## Precision measurements and new problems

Savvas M. Koushiappas











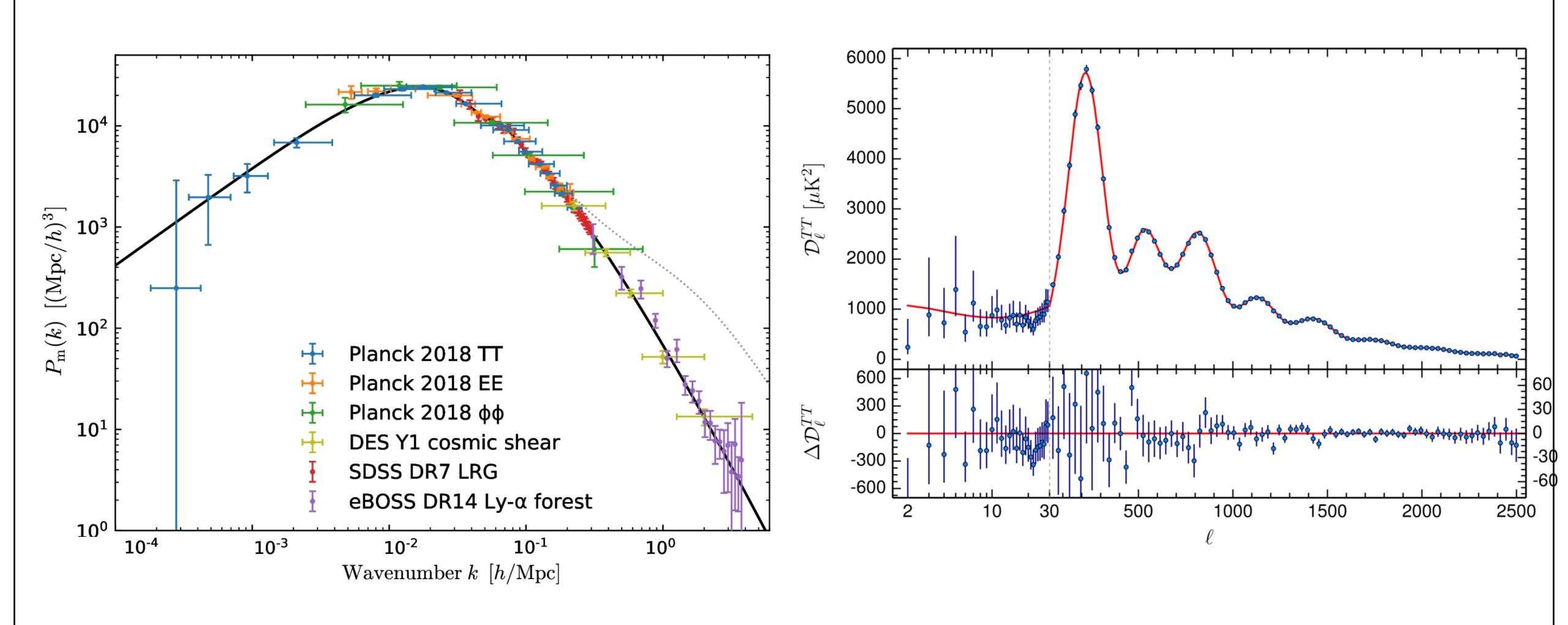




Many thanks to colleagues Stephon Alexander, **Gordon Blackadder**, **Steven Clark**, JiJi Fan, **Isabelle Goldstein, Lingfeng Liu**, **Michael Toomey**, **Kyriakos Vattis**.



# ACDM Cosmological model: very successful!



# Growing tensions in ACDM cosmology...

Despite its successes, recent precision measurements show disagreements

- •H0 tension  $H(a)\sim\sum \rho_i(a)$  •Large scale structure tension  $\sigma_8^2=\int W(kR)k^3P_M(k)d\log k$   $S_8=\sigma_8\sqrt{\Omega_M/0.3}$
- Sub-galactic dark matter structure problems (core/cusp, too big to fail, dwarf galaxies, etc.)

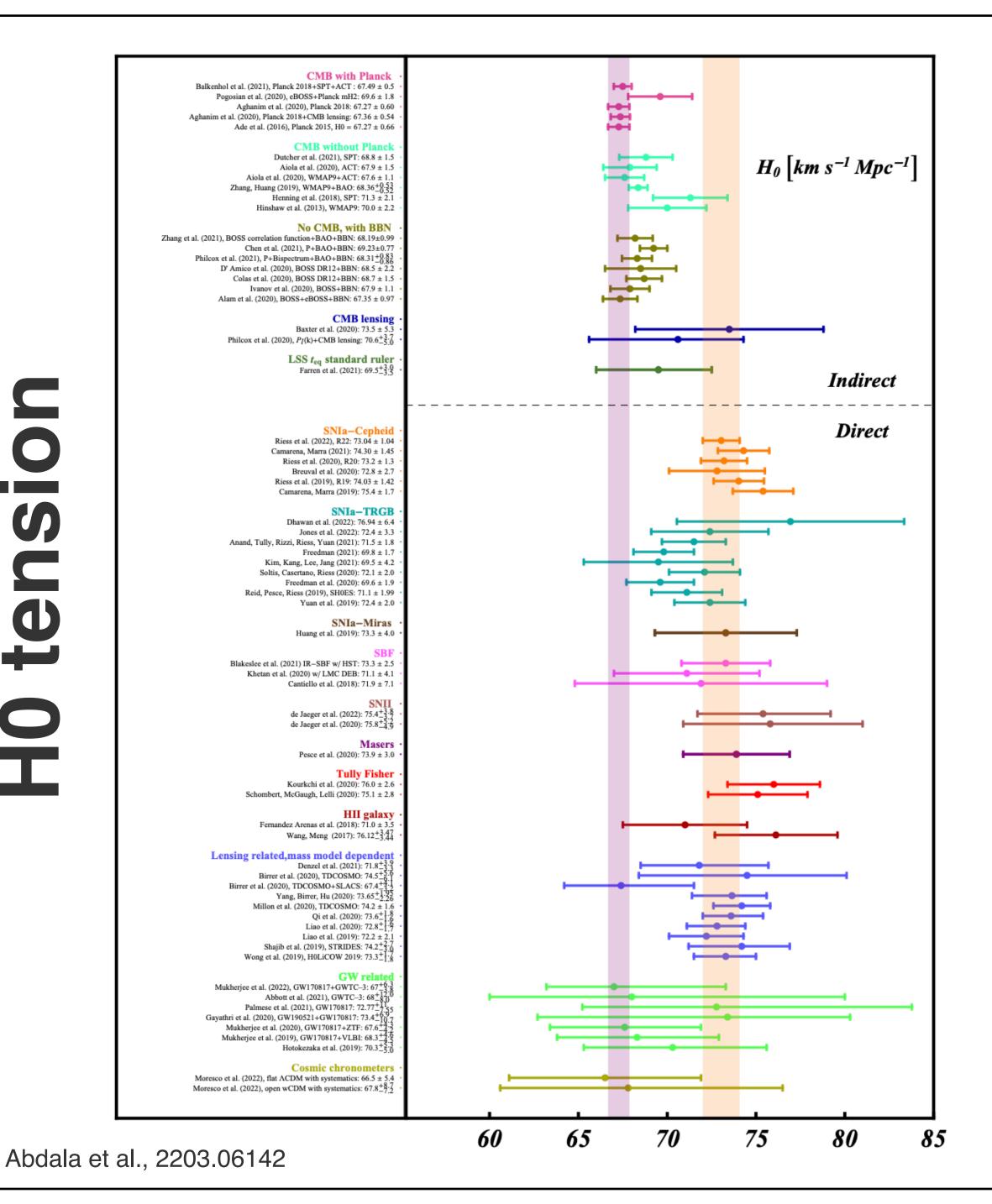
# Growing tensions in ACDM cosmology...

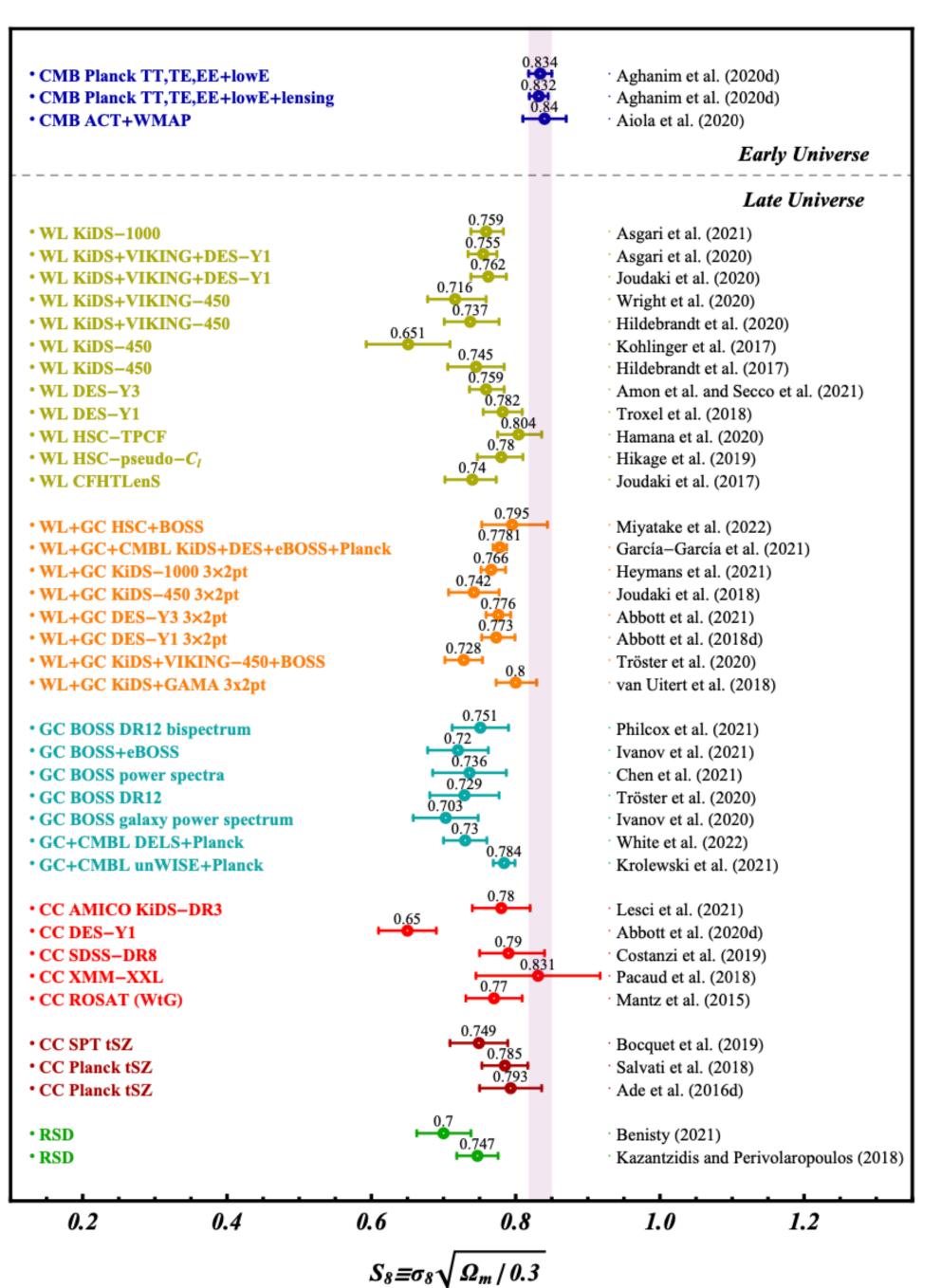
Despite its successes, recent precision measurements show disagreements

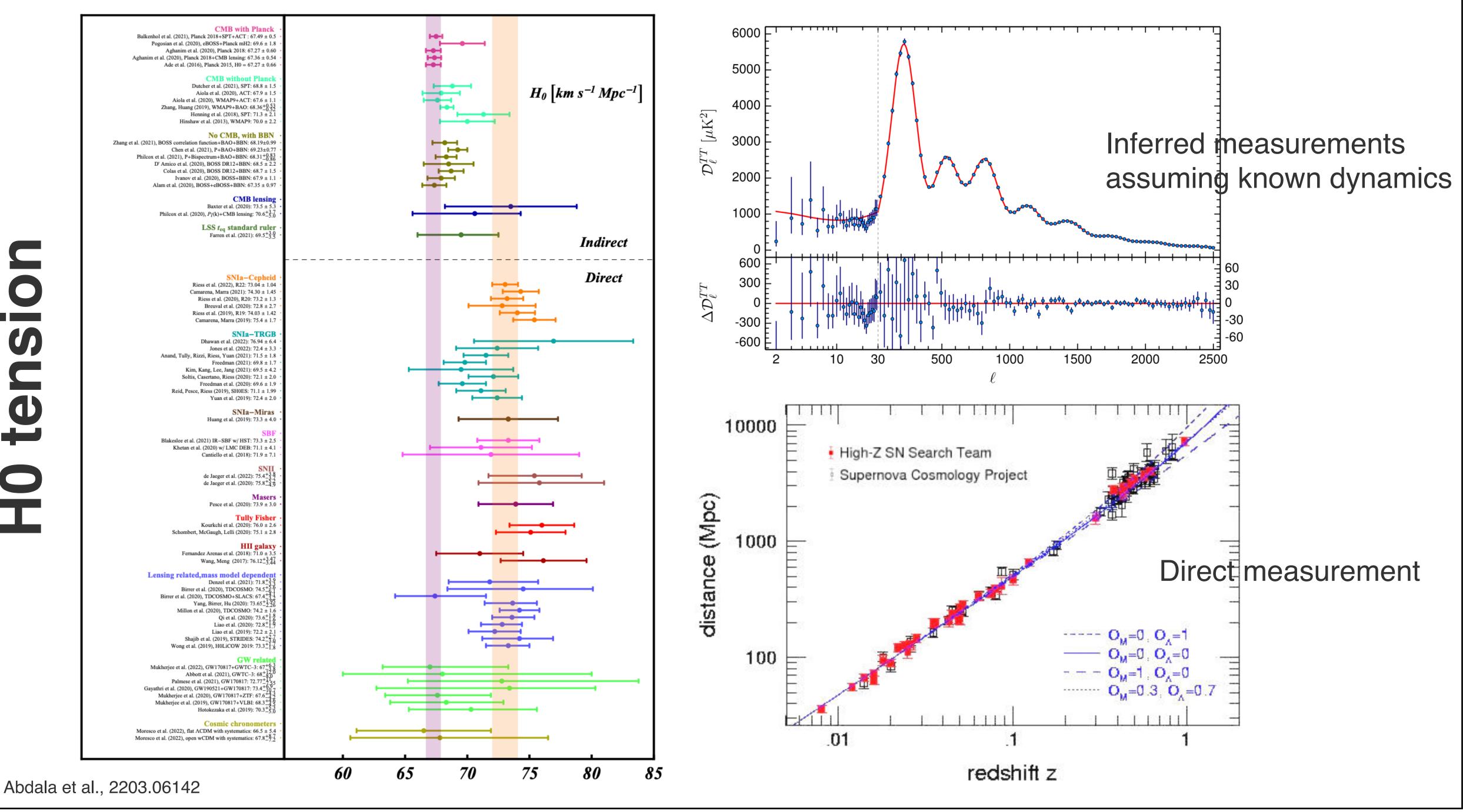
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## Is it surprising we see tensions?

- ACDM is only a macroscopic model
- Precision cosmology necessitates a microphysical model whose "coarse graining" should mimic  $\Lambda$ CDM.







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#### Two forms of modifications to \CDM

Early universe solutions (change the distance to the last scattering surface)

Late universe solutions (reshuffle the energy density of the universe at late times)

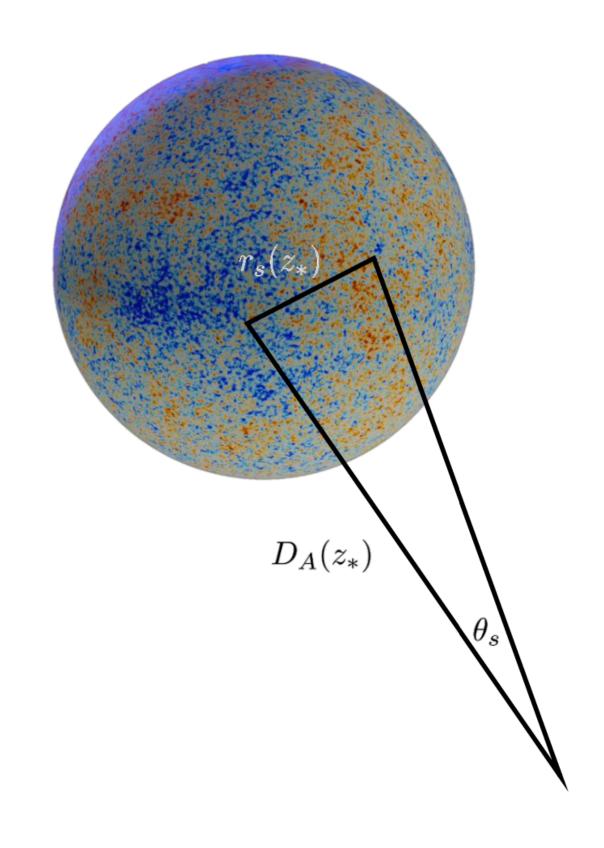
## Early dark energy solution

Increase the energy density by about 10% before recombination, i.e., move the sound horizon to earlier times.

$$\theta_s = \frac{r_s(z_\star)}{D_A(z_\star)}$$

Requirement: 
$$\theta_s = \frac{r_s(z_\star)}{D_A(z_\star)} \qquad r_s(z_\star) = \int_{z_\star}^\infty \frac{c_s(z)}{H(z)} dz$$

$$D_A(z_\star) = \int_0^{z_\star} \frac{dz}{H(z)}$$



A light scalar field can act as dark energy (Early Dark energy) 
$$\ddot{\phi} + 3H\dot{\phi} + V_{\phi} = 0$$

Equation of state 
$$w_\phi=rac{\dot\phi^2/2-V(\phi)}{\dot\phi^2/2+V(\phi)}$$
  $V=V_0[1-\cos(\phi/f)]^n, \quad V_0\equiv m^2f^2$ 

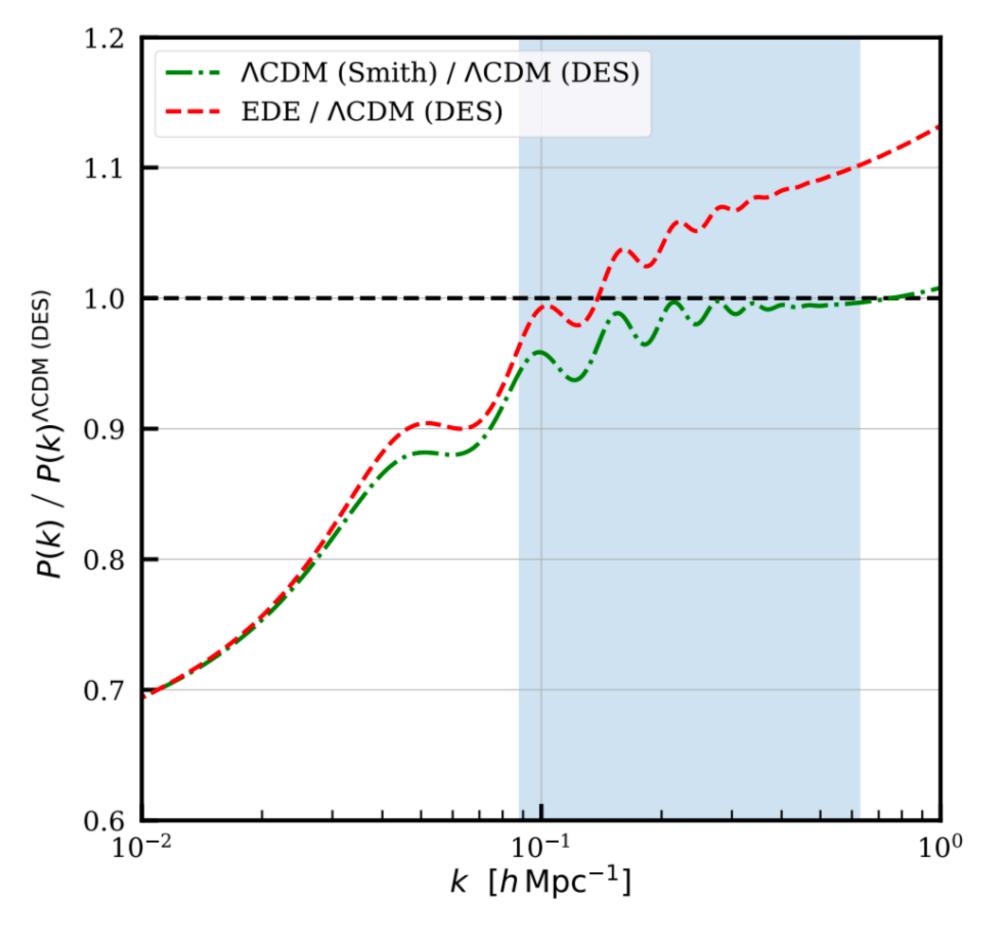
$$V = V_0[1 - \cos(\phi/f)]^n, \quad V_0 \equiv m^2 f$$

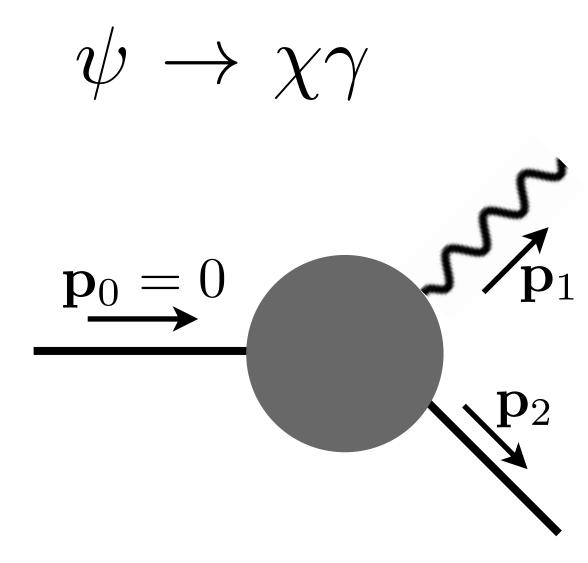
Axion-like potential

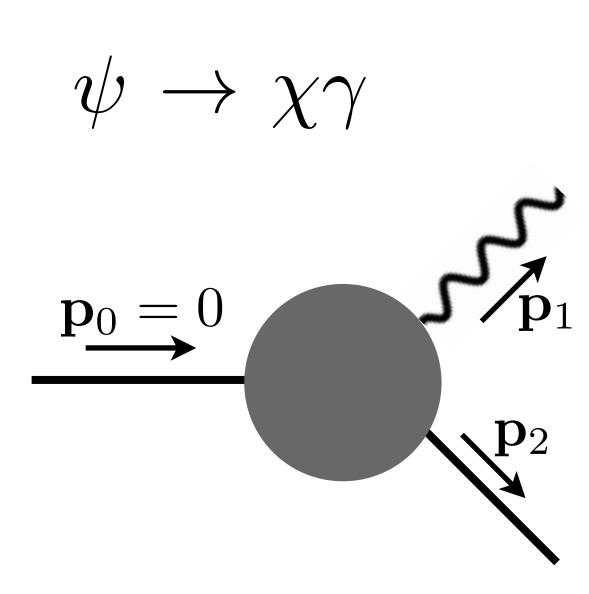
For 
$$H>m$$
 we have  $w \approx -1$ 

## EDE in significant conflict with large scale structure









$$\begin{split} &\dot{\overline{\rho}}_0 \ = \ -3\mathcal{H}\overline{\rho}_0 - a\Gamma\overline{\rho}_0 \,, \\ &\dot{\overline{\rho}}_1 \ = \ -4\mathcal{H}\overline{\rho}_1 + \epsilon a\Gamma\overline{\rho}_0 \,, \\ &\dot{\overline{\rho}}_2 \ = \ -3(1+w_2)\mathcal{H}\overline{\rho}_2 + (1-\epsilon)a\Gamma\overline{\rho}_0 \end{split}$$

$$\psi \rightarrow \chi \gamma$$

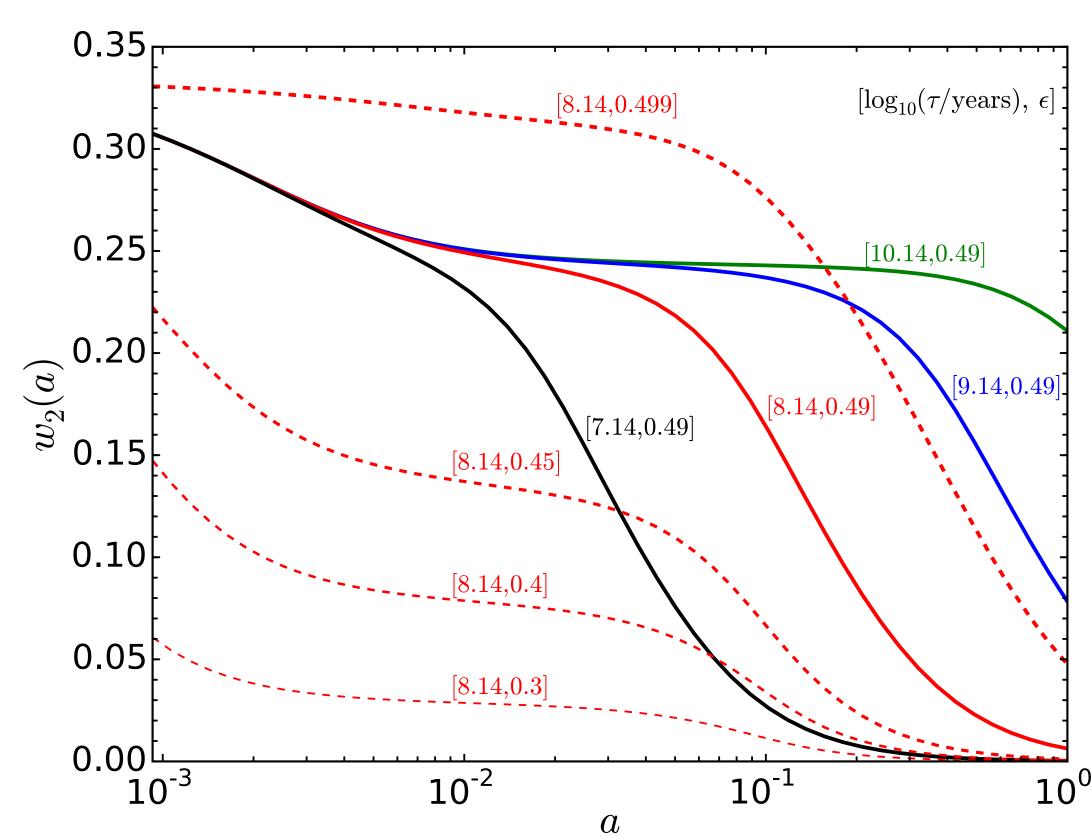
$$p_0 = 0$$

$$v_2(a) = \frac{1}{3} \langle v_2^2(a) \rangle$$

$$\langle v^2(\eta) \rangle = \int_{\eta_{\star}}^{\eta} v^2(\tilde{a}) \dot{n}_2 d\eta_D / \int_{\eta_{\star}}^{\eta} \dot{n}_2 d\eta_D$$

$$v^2(\tilde{a}) = \frac{\tilde{a}^2 \beta_2^2}{1 + \beta_2^2 [\tilde{a}^2 - 1]},$$

$$egin{array}{lll} ar{ar{
ho}}_0 &=& -3\mathcal{H}\overline{
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ho}_0 \,, \ ar{ar{
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Blackadder & Koushiappas PRD 90, 103527 (2014), PRD 023510 (2016), and Clark et al., PRD 107, 8, 083527 (2023)

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$$\begin{split} (\delta_{1}\dot{r}_{1}) &= -\frac{4}{3}r_{1}\theta_{1} - \frac{2}{3}r_{1}\dot{h} + \dot{r}_{1}\delta_{0} \,, \\ \frac{4}{3k}(\theta_{1}\dot{r}_{1}) &= \frac{k}{3}\delta_{1}r_{1} - \frac{4k}{3}r_{1}\sigma_{1} \,, \\ 2(\sigma_{1}\dot{r}_{1}) &= \frac{8}{15}\theta_{1}r_{1} + \frac{4}{15}r_{1}(\dot{h} + 6\dot{\eta}) + \text{h.o.} \\ \dot{\delta}_{2} &= -3\mathcal{H}(c_{sg}^{2} - w_{2})\delta_{2} - (1 + w_{2})\left(\theta_{2} + \frac{\dot{h}}{2}\right) \\ &+ (1 - \epsilon)a\Gamma\frac{\overline{\rho}_{0}}{\overline{\rho}_{2}}\left(\delta_{0} - \delta_{2}\right) \,, \\ \dot{\theta}_{2} &= -\mathcal{H}(1 - 3c_{g}^{2})\theta_{2} + \frac{c_{sg}^{2}}{1 + w_{2}}k^{2}\delta_{2} - k^{2}\sigma_{2} \\ &- (1 - \epsilon)a\Gamma\frac{1 + c_{g}^{2}}{1 + w_{2}}\frac{\overline{\rho}_{0}}{\overline{\rho}_{2}}\theta_{2} \,. \end{split}$$

Blackadder & Koushiappas PRD 90, 103527 (2014), PRD 023510 (2016), and Clark et al., PRD 107, 8, 083527 (2023)

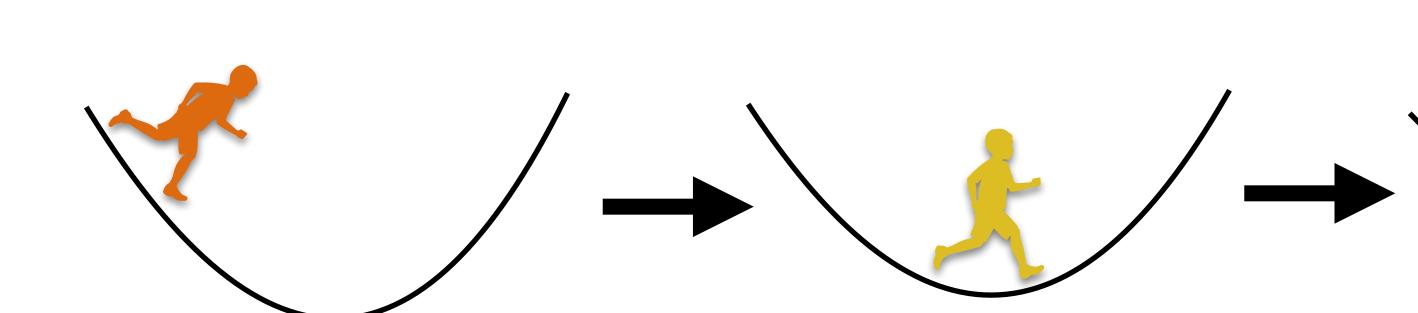
## Decays and the Integrated ISW effect

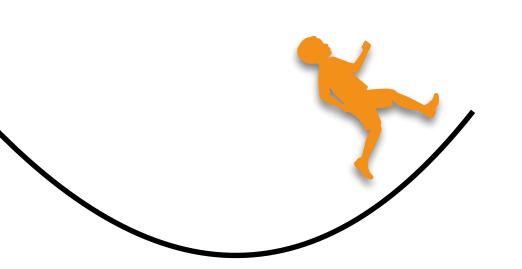
Photon enters well at some energy

Photon gains energy as it falls in the potential well

Photon loses less energy than it gained on the way out of the shallower well







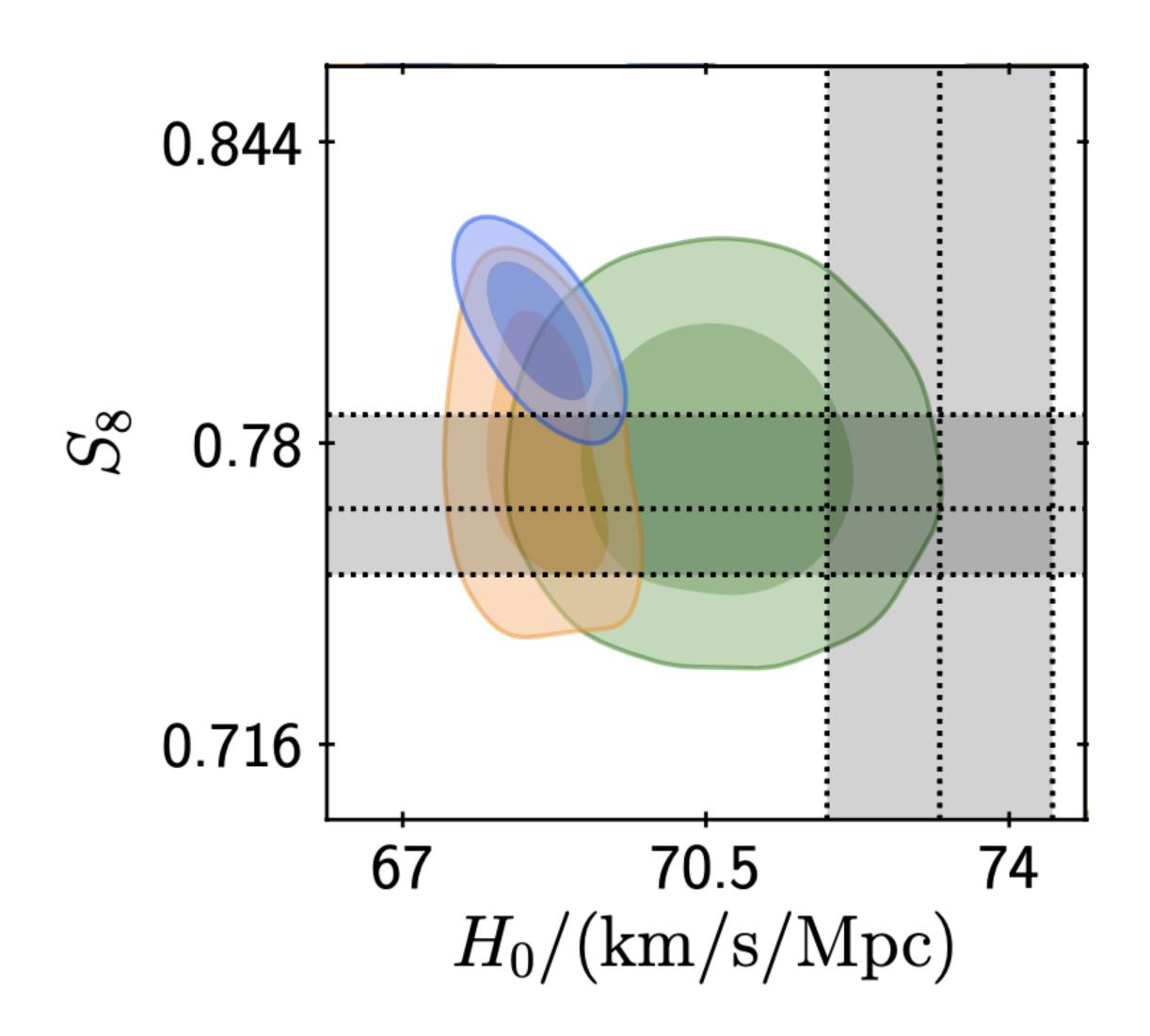
Gravitational well shrinks as the universe expands

$$\Theta_{\rm ISW}(\hat{\mathbf{p}}) \equiv \frac{\Delta T^{(s)}(\hat{\mathbf{p}})}{T} \sim \int \frac{\partial \Phi}{\partial \eta} \, \mathrm{d}\eta.$$

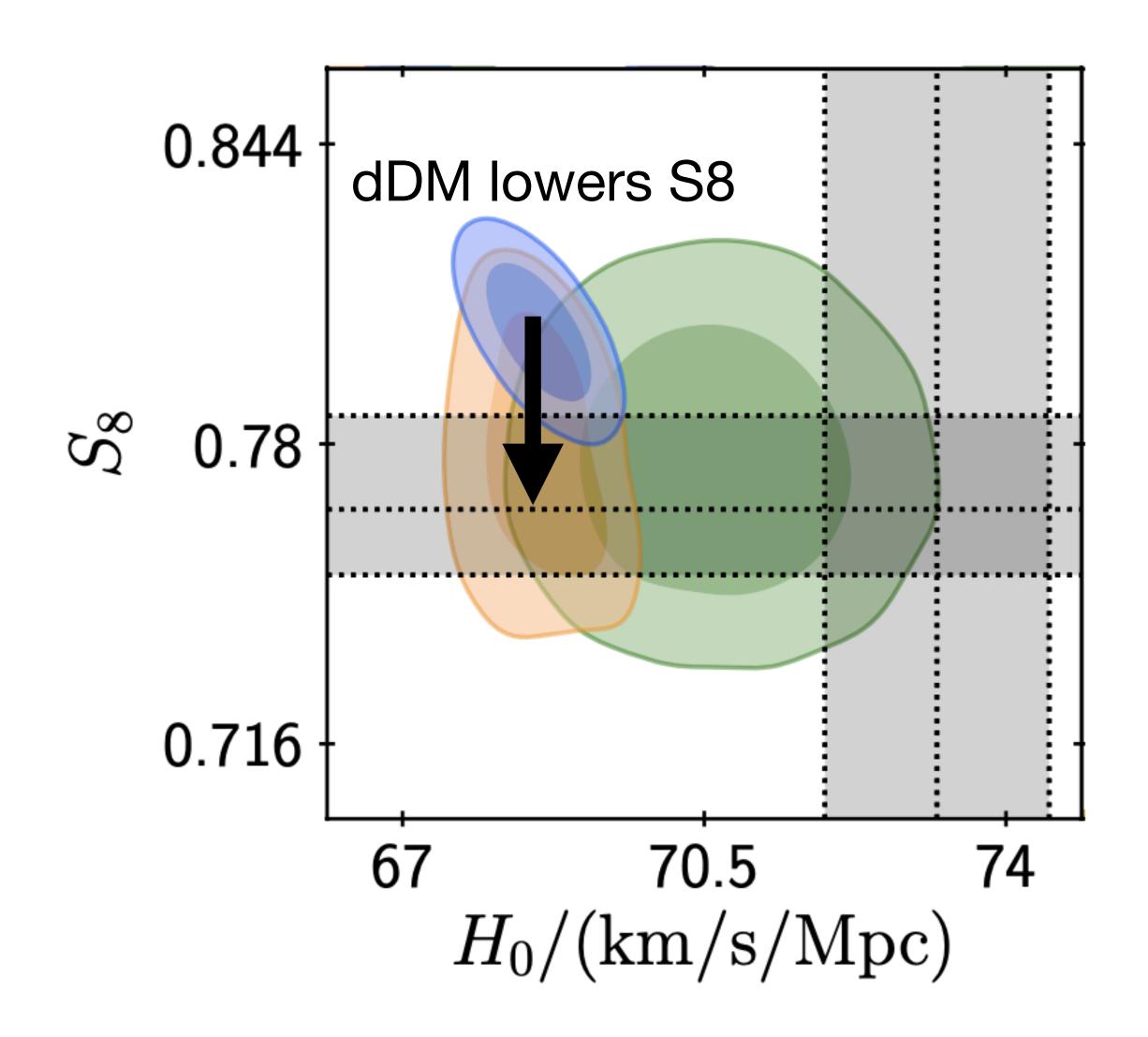
$$C_{\ell} = \langle \Theta_{\ell m} \Theta_{\ell m}^* \rangle$$

$$\sim \int dk P(k) \left[ \int d\eta \, a^2 \left( \frac{\partial \lambda}{\partial \eta} + 2\mathcal{H}\lambda \right) \right]^{\frac{1}{2}}$$

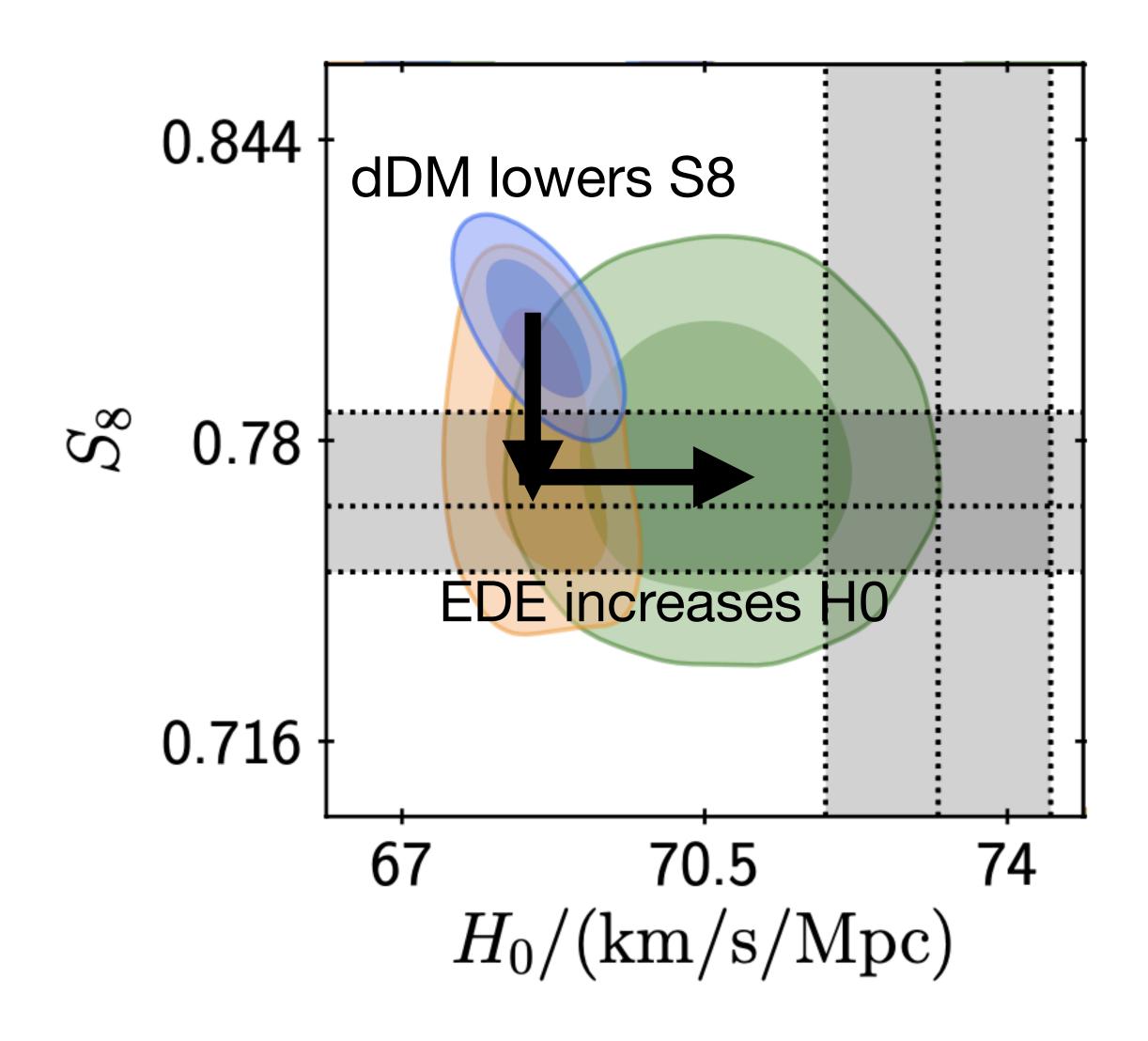
#### EDE + dDM as an example of 2-level modification of \( \Lambda CDM \) to solve tensions



#### EDE + dDM as an example of 2-level modification of ΛCDM to solve tensions



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#### Quantum Gravity Signatures in the Late-Universe

Michael W. Toomey, 1,2 Savvas Koushiappas, 1,2 Bruno Alexandre, 3 and João Magueijo 3

1 Department of Physics, Brown University, Providence, RI 02912-1843, USA
2 Brown Theoretical Physics Center, Brown University, Providence, RI 02912-1843, USA
3 Theoretical Physics Group, The Blackett Laboratory, Imperial College,
Prince Consort Rd., London, SW7 2BZ, UK



The transition from dark matter to dark energy domination is well understood in the metric formulation of GR.

Alternative view: Hamiltonian formulation of GR

Lapse function, lapse of proper time between two hyper surfaces

Hypersurfaces of same time coordinate

$$b = \frac{a}{N}$$

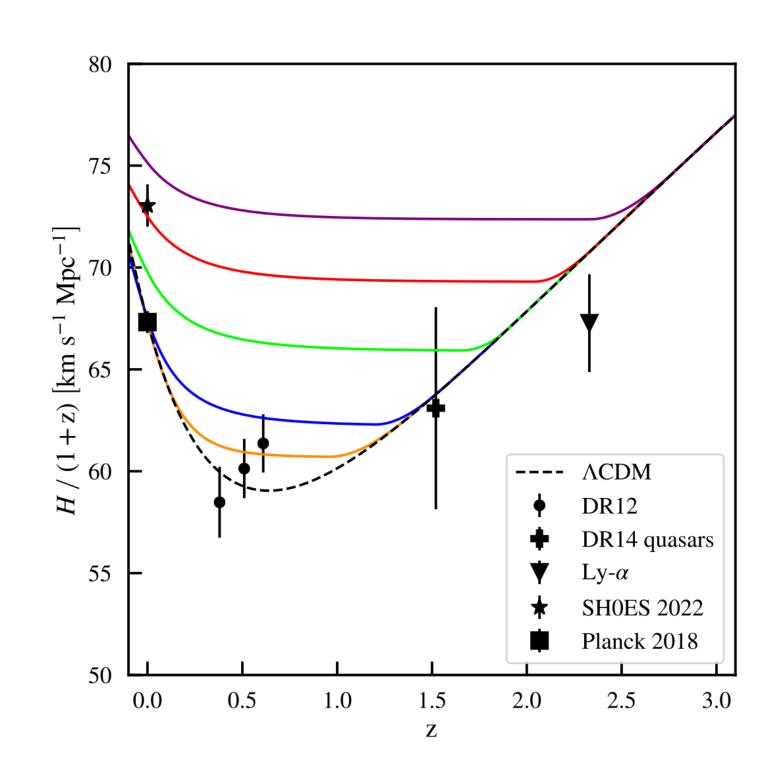
Connection variable

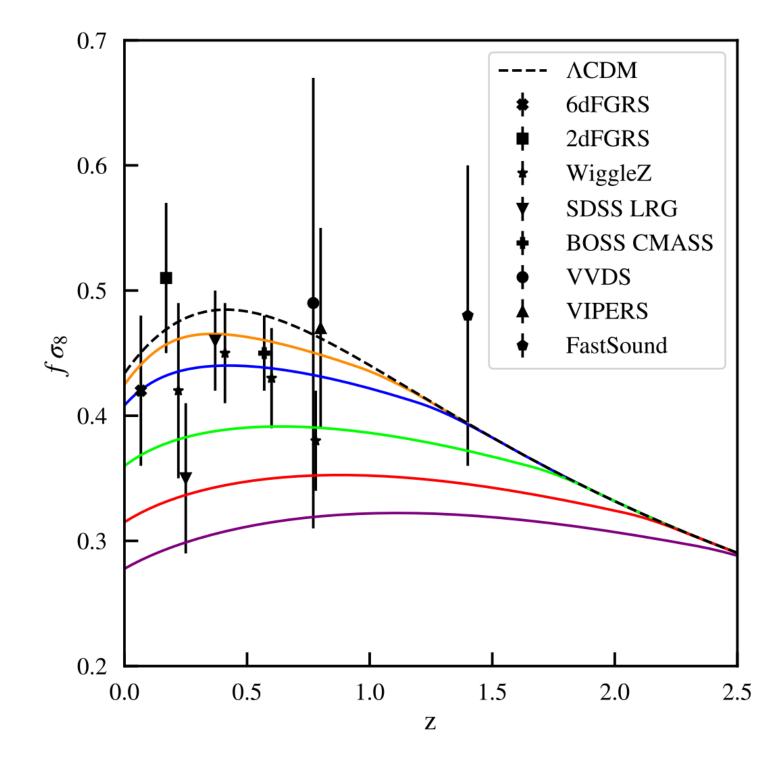
Decreases during decelerated expansion, increases during accelerated expansion.

Connection must have "reflected" off a minimum at matter — dark energy transition

Toomey et al., arXiv:2301.13855, see also 2207.03854

Interference effects at the matter—dark energy transition can lead to deviations in the evolution of the hubble parameter



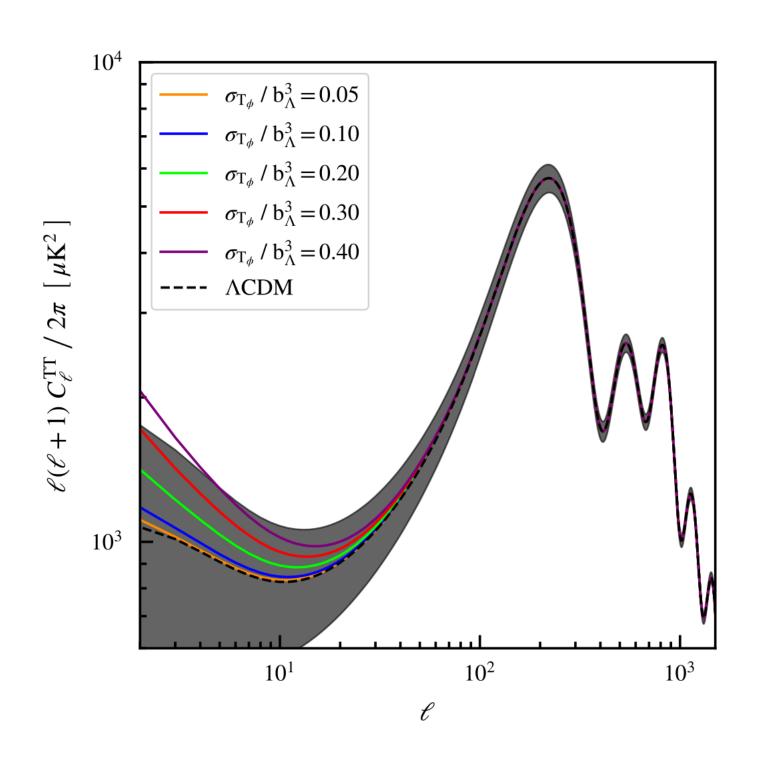


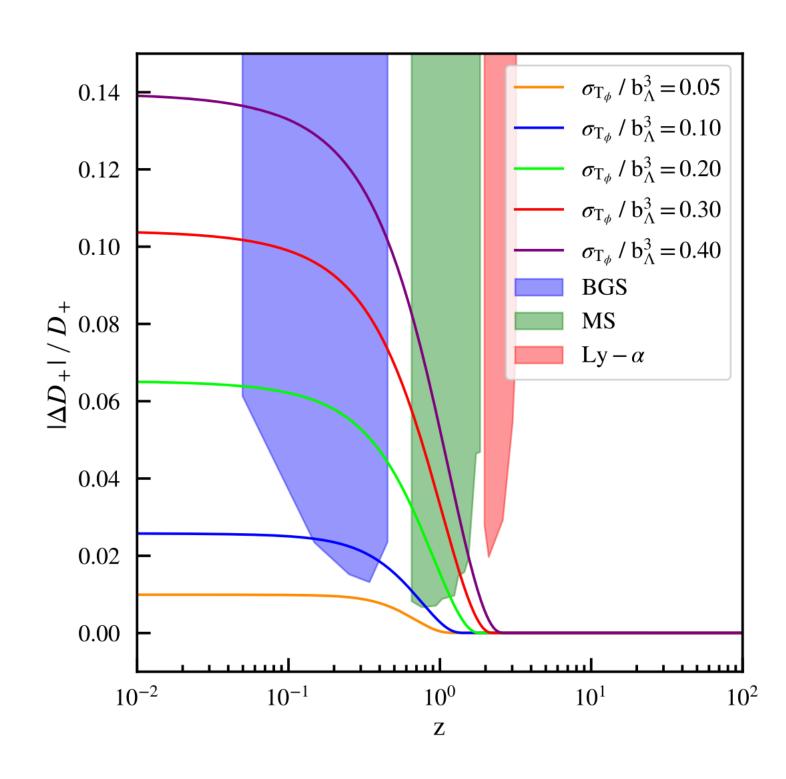
$$f\sigma_8 \equiv \sigma_8 \frac{d \ln D}{d \ln a}$$

$$D'' = -aHD' + \frac{3}{2}a^2 \rho_M D$$

Toomey et al., arXiv:2301.13855, see also 2207.03854

Interference effects at the matter—dark energy transition can lead to deviations in the evolution of the hubble parameter



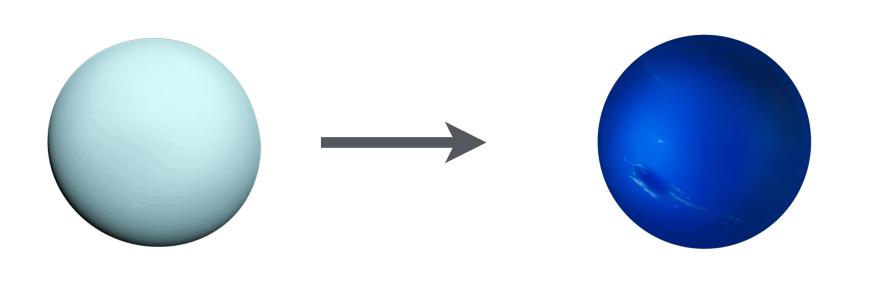


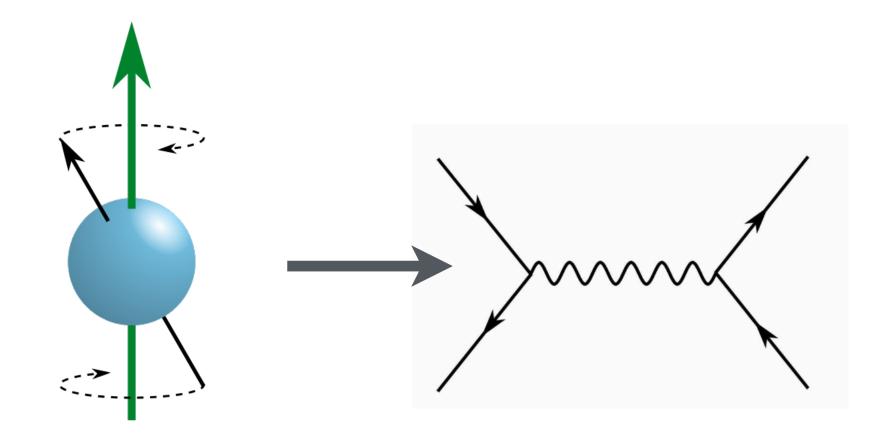
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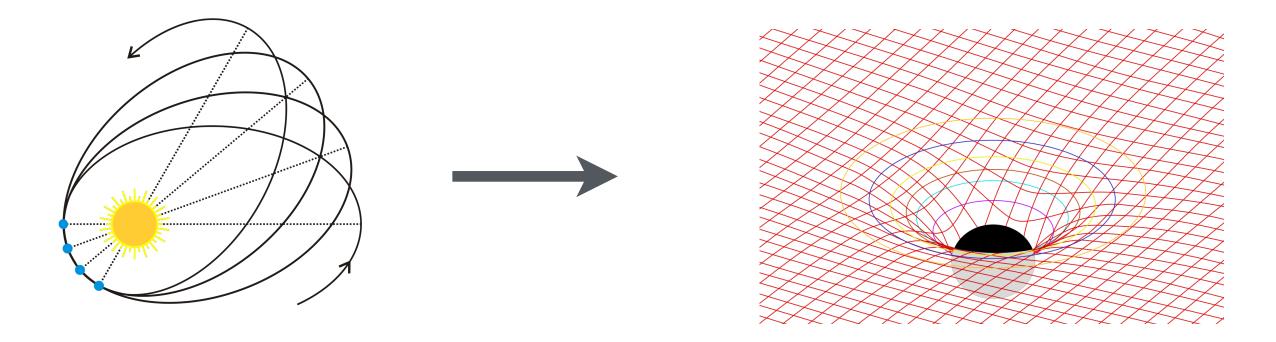
$$D'' = -aHD' + \frac{3}{2}a^2 \rho_M D$$

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#### Precision always leads to breakthroughs...



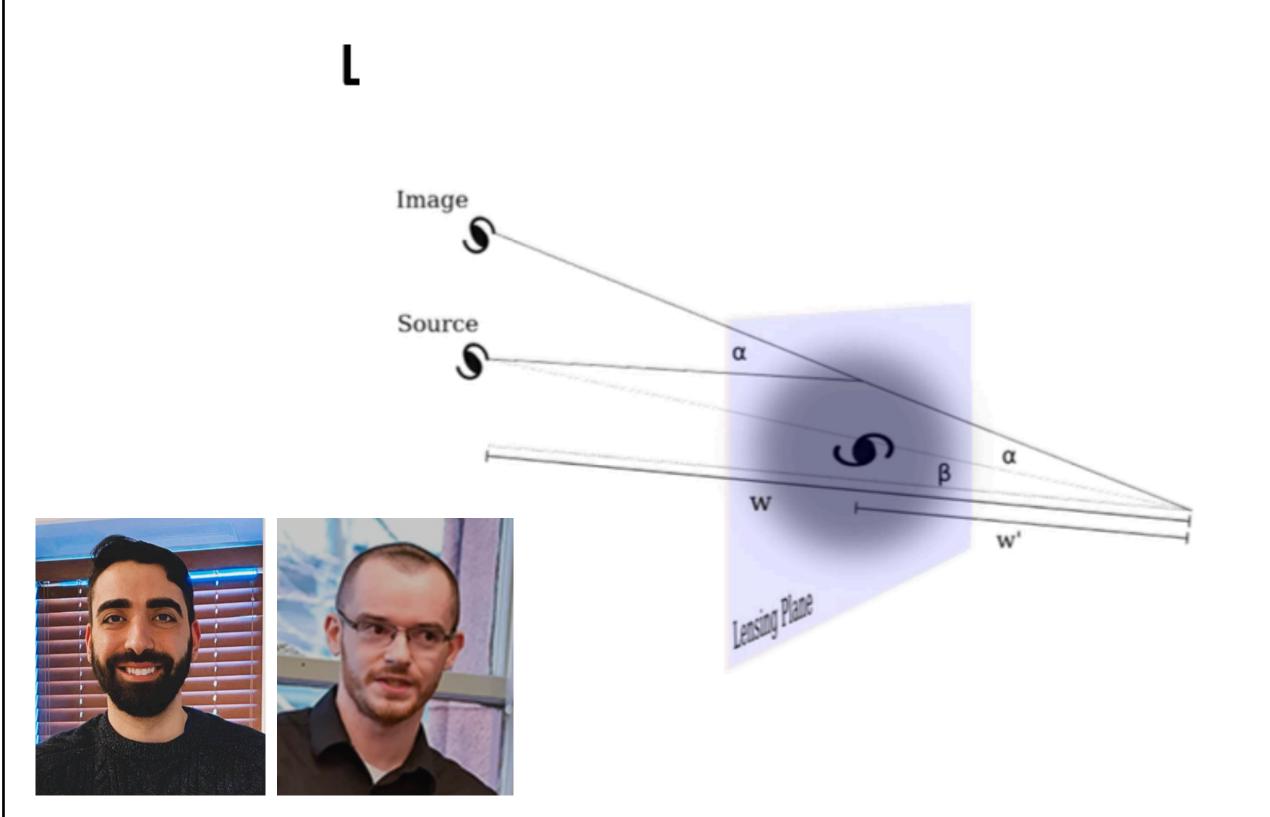


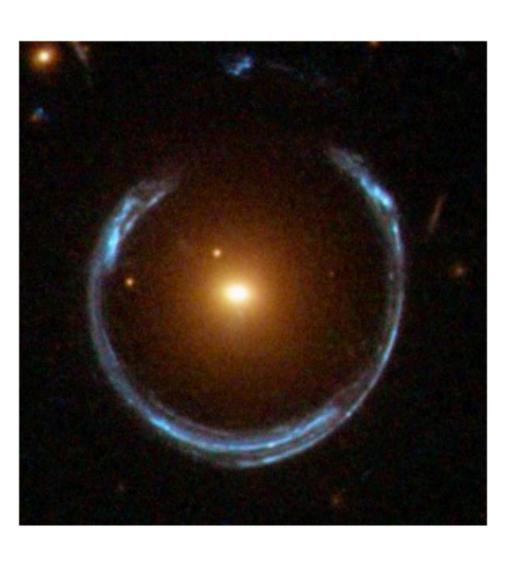


..it seems we may be heading in the same direction in cosmology today.

#### Deep learning the astrometric signature of dark matter substructure

Kyriakos Vattis<sup>®</sup>, Michael W. Toomey<sup>®</sup>, and Savvas M. Koushiappas<sup>®</sup> Department of Physics, Brown University, Providence, Rhode Island 02912-1843, USA and Brown Theoretical Physics Center, Brown University, Providence, Rhode Island 02912-1843, USA





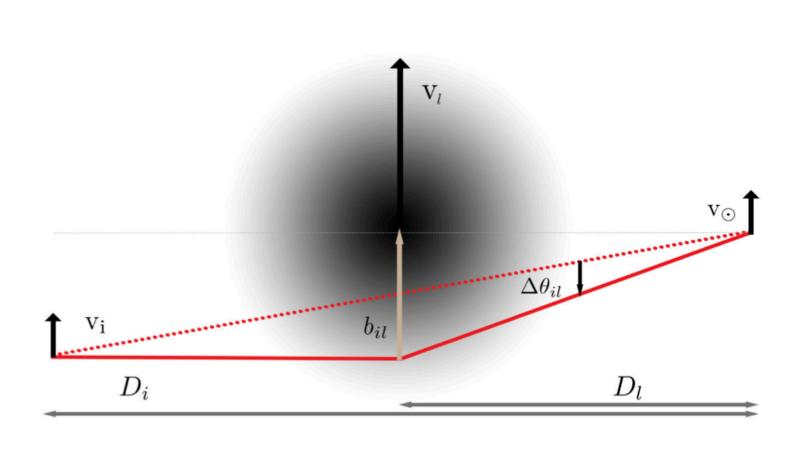
Here is an outline of how deep learning can be utilized to study the astrometric signature of dark matter substructure:

- **Data Collection**: Gather astrometric data from telescopes or observational surveys. This data may include precise measurements of positions, velocities, redshifts, or lensing effects of galaxies, stars, or other astrophysical sources.

No data yet, but we can assume that a survey like SKA can observe a large number of quasars. We call them background sources.



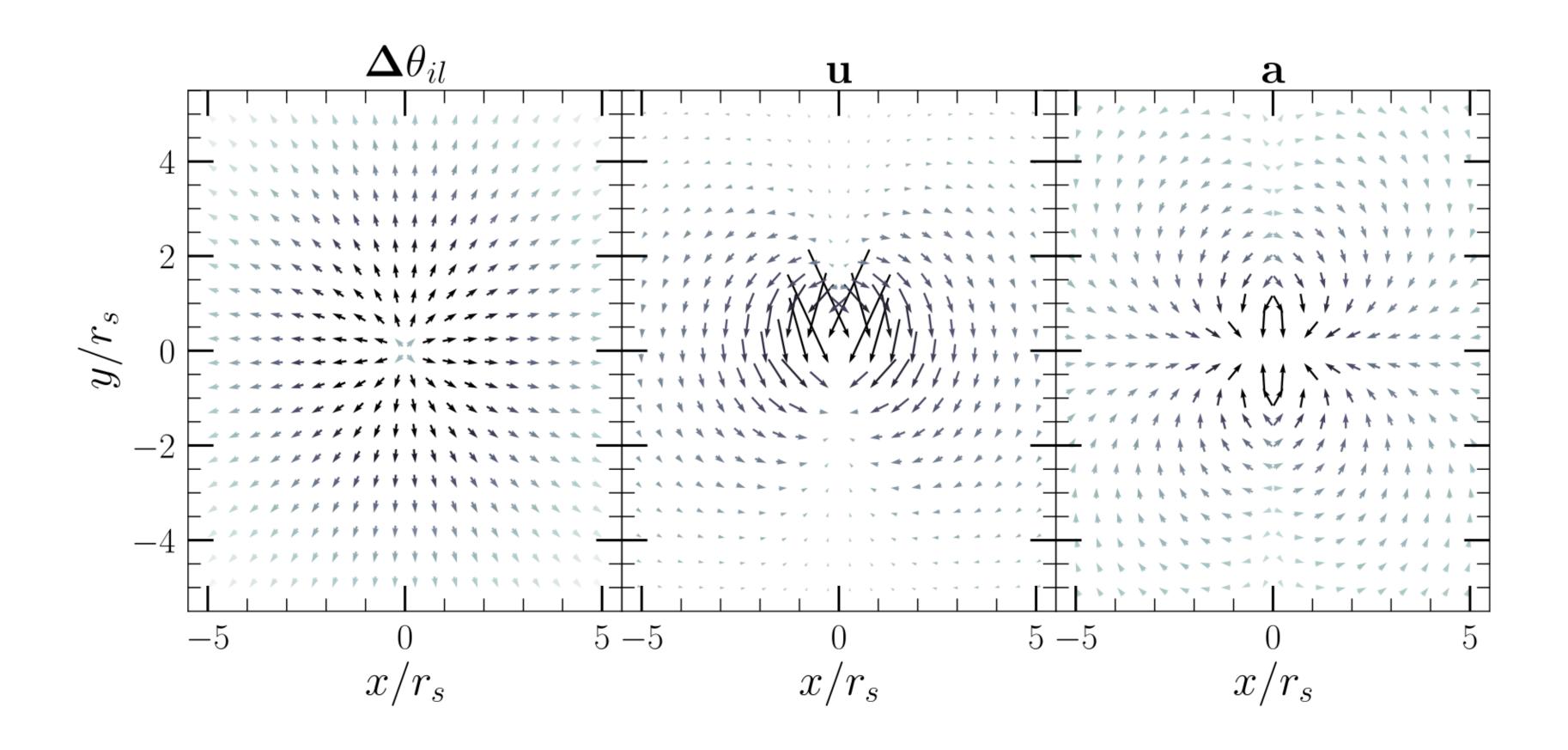
- **Simulated Training Data:** Generate simulated astrometric data that incorporates the effects of dark matter substructure. Numerical simulations or theoretical models can be used to create a training dataset that accurately represents the astrometric signature of dark mater substructure.



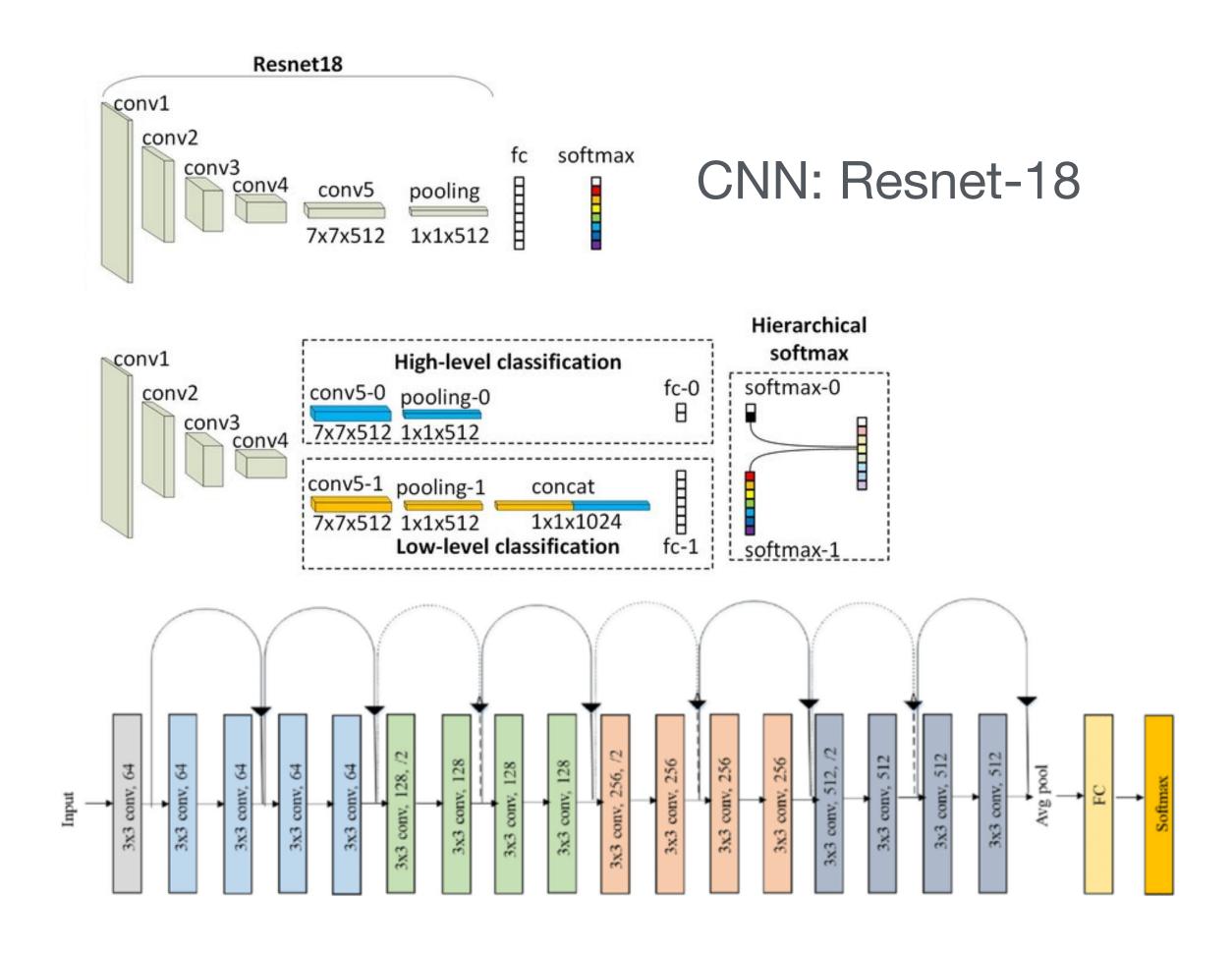
$$\Delta \theta_{il} = -\left(1 - \frac{D_l}{D_i}\right) \frac{4G_N M(b_{il})}{c^2 b_{il}} \hat{\mathbf{b}}_{il}$$

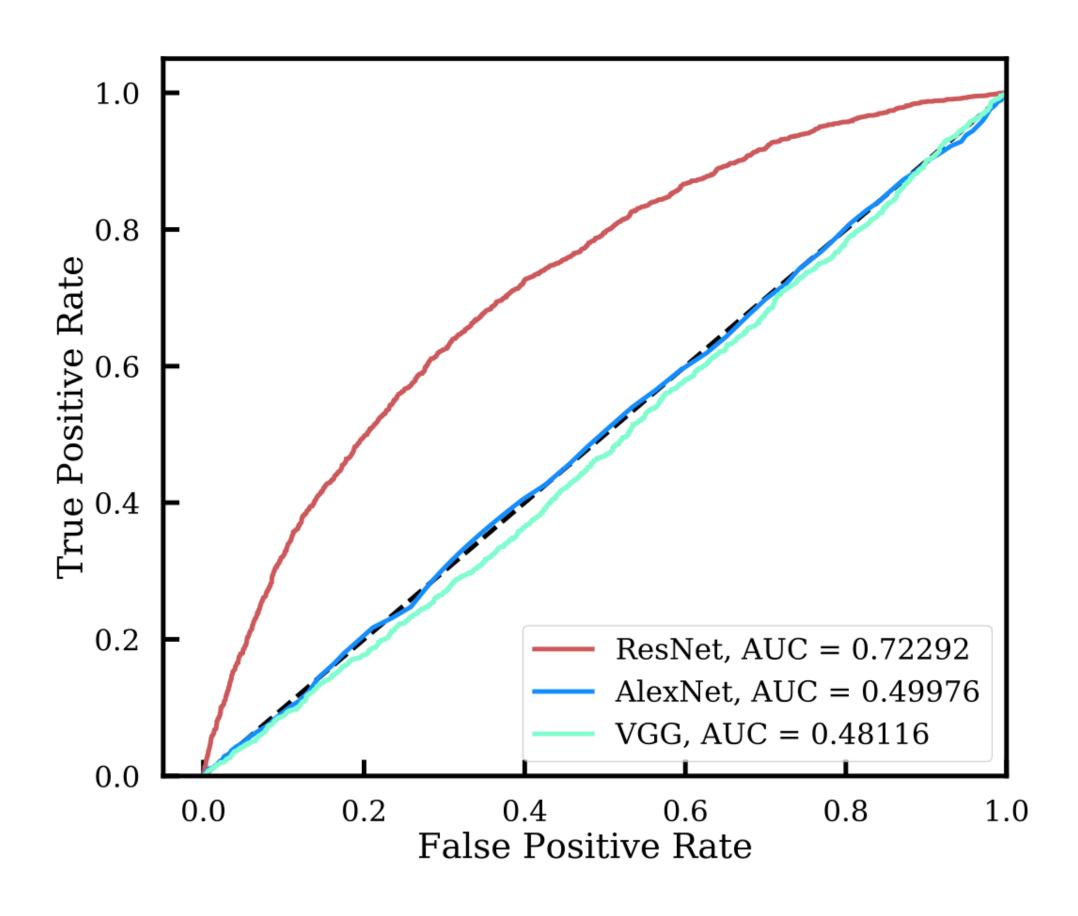
$$\begin{split} \mathbf{u} &= \dot{\Delta \theta_{il}} \\ &= - \left( 1 - \frac{D_l}{D_i} \right) \frac{4G_N}{c^2} \left\{ \frac{M'(b_{il})|b_{il}|}{b_{il}} \hat{\mathbf{b}}_{il} \right. \\ &\quad + \frac{M(b_{il})}{b_{il}^2} [\mathbf{v}_{il} - 2|b_{il}|\hat{\mathbf{b}}_{il}] \right\} \\ \mathbf{a} &= \dot{\Delta \theta_{il}} \\ &= - \left( 1 - \frac{D_l}{D_i} \right) \frac{4G_N}{c^2} \left\{ \frac{M''(b_{il})|b_{il}|^2}{b_{il}} \hat{\mathbf{b}}_{il} \right. \\ &\quad + \frac{M'(b_{il})}{b_{il}^2} [2|b_{il}|\mathbf{v}_{il} + |b_{il}|\mathbf{b}_{il} - 4|b_{il}|^2 \hat{\mathbf{b}}_{il}] \\ &\quad - \frac{2M(b_{il})}{b_{il}^3} [2|b_{il}|\mathbf{v}_{il} + |b_{il}|\mathbf{b}_{il} + 3|b_{il}|^2 \hat{\mathbf{b}}_{il}] \right\} \end{split}$$

- **Feature Extraction**: Extract relevant features from the collected or simulated data that are likely influenced by dark matter substructure. These features could include deviations in the observed positions or motions of celestial objects, distortions in their shapes due to gravitational lensing, or clustering patterns in their distribution.

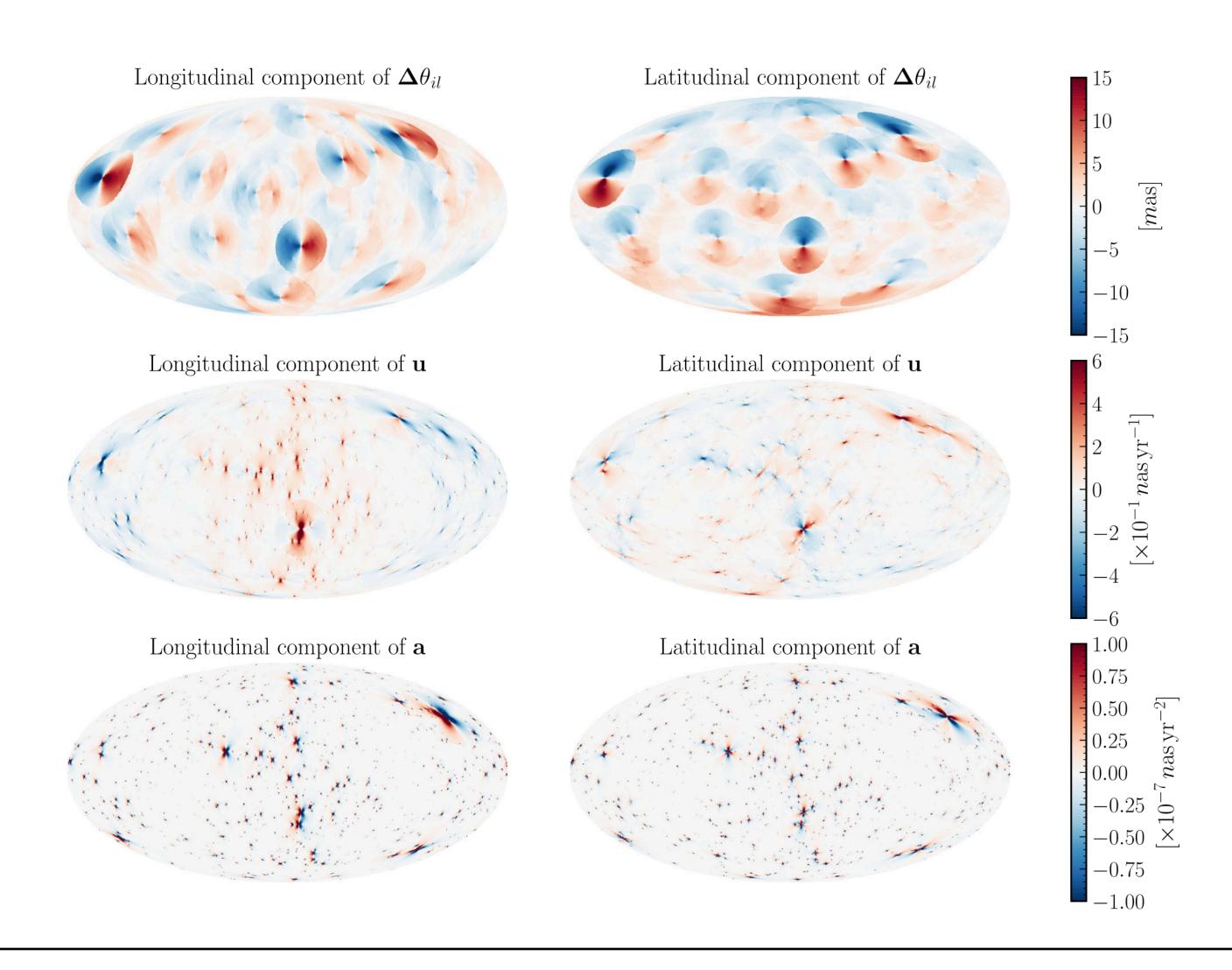


- **Deep Learning Model Design**: Design a deep learning architecture suitable for capturing the astrometric signature of dark matter substructure. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), or other architectures can be used depending on the specific features and data characteristics.

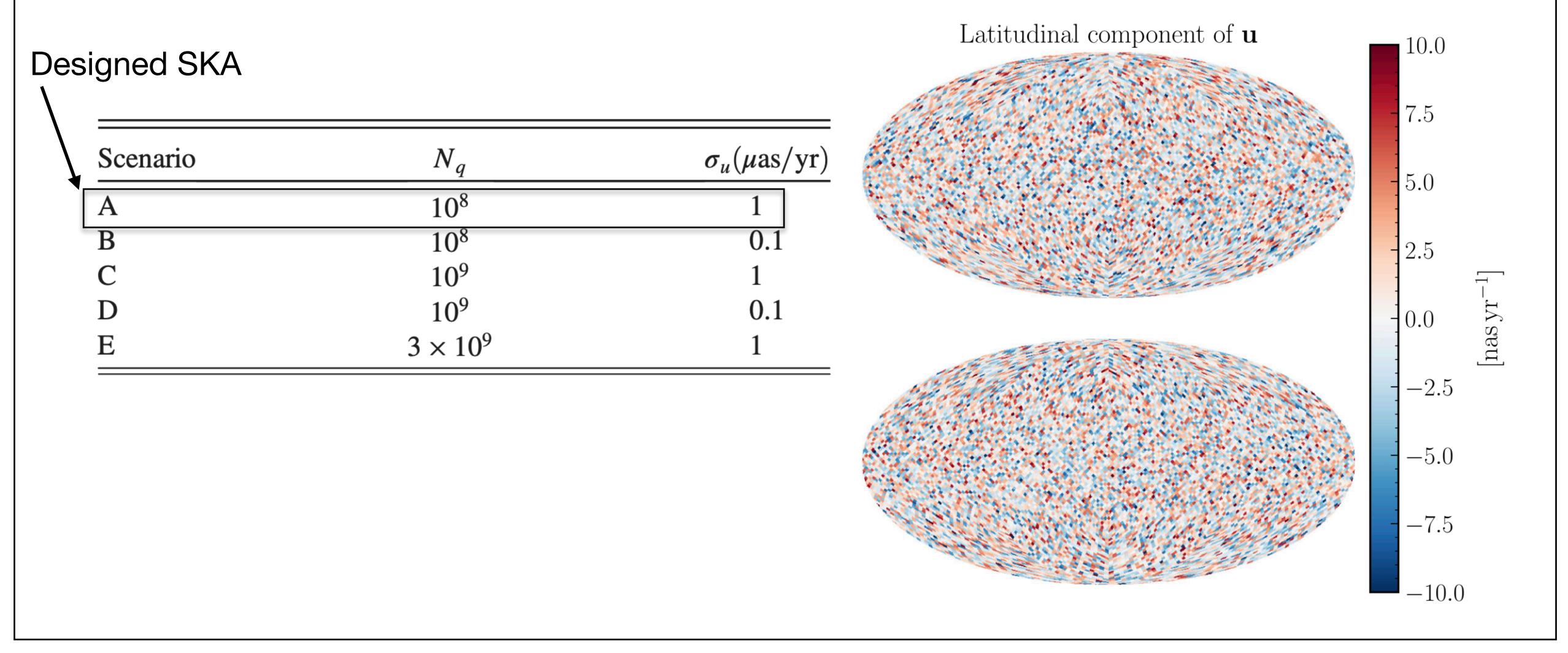




- **Model Training:** Train the deep learning model using the simulated training dataset. This involves feeding the data through the network, adjusting the model's parameters using backpropagation, and optimizing the model's performance through appropriate loss functions and optimization algorithms.



- **Model Evaluation**: Evaluate the trained model using validation data to assess its performance in capturing the astrometric signature of dark matter substructure. This evaluation helps ensure the model's generalization capability and its ability to accurately predict the astrometric effects of substructure.

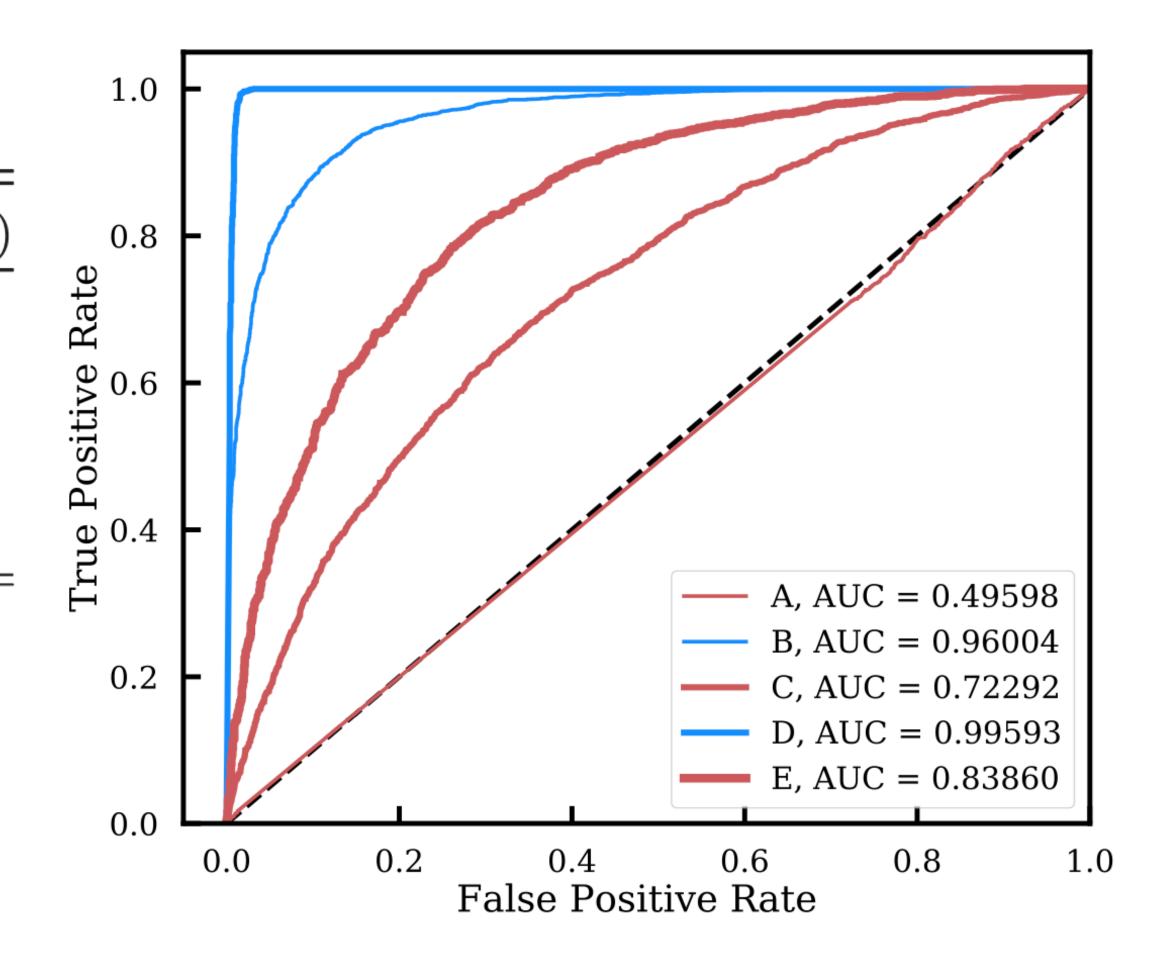


- **Astrometric Signature Inference:** Apply the trained deep learning model to real astrometric data to infer the presence and characteristics of dark matter substructure. The model can predict the astrometric signature associated with substructures and provide insights into their distribution, abundance, or other properties.

#### Designed SKA

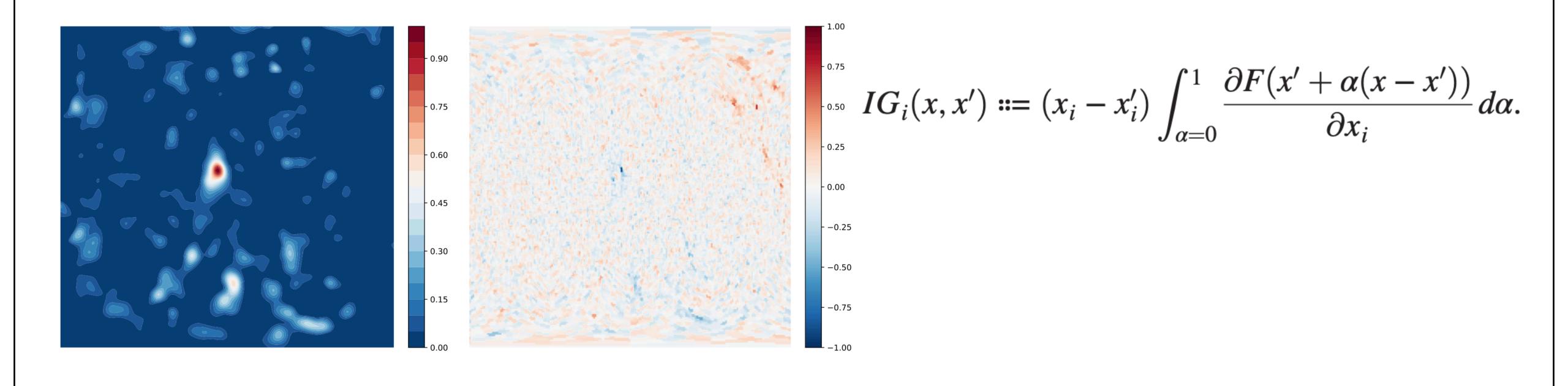
Scenario	$N_q$	$\sigma_u(\mu as/yr)$
A	108	1
В	$10^{8}$	0.1
C	$10^{9}$	1
D	$10^{9}$	0.1
E	$10^9$ $3 \times 10^9$	1

Doubling the operational time of SKA allows for a reliable probe of the substructure content of the Milky Way through astrometry.



- **Astrometric Signature Inference**: Apply the trained deep learning model to real astrometric data to infer the presence and characteristics of dark matter substructure. The model can predict the astrometric signature associated with substructures and provide insights into their distribution, abundance, or other properties.

Use of Integrated Gradients (path integral of gradients of baseline and desired inputs) allows deterministic localizations of substructure.



## **ChatGPT**



deep learning the astrometric signature of dark matter substructure



Deep learning techniques can be employed to learn and analyze the astrometric signature of dark matter substructure. Dark matter substructure refers to smaller clumps or concentrations of dark matter within larger dark matter halos, and its astrometric signature refers to the measurable effects it produces in the positions, motions, or gravitational lensing of celestial objects. Applying deep learning to understand and extract this astrometric signature can aid in the detection and characterization of dark matter substructures.

Here is a general outline of how deep learning can be utilized to study the astrometric signature of dark matter substructure:

