

Dark Matter Physics from our local galactic neighborhood

TACOS 2025 @SHSU
October 13, 2025

Francis-Yan Cyr-Racine

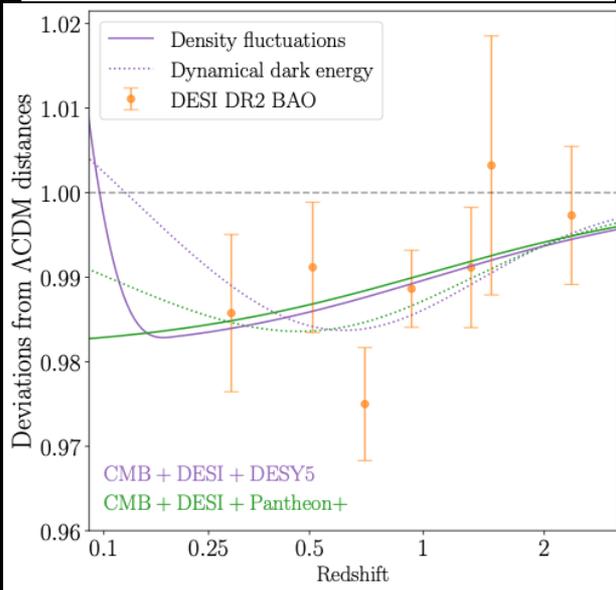
Department of Physics and Astronomy, University of New Mexico

Soumyodipta
Karmakar



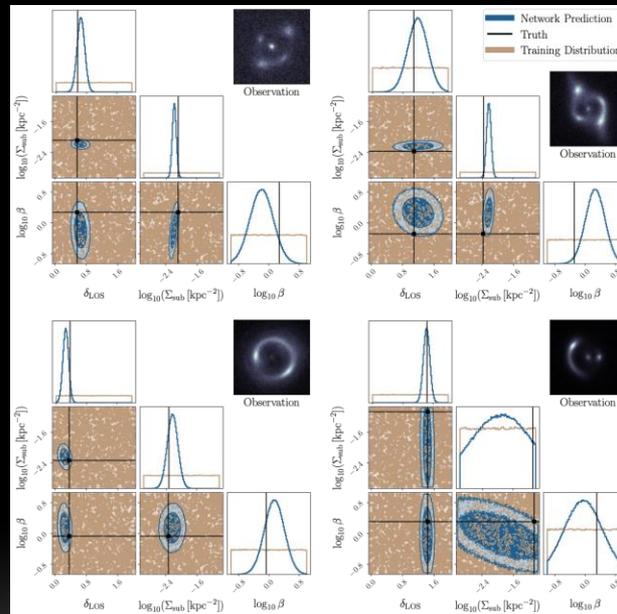
Dark Universe @ UNM

Large-scale inhomogeneities as an alternative to dynamical DE



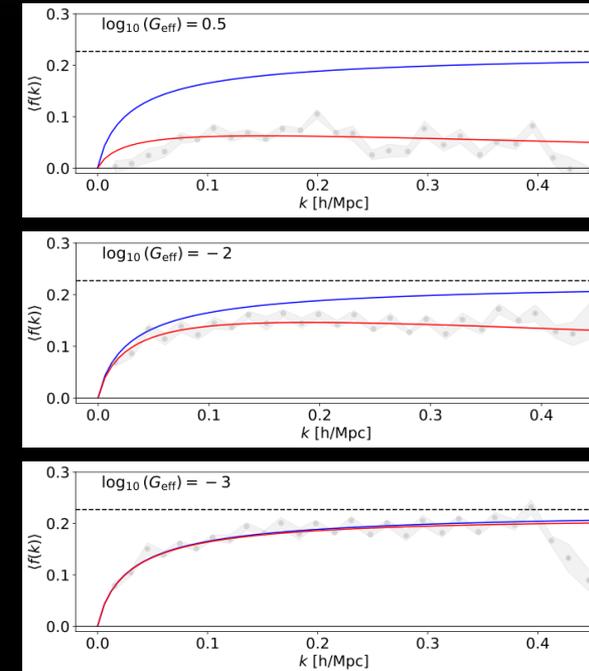
Camarena, Houghteling, Greene & FYCR, accepted PRD (2025)

Statistical detection of small-scale dark matter structure in strong lenses



Dhanasingham, FYCR & Gilman, to be submitted.

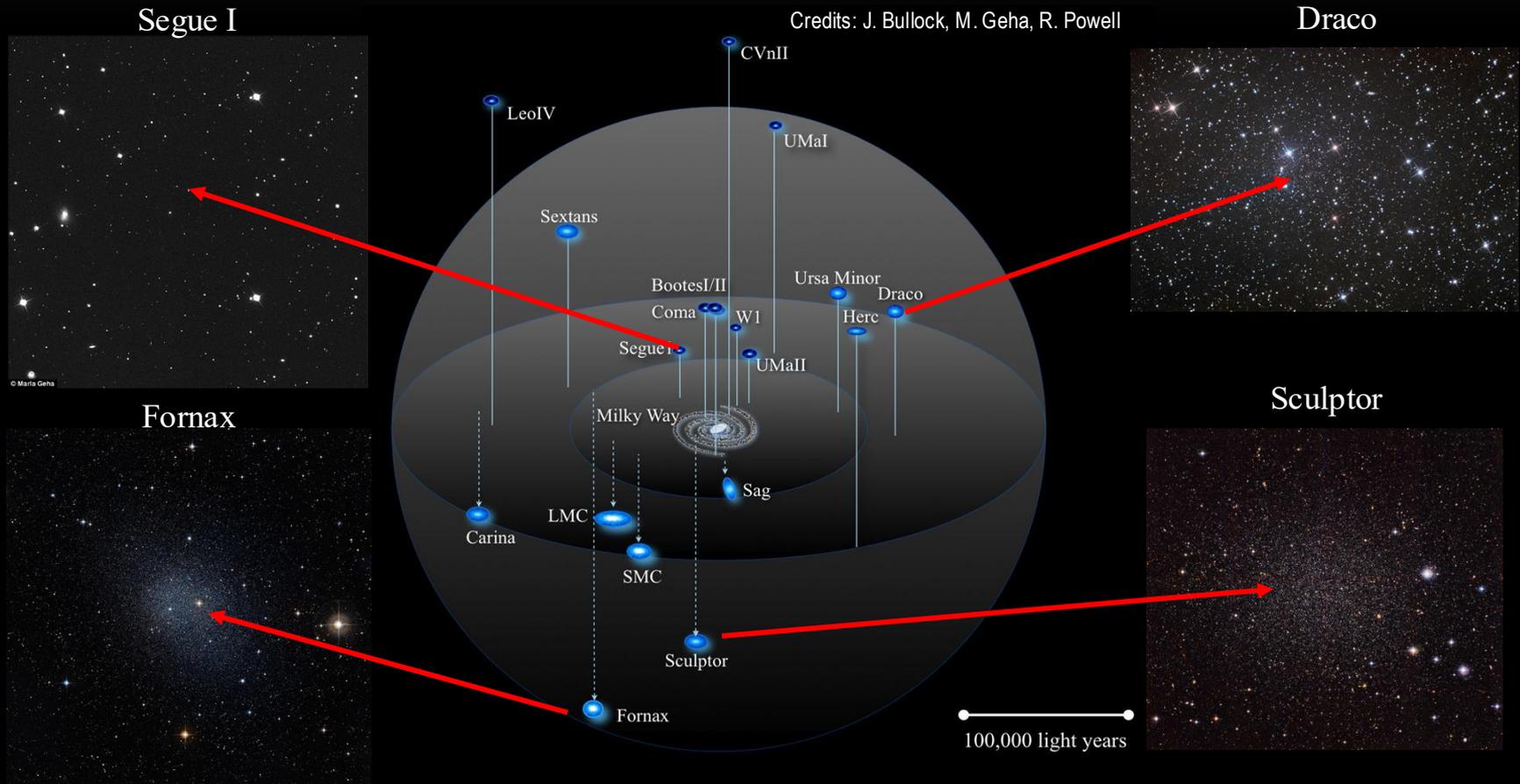
Probing neutrino physics from BAO phase shift



Whitford, Howlett, Davis, Camarena & FYCR, to be submitted.

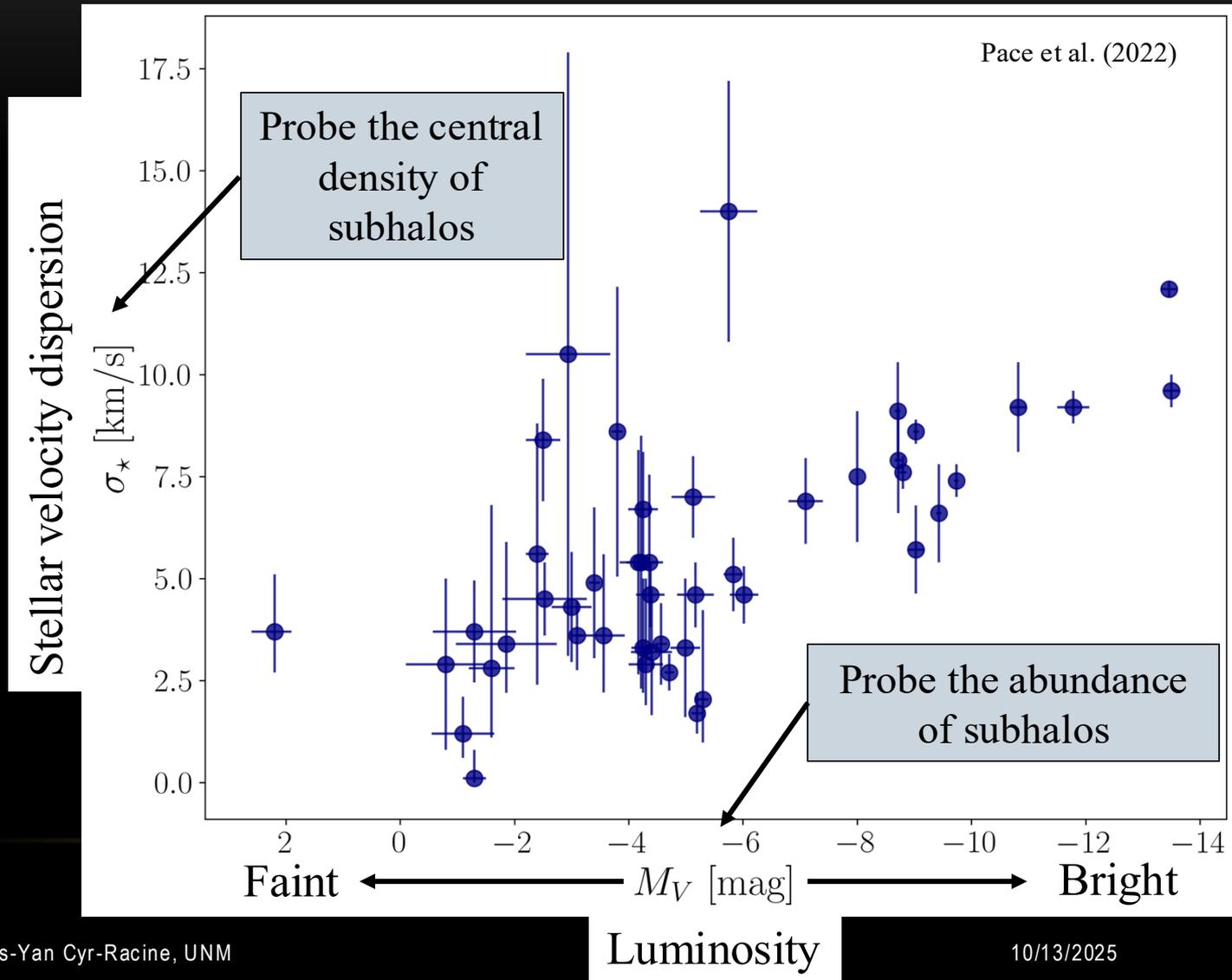
Milky Way satellites: Beyond single-object analysis

- Probing dark matter in the **local** Universe



What do we actually observe?

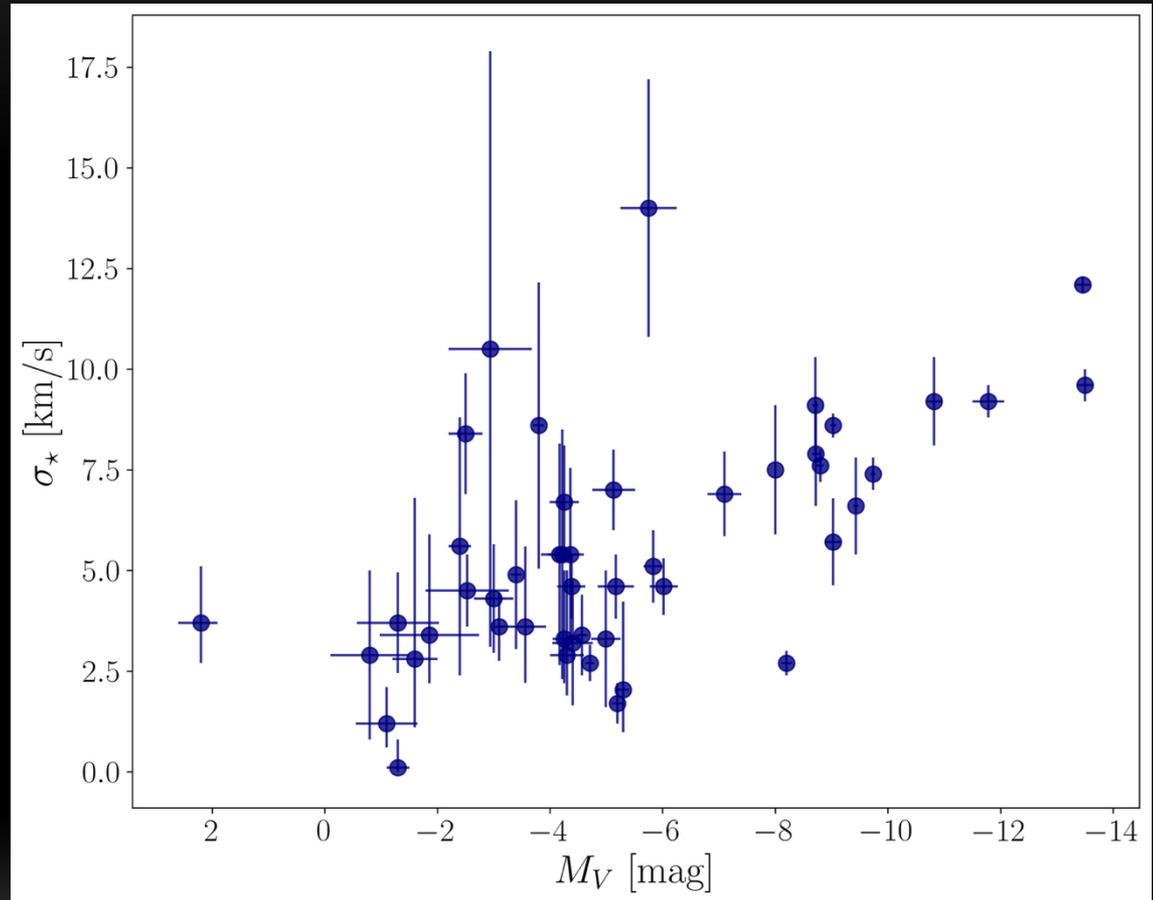
- We measure two primary quantities:



Population-level analysis: Joint-distribution of observables

- Dark matter microphysics **correlates the properties of MW satellites**.
- We focus here on the most readily available MW sats observations:

$$\{M_V, r_{1/2}, \sigma_\star\}$$



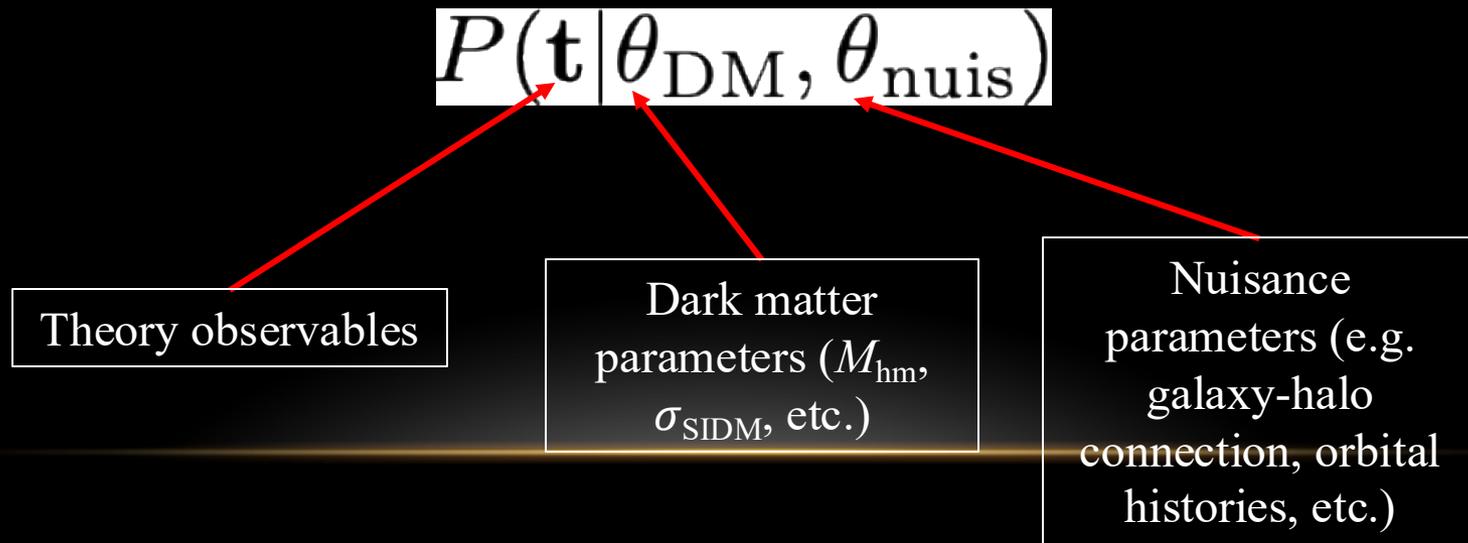
Pace et al. (2022)

Statistical Challenge I

- Our data:

$$\mathcal{D} = \left\{ \left\{ M_V, r_{1/2}, \sigma_{\star} \right\}_i \right\}_{i=1 \dots N_{\text{sats}}}$$

- Large latent space since **dark matter and nuisance parameters** can only predict the **distribution of observables**



Statistical Challenge II

- Need to marginalize over possible realizations of mock data. Hard!

$$\mathcal{L}(\mathcal{D}|\theta_{\text{DM}}, \theta_{\text{nuis}}) = \int d\mathbf{t} P(\mathbf{t}|\theta_{\text{DM}}, \theta_{\text{nuis}}) \mathcal{L}(\mathcal{D}|\mathbf{t})$$

- If we could **rapidly** simulate our data however, could approximate likelihood as:

$$\mathcal{L}(\mathcal{D}|\theta_{\text{DM}}, \theta_{\text{nuis}}) \simeq \sum_{\mathbf{t} \sim P(\mathbf{t}|\theta_{\text{DM}}, \theta_{\text{nuis}})} \mathcal{L}(\mathcal{D}|\mathbf{t})$$

Statistical Challenge

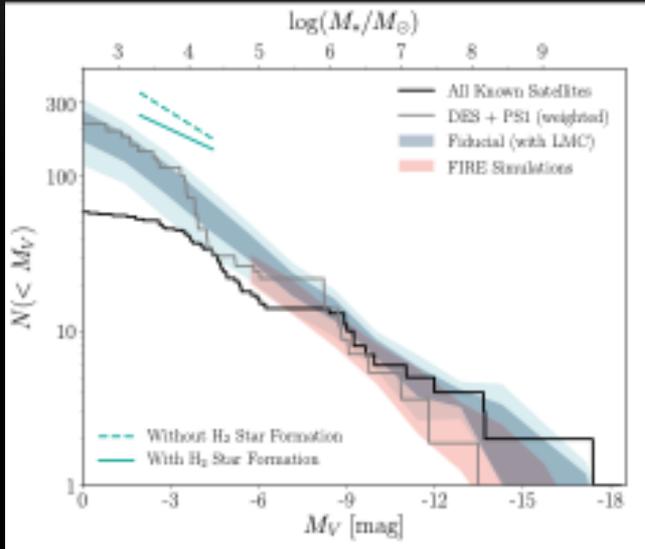
- Marginalization over nuisance parameters can be handled via Markov chain Monte Carlo methods, **assuming that the likelihood and prior are fast to evaluate.**

$$P(\theta_{\text{DM}}|\mathcal{D}) \propto \int d\theta_{\text{nuis}} \mathcal{L}(\mathcal{D}|\theta_{\text{DM}}, \theta_{\text{nuis}}) \Pi(\theta_{\text{DM}}, \theta_{\text{nuis}})$$

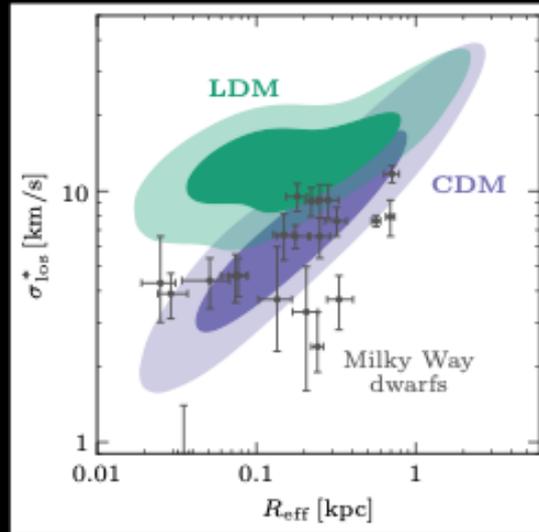
- Essentially, given the observed properties $\{M_V, r_{1/2}, \sigma_\star\}$ we are asking **which dark matter properties are compatible with them, marginalizing over all possible subhalo properties that could host that galaxy.**

Hopeless for a single satellite, but this should be possible with a population-level analysis

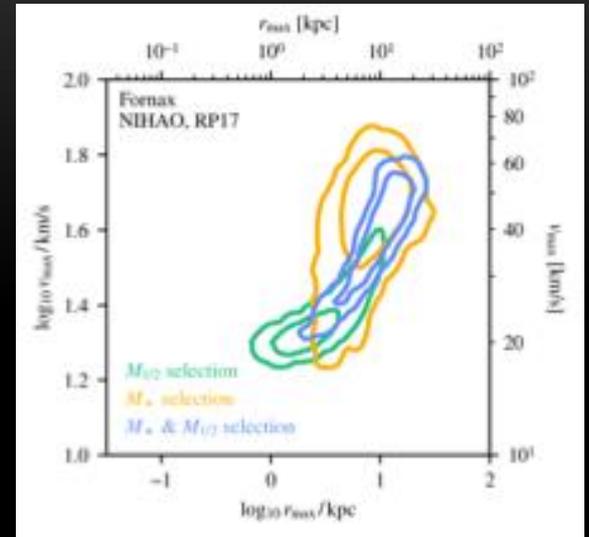
Recent-ish related analyses



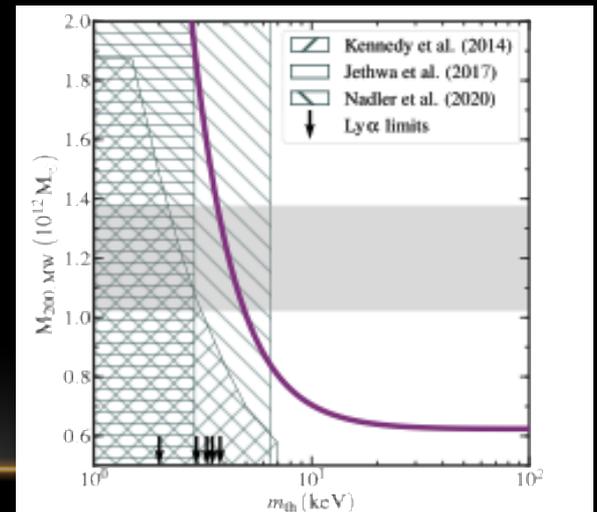
Nadler, Wechsler, et al. (2020)



Esteban, Peter & Kim (2024)



Folsom et al. (2025)



Newton et al. (2021)

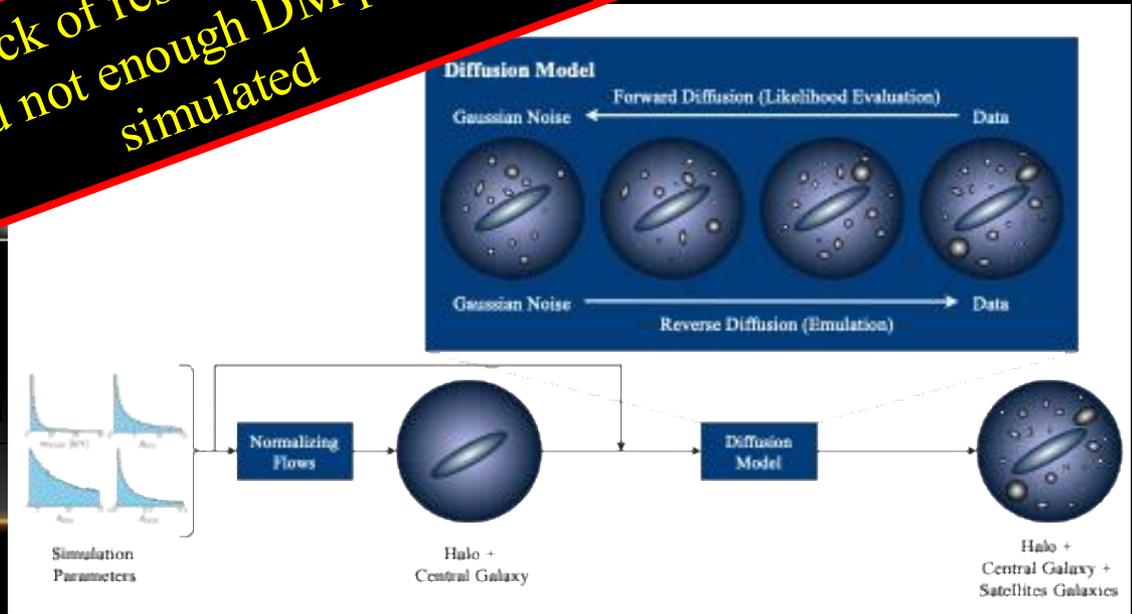
Fast sampling of MW satellite populations

- One possible approach: **Baryonic simulations + Emulation**



DREAMS Collab,
Rose et al. (2025)

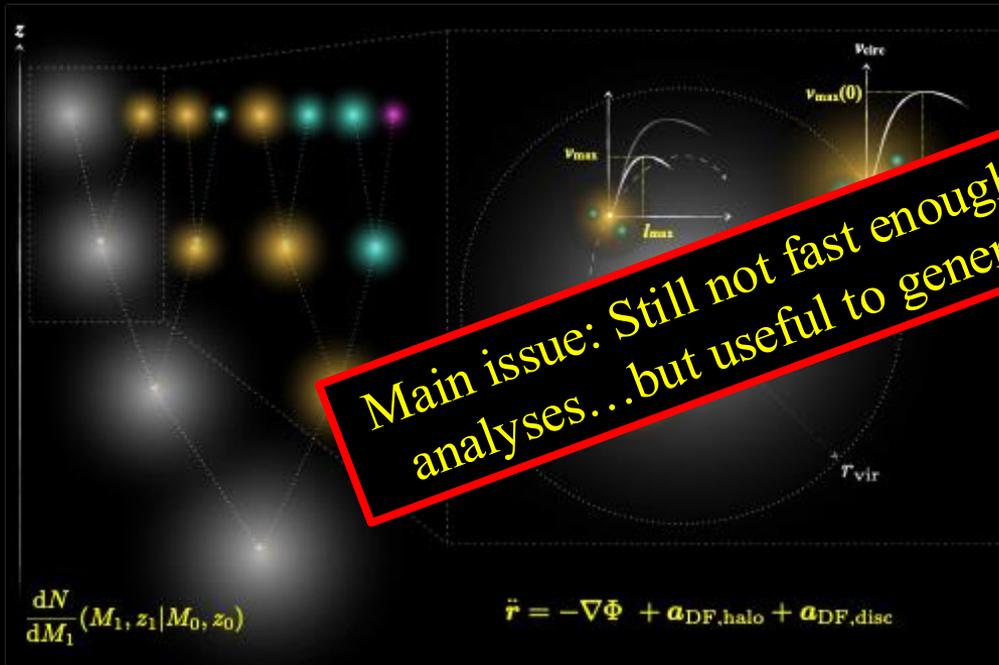
Main issue: lack of resolution in the ultrafaint regime, and not enough DM physics cases simulated



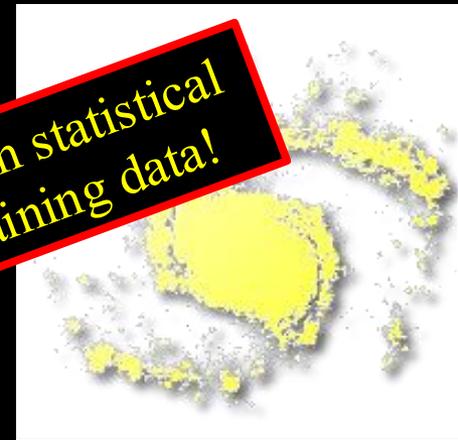
DREAMS Collab,
Nguyen et al. (2025)

Fast sampling of MW satellite populations

- Another possible approach: **Semi-analytic models** (e.g. **Galacticus** and **SatGen**): High-resolution and quite fast!



Main issue: Still not fast enough to run statistical analyses...but useful to generate training data!

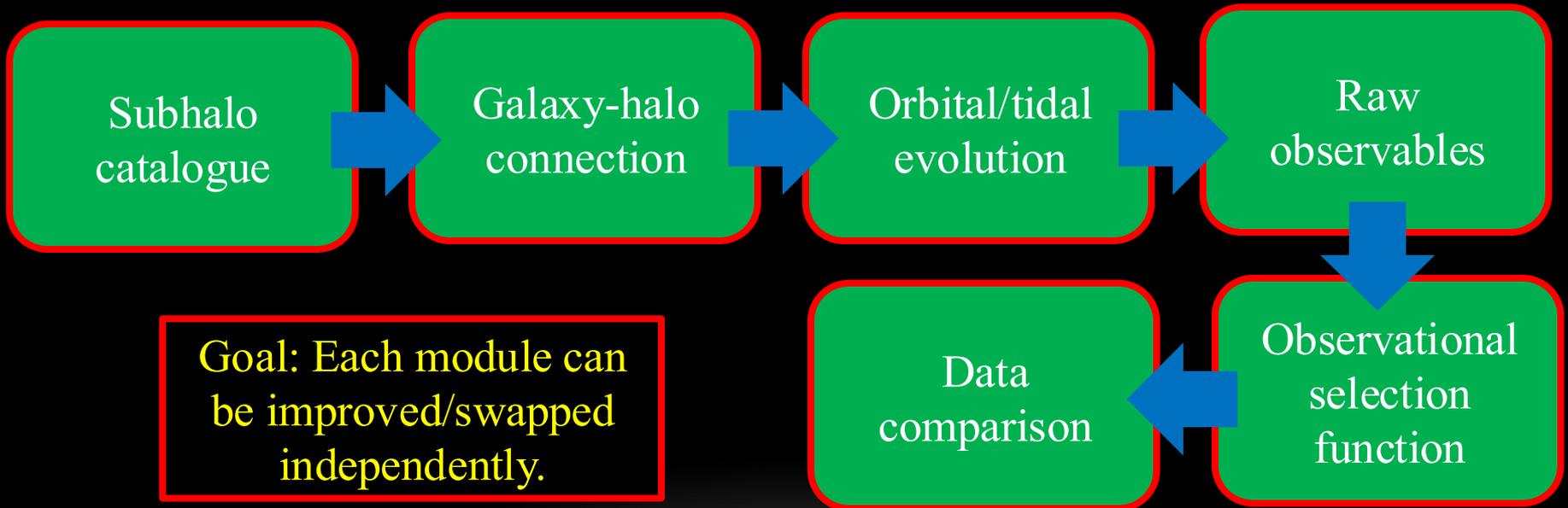


Benson et al. (2012)

Jiang et al. (2020),
Green et al. (2021ab)

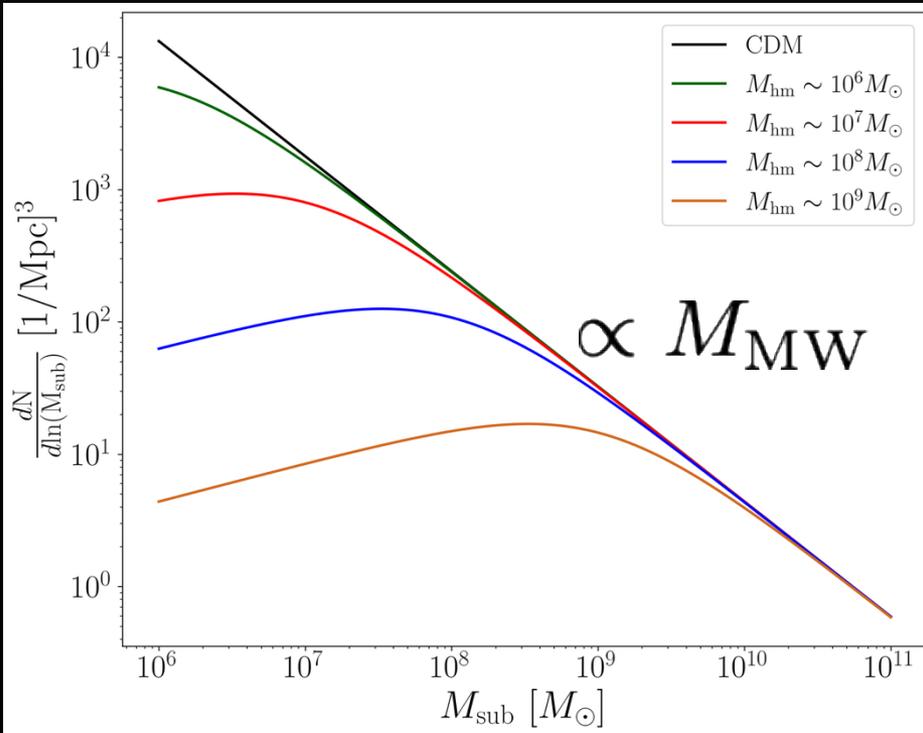
Fast sampling of MW satellite populations

- Our approach: Build a modular approach focused on forward-modeling the data.



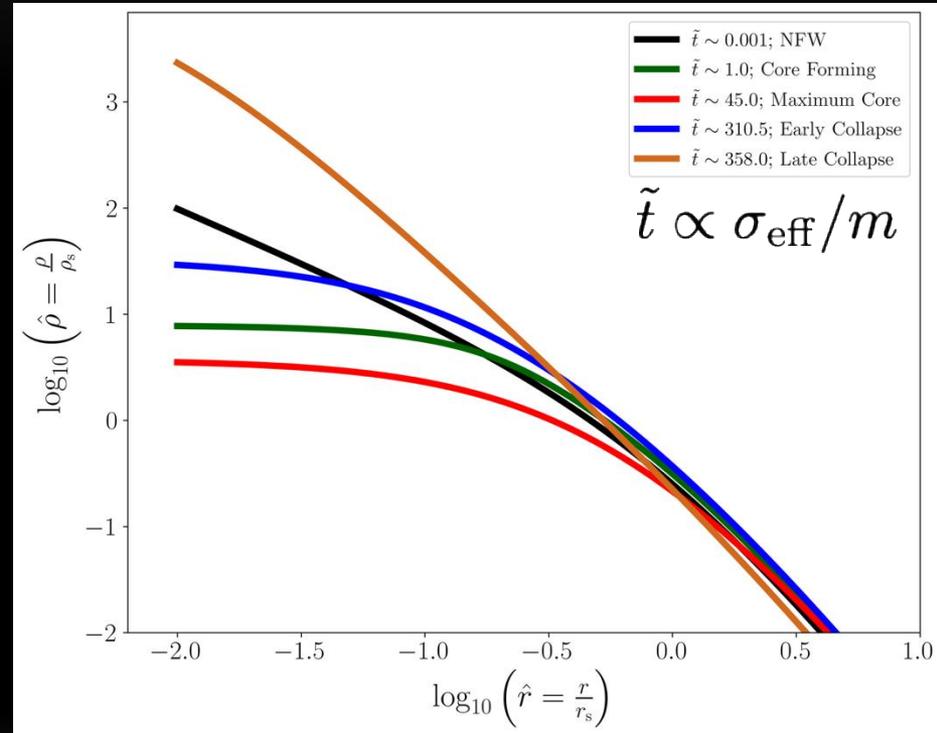
Generating a fast subhalo catalogue

Power-law mass function, with possible truncation



Dooley et al. (2017),
Schneider et al. (2012)

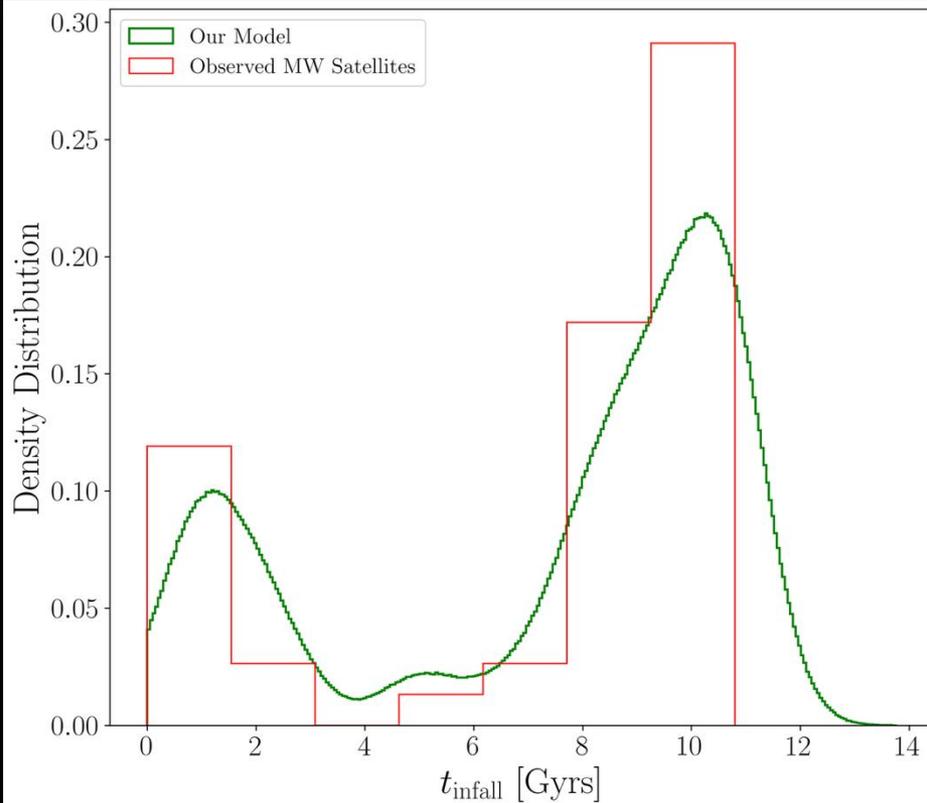
Tidally-truncated, gravothermal-evolved profile



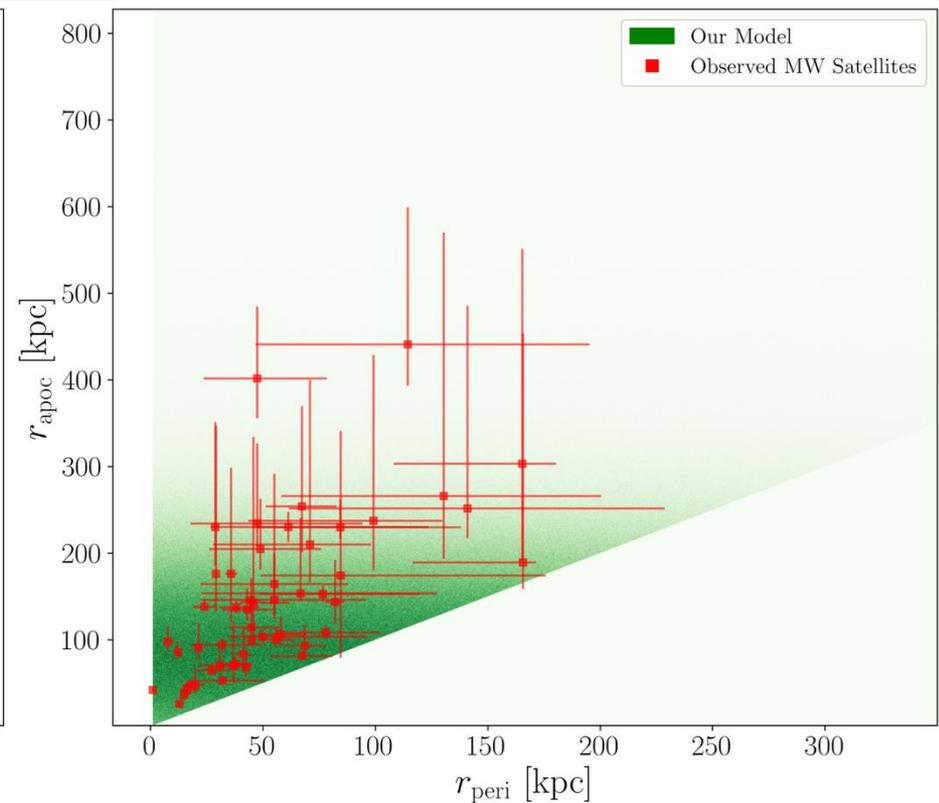
Yang et al. (2023)

Evolution: Halo infall and orbits

Satellite Infall time



Satellite orbital properties



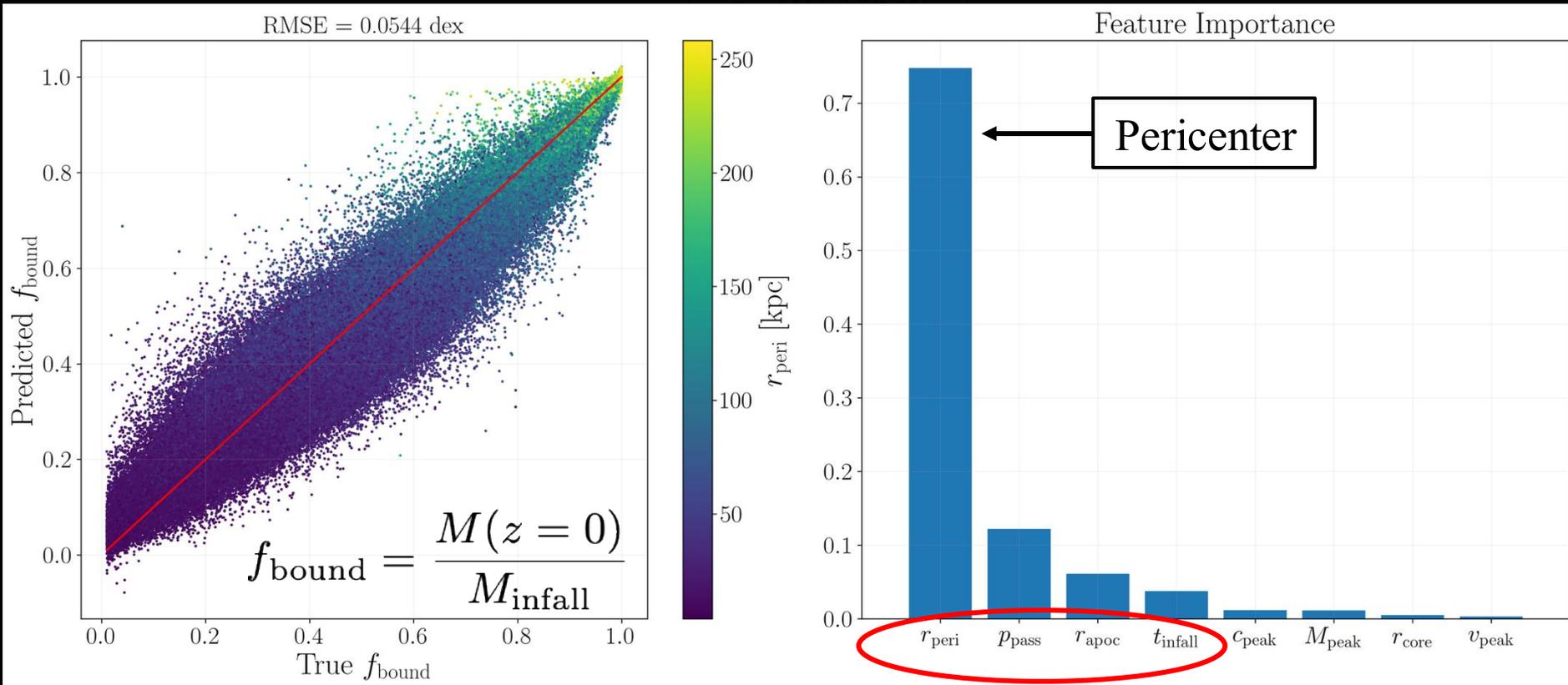
Fillingham et al. (2019)

Barmantloo & Cautun (2023)

Pace et al. (2022)

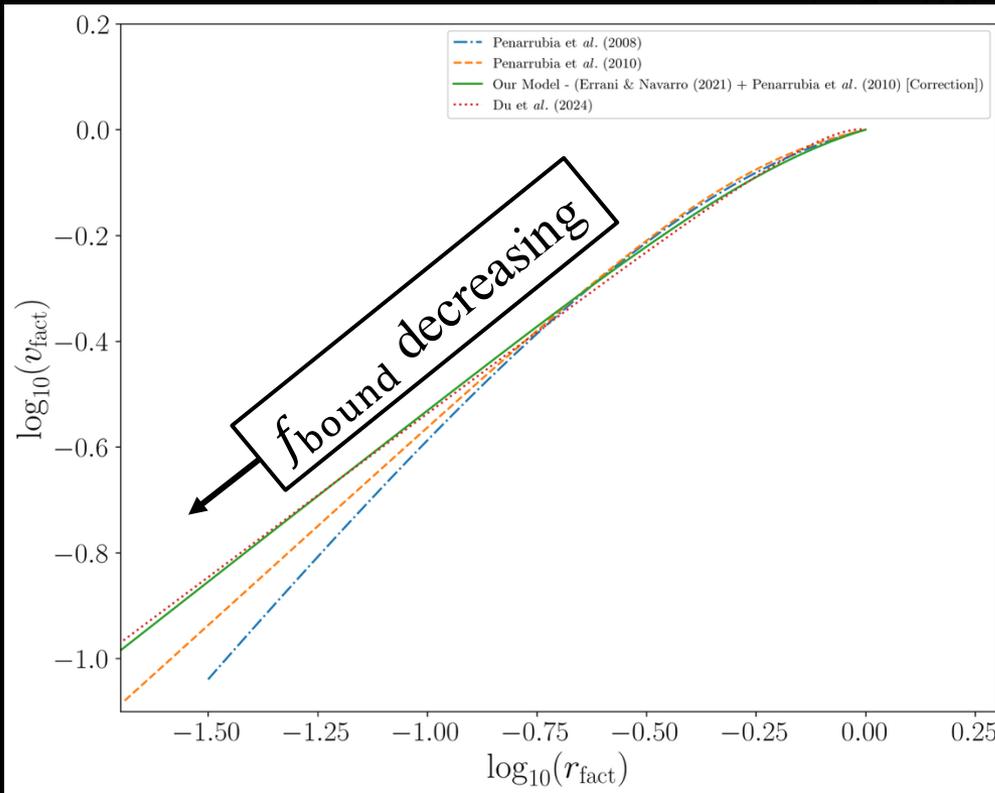
Orbital mass loss: Fast SatGen emulation

Build a supervised learning model to predict mass loss, given subhalo properties



Folsom et al. (2024)

Orbital mass loss: Tidal track and profile evolution



Take into account tidal acceleration of core-collapse, and tidal transfer function

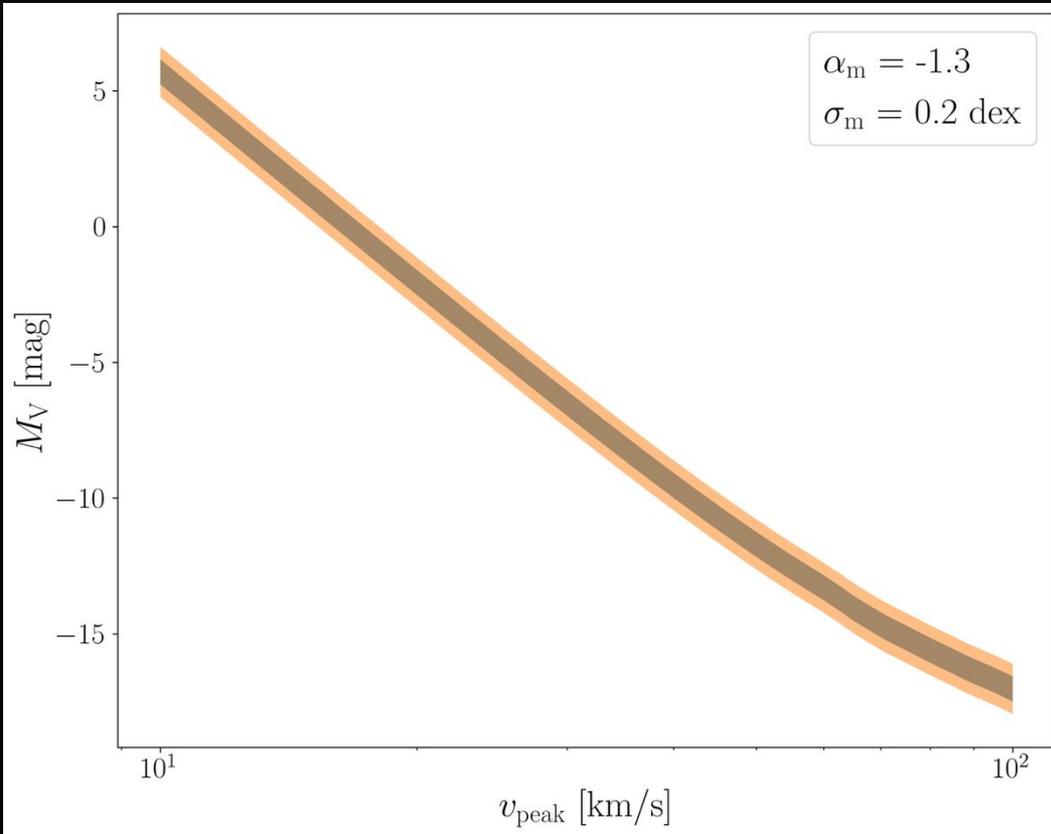
$$\rho_{z=0}(r) = \rho \left(\tilde{t} \rightarrow \frac{v_{\text{fact}}^3}{r_{\text{fact}}^2} \tilde{t} \right) \times \frac{\exp(-r/r_{\text{cut}})}{(1 + r_s/r_{\text{cut}})^\kappa}$$

$$r_{\text{cut}}(f_{\text{bound}})$$

Errani & Navarro (2021)
Nishikawa et al. (2020)

Galaxy-halo connection: Observational properties

GAMA-survey calibrated at bright end, with power law extrapolation



Nadler et al. (2020)

Geha et al. (2017)

Galaxy size

$$r_{1/2} = A \left(\frac{r_{\text{vir}}}{10 \text{ kpc}} \right)^n$$

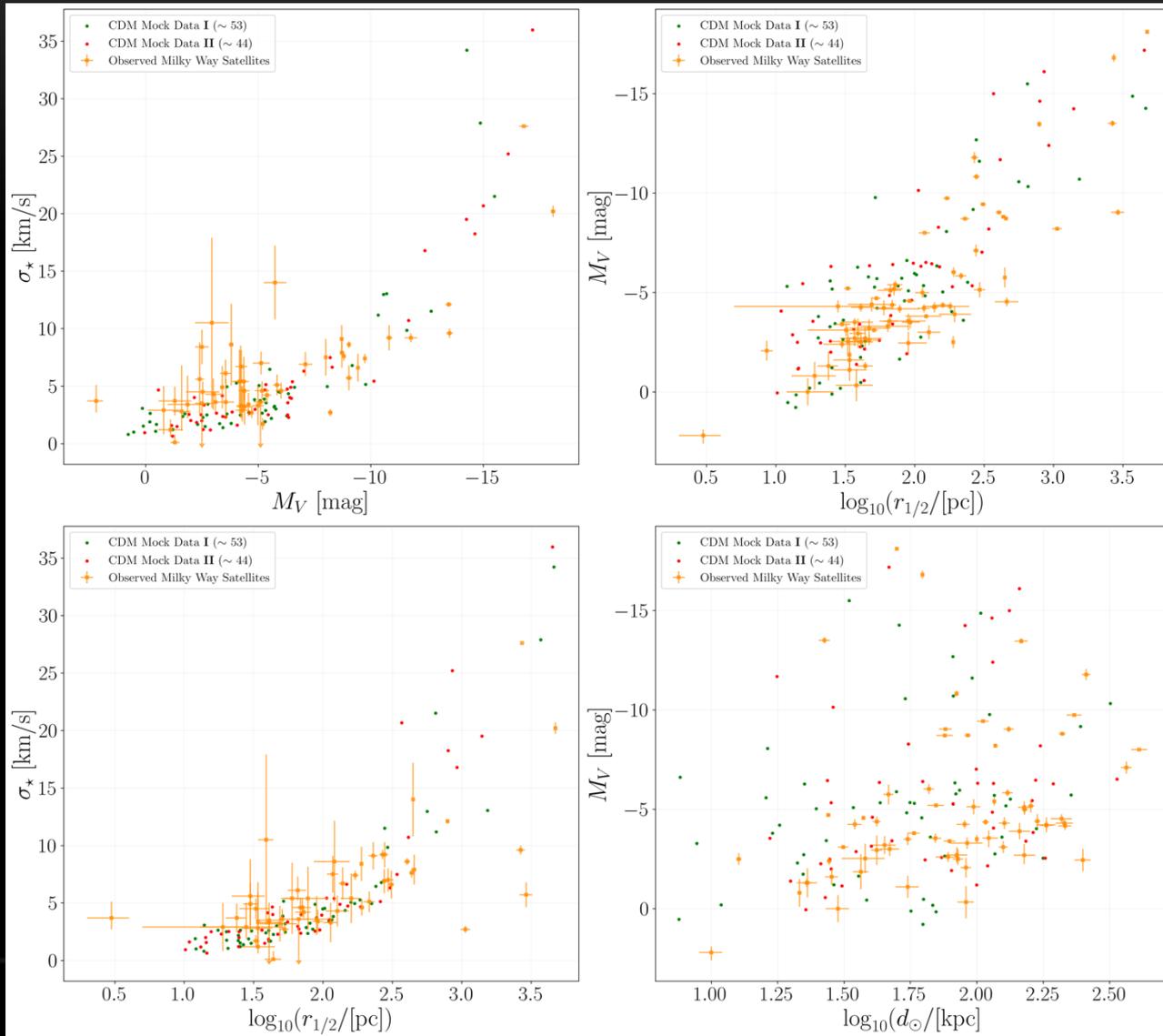
Kratsov (2013)

Stellar Dispersion

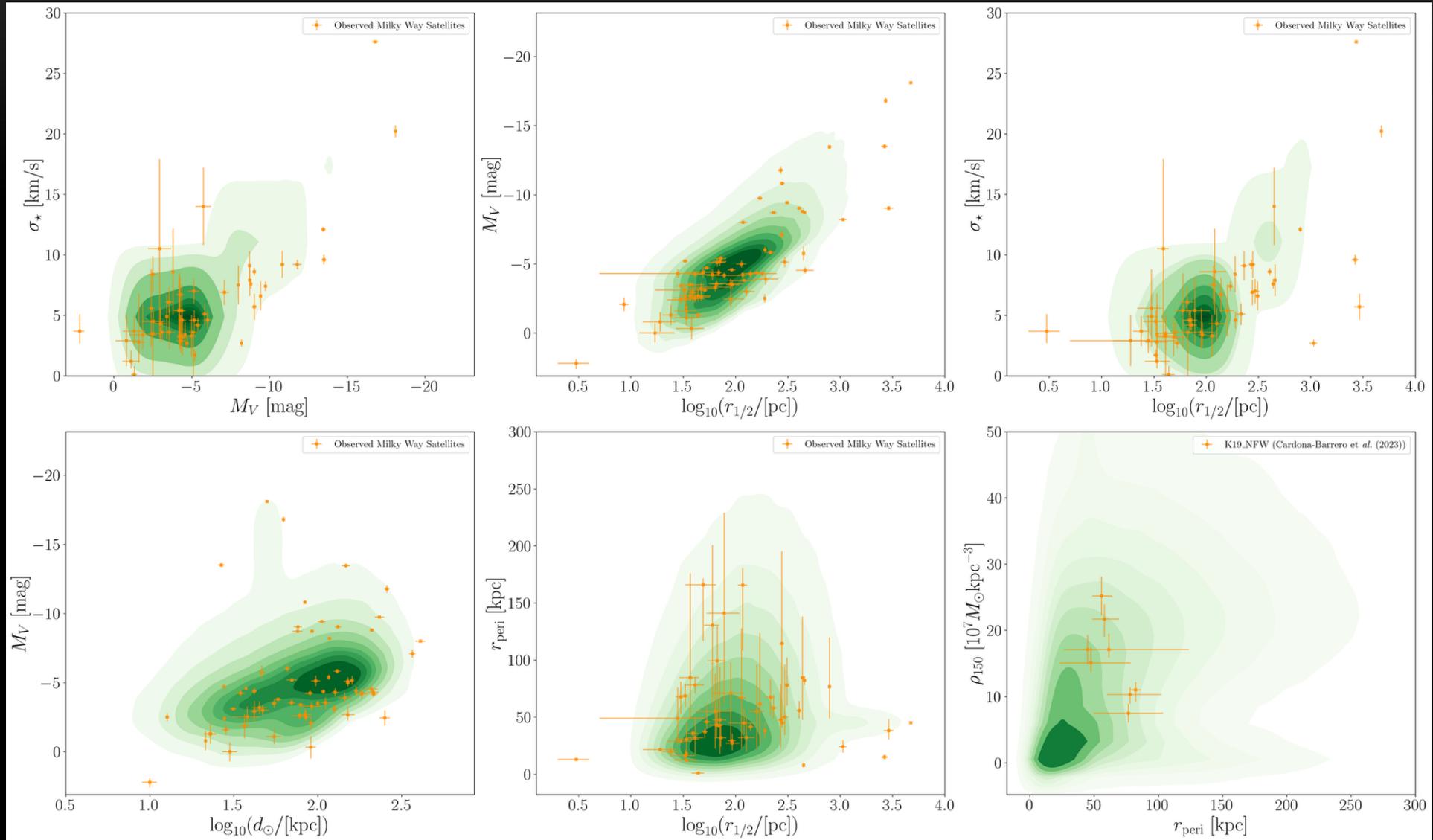
$$\sigma_* = \sqrt{\frac{1}{930} \left(\frac{\text{pc}}{r_{1/2}} \right) \left(\frac{M_{1/2}}{M_\odot} \right)} \text{ (km/s)}$$

Wolf et al. (2010)

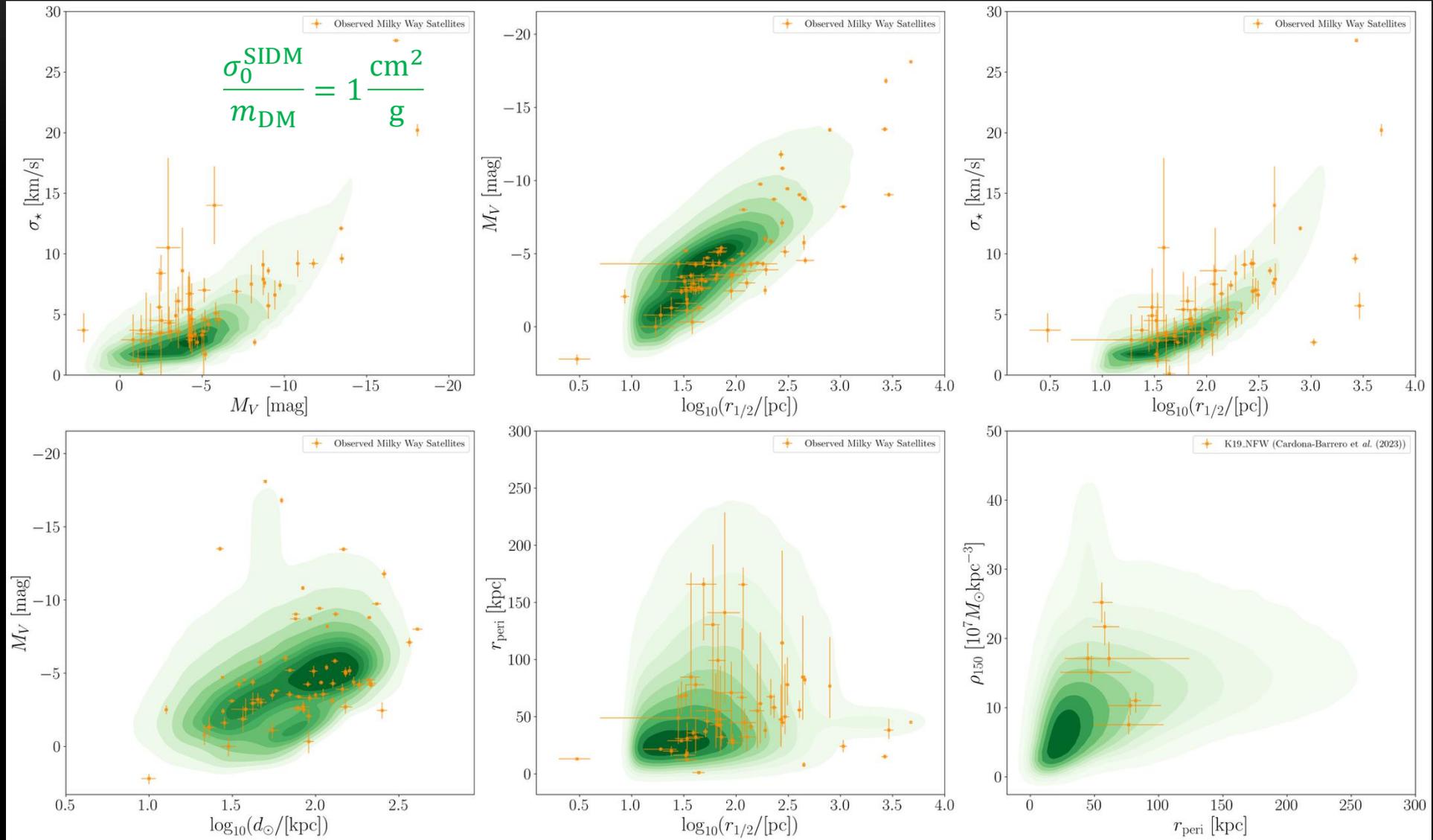
Fast generation of satellite population



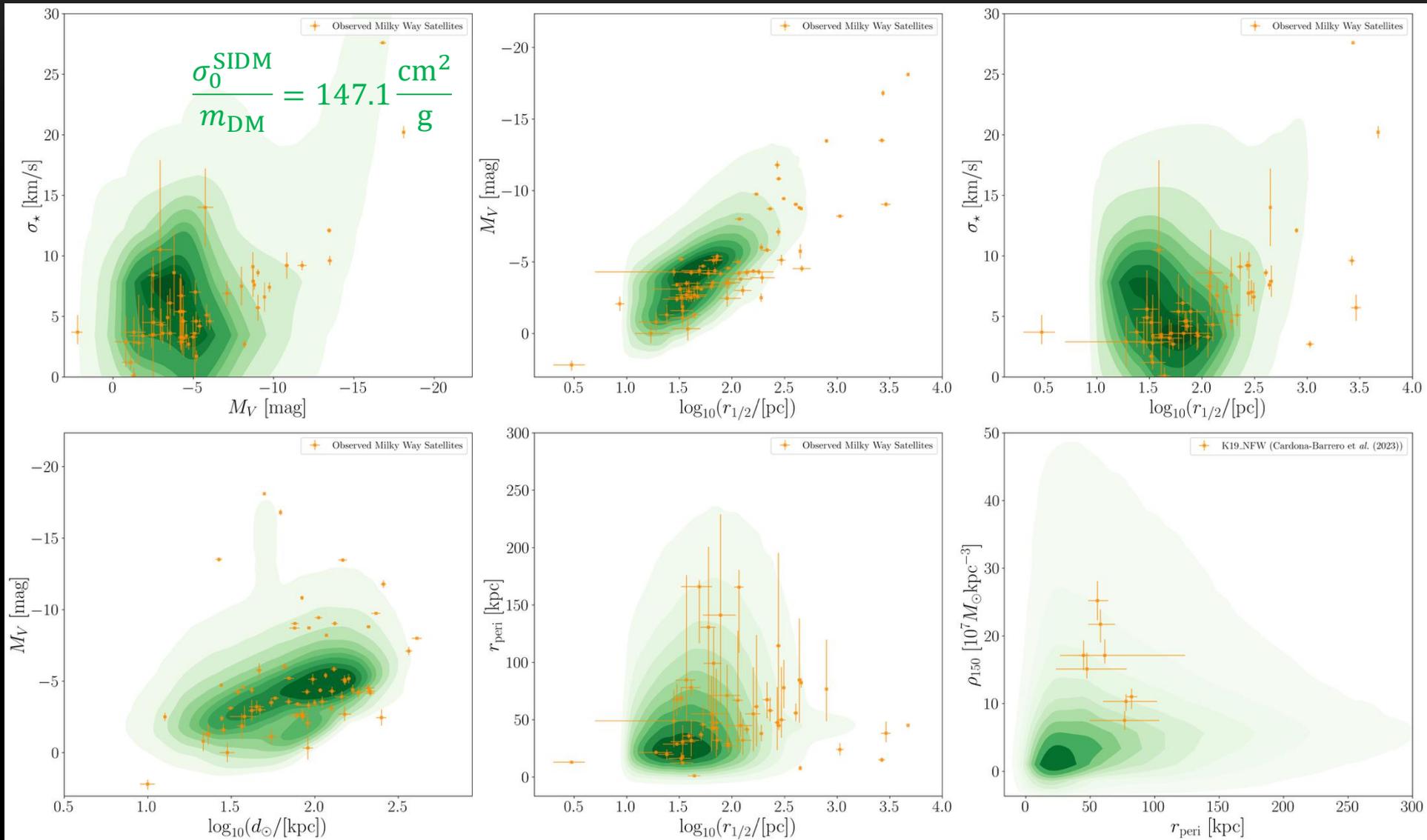
Correlated distribution of observables - CDM



Correlated distribution of observables - SIDM

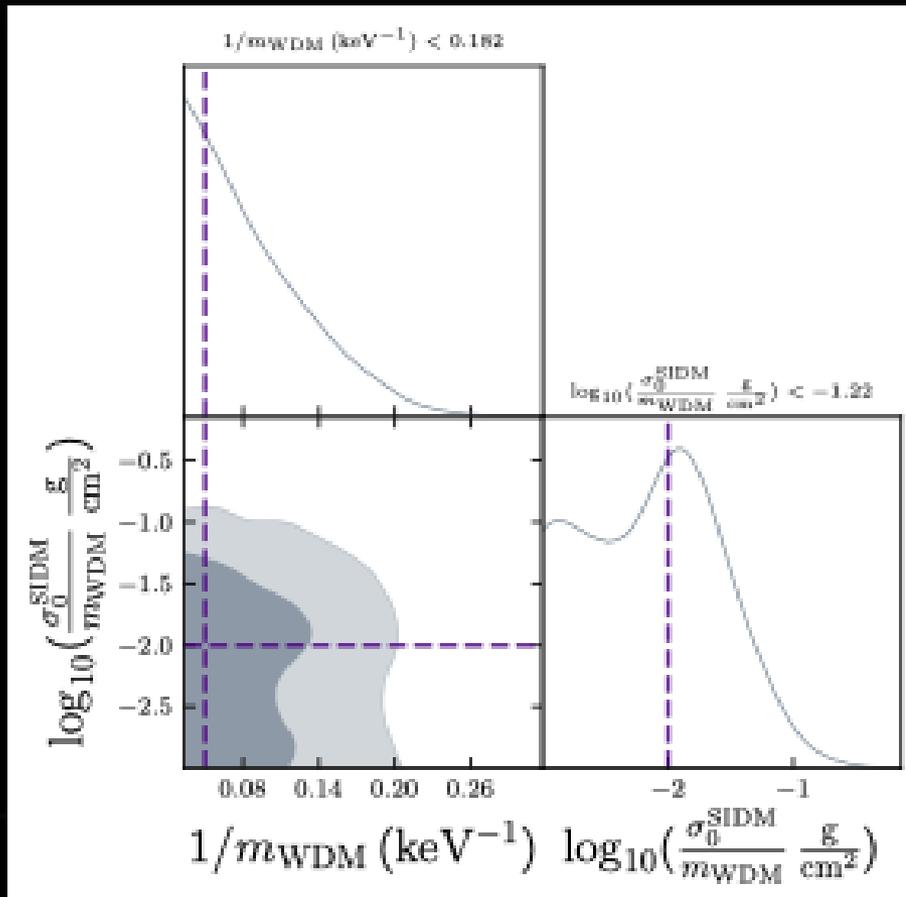


Correlated distribution of observables - SIDM



Forecast for what Rubin LSST + spectroscopic follow-up will be able to achieve

- Joint sensitivity to both the matter power spectrum and dark matter self-interaction



Proof of principle that dark matter physics can be extracted from the MW sats population.

Current limitations

- No SIDM ram-pressure stripping (relevant for models with large cross section).
- Galaxy size modeling.
- Need to give more freedom to density profiles.
- Better implementation of angular distribution of satellites.
- Many more small improvements necessary...

Executive summary

- **Population-level analyses** of MW satellites can exploit the **correlation among observables** to extract DM constraints.
- This requires **fast generation** of mock satellite populations.

$$\mathcal{L}(\mathcal{D}|\theta_{\text{DM}}, \theta_{\text{nuis}}) \simeq \sum_{\mathbf{t} \sim P(\mathbf{t}|\theta_{\text{DM}}, \theta_{\text{nuis}})} \mathcal{L}(\mathcal{D}|\mathbf{t})$$

- We have created a **modular and flexible framework** that can do this, allowing us to understand **how different choices propagate to the observable space**.
- Currently **finalizing forecasts** and current data analysis.