

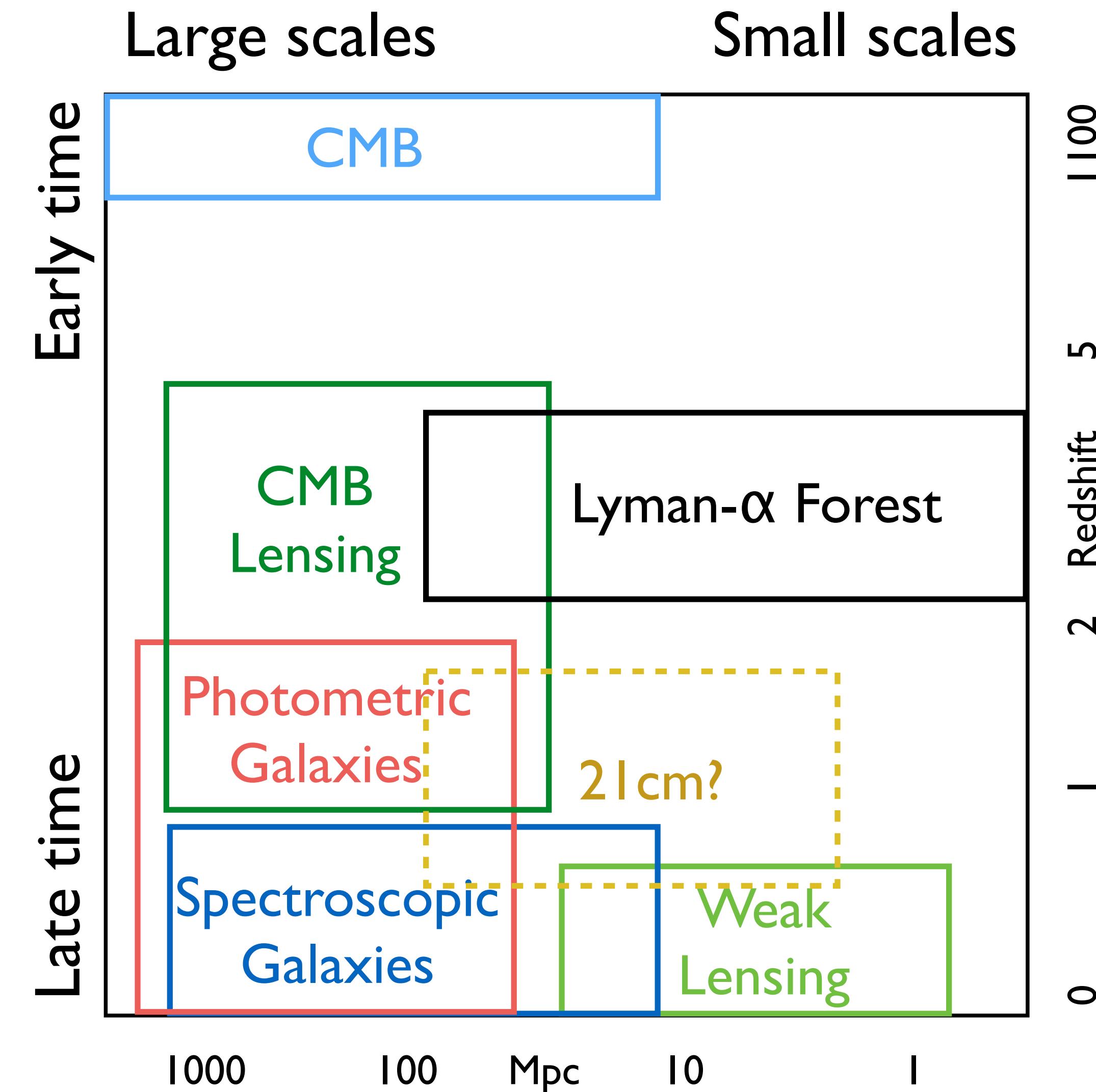
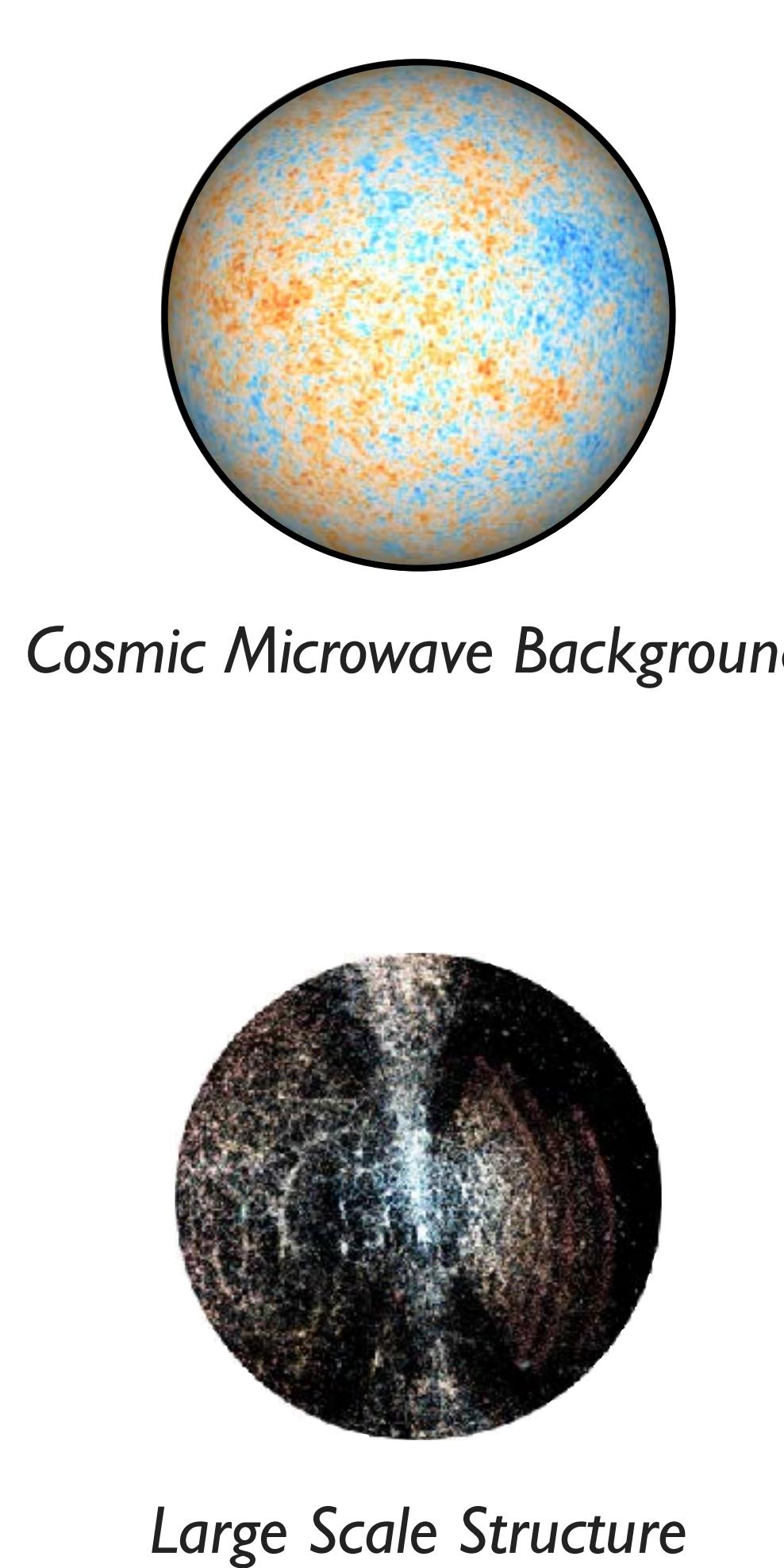
Survey Cosmology in the Rubin Era

Hiranya V. Peiris

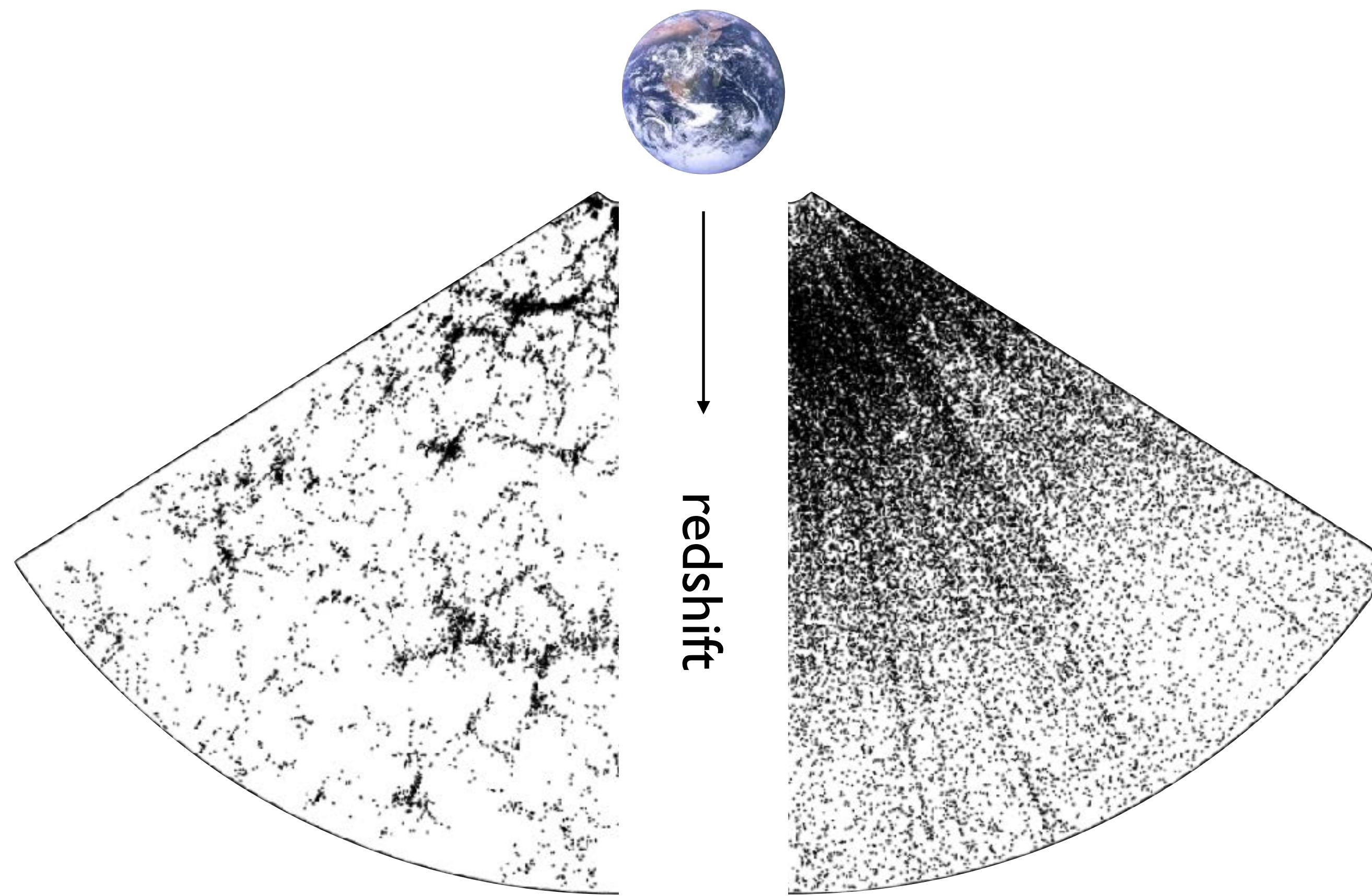
UCL and Oskar Klein Centre Stockholm



Electromagnetic cosmological probes in the next decade



Observational frontier with galaxy surveys



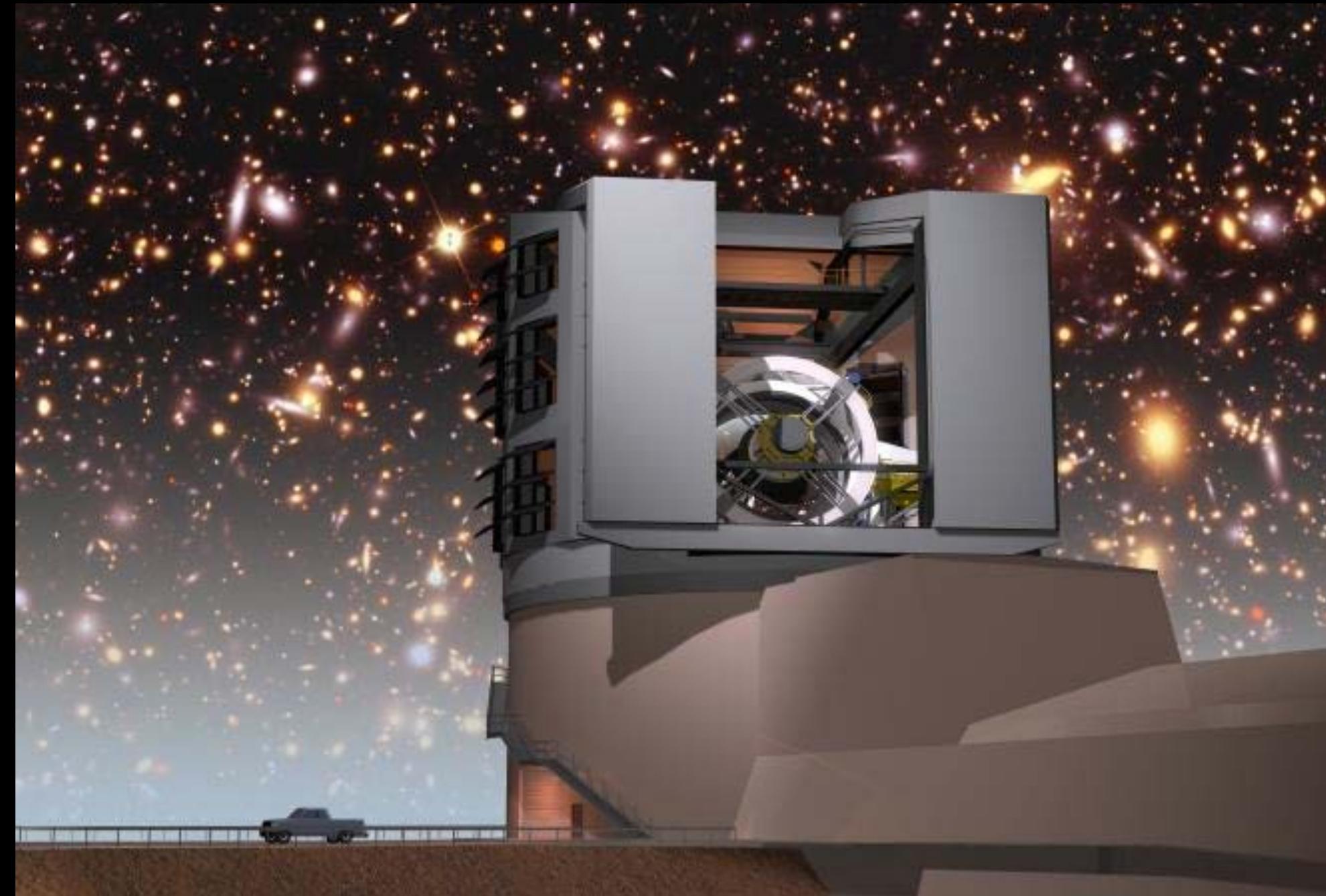
Spectroscopic
DESI (ground)

Photometric
LSST (ground), Euclid (space), Roman (space)



LSST: survey of 18,000 sq deg
(half the sky)

Dark matter-Dark energy Solar system inventory



37 billion objects in space and time
30 trillion measurements
60 PB raw data (20 TB/night)



“Movie of the Universe”



Mapping the Milky Way

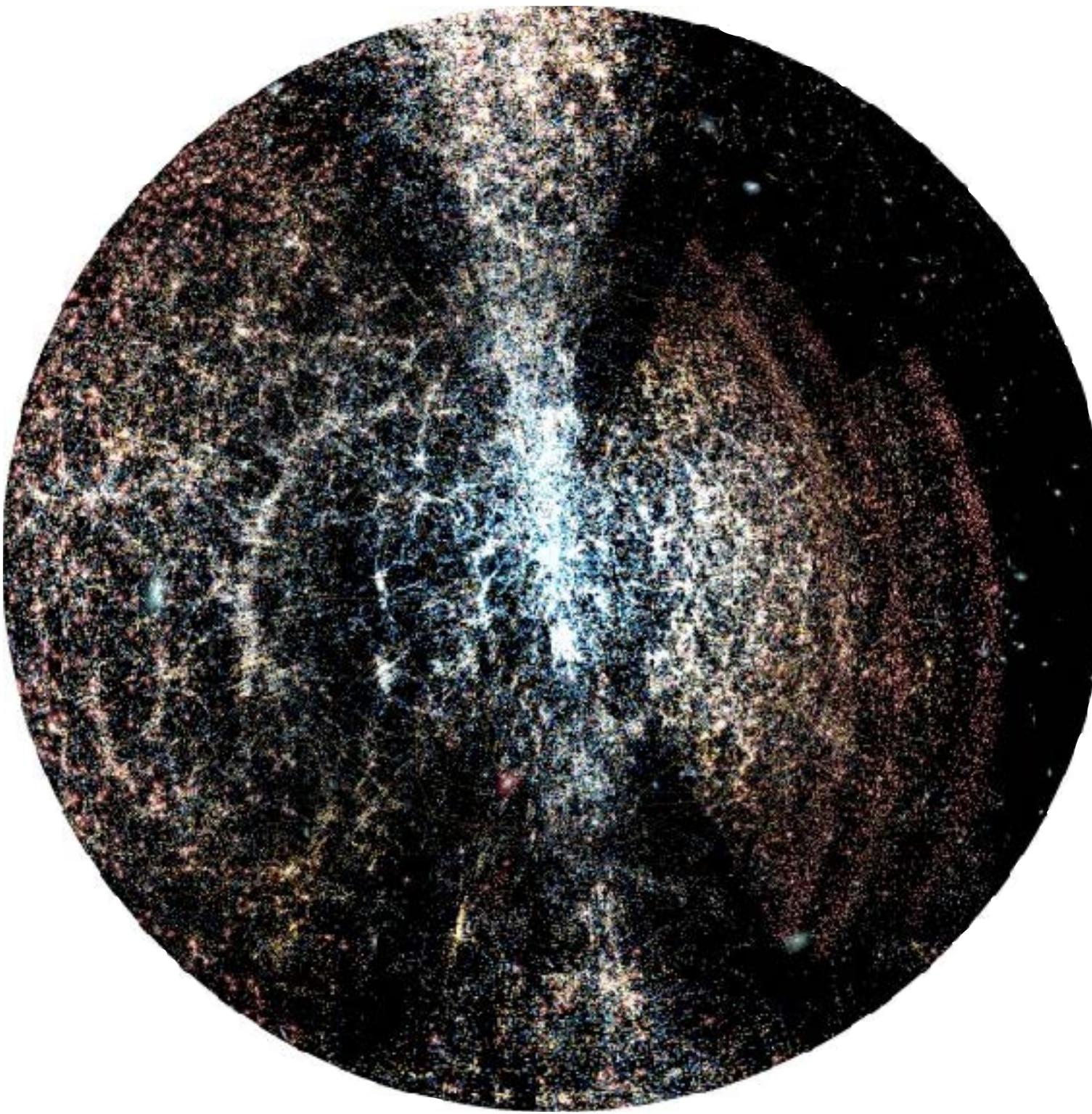


How should we compare



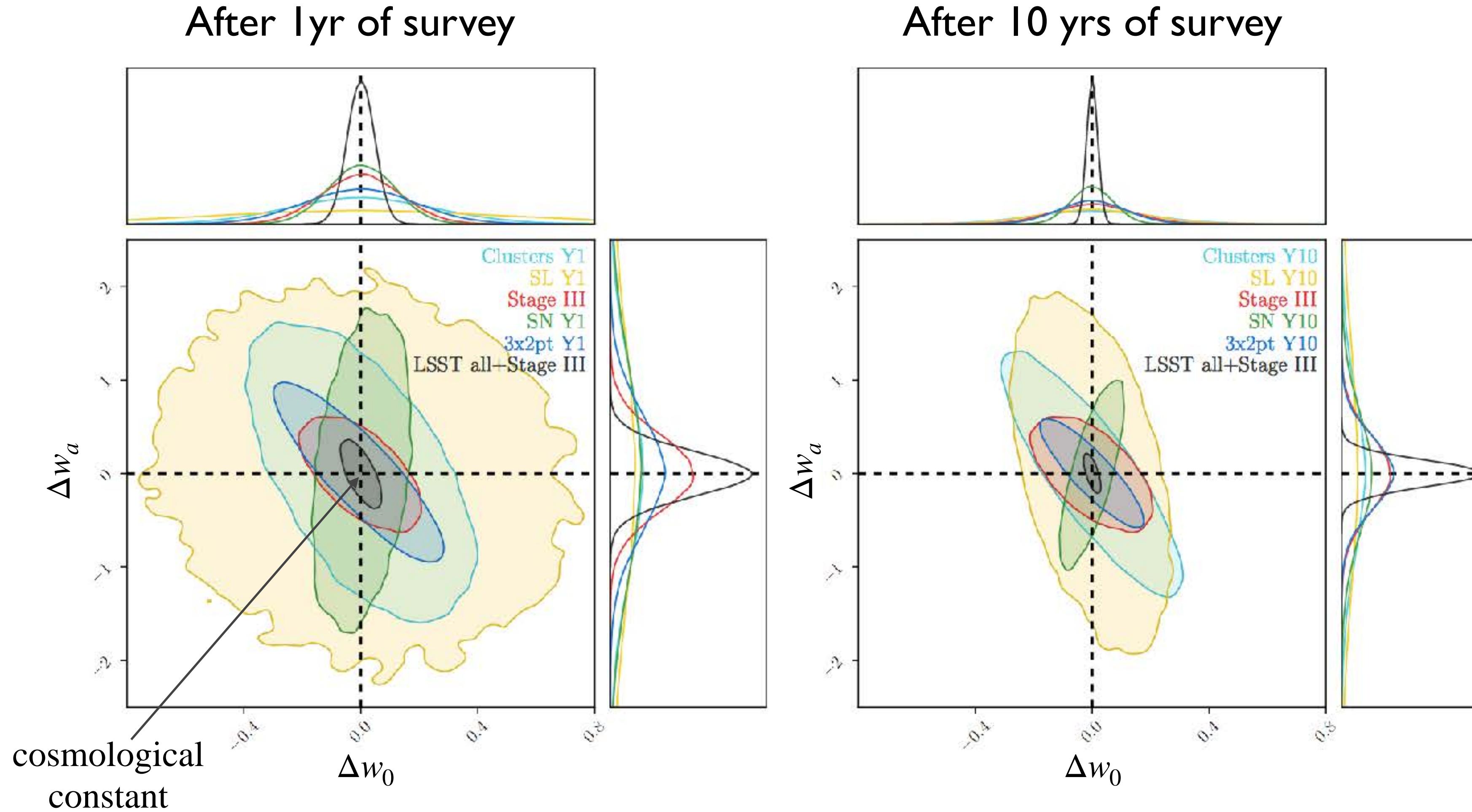
Theory

vs



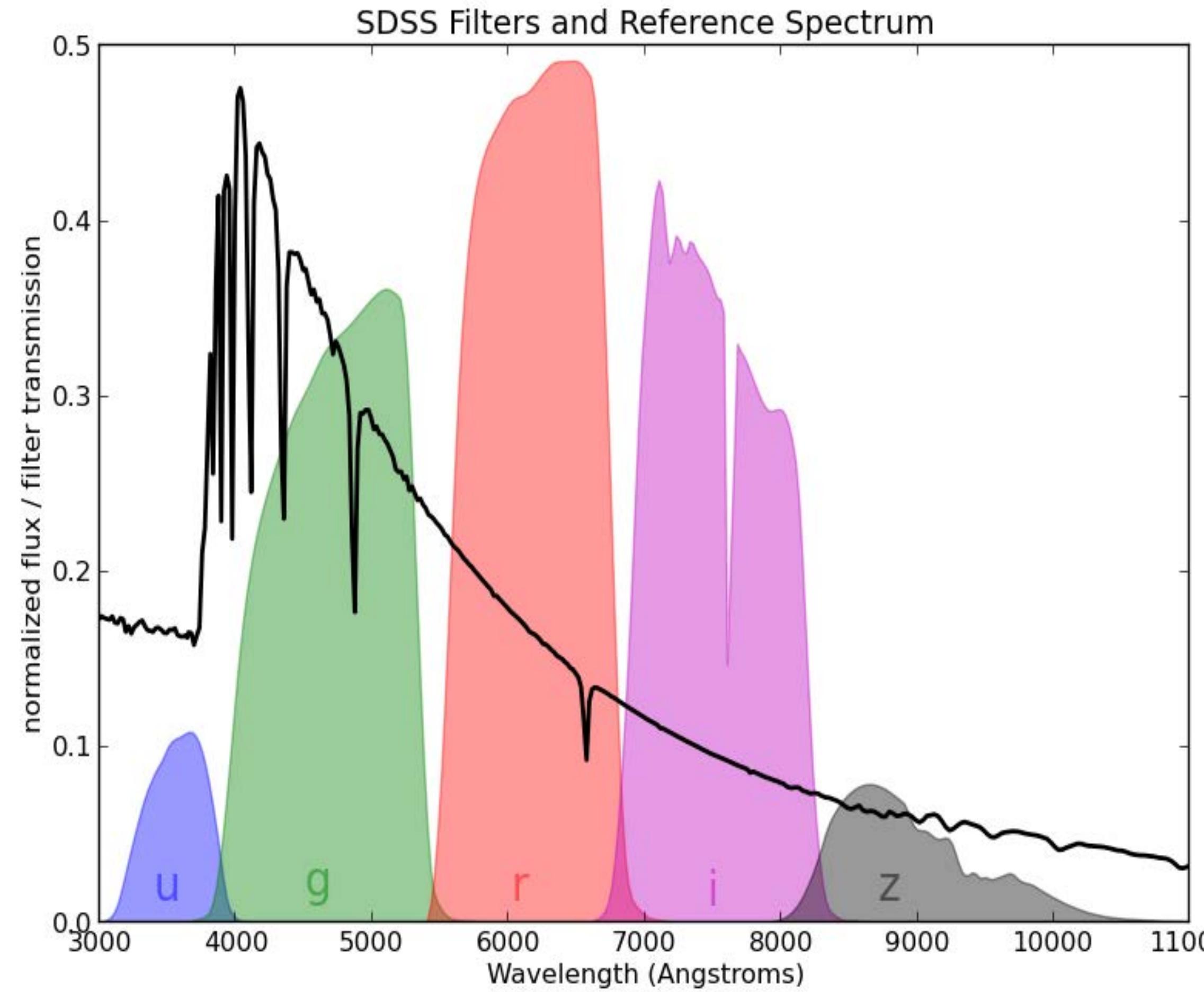
Data?

LSST and Dark Energy Science



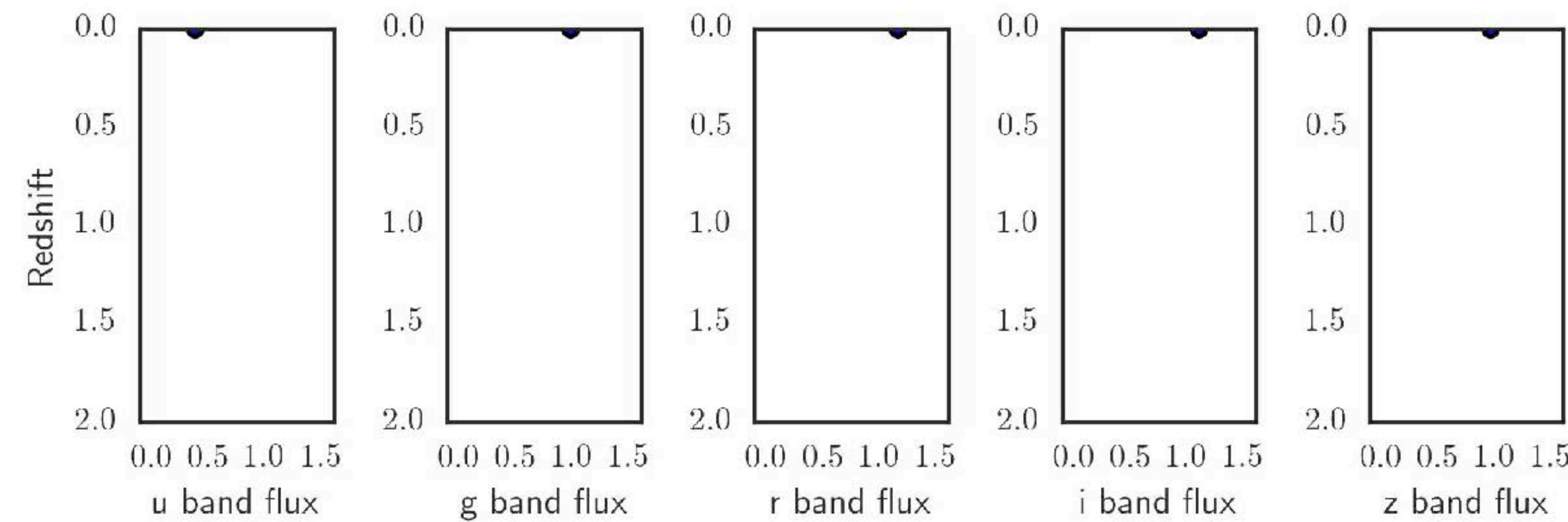
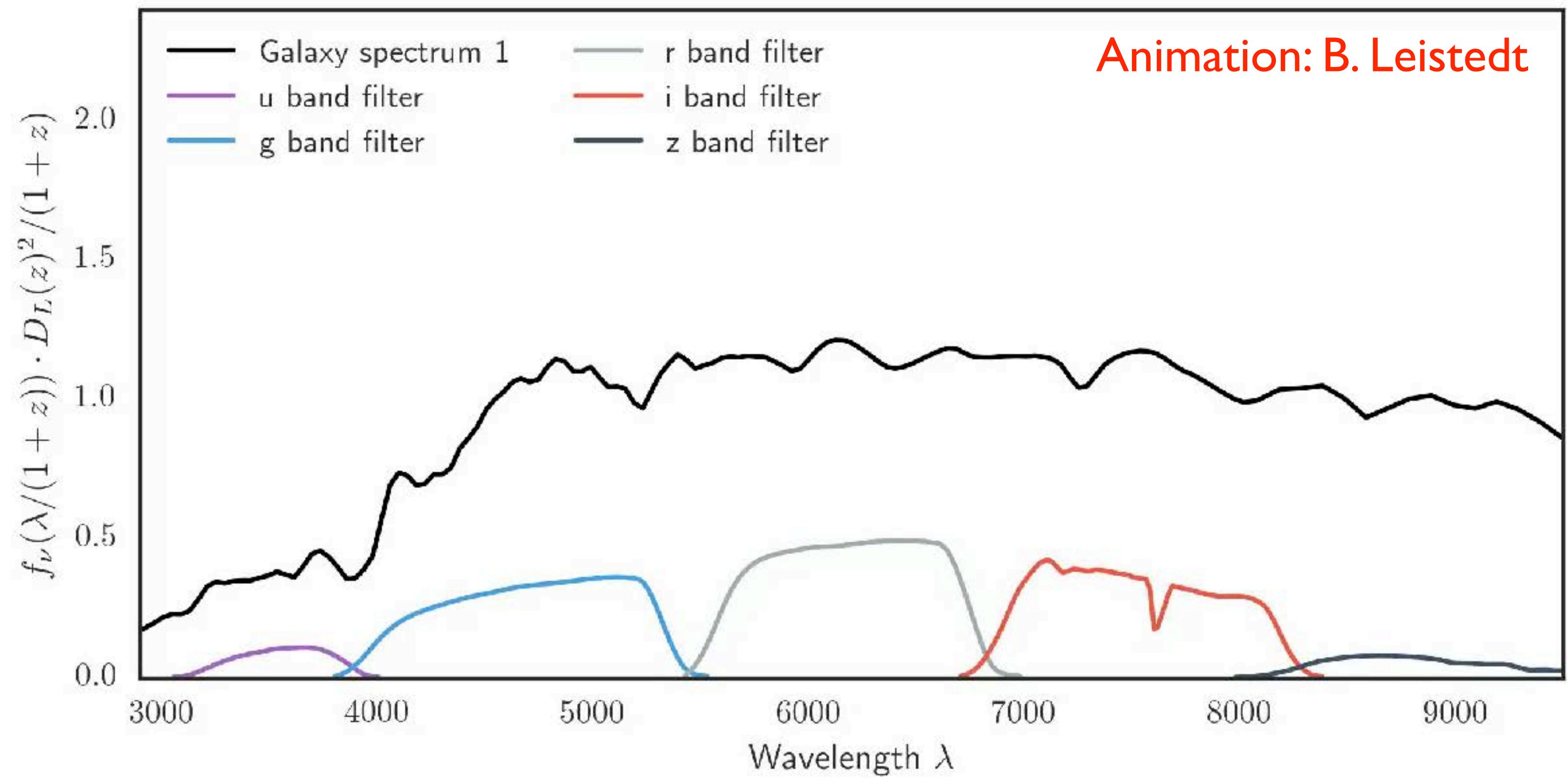
Measuring if / how dark energy evolves with time

Spectroscopic vs photometric samples

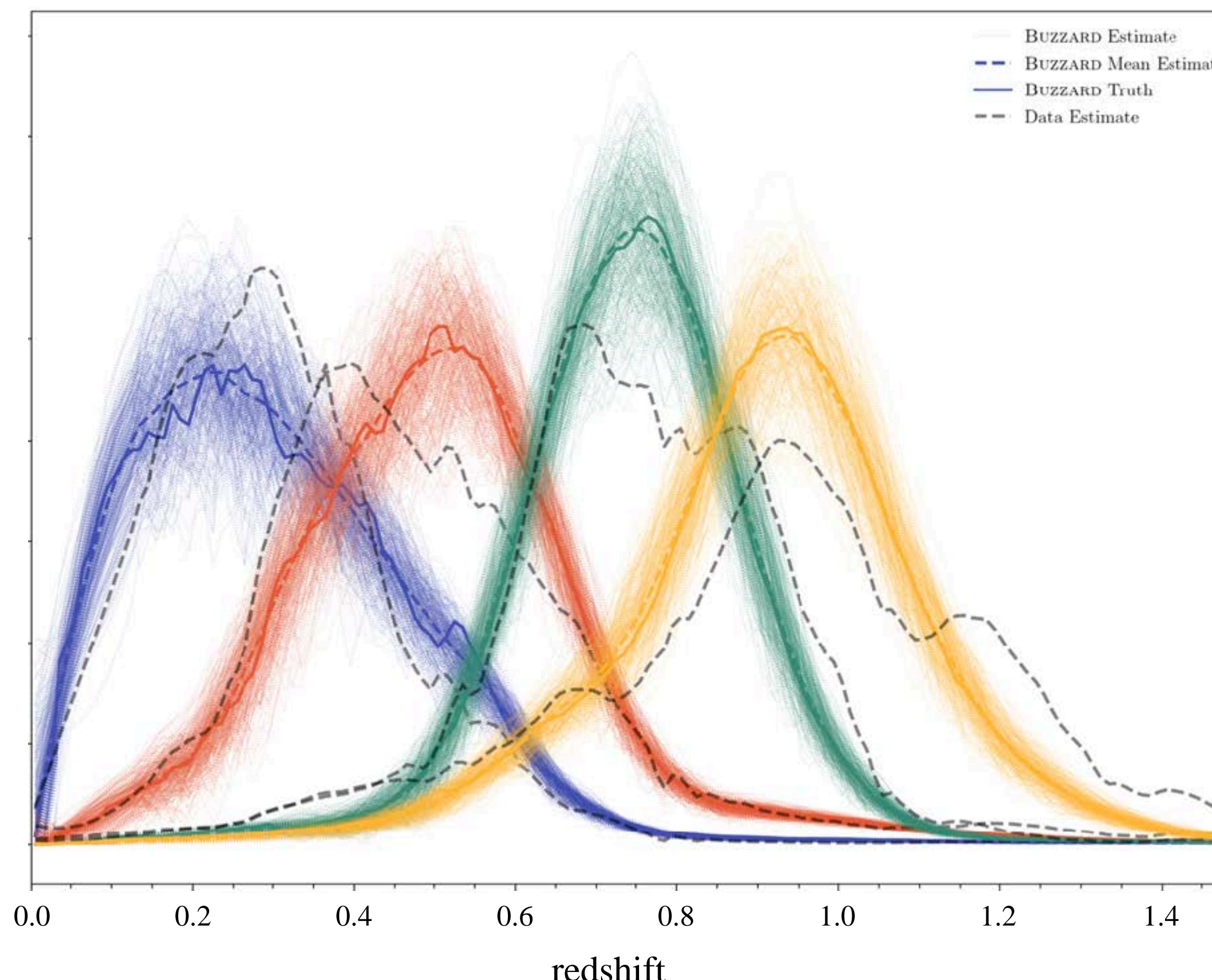


Photometric catalogues require **redshift estimation**

Animation: B. Leistedt



$N(z)$: redshift distribution inference is challenging



- Spectroscopic training / calibration samples are:
 - ▶ not representative of photometric catalogues (due to brighter flux limits and population evolution)
 - ▶ heterogeneous and contain difficult-to-model selection effects
- Introduces biases which are difficult to mitigate at required precision

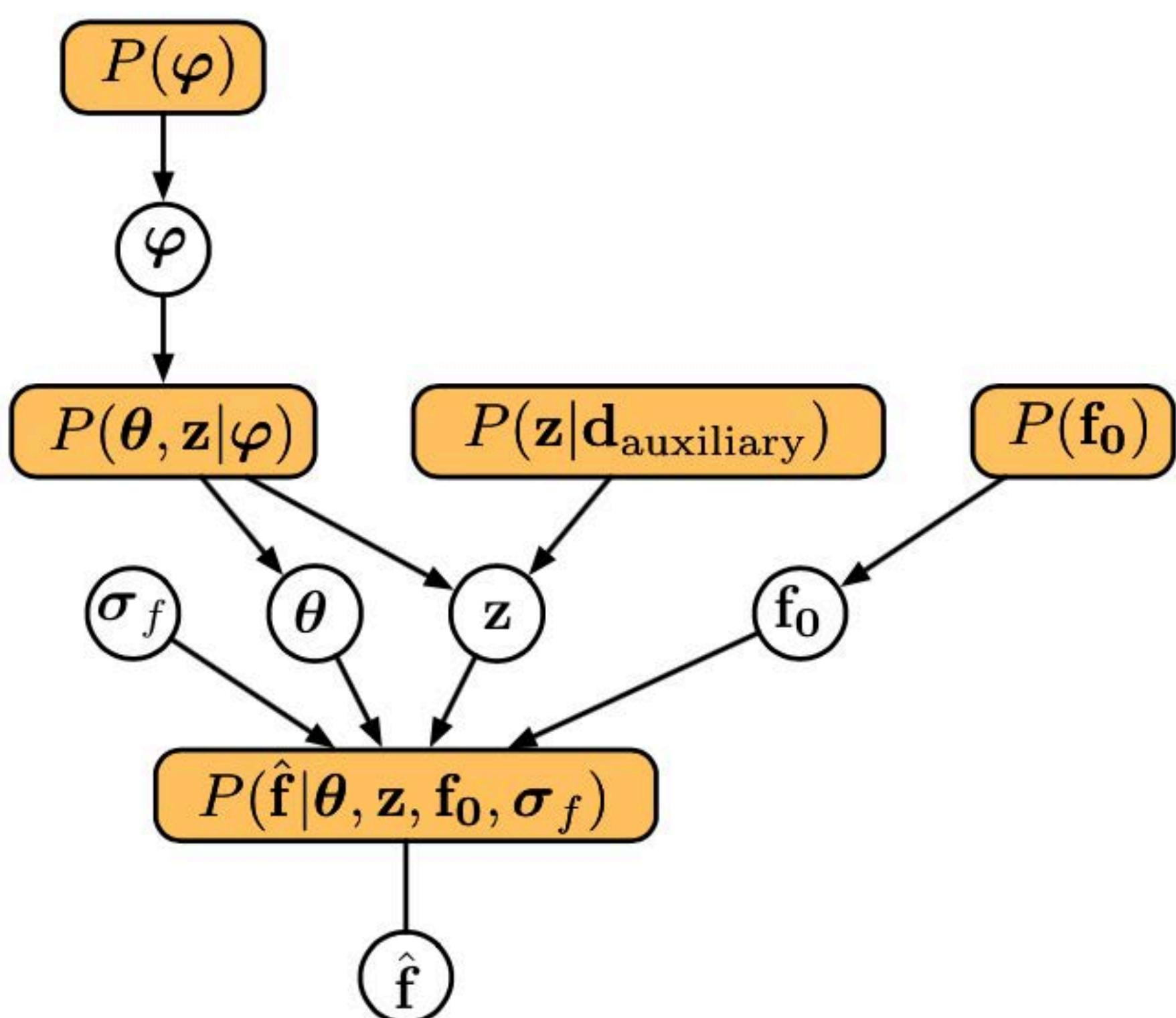
Forward modelling for $n(z)$

$n(z)$: integral over **selection** x **data model** x **population model**

$$n(z) \equiv P(z|S)$$
$$= \frac{1}{P(S)} \int \left[\iint P(S|\hat{\mathbf{f}}, \theta, z) P(\hat{\mathbf{f}}|\theta, z, \sigma) P(\sigma) d\hat{\mathbf{f}} d\sigma \right] P(\theta, z) d\theta$$

Redshift distribution inference for static cosmology

- **Key idea:** high-dimensional Bayesian hierarchical model with machine-learned parts.



- Neural network emulation of FSPPS population synthesis model, describing realistic galaxy populations (*replace templates*).
- Flexible NN-parameterised probability density models (e.g. normalising flows) to describe population prior and selection effects.

Forward modelling for $n(z)$

$n(z)$: integral over **selection** x **data model** x **population model**

$$\begin{aligned} n(z) &\equiv P(z|S) \\ &= \frac{1}{P(S)} \int \left[\iint P(S|\hat{\mathbf{f}}, \theta, z) P(\hat{\mathbf{f}}|\theta, z, \sigma) P(\sigma) d\hat{\mathbf{f}} d\sigma \right] P(\theta, z) d\theta \end{aligned}$$

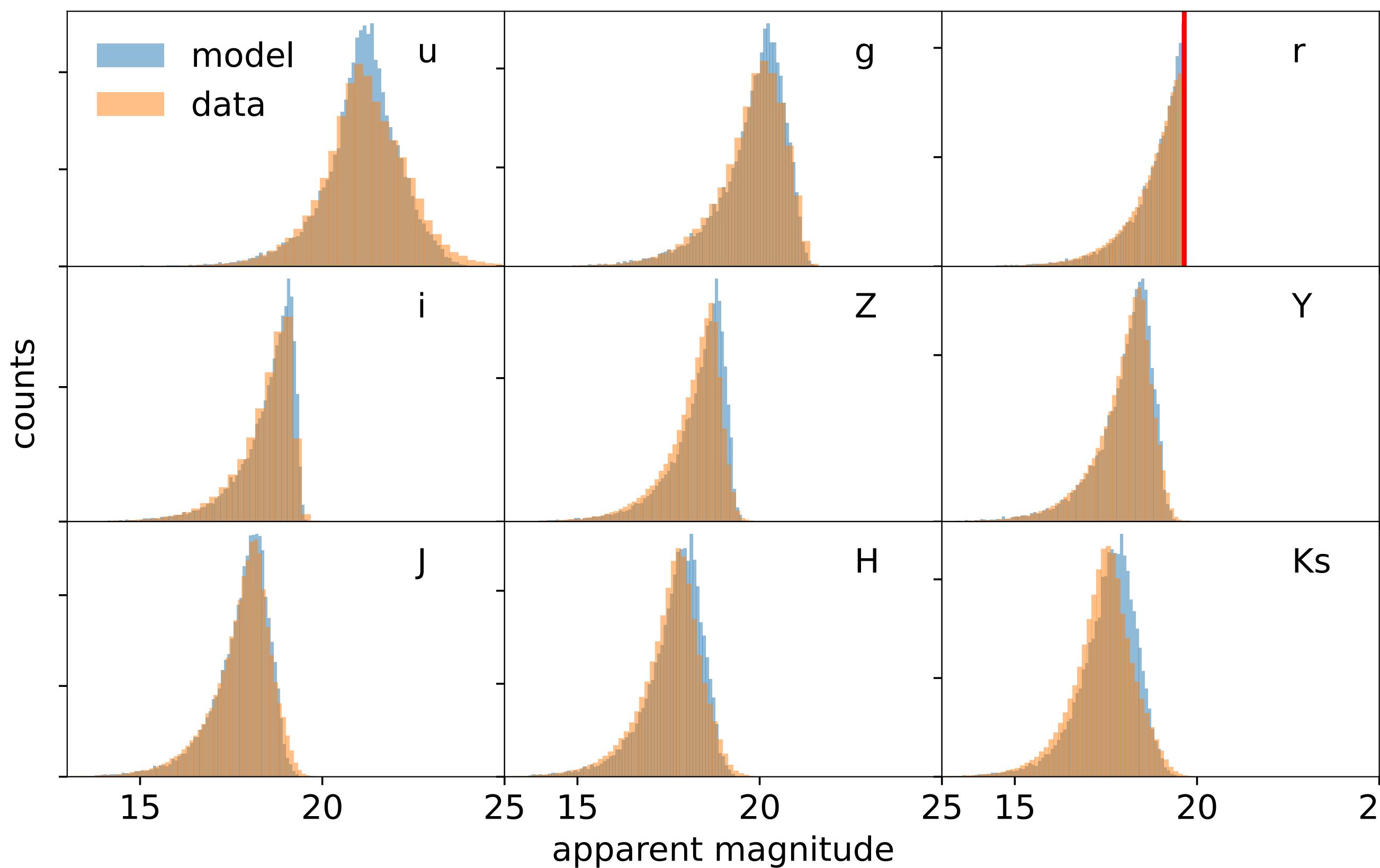
Advantages:

- Does not rely on spectroscopic redshift calibration — spec-z catalogues not representative of photometric catalogues (due to brighter flux limits and population evolution)
- Auxiliary data (spec-z, extra surveys) can be included seamlessly (extended data vector or extra priors for objects with extra information)
- Connects cosmology with galaxy evolution

“Turns photo-z back into an astrophysics problem” — Justin Alsing

Broadband data: does it work?

Simulated galaxy population (encoding galaxy evolution calibrated to observations), combined with data model and selection cuts, should be able to predict redshift distribution.

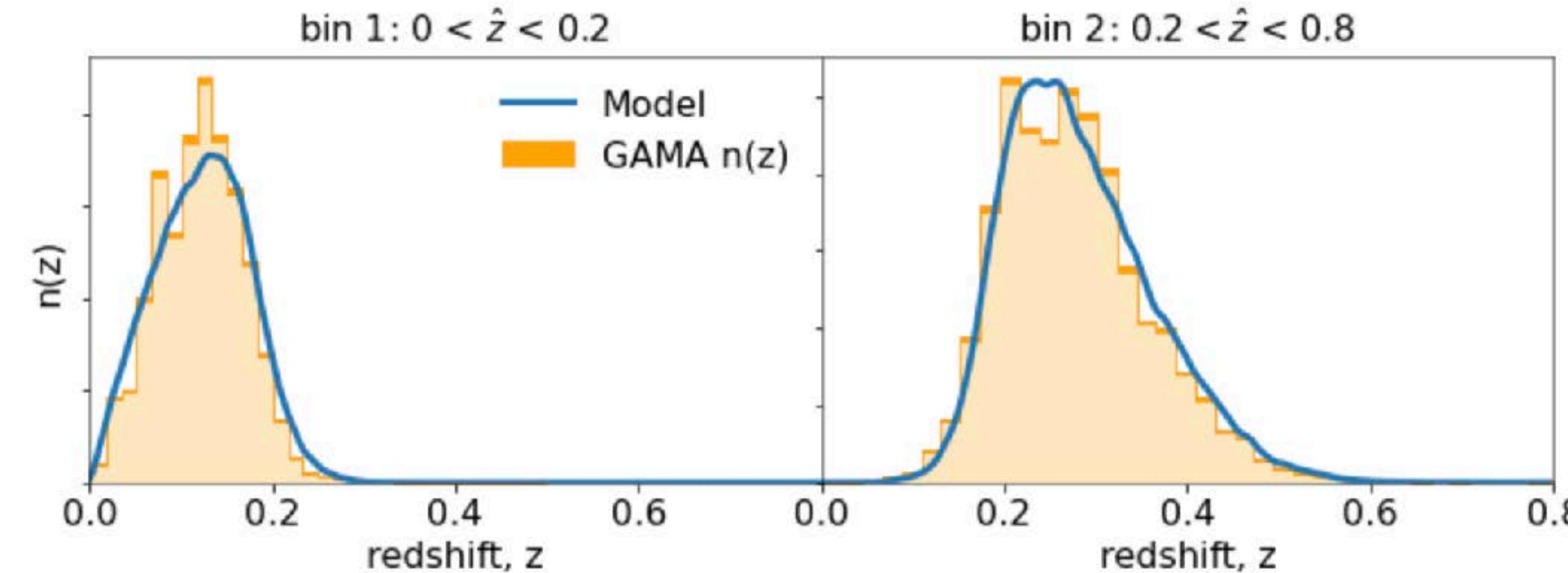


Validation: two spectroscopic surveys with straightforward selection cuts

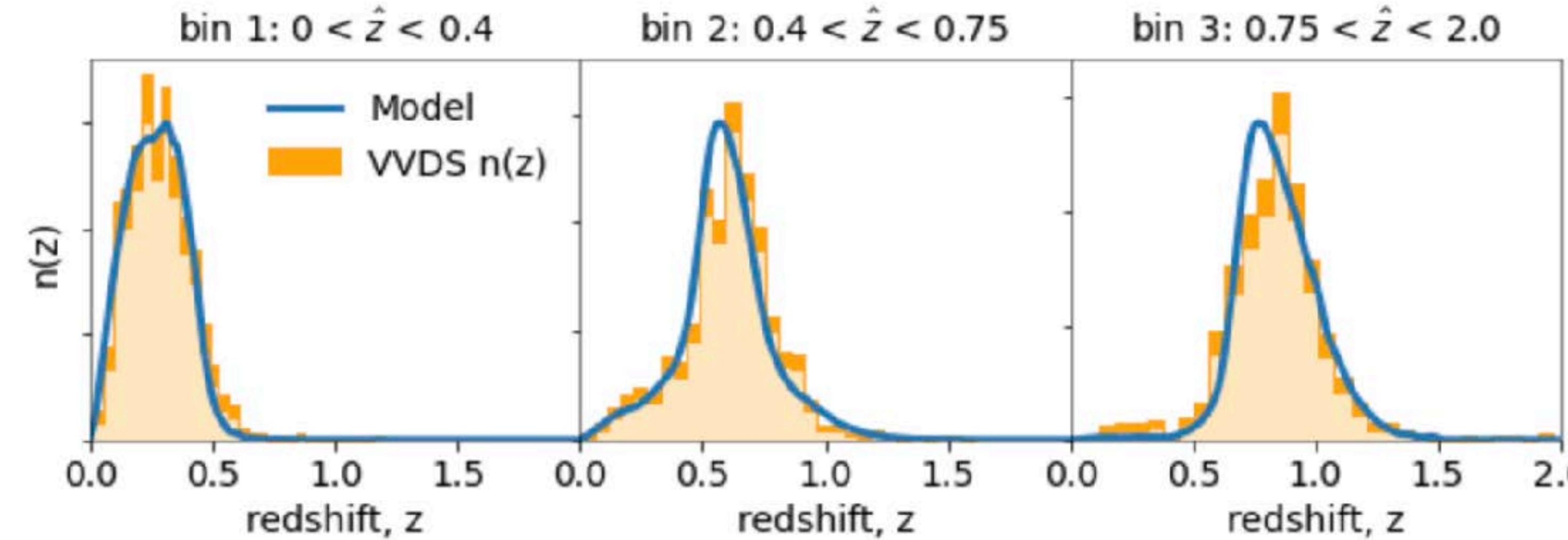
- I. GAMA (ugriZYJHKs): $r < 19.65, (J-Ks) > 0.01$
2. VVDS (UBVRI): $I < 22.5$, star-galaxy separation done at level of spectra

Validation with broadband data

GAMA n(z)
tomography
population model X
data model X selection



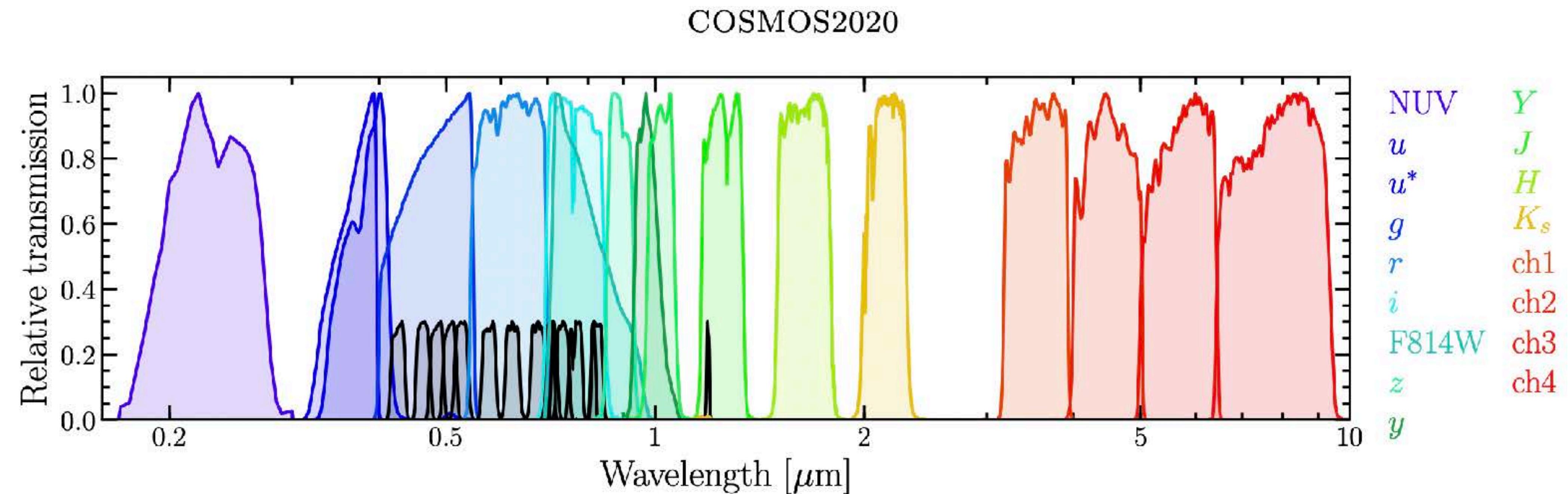
VVDS n(z)
tomography
population model X
data model X selection



Baseline model $n(z)$ bias < 0.01 before parameter inference (no data!)



Narrow-band data: validation with COSMOS2020

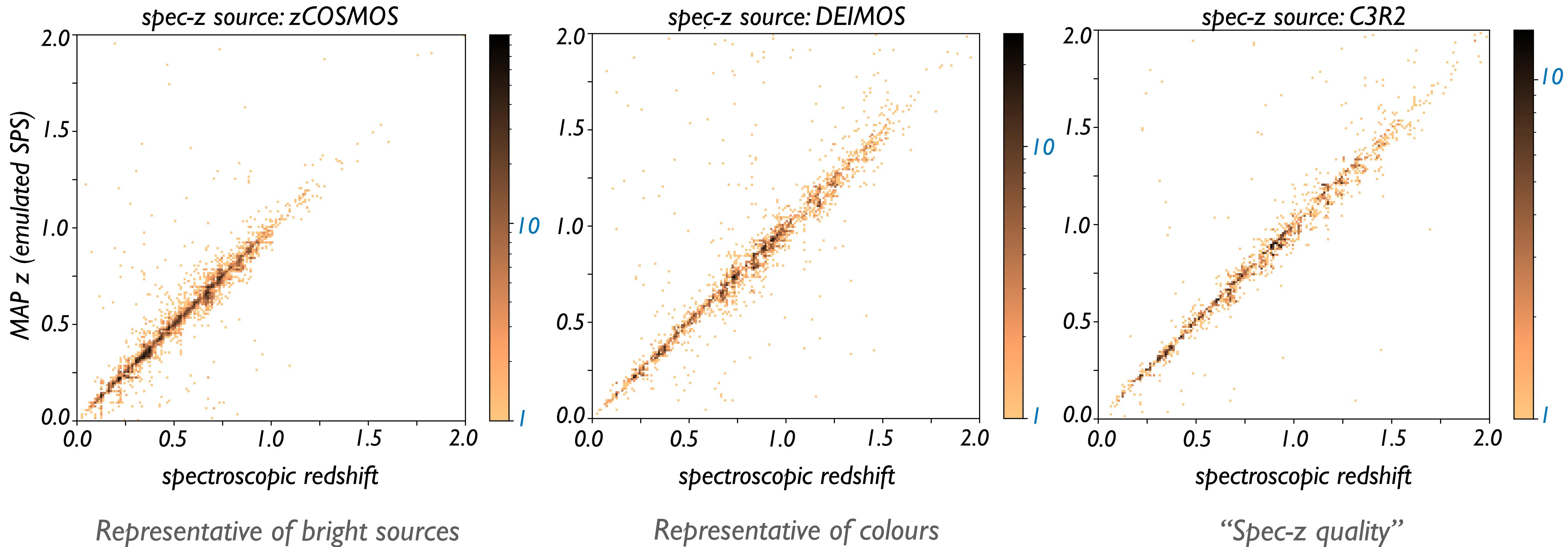


Photometric data: COSMOS2020 multiwavelength Farmer catalogue

Population model: Prospector-alpha emulators of both fluxes and emission lines

Data model: Optimization of zero-points per band and (broadband and emission line) hyperparameters

Validation with narrow-band data



Photometric data: COSMOS2020 multiwavelength Farmer catalogue

Population model: Prospector-alpha emulators of both fluxes and emission lines

Data model: Optimization of zero-points per band and (broadband and emission line) hyperparameters



Next steps!

- **Hierarchical inference not scalable?**

Already made progress on simulation-based inference approach — advantage of not needing to explicitly model selection effects parametrically, only to forward model them in a simulation.

- **Is the SPS population prior good enough for deeper data?**

Improvements to population prior (star formation history and dust modelling). Population prior being calibrated on COSMOS2020 catalogue.

- **How do we validate analyses of deeper data when little spectroscopy available?**

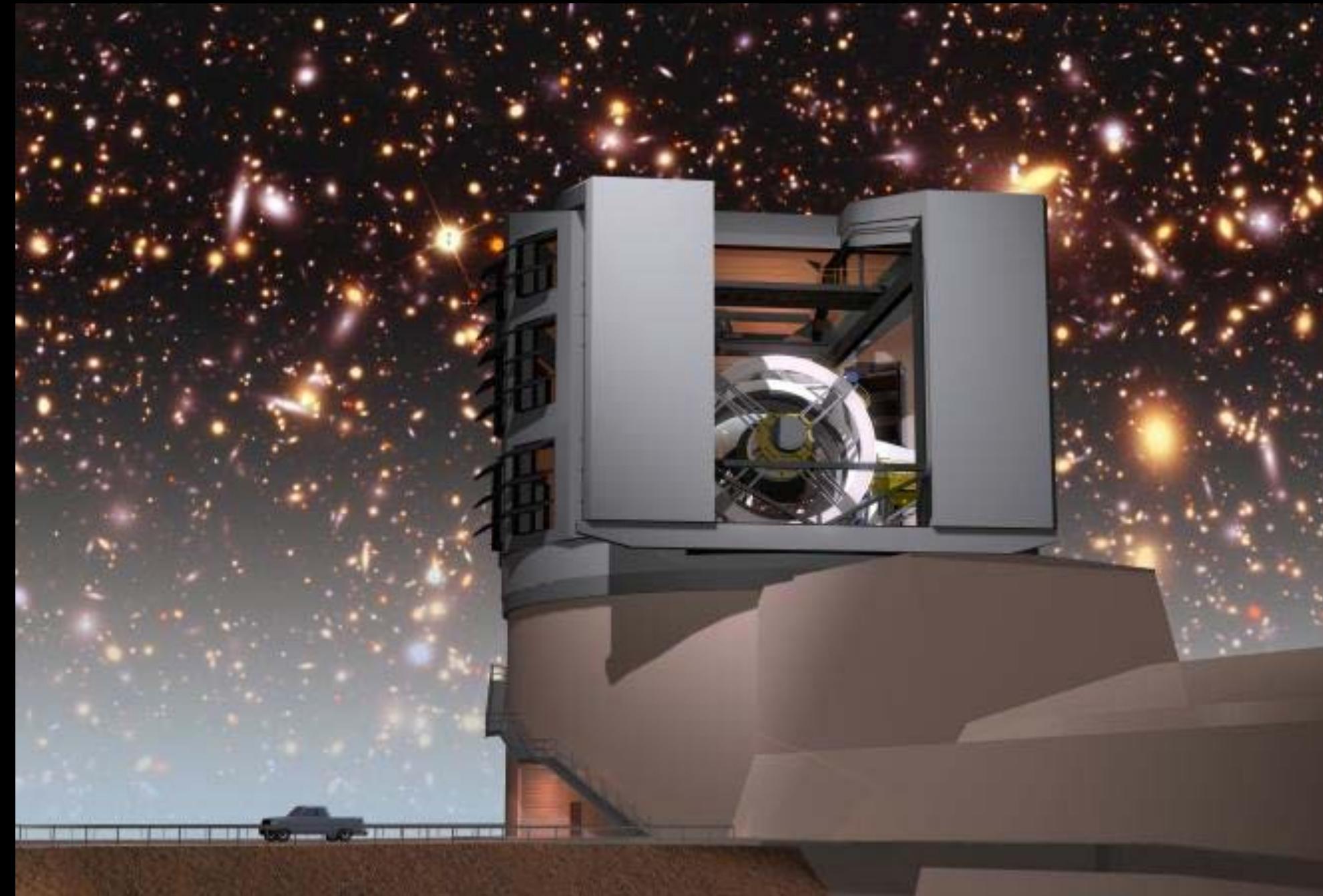
Developing posterior predictive checks in colour/flux space (Bayesian “cross-validation”)





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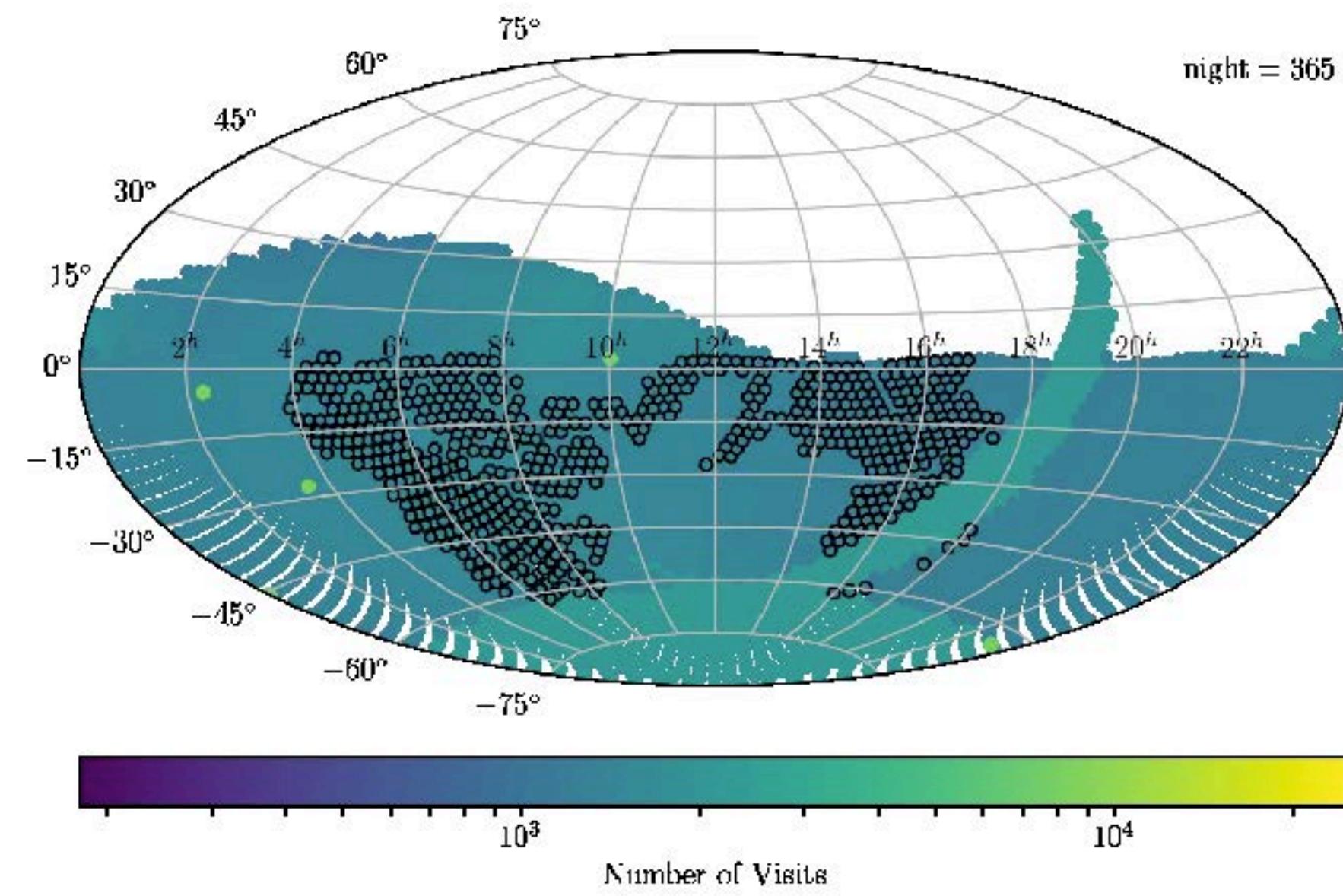


Mapping the Milky Way

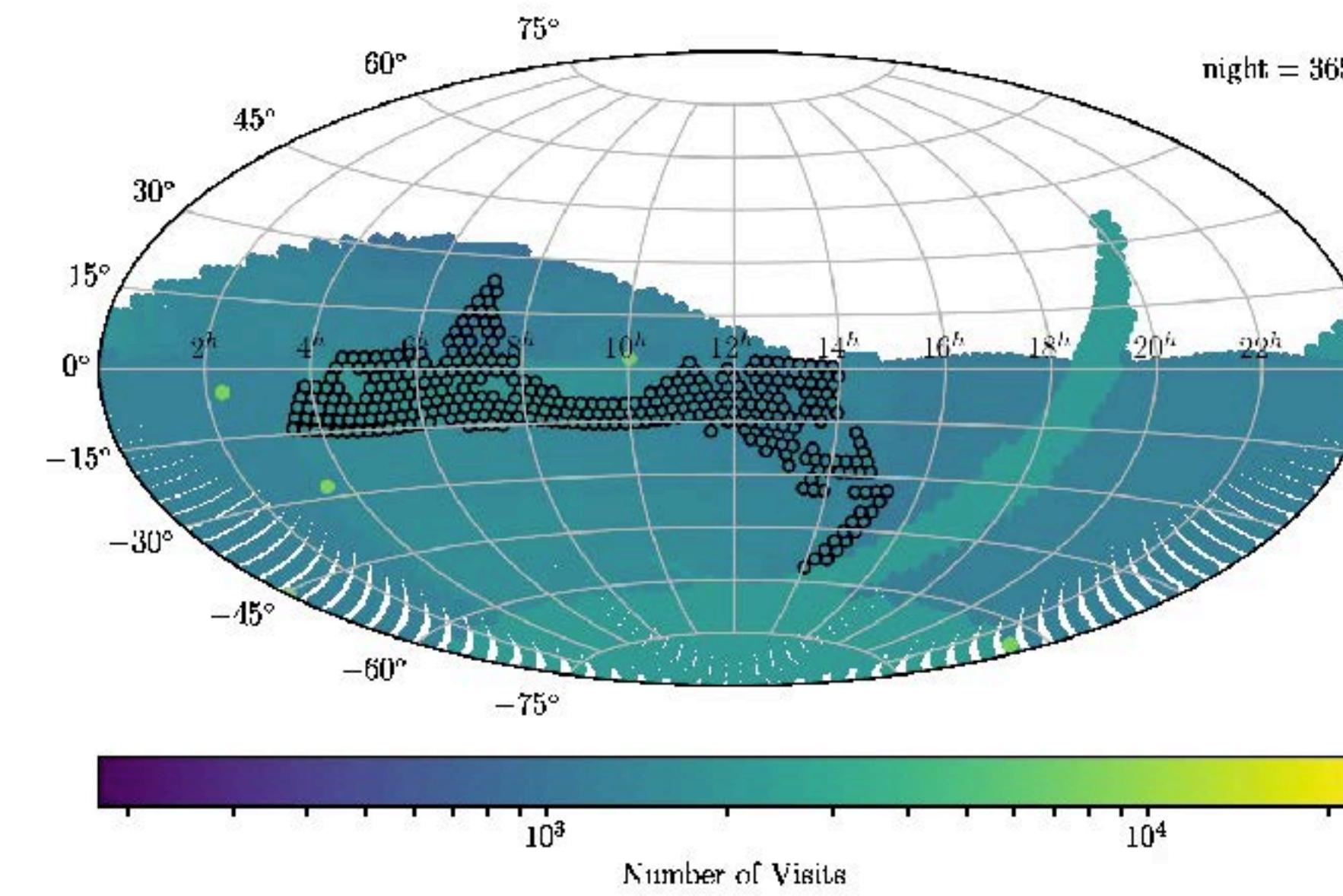


Slide adapted from Ian Shipsey

LSST observing strategy

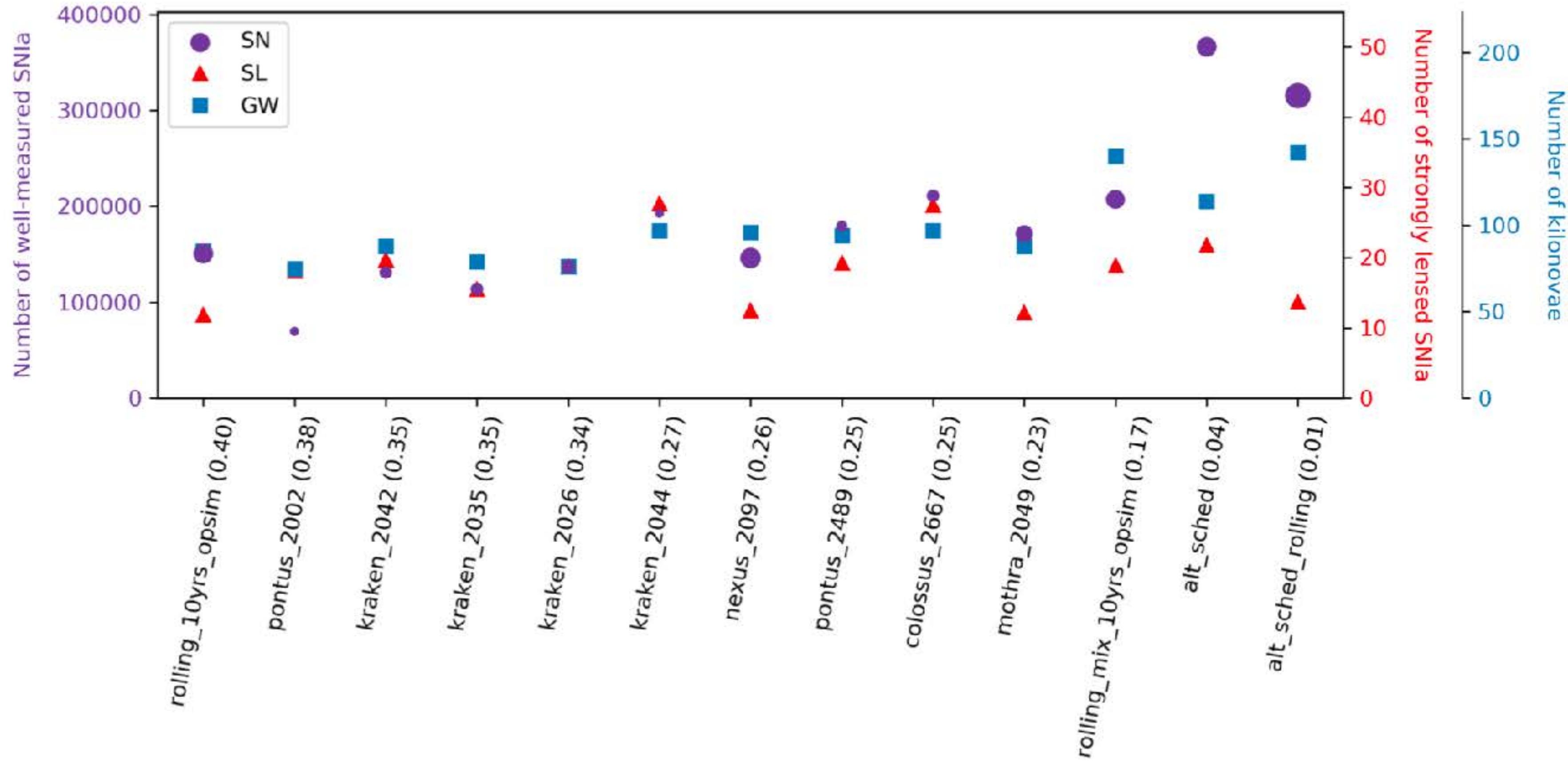


WFD baseline strategy



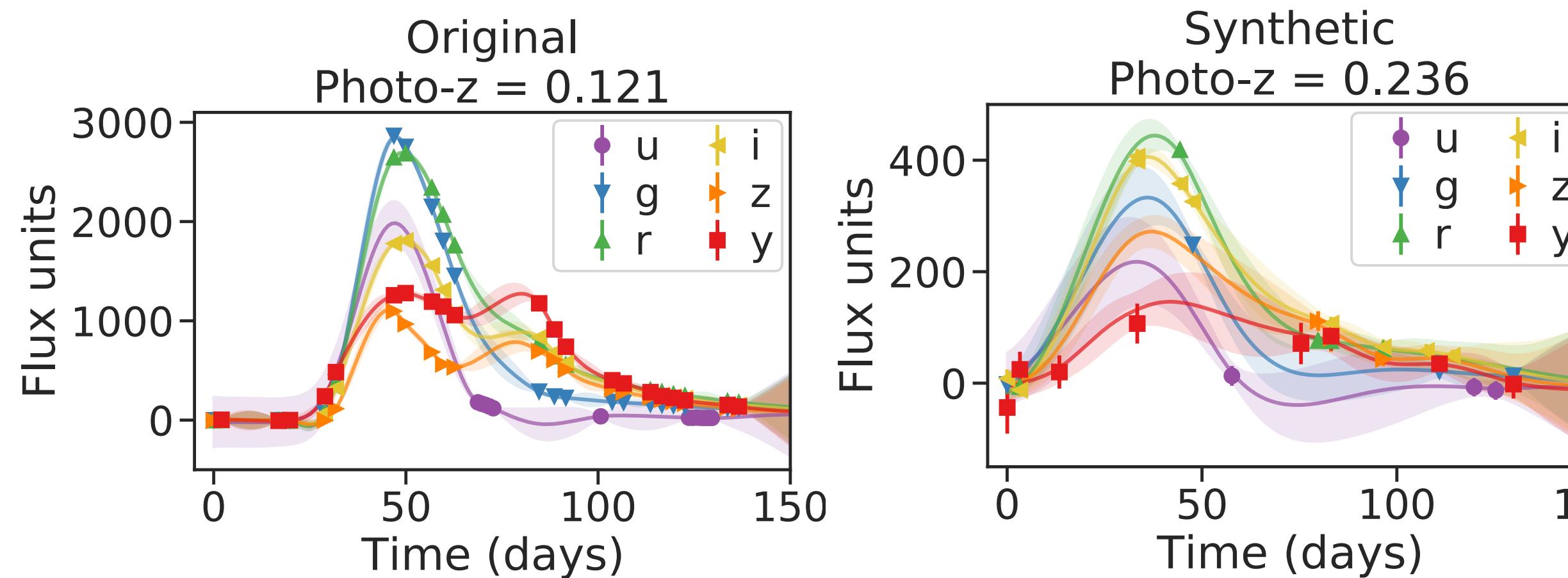
A rolling WFD proposal

LSST and the transient universe

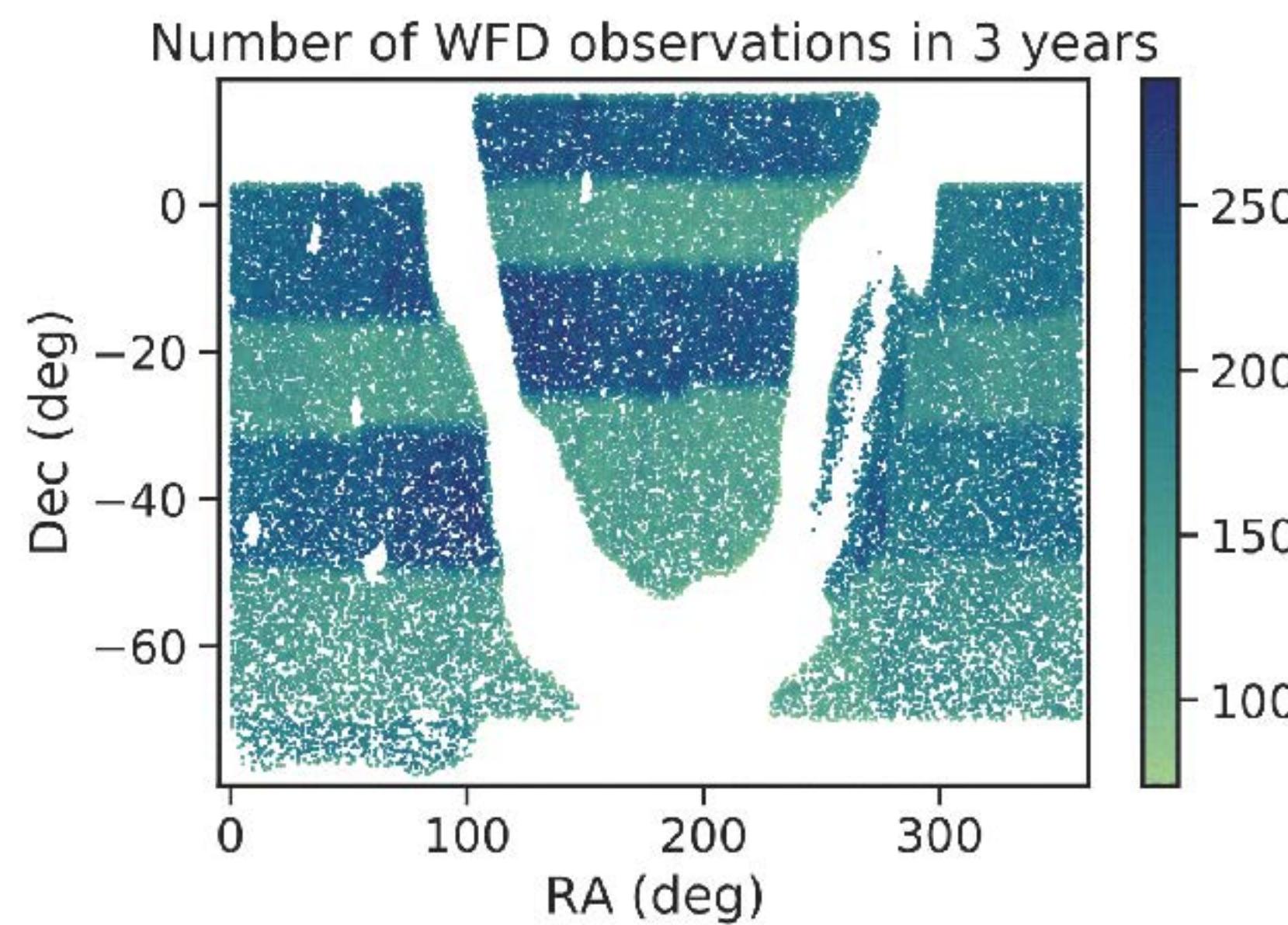


Number of kilonovae, strongly lensed type Ia supernovae with well-measured time delays (both assuming follow-up with other telescopes) and well-measured type Ia supernovae for Y10 as a function of observing strategy, ordered by percentage of visits in r-band separated by more than 15 days (in brackets).

Observing strategy and photometric supernovae classification



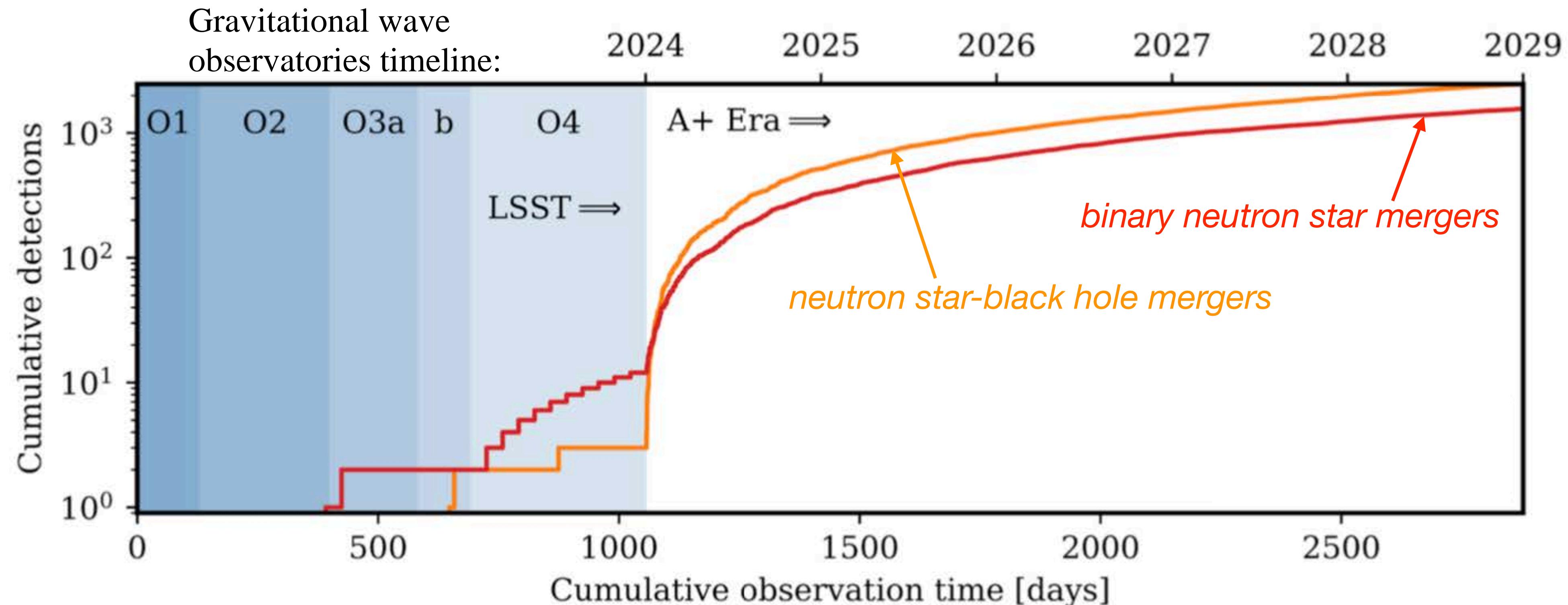
- Data augmentation of spectroscopic training samples essential for classification
- Median inter-night gap should be <3.5-5 days



- Actively-rolling region yields ~ 3 x cosmologically useful SNe than background region.
- Strongly advocates **rolling cadence**



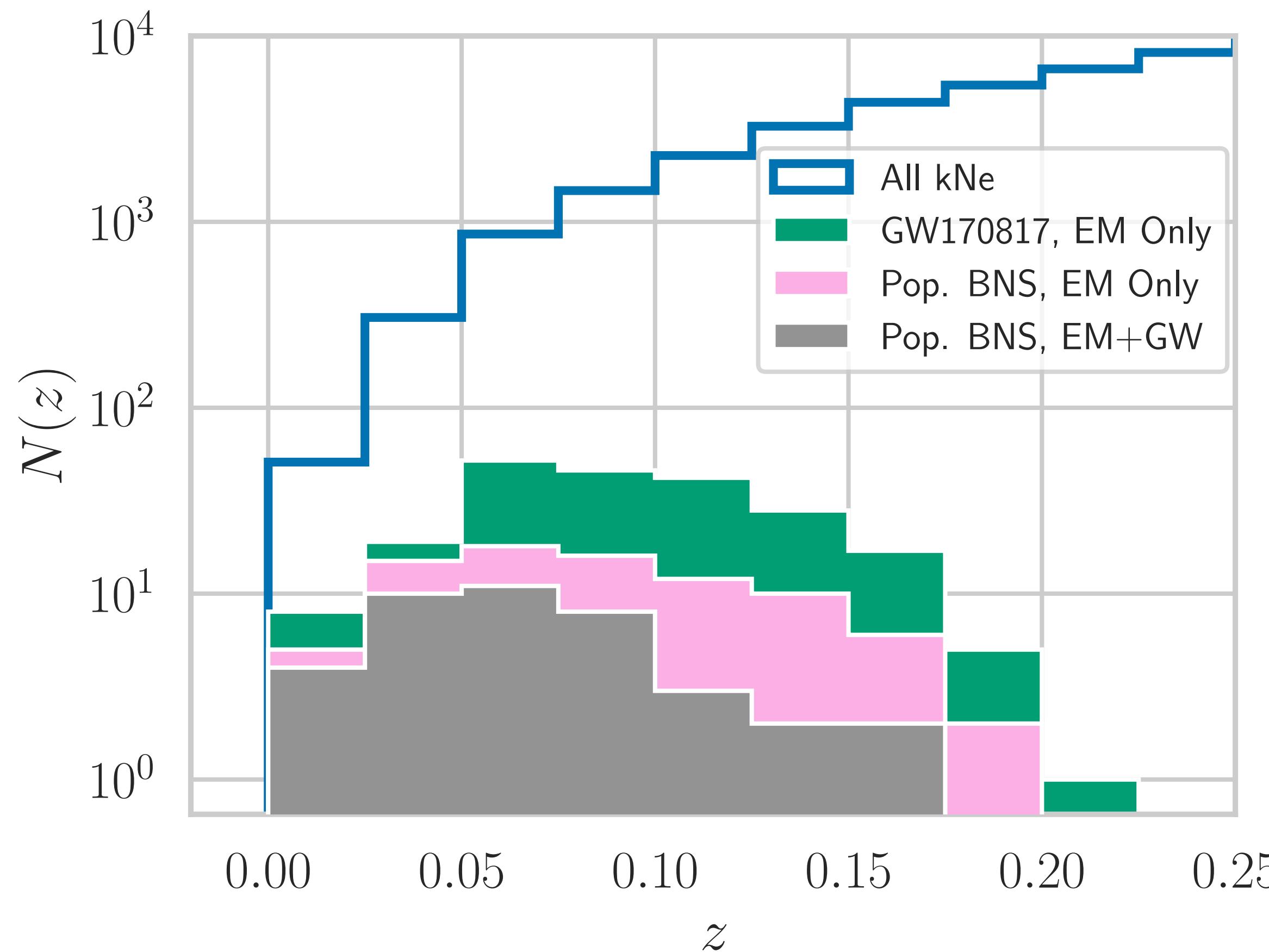
Multimessenger observational frontier



Expected yield of gravitational wave events with potential electromagnetic counterparts

Figure: S. Feeney

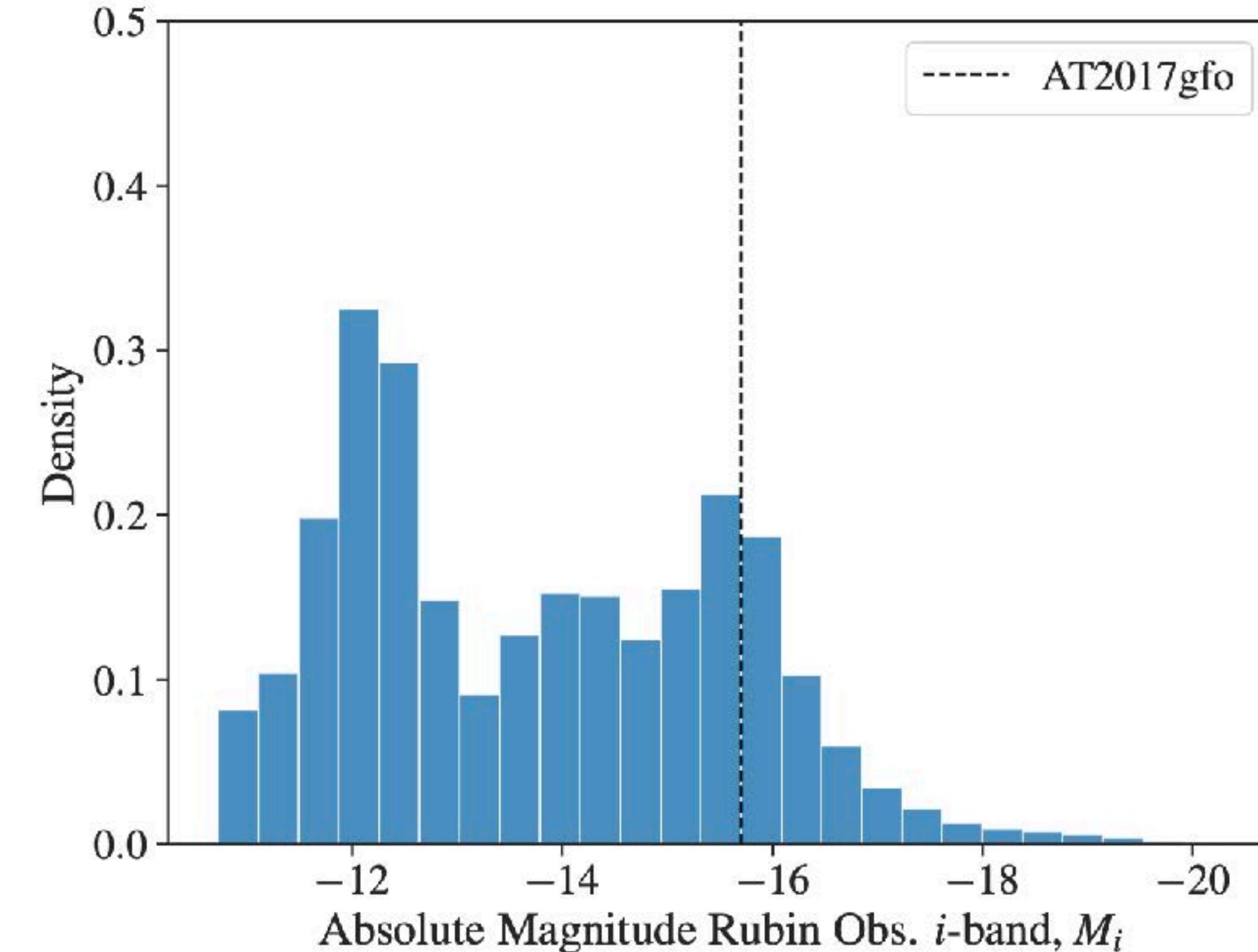
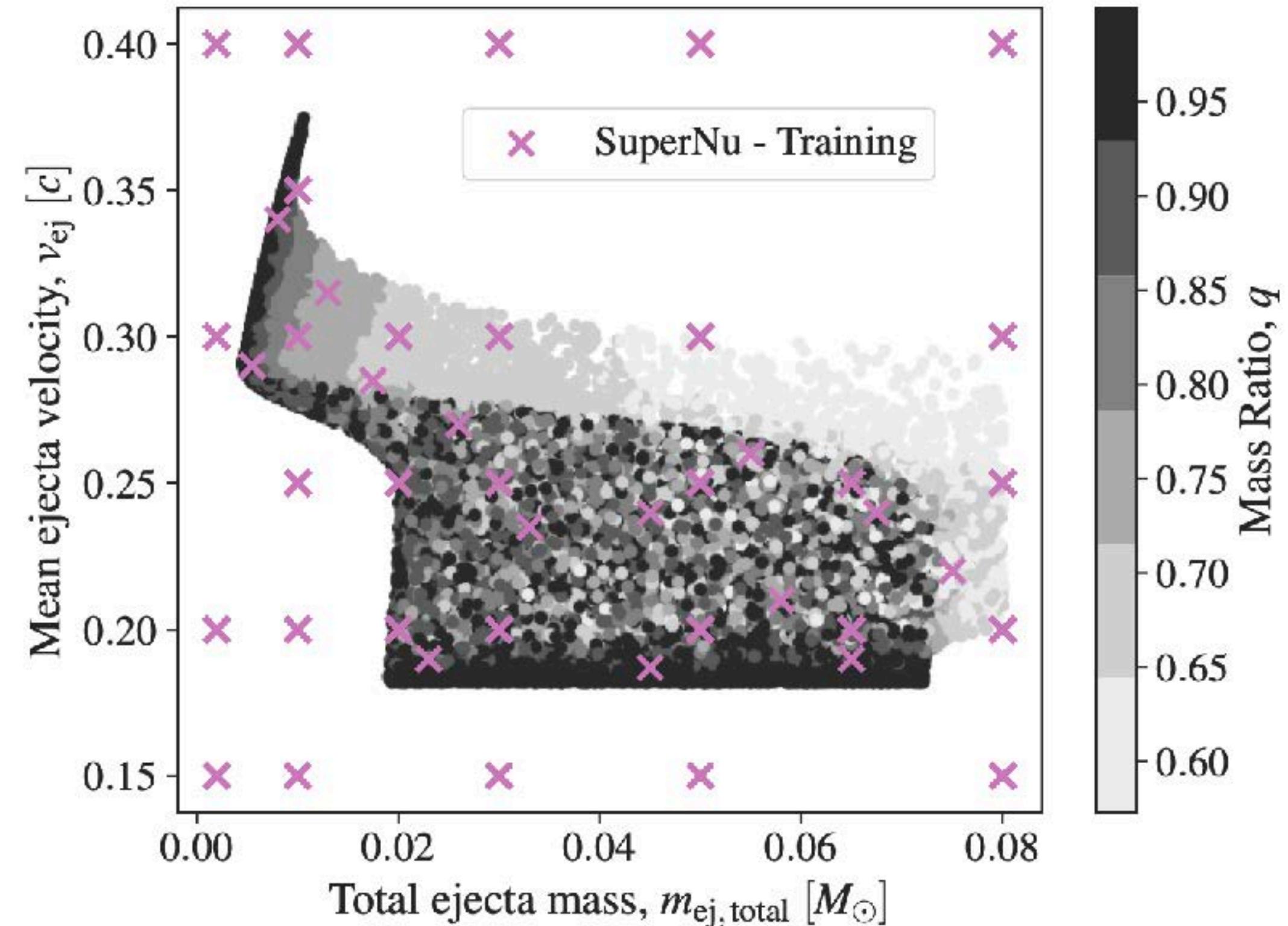
Serendipitous detections of kilonovae in LSST



Can optical kilonovae detections be used to “reverse-trigger” searches for sub-threshold GW events in archival data?



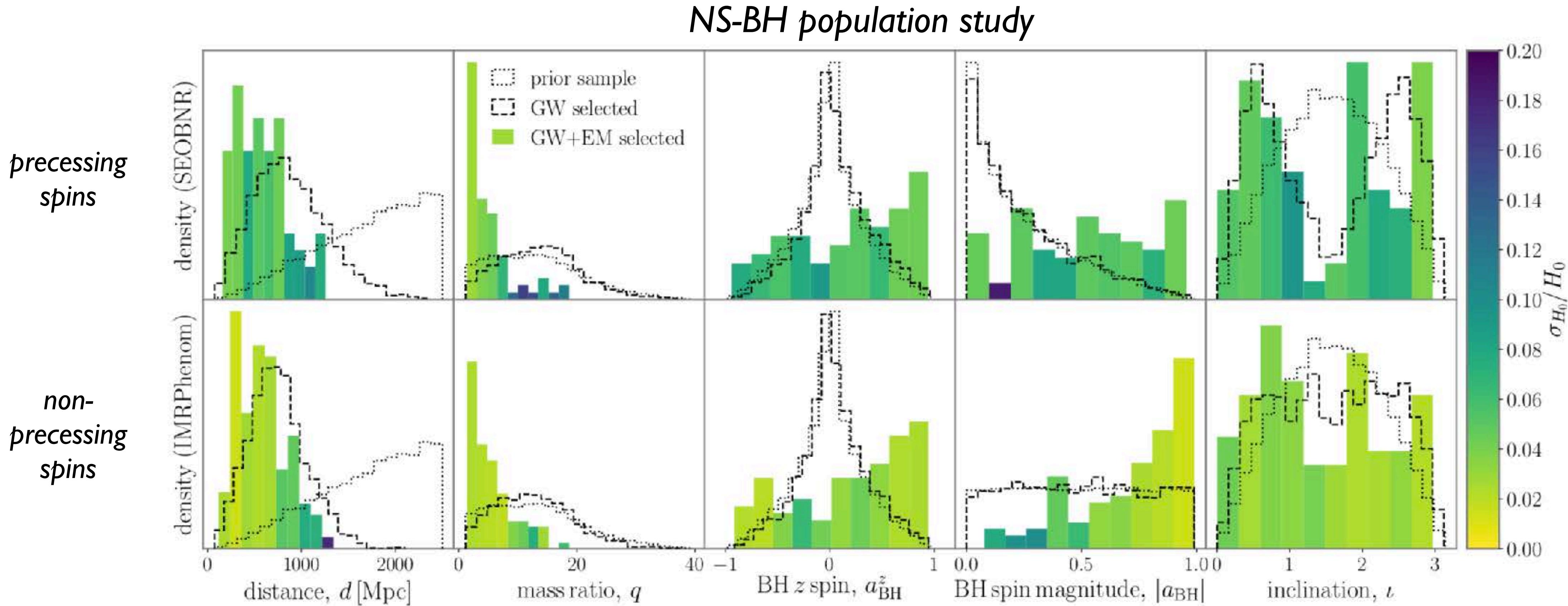
Serendipitous detections of kilonovae in LSST



- Gaussian process Grey Opacity emulator calibrated to SuperNu radiative transfer simulations
- Self-consistent EM-GW kilonova population model designed for optical surveys



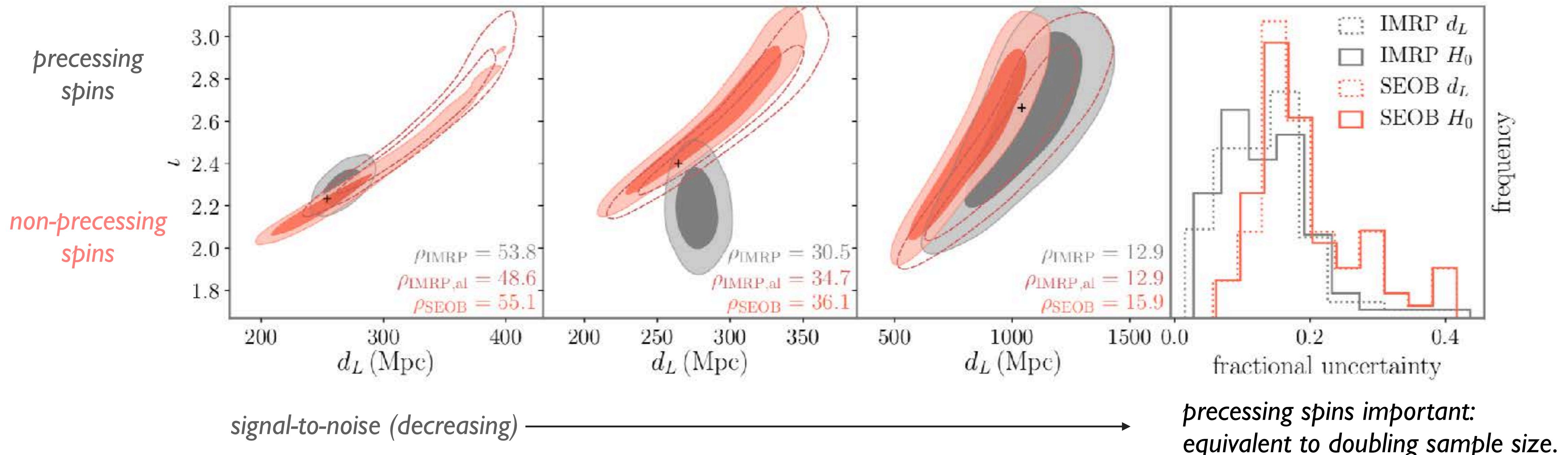
Planning for A+ era science with GW-EM populations

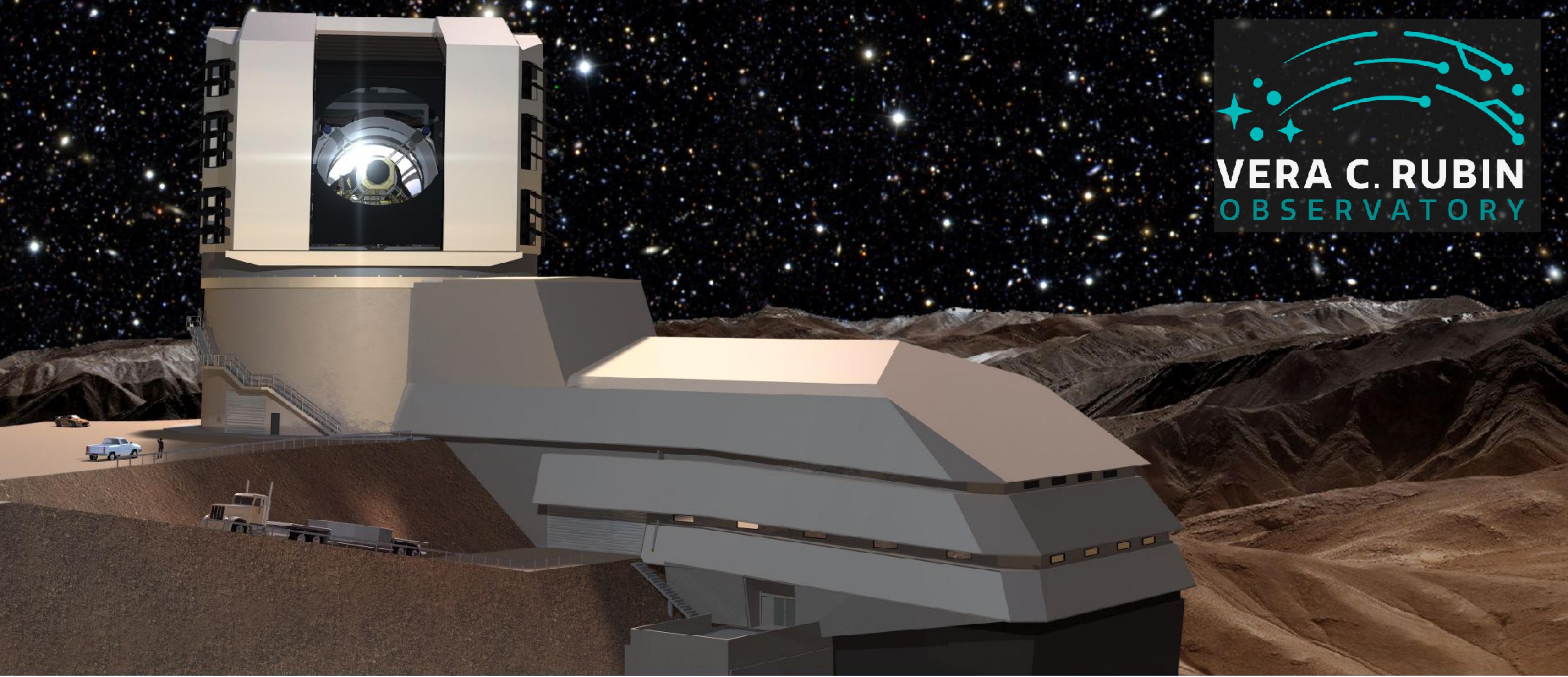


- Hierarchical Bayesian pipeline for population studies at A+ scale.
- Customised bilby wrapper + lalsimulation library + tuned polychord sampler.
- Accounting for selection effects crucial; understanding EM selection likely to be challenging.

Planning for A+ era science with GW-EM populations

NS-BH population study





COSMICEXPLORER: Exploring the Cosmos with the Vera Rubin Observatory



European Research Council
Established by the European Commission

Aims: (i) AI-boosted modelling for cosmological analysis (ii) new cross-validation methods for diagnosis of systematics (iii) explainable AI to develop cosmic web as robust cosmological probe.



COSMOPARTICLE, WWW.PENELOPEROSECOWLEY.COM