



From Fusion to the Ionosphere to the Universe: Statistical Vignettes from Los Alamos National Laboratory

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What I will do in this talk:

- Introduce myself, Los Alamos, and my teammates
- Dive into three ongoing statistical projects at LANL
 1. Hypothesis testing for shapes in neutron images
 2. On-orbit calibration for ionospheric plasma monitoring
 3. Statistical emulation for cosmic discovery
- Give a(n incomplete, statistician-minded) introduction to each of the applications, then move on to some statistical methods work
- Close with some plugs

Introductions





Los Alamos National Laboratory (LANL)



LANL Statistics Group (CAI-4)



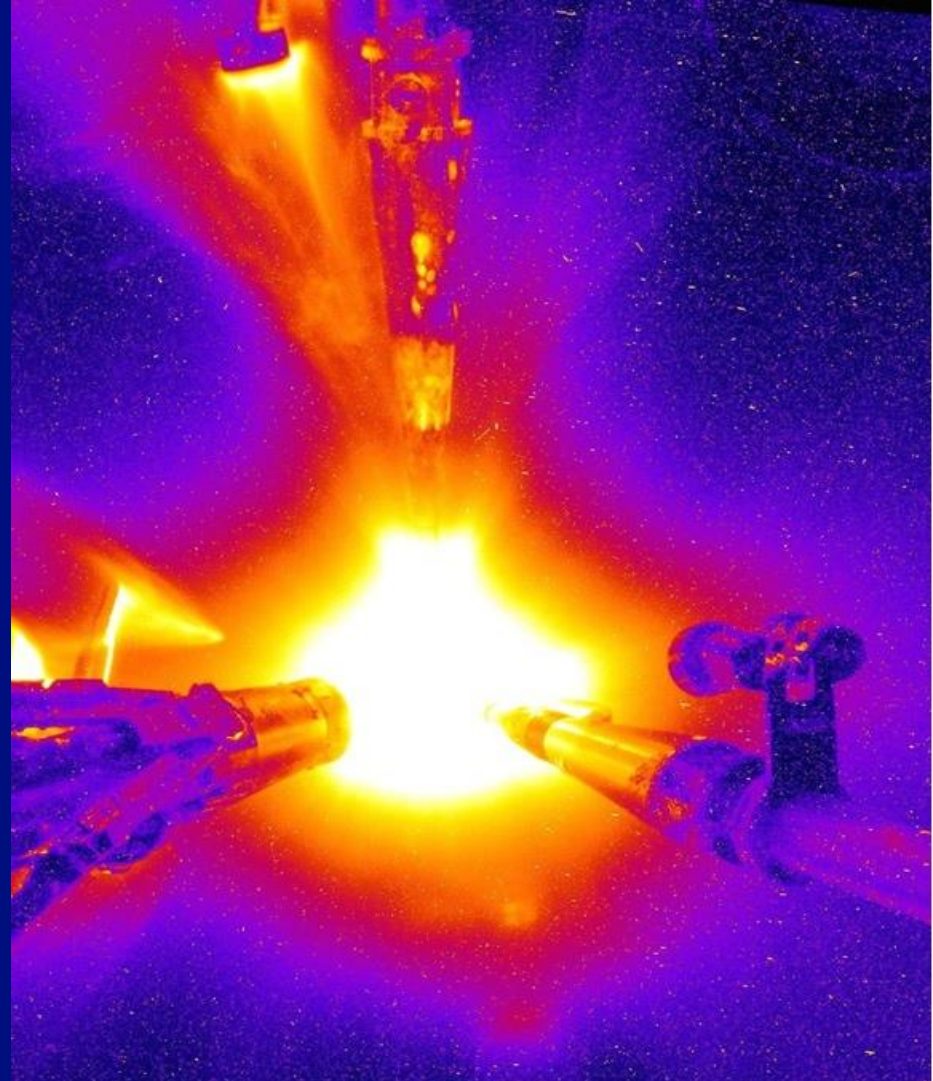
Then: make uncertainty computable.



Now: make complex scientific conclusions defensible.

CMU alums: Kary Myers,
Natalie Klein, Thea Sukianto

Inertial Confinement Fusion

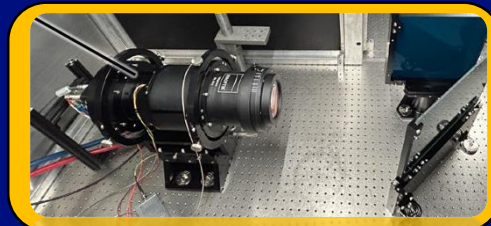


Highlighted team members: Ky Potter, Susan Glenn, and Chris Danly

**“Bayesian Reconstruction of
Ion Temperature and
Amplitude Profiles in
Inertial Confinement Fusion
using Gaussian Processes”
— Ky Potter et al.**



**“Bootstrap-based
Hypothesis Test of 2D
Contours using Elastic
Shape Analysis”
— Susan Glenn et al.**

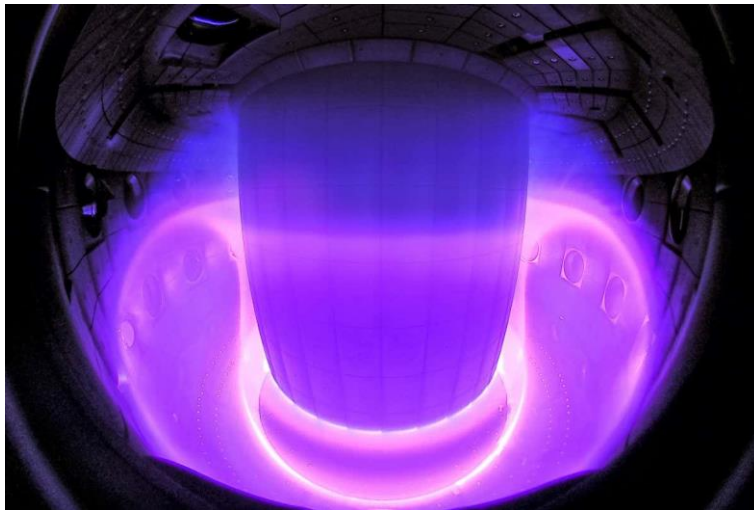


Confinement: how do you hold a 400,000,000°F plasma? (and why?)

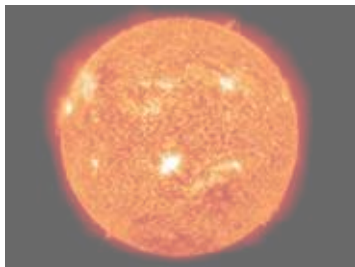
Lawson Criterion for net energy production

$$n\tau_E \geq 1.5 \cdot 10^{20} \frac{\text{s}}{\text{m}^3}$$

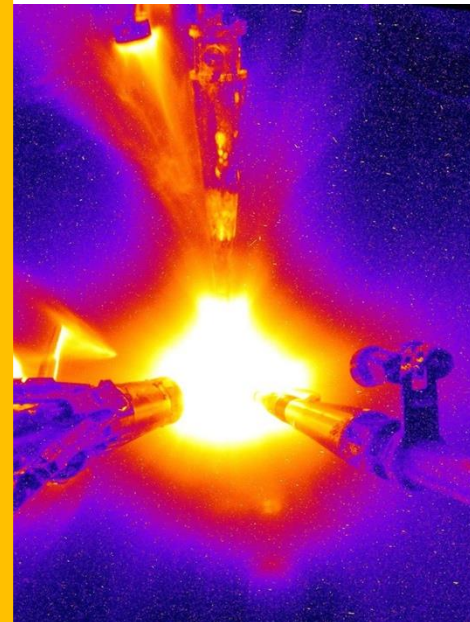
Magnetic confinement:
long time (~ minutes), low density



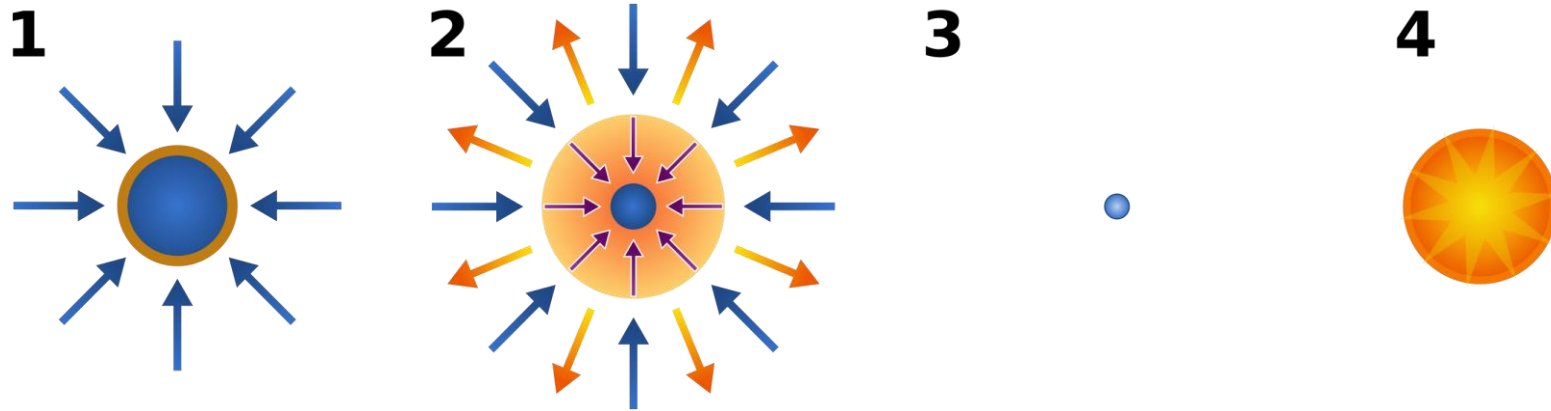
Gravitational confinement:
Very long time (billions yr)
High density, “Low” T



Inertial confinement:
short time (~ nanosecond),
very high density



Implode a small capsule at very high velocity – takes time to “bounce” and start expanding again



Lawson Criterion for net energy production

$$n\tau_E \geq 1.5 \cdot 10^{20} \frac{\text{s}}{\text{m}^3}$$

Key scales:

Implosion velocity $\sim 300 \text{ km/s}$

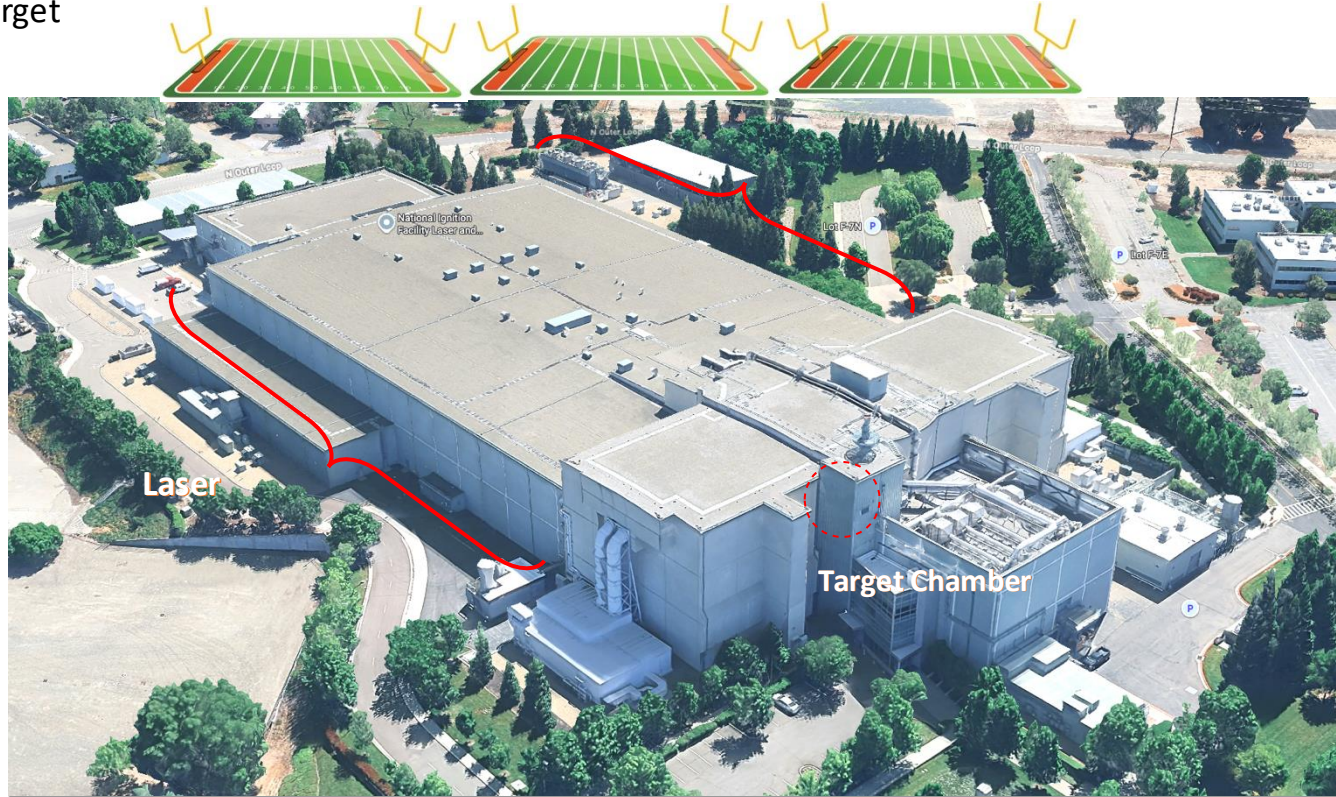
Nuclear burn $\sim 100 \text{ ps} = 10^{-10} \text{ s}$

Burn region $\sim 100 \mu\text{m}$

Really big lasers

National Ignition Facility
2.2 MJ laser facility (largest in the world)
192 beams impinging on a $\sim 1\text{mm}$ target

Key scales:
Implosion velocity $\sim 300\text{ km/s}$
Nuclear burn $\sim 100\text{ ps} = 10^{-10}\text{ s}$
Burn region $\sim 100\text{ }\mu\text{m}$



Not as simple as that



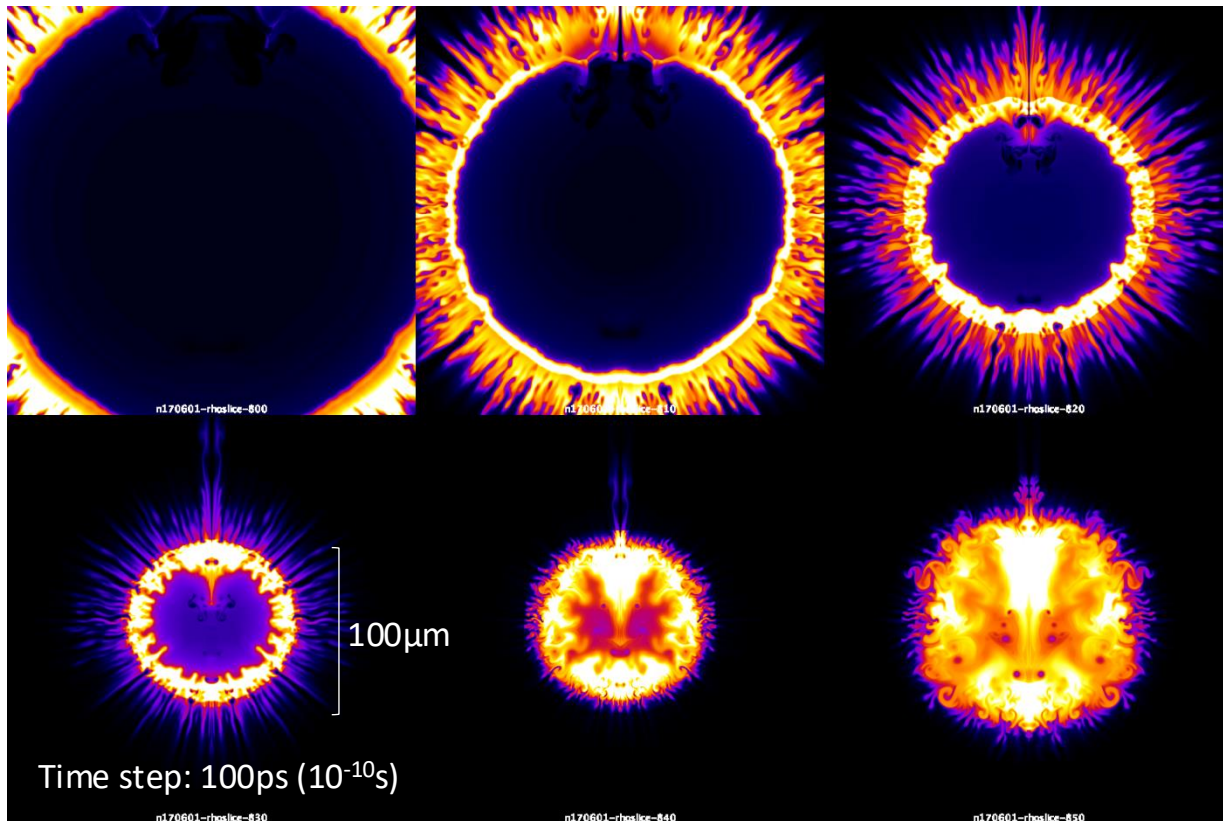
We need:

High enough density

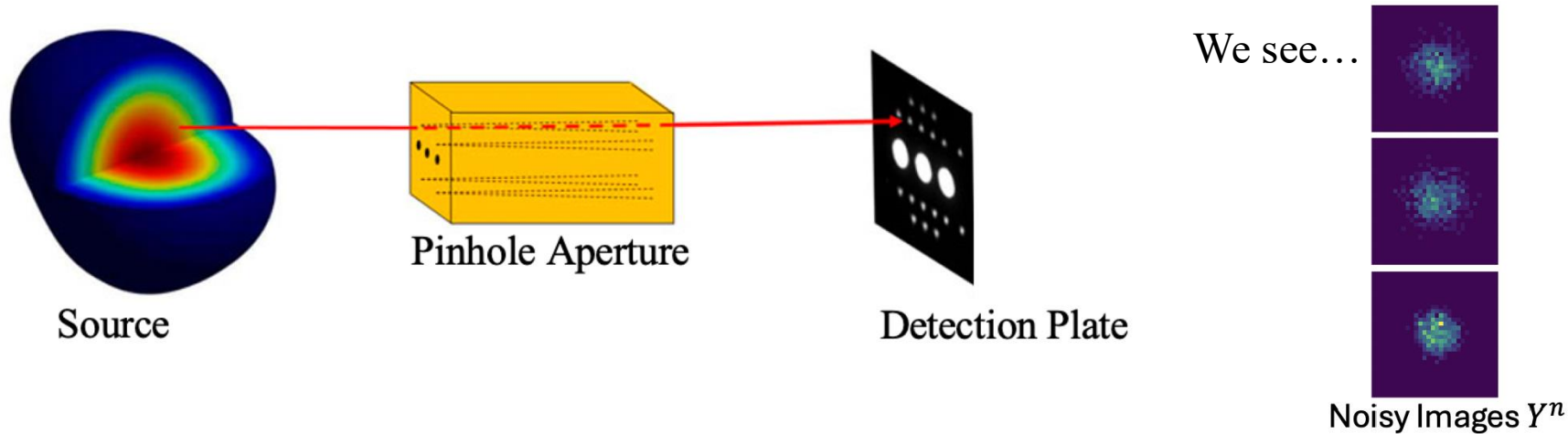
→ Symmetric, correct adiabat, velocity

High enough temperature

→ low carbon mix

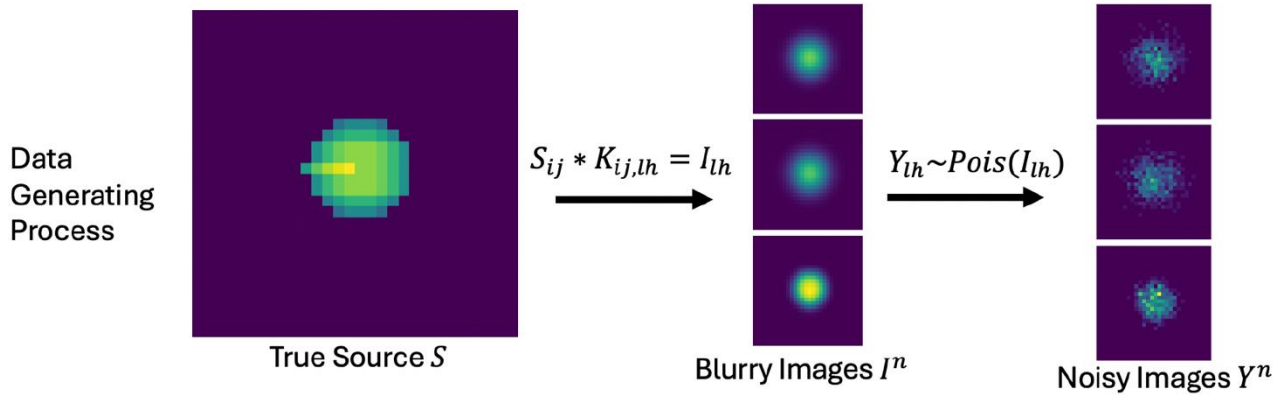


Statistical Issue: We didn't have ways to formally ask whether a source is of a given shape

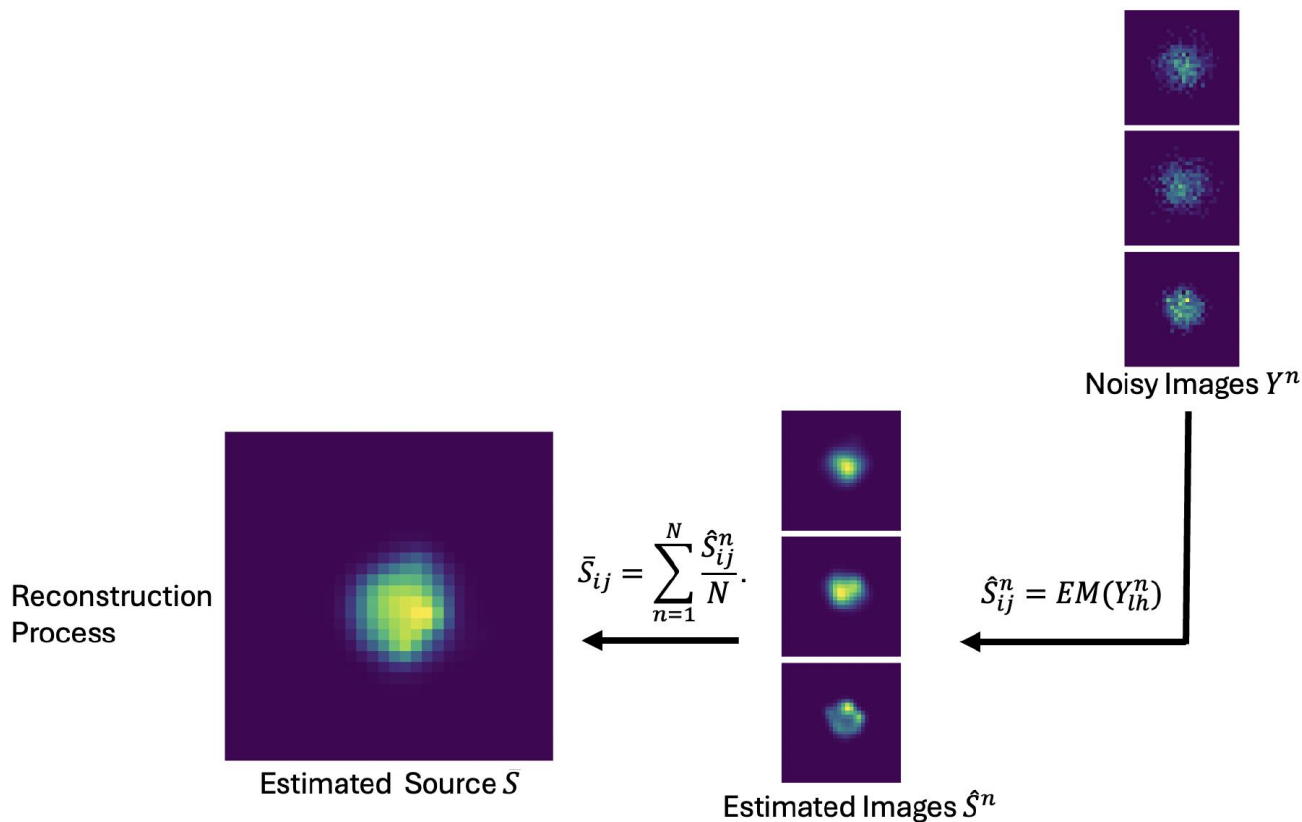


Being able to formally test the shape of the source unlocks diagnoses and comparison to simulation.

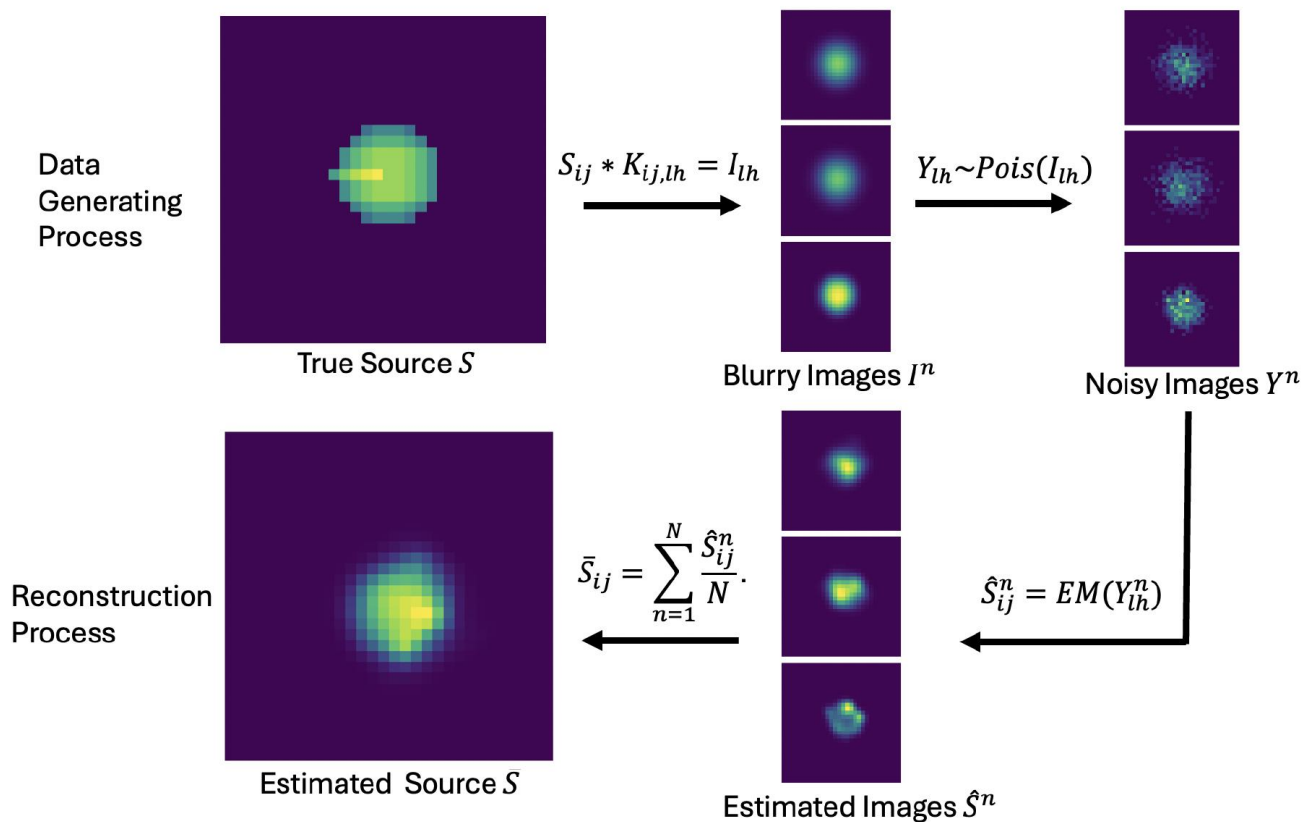
Data Generating and Image Reconstruction Process



Data Generating and Image Reconstruction Process

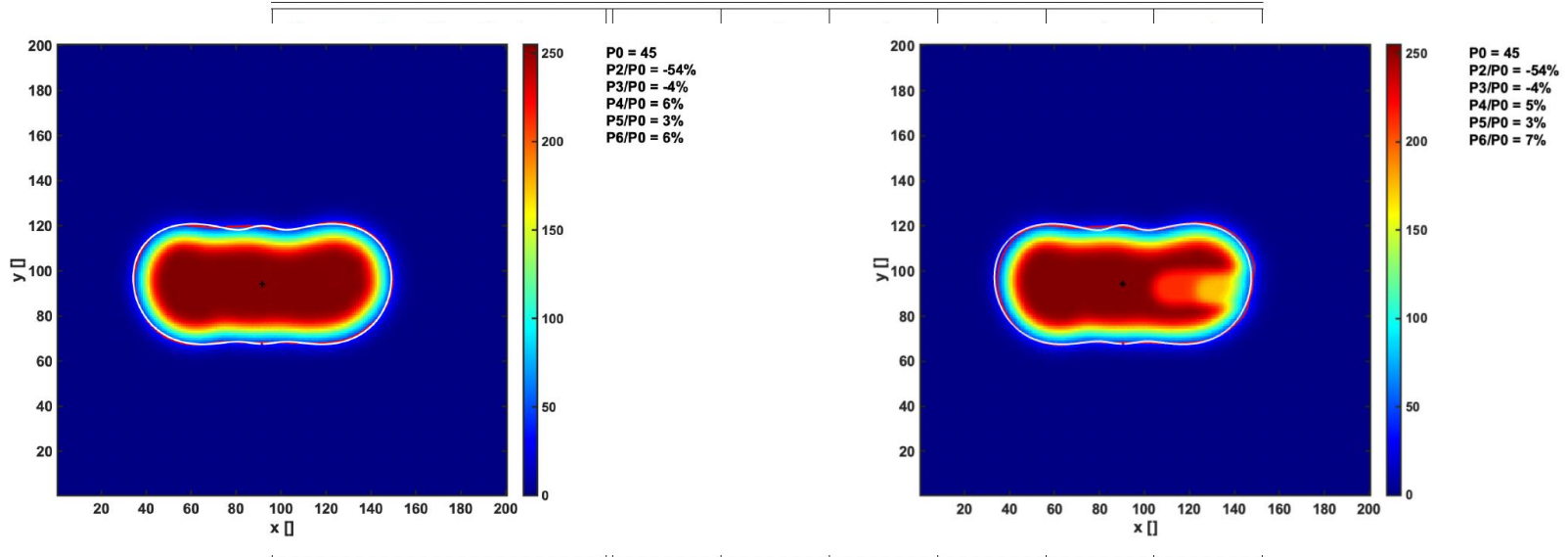


Data Generating and Image Reconstruction Process



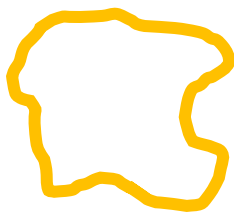
Characterizing Shape in Diagnostic Images: What's Currently Done

Get the 17th percent contour c_{17} and apply a Legendre polynomial decomposition to create a basis representation of that shape.

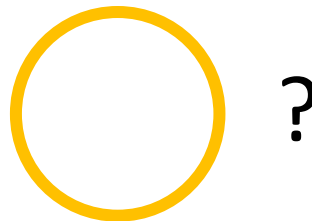


Characterizing Shape in Diagnostic Images: A Simple Question

Question: Could our observed contour c^p have plausibly come from this shape?



from



H_0 :  generated c^p

H_A :  did not generate c^p

Characterizing Shape in Diagnostic Images: A Simple Question

Question: Could our observed contour c^p have plausibly come from this shape?

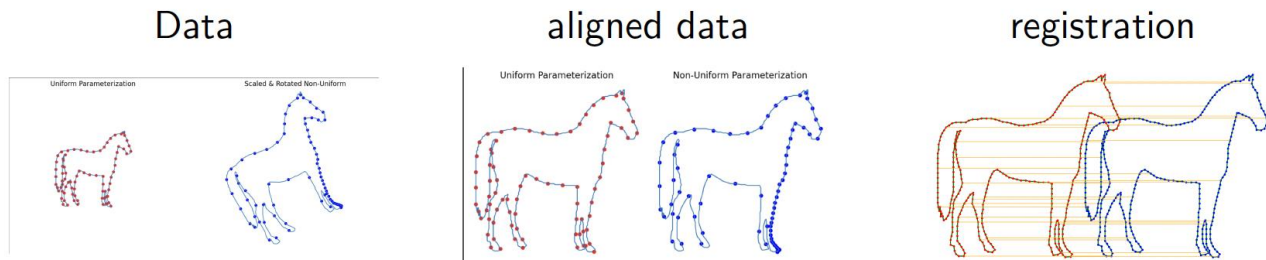


H_0 : ♥ generated c^p

H_A : ♥ did not generate c^p

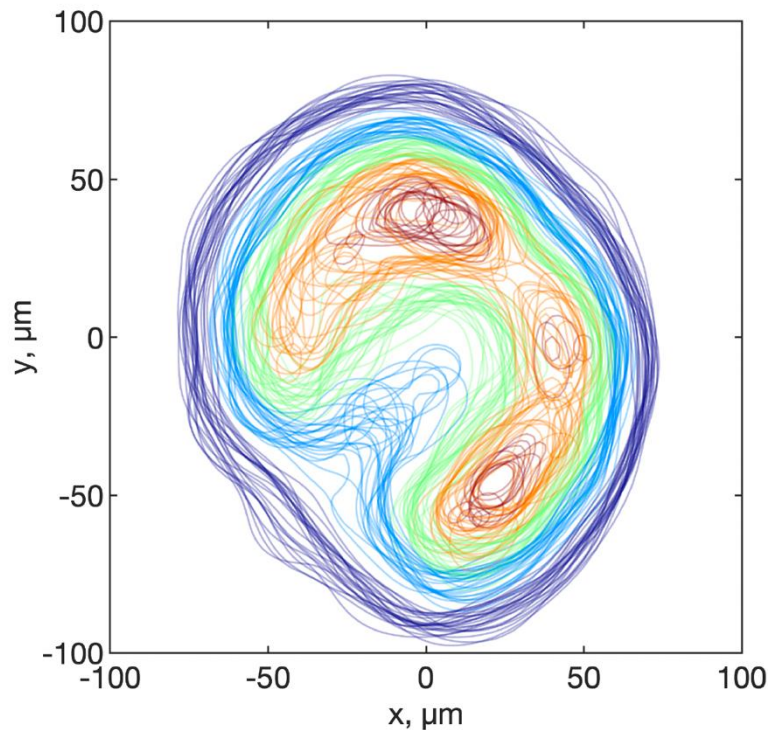
Updating the Framework: Elastic Shape Analysis (ESA)

- Motivation: We want to be able to compare two shapes without assuming some rigid basis structure underlying them.
- Geometry tells us information about an object independent of shape-preserving transformations (position, scale, and orientation)



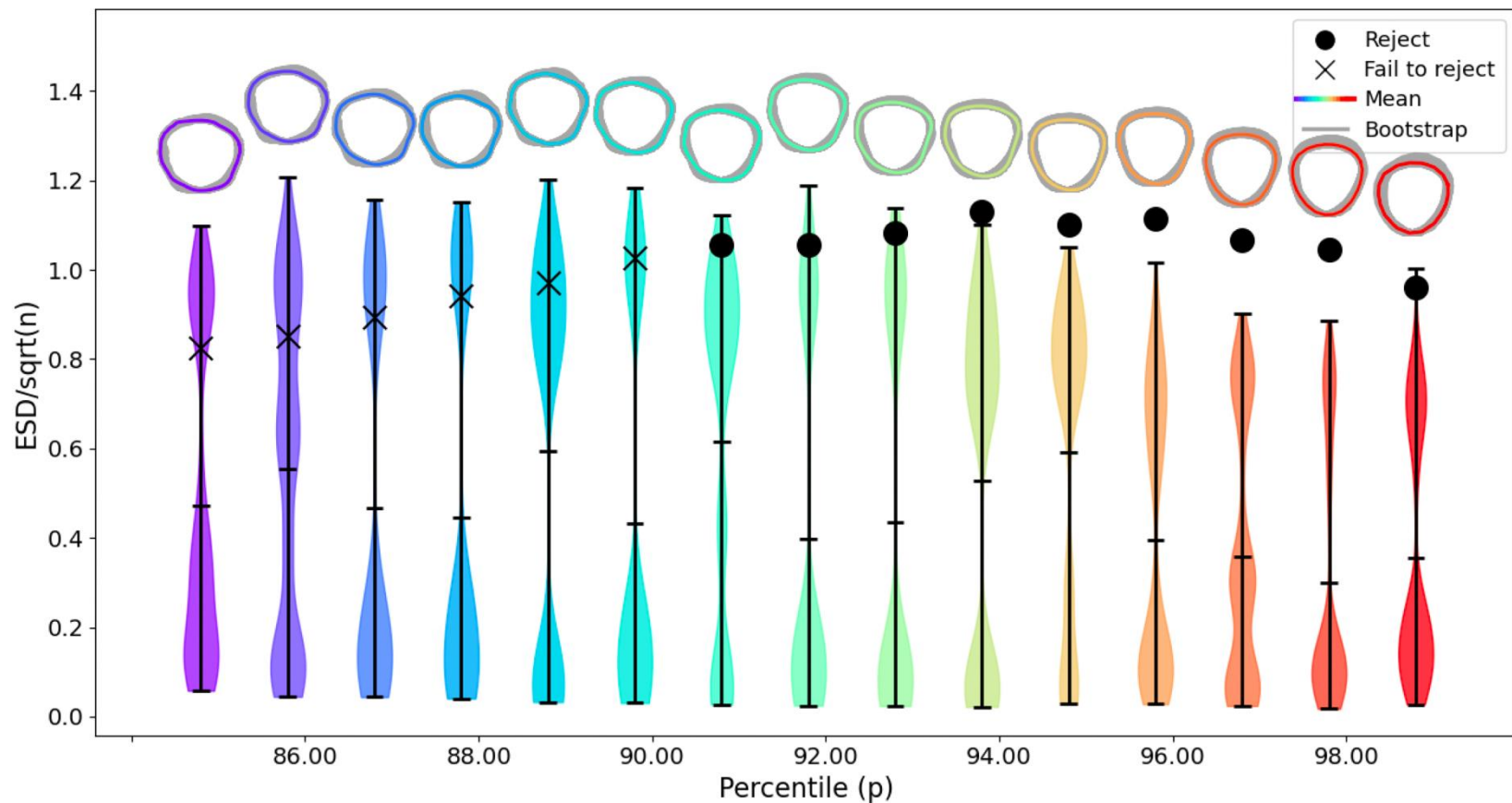
- We'll use the Elastic Shape Distance (ESD) between two objects, which measures "intrinsic" shape difference between curves transformed into their square root velocity functions.

Bootstrap Procedure for Shapes



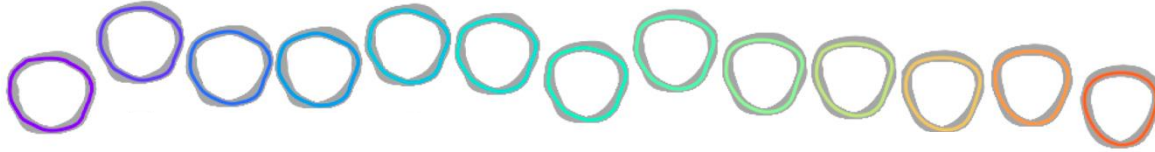
- We're building a test statistic for comparing an observed and proposed contour.
- We approximate $d(c_p, \hat{c}_p)$, the distance between c_p and our mean contour $\hat{c}_p$, with bootstrapped distance $d(\hat{c}_p, \hat{c}_p^*)$. Note c_p can be any shape we wish to test.
- The distribution of $d(\hat{c}_p, \hat{c}_p^*)$ can give us a test statistic for asking whether c_p could have plausibly produced our image.

Hypothesis Test for an ICF Shot

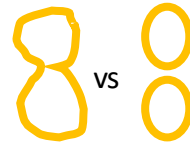
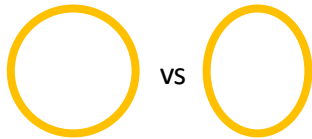


Planned Work

- Doing hypothesis testing for multiple quantiles simultaneously



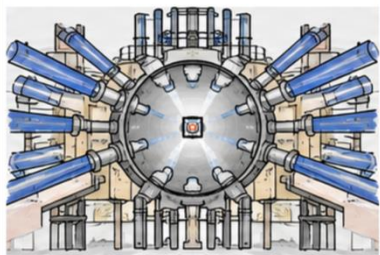
- Building discrepancy maps (asking “where/how are these shapes different?”) to describe both geometric (bending, stretching) and topological (splitting, merging) shape differences between pairs of images



- We are focusing on two key questions in ICF image analysis:
 - I. how confident are we that a shape feature of interest is “real” or an artifact due to uncertainty?
 - II. do shapes in ICF experimental images agree with 2-D hydrodynamic simulations?

NIF

Livermore, California



California



NIF

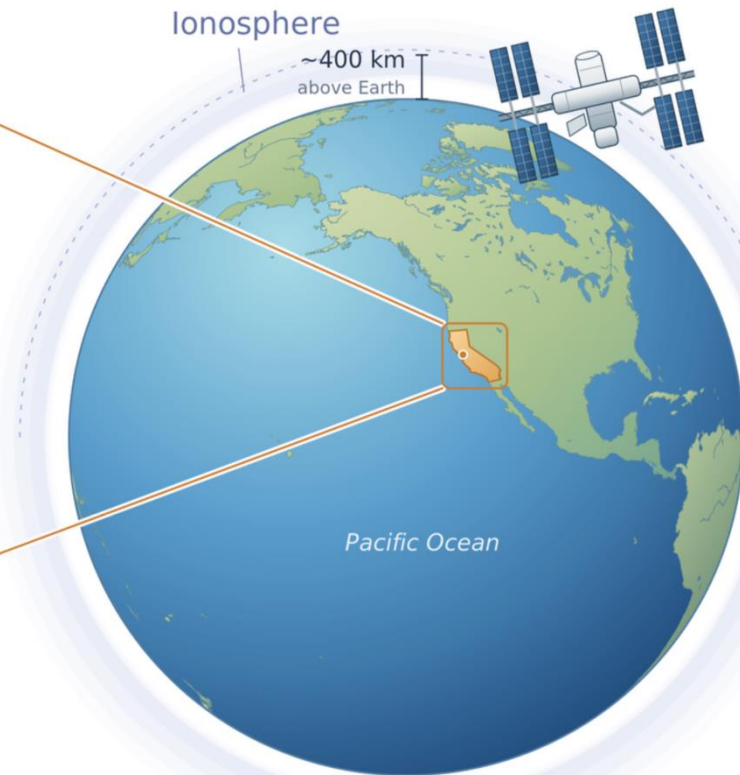
Livermore

Pacific
Ocean

Ionosphere

~400 km
above Earth

ISS



Pacific
Ocean

Schematic. ISS size, atmospheric thickness and locator boxes are exaggerated for visibility.

Ionospheric Plasma Monitoring



Personnel (>30 scientists involved)

- Large percentage of early career staff
- Staff from four Divisions at LANL: ISR, CAI, T, & AOT
- Team members across four institutions: United States Air Force Academy, Colorado State University, Space Test Program, & LANL

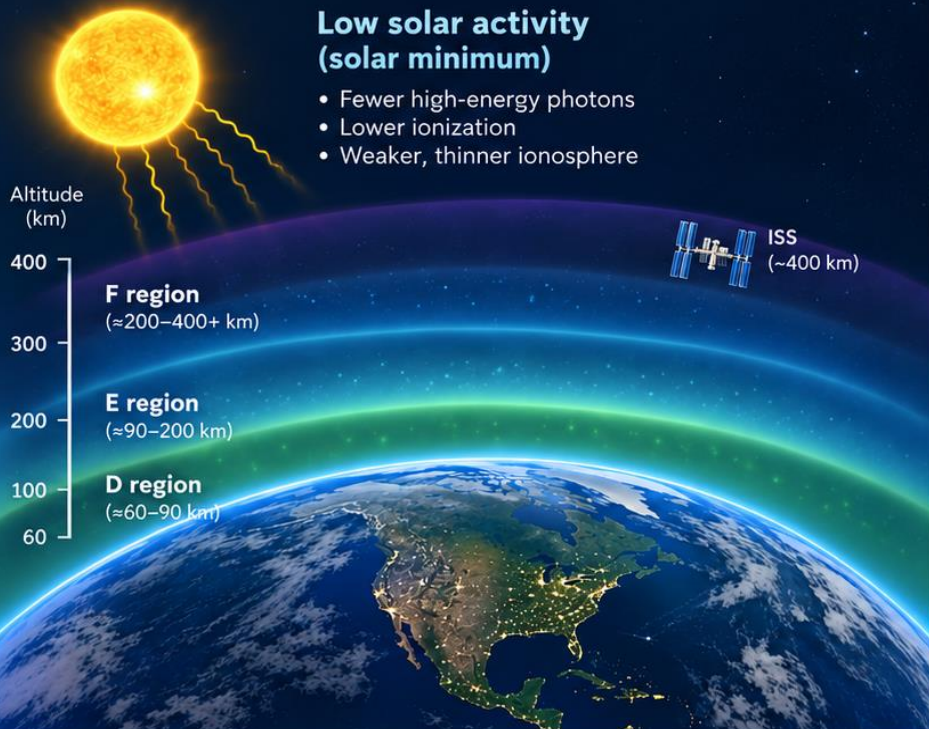


The Ionosphere

A layer of Earth's upper atmosphere (~60–400+ km) filled with charged particles (ions and electrons) that responds to sunlight.

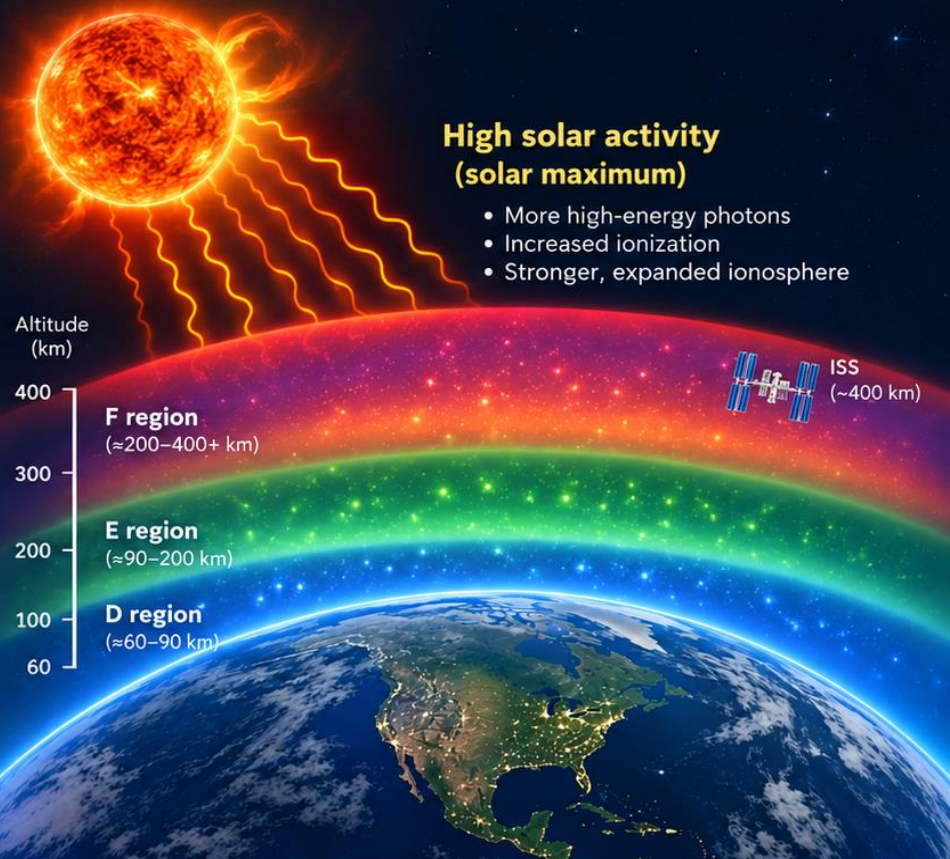
Low solar activity (solar minimum)

- Fewer high-energy photons
- Lower ionization
- Weaker, thinner ionosphere



High solar activity (solar maximum)

- More high-energy photons
- Increased ionization
- Stronger, expanded ionosphere



Impacts Technology

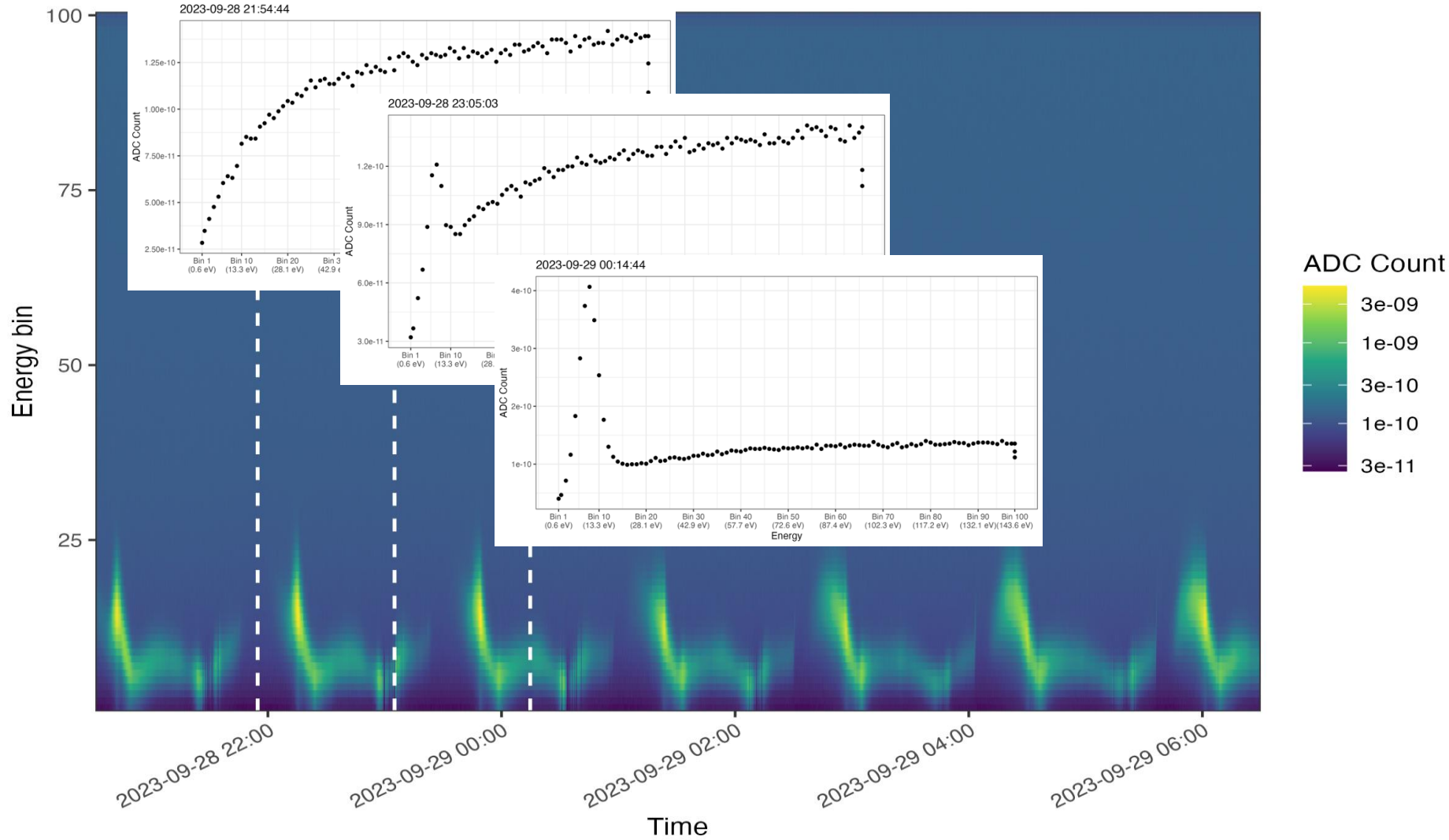
- Affects radio communication and GPS
- Drives satellite drag
- Influences space weather

**The ionosphere is dynamic –
it changes with the Sun.**



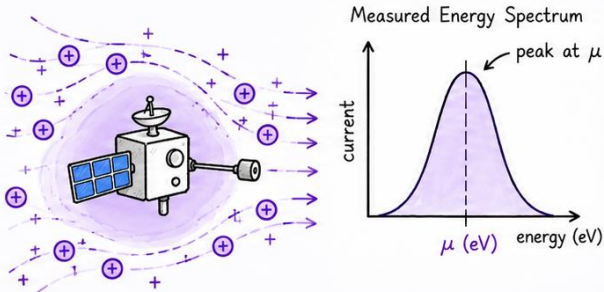
Solar activity varies on multiple timescales

- 11-year solar cycle
- Solar flares (hours–days)
- Coronal mass ejections (days)



Moments and plasma parameters

Spacecraft Potential (Φ)



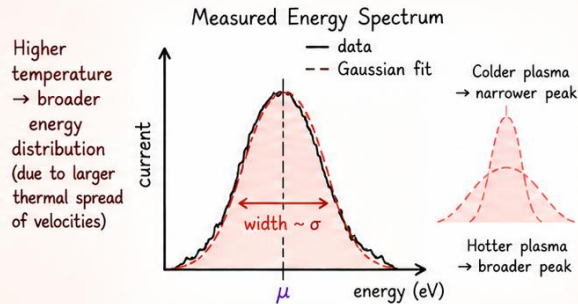
At peak current (μ):

$$\begin{aligned}\text{Measured Energy} &= \Phi + KE_o \\ &= \Phi + 4.48 \text{ eV}\end{aligned}$$

Therefore: $\Phi = \mu - 4.48 \text{ eV}$

where 4.48 eV is the kinetic energy of atomic oxygen at the ISS velocity

Plasma Temperature (T)

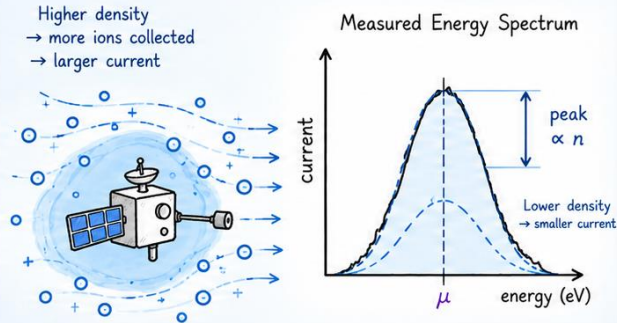


The width of the Gaussian fit (σ) is related to the plasma temperature:

$$T = \frac{m\sigma^2}{k_B}$$

where m is the ion mass (e.g., atomic oxygen) and k_B is Boltzmann's constant

Plasma Density (n)

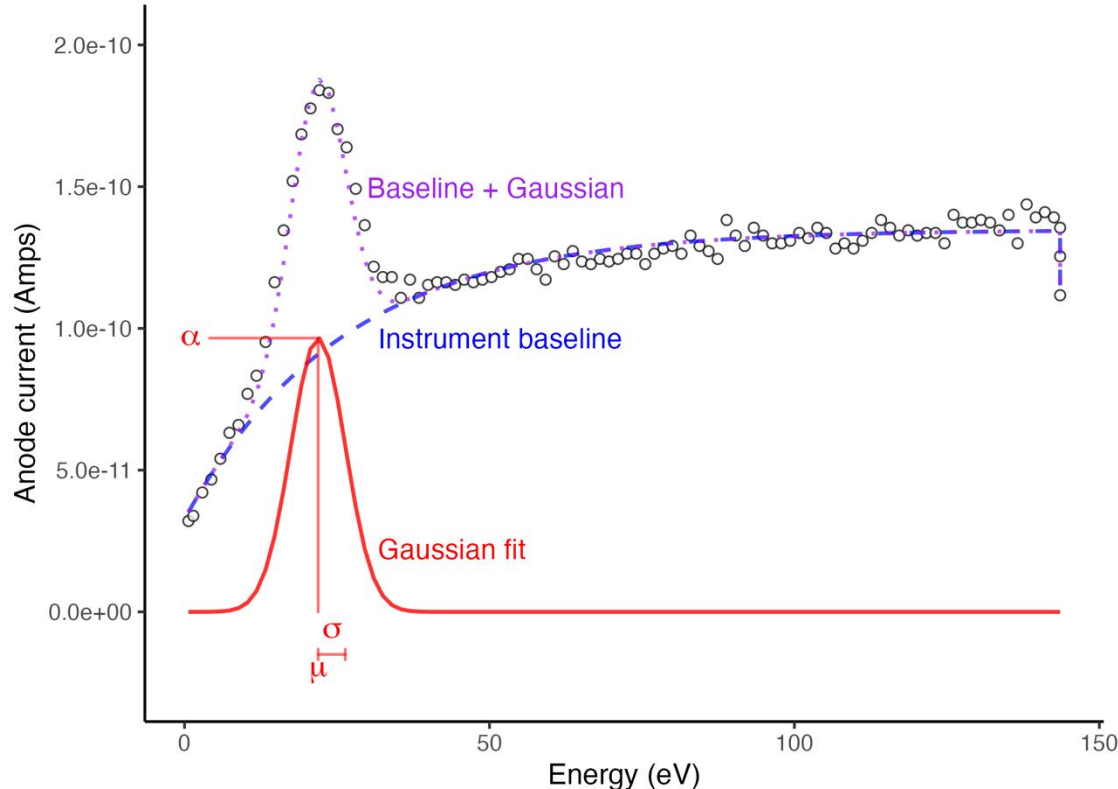


The area under the Gaussian fit is proportional to the plasma density:

$$n = \frac{1}{C} \int I(E) dE$$

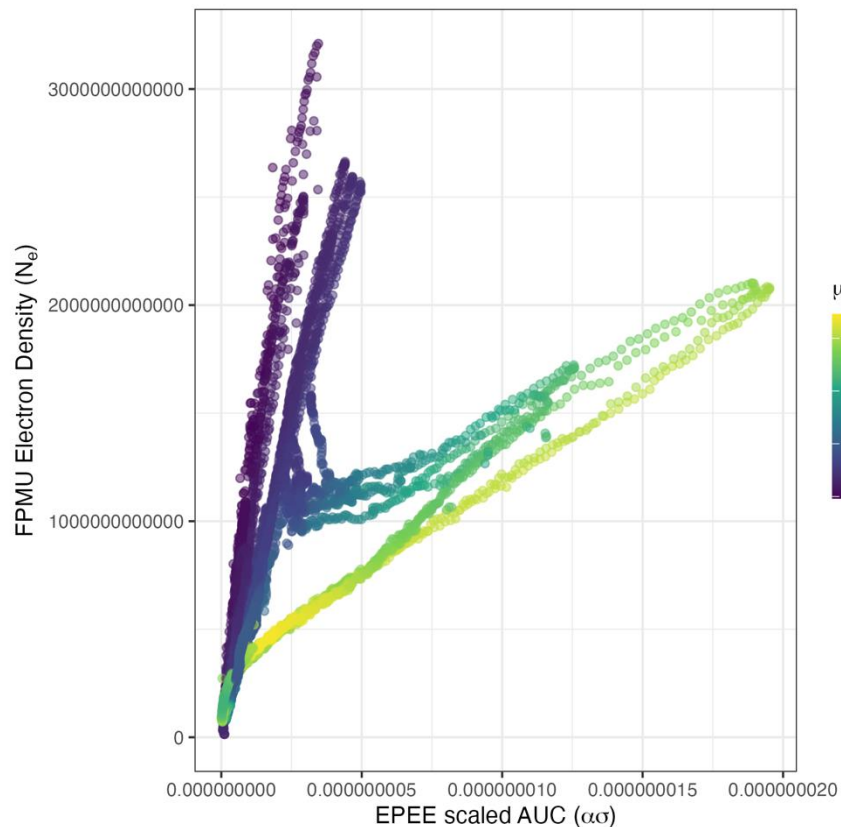
where $I(E)$ is the measured current, and C depends on the instrument collection area, geometry, and efficiency

A single “moment” in time



- Instrument baseline is fit using a 2-parameter model over 6-hour windows using the low-signal times.
- From the remaining signal we learn the Gaussian fit parameters, which are proportional to the plasma moments.
- Info is shared across time slices via a random walk prior over each parameter.

On-orbit calibration (or: an aside on collaboration)



Let $\ell_v = \log_{10}(v)$ for variable v .

Then:

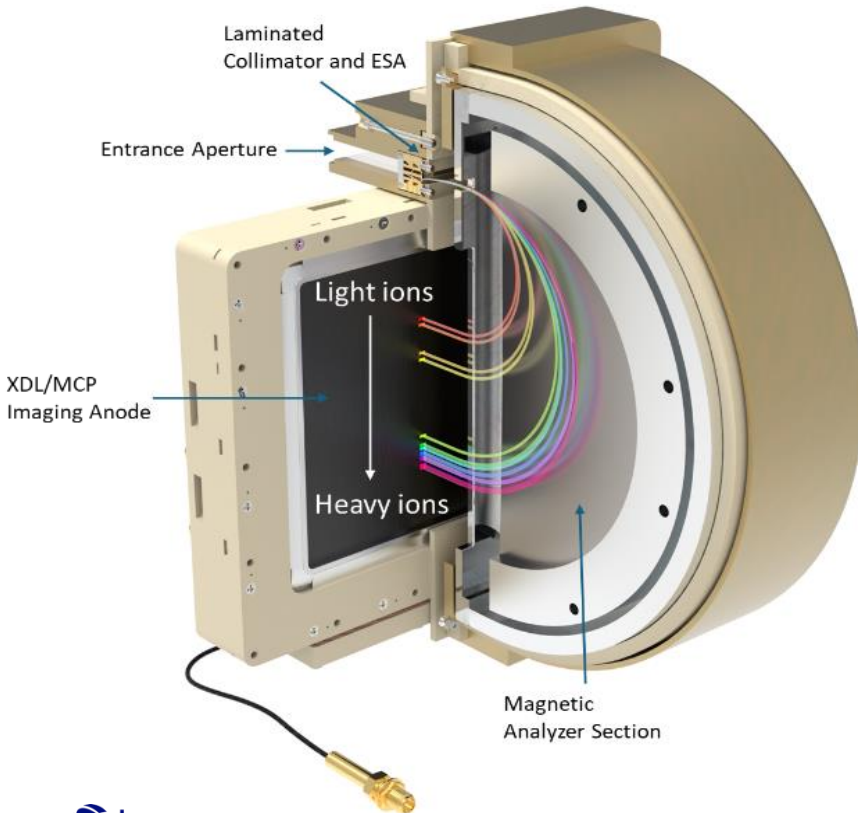
$$\ell_{Ne} = a + b\ell_{\text{AUC}} + c\ell_{\mu},$$

implying

$$Ne_{FPMU} = 10^a \text{AUC}^b \mu^c.$$

Here 10^a scales the amplitude to the magnitude of the density, b is the slope of the relationship between log AUC and log density, and c is the elasticity due to potential.

Ongoing and future work



1. Storm and sub-storm survey using historic instruments
2. Mass calibration of new instrument
3. Algorithm development for **anomaly detection**
4. Software package for Heteroskedastic Normalized Vecchia Gaussian Process
5. Apply developed distributional emulator method to plasma simulations

Earth + ISS

Near-Earth space (~ 400 km)

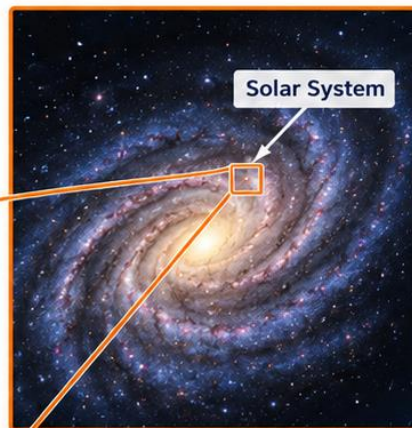


The Solar System

Our planetary neighborhood
($\sim 10^{13}$ m)

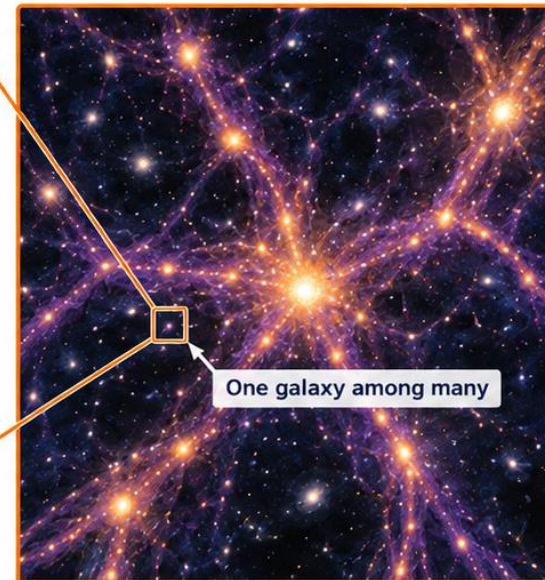
The Milky Way

Our galaxy (schematic)
($\sim 10^{21}$ m)



The large-scale Universe

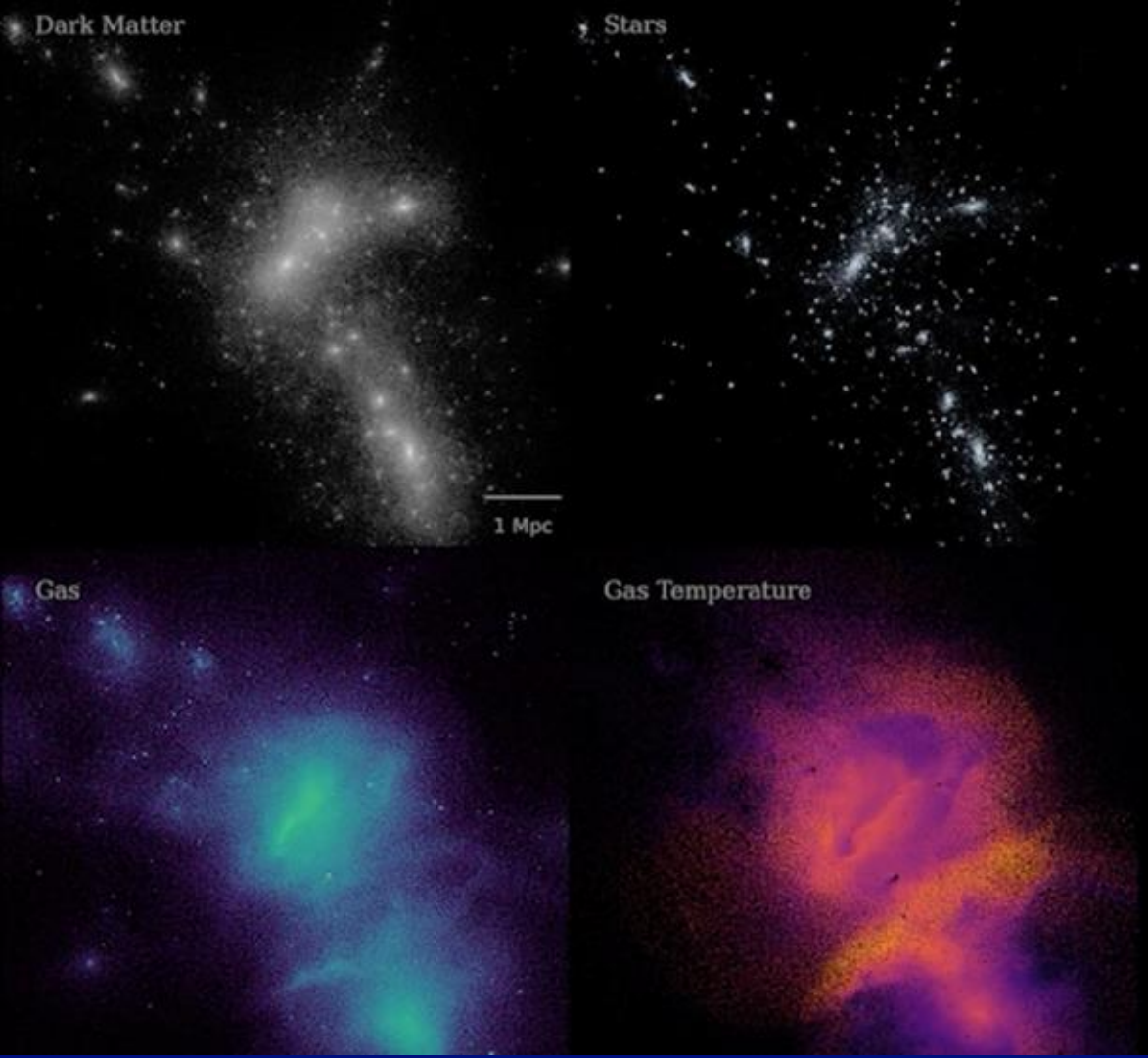
Galaxies, filaments and voids
($\sim 10^{26}$ m)



Smaller scales
(higher energies)

Many orders of magnitude

Larger scales
(bigger questions)



Cosmology Emulators

**Highlighted team members: Earl Lawrence, Katrin Heitmann (PI),
Nesar Ramachandra, Dave Higdon, Jared Clark**

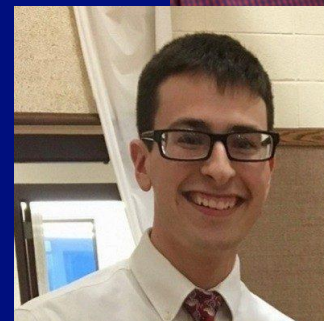
LANL



Argonne National Lab

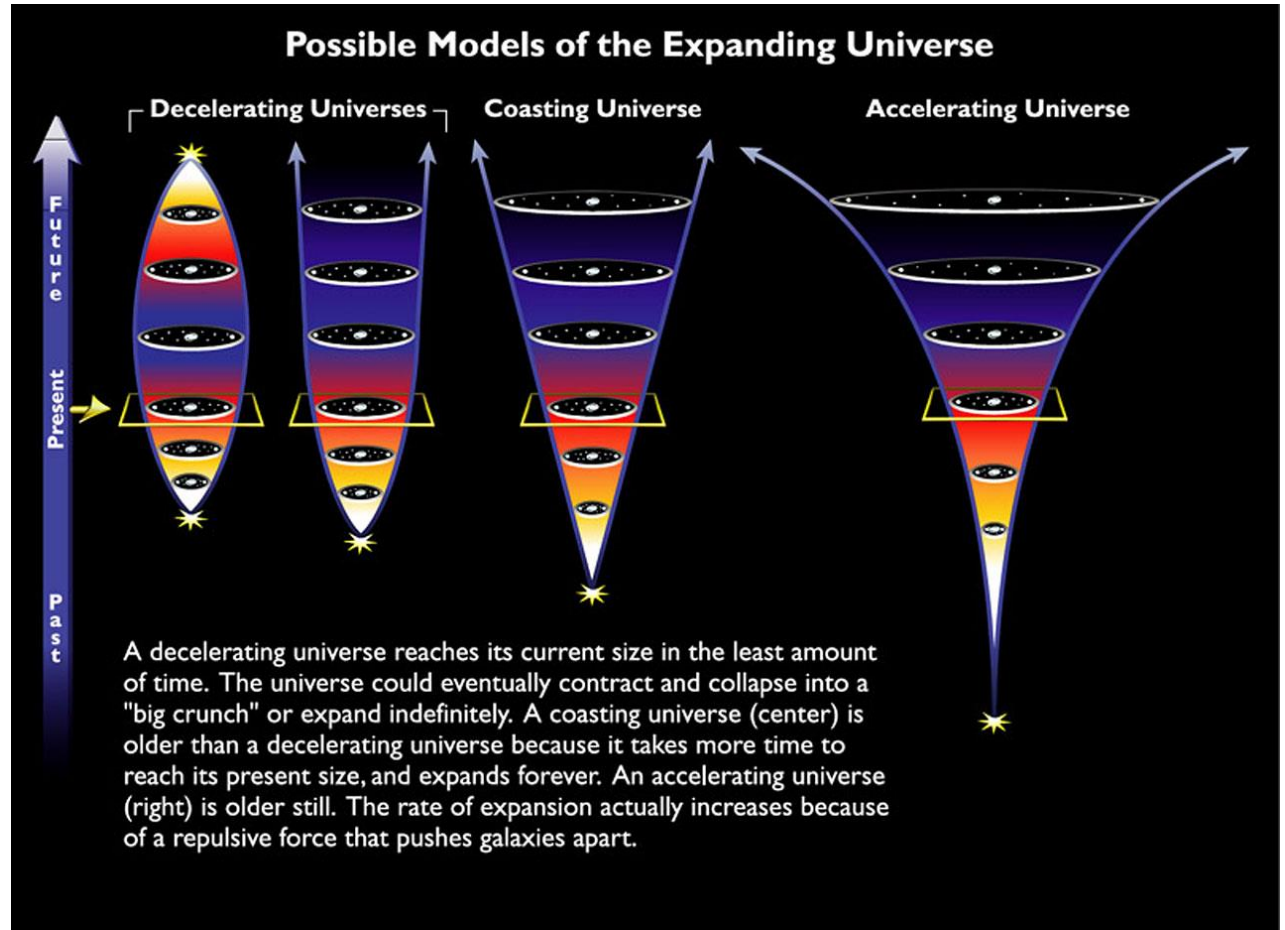


Virginia Tech

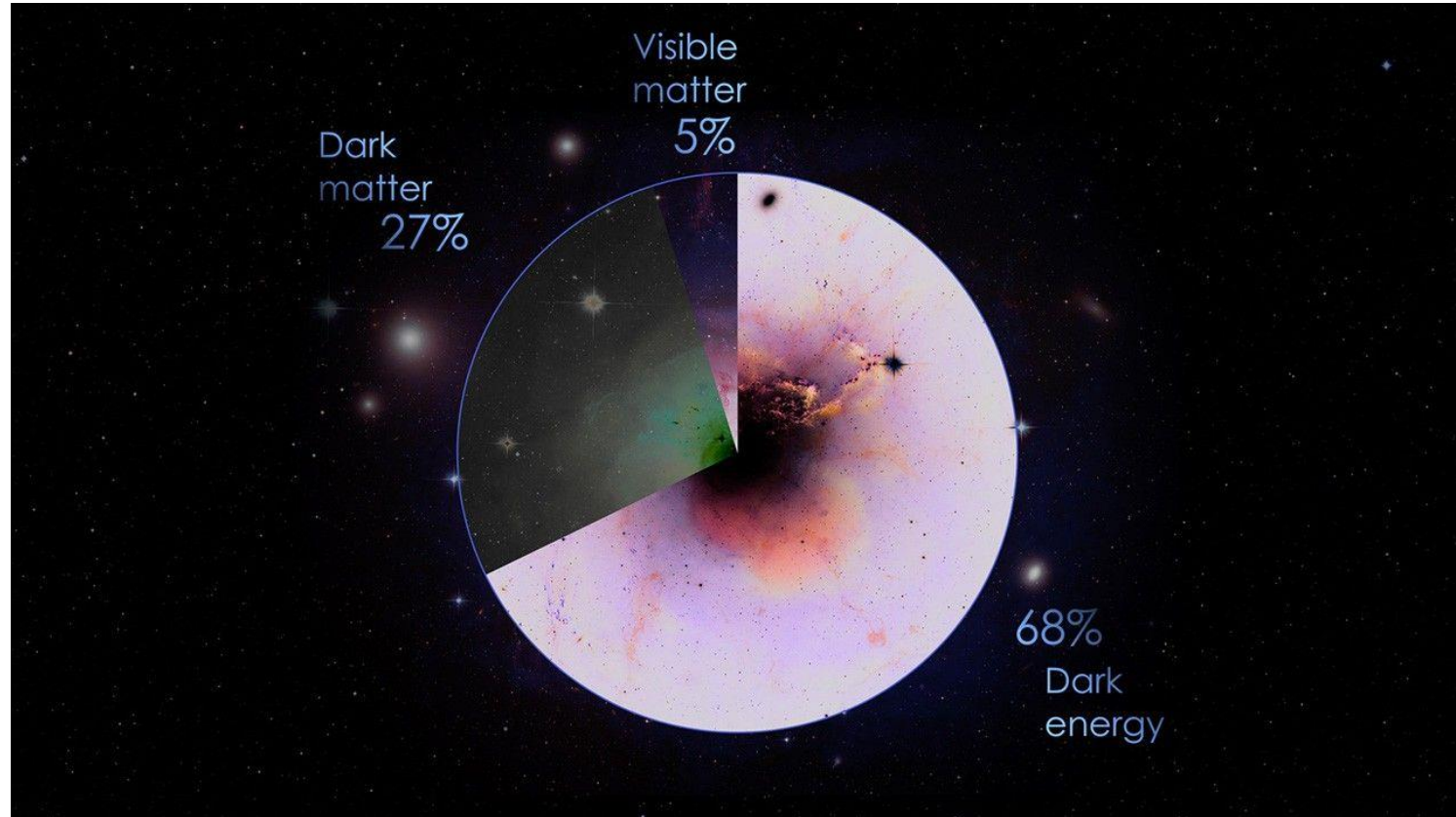


The Universe:

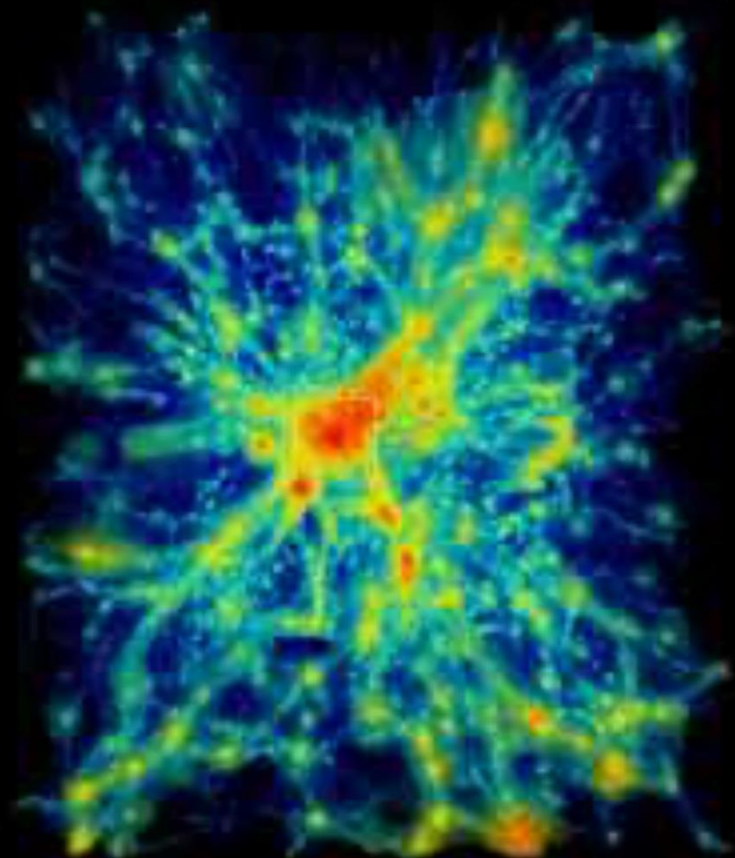
What we know



The Universe: Mostly *not* regular ol' matter



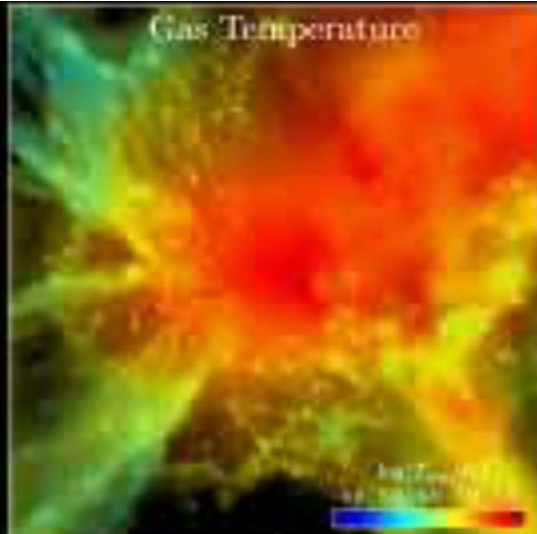
$64 h^{-1} \text{Mpc}$



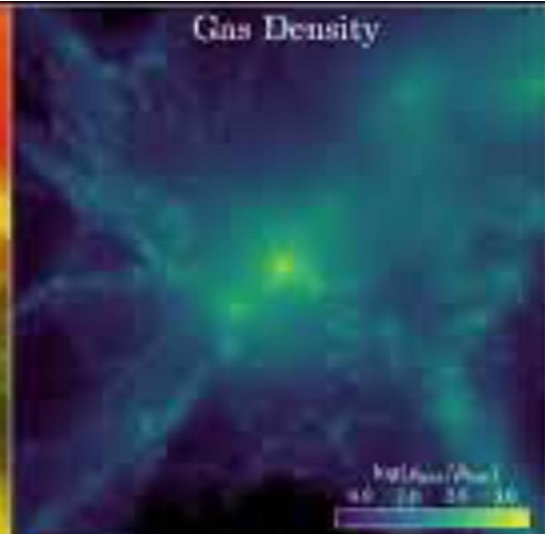
$z = 0.34$

$M_{200} = 1.1 \times 10^{15} h^{-1} M_{\odot}$

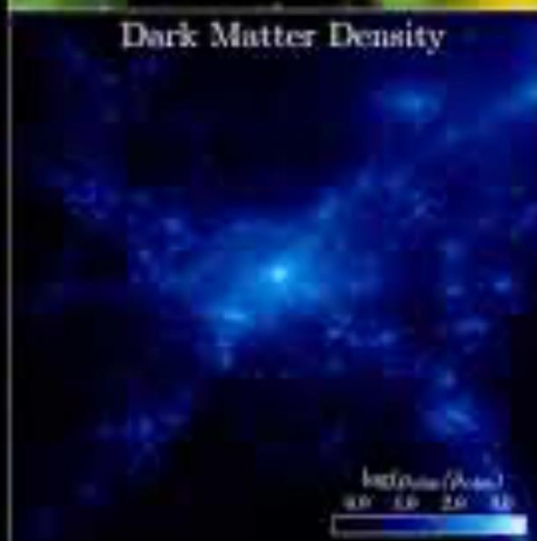
Gas Temperature



Gas Density



Dark Matter Density



Stellar Density



Frontier-E Simulation: A really really big simulation!

- Largest astrophysical simulation of the Universe ever conducted
- CRK-HACC ran on 9,000 nodes of OLCF's Frontier machine for ~one week (compared to one year on a CPU machine)
- Unprecedented statistics for a range of cosmological investigations
- Developed AI assistant to sort through the data

Cosmological Hydrodynamics at Exascale: A Trillion-Particle Leap in Capability

Gordon Bell Finalist!

Nicholas Frontiere*, J.D. Emberson*, Michael Buehlmann*, Esteban M. Rangel*,
Salman Habib*[†], Katrin Heitmann[†], Patricia Larsen*, Vitali Morozov[‡], Adrian Pope*,
Claude-André Faucher-Giguère[§], Antigoni Georgiadou[¶], Damien Lebrun-Grandicé^{||}, Andrey Prokopenko^{||}

*Computational Science Division, Argonne National Laboratory

[†]High Energy Physics Division, Argonne National Laboratory

[‡]Argonne Leadership Computing Facility, Argonne National Laboratory

[§]Department of Physics and Astronomy, Northwestern University

[¶]National Center for Computational Sciences, Oak Ridge National Laboratory

^{||}Computational Sciences and Engineering Division, Oak Ridge National Laboratory

The path to a “hero” run involves a lot of stats

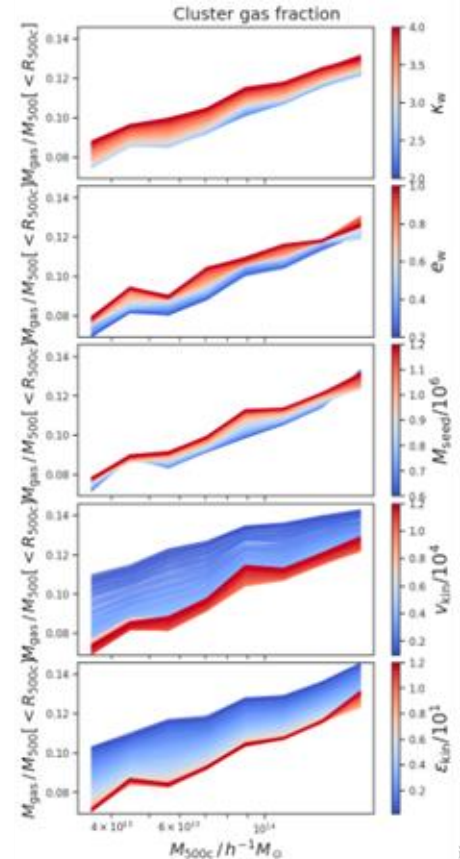
1. Design a simulation suite
2. Statistically emulate the simulator
3. Calibrate your simulator to observables
4. Refine, iterate if needed
5. Pick “best” parameter settings

Some of our previous work on gravity or hydrodynamics



Gravity only example:
The CosmicEmu (on GitHub).

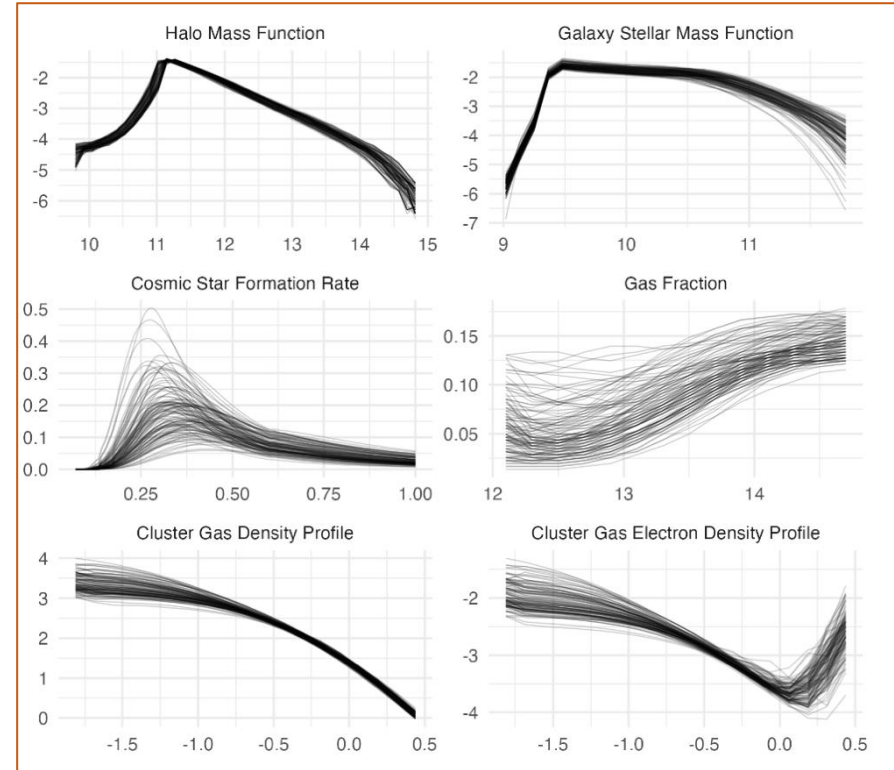
Hydro example:
Sensitivity of CGF
(paper in preparation).



Our current work focuses on cosmo *and* hydro



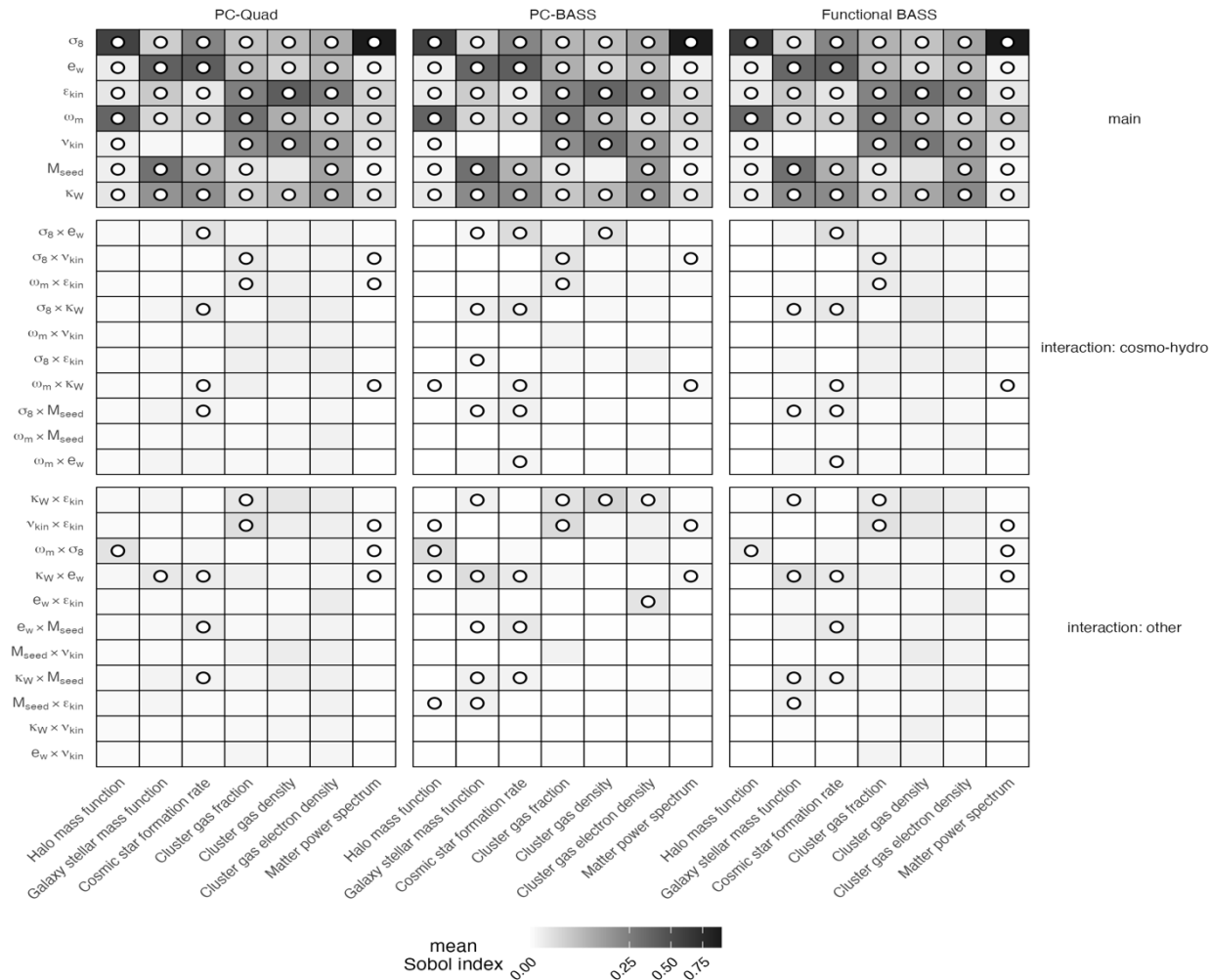
110 sims
Vary 5 hydro
and 2 cosmo
parameters



Across emulation method and observable, main effects dominate

Sobol indices
measure signal
in each function
component

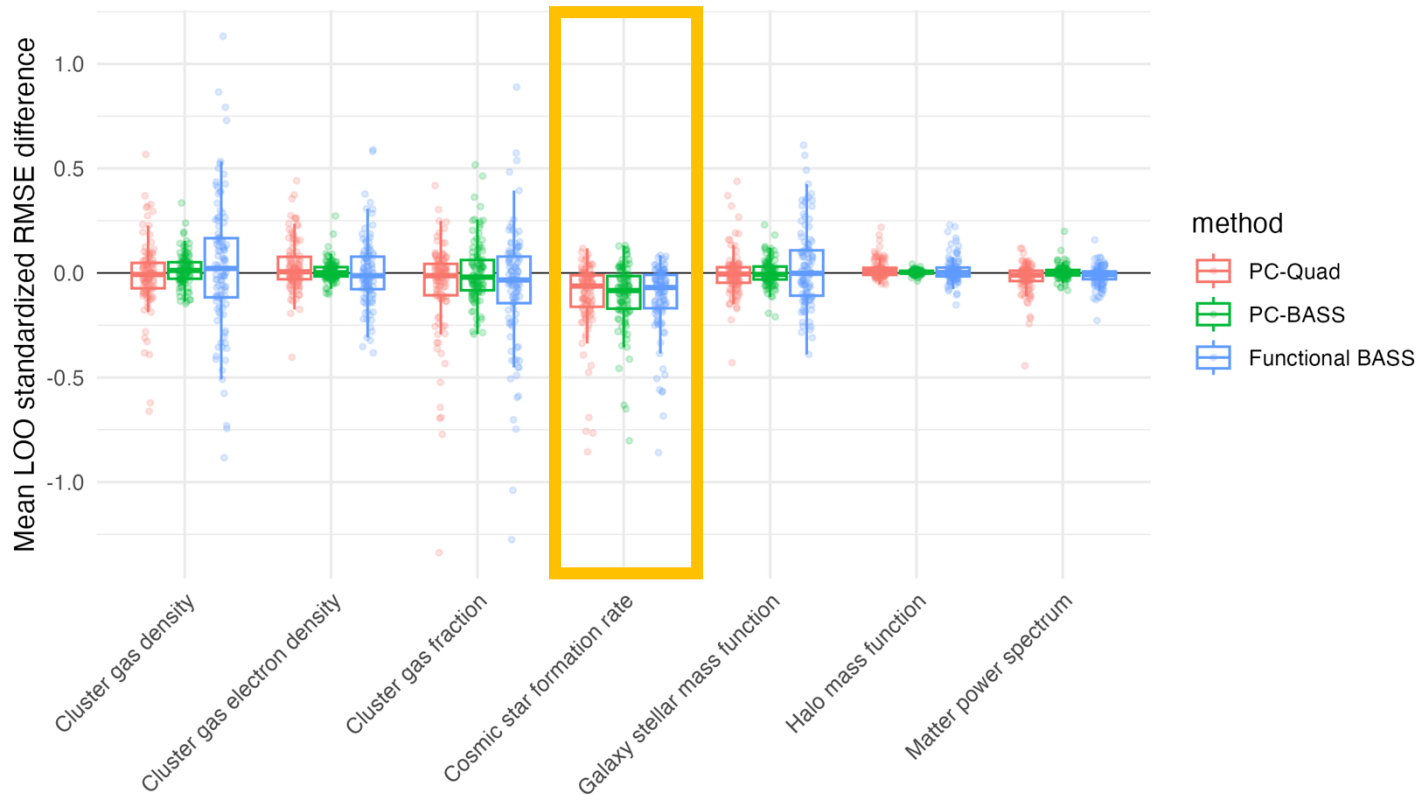
Sobol components across outcomes
Open circles mark repeated-fit means above the method- and observable-specific 95th-percentile maximum-null threshold.



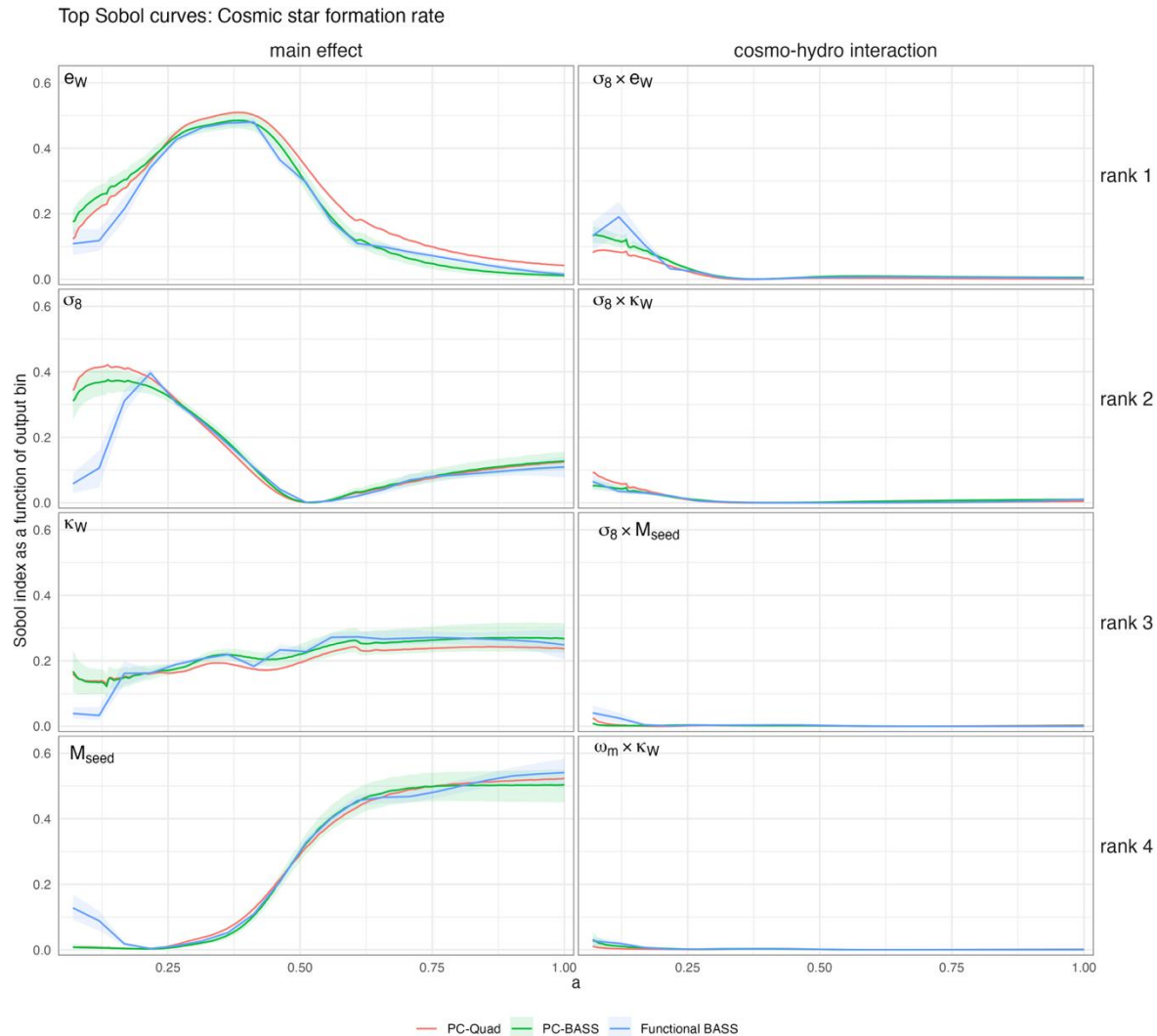
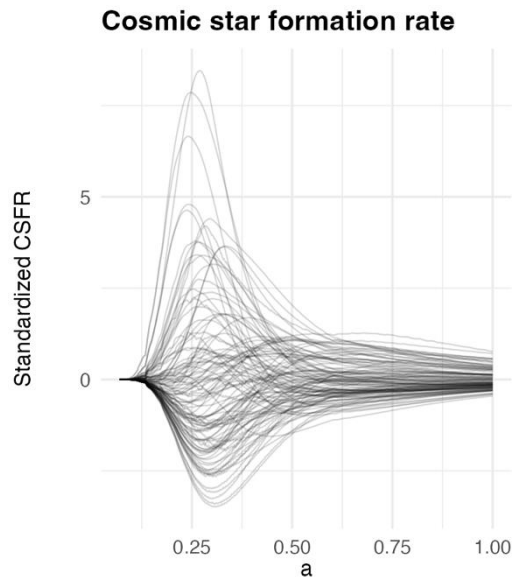
Do the interaction terms actually matter?

Difference in mean LOO RMSE for full versus reduced emulators

Negative values favor the emulator including cosmo-hydro features

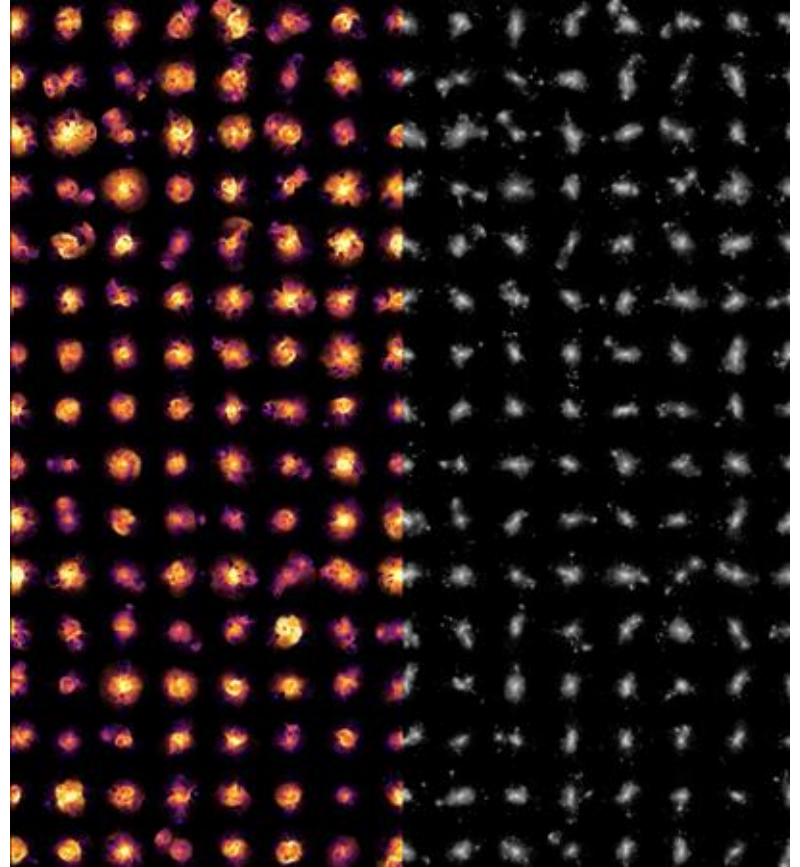


Where does the interaction matter?



Ongoing and future work

1. Calibration with uncertainty in "x" and "y" direction in 'complicated' regimes
2. Novel approaches for 'longies and shorties' (i.e., outputs available at different scales)
3. Visualization of ensembles of hydrodynamic simulations
4. The big goal: accounting for uncertainty about hydrodynamics when learning cosmology parameters from observation

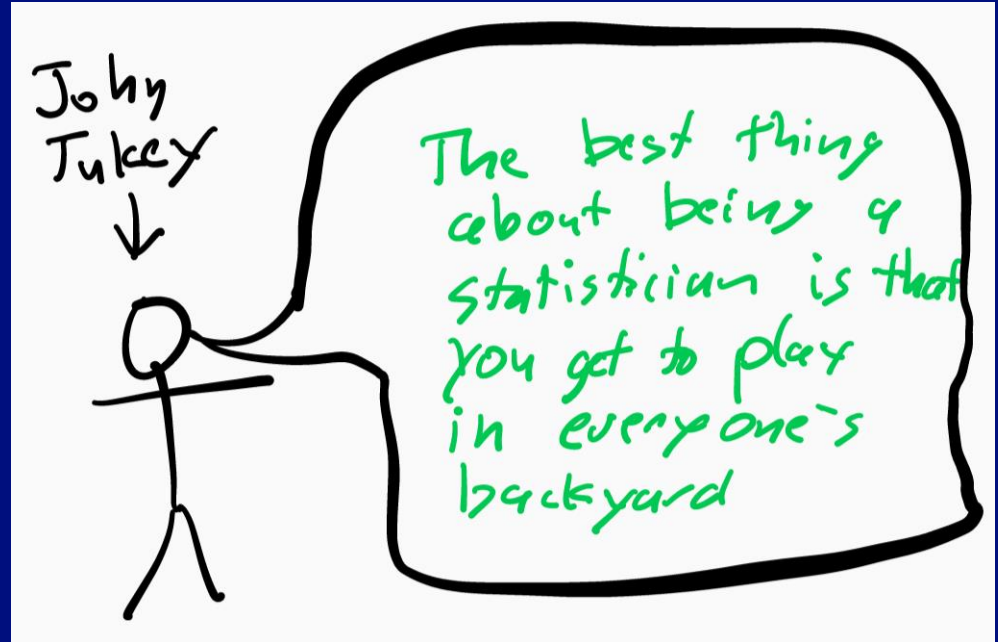


Plug 1: I'm looking for collaborations

- I'll be a visiting professor at CMU this academic year, and would love to help bolster the LANL/CMU pipeline.
- I'm also in particular need of students with anomaly detection or shape expertise!
- My email: krmoran@lanl.gov

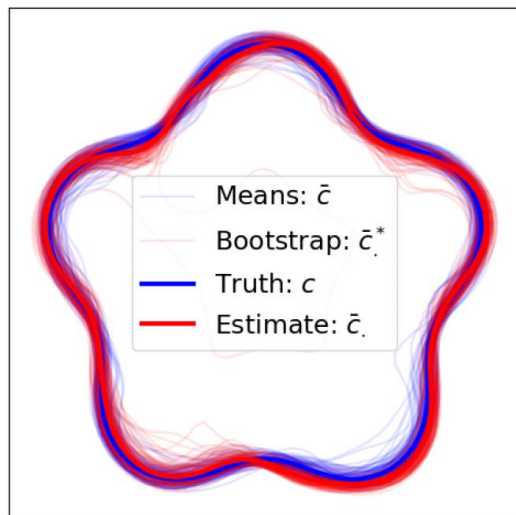
Plug 2: CAI-4 Is Looking for Summer Students

- Work with a statistical mentor on one or more cool science applications with domain experts
- Email your CV to me or to cai4-summer-students@lanl.gov if interested.

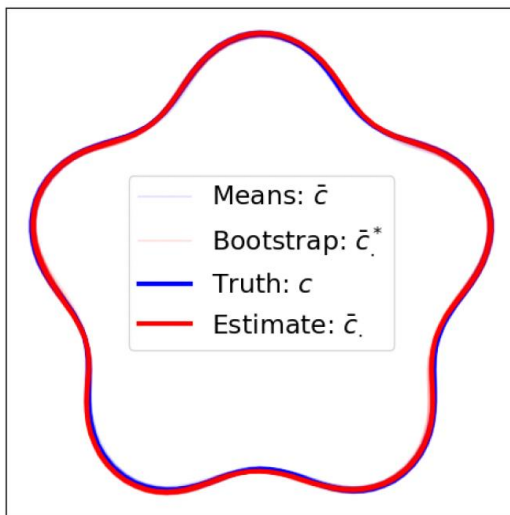


Backup Slides (ICF)

Bootstrap Simulation

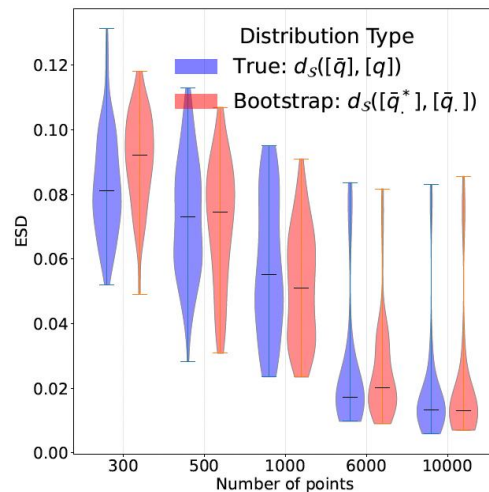


(a) $\bar{c}_{0.6}, \bar{c}_{0.6}^*$ for $N = 200$



(b) $\bar{c}_{0.6}, \bar{c}_{0.6}^*$ for $N = 5000$

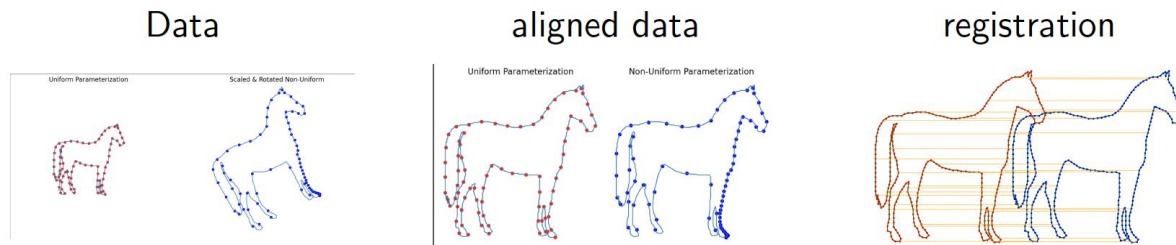
If the red and blue distributions are very different, we should worry.



(c) Violin plots ESD

More ESA details

- ▶ We use the *Riemannian metric* which measures distance between nearby points in curved spaces (manifolds).
- ▶ A *planar curves* is a continuous function with maps the parameter (time, arc length) to a 2D plane: $\beta : \mathcal{D} \longrightarrow \mathbb{R}^2$
- ▶ The *square root velocity function* is $q(t) = \frac{\dot{\beta}(t)}{\sqrt{|\dot{\beta}(t)|}}$ optimizes over reparameterizations to align curves for fair comparison.
- ▶ The *elastic shape* of β : $[q] = \{O(q, \gamma) | O \in SO(2), \gamma \in \Gamma, \|q\|_{\mathbb{L}^2}^2 = 1\} \in \mathcal{S}$ where $\mathcal{S}$ is the unit Hilbert sphere in the space of SRVF, modulo rotation ($SO(2)$), scale ($\|q\|_{\mathbb{L}^2}^2 = 1$), and reparameterization (Γ).

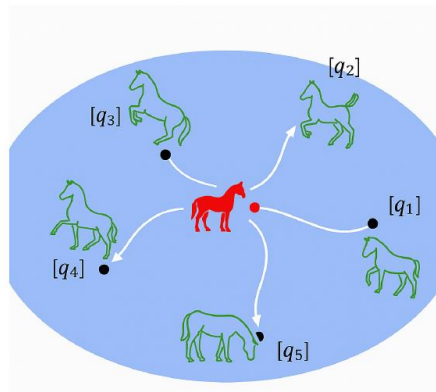


More ESD details

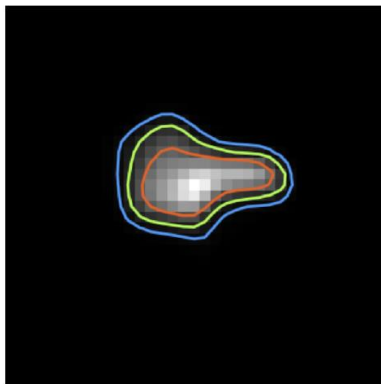
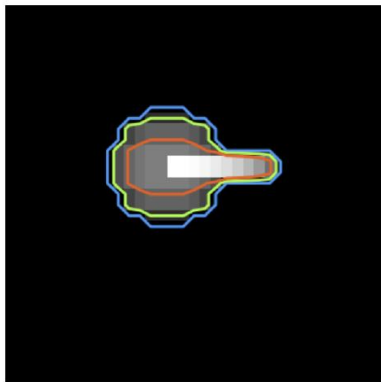
- ▶ The *Elastic Shape Distance (ESD)* between curves β_1 and β_2 which have the SRVF transform is defined as:

$$d_S([q_1], [q_2]) = \min_{O \in SO(2), \gamma \in \Gamma} \cos^{-1} \left(\int_S \langle q_1(t), Oq_2(\gamma(t))\sqrt{\dot{\gamma}} \rangle \right)$$

- ▶ Fix one curve $q_1(t)$ and search through all possible rotations $\times$ re-parameterizations of the second curve and select the one that is “closest” to the first curve ($Oq_2(\gamma(t))\sqrt{\dot{\gamma}}$).

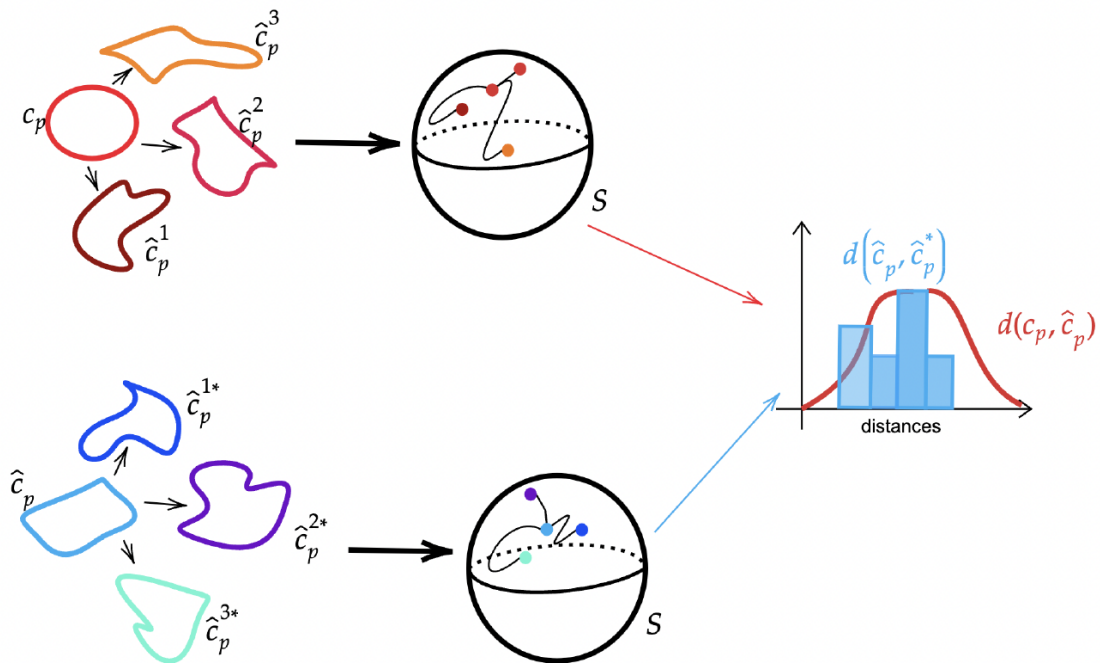


How can we get two curves?



- ▶ We can get three contours from the source $\mathbf{S}$ for different percentiles $p = \{p_1, p_2, p_3\}$ denoted $c_{p_1}, c_{p_2}, c_{p_3}$.
- ▶ We can get corresponding three contours from the estimated source $\hat{\mathbf{S}}$ for different percentiles $p = \{p_1, p_2, p_3\}$ denoted $\hat{c}_{p_1}, \hat{c}_{p_2}, \hat{c}_{p_3}$.
- ▶ Then for fixed p we get look at the ESD $d(c_p, \hat{c}_p)$.
- ▶ Small distances $\rightarrow$ we can 'trust' our estimate more. Large distances $\rightarrow$ we can't 'trust' our estimate more.

Distribution of Distances



We want to approximate the distribution of Elastic distances between the source contour and the data contours $d(c_p, \hat{c}_p)$ with the bootstrap samples and the data $d(\hat{c}_p, \hat{c}_p^*)$.

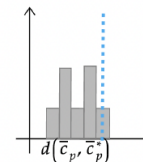
Confidence Intervals and Hypothesis Test

1. Make null hypothesis:

- ▶ $H_0 : c_p^0 \in \mathcal{C}_\alpha$ the null hypothesis is if c_p^0 is a likely source.
- ▶ $H_A : c_p^0 \notin \mathcal{C}_\alpha$ the alternative hypothesis is if c_p^0 is not a likely source.

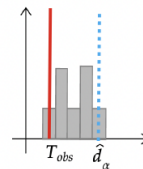
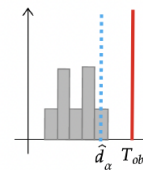


2. Generate confidence interval $\mathcal{C}_\alpha = \{c_p | d(c_p, \hat{c}_p) < d_\alpha\}$ which we calculate using $d(\hat{c}_p, \hat{c}_p^*)$ to get an estimated $\hat{d}_\alpha$ ($1 - \alpha$ percentile in distribution of distances).

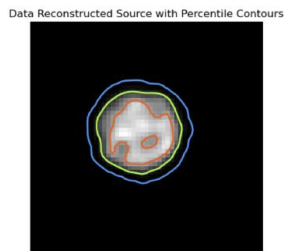
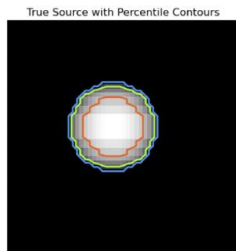


3. See if test statistic $T_{obs} = d(c_p^0, \hat{c}_p)$ is in confidence interval:

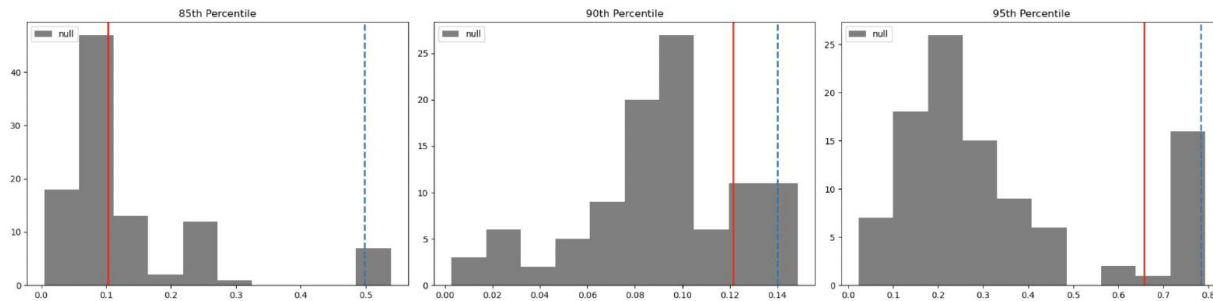
- ▶ reject null if $d(c_p^0, \hat{c}_p) \geq \hat{d}_\alpha$.
- ▶ fail to reject null if $d(c_p^0, \hat{c}_p) < \hat{d}_\alpha$.



Simulations Circle Example

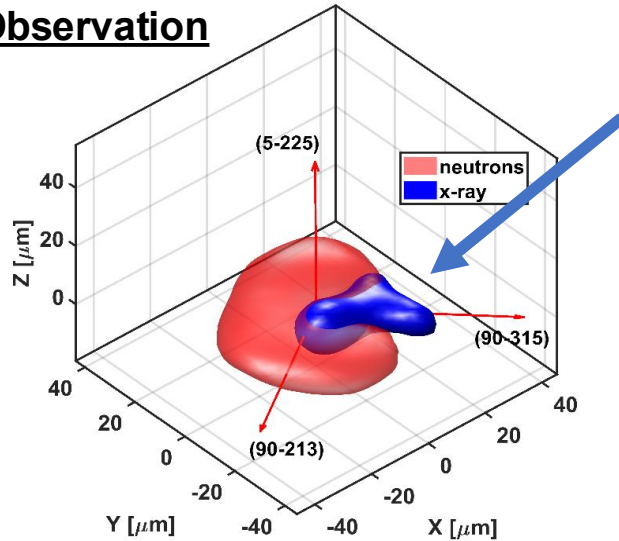


- ▶ The gray distributions are $d(\hat{c}_p, \hat{c}_p^*)$ for percentiles $p = \{85^{\text{th}}, 90^{\text{th}}, 95^{\text{th}}\}$.
- ▶ the red line is the test statistic $d(c_p^0, \hat{c}_p^*)$.
- ▶ the dotted blue line is the 95th percentile of the distribution of distances $\hat{d}_\alpha$ where $\mathcal{C}_\alpha = [0, \hat{d}_\alpha]$.



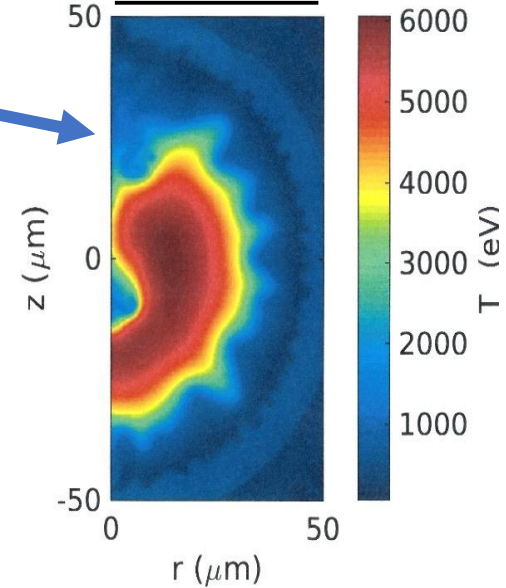
Deep Dive Issue 2: We couldn't observe spatially resolved ion temperature

Observation



Fill tube-induced jet introduces cold material into hotspot

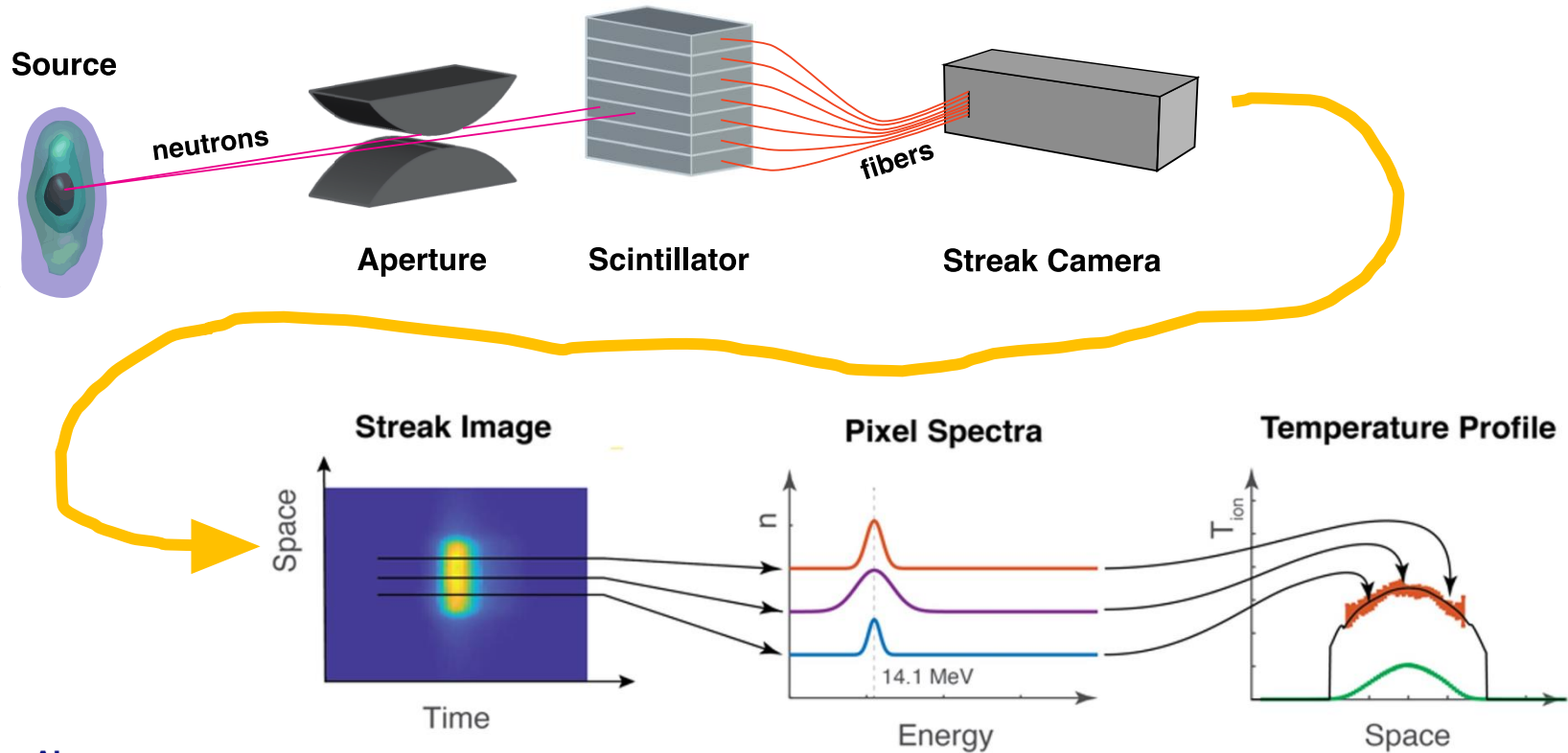
Simulation



Figs: B. Haines et al., *Nature Comm* **11**, 544 (2020) and *Phys. Plasmas* **27**, 102701 (2020).

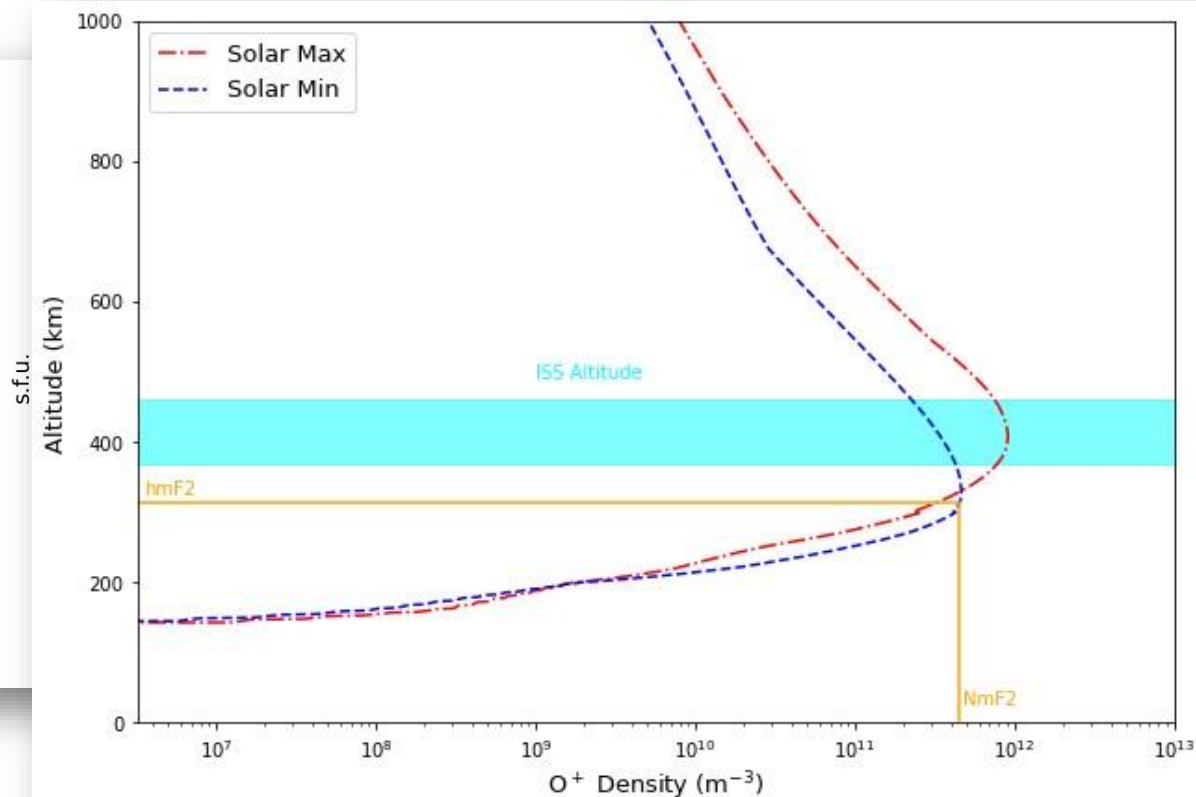
Temperature measurement could diagnose reaction rates, plasma performance, asymmetries, instabilities, etc.

The effect of temperature



Backup Slides (AIMSS)

APS and ÈPÈÈ data products



Sharing information across time slices

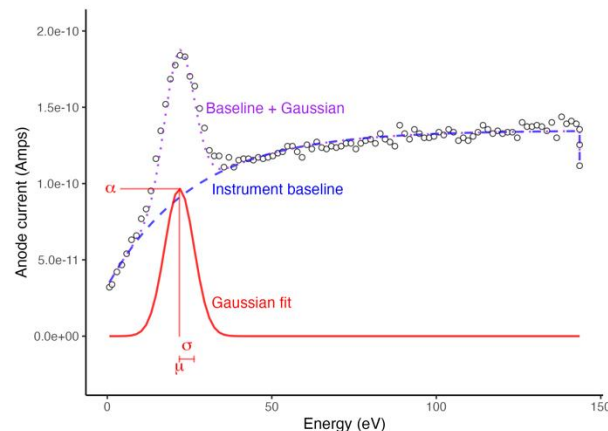
Gaussian model:
$$y_t(x) = \alpha_t \exp\left(-\frac{(x - \mu_t)^2}{2\sigma_t^2}\right) + \varepsilon_t(x), \quad \varepsilon_t(x) \sim \mathcal{N}(0, \sigma_{\text{obs}}^2)$$

Smooth drift:
$$\mathbf{z}_t = (\log \alpha_t, \mu_t, \log \sigma_t), \quad \mathbf{z}_t - \mathbf{z}_{t-1} \sim \mathcal{N}(\mathbf{0}, \text{diag}(\tau_\alpha^2, \tau_\mu^2, \tau_\sigma^2))$$

Penalized fit:
$$\min_{\{\mathbf{z}_t\}} \sum_{t,i} [y_t(x_i) - g(x_i; \mathbf{z}_t)]^2 + \sum_{t=2}^T (\mathbf{z}_t - \mathbf{z}_{t-1})^\top \mathbf{W} (\mathbf{z}_t - \mathbf{z}_{t-1}), \quad \mathbf{W} = \text{diag}\left(\frac{\sigma_{\text{obs}}^2}{\tau_j^2}\right)$$

Fitting process:

- Independent Gaussian fits initialize $\mathbf{z}_t$
- Alternating (Gauss–Seidel) updates over t
- Converges when $\max_t \|\Delta \mathbf{z}_t\| < \varepsilon$
- Empirical Bayes estimation of penalty weights

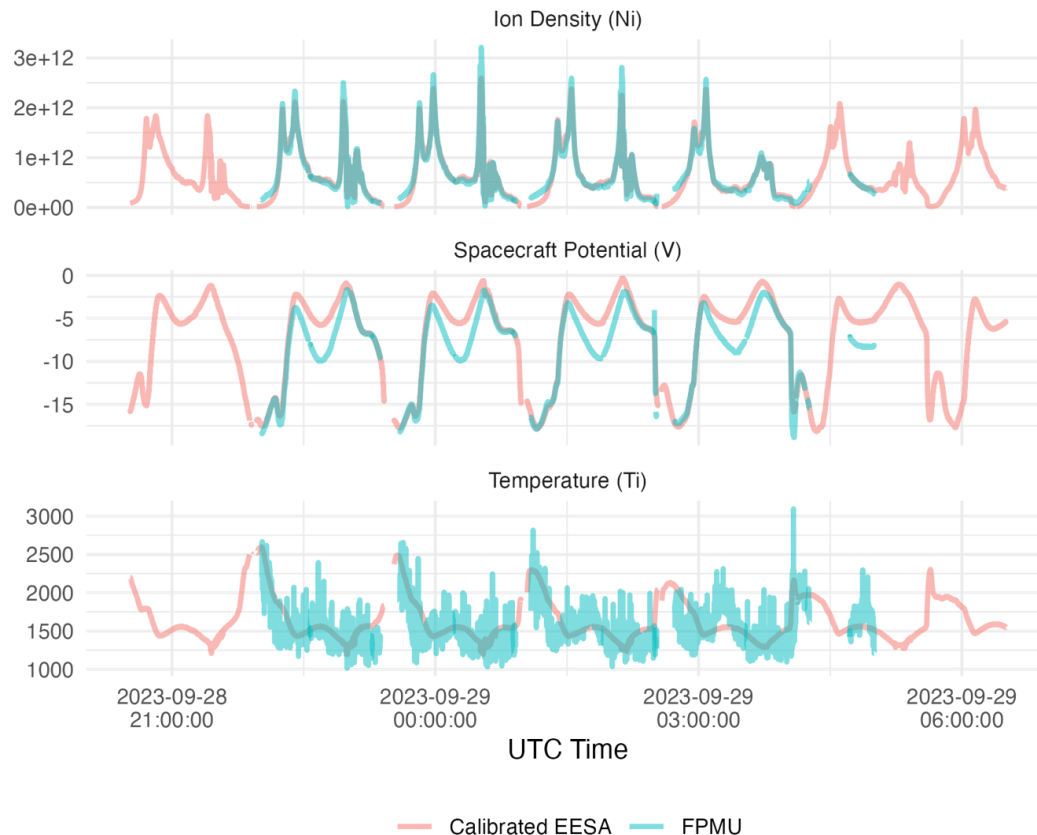


Cross Calibration Snapshot

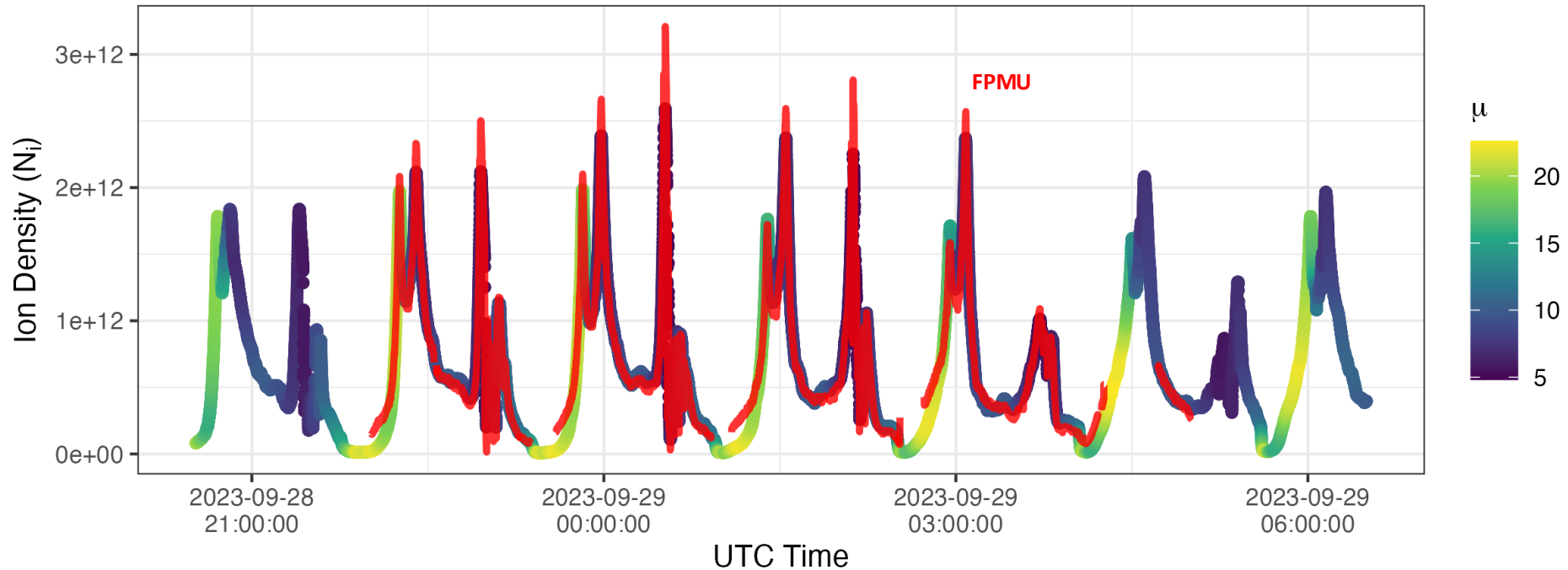
Signal
Extract

EPEE/FP
MU Cali
b.

EPEE
first
light



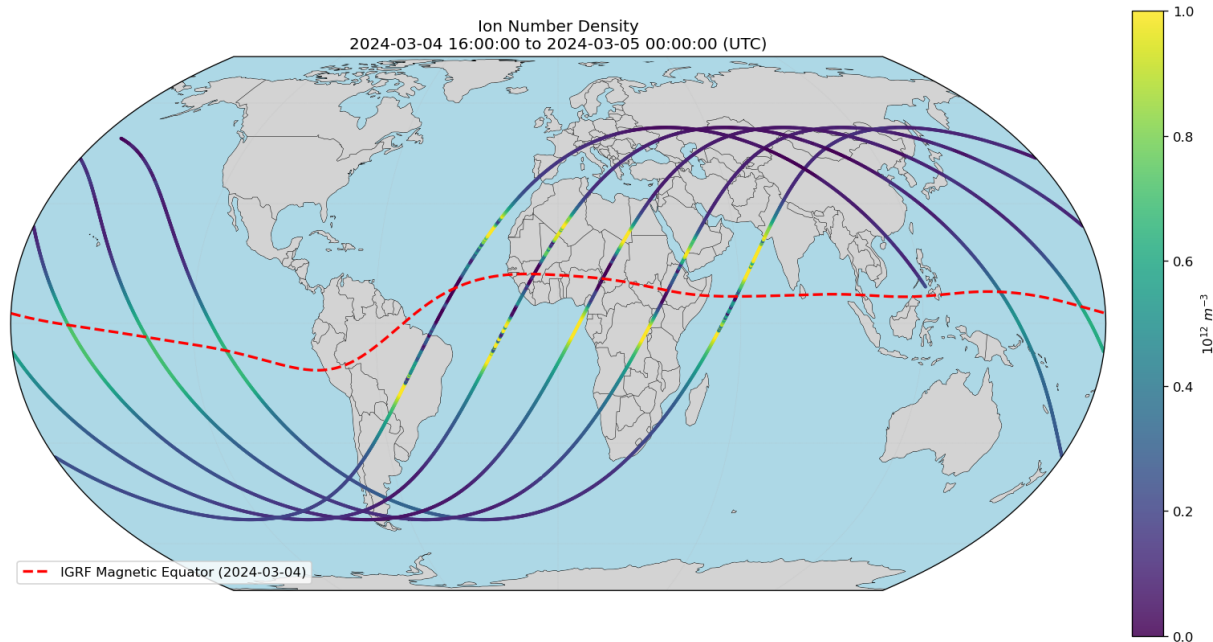
Model performance against FPMU data



Equatorial Ionization Anomaly (EIA) Crest Dynamics

EIA
Crest

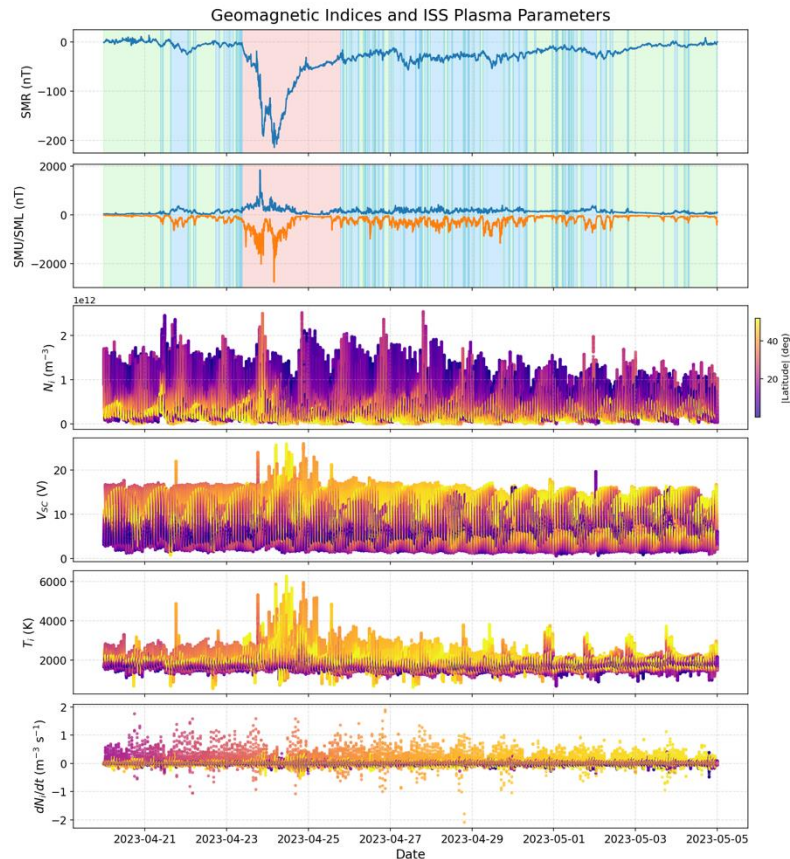
- Geomagnetic storms and auroral substorms modify the EIA crest
 - Prompt penetration electric field drives the dynamics
 - Cold ion heating, EIA crest spreading, instability (equatorial plasma bubble!)



23 April 2023 Geomagnetic Storm (Example)

Storm
survey

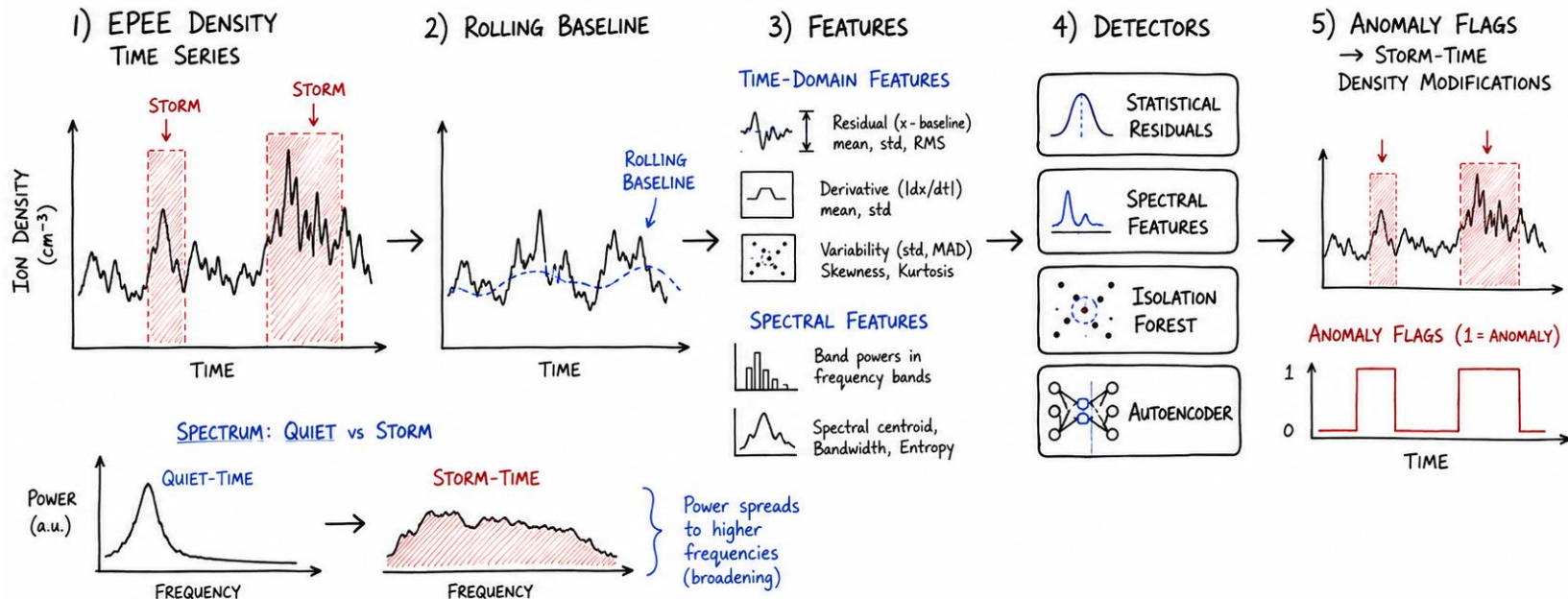
- Top two panels show extreme ring current enhancements and ionospheric electrojet currents at high latitudes, respectively
- Ion density enhancements
 - Possibly from uplift of lower altitude ions
 - Possibly from enhanced ionization
- Enhancements in spacecraft potential from frame charging
- Substantial ion temperature enhancements
- Possible that mid-latitude enhancements are resulting from substorm activity in the sub-auroral regions



Anomaly detection – demonstrated on storms

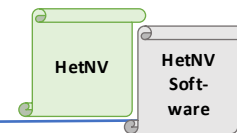
Event
detect.

Using EPEE Ion Density Observations

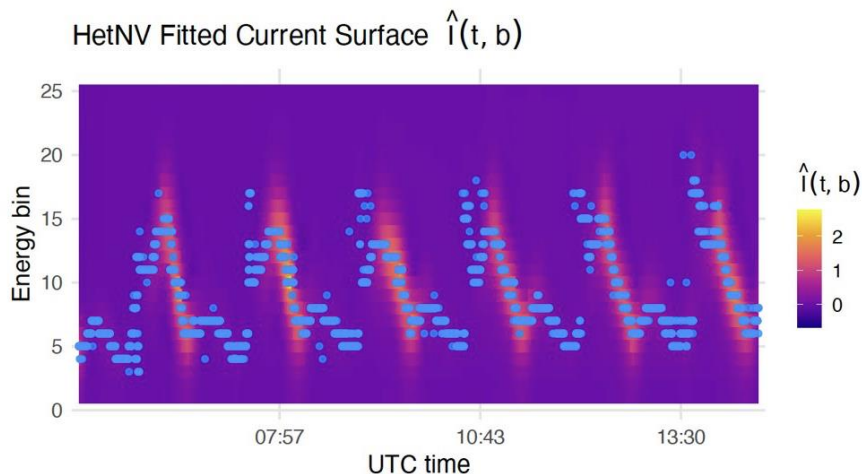


GOAL: detect deviations from baseline behavior, then merge flags into events.

Novel methods 1: HetNV



Turning instrument spectrograms into reliable signal picks



Example window: fitted current surface with candidate peak locations

HetNV contributions

Separates signal from instrument noise

Fits a smooth current surface while learning where APS noise changes over time and energy

Adds local uncertainty to peak detection

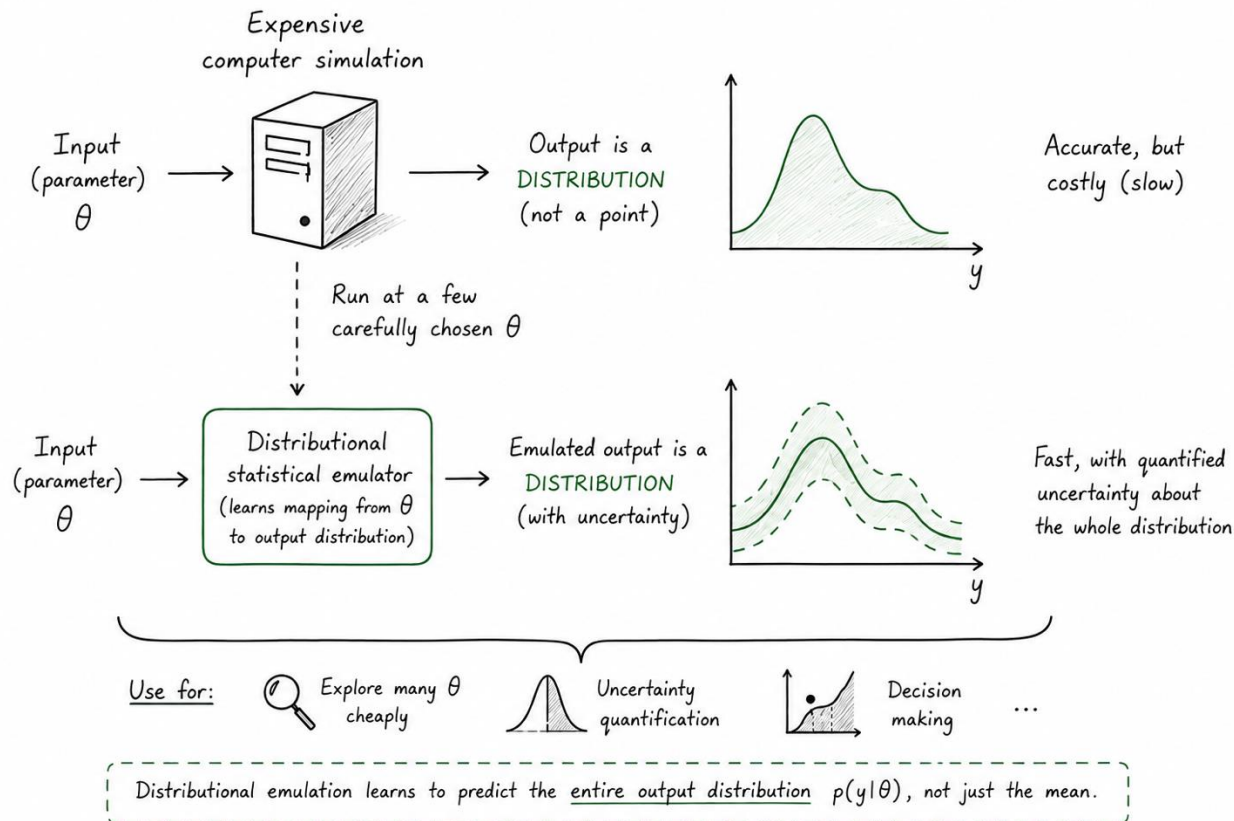
Peak picks are retained only when the local predictive interval indicates the signal is distinguishable from noise

Scales to operational data volumes

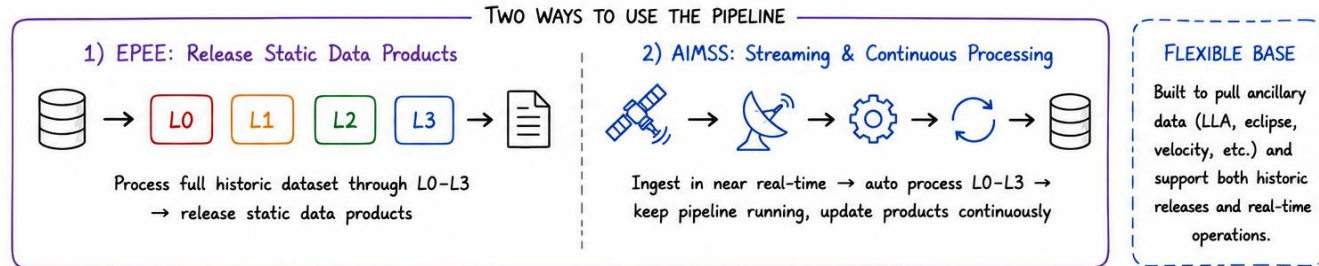
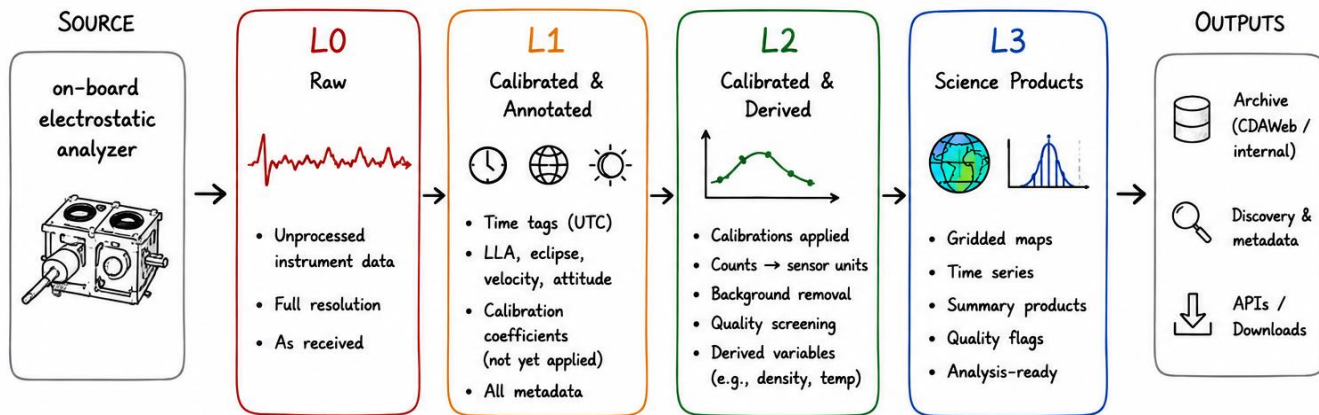
Vecchia nearest-neighbor conditioning keeps GP-style uncertainty feasible for dense APS windows

Novel methods 2: Distributional emulation

Dist.
Emu.



Data Pipeline – legacy and AIMSS (with ISR-3)

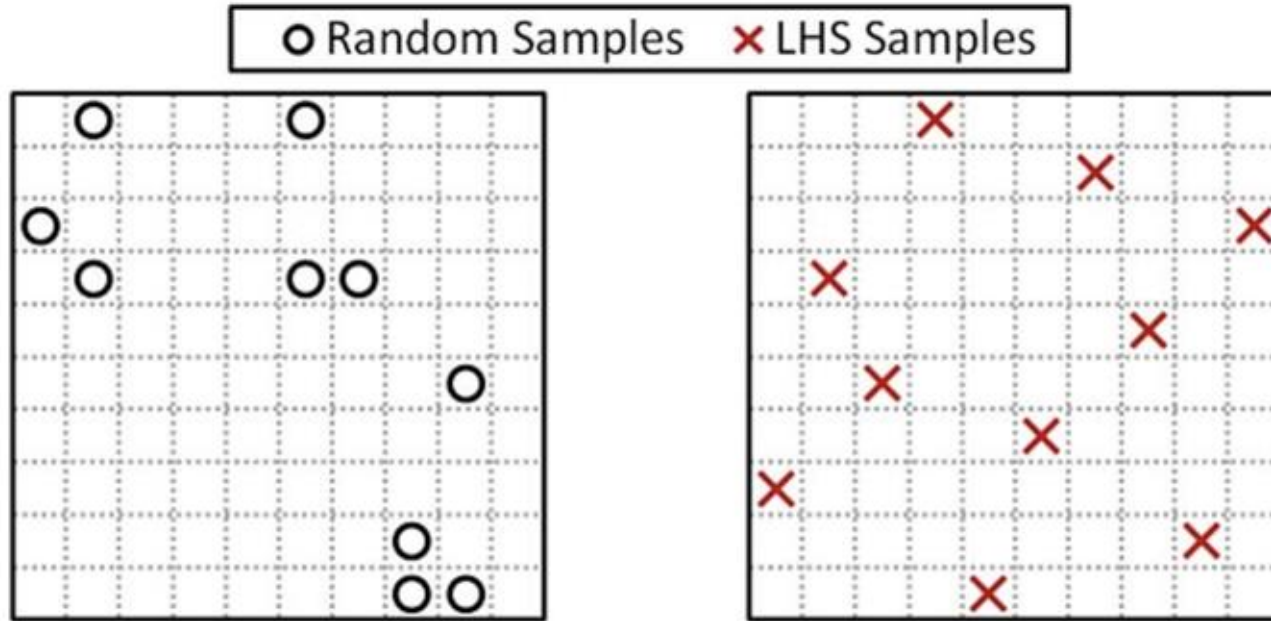


Backup Slides (Cosmo)

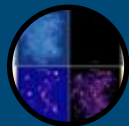


SCIDAC-5: COSMIC DISCOVERIES IN THE EXASCALE ERA

The Path to a “Hero” Run: Design



Comparison of random and Latin hypercube sampling examples in two dimensions (every row and column is sampled with LHS).

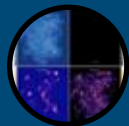


An emulator is a statistical approximation of computational model or simulator.

- ▶ Simulator: $y_{sim} = \eta(\theta)$.
- ▶ Emulator: $y_{emu} = \hat{\eta}(\theta)$.
- ▶ Hopefully: $\eta(\theta) \approx \hat{\eta}(\theta)$.

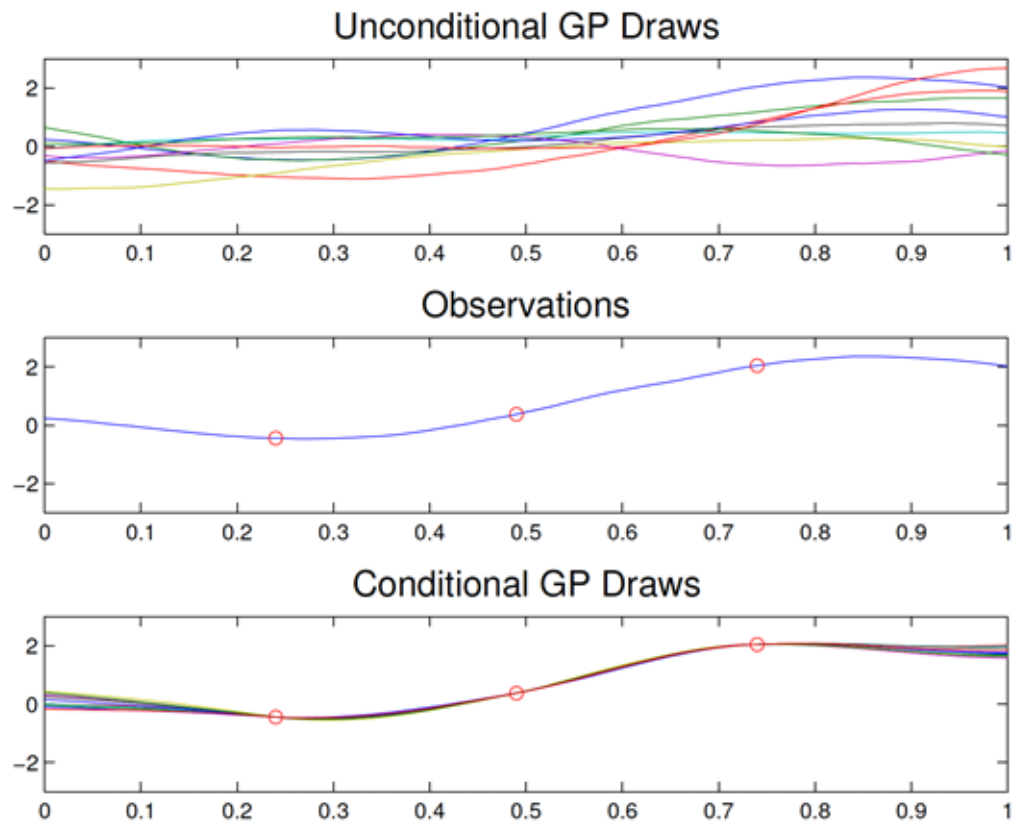
Flexible surface modeling procedures are usually used here: e.g. Gaussian processes, neural nets, polynomial chaos, etc.

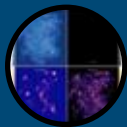
Emulators are helpful when the simulators are too slow for our needs. Parameter inference is an important example. Which θ make $\eta(\theta)$ close to the y measured in an experiment?



SCIDAC-5: COSMIC DISCOVERIES IN THE EXASCALE ERA

The Path to a “Hero” Run: Emulate

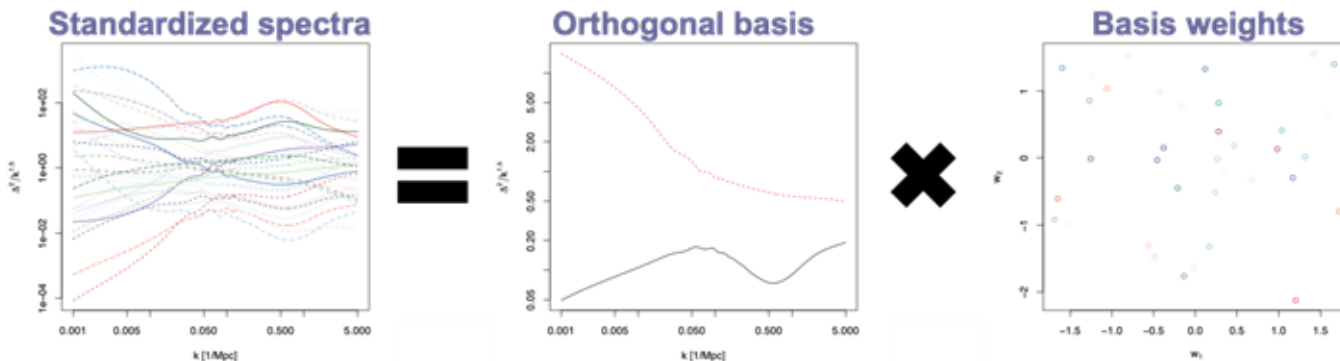




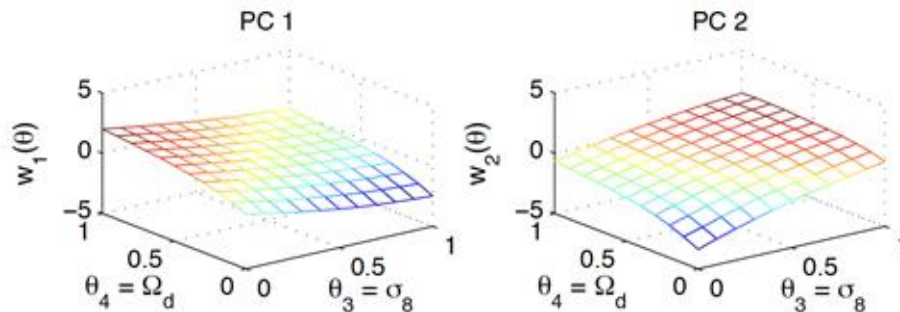
SCIDAC-5: COSMIC DISCOVERIES IN THE EXASCALE ERA

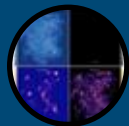
The Path to a “Hero” Run: Emulate

Center, scale, project onto an orthogonal basis (e.g. principal components).



Model each weight vector independently with a GP.

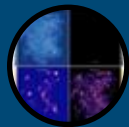




The data is a noisy version of the model at the “correct” input.

$$\begin{aligned}y &= \eta(\theta) + \epsilon \\ \epsilon &\sim \mathcal{N}(\vec{0}, \Sigma_y) \\ \pi(\theta) &= 1, \theta \in \mathcal{C} \\ p(\theta|y) &\propto \exp \left\{ \frac{1}{2} (y - \eta(\theta))' \Sigma_y^{-1} (y - \eta(\theta)) \right\}\end{aligned}$$

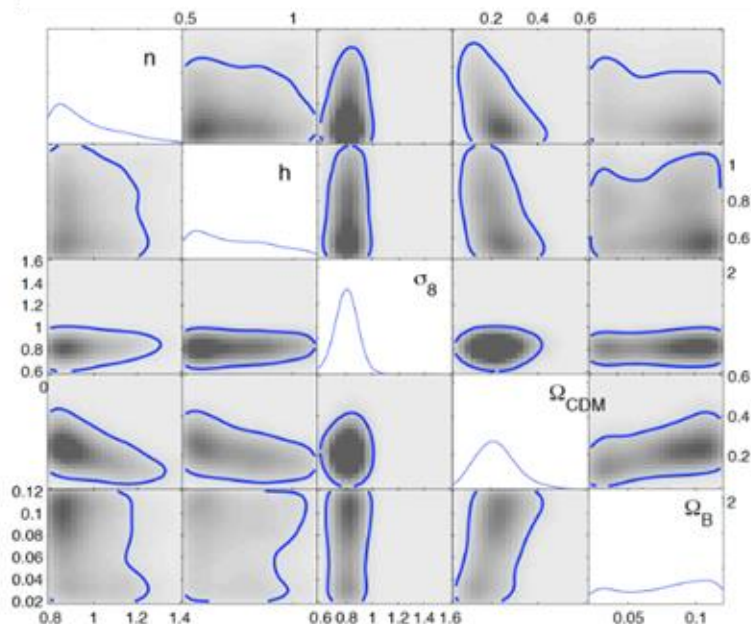
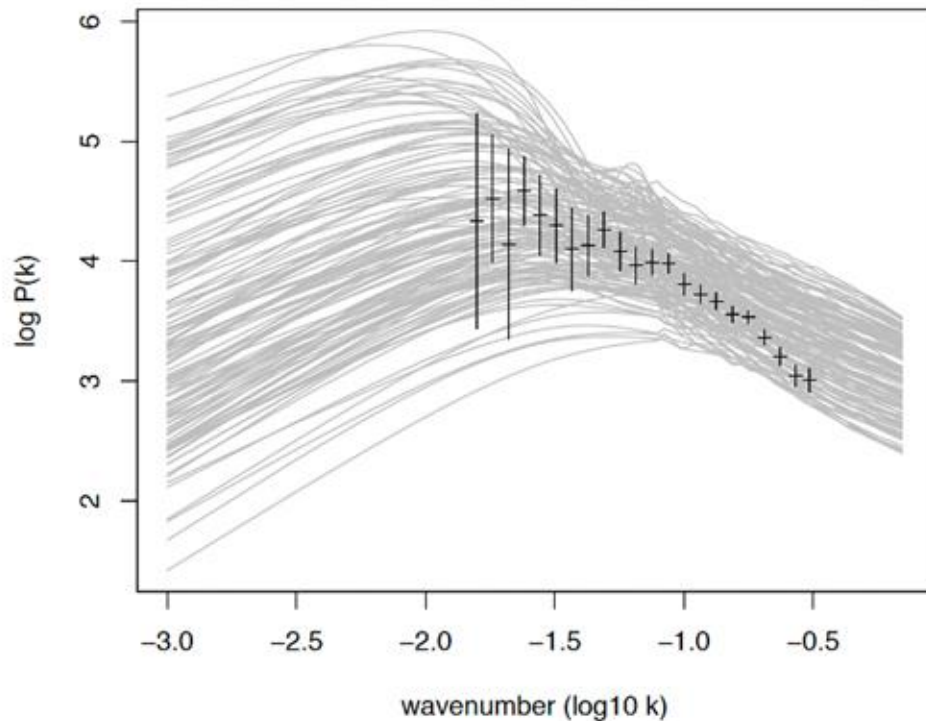
Recall simulation
is approximated
by the emulator



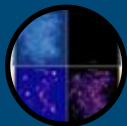
SCIDAC-5: COSMIC DISCOVERIES IN THE EXASCALE ERA

The Path to a “Hero” Run: Calibrate

large scale structure data & simulations



Simple 6-parameter gravity only example:
Higdon, Lawrence, Heitmann, Habib (2012).



θ_{sub}	$\min(\theta_{\text{sub}})$	$\max(\theta_{\text{sub}})$
κ_{w}	2	4
e_{w}	0.2	1
M_{seed}	0.6×10^6	1.2×10^6
v_{kin}	0.1×10^4	1.2×10^4
ϵ_{kin}	0.02×10^1	1.2×10^1

Five hydro parameters

$$0.12 \leq \omega_m \leq 0.155,$$

$$0.0215 \leq \omega_b \leq 0.0235,$$

$$0.7 \leq \sigma_8 \leq 0.9,$$

$$0.55 \leq h \leq 0.85,$$

$$0.85 \leq n_s \leq 1.05,$$

$$-1.3 \leq w_0 \leq -0.7,$$

$$-1.73 \leq w_a \leq 1.28,$$

$$0.0 \leq \omega_{\nu} \leq 0.01,$$

Two cosmology parameters