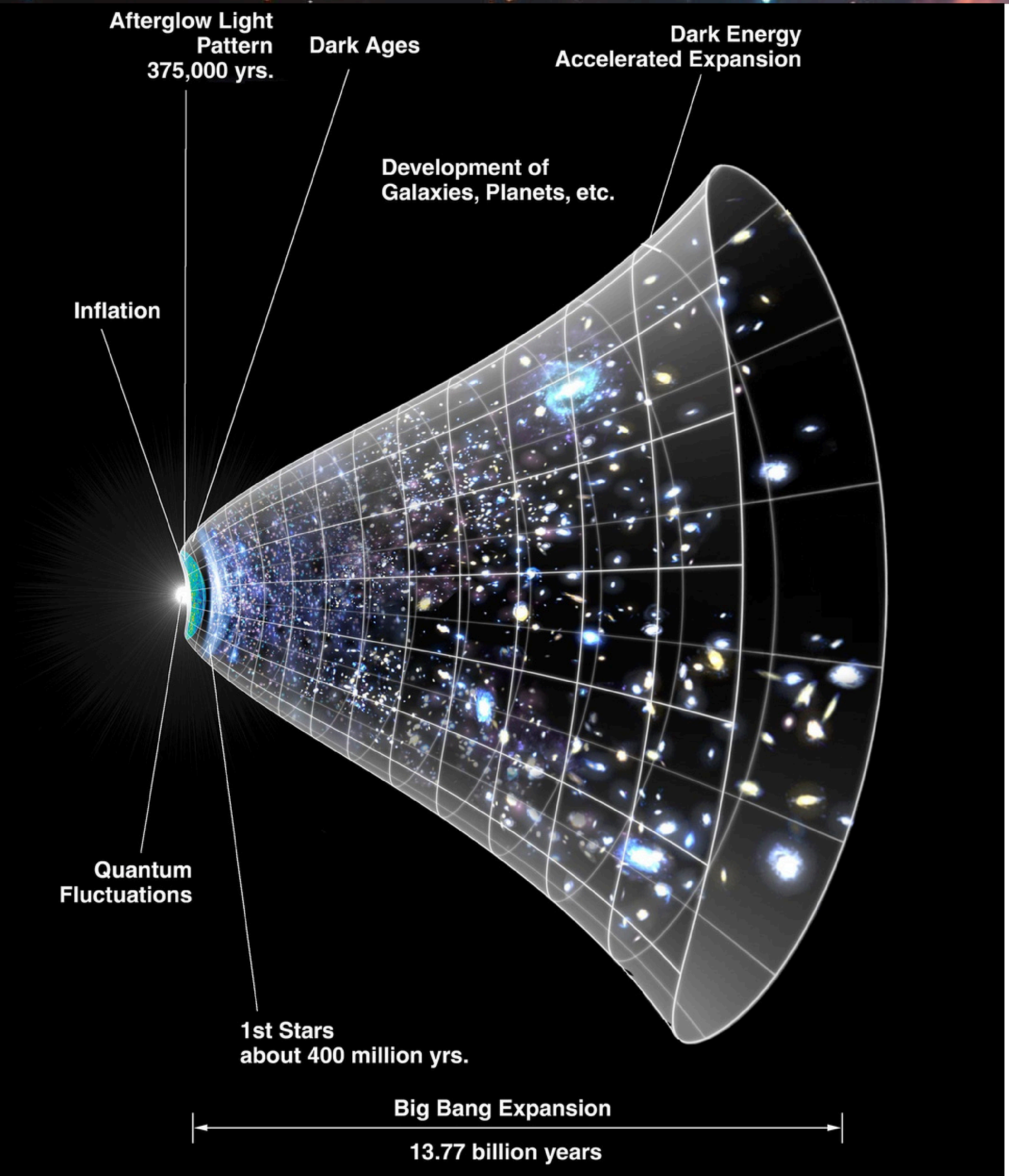
Growth-Rate measurement using peculiar velocities from LSST type Ia Supenovae

Damiano Rosselli

Supervisors: Dominique Fouchez (CPPM), Stephane Arnouts (LAM)

ΛCDM Model



The standard cosmological model **(ΛCDM)**

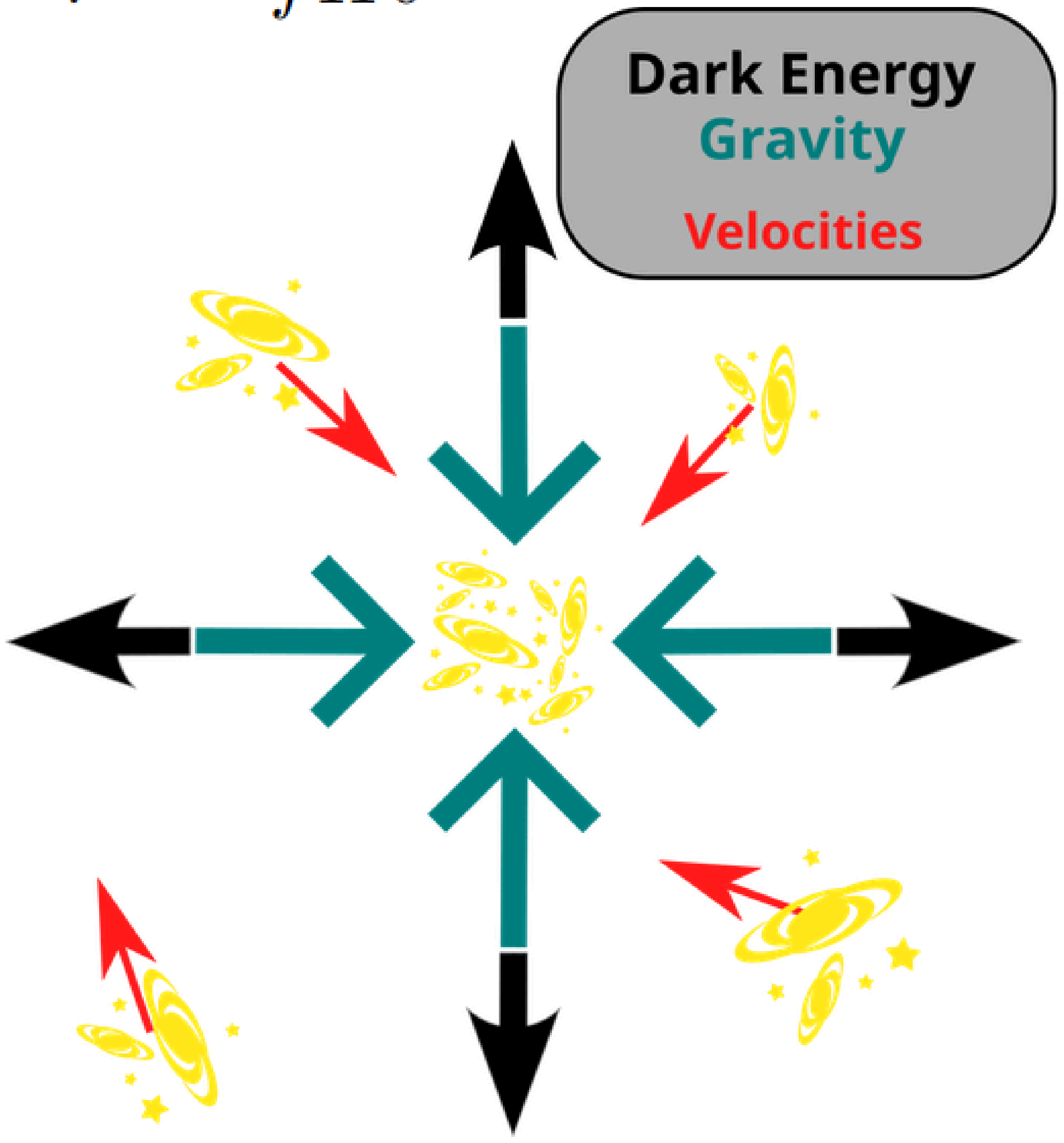
Λ: dark energy (70%) , **CDM**: cold dark matter (25%)
+ **GR**

This model fit really well the data, but:

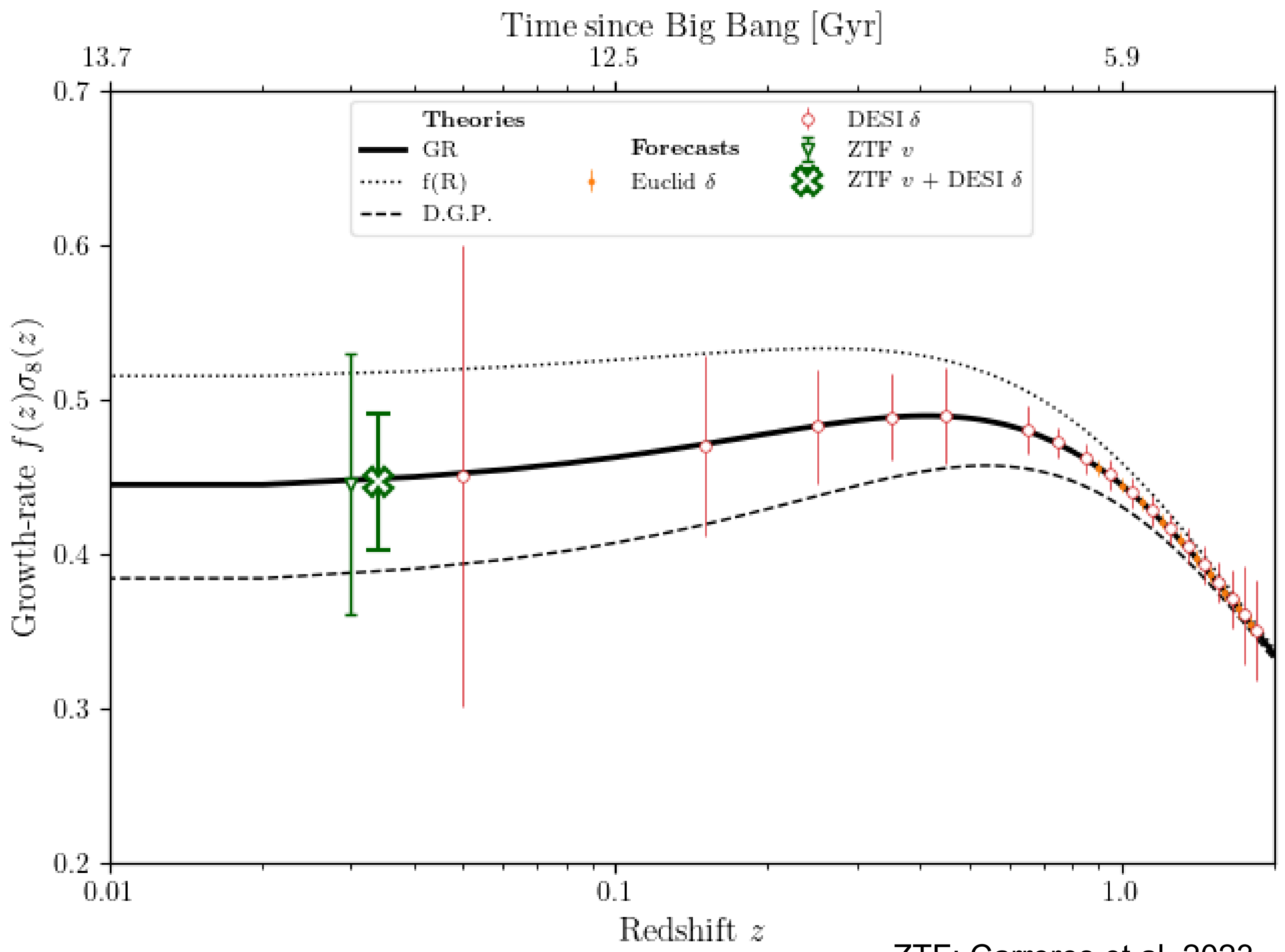
Why the Universe is accelerating?
What is the dark energy?
Is it really a constant?
GR is the correct theory for gravity on large scale?

The growth rate of strucutres

$$\nabla_r \cdot \mathbf{v} = -fH\delta$$



$$f\sigma_8 \simeq \Omega_m^\gamma \sigma_8 \quad \gamma \simeq 0.55 \quad \text{(GR + } \Lambda\text{CDM)}$$



ZTF: Carreres et al. 2023
DESI: DESI Collaboration 2016a
Euclid: Amendola et al. 2018

Hubble diagram & velocities

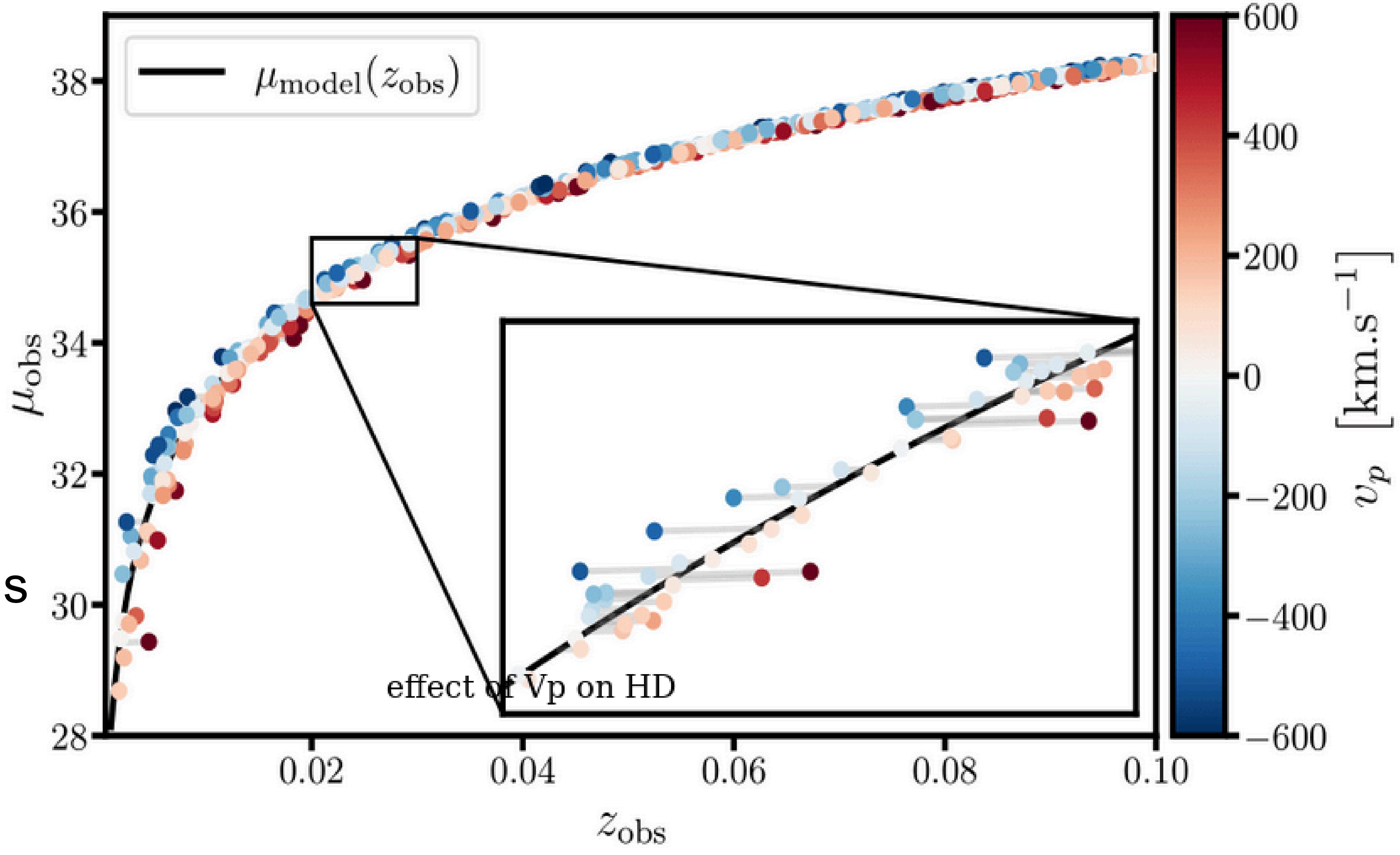
Knowing redshift and distance of an object we can estimate its peculiar velocity (PV). For SNe Ia we use the Hubble diagram residuals

PVs have two effects on the SNe Ia Hubble diagram :

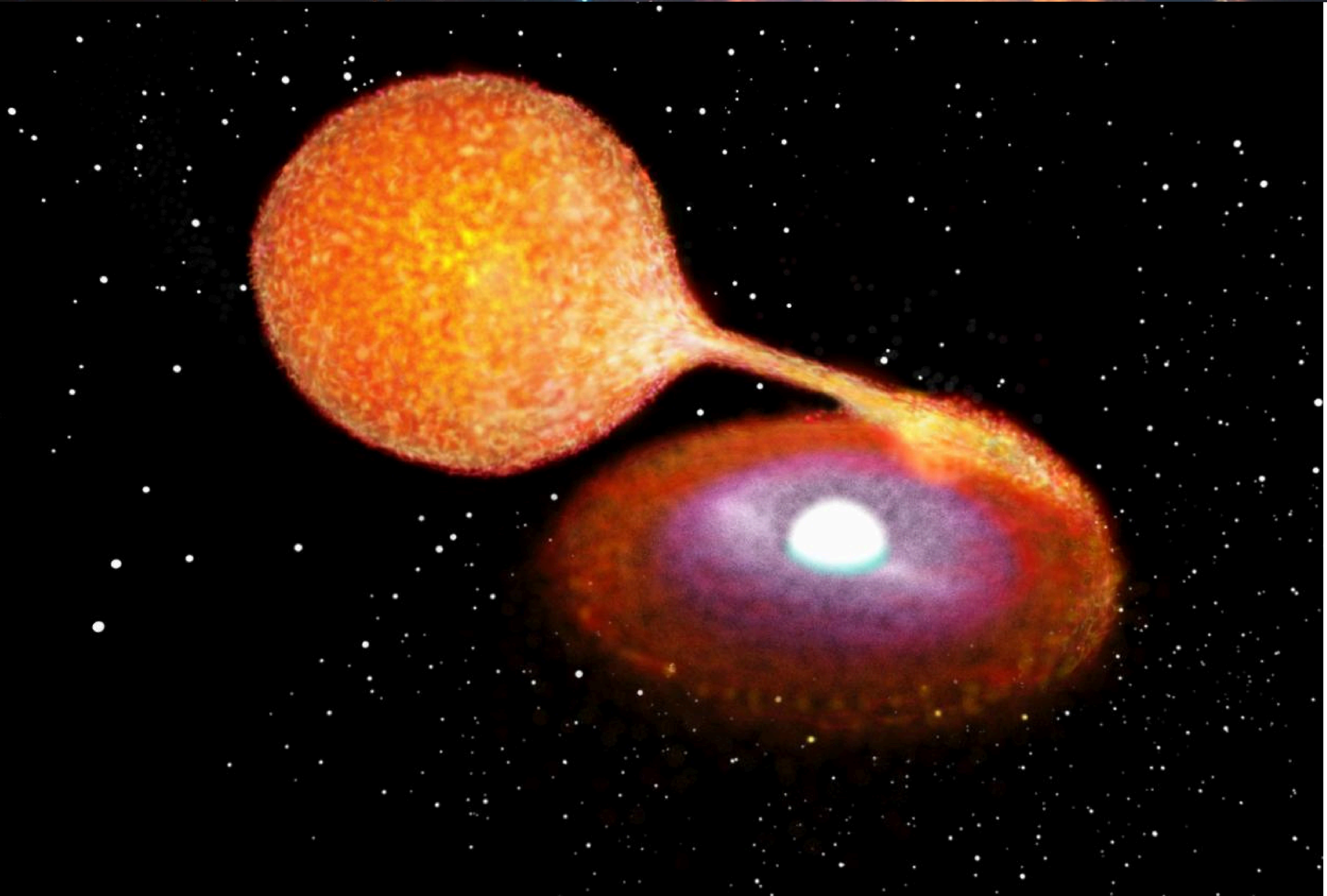
- Change in redshift due to Doppler effect.

$$1 + z_{\mathrm{obs}} = (1 + z_{\mathrm{cos}})(1 + z_p)$$

- Change in apparent distance modulus due to relativistic beaming (second order).



Type Ia supernovae



Type Ia Supernovae (SNe Ia)
Explosion of a with dwarf that surpass the Chandrasekhar mass limit

Type Ia supernovae

Type Ia supernovae (SNe Ia) are **standardizable candles**

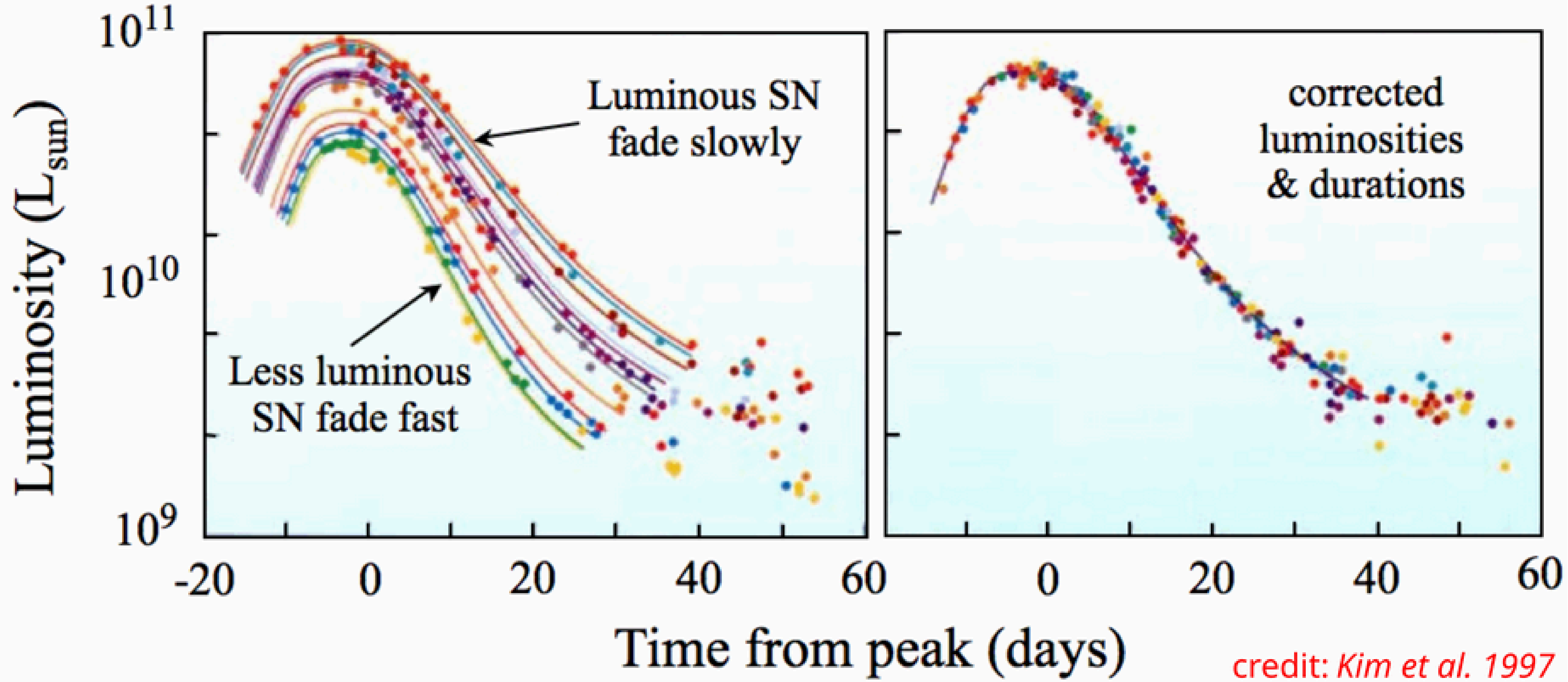
3 parameters of interest to recover the distances:

mB : apperent magnitude in B-band

c : color

x1 : stretch

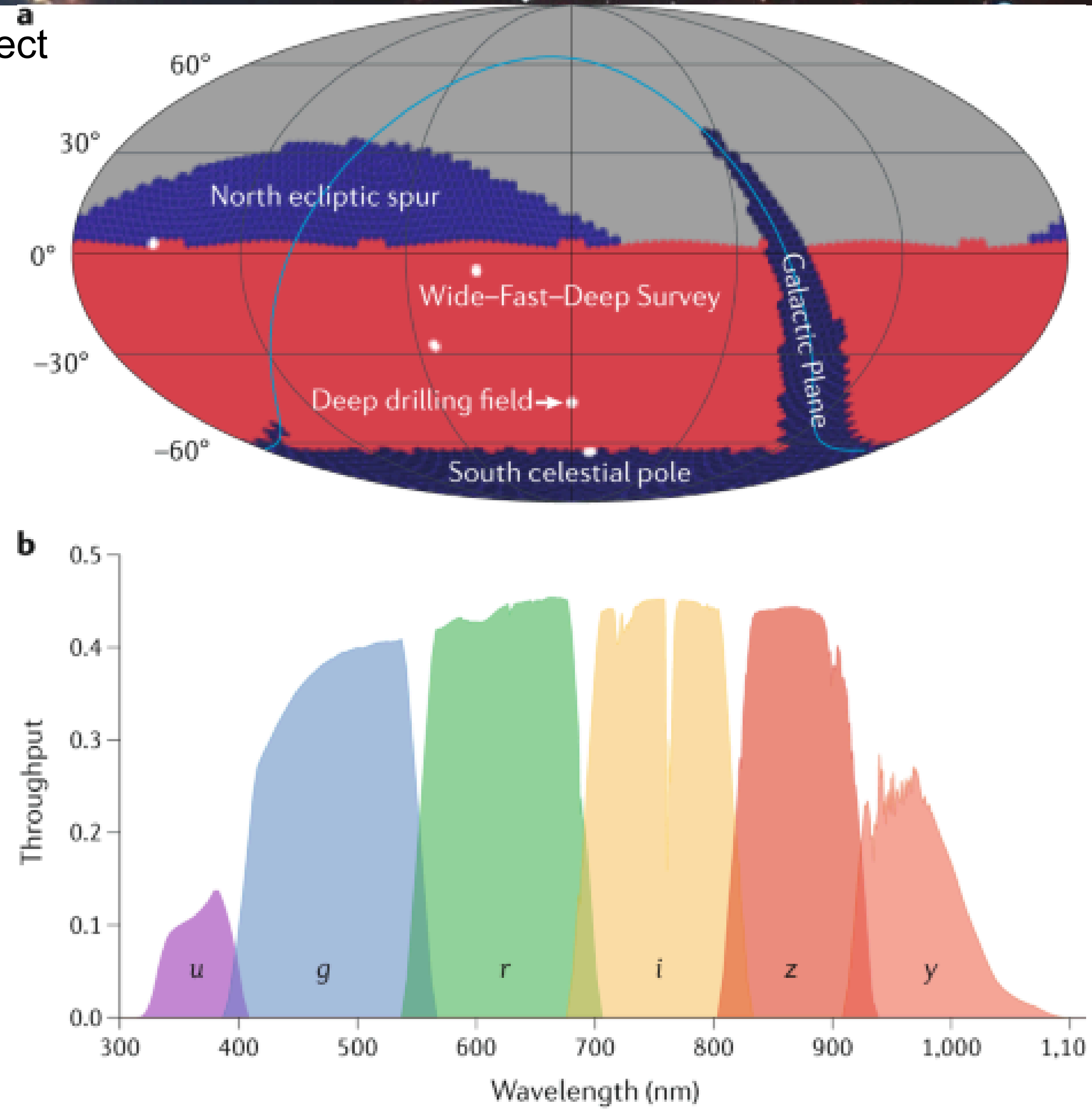
redder SN are less luminous



credit: *Kim et al. 1997*

LSST survey

credit: LSST Rubin project



c

Aperture size	8.4 m (6.4 m effective)
Field of view	9.6 deg²
Camera	3.2 gigapixels
WFD Survey area	~18,000 deg²
Expected WFD single-visit depths	u = 23.9, g = 25.0, r = 24.7, i = 24.0, z = 23.3, y = 22.1 (AB magnitudes)
Approximate WFD final depths	u = 26.1, g = 27.4, r = 27.5, i = 26.8, z = 26.1, y = 24.9 (AB magnitudes)
DDF Survey area	≥4 × 9.6 deg²
Approximate DDF final depths	r ≈ 28–28.5 AB magnitudes
Nominal operational lifetime	10 years

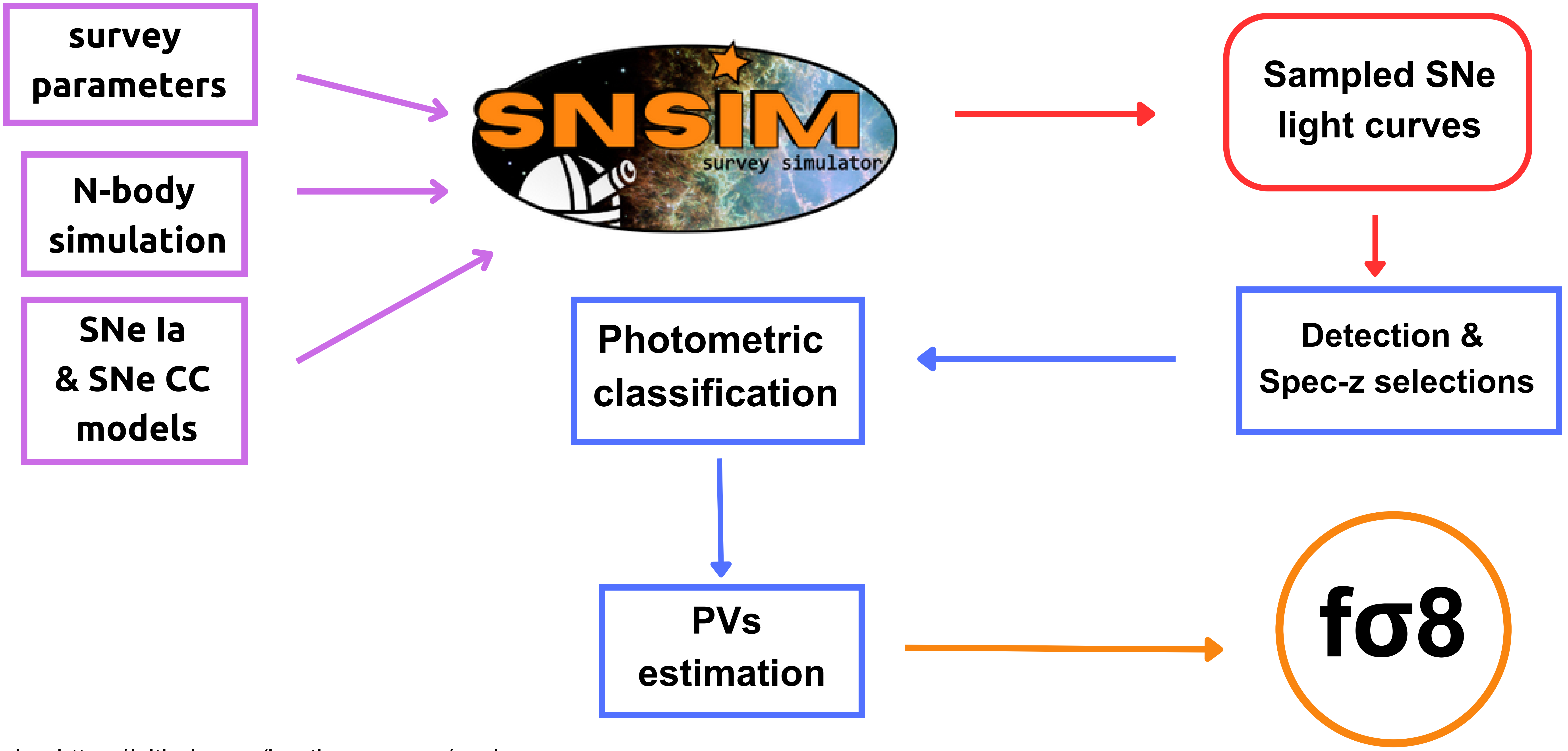
The Rubin Observatory telescope with an **8.4-meter primary mirror**.
Observation of the entire southern available sky every few nights.
Observations in **6 passbands u,g,r,i,y,z.** Images will be recorded by a 3.2-gigapixel charge coupled device imaging (CCD) camera, the largest digital camera ever constructed.

Legacy Survey of Space and Time (LSST)

Many scientific goals: cosmology (weak and strong lensing and SNe Ia), galaxy evolution, AGN, solar system objects, Milky Way

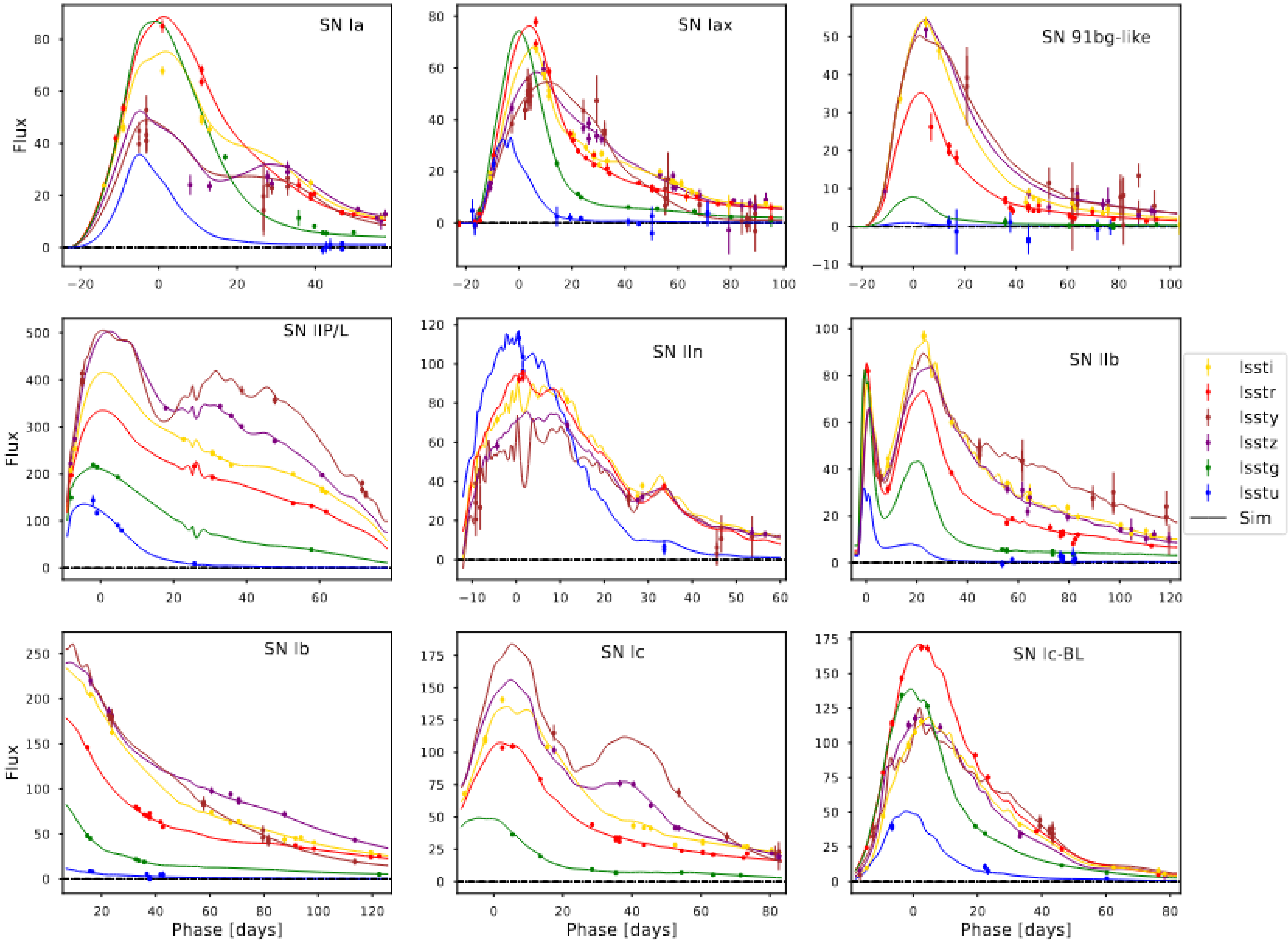
10 years duration starting at end of 2025

Simulation Pipeline

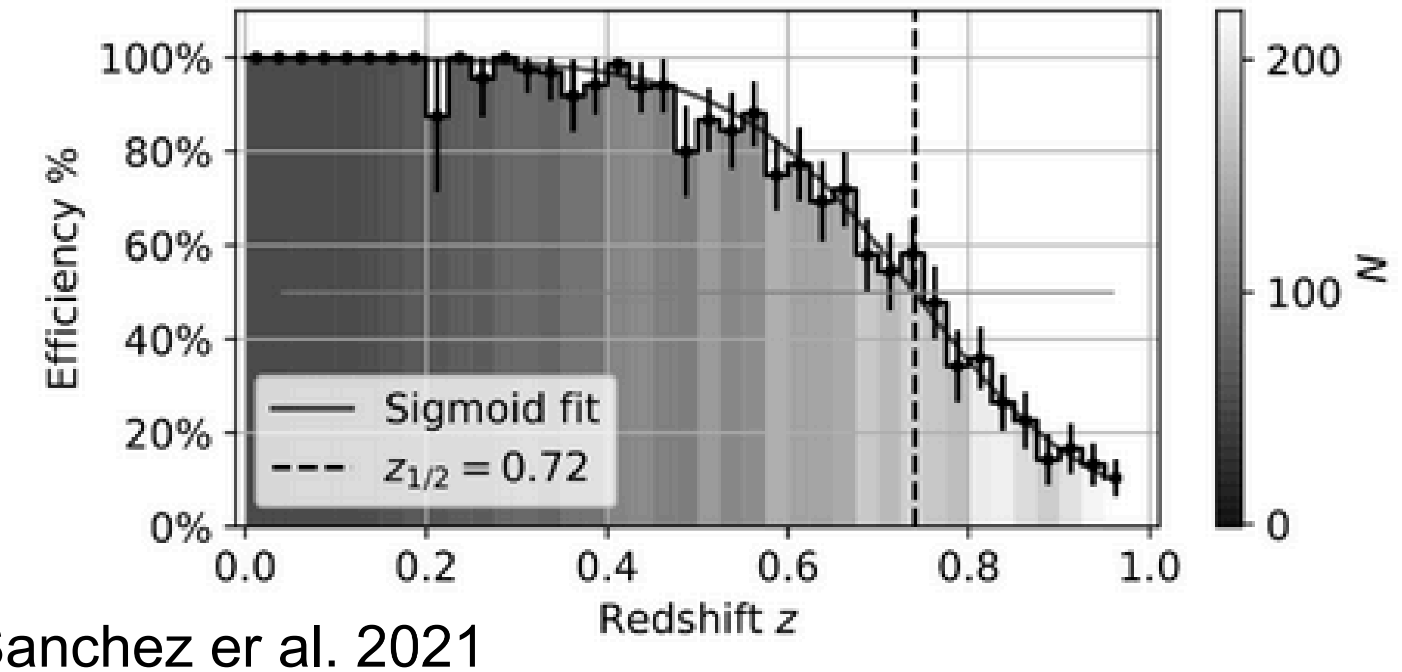


snsim: https://github.com/bastiencarreres/snsim

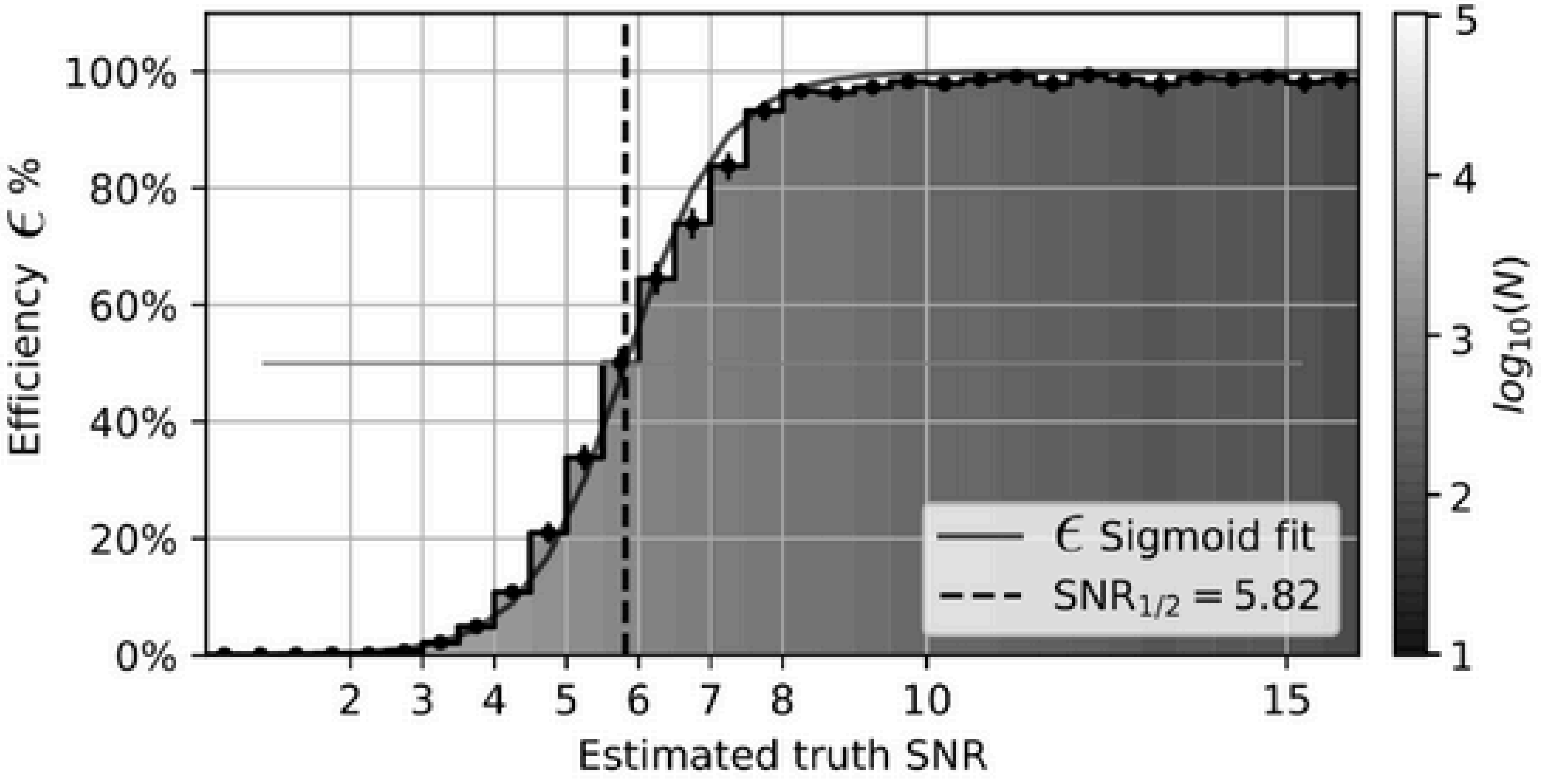
Simulation Output



Selections



B. Sanchez er al. 2021



Light curves selection procedure is composed of 4 steps:

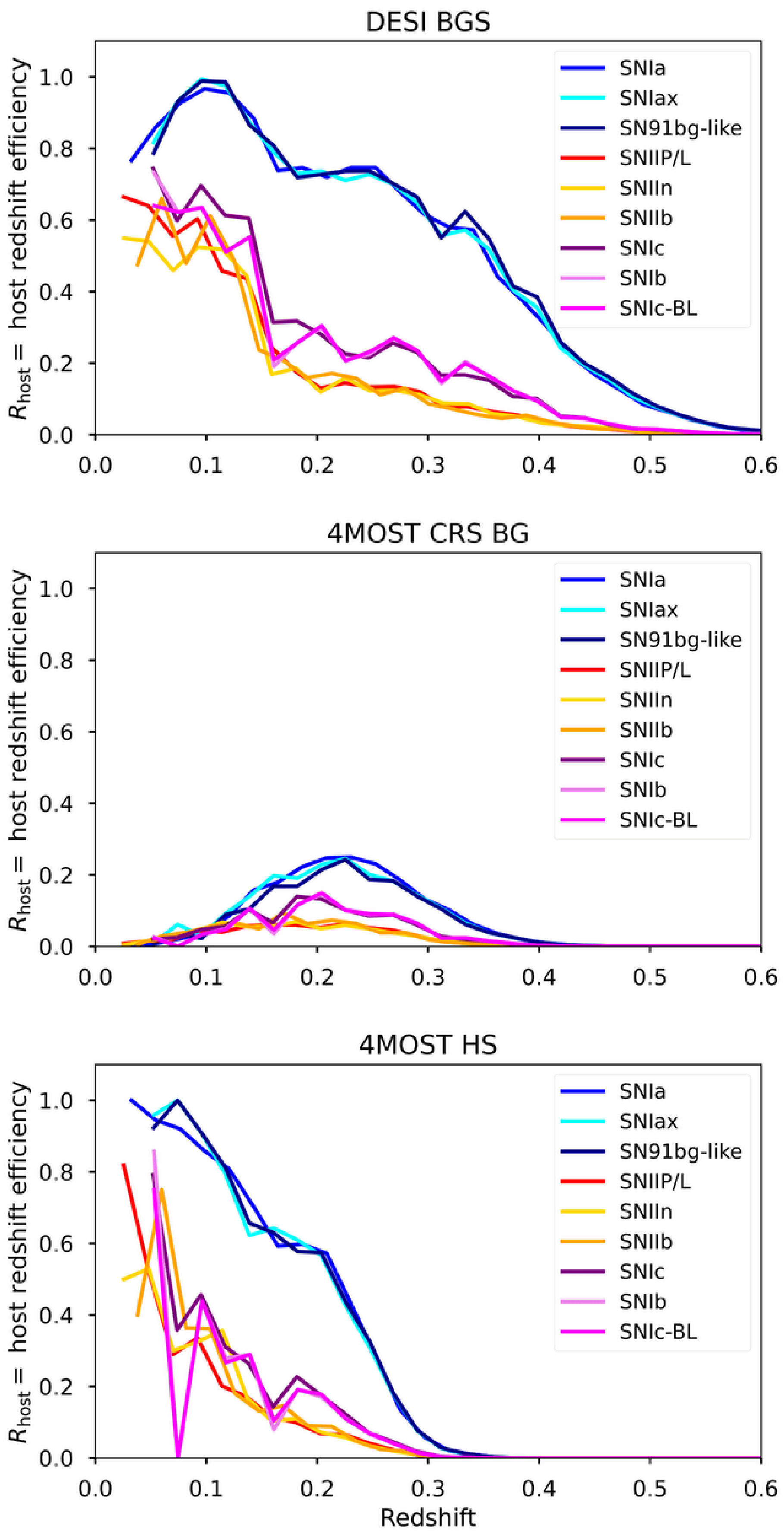
- Remove all saturated observations *
- Detection probability from DIA pipeline

Efficiency of the LSST discovery pipeline
to detect a point (flux) in the light curves
as a function of the redshift (top)
and signal-to-noise (bottom)

* u, g, r, i, z, y = 14.7, 15.7, 15.8, 15.8, 15.3, 13.9 LSST saturation limit at 0.7” seeing form https://www.lsst.org/sites/default/files/docs/sciencebook/SB_3.pdf

Selections

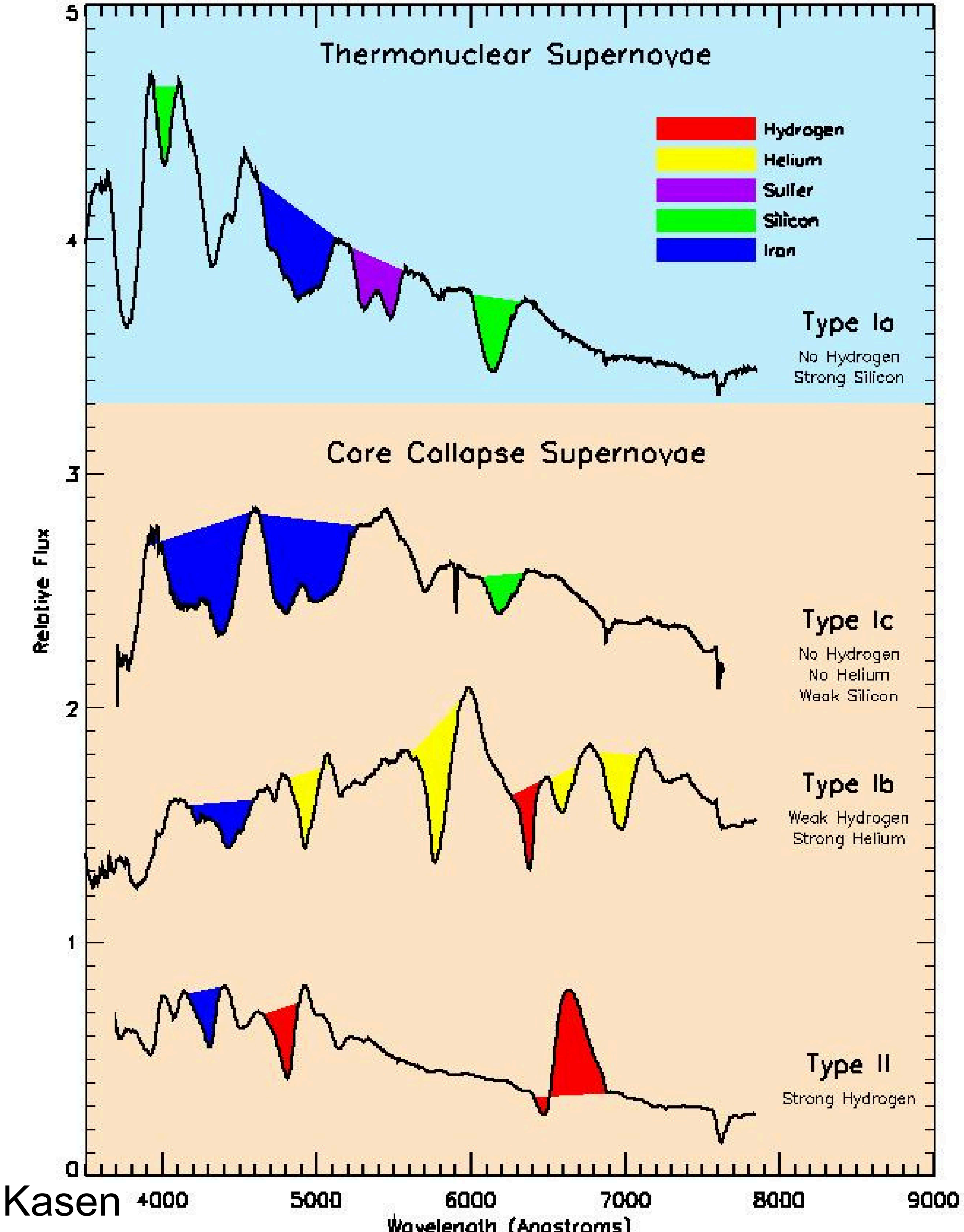
Probability of different spectroscopic surveys DESI (top) and 4MOST (middle, bottom) to observe the host galaxies of LSST SNe.
the different colors show the different type of SNe



Light curves selection procedure is composed of 4 steps:

- Remove all saturated observations
- Detection probability from DIA pipeline
- Host spectroscopic redshift efficency
- Coadd observations by night
- SNR > 4 in at least 3 separate passbands

Classification



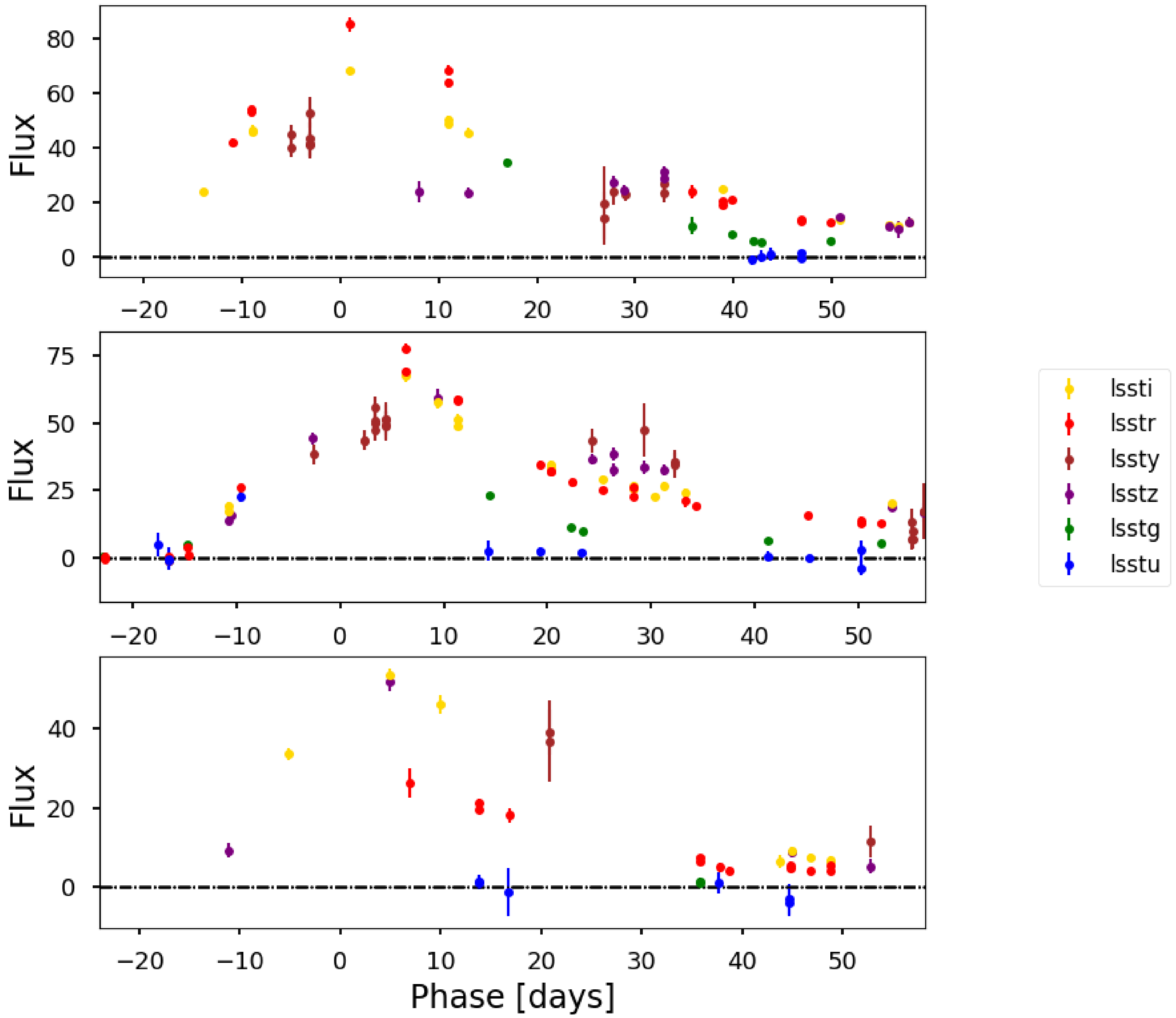
credit: Daniel Kasen

SNe usually classfied using spectra
(for cosmology we use only SNe Ia)

LSST too many SNe and few spectroscopic resources available. No spectra for everything

we rely on machine learning algorithms

Classification



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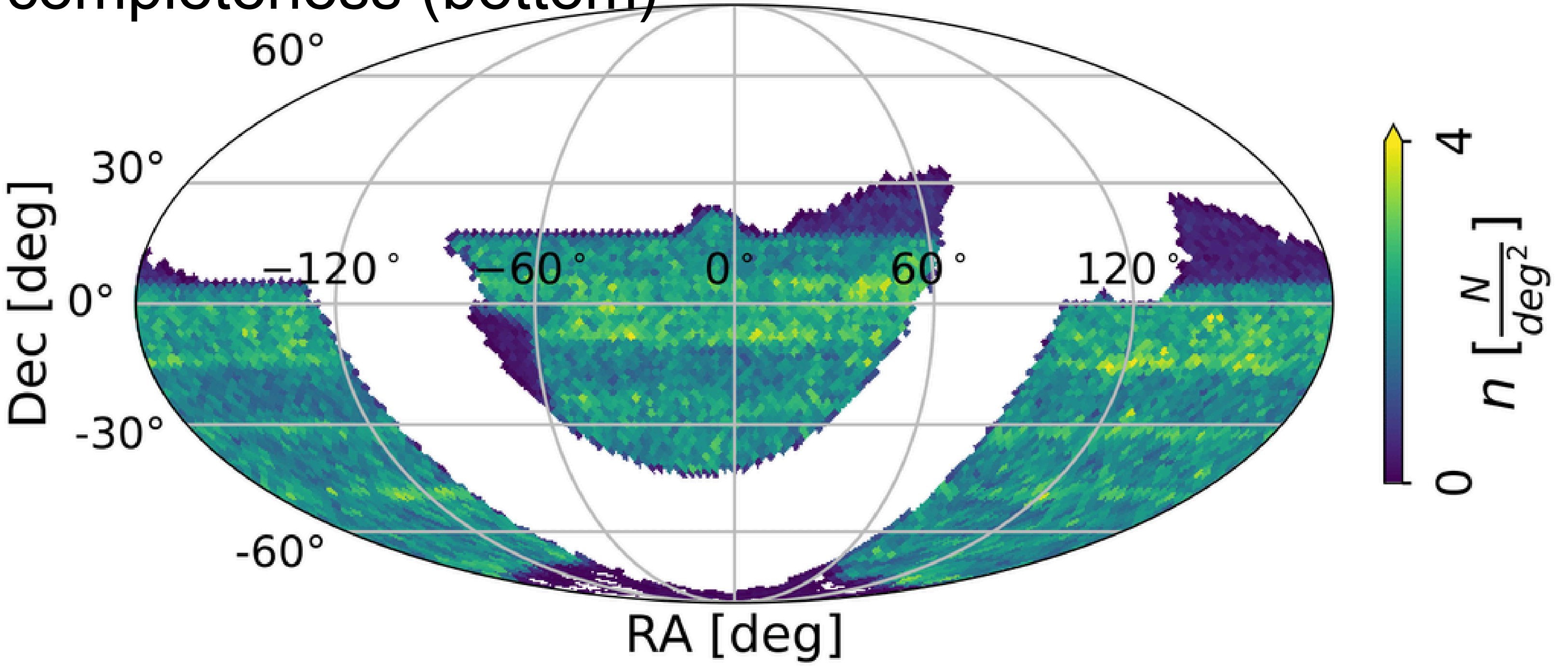
We use Supernnovae (SNN, Moller et al. 2019)
We train SNN using a new LSST simulation on which we apply the same selection cuts

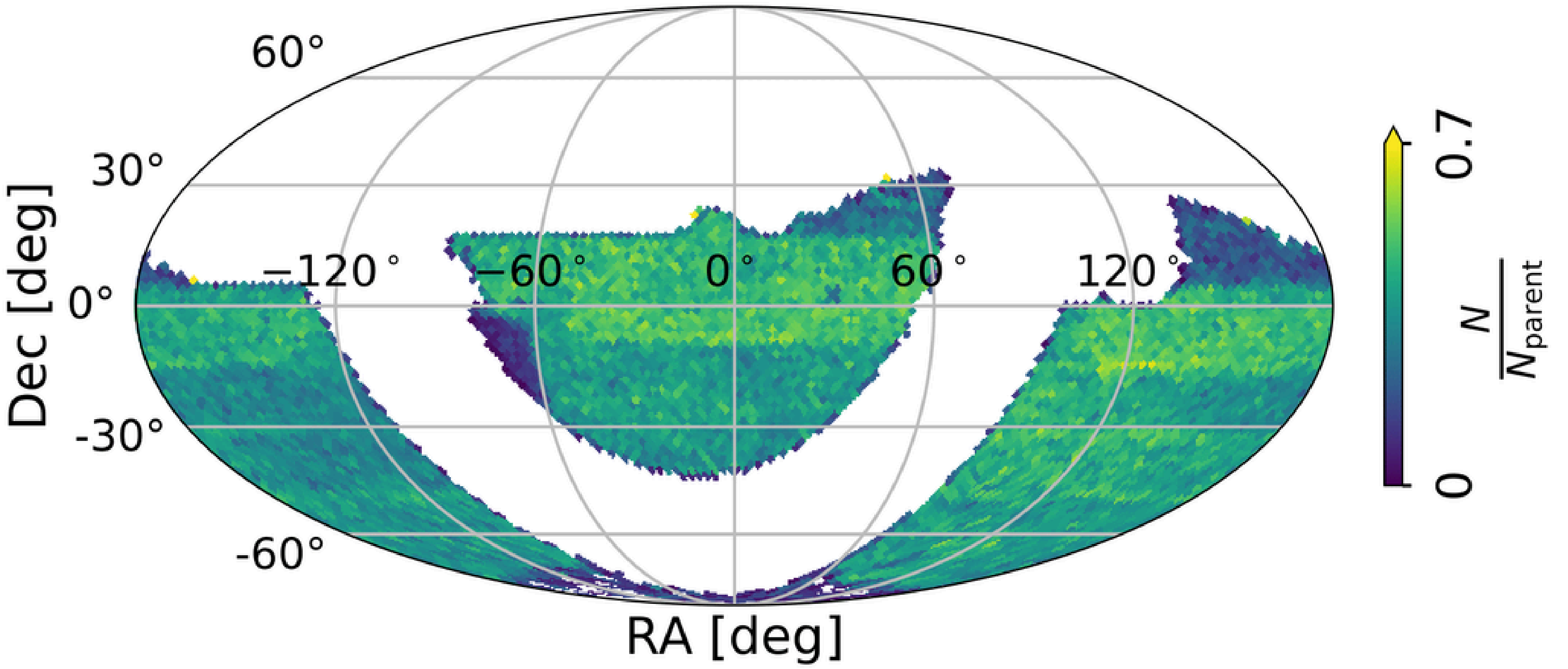
The model return the probability to be SN Ia
we select **P(SNIa)>0.5**
At the end **0.02% contamination**

Final Sample

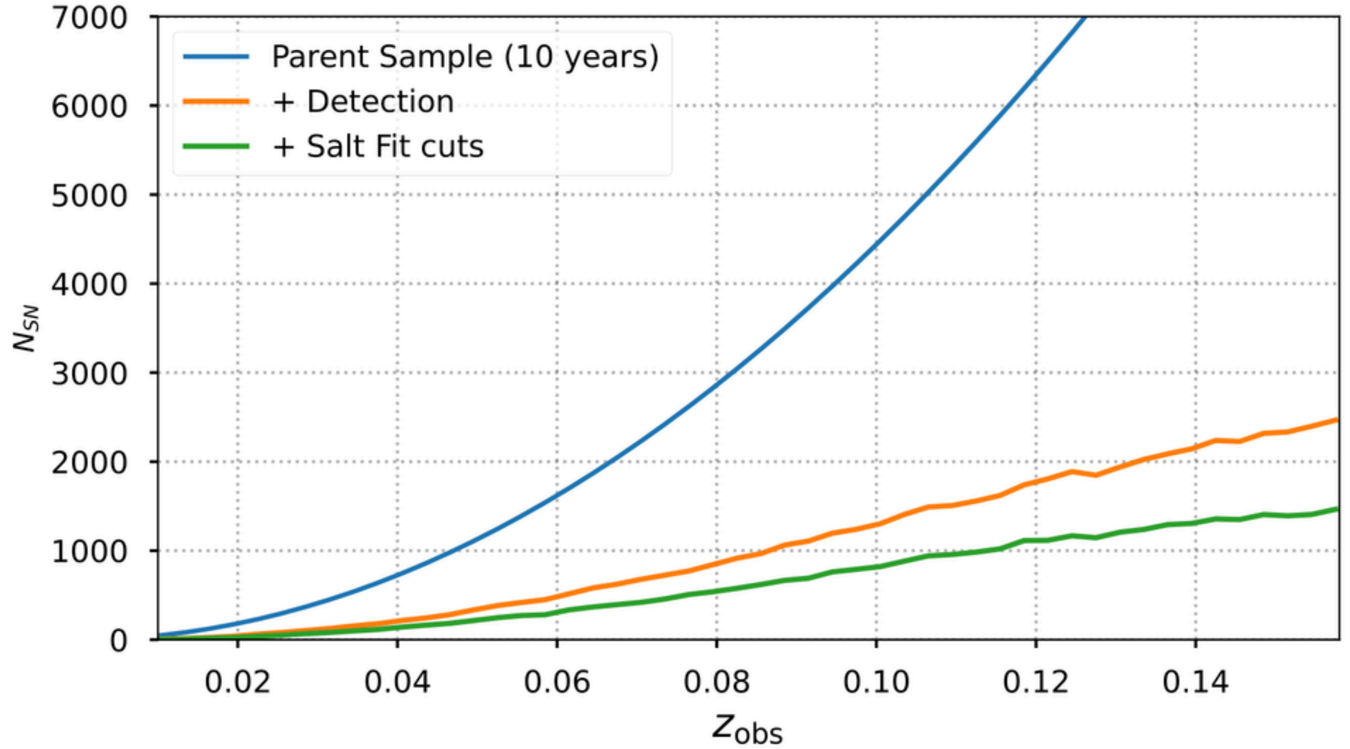
about 33k SNe with z<0.16

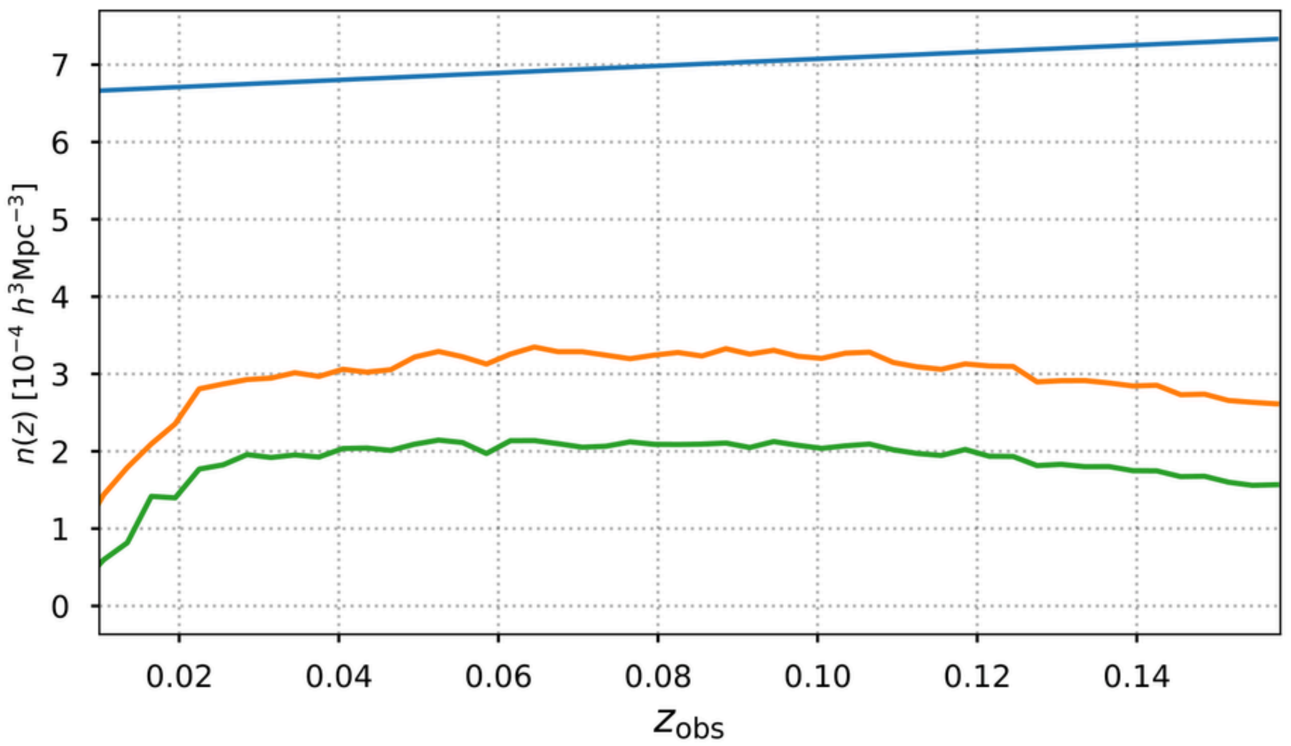
SNe surface density (top)
and completeness (bottom)





SNe redshift distribution (top)
and density vs redshift (bottom)





Velocity measurement

$$\mu = m_B - M_0 + \alpha x_1 - \beta c$$

$$\mathbf{\Theta}_{HD} = (\alpha, -\beta, -M_0)$$

$$\Delta\mu_i(\mathbf{\Theta}_{HD}) = \mu_{obs,i}(\mathbf{\Theta}_{HD}) - \mu_{\text{model},i}$$

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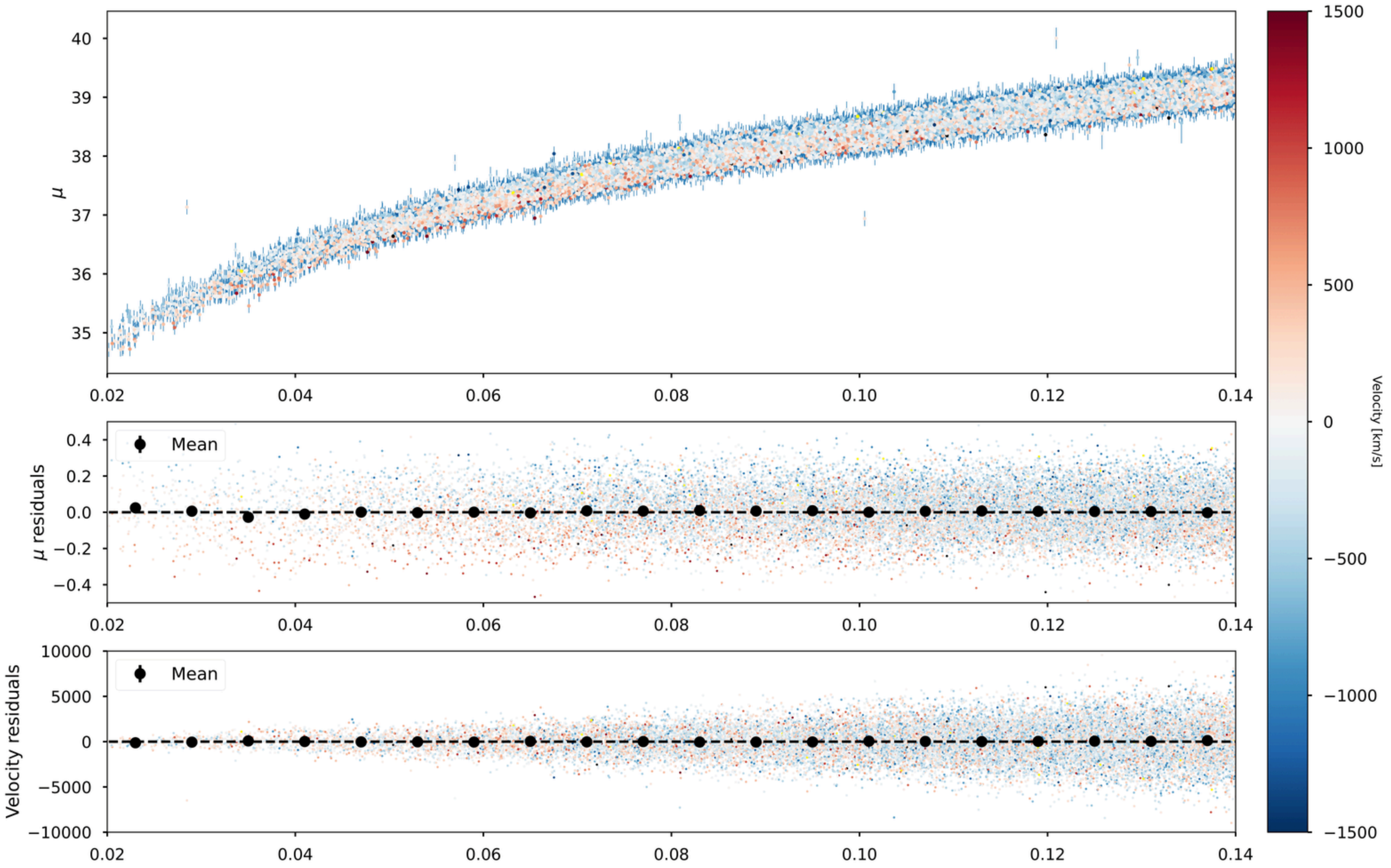
$$v_i(\boldsymbol{\Theta}_{HD}) = -\frac{\ln(10)c}{5}\left(\frac{(1+z_{obs,i})c}{H(z_{obs,i})r(z_{obs,i})} - 1\right)^{-1}\Delta\mu_i(\boldsymbol{\Theta}_{HD})$$

$$\sigma_{v,i}(\boldsymbol{\Theta}_{HD}, \sigma_M) = \frac{\ln(10)c}{5}\left(\frac{(1+z_{obs,i})c}{H(z_{obs,i})r(z_{obs,i})} - 1\right)^{-1} \times \sigma^2_{\mu,i}(\boldsymbol{\Theta}_{HD}, \sigma_M).$$



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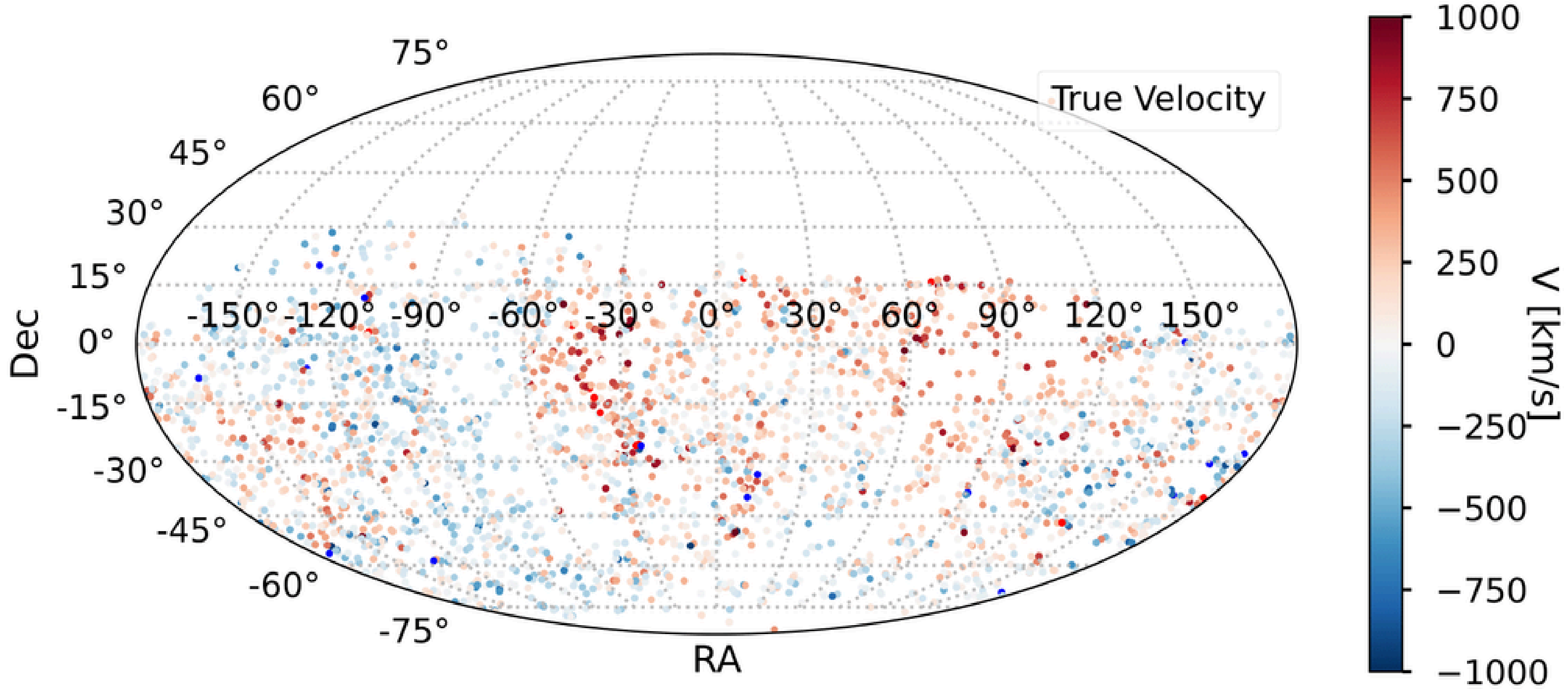

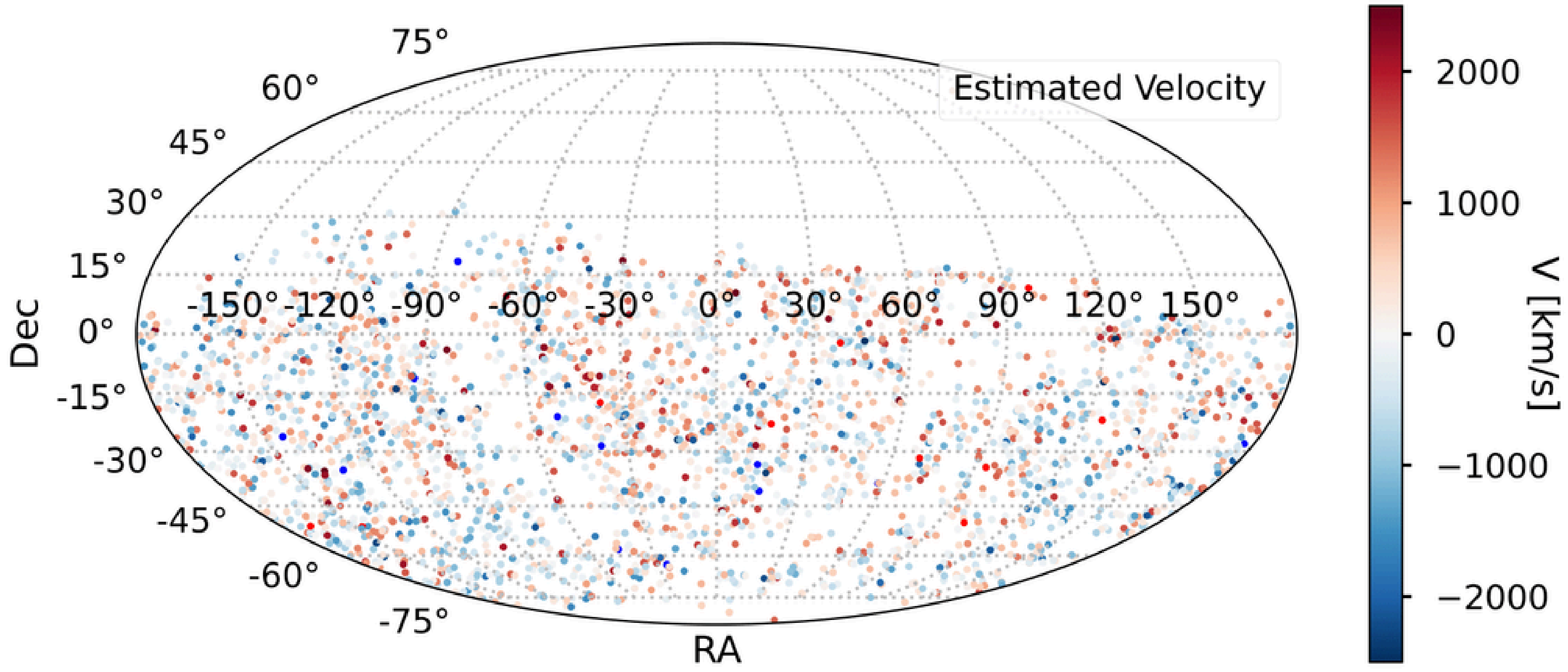

Likelihood

$$L(f\sigma_8, \mathbf{\Theta}, \mathbf{\Theta}_{\rm HD}) = (2\pi)^{-\frac{n}{2}} |C(f\sigma_8, \mathbf{\Theta}, \mathbf{\Theta}_{\rm HD})|^{-\frac{1}{2}}$$
$$\times \exp\left[-\frac{1}{2}\mathbf{v}^T(\mathbf{\Theta}_{\rm HD}) C(f\sigma_8, \mathbf{\Theta}, \mathbf{\Theta}_{\rm HD}) \mathbf{v}^T(\mathbf{\Theta}_{\rm HD})\right],$$

$$C_{ij}(f\sigma_8, \mathbf{\Theta}, \mathbf{\Theta}_{\rm HD}) = C_{ij}^{vv}(f\sigma_8, \sigma_u) + [\sigma_v^2 + \sigma_{v,i}^2(\mathbf{\Theta_{HD}}, \sigma_m)]\delta_{i,j}^K,$$

We use PVs as the data vector and we fit fσ8 using Gaussian likelihood and a covariance rescaled for the growth rate value from Uchuu.

Covariance Matrix implemented in FLIP (Field Level Inference Package) https://github.com/corentinravoux/flip

Likelihood

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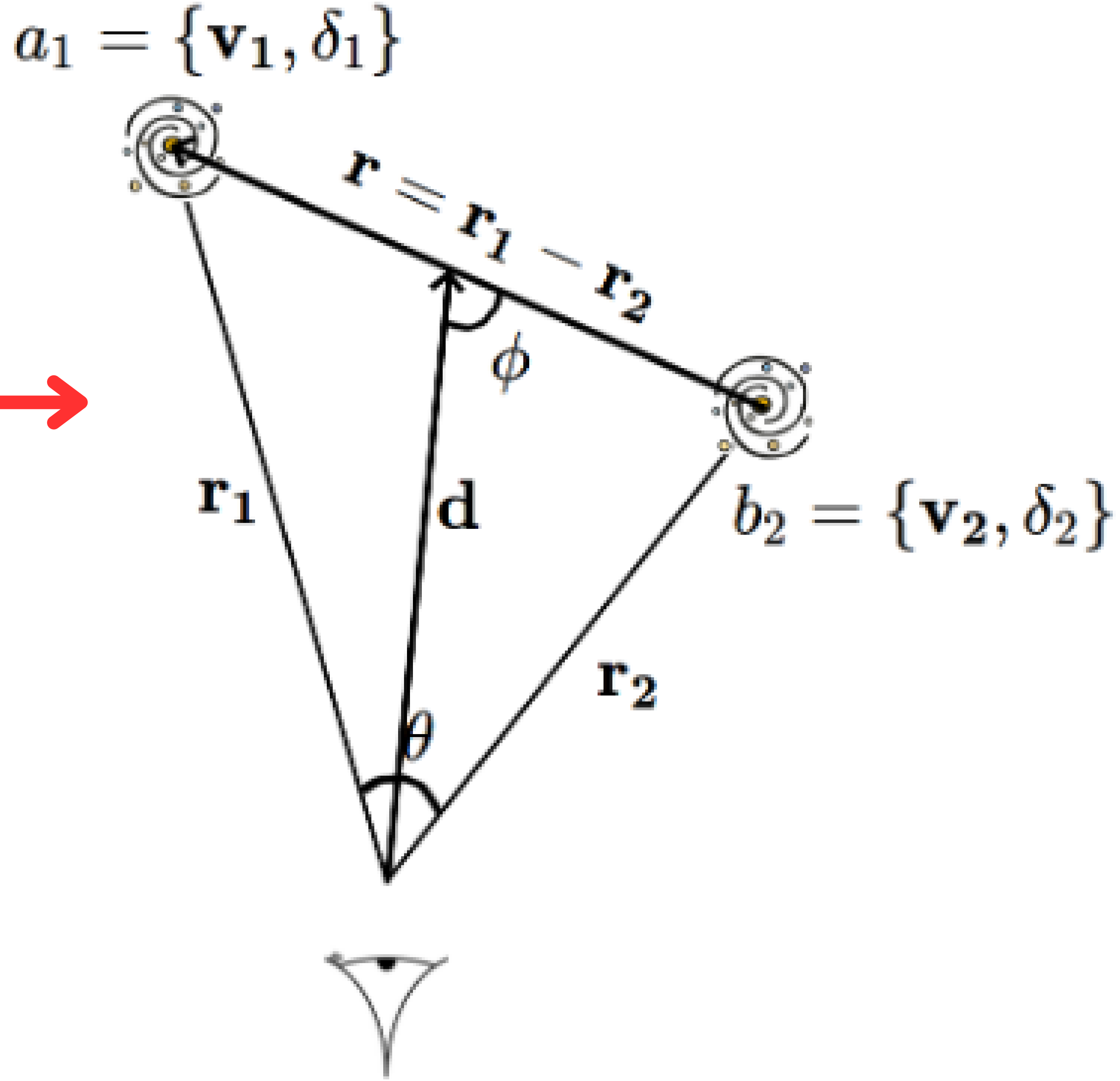

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credit: Corentin Ravoux

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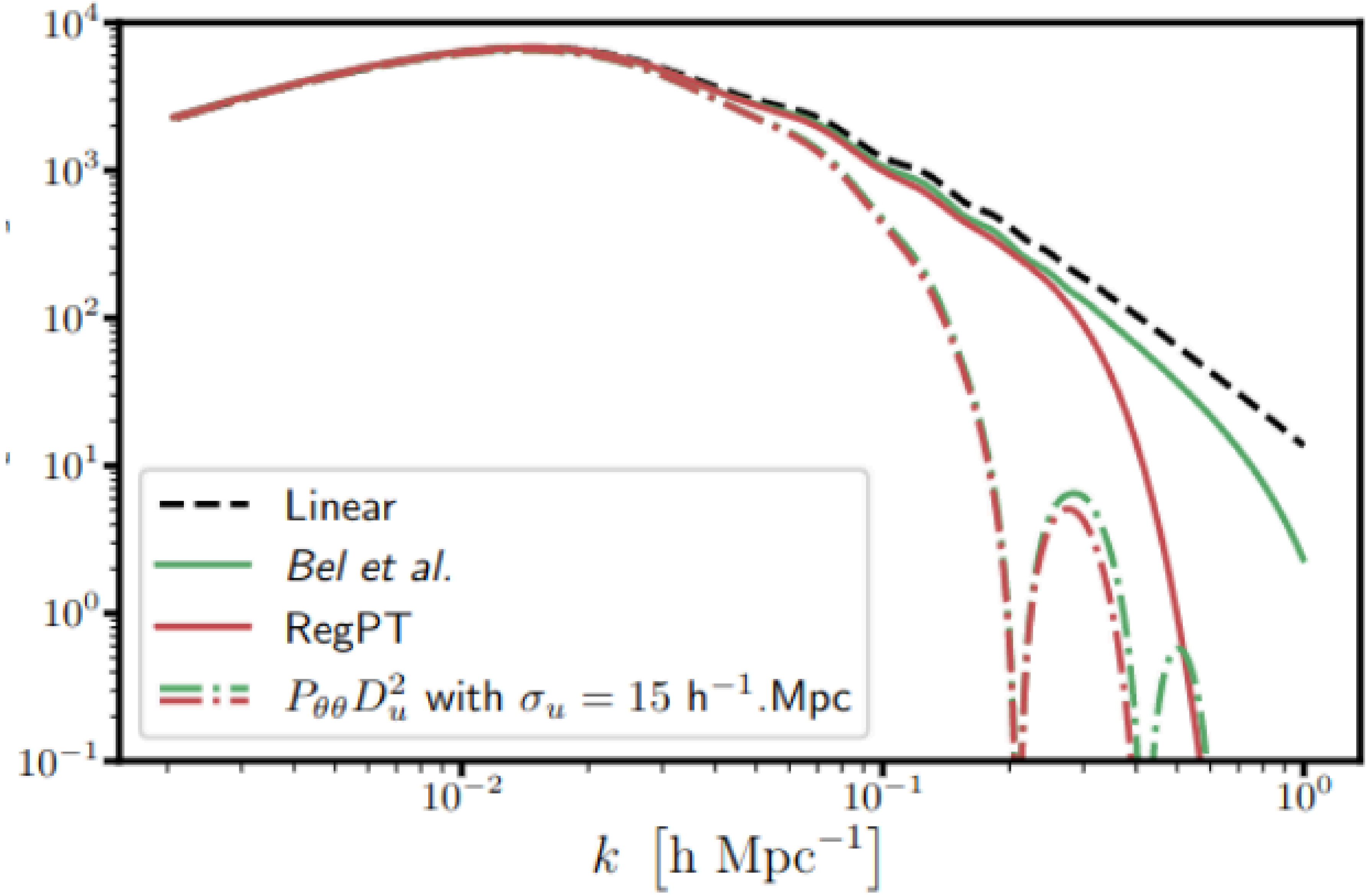
Covariance

$$C_{ij}^{vv} = \frac{H_0^2}{2\pi}\frac{(f\sigma_8)^2}{(f\sigma_8)^2_{fid}}\int f^2_{fid}P_{\theta\theta}(k)D_u^2(k)W(k;\mathbf{x}_i,\mathbf{x}_j)dk$$

Koda et al 2014

$$D_u(k) = \frac{sin(k\sigma_u)}{(k\sigma_u)}$$



Carreres et al. 2023

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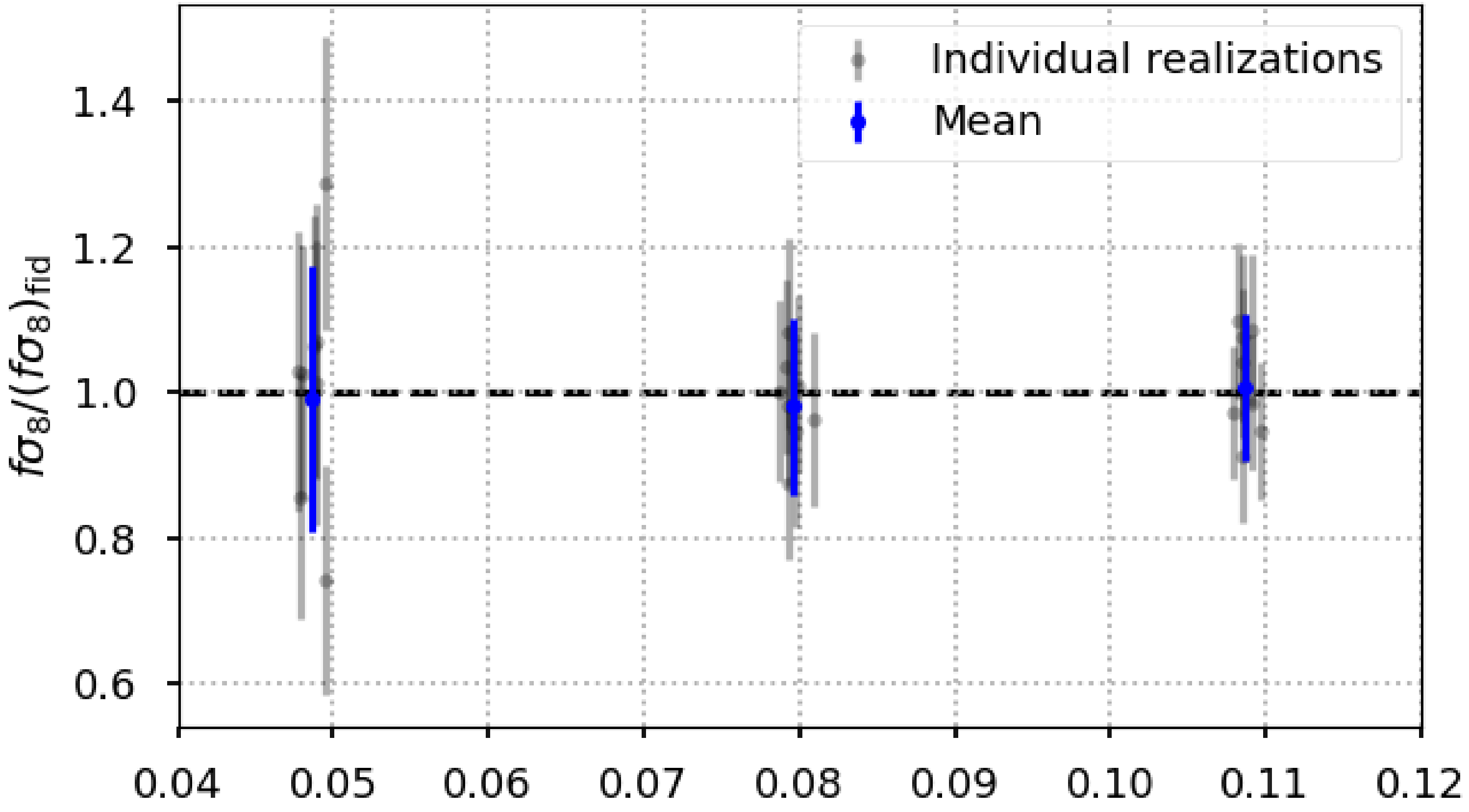
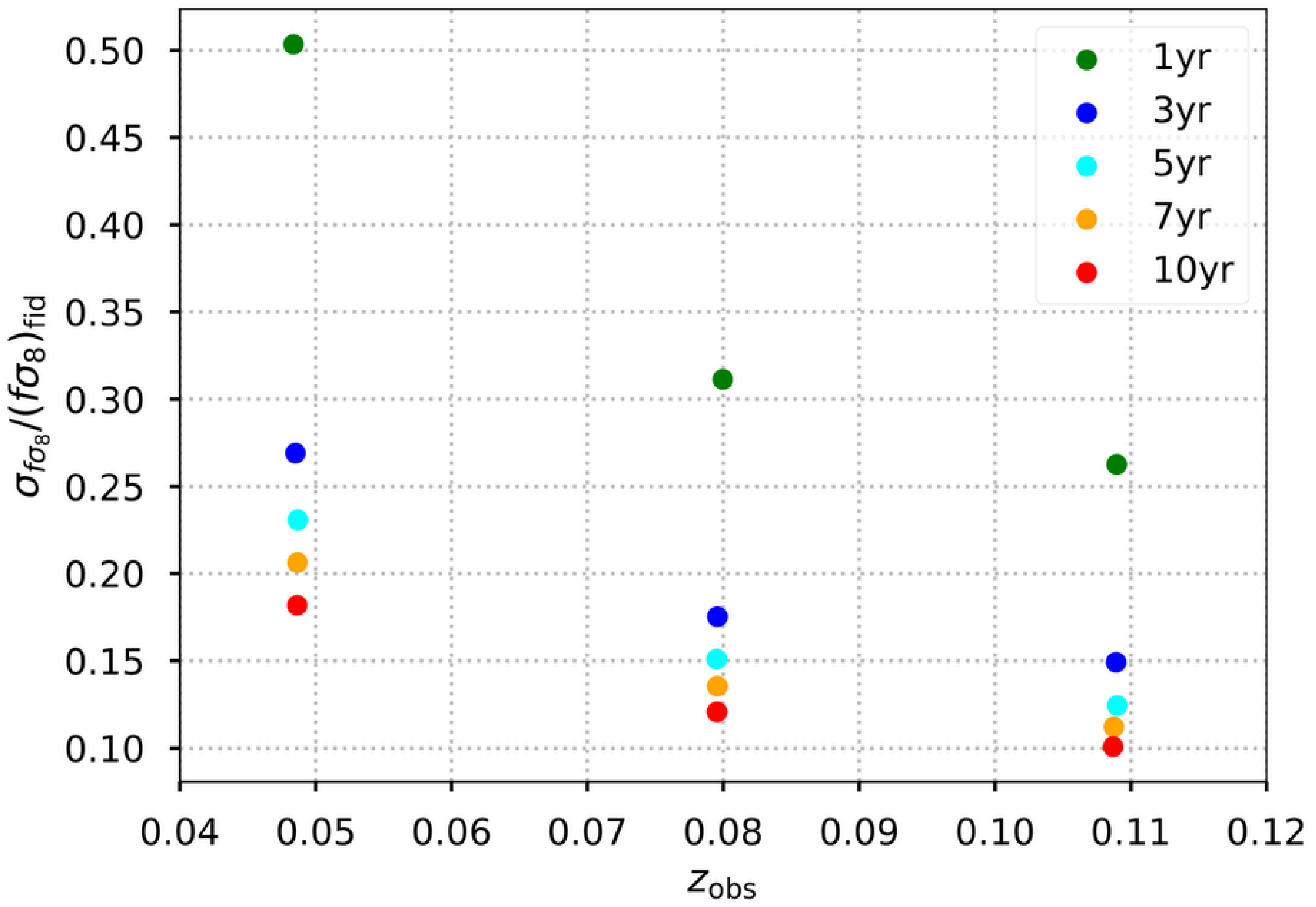
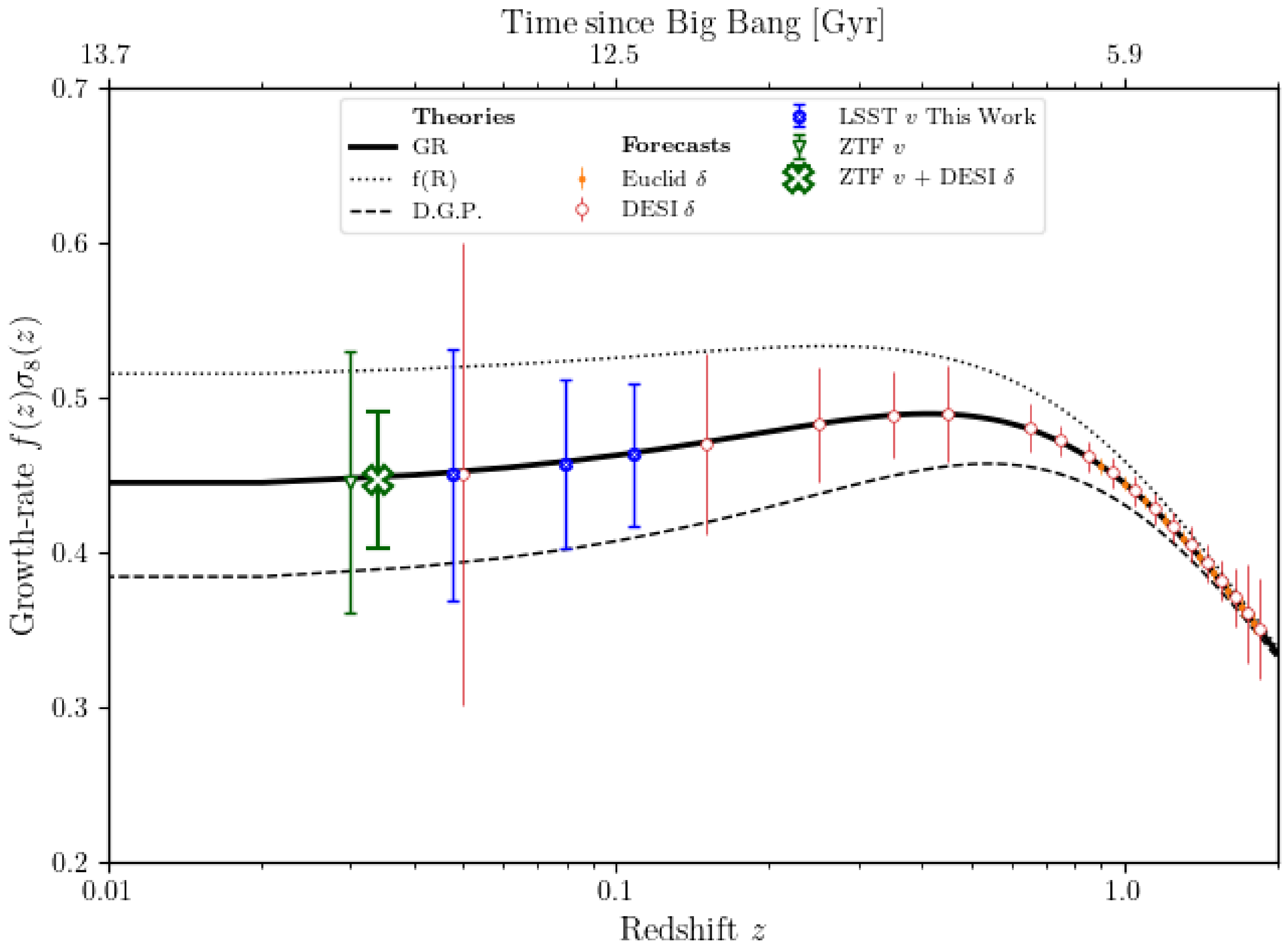
Results





DESI PV: about 20% up to z = 0.1 (Saulder et al. 2023)
ZTF PV: about 19% up to z= 0.06 (Carreres et al 2023)



ZTF: Carreres et al. 2023
DESI: DESI Collaboration 2016a
Euclid: Amendola et al. 2018

Conclusions

- First complete simulation of LSST 10yr SNe sample at low redshift
- Contamination seems to not bias when below 2%, but increase the error on final constraints
- LSST combined with DESI & 4MOST will be great to measure the growth rate of structures (attention to the systematics!)
- Future works:
  - improve model covariance (new redshift dependent model coming soon)
  - include classifier probability in the likelihood


THANK YOU !!