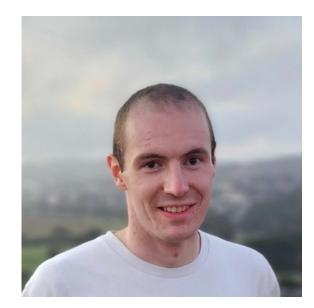
#### pop-cosmos: Funded by the European Union Scaleable Bayesian inference of galaxy properties under a diffusion model prior



**Stephen Thorp** 



**Sinan Deger** 



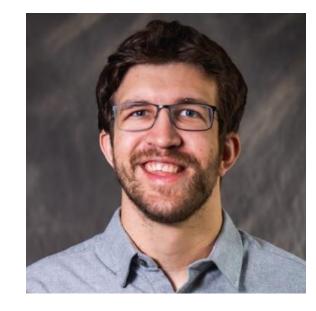
**Anik Halder** 



**Justin Alsing** 



**Boris Leistedt** 











**Gurjeet Jagwani** 



Hiranya Peiris



Madalina Tudorache

Joel Leja



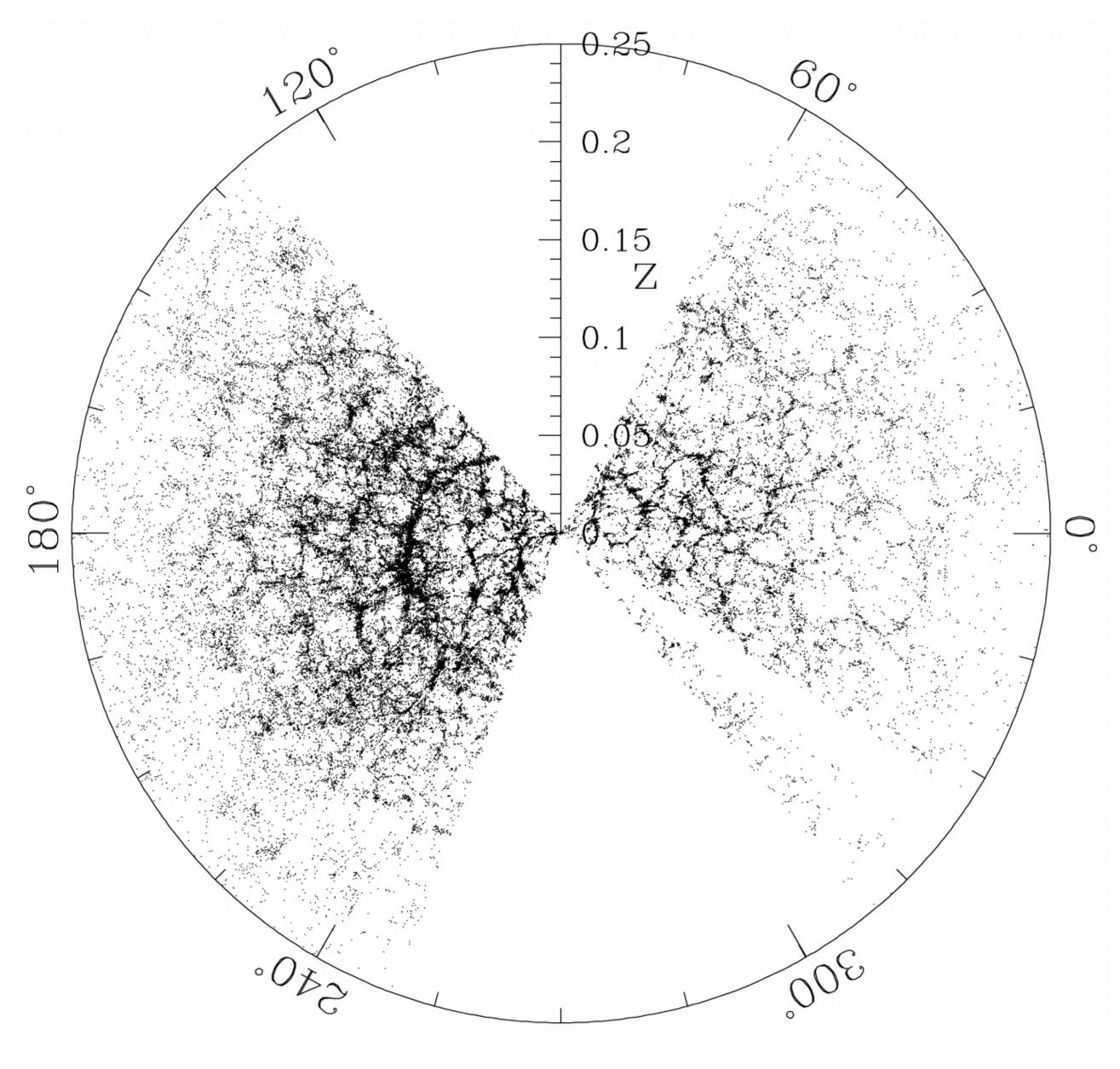
**Arthur Loureiro** 



**Daniel Mortlock** 

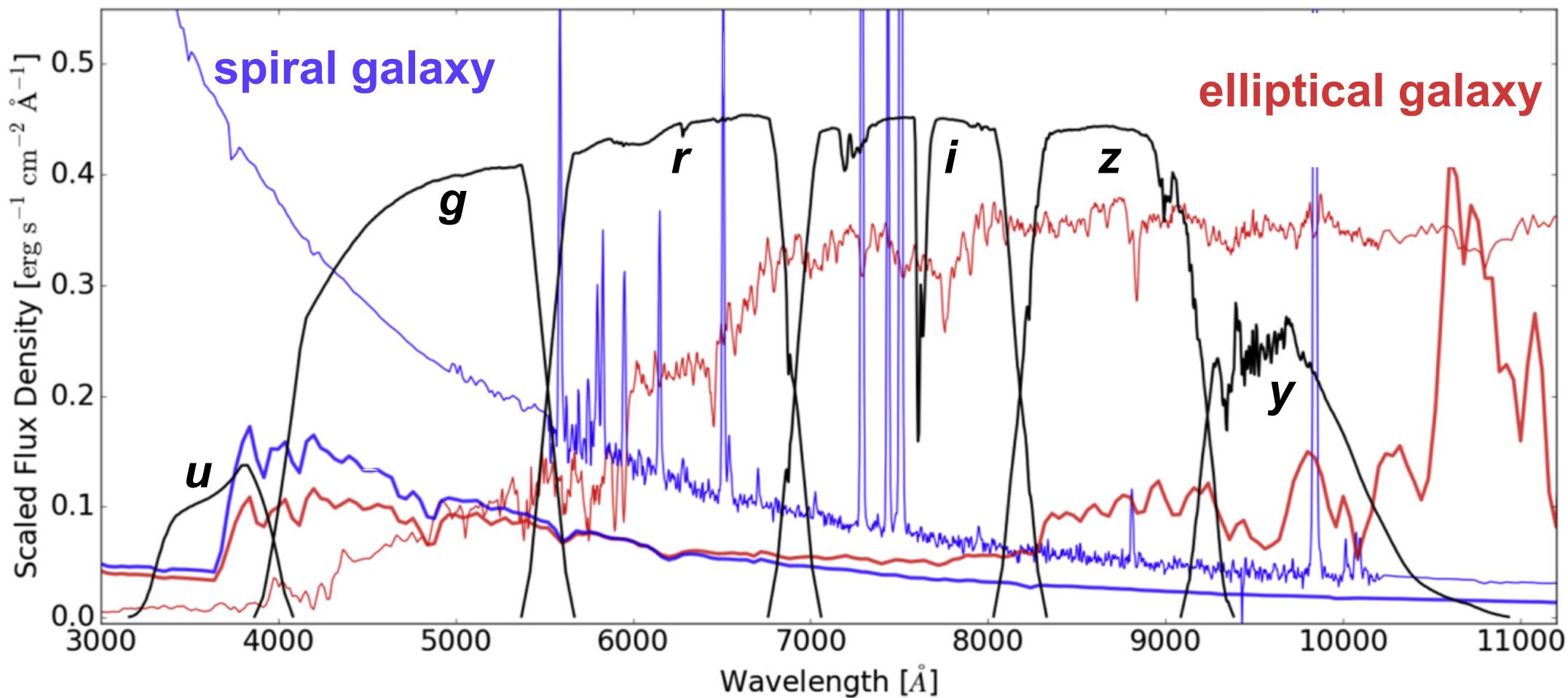
#### Large Scale Structure Cosmology

- Map the matter distribution in the universe using spectra or photometry of galaxies
- Galaxy clustering (positions), or weak lensing (shapes) sensitive to cosmological parameters
- Photometric surveys depend more on our ability to model galaxies well (either individually or as a population)



SDSS: Blanton et al. (2003)

#### Photometry vs. Spectroscopy



Graham et al. (2017)



#### Coming (very) soon...

- First-look events June 23rd: https://rubinobservatory.org
- First data June 30th!
- 20 billion galaxies; 18,000 deg<sup>2</sup>
- Deep imaging in *ugrizy*
- Single epoch:  $r \leq 24$  mag; 10 year co-add: r < 26.9 mag
- Photometric data only; need to model galaxies with very limited information (just 6 numbers)









Credit: Rubin Observatory/NOIRLab/SLAC/DOE/NSF/AURA/B. Quint

Population Distribution

**Population** Distribution



#### **Intrinsic Properties**

Population Distribution



#### **Intrinsic Properties**



**Observable Features** 

Population Distribution



#### **Intrinsic Properties**



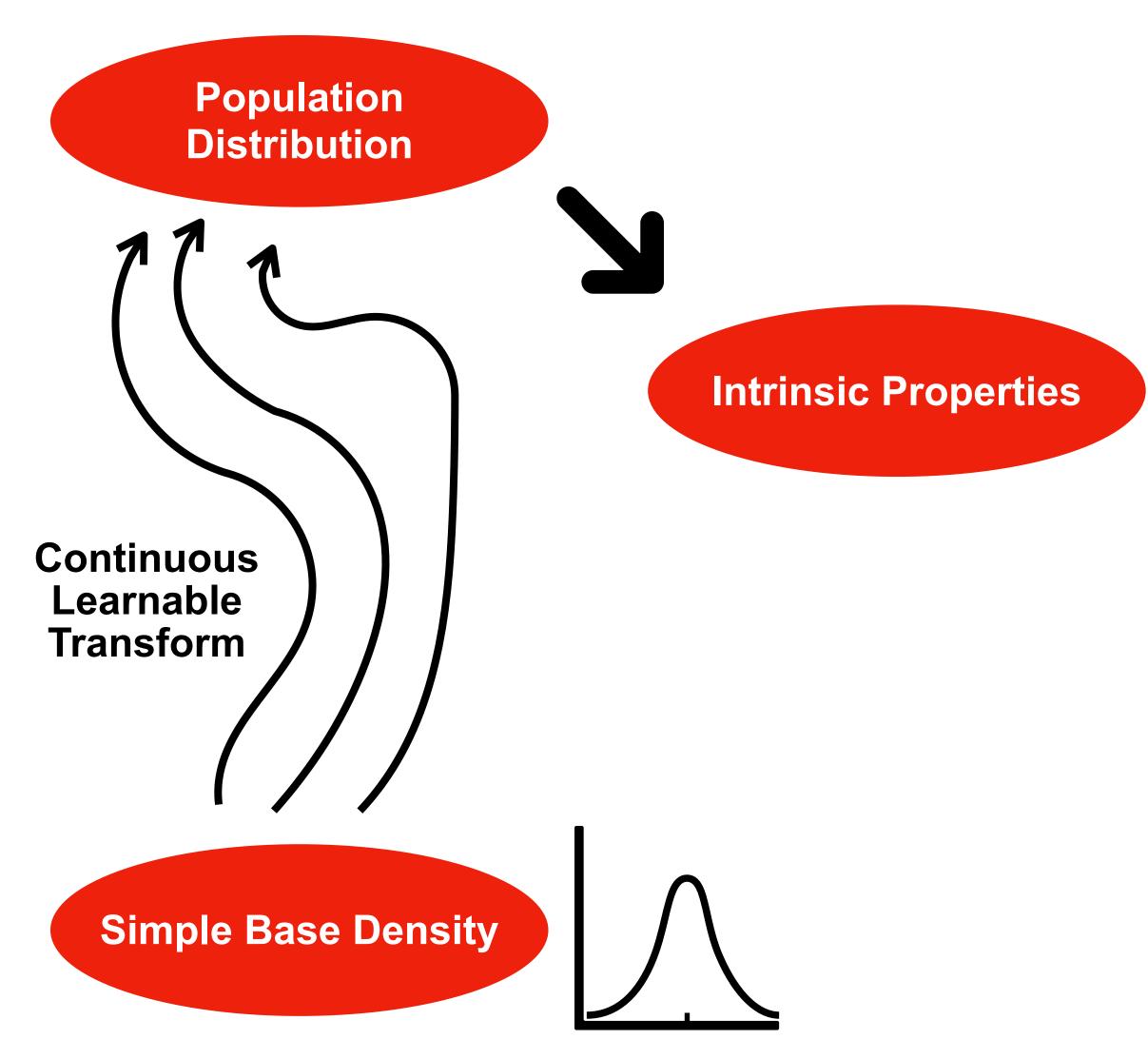
**Observable Features** 



**Mock Observations** 



#### **Diffusion models**



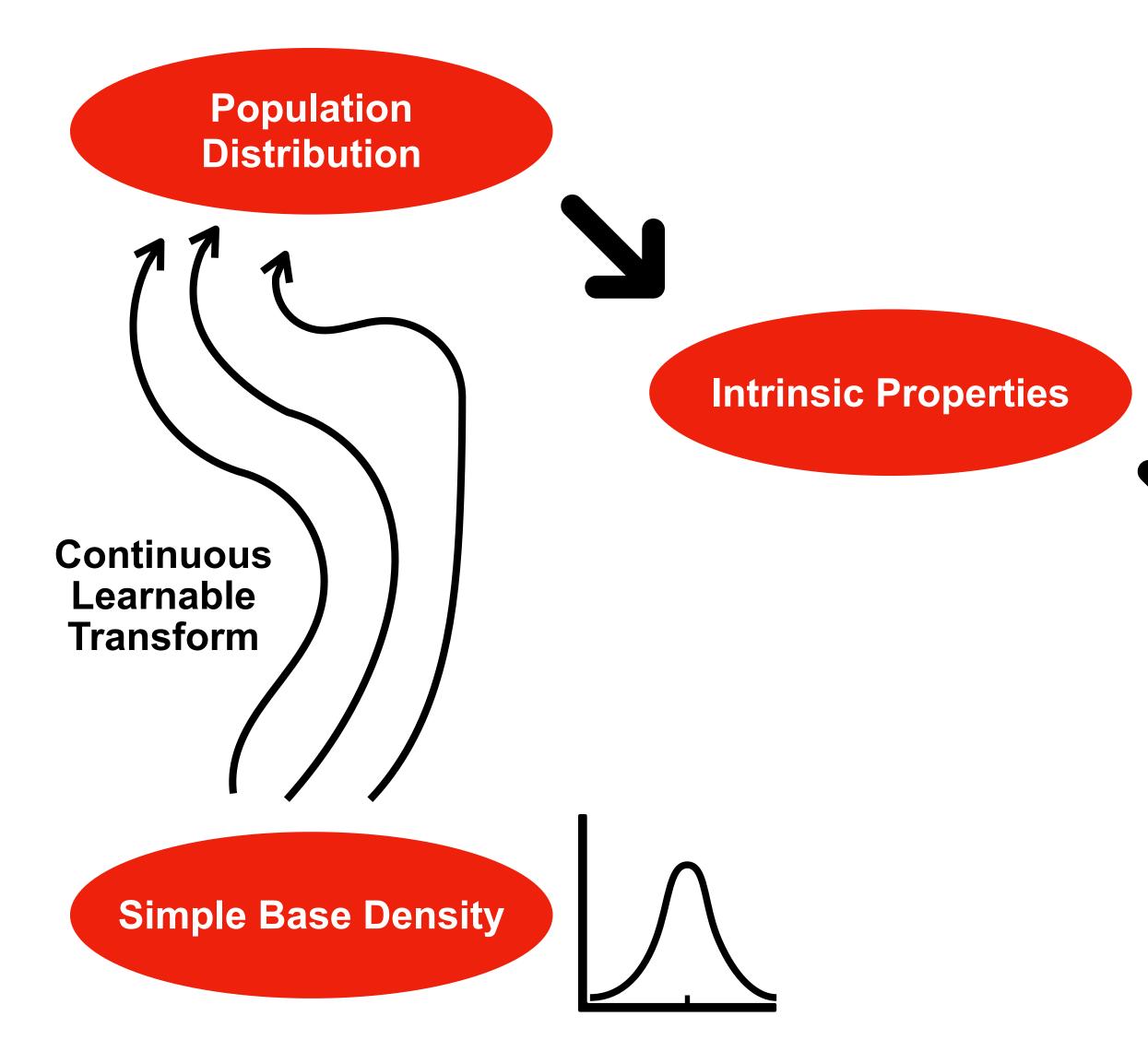
#### **Observable Features**



**Mock Observations** 



## Fitting a generative model to data





**Observable Features** 

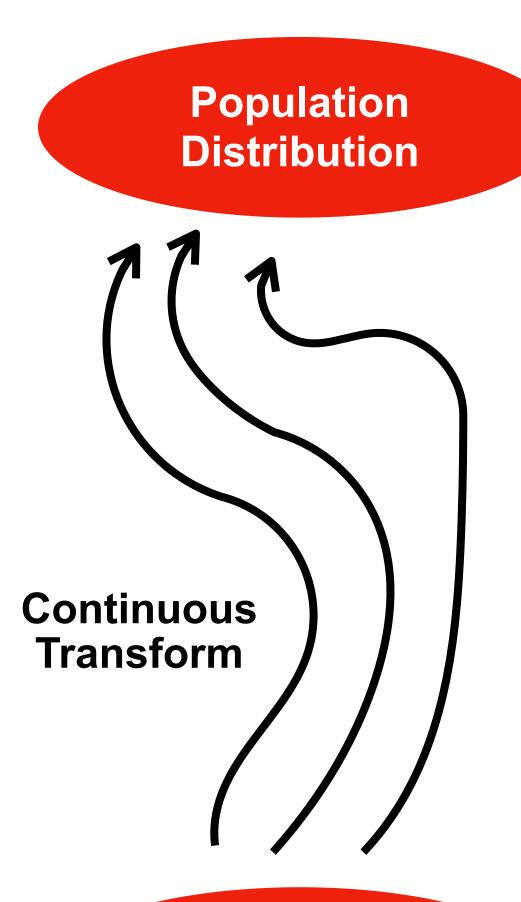
Distance Metric

**Mock Observations** 



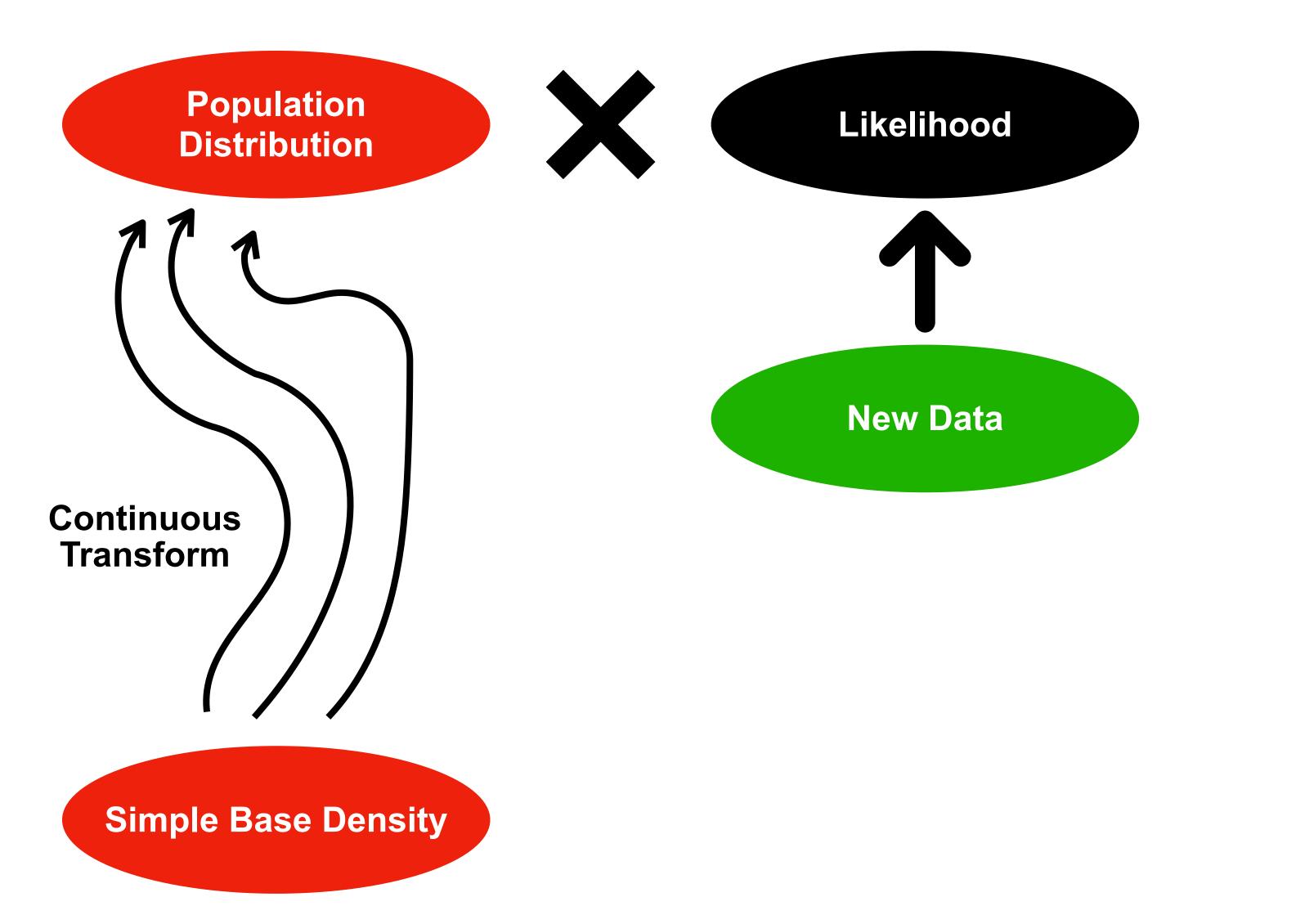
s

#### Inference under a diffusion model prior

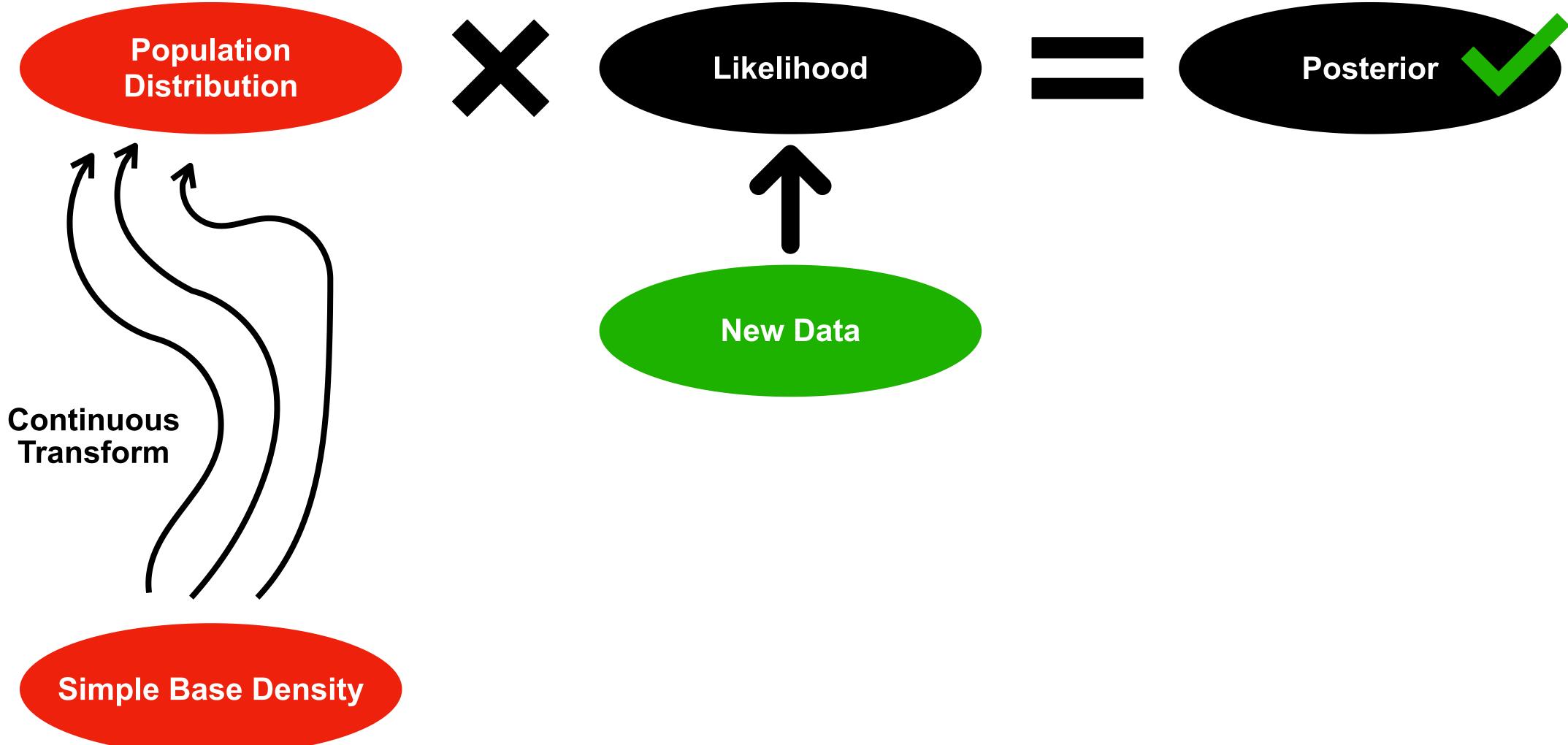


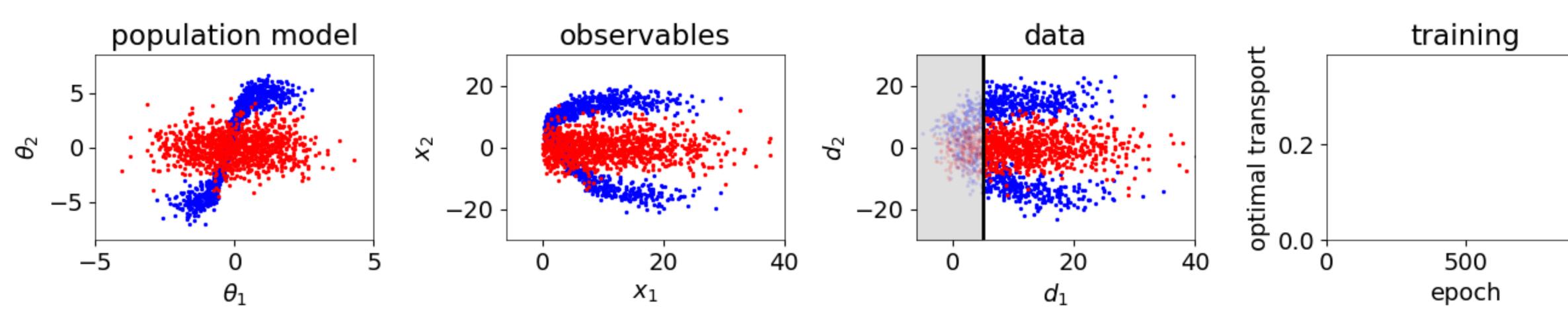
**Simple Base Density** 

#### Inference under a diffusion model prior



#### Inference under a diffusion model prior

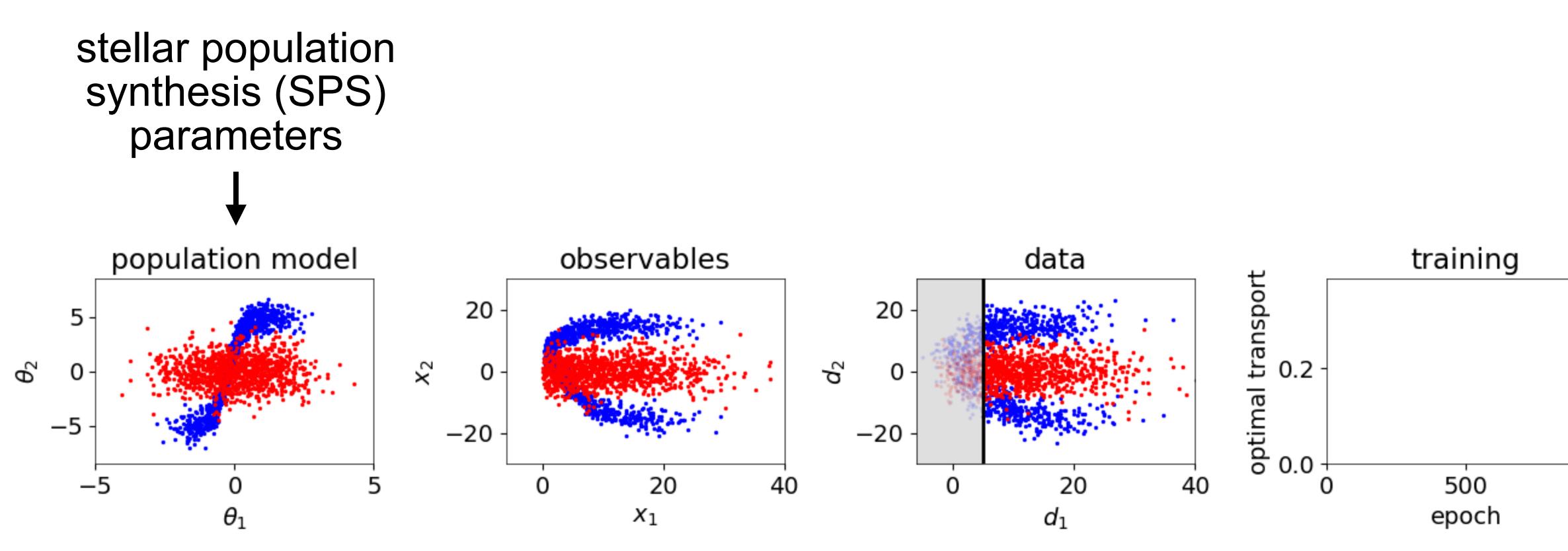








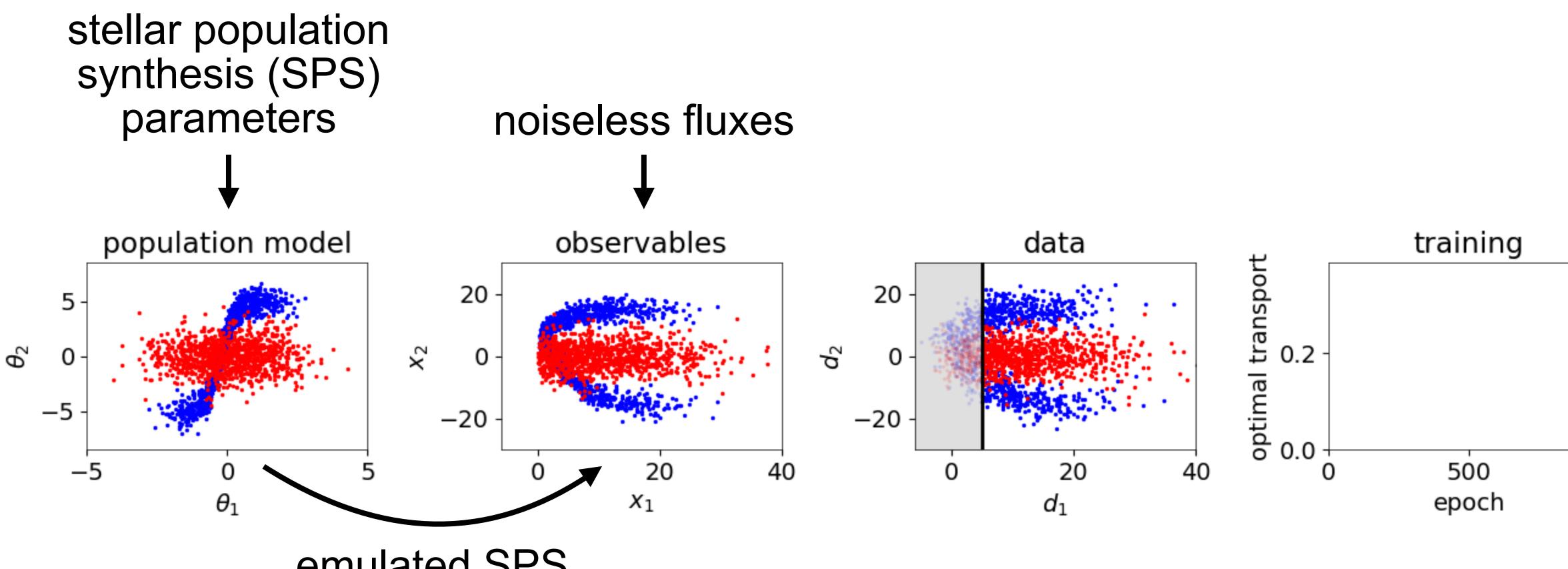






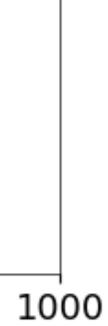




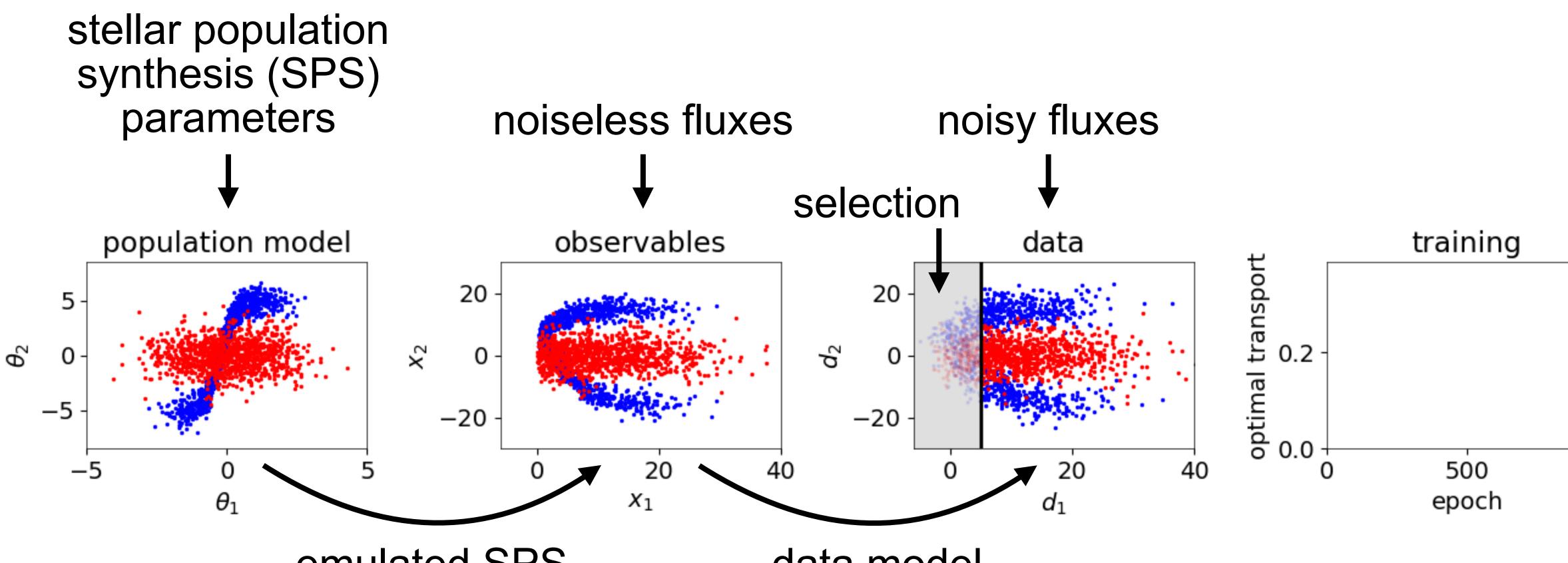


emulated SPS









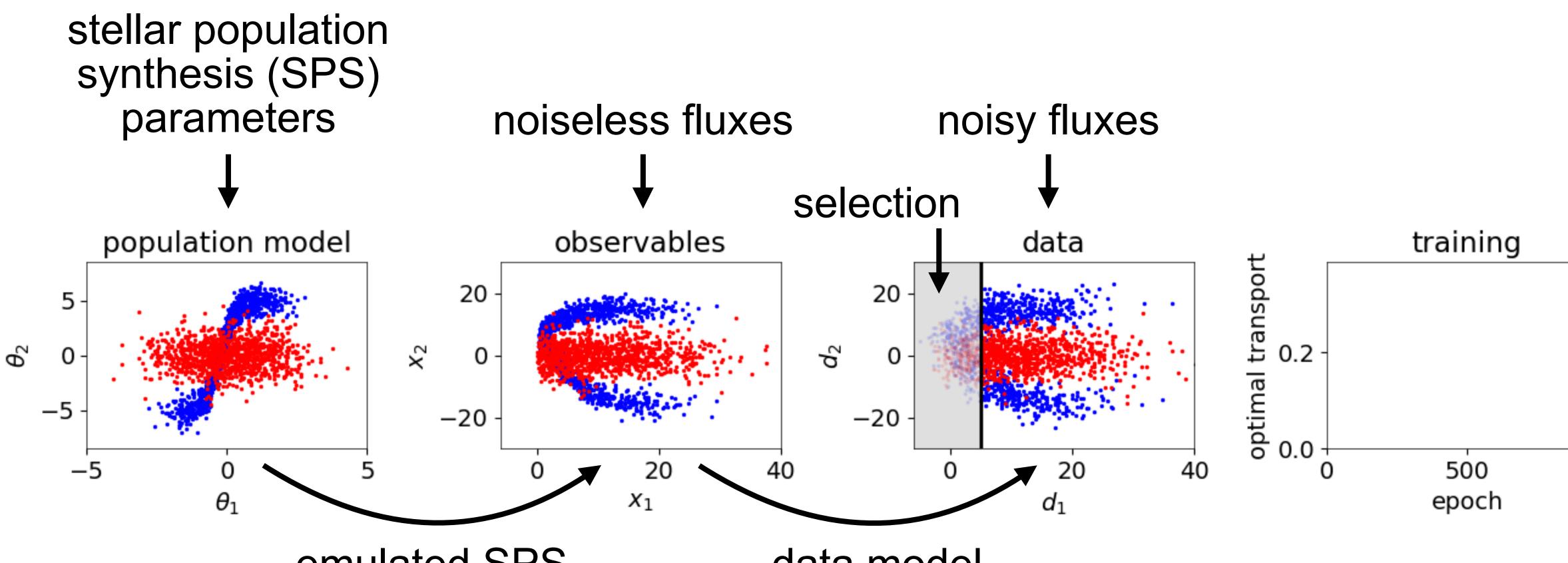
emulated SPS

data model









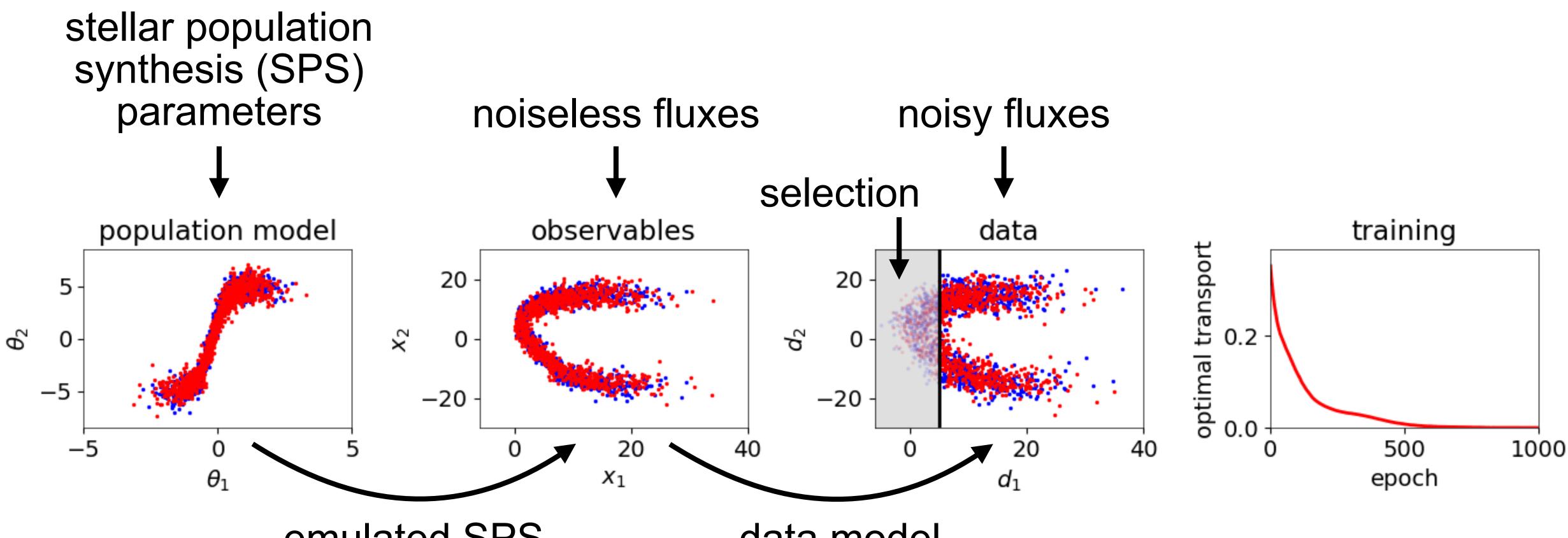
emulated SPS

data model







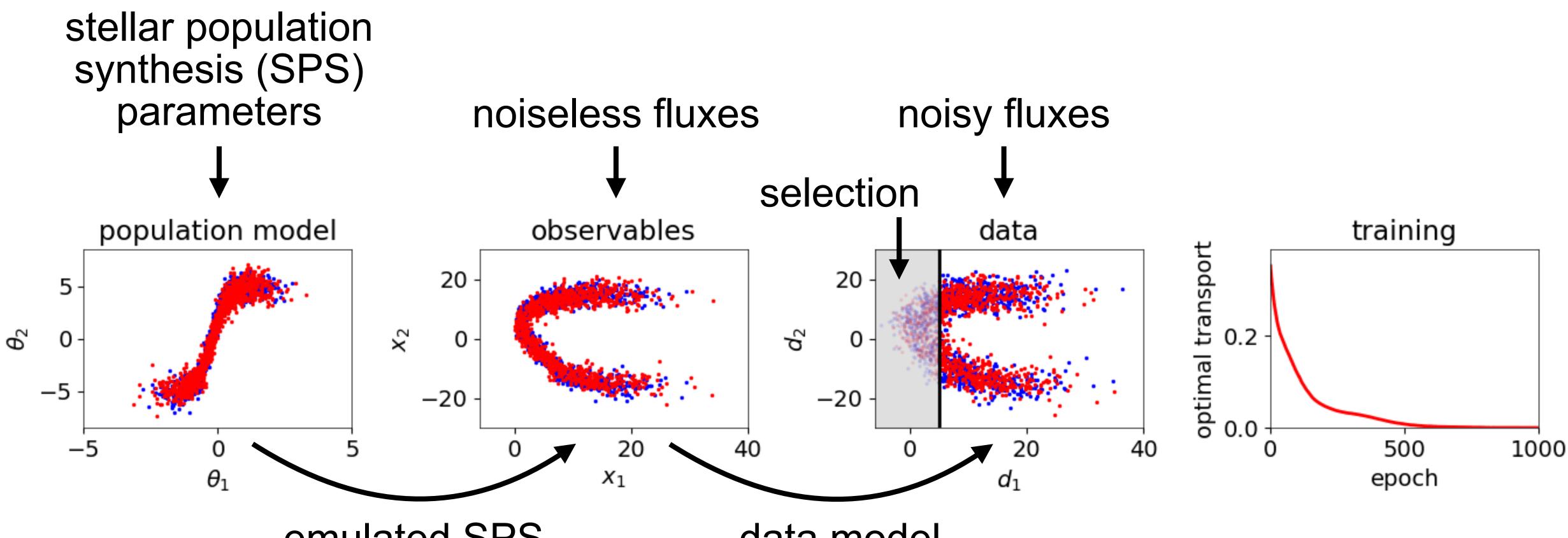


emulated SPS

data model







emulated SPS

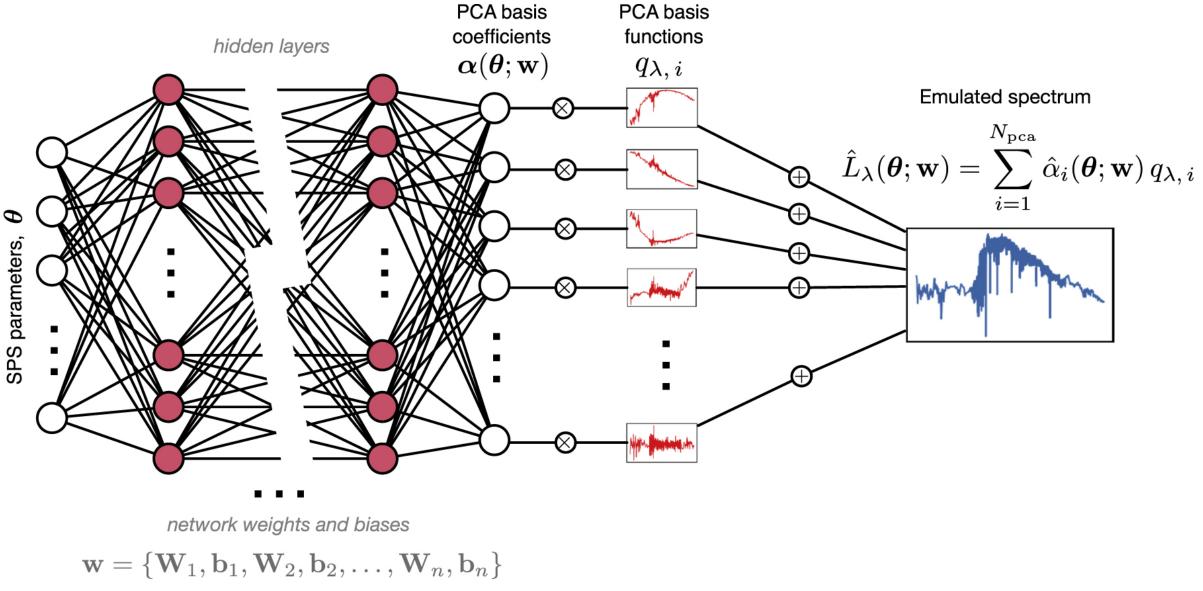
data model



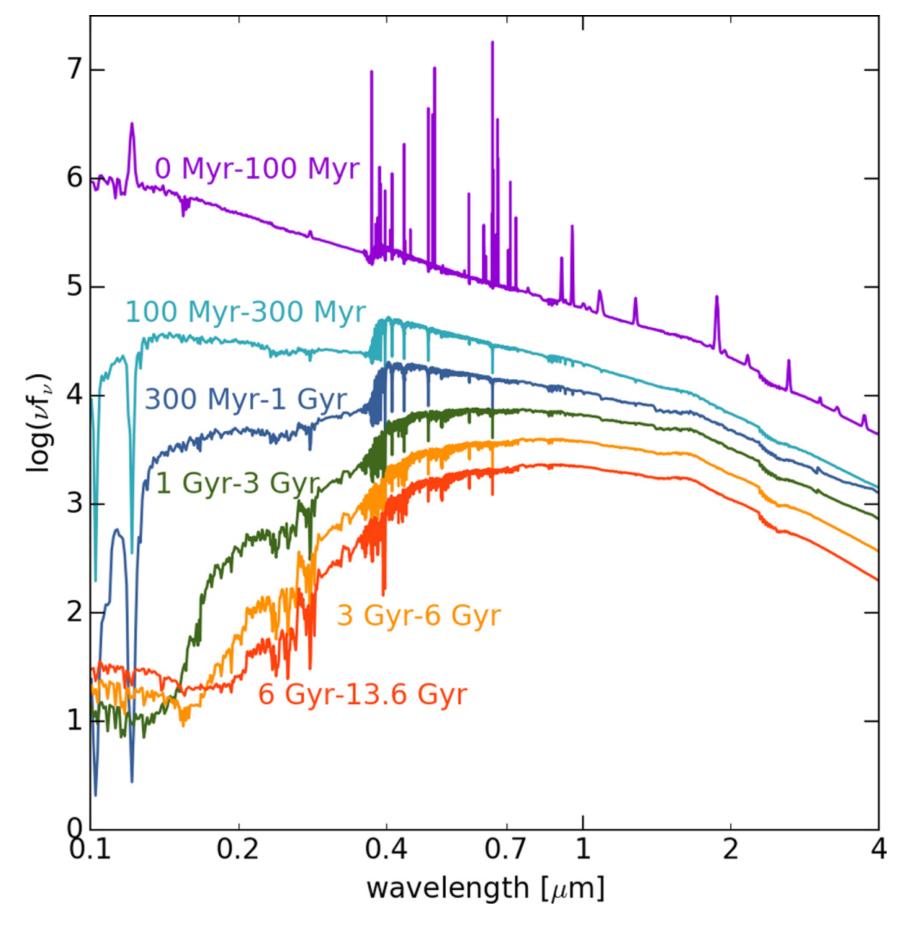


#### How do we represent a galaxy? **Stellar Population Synthesis (SPS)**

- 16 parameters ( $\approx$  Prospector- $\alpha$ )
- Emulated with Speculator



Alsing et al. (2020)

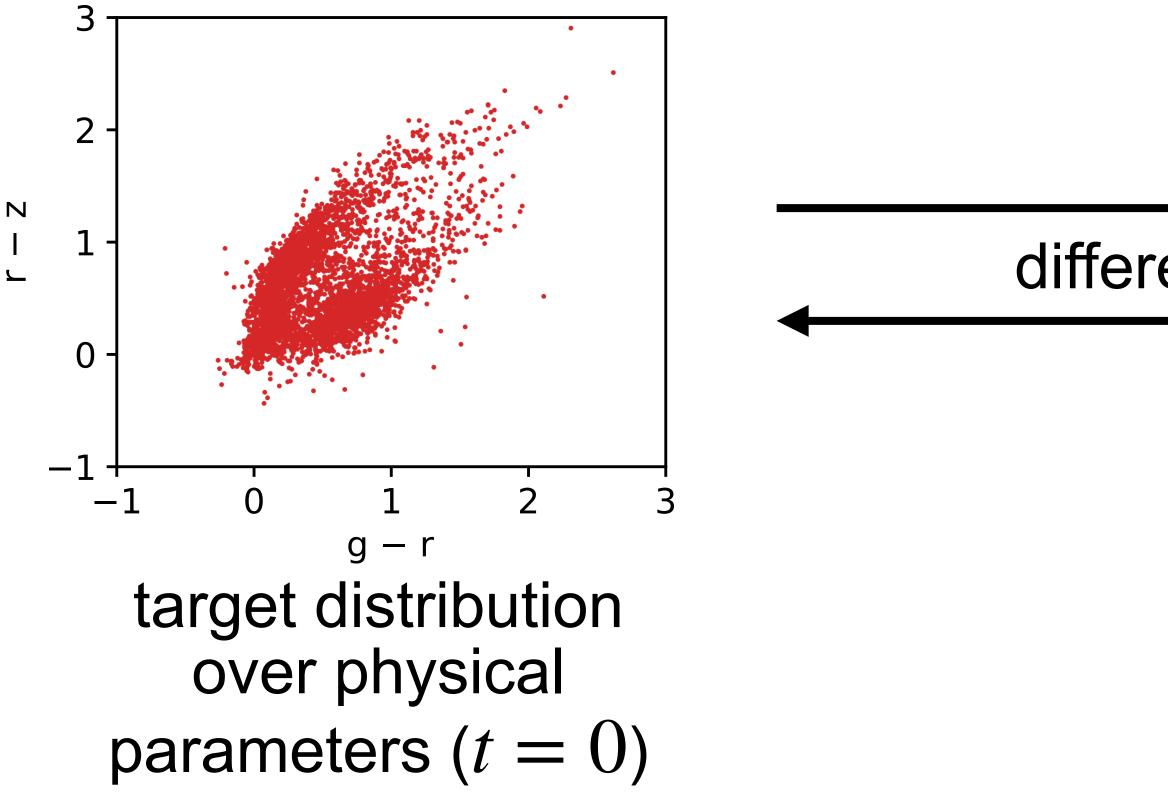






Leja et al. (2017)

#### What will our population model be? A score-based diffusion model

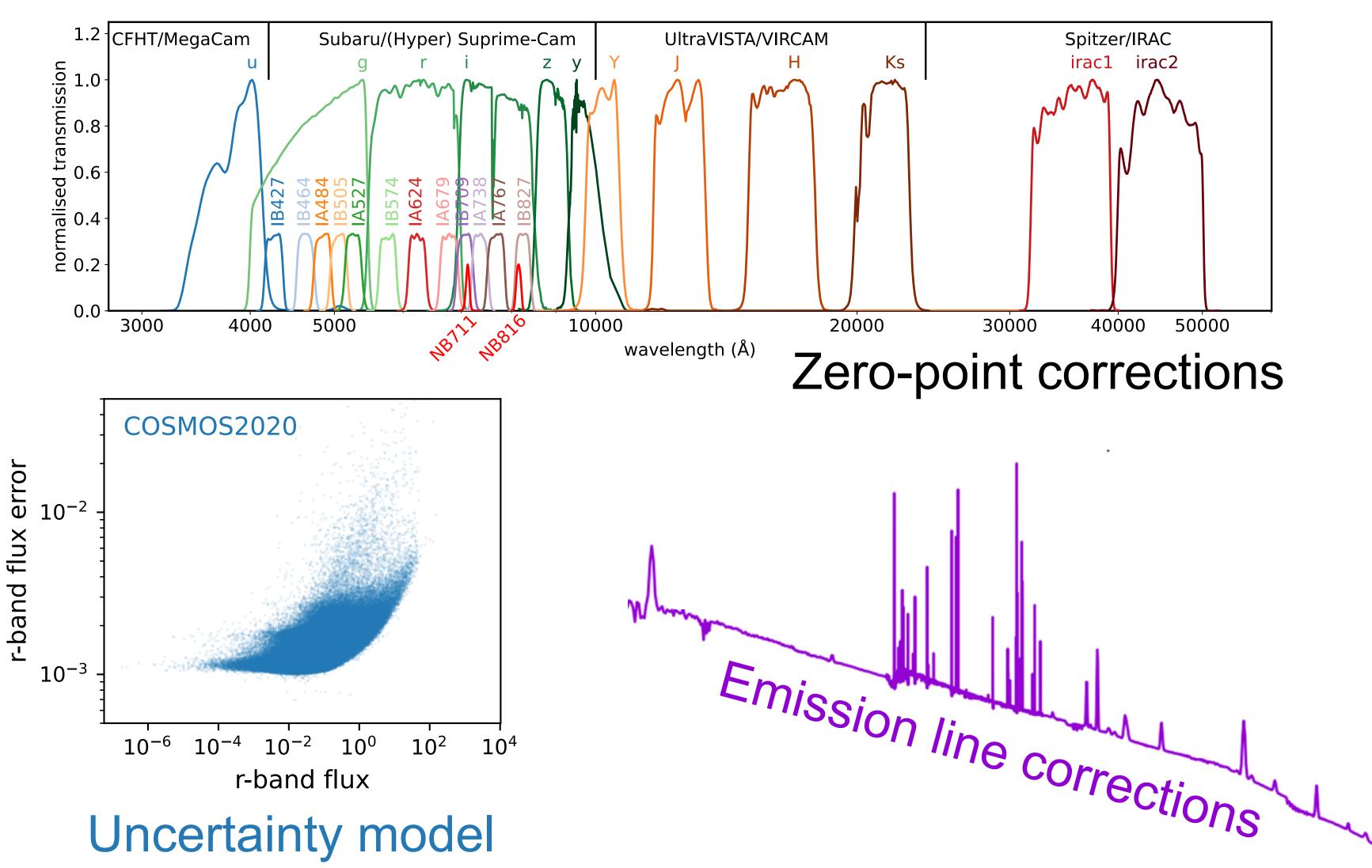


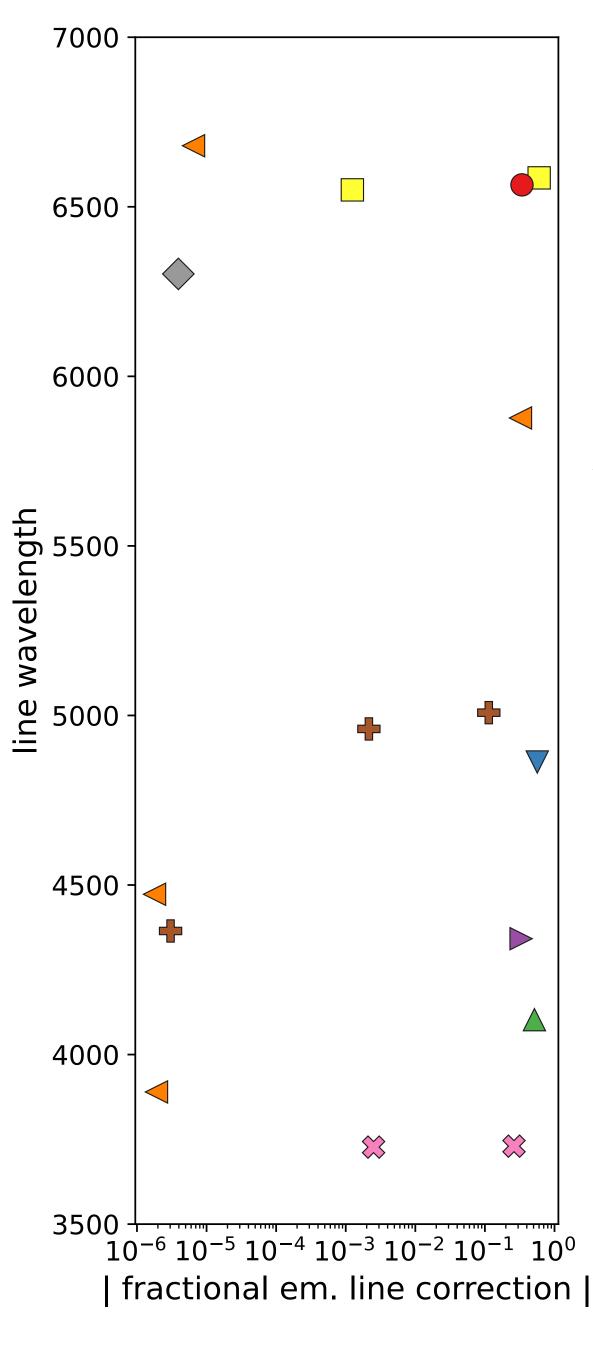
differential equation

## iid Gaussian noise (t = T)



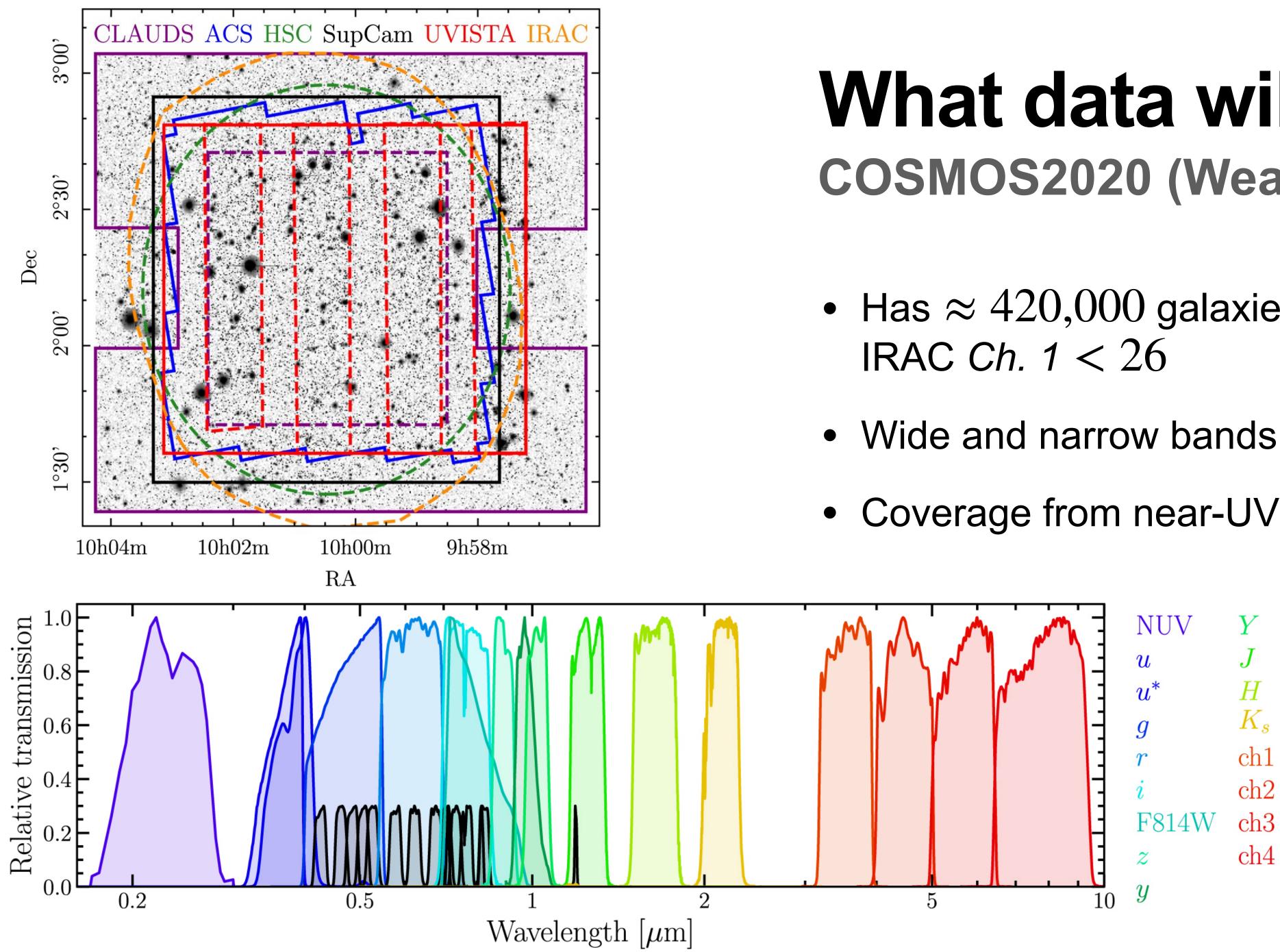
#### What goes into the data model? Uncertainty and calibration







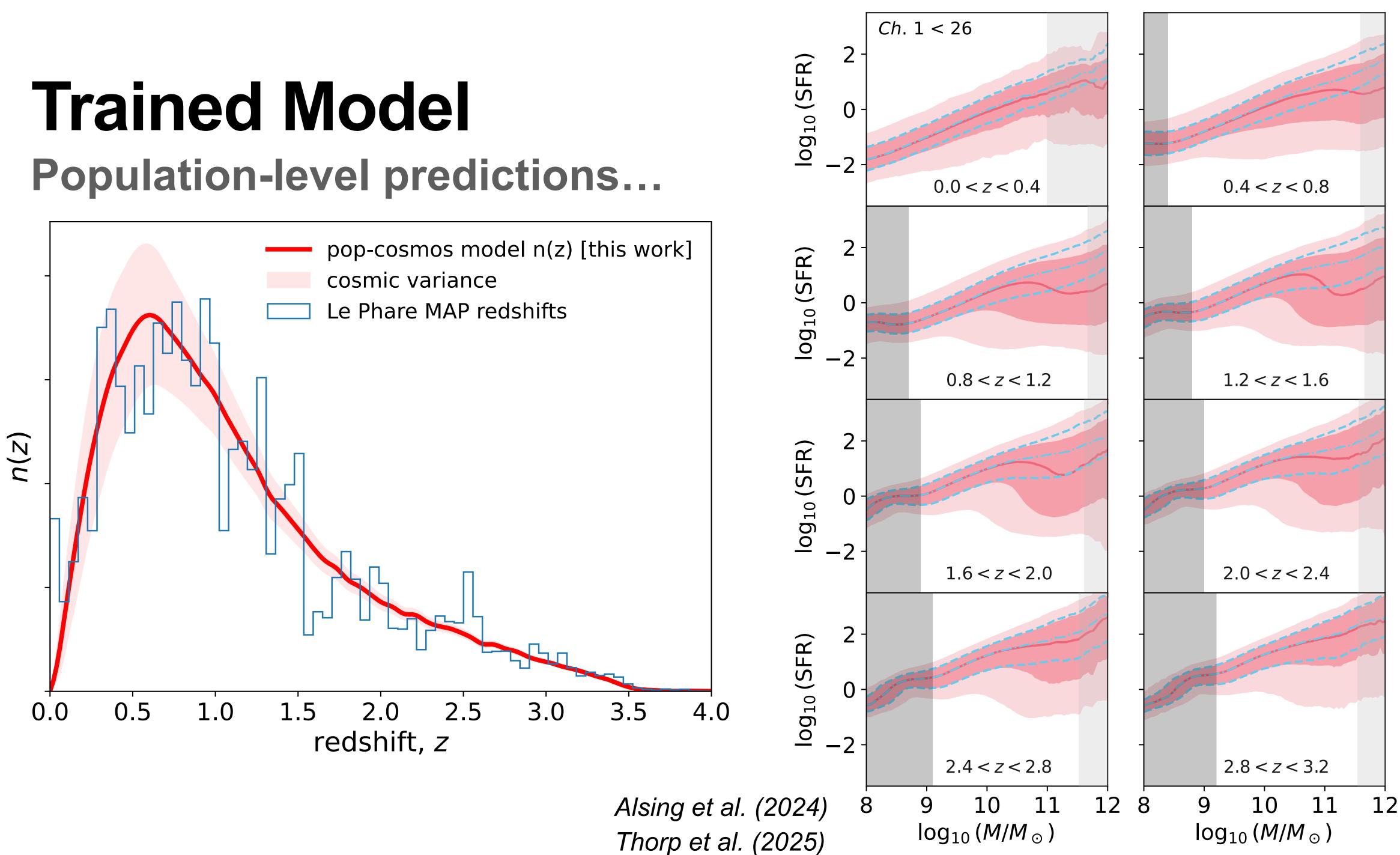
[O I] [N II] He I [O III] [O II] H-δH-γH-βH-α



#### What data will we use? **COSMOS2020 (Weaver et al. 2022)**

- Has  $\approx 420,000$  galaxies with Spitzer
- Coverage from near-UV to mid-IR





#### **Trained Model** As a prior...

- The learned population distribution over SPS parameters can be used for downstream inference for individual galaxies
- Why? Some science applications need redshift/ parameter inference for specific galaxies, not just population-level constraints

ندي. م.د. م. م. م. د

log<sub>10</sub> (SFR)

log<sub>10</sub> (Z/Z<sub>0</sub>)

 $\tau_2/mag$ 

 $\tau_1/\tau_2$ 

 $\ln(f_{\rm AGN})$ 

 $(U_{gas}) \log_{10} (Z_{gas}/Z_{\odot}) \ln(\tau_{AGN})$ 

0.

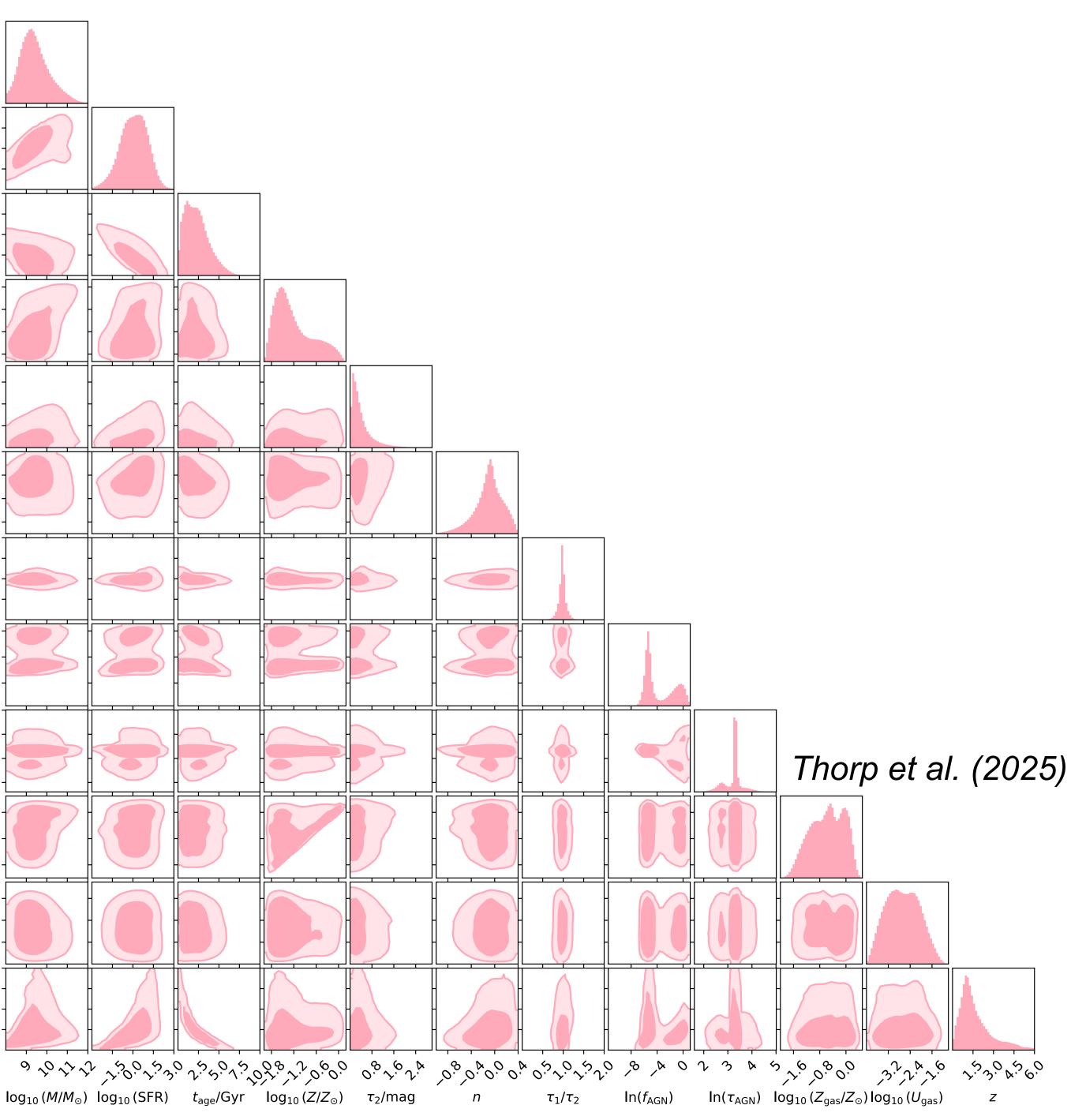
,0<sup>,8</sup>

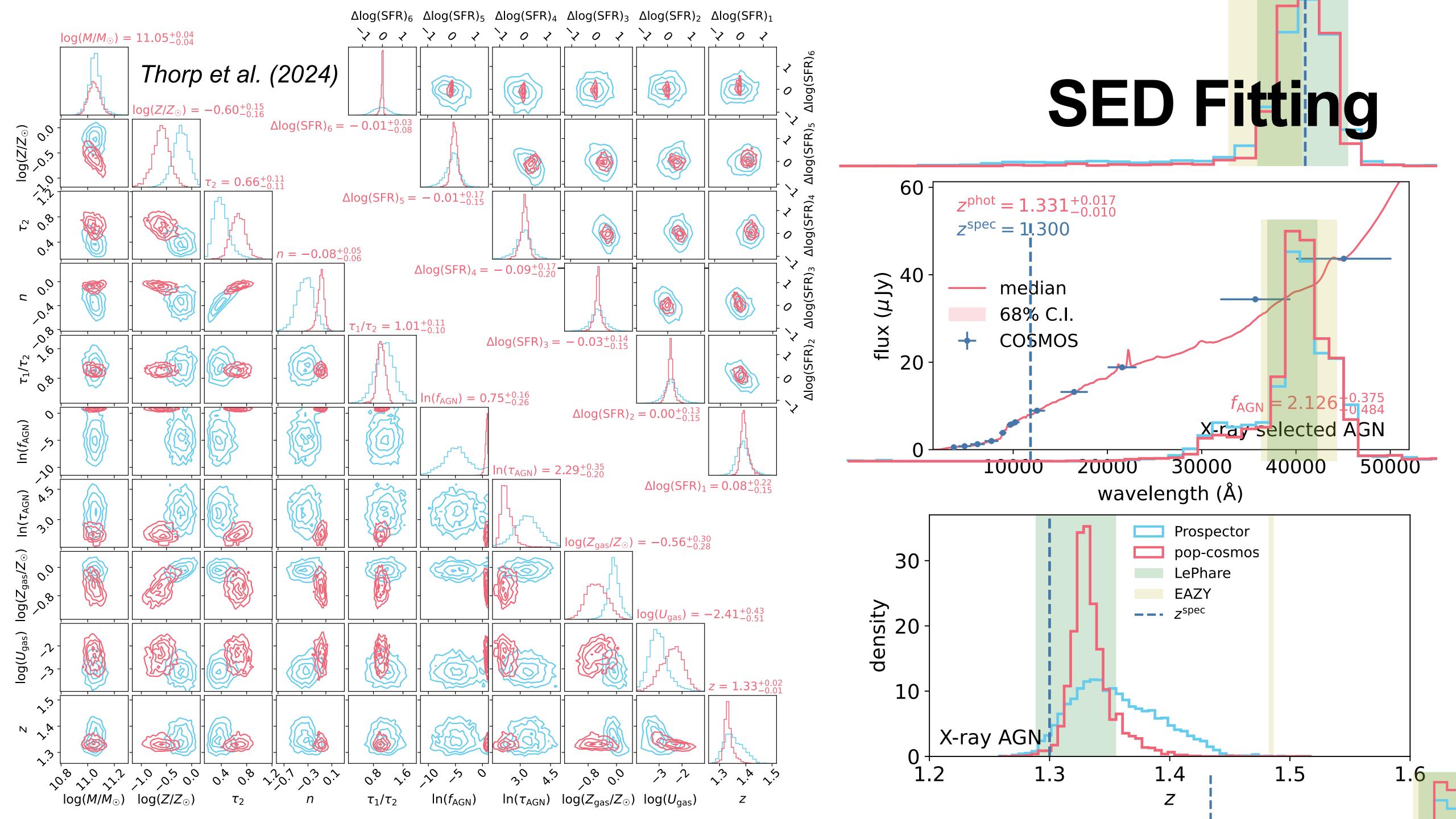
log\_10 (

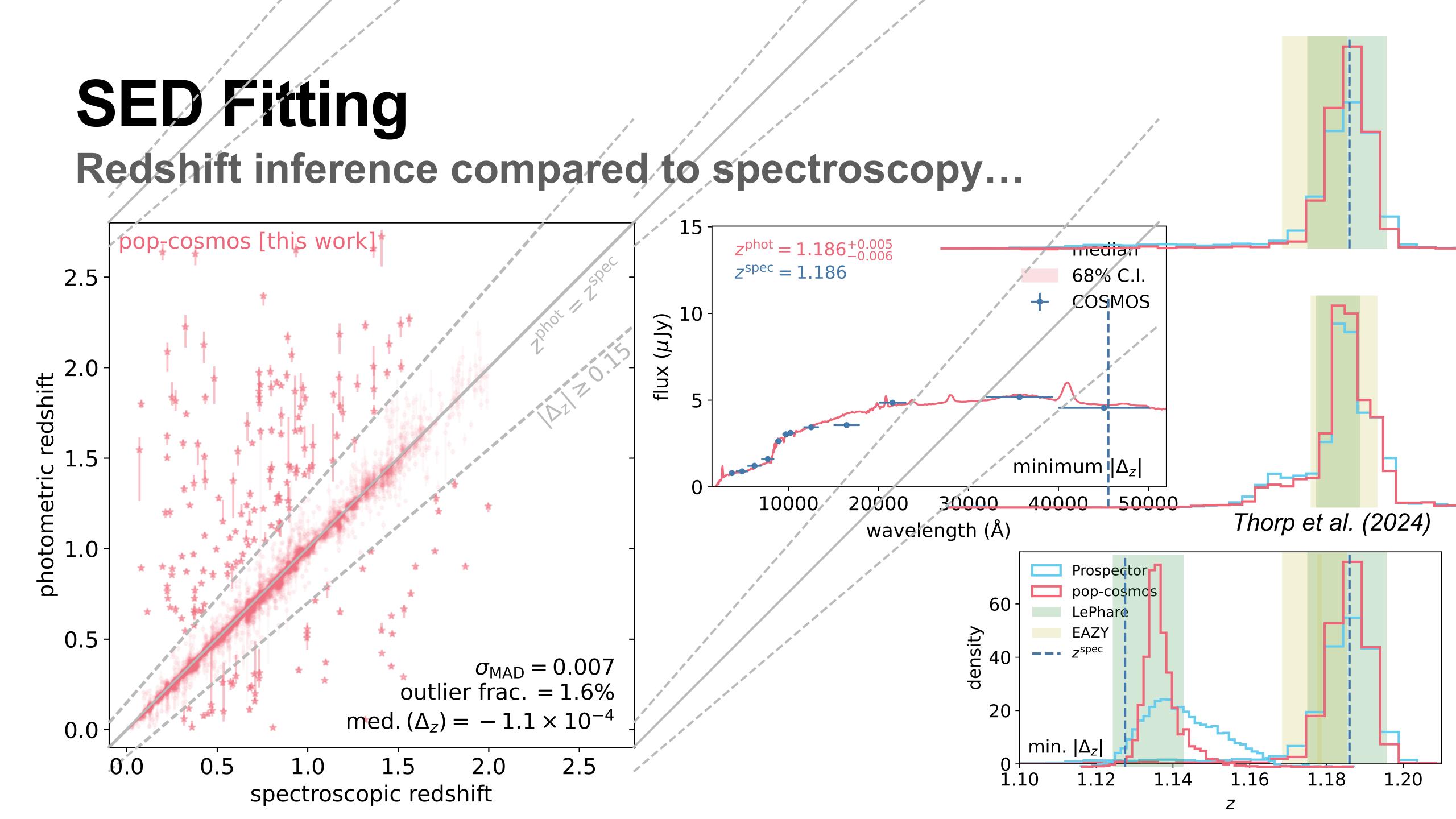
Ν

6. Å.

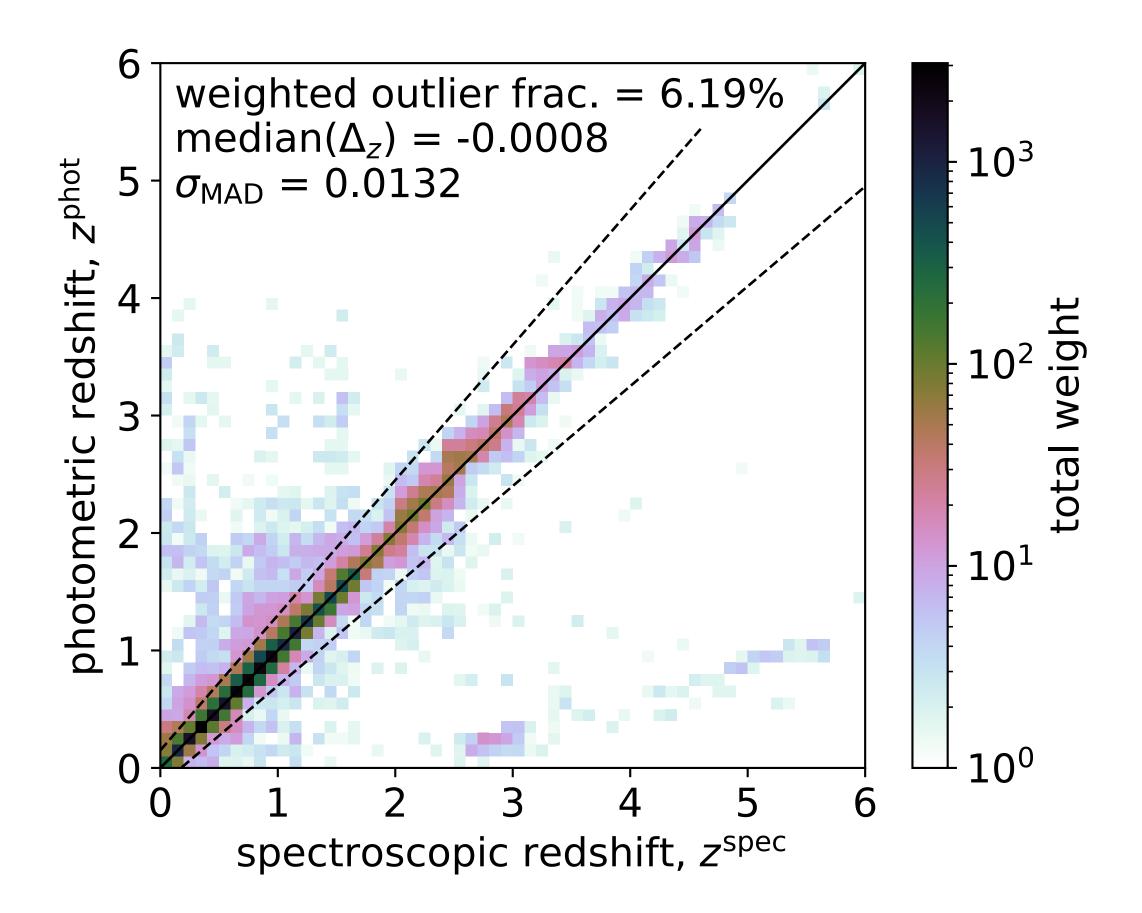
3. N.S.

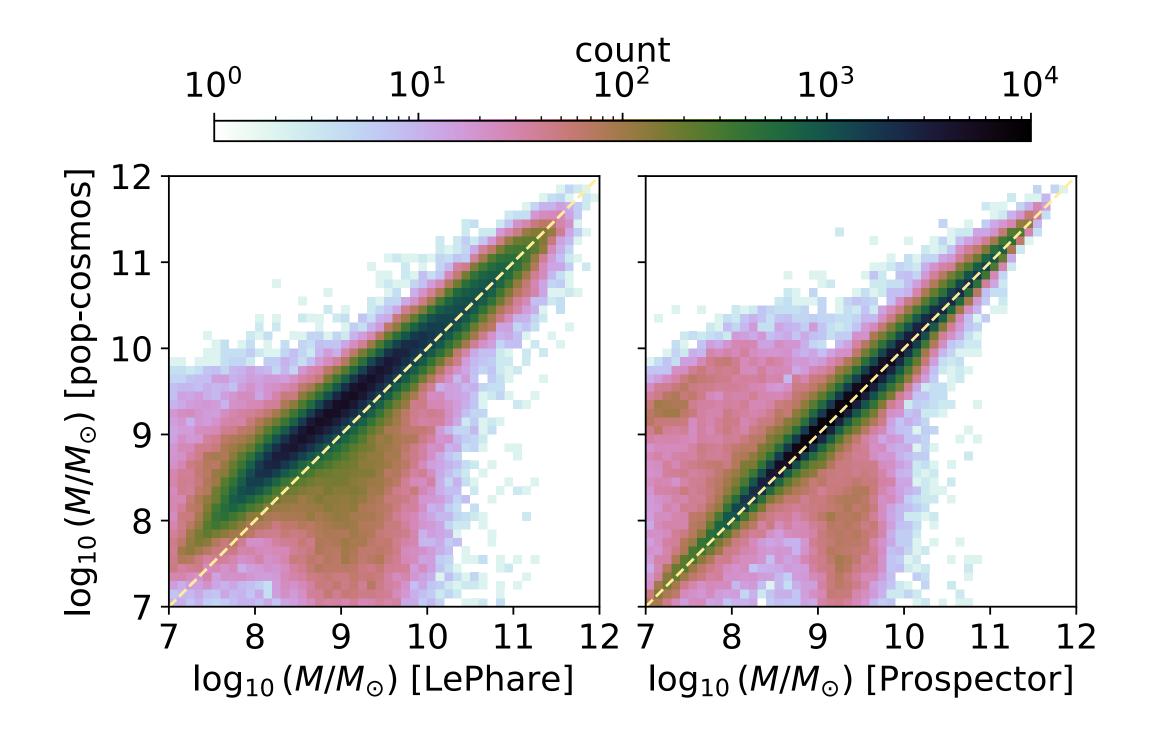






#### **SED Fitting Redshift and stellar mass inference...**



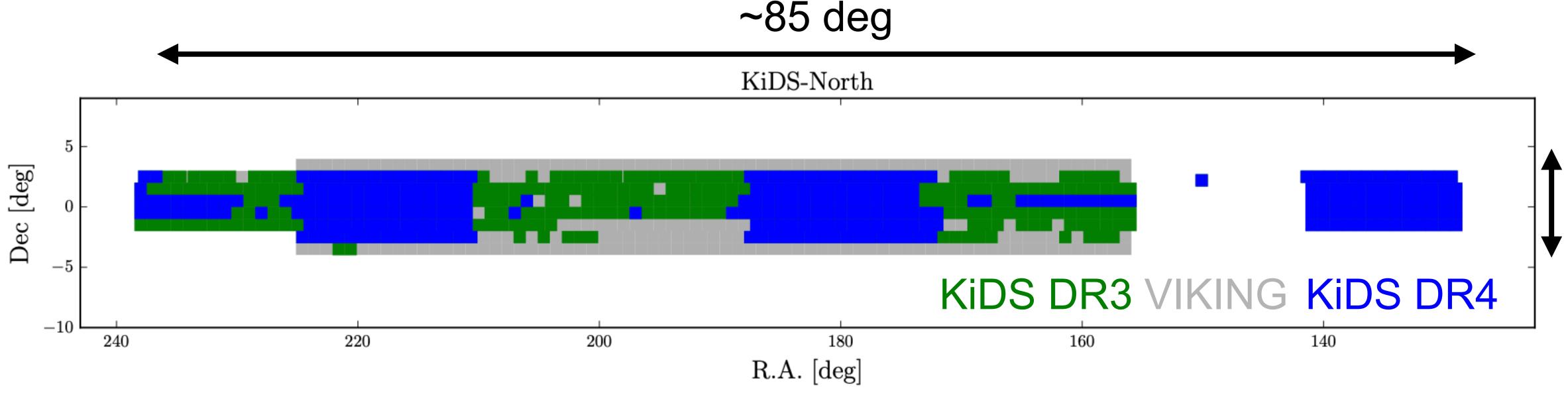


Thorp et al. (2025)



#### **Transferring to other surveys?** Kilo Degree Survey (KiDS; Kuijken et al. 2019)





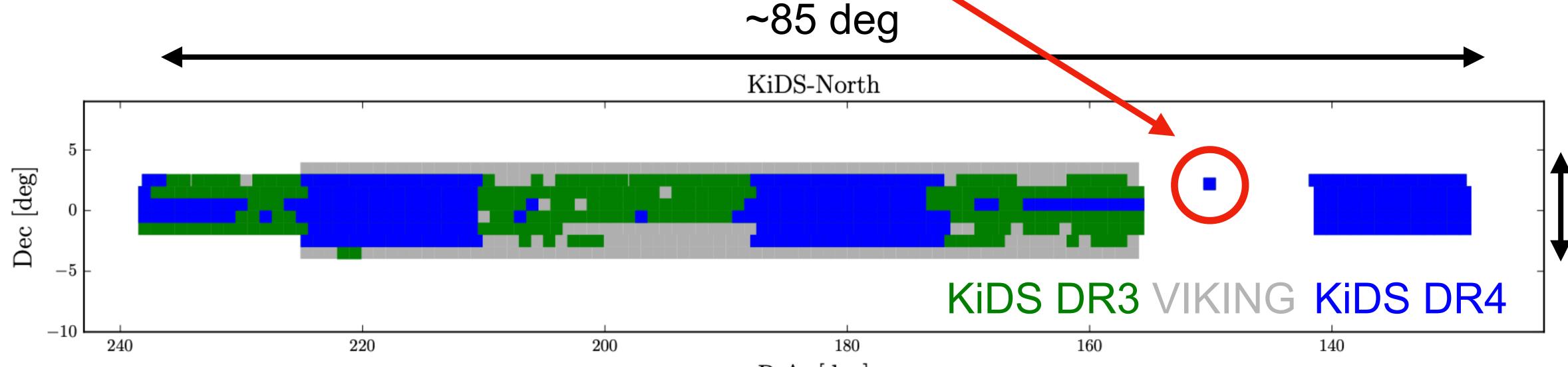
- Has  $\approx 70,000,000$  galaxies
- Broadband only:  $ugriZYJHK_{S}$
- Much larger area (1,000 deg<sup>2</sup>)





#### **Transferring to other surveys?** Kilo Degree Survey (KiDS; Kuijken et al. 2019)

#### **COSMOS** (our training data)



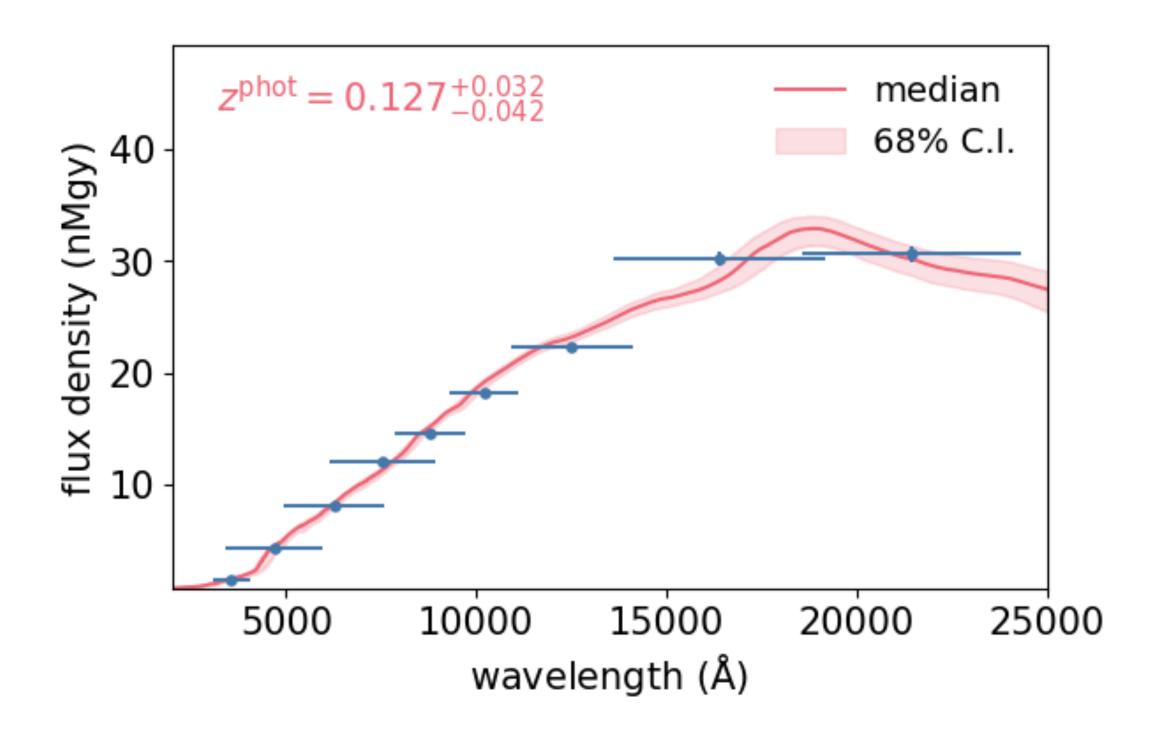
R.A. [deg]

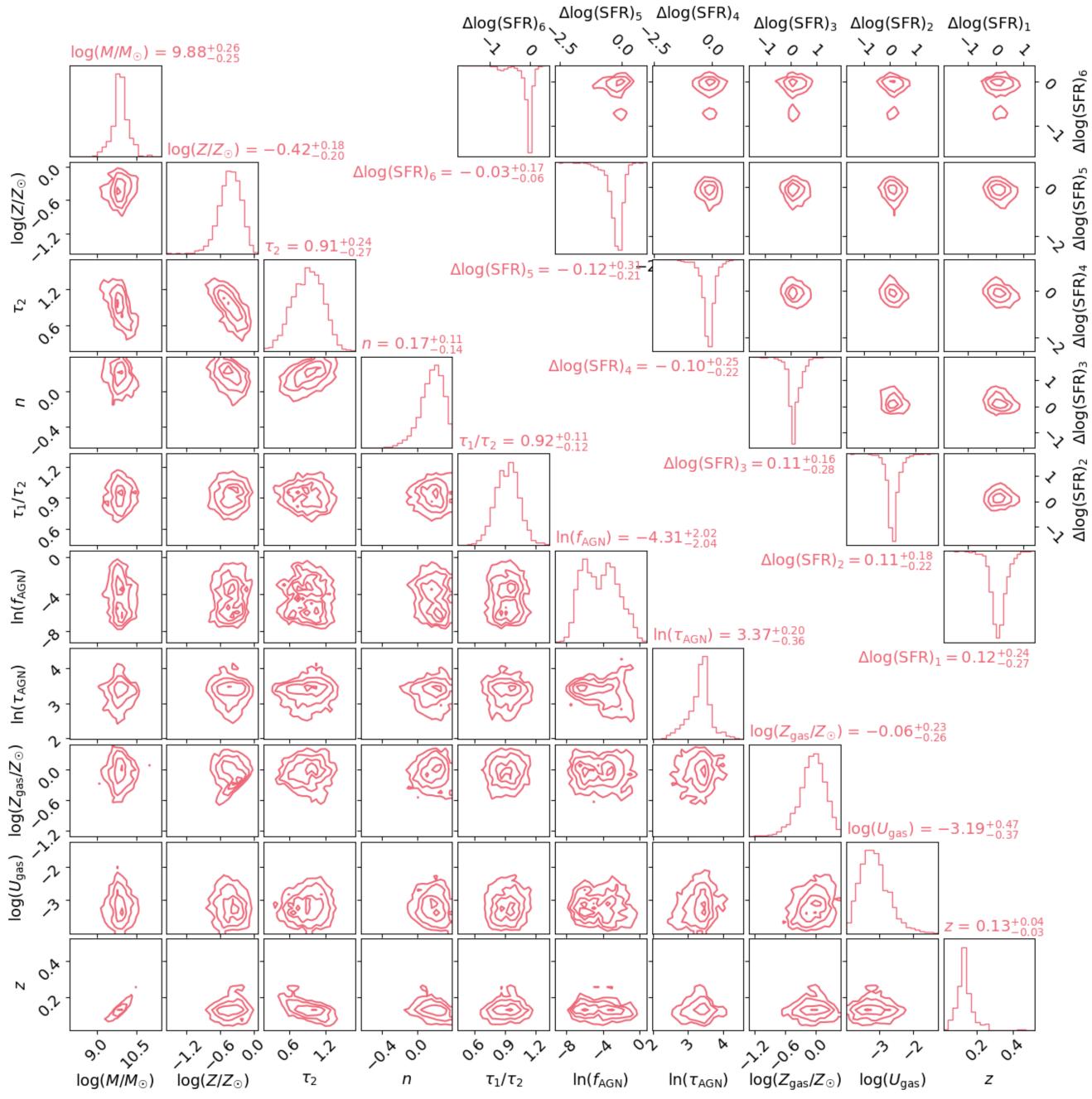
- Has  $\approx 70,000,000$  galaxies
- Broadband only: *ugriZYJHK*<sub>s</sub>
- Much larger area (1,000 deg<sup>2</sup>)





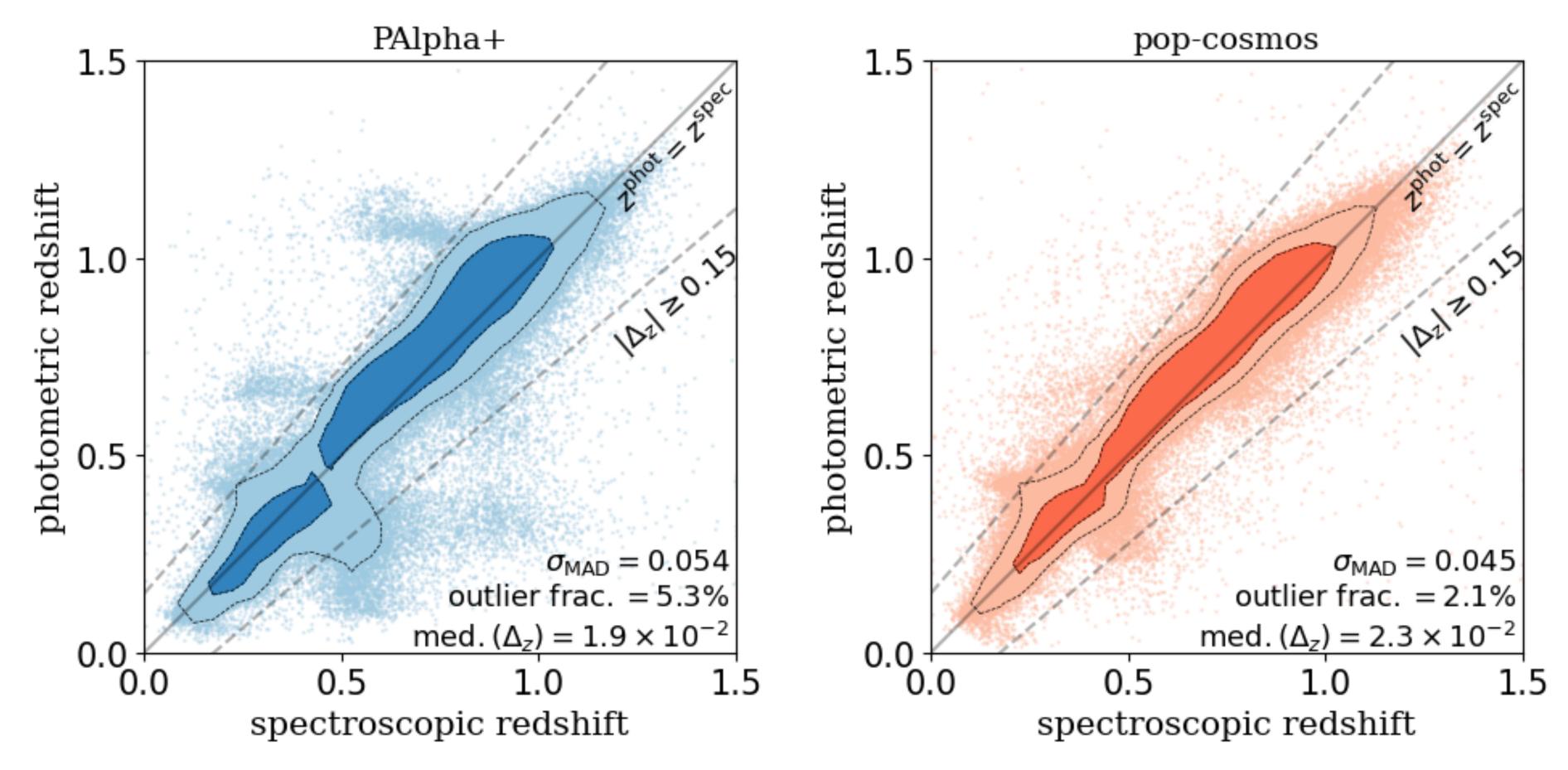
#### **SED Fitting** Kilo Degree Survey data...





Halder et al. (in prep.)

#### **SED Fitting** Kilo Degree Survey data...

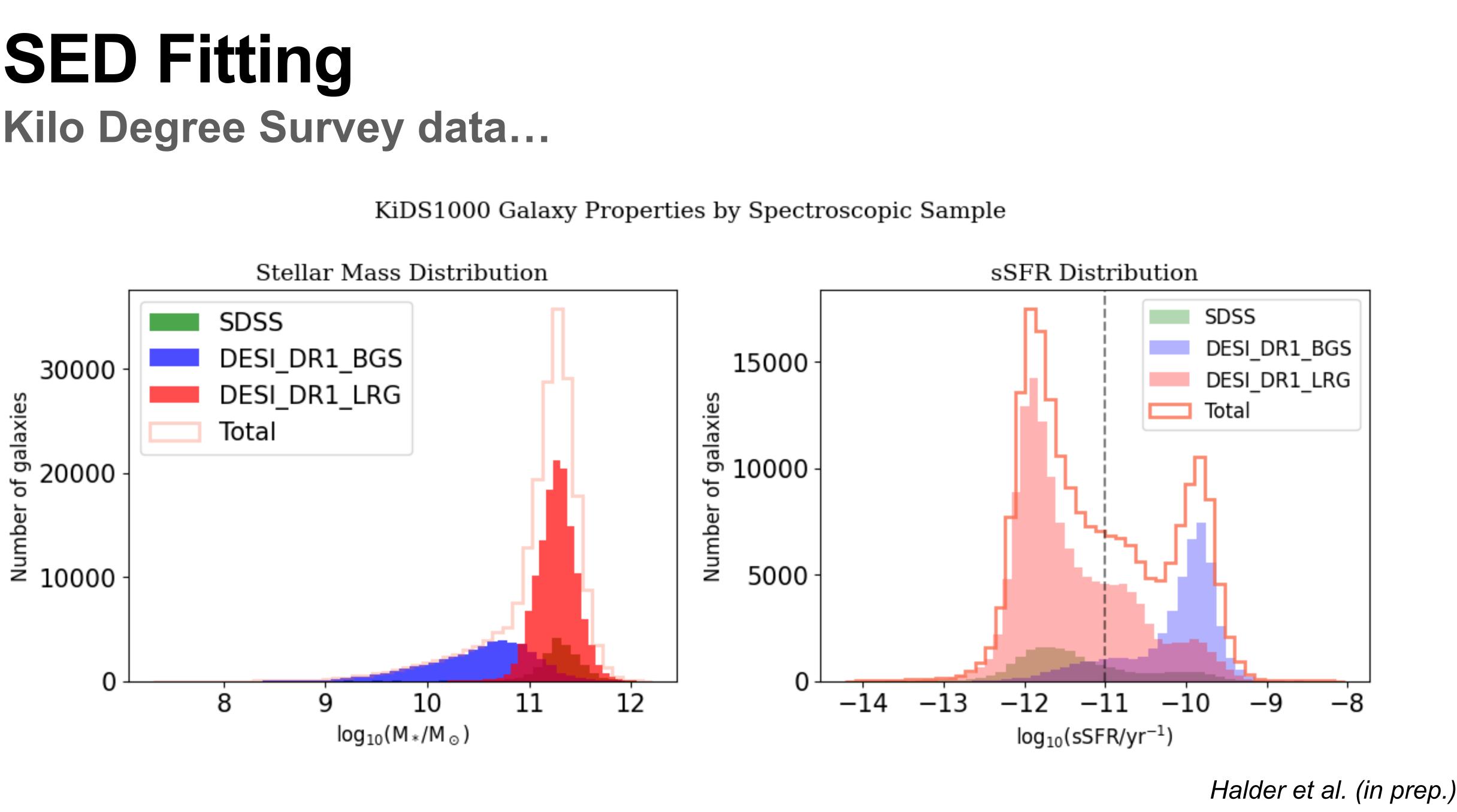


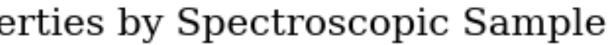


Halder et al. (in prep.)



# **SED Fitting**





#### Scaleability

- Currently using emulated SPS + diffusion prior + affine-invariant sampler
- Gets full MCMC chains with throughput of ~7 GPU-sec per galaxy (or ~0.7 GPU-sec per galaxy with a simpler analytic prior)
- Good enough for Stage III surveys; could be faster for Stage IV
- Bottleneck is flow/diffusion model log probability; room for improvement there, e.g. distillation/consistency models, ANPE, bespoke solvers (a cool idea from Luigi's highlight talk on Monday!)

#### Summary

- Data-driven prior over galaxy physical parameters, using a score-based diffusion model
- Train on the deepest, highestfidelity data that we have
- Use the model as a prior over physical parameters when doing inference for new surveys
- Scaling to ~few millions of galaxies possible with emulation, parallelised MCMC, GPUs
- Bigger data with ANPE, distillation, bespoke solvers?

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