Title: The Most Distant Quasars and the First Super-massive Black Holes

Speakers: Daniel Mortlock

Collection/Series: Cosmology and Gravitation

Subject: Cosmology

Date: April 22, 2025 - 11:00 AM

URL: https://pirsa.org/25040120

Abstract:

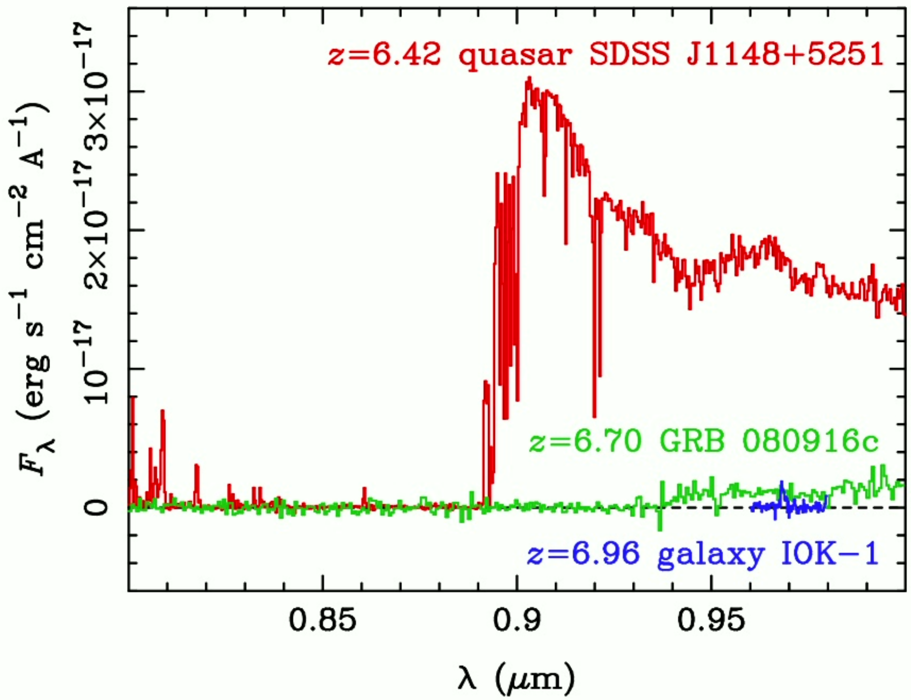
Quasars - accreting super-massive black holes - are the most luminous non-transient sources known and can be seen at redshifts of z > 7, when the Universe was just ~5% of its current age. This implies that black holes with masses of up to ~10^9 M_Sun formed less than 800 Myr after the Big Bang, impossible under the default paradigm of Eddington-limited accretion onto stellar mass black holes. The greatest barrier to understanding the formation and growth of these objects is the lack of data: quasars are very rare at these distances/times with fewer than ten known with z > 7 at present. I will report on recent observational developments in this field, with a particular focus on the early results from the Euclid mission, for which the Wide Survey has the necessary combination of area, wavelength coverage and depth to increase the number of known quasars by an order of magnitude and to push to redshifts z > 8 and beyond.

The most distant quasars and the first super-massive black holes

Daniel Mortlock
Imperial College London

Perimeter Institute, April 2025

Why search for HZQs?

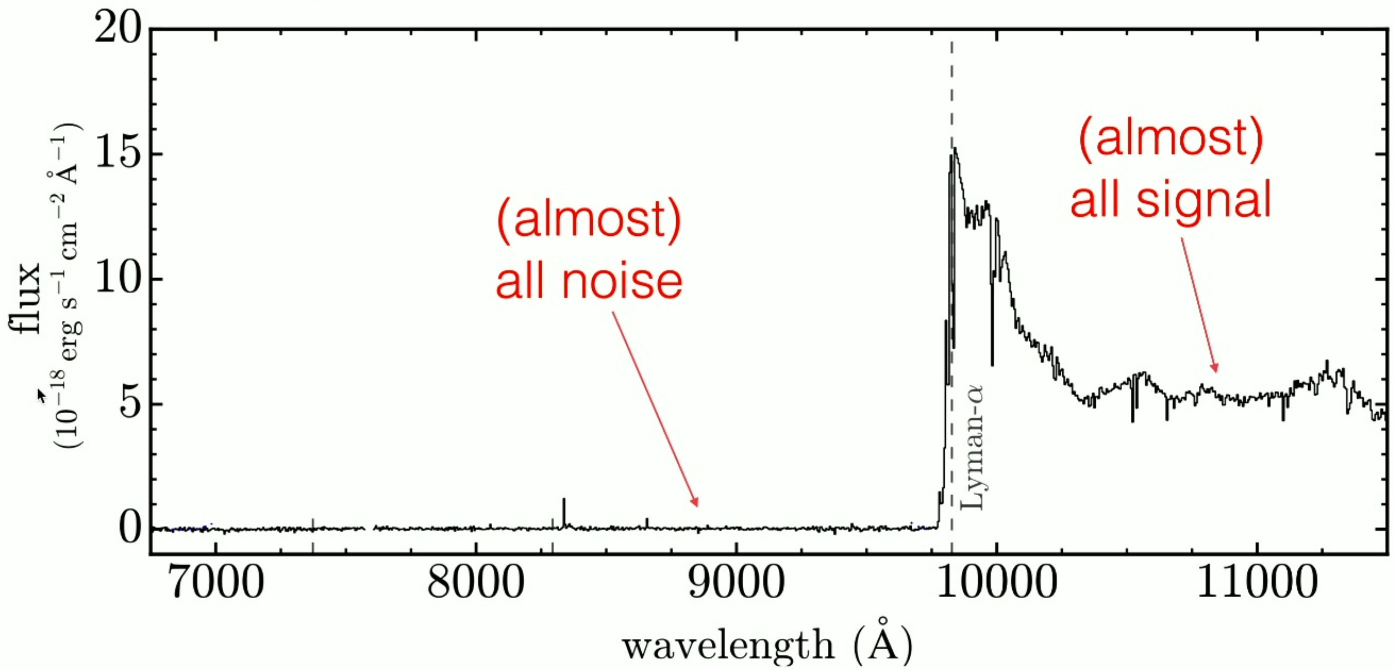


Implication: focus on highest *flux* objects

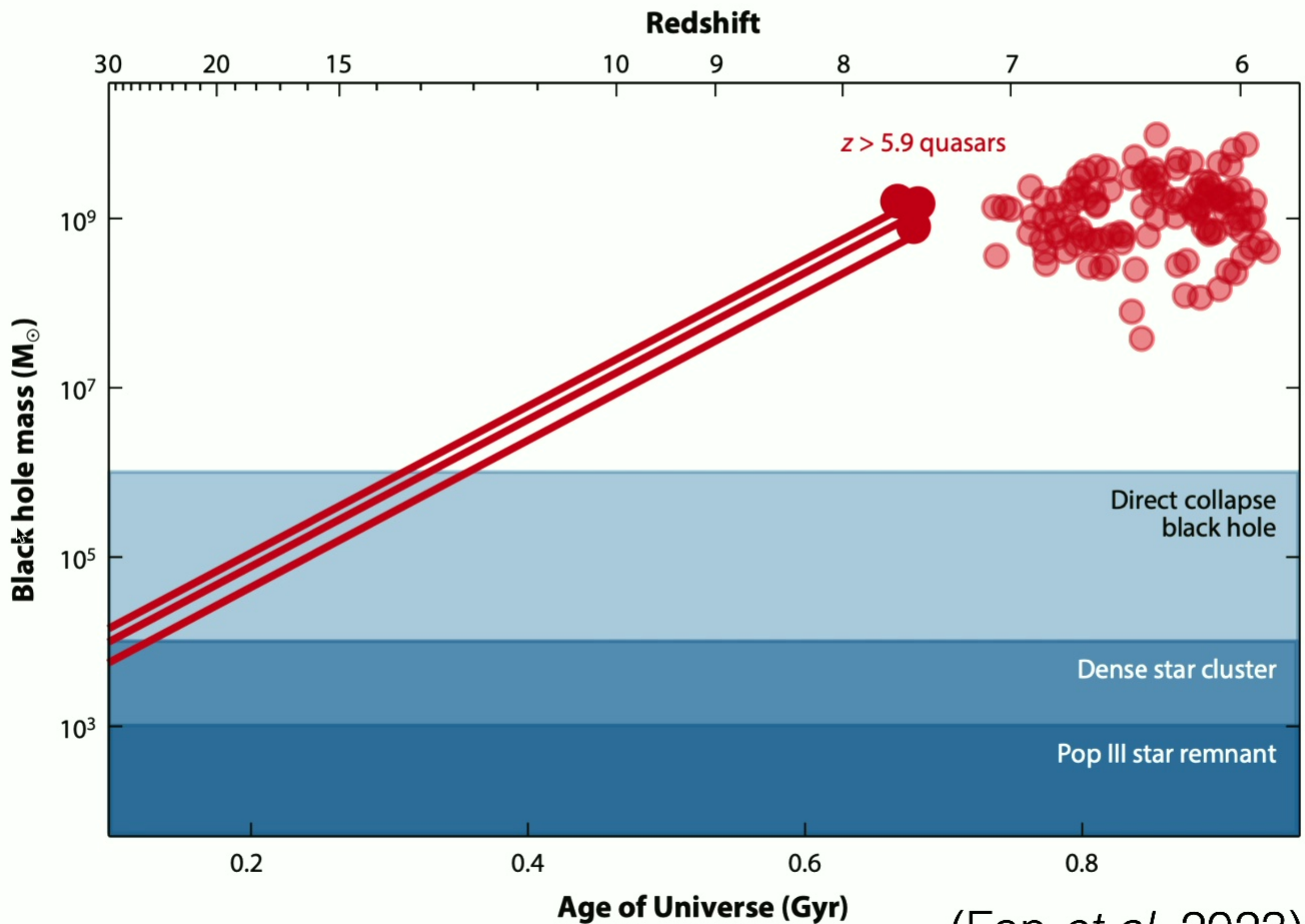
Why search for HZQs?

- Quasars are the **most useful sources of photons from the reionization epoch** (more luminous than galaxies; longer-lived than GRBs).
- Quasars have a direct link to the **earliest super-massive black holes** ($M_{BH} > 10^9$ $M_\odot$ less than 0.8 Gyr after Big Bang).
- Quasars are probes (and causes) of **cosmological hydrogen reionization** (GP absorption; dark gaps; Ly α damping wing; near zones; *etc.*).
- Quasars reveal **early elemental abundances** (from both absorption and emission).
- Quasars are tracers of **large-scale structures**.

Why search for HZQs?



30-hour Very Large Telescope X-Shooter spectrum of ULAS J1120+0641 (z = 7.1) from Barnett *et al.* (2017)



(Fan *et al.* 2023)

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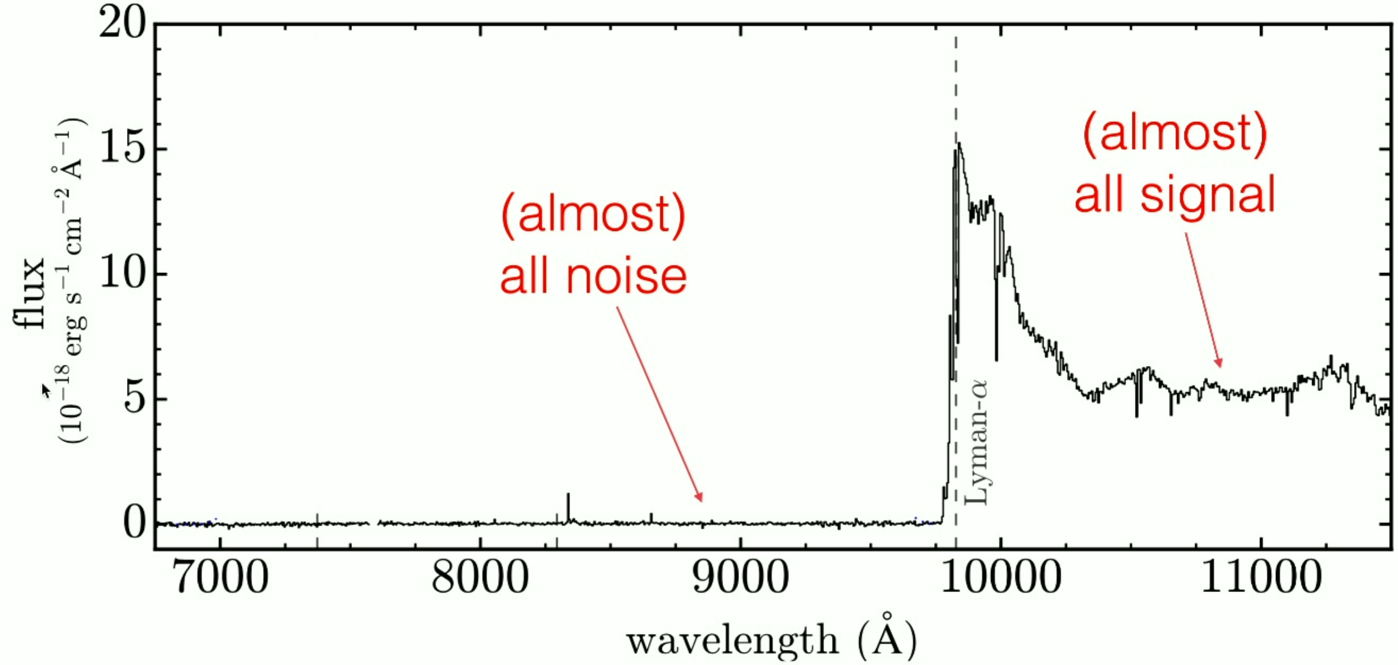

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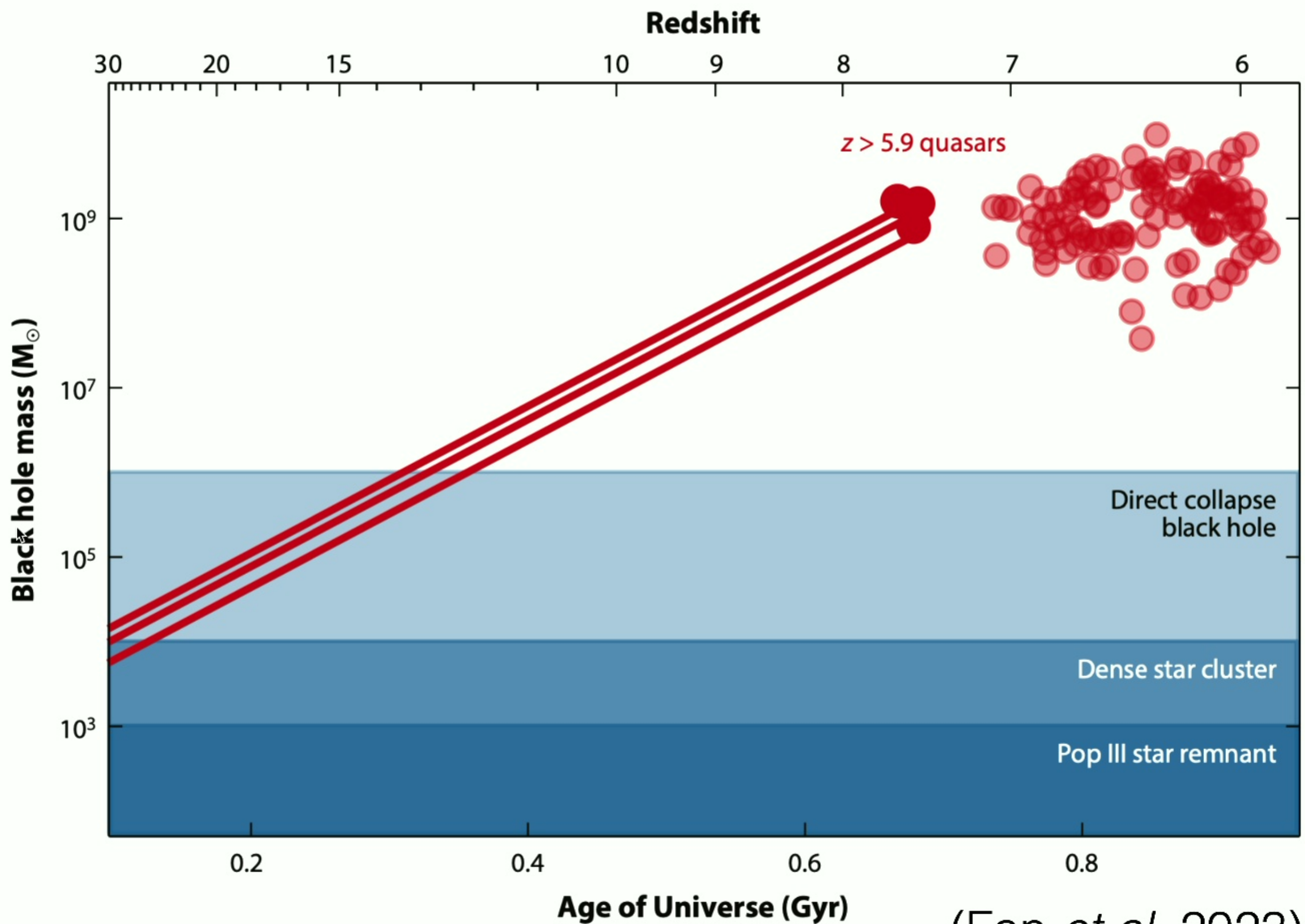

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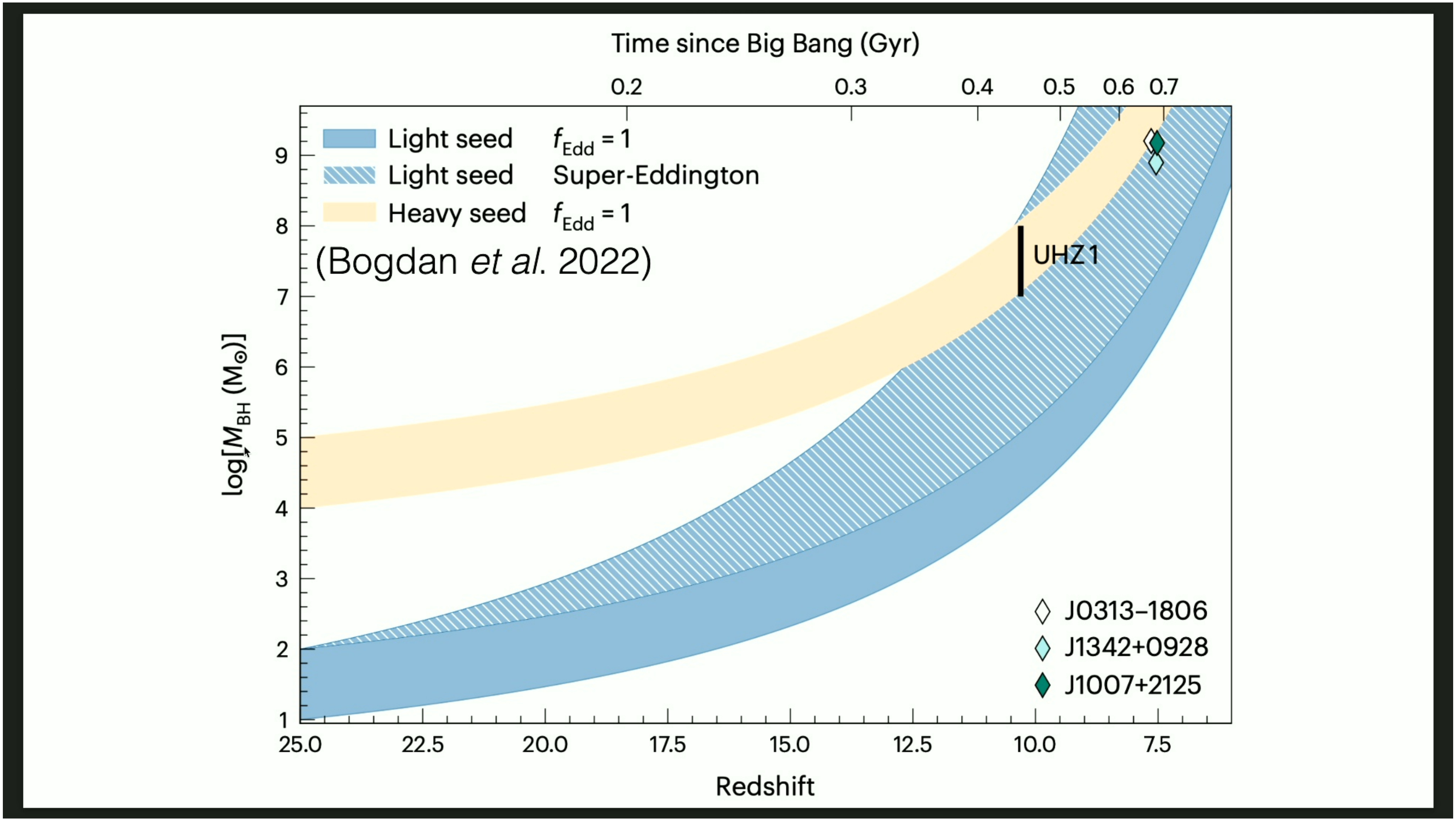
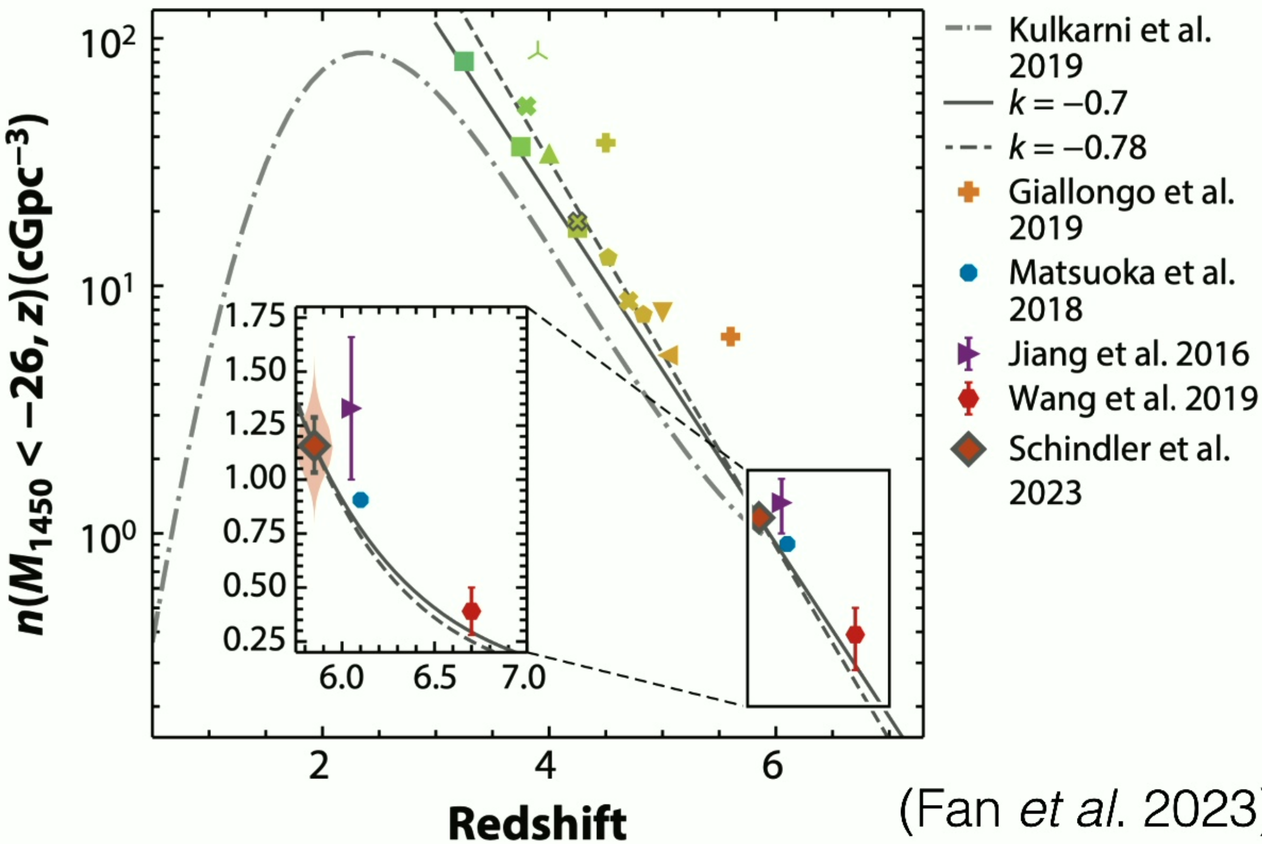


Time since Big Bang (Gyr)
0.2
0.3
0.4
0.5
0.6
0.7
Light seed $f_{Edd} = 1$
Light seed Super-Eddington
Heavy seed $f_{Edd} = 1$
(Bogdan *et al.* 2022)
UHZ1
$\log[M_{BH} (M_\odot)]$
9
8
7
6
5
4
3
2
1
J0313–1806
J1342+0928
J1007+2125
25.0
22.5
20.0
17.5
15.0
12.5
10.0
7.5
Redshift

Observed numbers

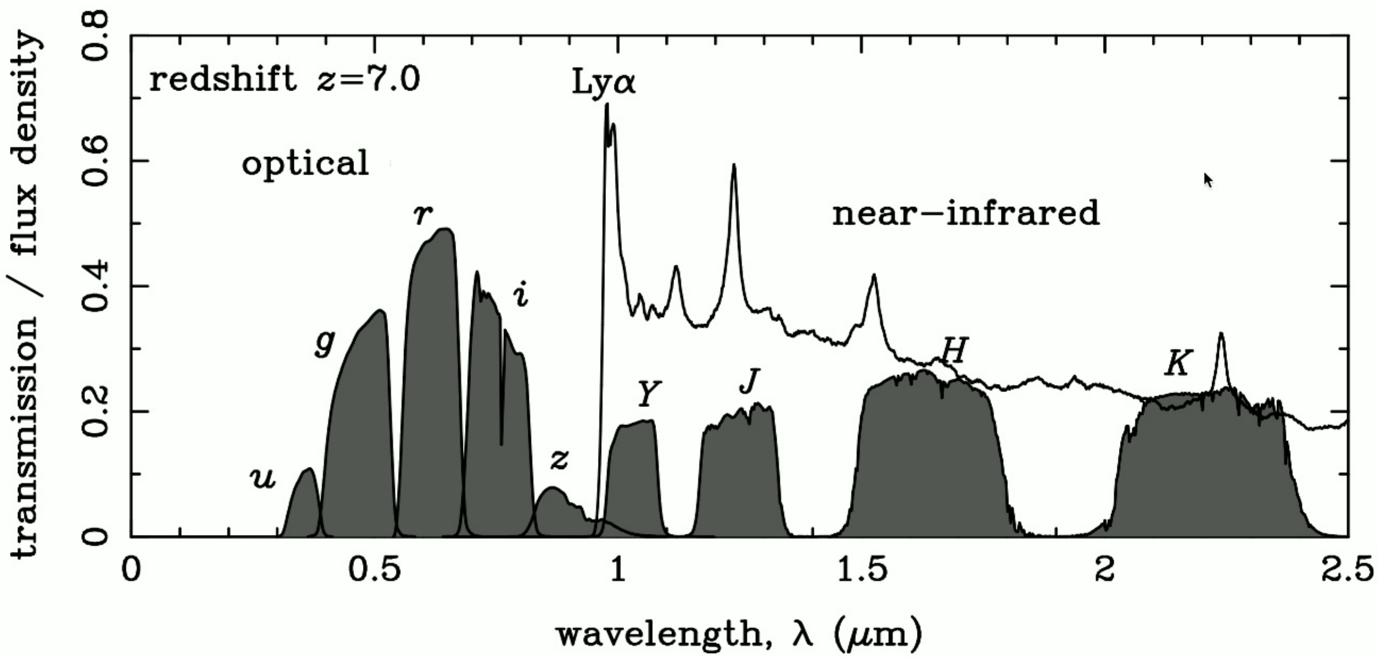
Very few on sky;
need large area, >10³ deg²

Difficult to simulate;
need large volumes;
models need tuning;
empirical predictions used.



(Fan *et al.* 2023)

HZQ SEDs

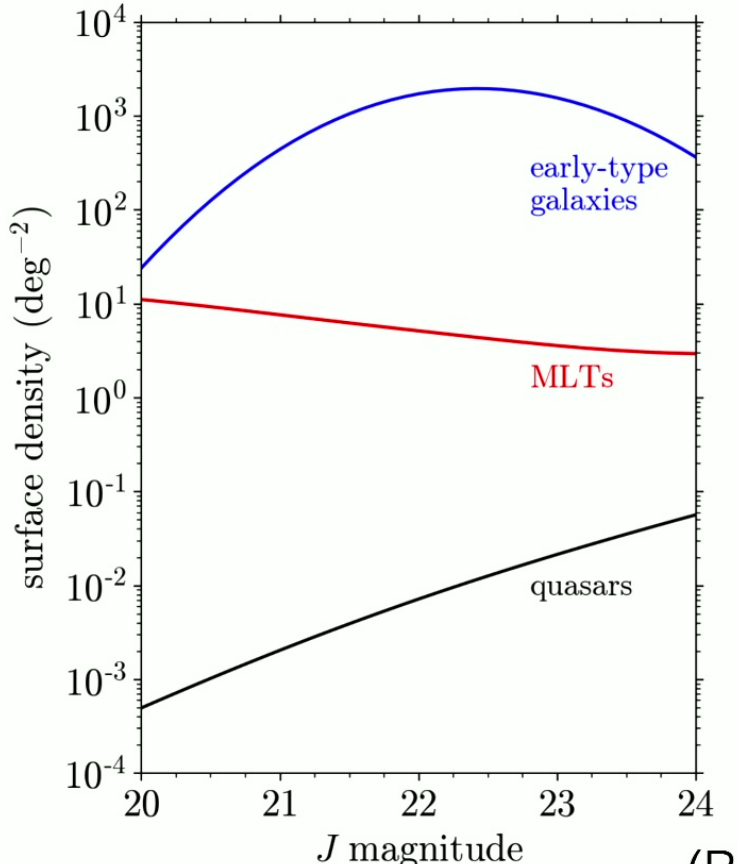


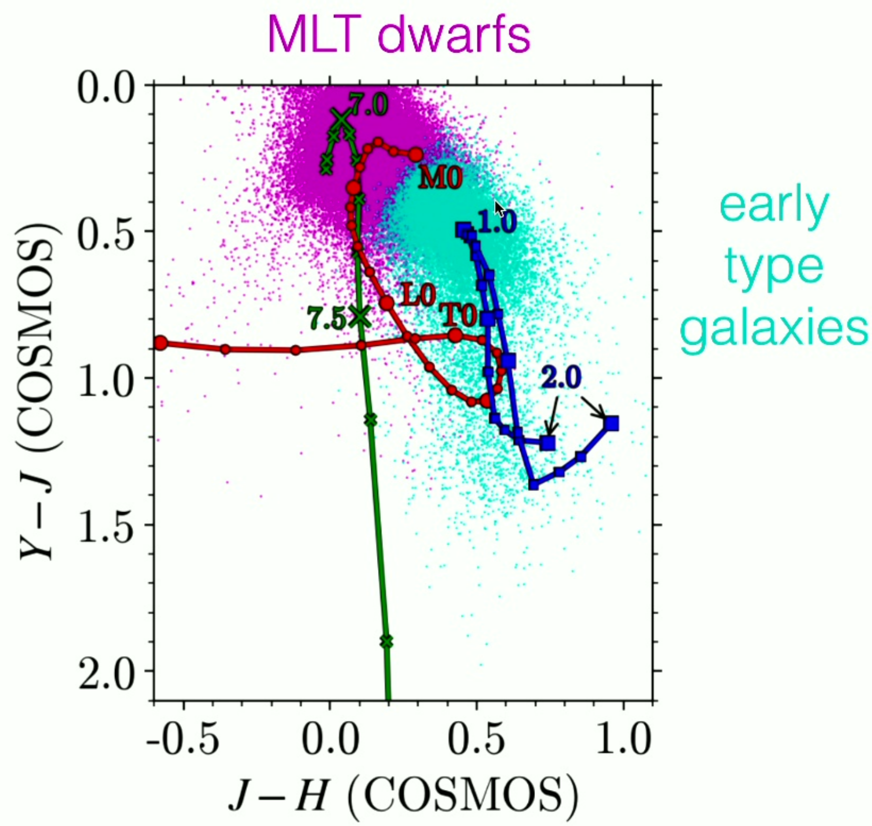
Hence seems easy to find HZQs:

Search for optical drop-outs with blue NIR colours;

Also: variability; radio emission; proper motion; Galactic latitude, *b*; etc.

Contaminants





(Barnett *et al.* 2019)

Bayesian selection

$$P_{\mathrm{q}} = P(t = \mathrm{q} | \hat{F}_{1:B}, \boldsymbol{\theta}_{\mathrm{q}}, \boldsymbol{\theta}_{\mathrm{s}}, \boldsymbol{\theta}_{\mathrm{g}})$$
$$= \frac{W_{\mathrm{q}}(\hat{F}_{1:B}, \boldsymbol{\theta}_{\mathrm{q}})}{W_{\mathrm{q}}(\hat{F}_{1:B}, \boldsymbol{\theta}_{\mathrm{q}}) + W_{\mathrm{s}}(\hat{F}_{1:B}, \boldsymbol{\theta}_{\mathrm{s}}) + W_{\mathrm{g}}(\hat{F}_{1:B}, \boldsymbol{\theta}_{\mathrm{g}})}$$

$$W_t(\hat{F}_{1:B}, \boldsymbol{\theta}_t) = \int \mathrm{d}\boldsymbol{\theta}_t \, \Sigma_t(\boldsymbol{\theta}_t) \, P(\hat{F}_{1:B} | \boldsymbol{\theta}_t, t)$$

population demographics/numbers

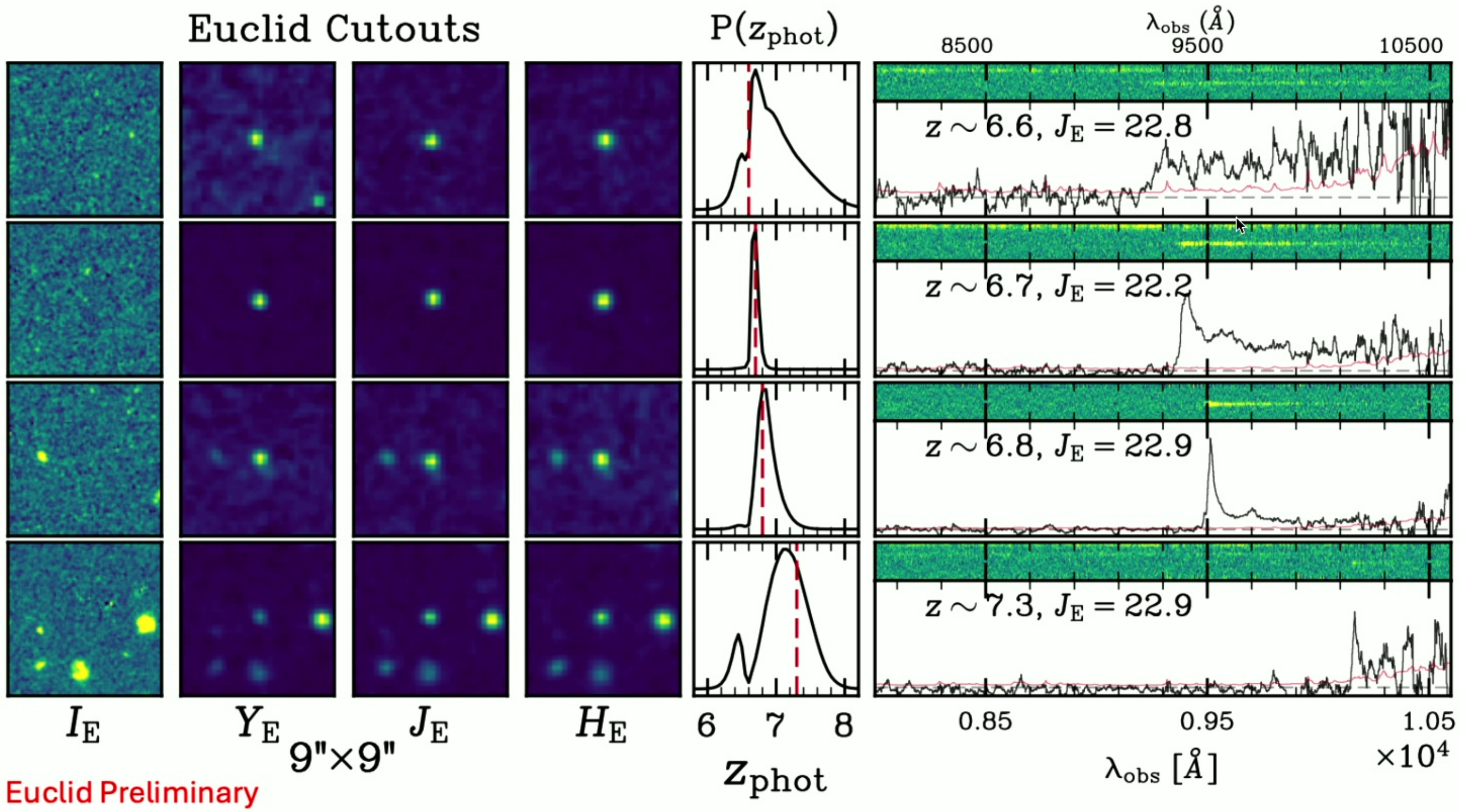
$$P(\hat{F}_{1:B} | \boldsymbol{\theta}_t, t) = \prod_{b=1}^{B} \mathrm{N}\left[\hat{F}_b; F_b(\boldsymbol{\theta}_t, t), \hat{\sigma}_b^2\right]$$

model-based (Mortlock *et al*. 2012; Barnett *et al*. 2019; Lenz *et al*. 2025)

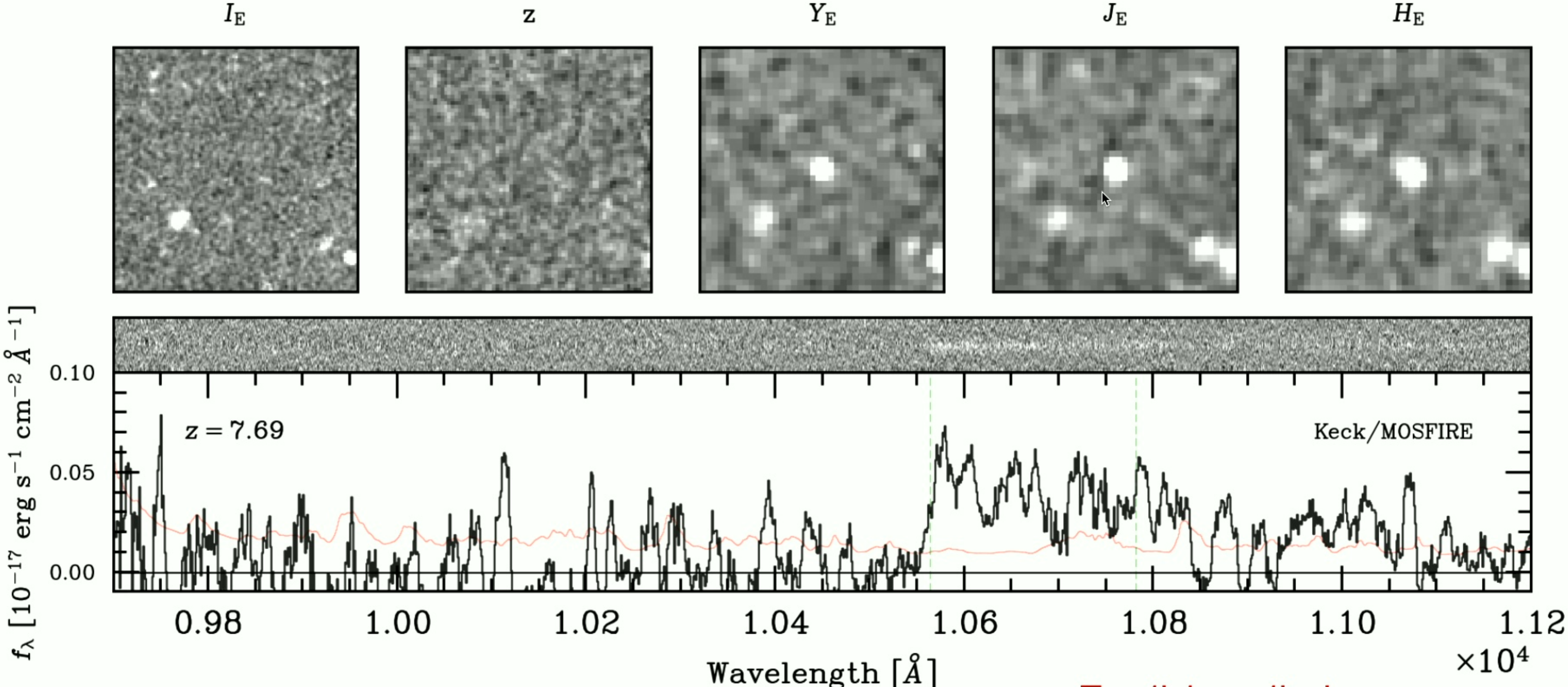
data-driven (Nanni *et al*. 2022)

machine learning (Wenzl *et al*. 2021)

In 200 deg^2 with 1.5 nights follow-up

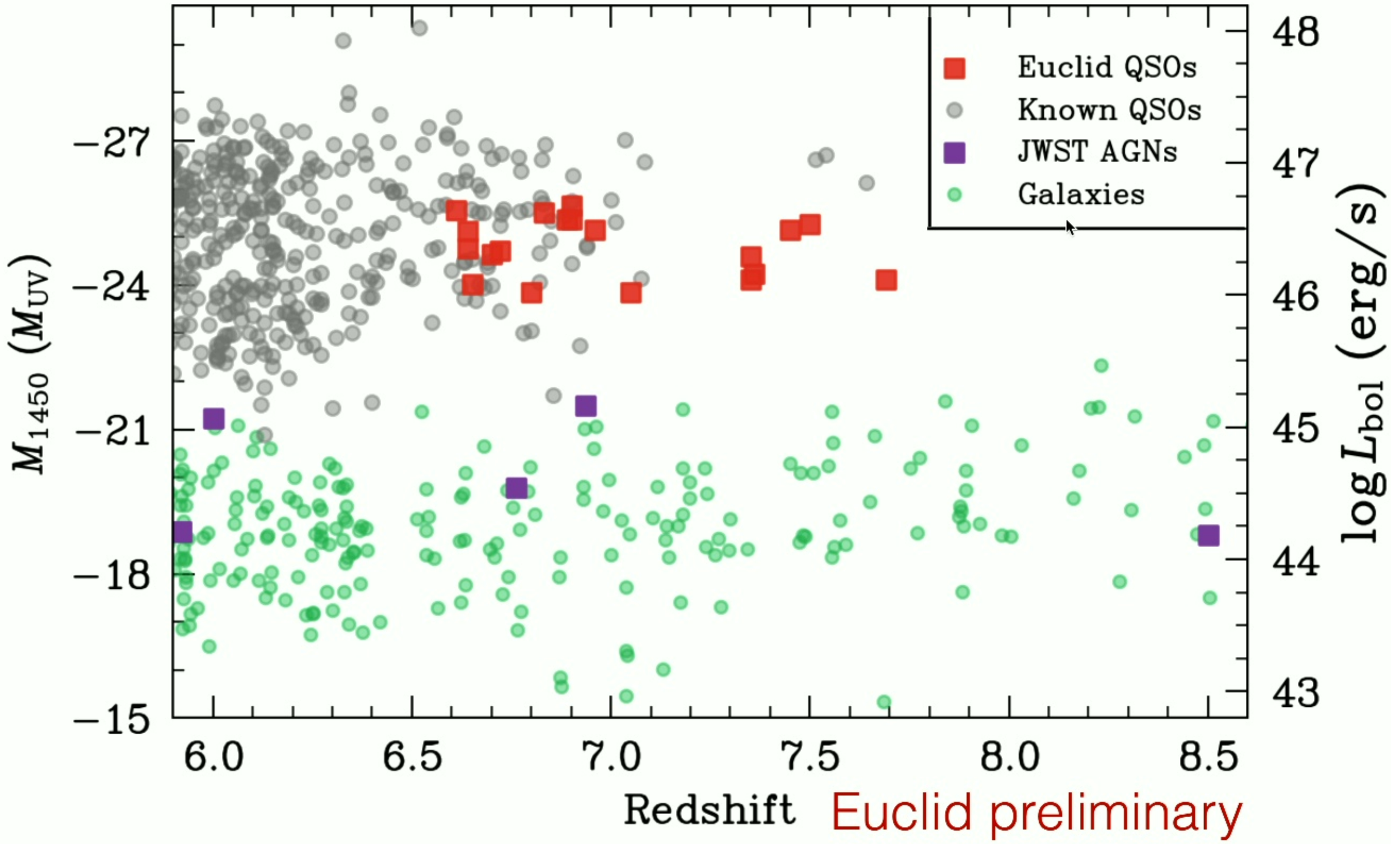


New quasar redshift record



Euclid preliminary

Current status



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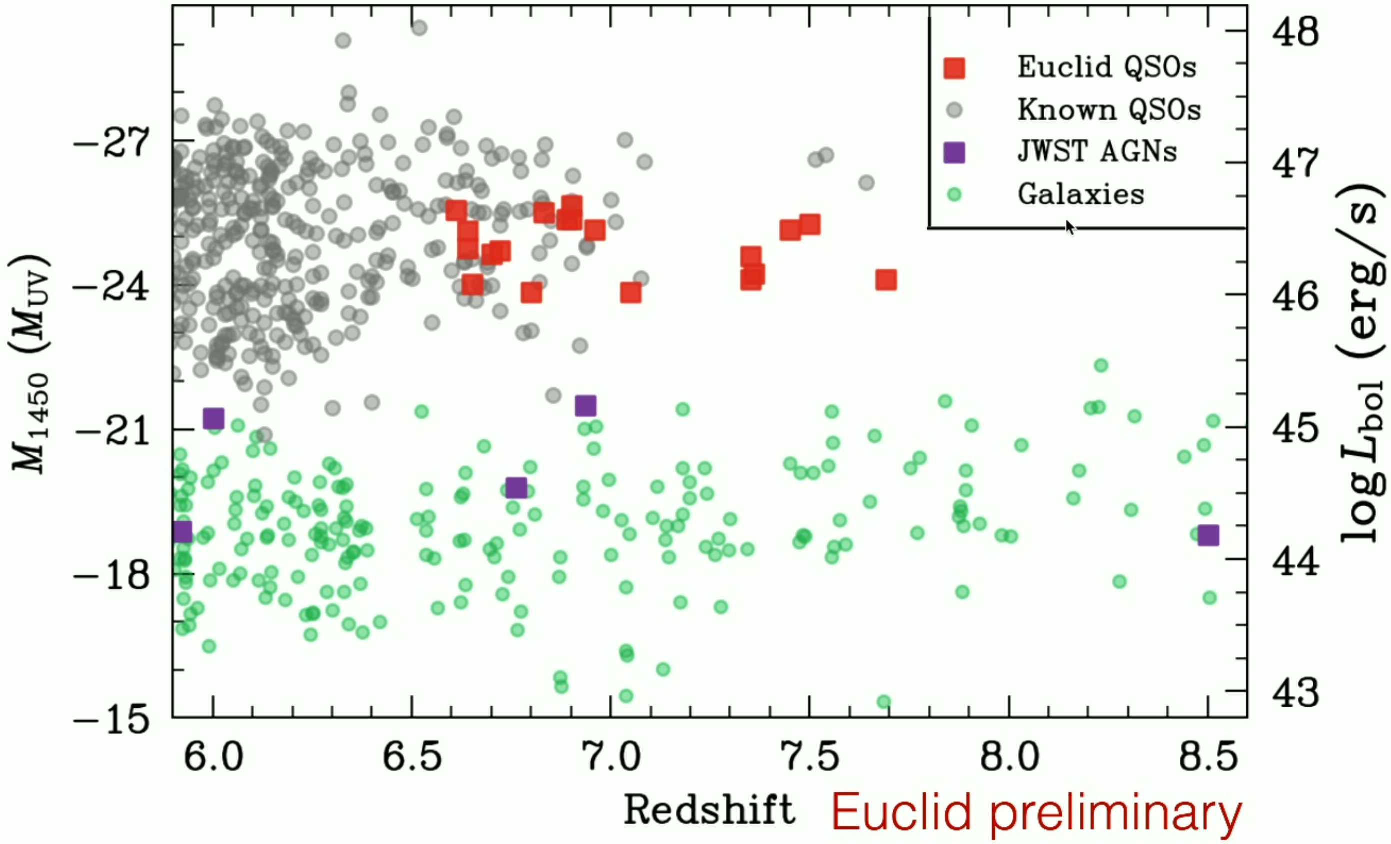

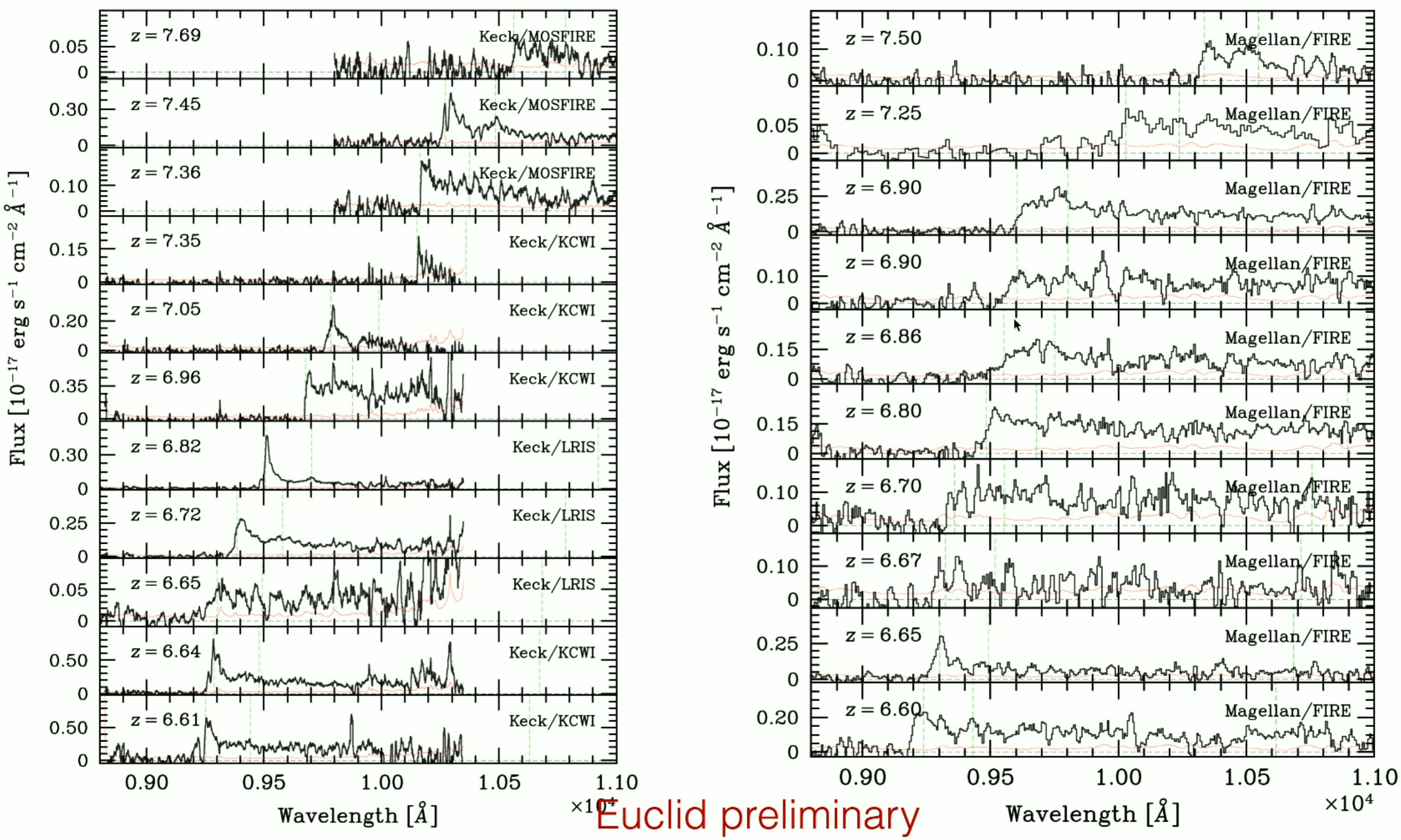
z = 7.69
Keck/MOSFIRE
z = 7.45
Keck/MOSFIRE
z = 7.36
Keck/MOSFIRE
z = 7.35
Keck/KCWI
z = 7.05
Keck/KCWI
z = 6.96
Keck/KCWI
z = 6.82
Keck/LRIS
z = 6.72
Keck/LRIS
z = 6.65
Keck/LRIS
z = 6.64
Keck/KCWI
z = 6.61
Keck/KCWI
Flux [10^-17 erg s^-1 cm^-2 Å^-1]
Wavelength [Å]
×10^4
z = 7.50
Magellan/FIRE
z = 7.25
Magellan/FIRE
z = 6.90
Magellan/FIRE
z = 6.90
Magellan/FIRE
z = 6.86
Magellan/FIRE
z = 6.80
Magellan/FIRE
z = 6.70
Magellan/FIRE
z = 6.67
Magellan/FIRE
z = 6.65
Magellan/FIRE
z = 6.60
Magellan/FIRE
Flux [10^-17 erg s^-1 cm^-2 Å^-1]
Wavelength [Å]
×10^4
Euclid preliminary

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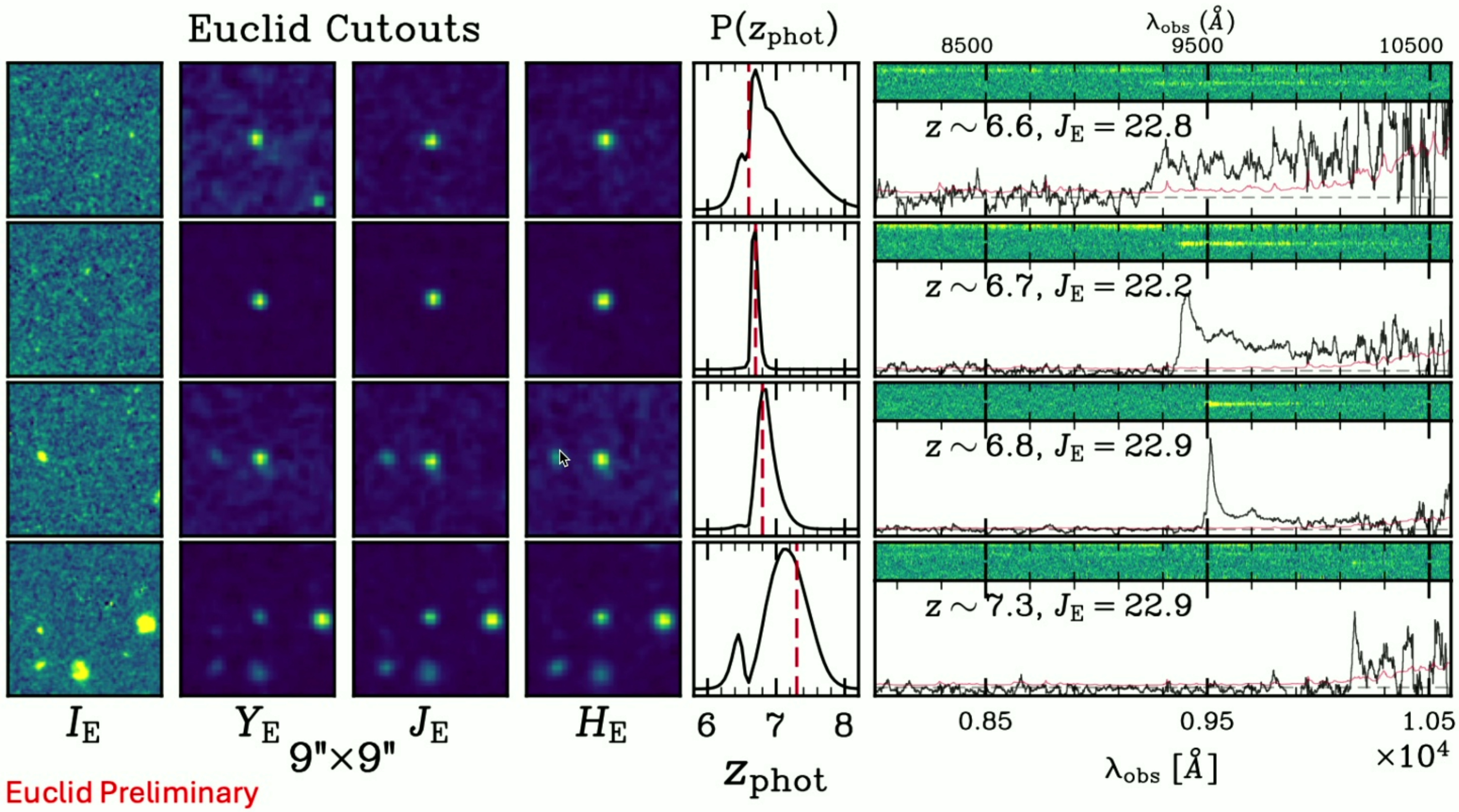

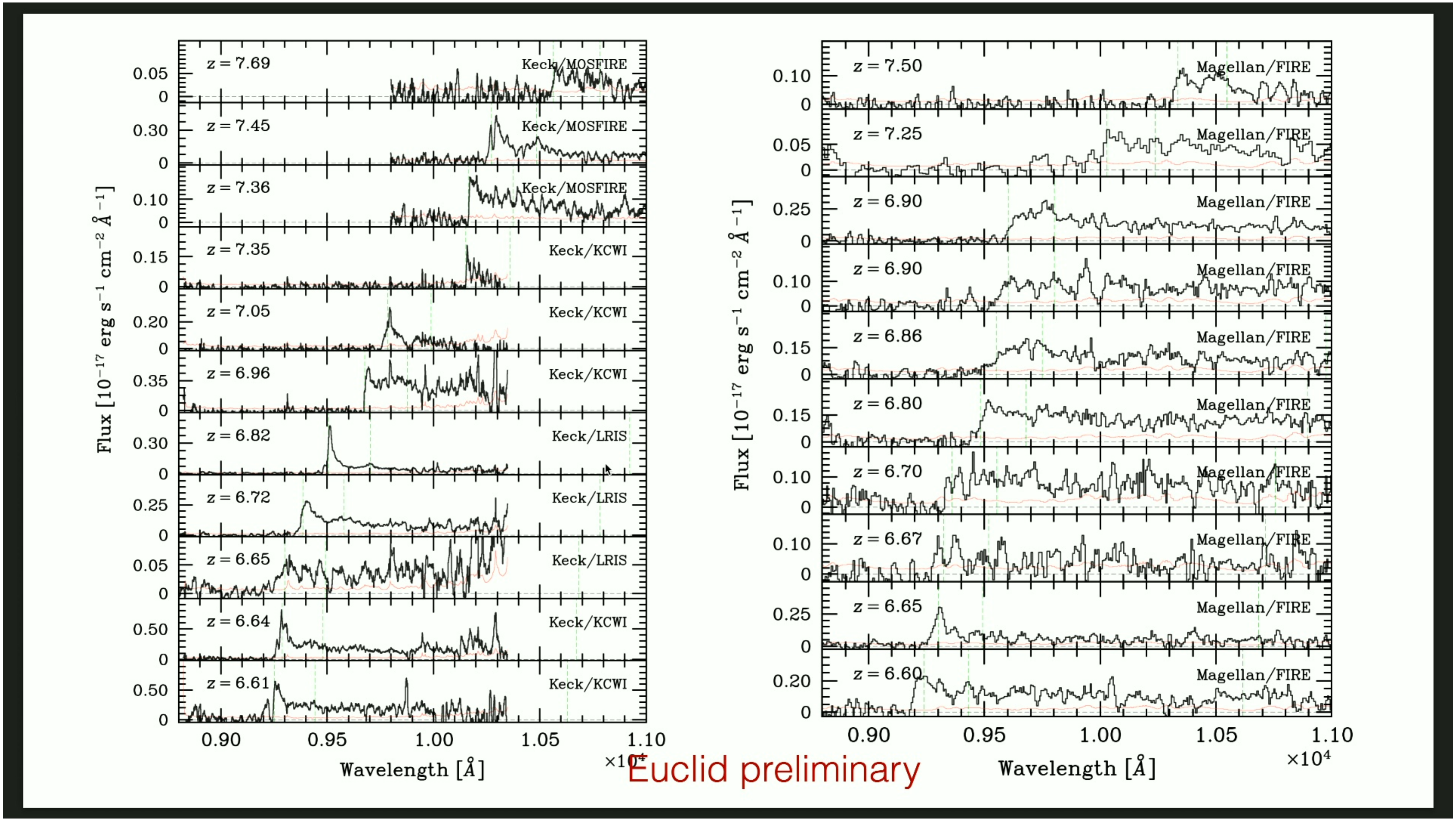
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Euclid preliminary