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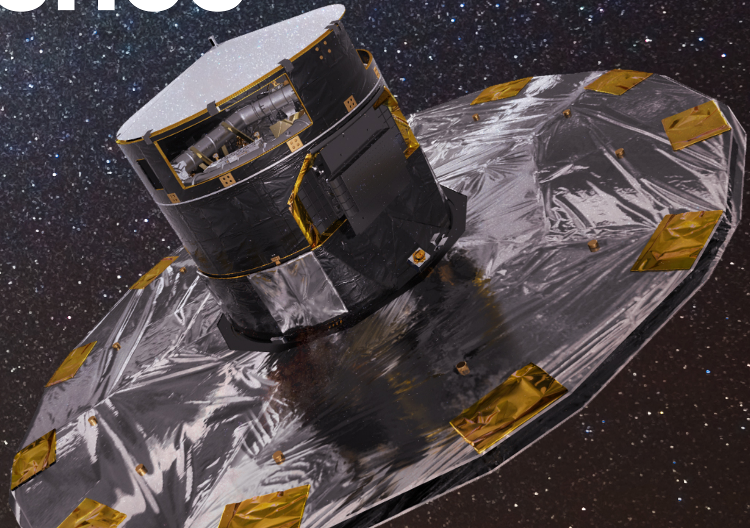
Credit: ESA Gaia Mission

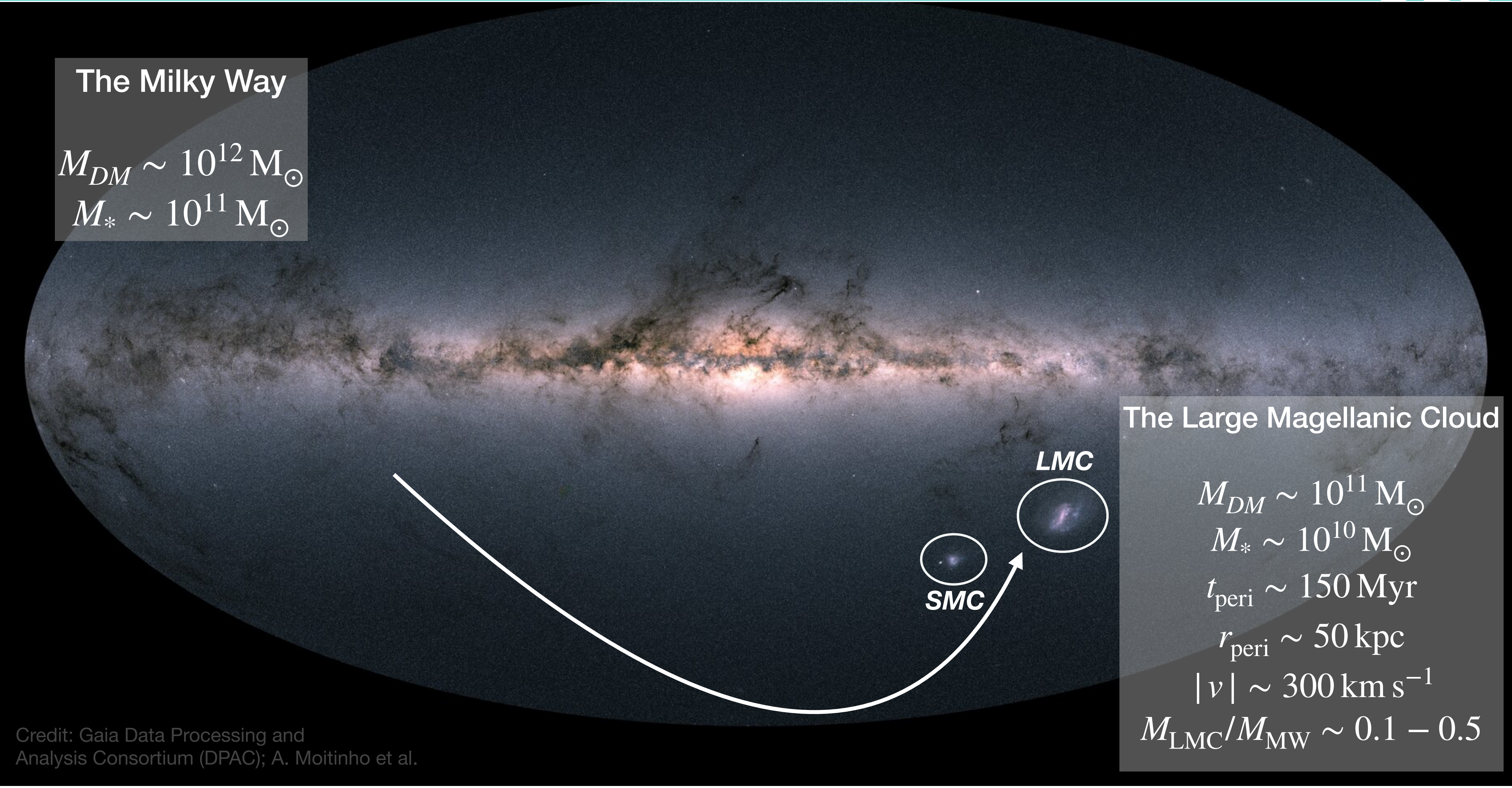
Properties of the Milky Way and Large Magellanic Cloud using Simulation Based Inference



Richard Brooks - National Astronomy Meeting 25’

richard.brooks.22@ucl.ac.uk

The Milky Way & Large Magellanic Cloud

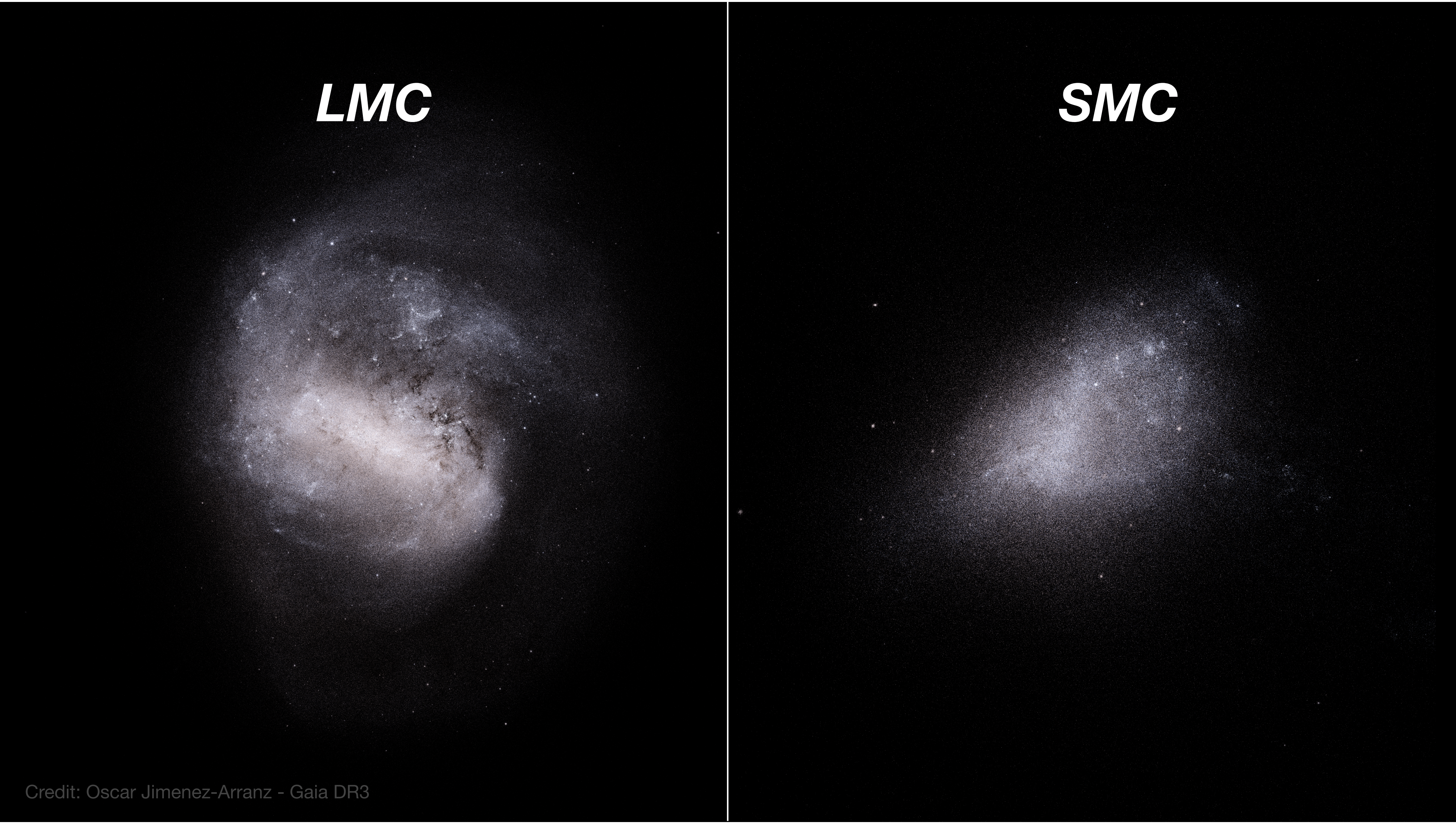


The Milky Way

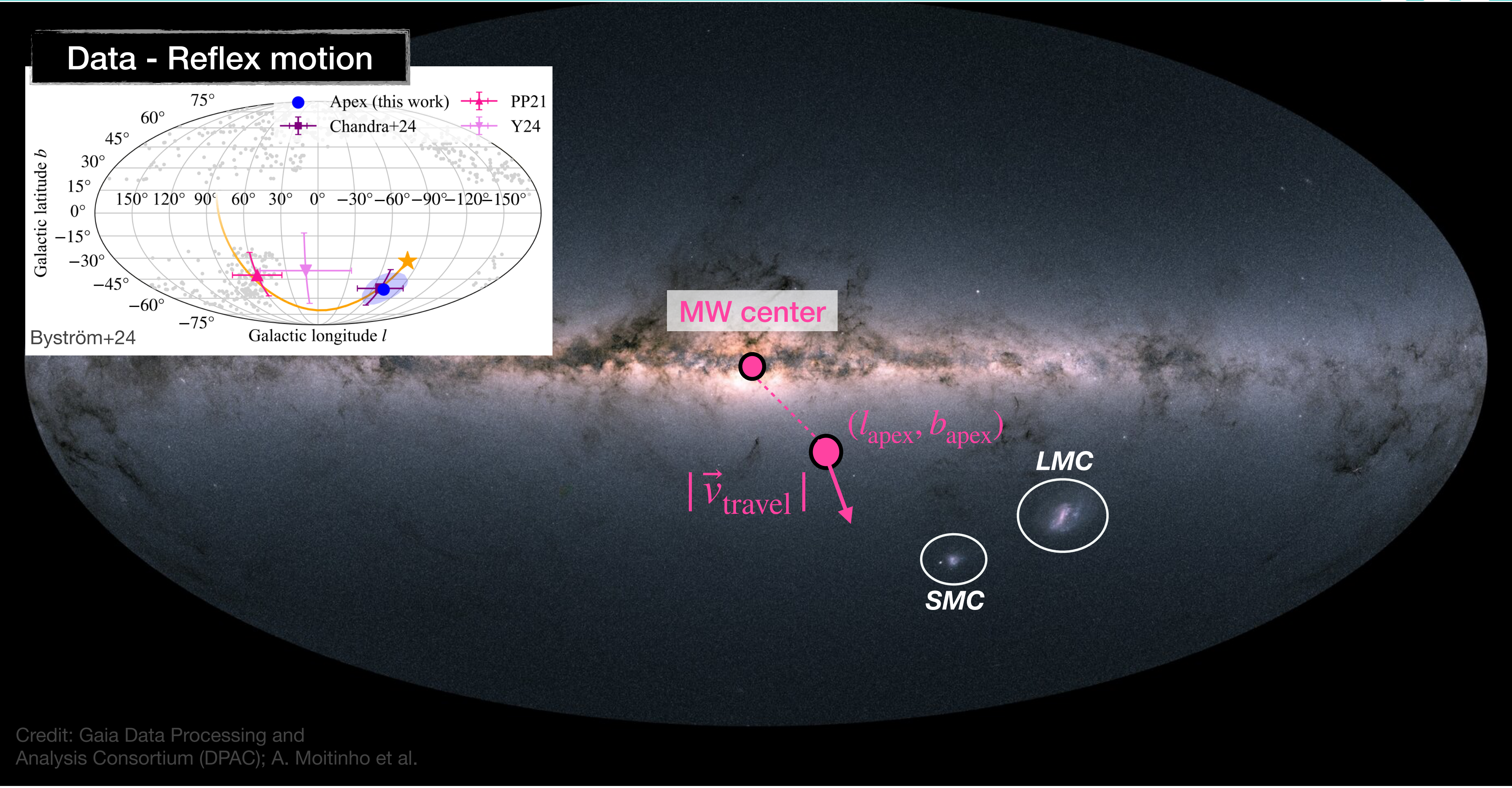
$$M_{DM} \sim 10^{12}\,\mathrm{M}_\odot$$
$$M_* \sim 10^{11}\,\mathrm{M}_\odot$$

The Large Magellanic Cloud

$$M_{DM} \sim 10^{11}\,\mathrm{M}_\odot$$
$$M_* \sim 10^{10}\,\mathrm{M}_\odot$$
$$t_{\mathrm{peri}} \sim 150\,\mathrm{Myr}$$
$$r_{\mathrm{peri}} \sim 50\,\mathrm{kpc}$$
$$|\,v\,| \sim 300\,\mathrm{km\,s^{-1}}$$
$$M_{\mathrm{LMC}}/M_{\mathrm{MW}} \sim 0.1 - 0.5$$


LMC
SMC
Credit: Oscar Jimenez-Arranz - Gaia DR3

The Milky Way & Large Magellanic Cloud



Credit: Gaia Data Processing and Analysis Consortium (DPAC); A. Moitinho et al.

Simulation Based Inference

- *Simulation Based Inference* (SBI) is a statistical framework for inference where traditional analytic methods are impractical. (Cranmer+2020)

- SBI can estimate the posterior distributions when likelihood functions cannot be explicitly defined.

- Must be able to produce and forward model many simulations with the output as observable summary statistics / measurables.

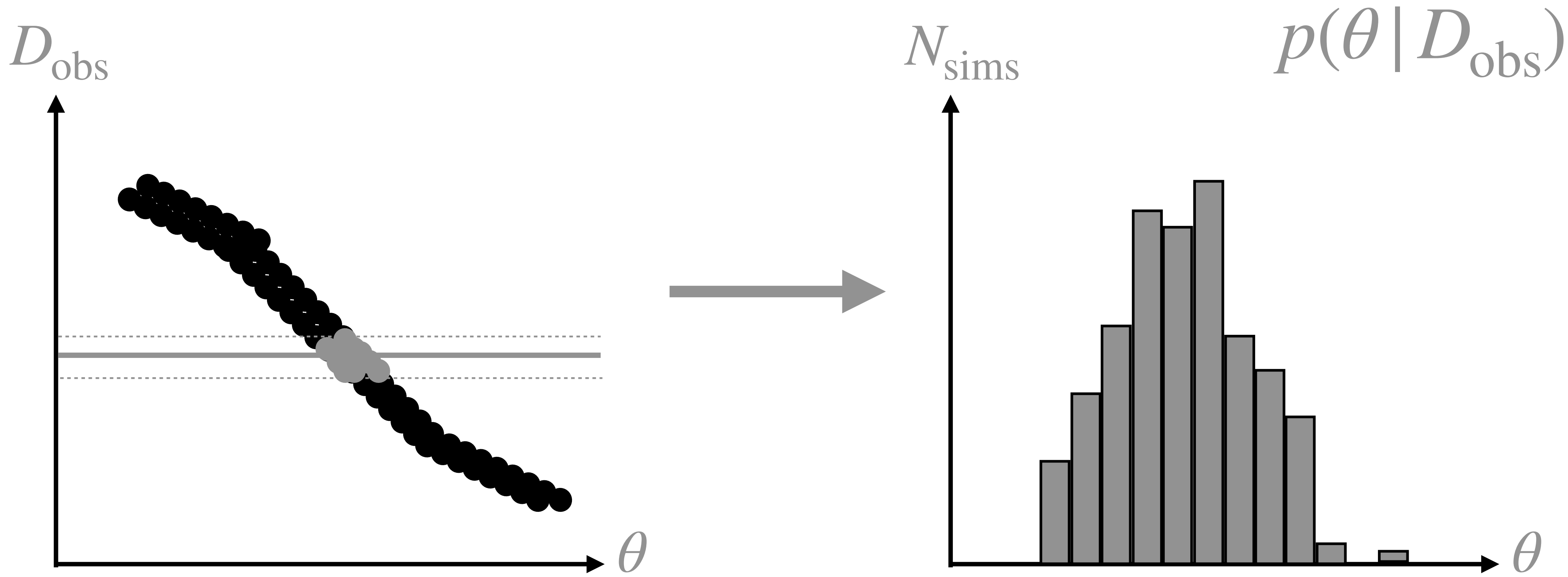
- This approach relates the choice of simulation parameters, $\vec{\theta}$, to the observed data, D_{obs}.

Posterior

Likelihood x Prior

$$p(\theta|D_{\mathrm{obs}}, I) = \frac{p(D_{\mathrm{obs}}|\theta, I)\,p(\theta|I)}{p(D_{\mathrm{obs}}|I)} \Leftrightarrow \mathcal{P} = \frac{\mathcal{L} \times \Pi}{\mathcal{Z}}$$

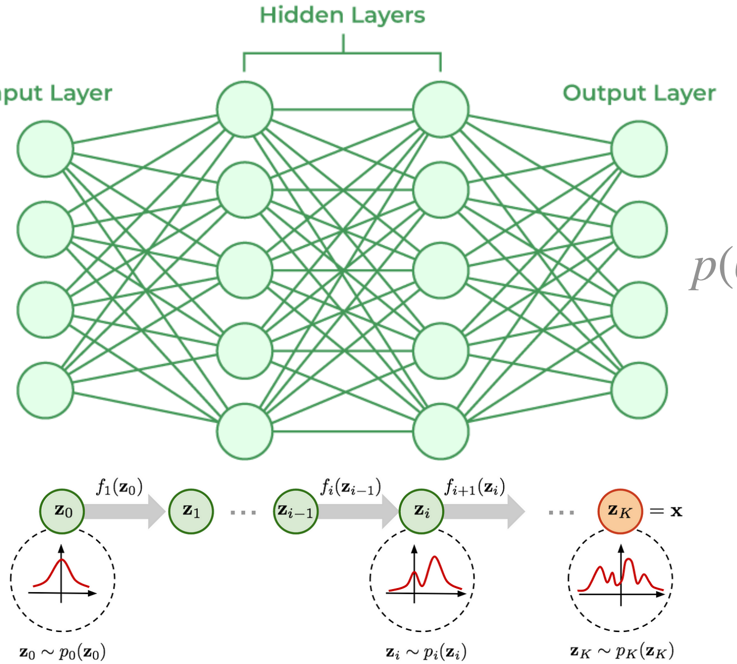
Simulation Based Inference: A simple example



Simulation Based Inference: A more complicated example

- Generally, models/data are not 1-D & require exploration of large/complex parameter spaces.
- Use simulations to learn the posterior using a density estimation algorithm, e.g., normalising flows.

All simulations



$p(\vec{\theta}\,|\,d_{\rm obs})$

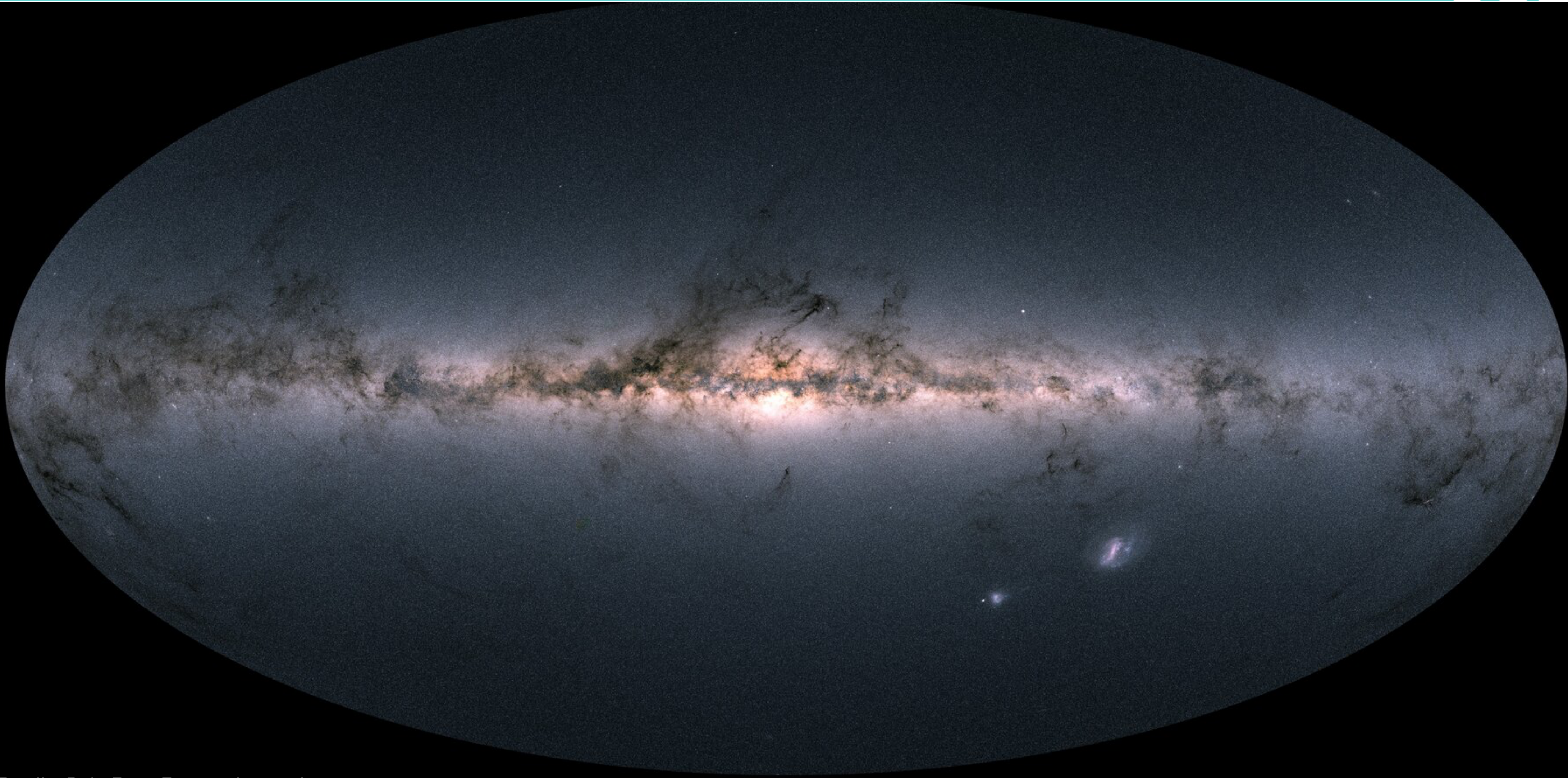
✅ **No need to explicitly define a likelihood function.**

✅ **Posterior evaluation is amortised.**

✅ **Able to bridge the fidelity gap between low and high resolution simulations**

✅ **Allows rapid exploration of large model parameter spaces.**

Modelling the Milky Way & Large Magellanic Cloud



Credit: Gaia Data Processing and
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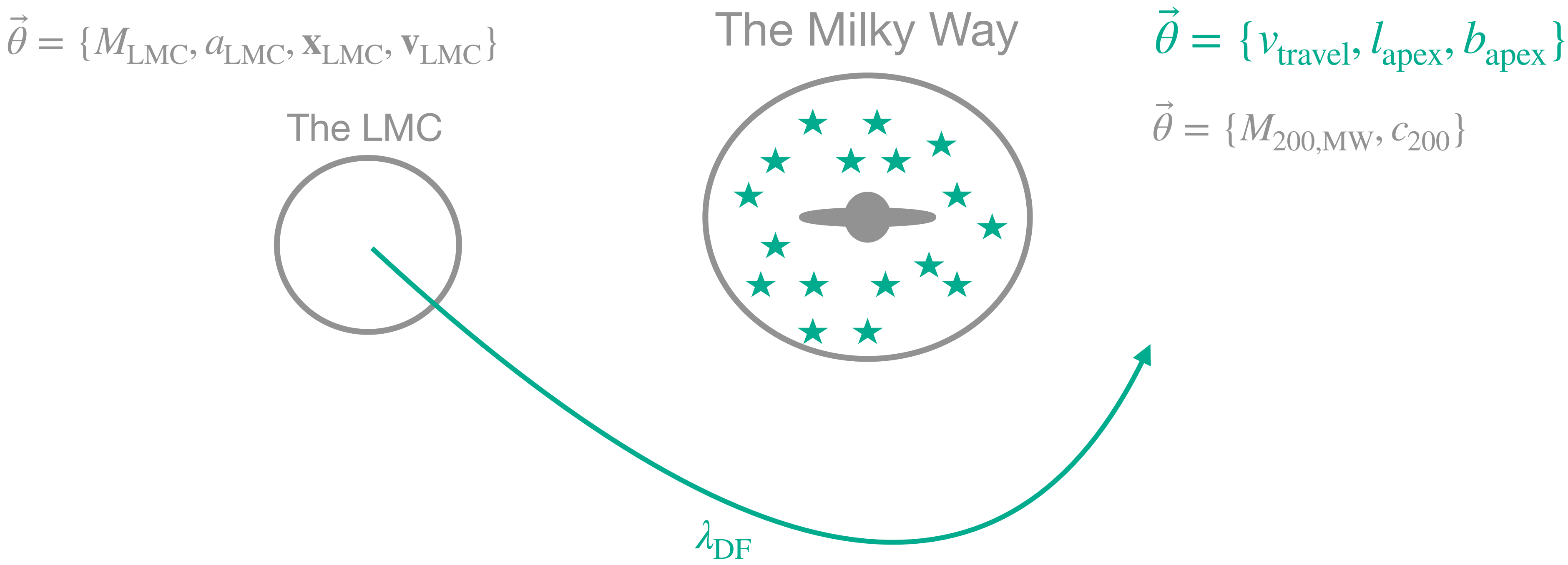
Modelling the Milky Way & Large Magellanic Cloud

\# Simulations with unique parameter values = *128,000*

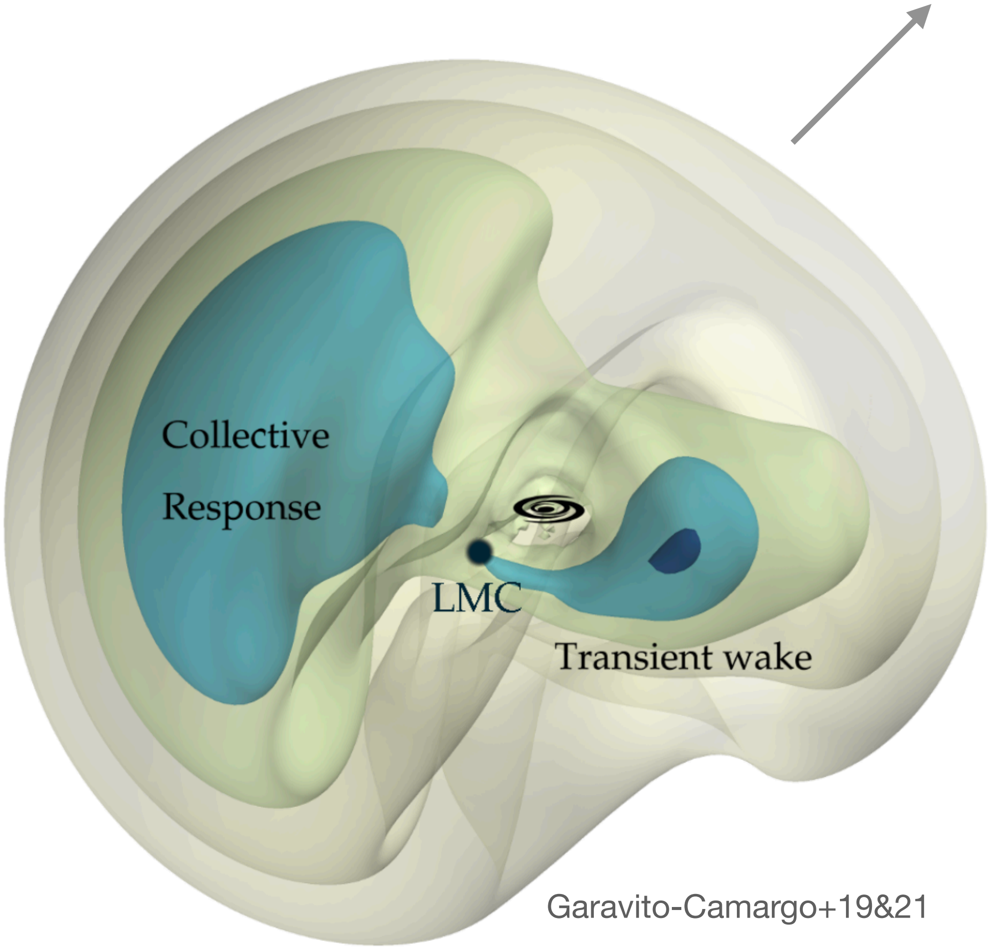


Can SBI with low-fidelity MW—LMC models capture more complicated models? + real data?

Upscaling fidelity: Deforming MW—LMC simulations

Basis Function Expansions

$$\rho(\mathbf{x},t) = \sum_{\mu} A_{\mu}(t)\varrho_{\mu}(\mathbf{x}), \quad \Phi(\mathbf{x},t) = \sum_{\mu} A_{\mu}(t)\phi_{\mu}(\mathbf{x}),$$

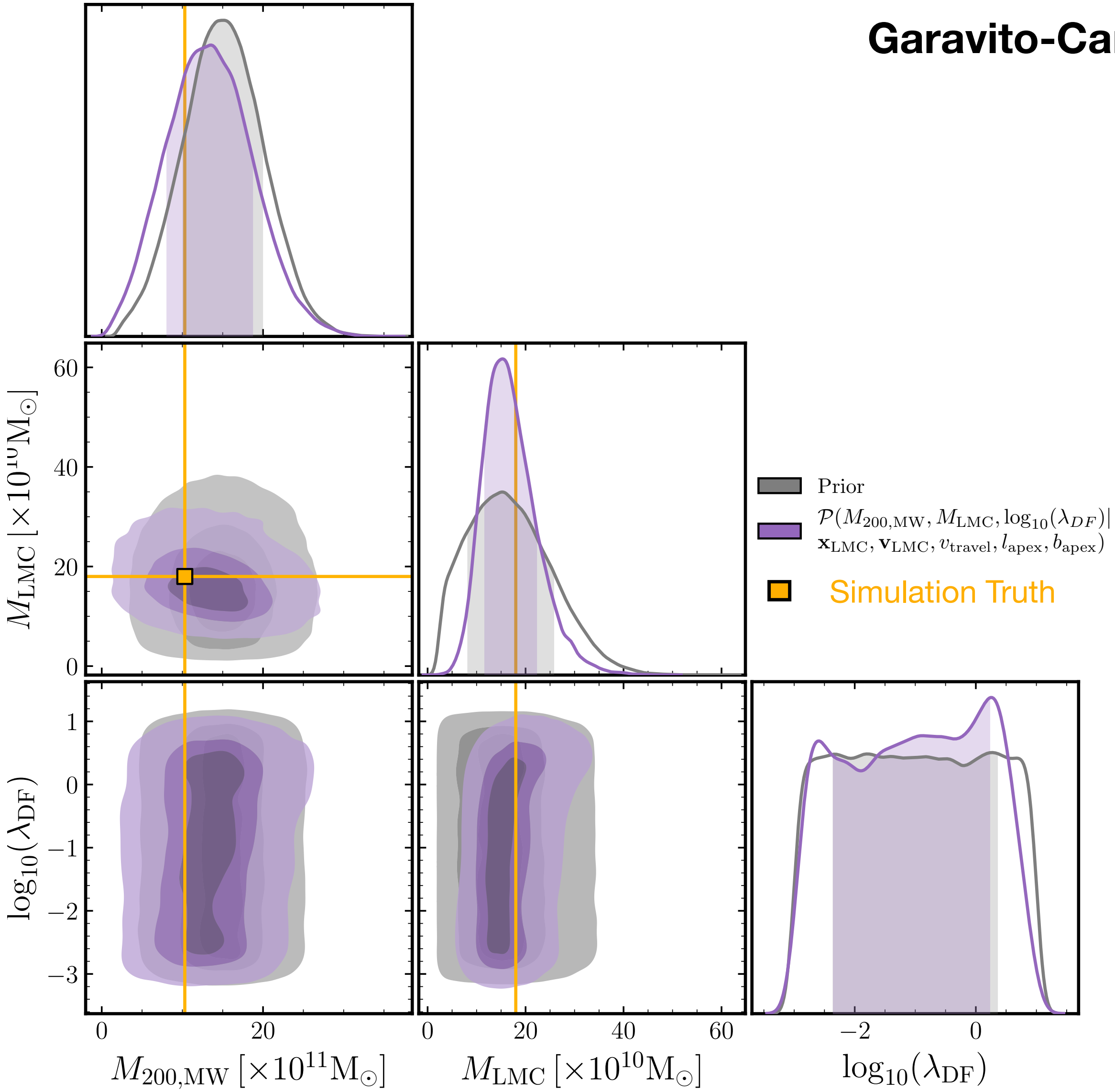


Garavito-Camargo+19&21

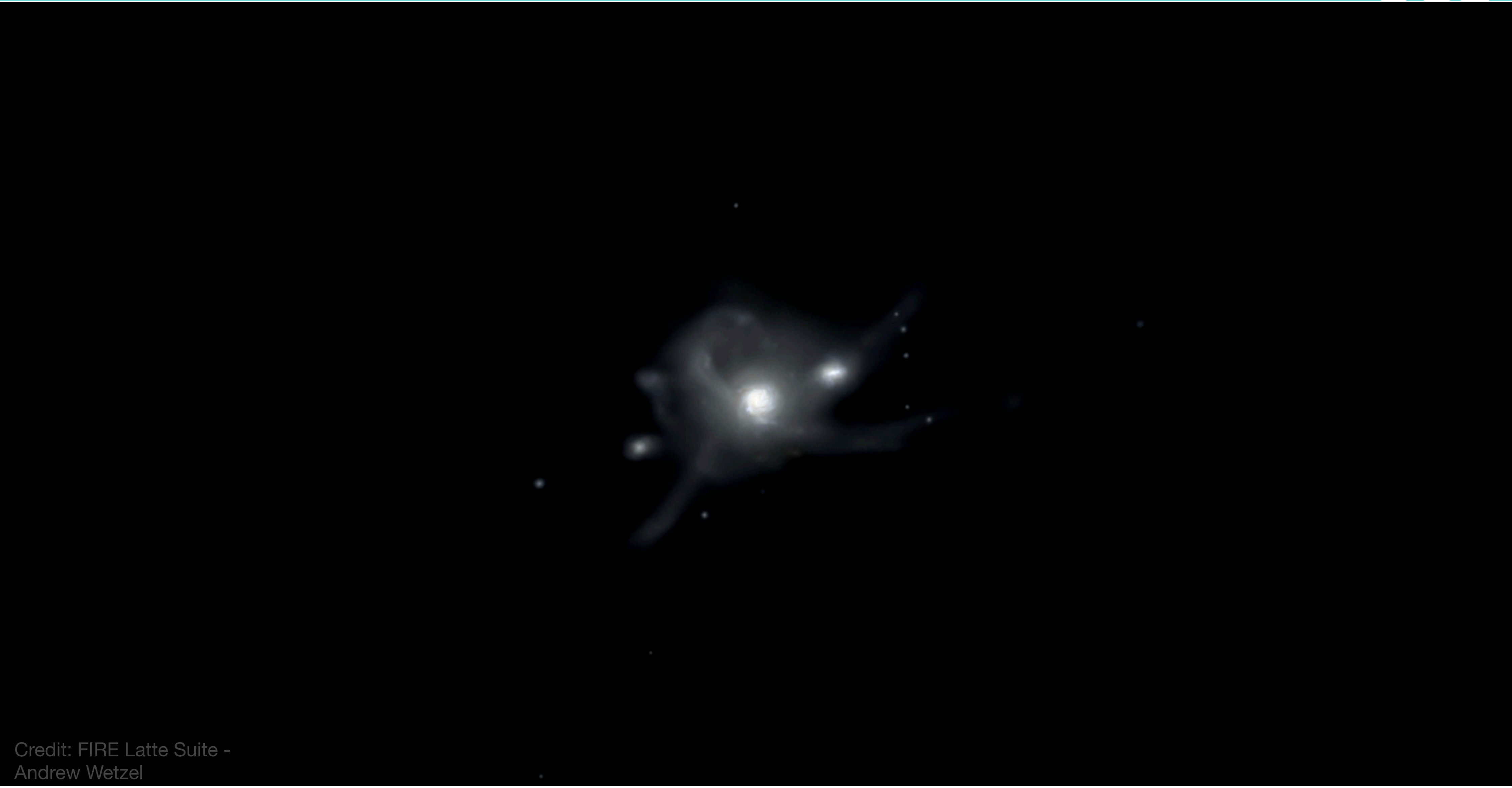
- Deforming models allow dark matter to redistribute itself.
- Described by basis function expansions.
- Much more computationally expensive to run.
- Can we leverage our simpler set-up + SBI to capture the dynamics of these tailored simulations?

Upscaling fidelity: Deforming MW—LMC simulations

Garavito-Camargo+19 fiducial model

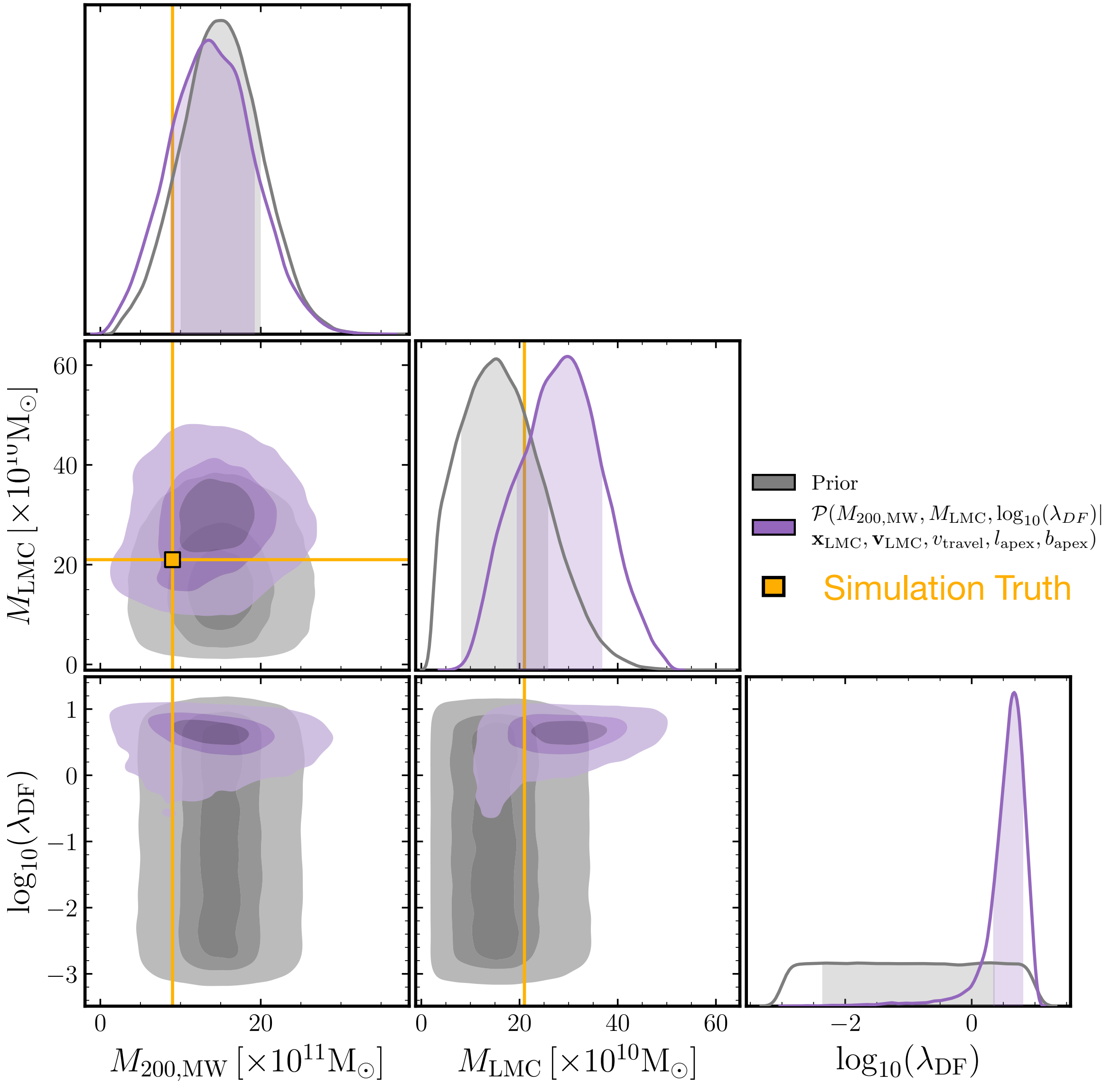


Upscaling fidelity: Cosmological MW—LMC analogues



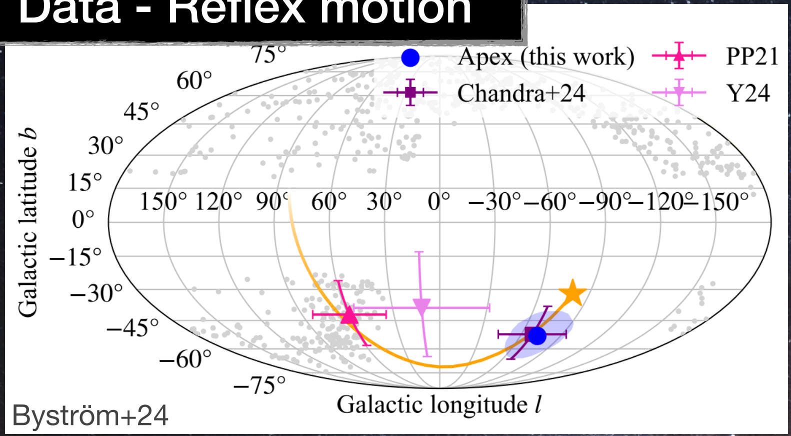
Upscaling fidelity: Cosmological MW—LMC analogues

FIRE m12b



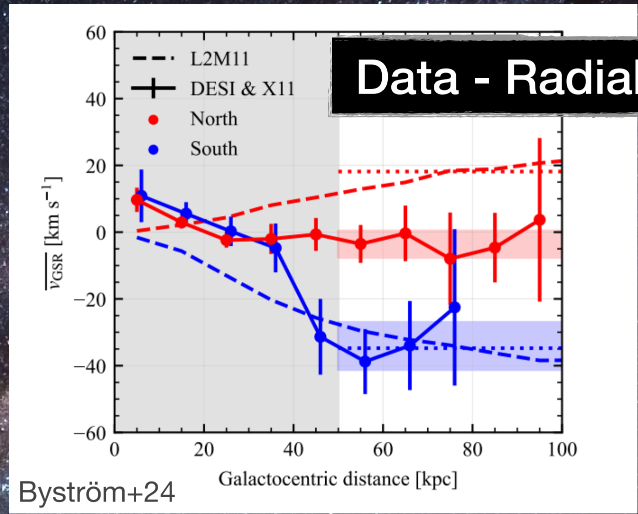
Application to real data - from H3, DESI, Gaia, etc!

Data - Reflex motion



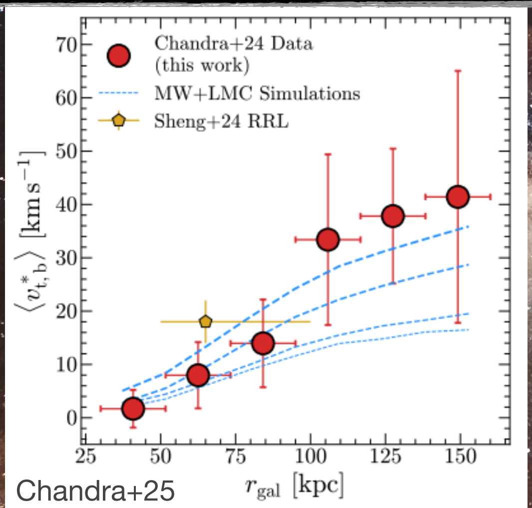
Byström+24

Data - Radial velocities

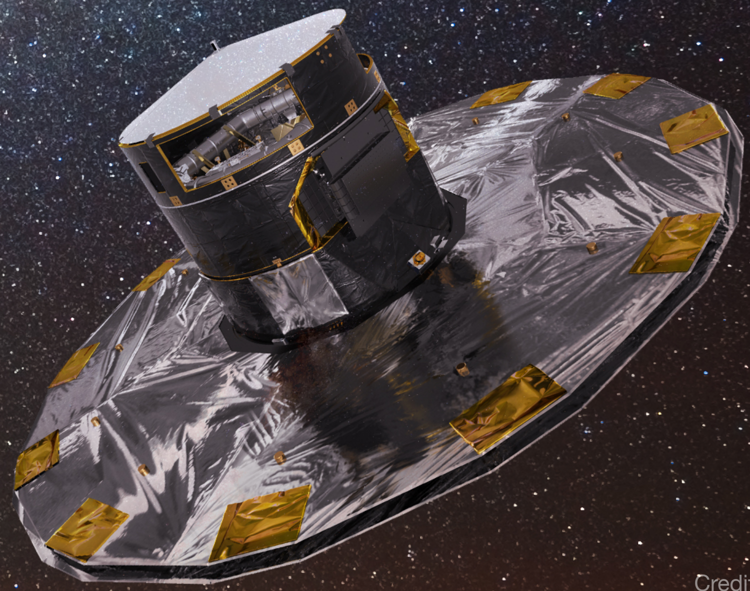


Byström+24

Data - Tangential velocities



Chandra+25



Credit: ESA Gaia Mission

Conclusions: MW—LMC & Simulation Based Inference

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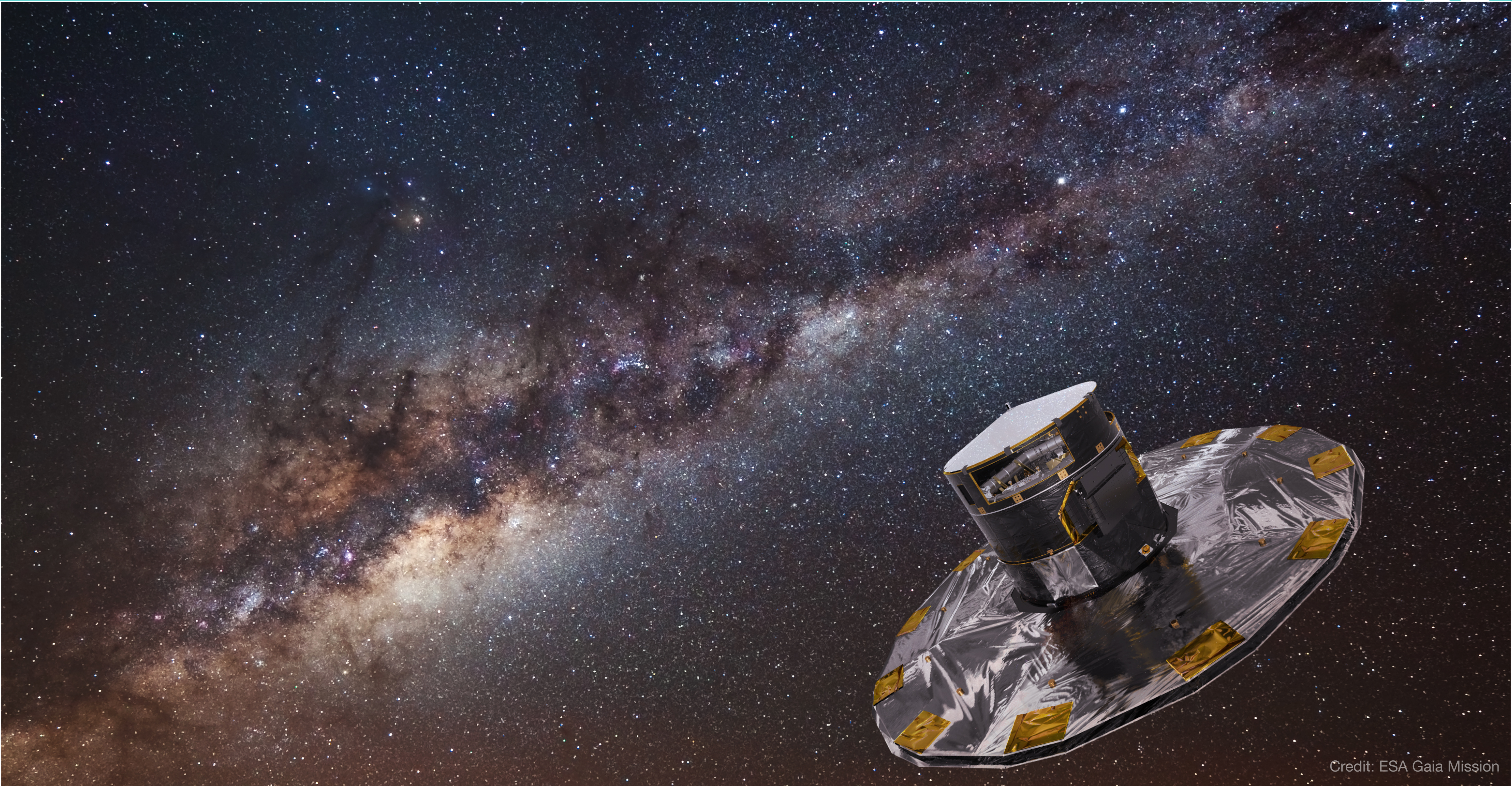
- This is the ***first application*** of SBI to the dynamics of the MW—LMC interaction.
- We release a set of ***128,000*** unique low-fidelity MW—LMC simulations, including a stellar halo, varying parameters such as $M_{\mathrm{MW}}, M_{\mathrm{LMC}}$ & λ_{DF}.
- We ***validated*** our SBI implementation on a simple, low-fidelity MW—LMC model.
- We can upscale to high-fidelity ***deforming and cosmological*** MW—LMC simulations using SBI + low-fidelity MW—LMC models.
- This will allow ***rapid exploration of large model parameter spaces*** at a fraction of the computational cost required to run the higher fidelity simulations.
- We are applying this to ***observed data from e.g., H3,*** **DESI, Gaia,** to infer properties of the MW and LMC!

Credit: ESA Gaia Mission

More slides

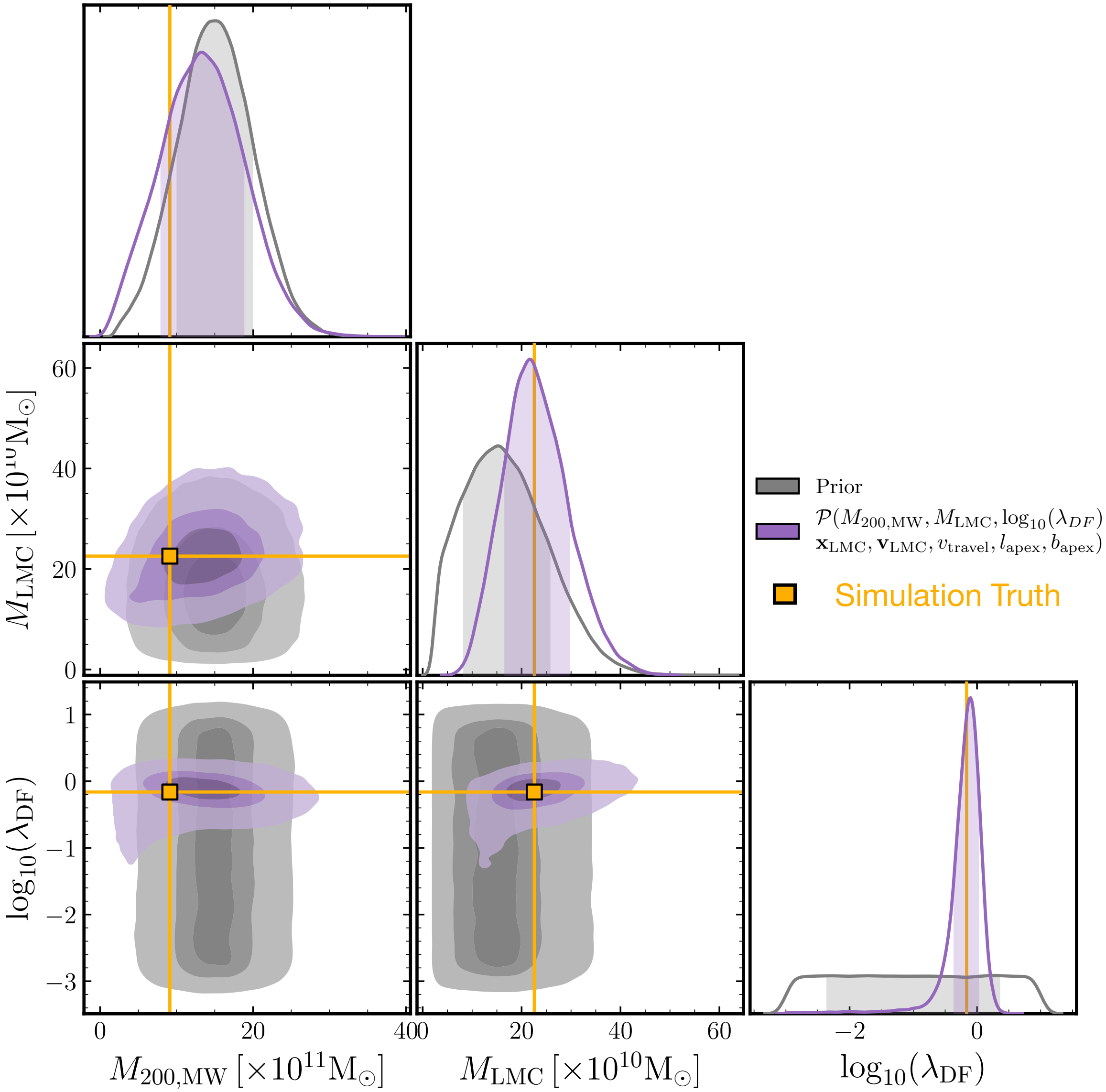


Simulation Prior Distributions

Table 1. Simulation model parameter prior distributions.

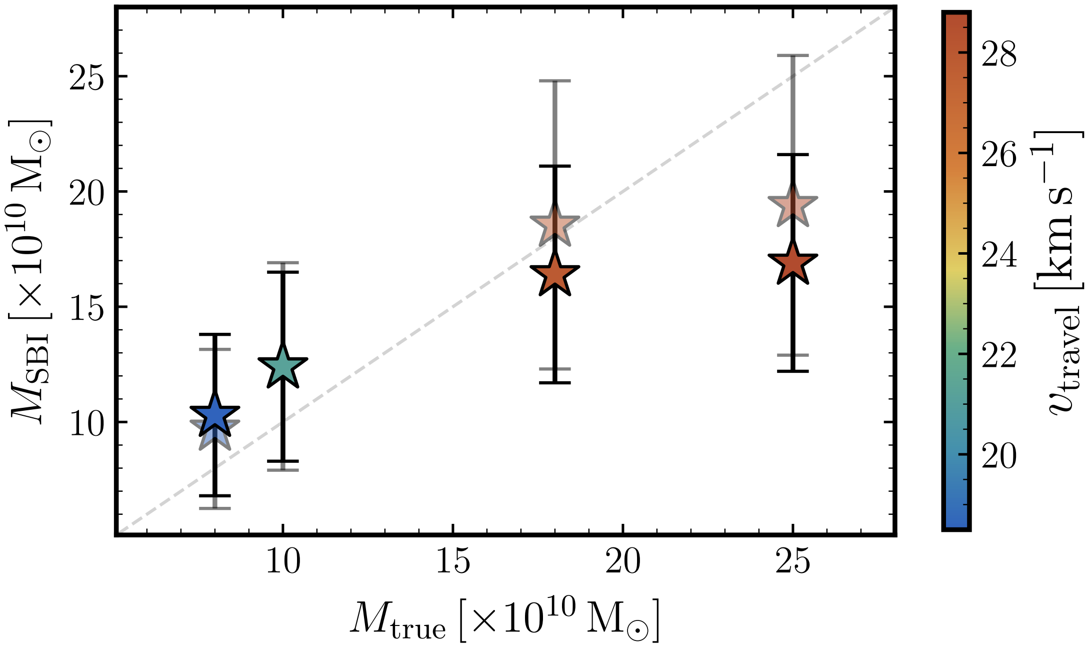
Model Parameter	Prior probability distribution
$M_{200,\mathrm{MW}}$	$\mathcal{N}(15,5)\times10^{11}M_\odot$
M_{LMC}	$\mathcal{N}(15,10)\times10^{10}M_\odot$
$\log_{10}(\lambda_{\mathrm{DF}})$	$\mathcal{U}(-3,1)$
α_{LMC}	$\mathcal{U}(60^\circ,90^\circ)$
δ_{LMC}	$\mathcal{U}(-80^\circ,-50^\circ)$
d_{LMC}	$\mathcal{N}(49.6,5)$ kpc
v_{los}	$\mathcal{N}(262.2,10)\ \mathrm{km\,s^{-1}}$
$\mu_{\alpha_{\mathrm{LMC}}}$	$\mathcal{N}(1.9,0.25)\ \mathrm{mas\,yr^{-1}}$
$\mu_{\delta_{\mathrm{LMC}}}$	$\mathcal{N}(0.33,0.25)\ \mathrm{mas\,yr^{-1}}$
β_0	$\mathcal{U}(0,0.9)$
r_{Dehnen}	$\mathcal{U}(10,15)$ kpc

Validation: On a simple MW—LMC simulation

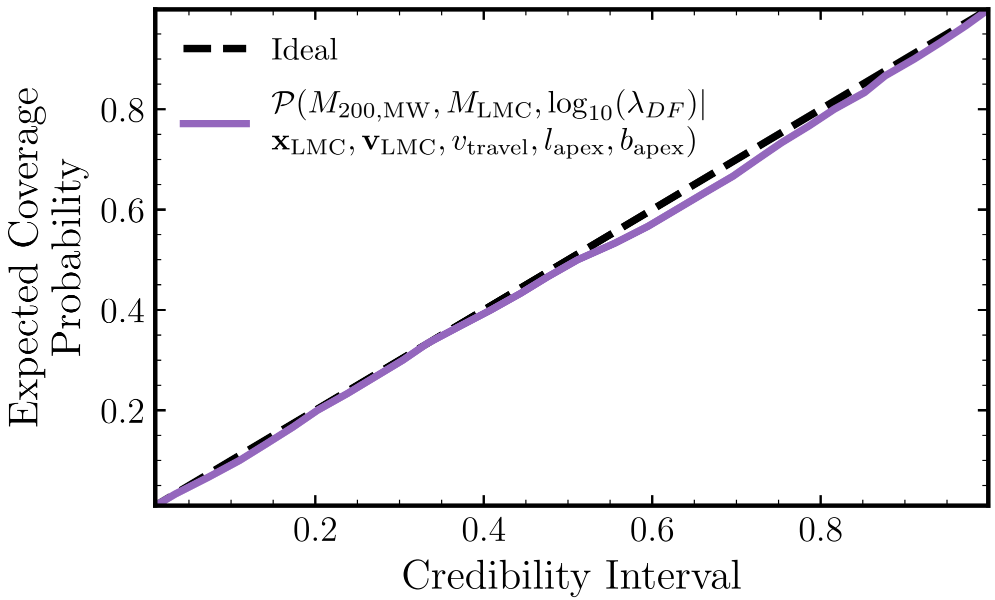


- We select a random simulation from our sample of 128,000.
- We take the "observed data" as some of its true simulation parameters.
- We estimate the MW mass, LMC mass and dynamical friction strength posteriors.

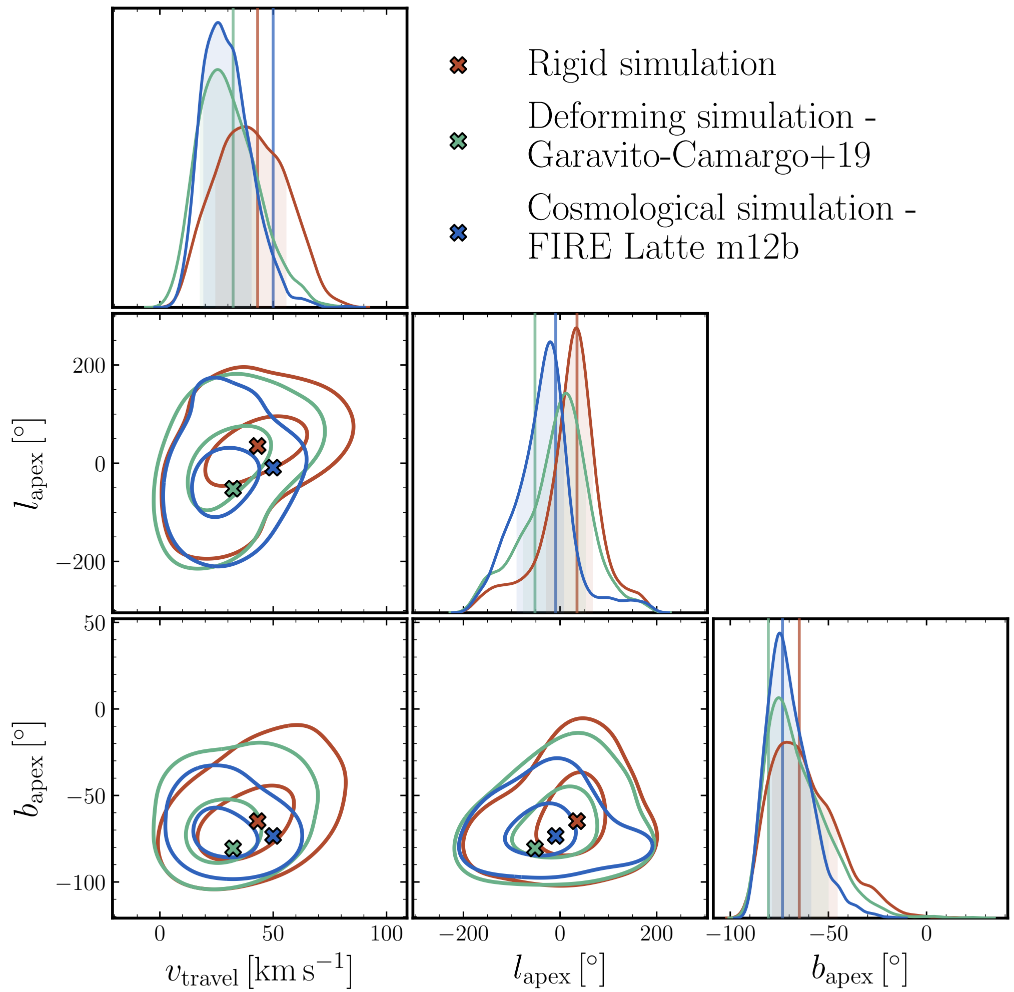
Upscaling fidelity: Deforming MW—LMC simulations



Coverage probability check



Posterior Predictive Check



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