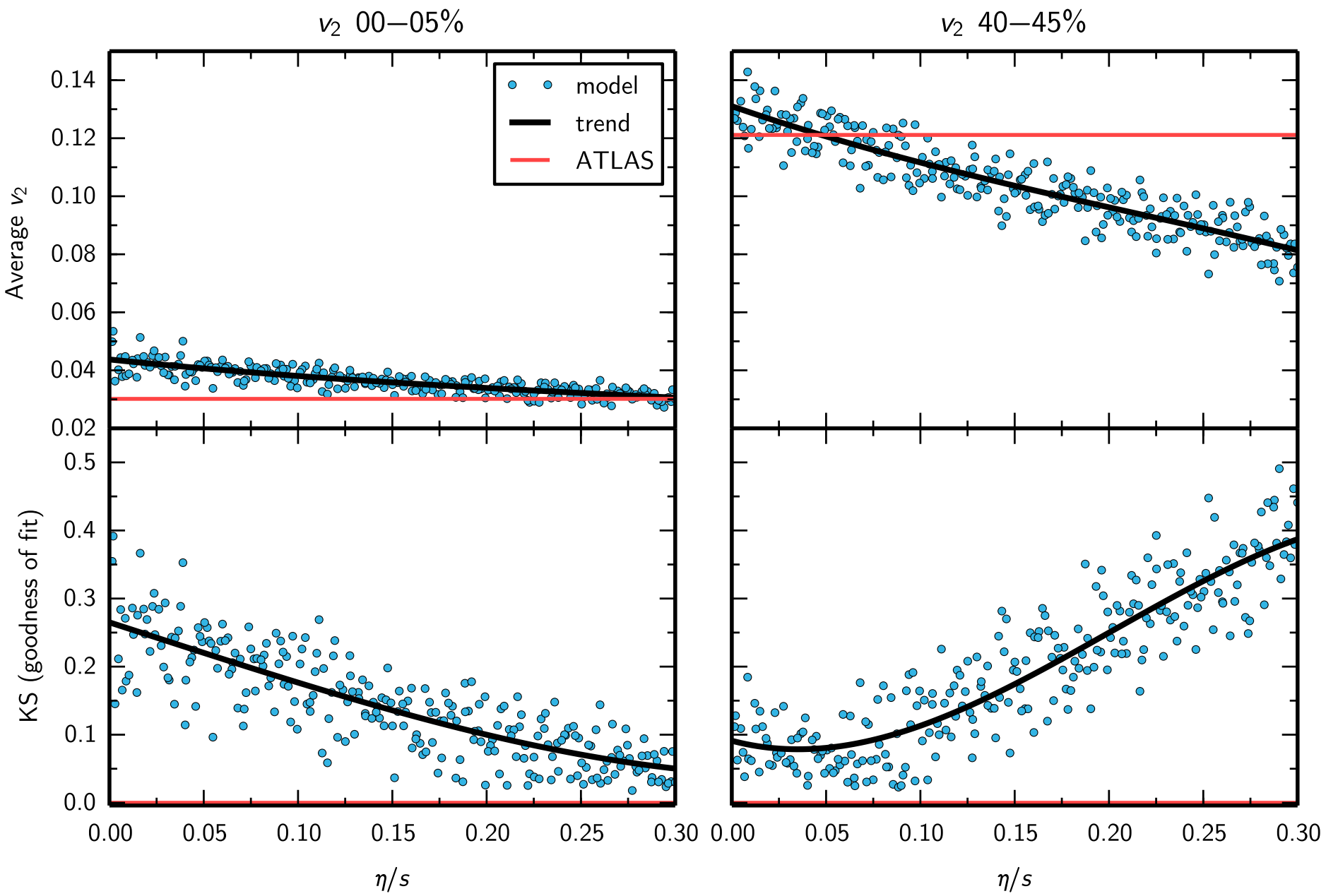
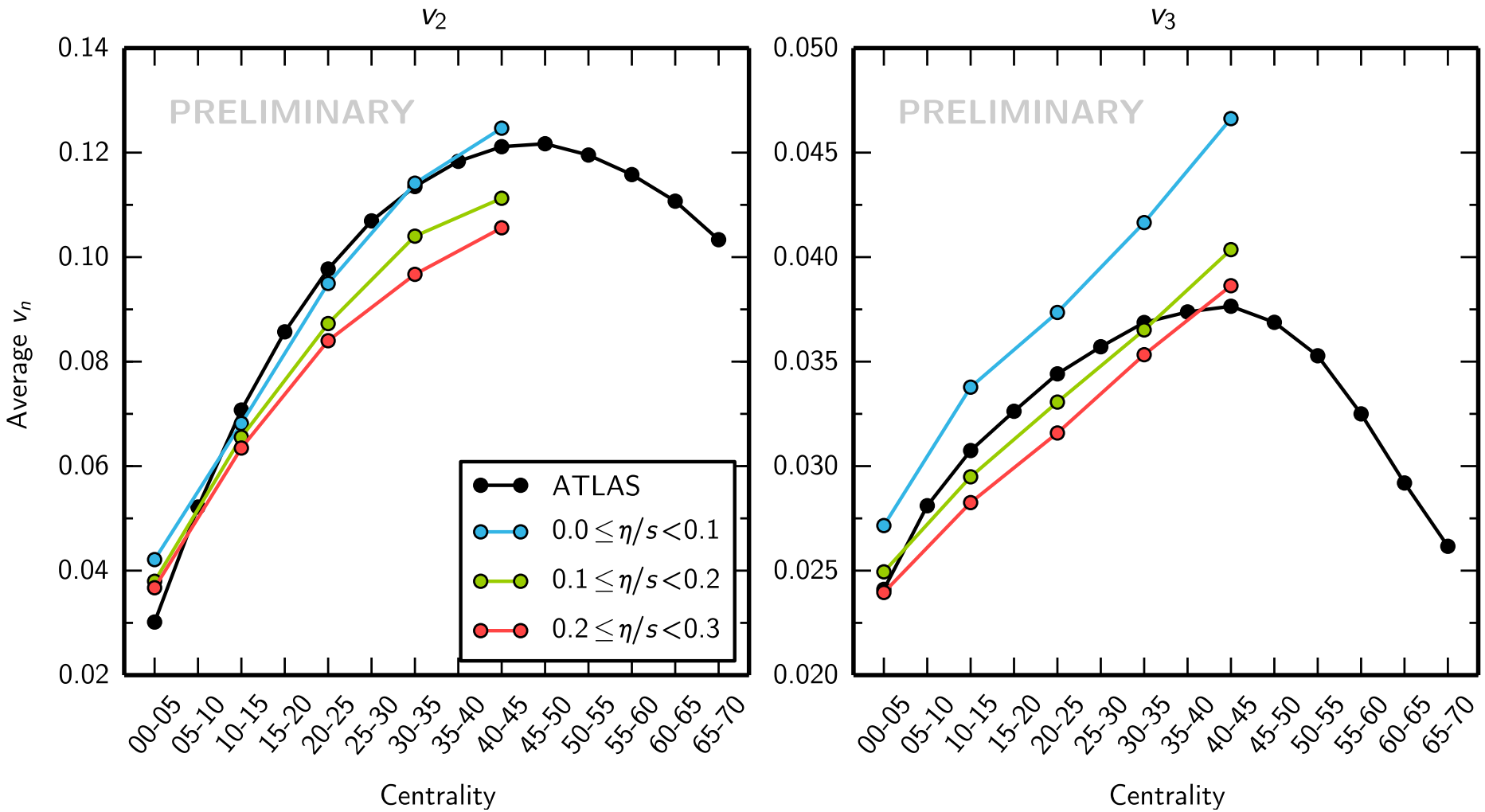


Focusing on viscosity

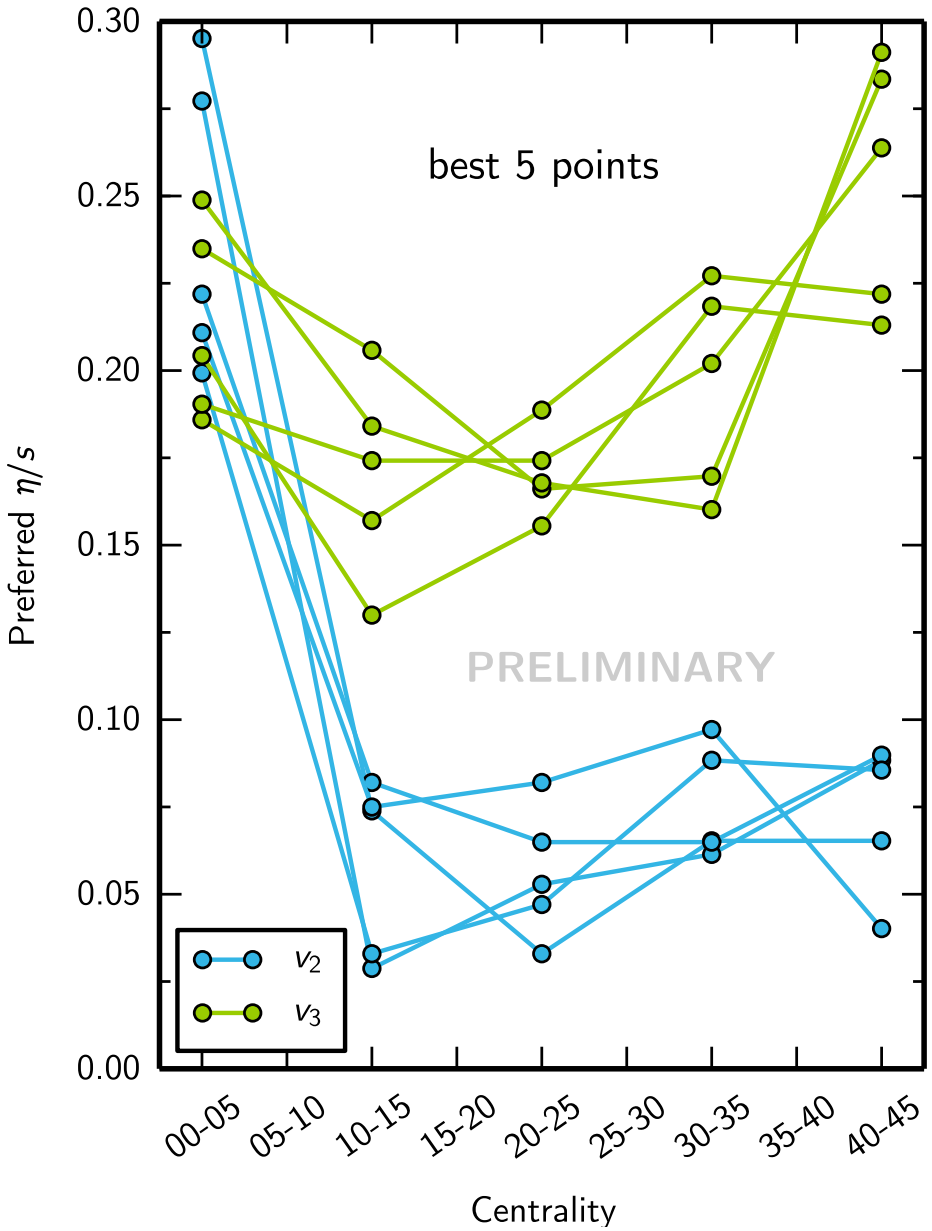


Best fits

- Split η/s range into sub-ranges.
- Pick parameter point with best overall fit in each η/s sub-range.



Summary & outlook

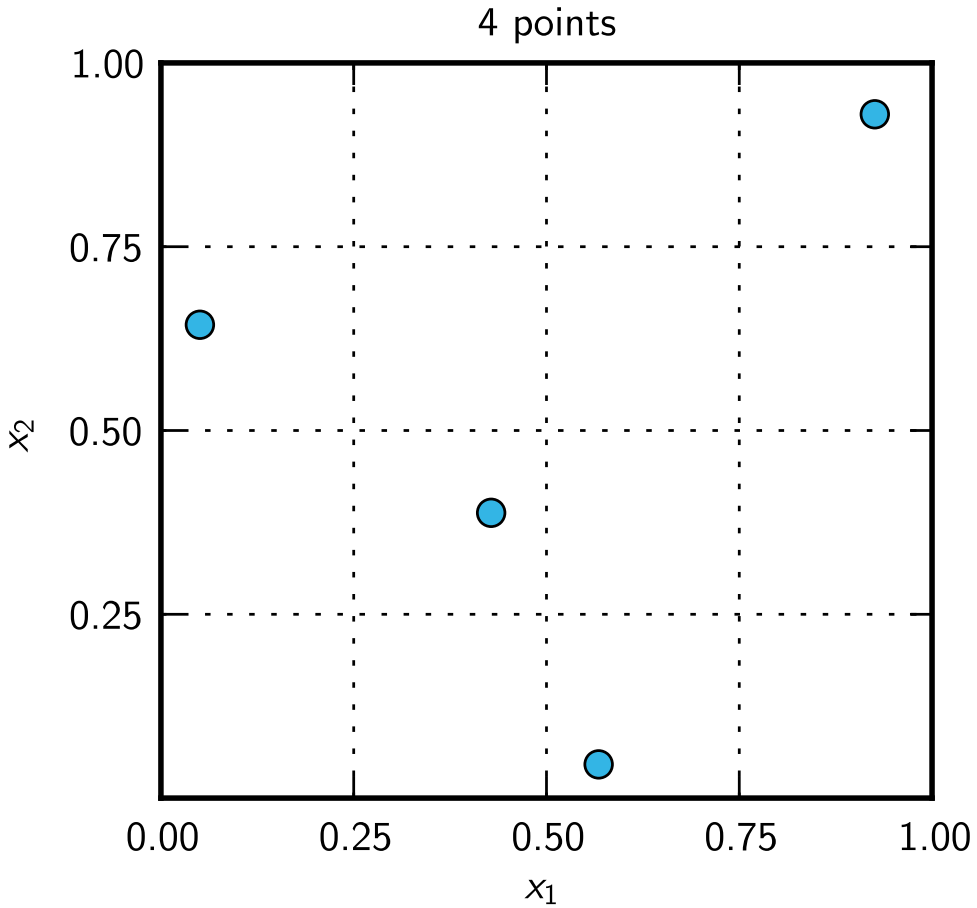


- η/s compromise
  - η/s temperature dependence?
  - Expand parameter space?
- Quantitative statistical metrics
- Calibrate simultaneously on multiplicity
- Improved initial conditions (KLN, IP-Glasma)

backup slides

Latin-hypercube sampling

- Optimally fills parameter space.
- Avoids clusters.



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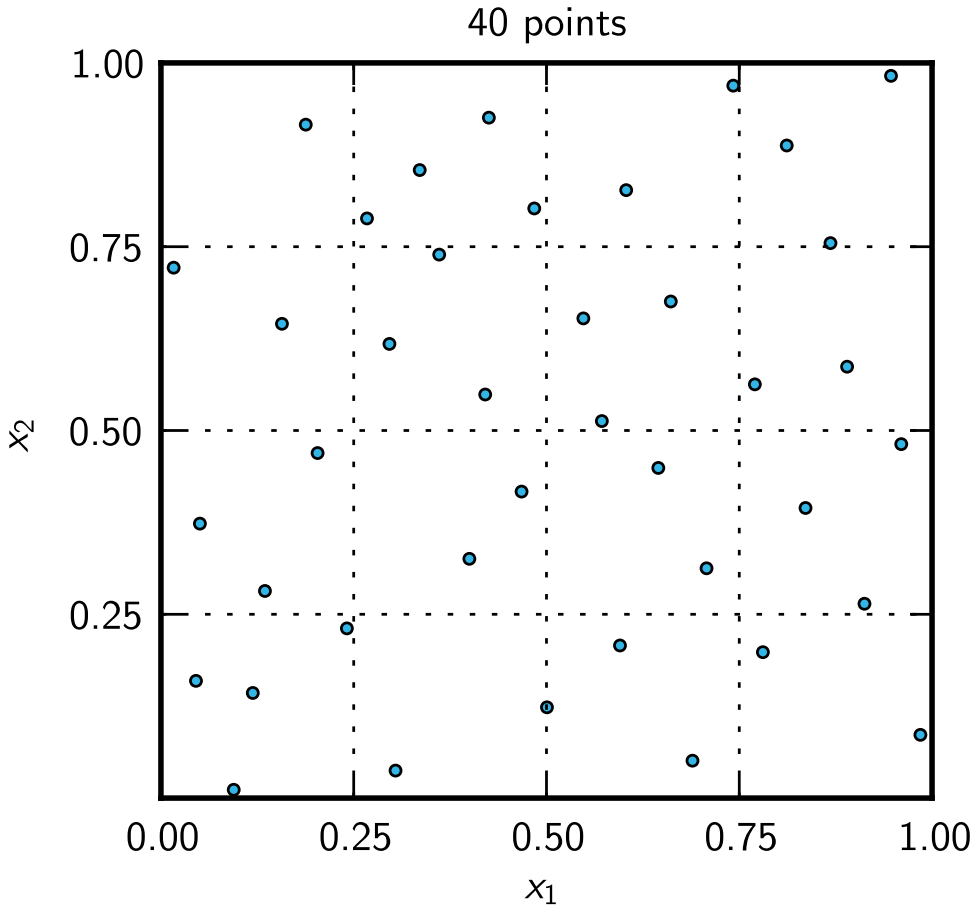
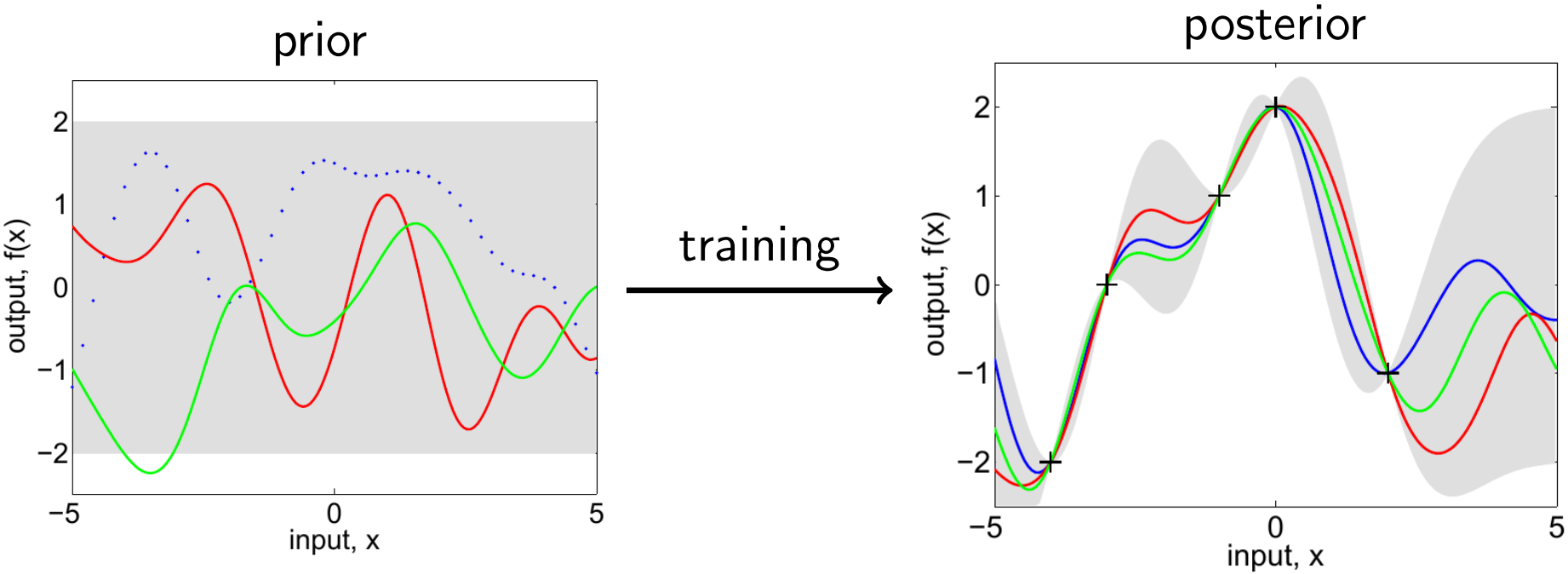


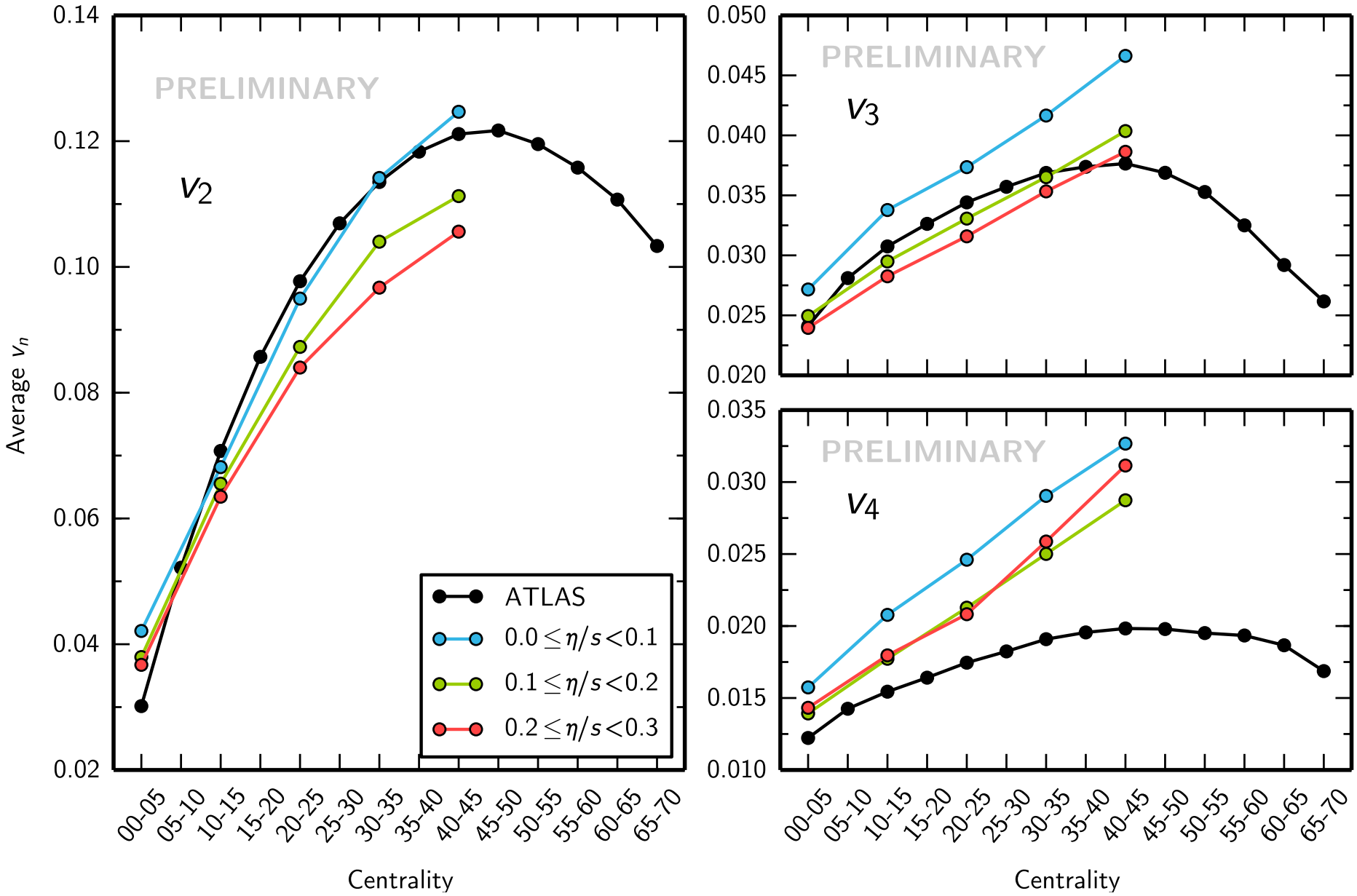
Gaussian process emulators

- Prior: the model is a Gaussian process.
- Posterior: Gaussian process conditioned on model outputs.

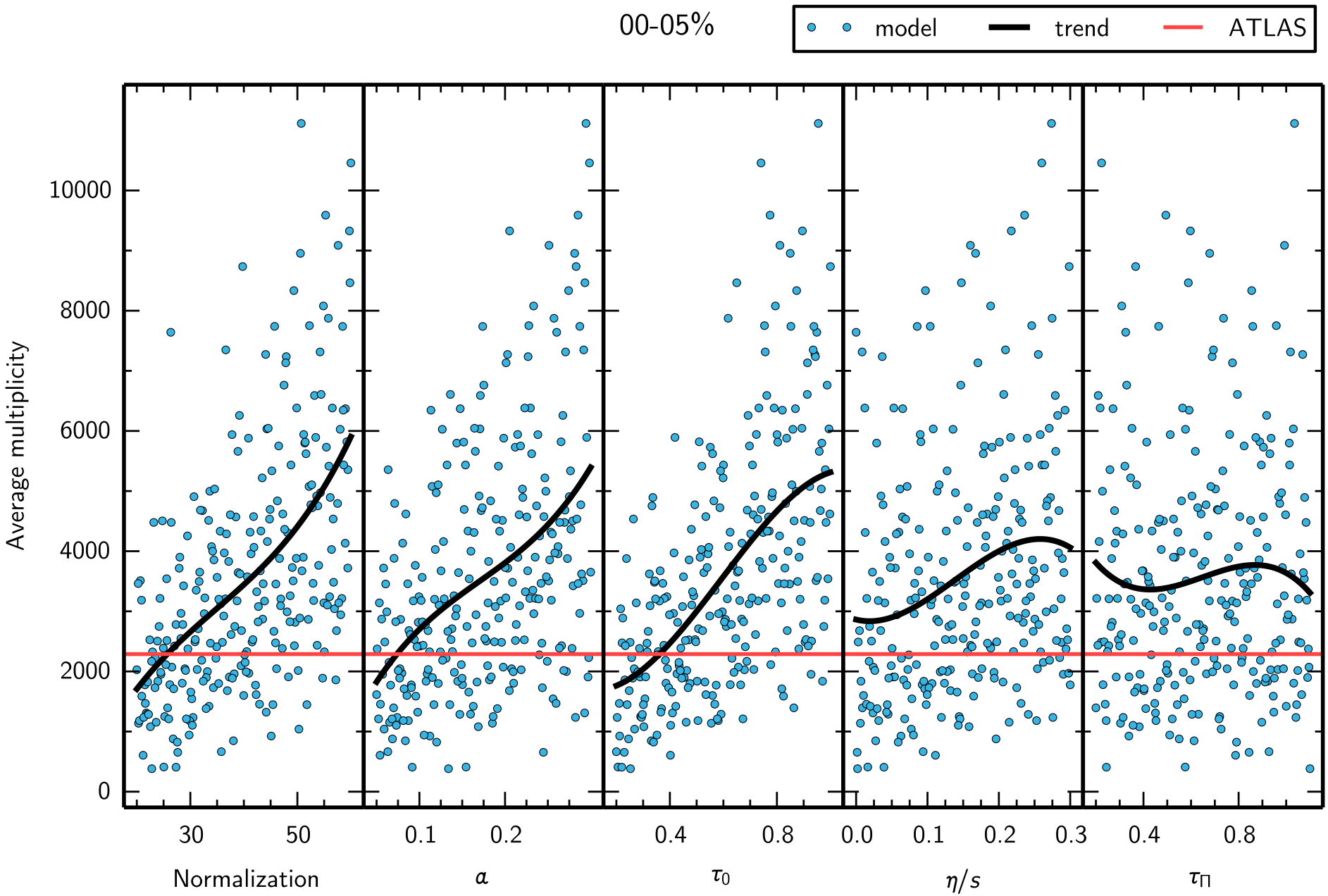


- Emulator is a fast surrogate to the actual model.
  - More certain near calculated points.
  - Less certain in gaps.

Testing v_4


PRELIMINARY
v_2
PRELIMINARY
v_3
PRELIMINARY
v_4
Average v_n
Centrality
Centrality
ATLAS
$0.0 \leq \eta/s < 0.1$
$0.1 \leq \eta/s < 0.2$
$0.2 \leq \eta/s < 0.3$
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.050
0.045
0.040
0.035
0.030
0.025
0.020
0.035
0.030
0.025
0.020
0.015
0.010
00-05
05-10
10-15
15-20
20-25
25-30
30-35
35-40
40-45
45-50
50-55
55-60
60-65
65-70

Multiplicity



Multiplicity