General

Basic

Advanced

Frontier in Exoplanet Characterization

Hajime Kawahara

RESCEU Online Summer School 2020

Purpose

Why Exoplanets?

Universality of Us and Where We Live in

“Exoplanet Characterization”

Like Earth?
Water, oxygen?
Has ocean?
Comfortable?

Like Jupiter?
Very different?

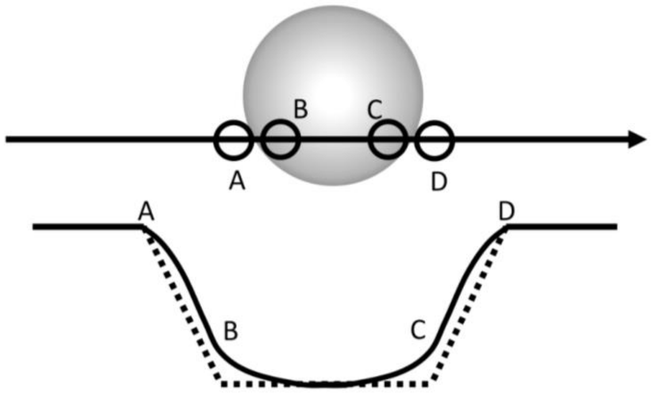
Contents

1. What kind of exoplanets can we characterize?
   Landscape of transit/directly-imaged exoplanets

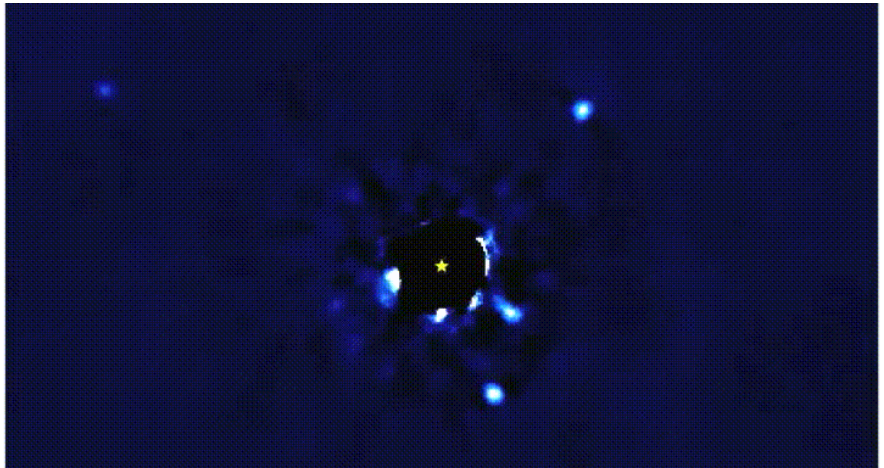
2. How do we characterize exoplanets?
   Established techniques for exoplanet characterization

3. How will we characterize exoplanets?
   On-going and future techniques toward exo Earths

Transit exoplanet

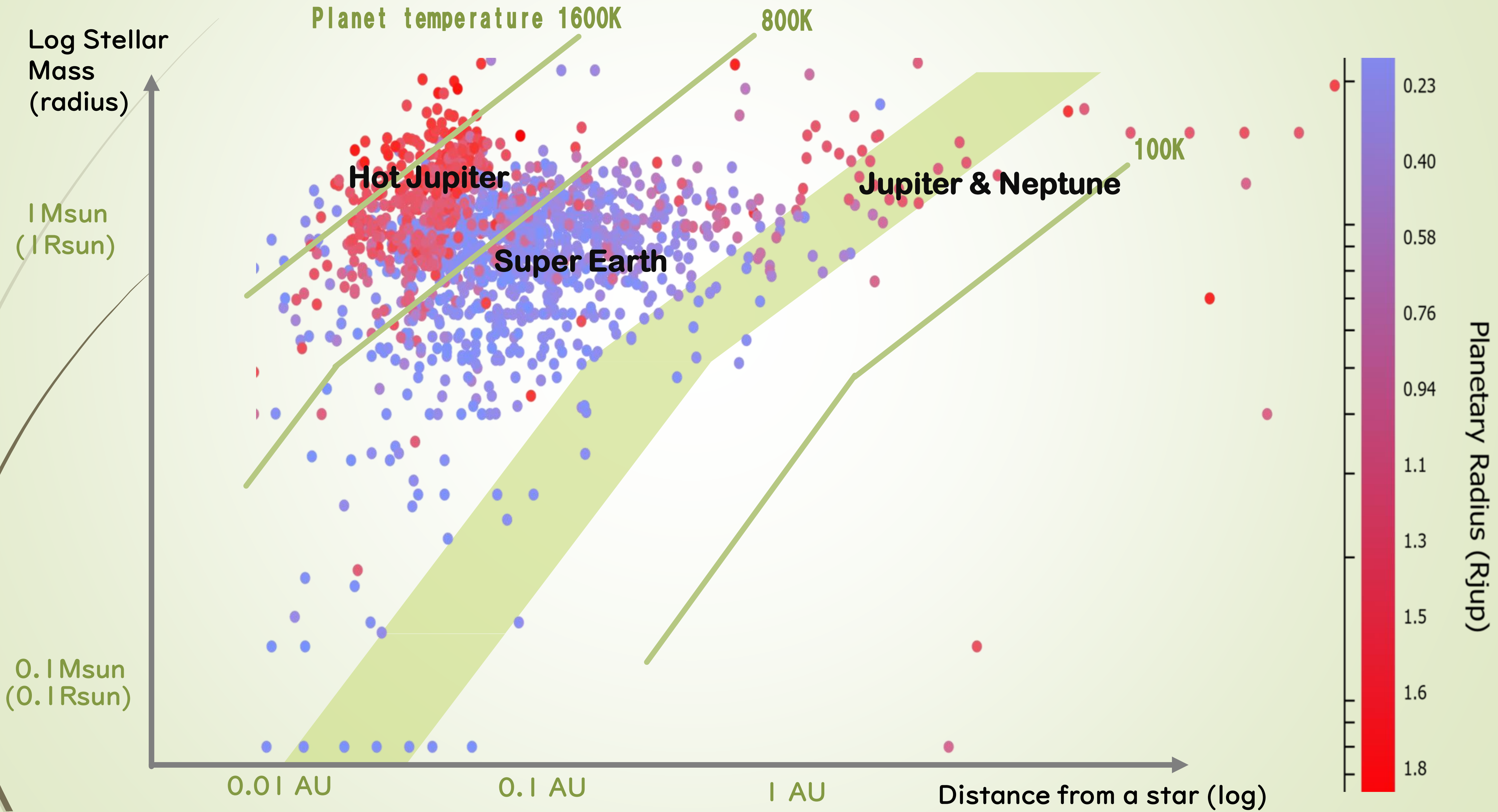


Direct imaging



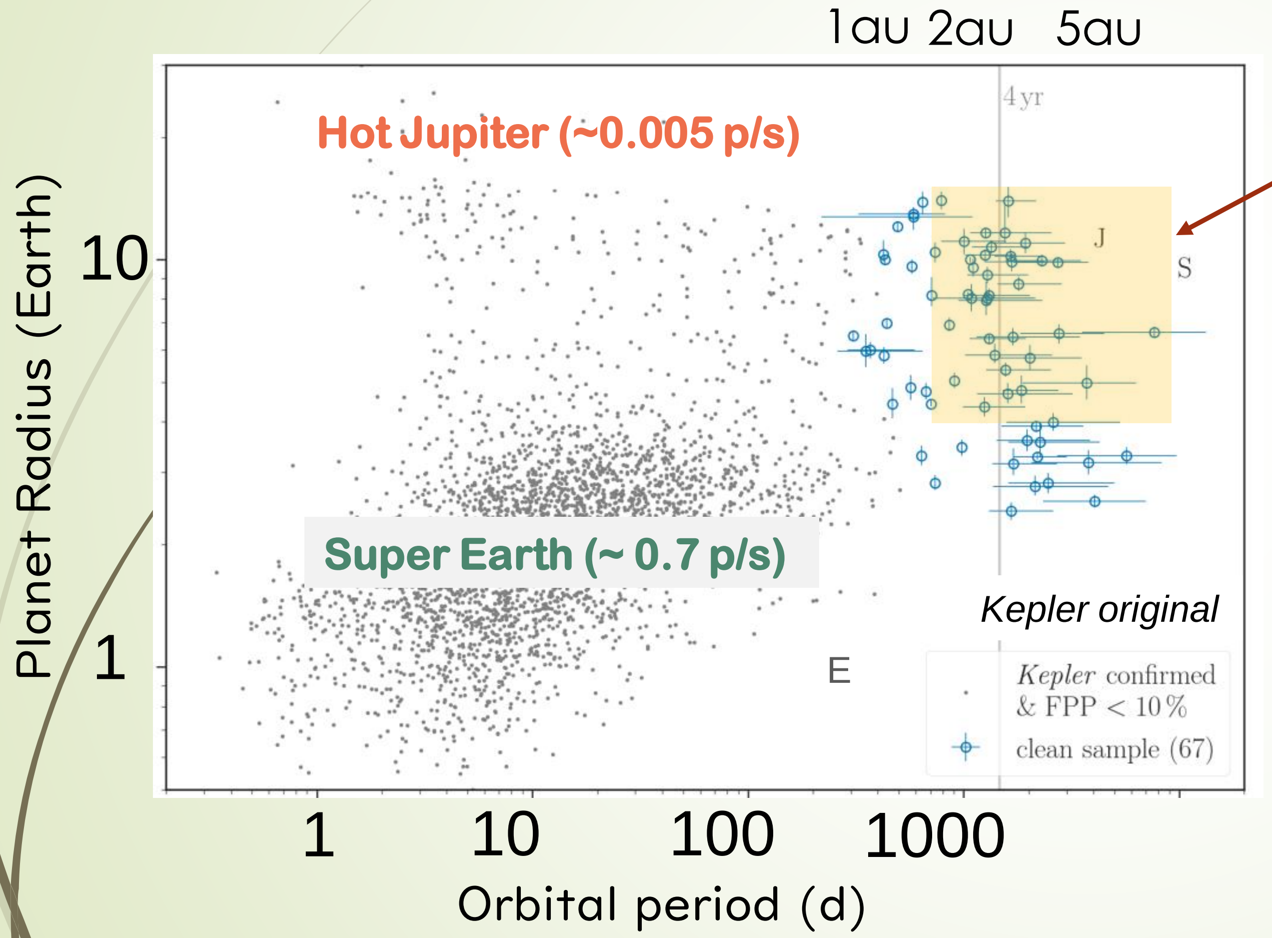
Basic

Exoplanet landscape



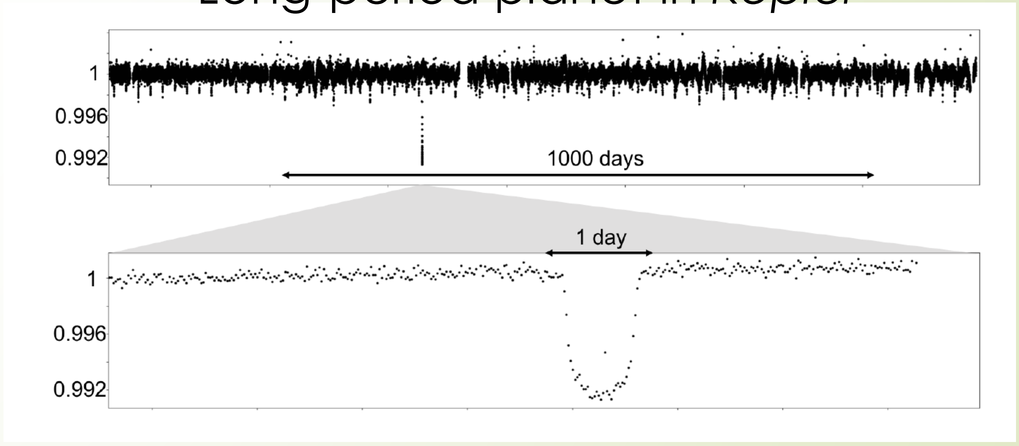
Basic

Exoplanet landscape (solar-type star by *Kepler*)



0.39+-0.07 planets/star
assuming 100% completeness
Consistent with RV

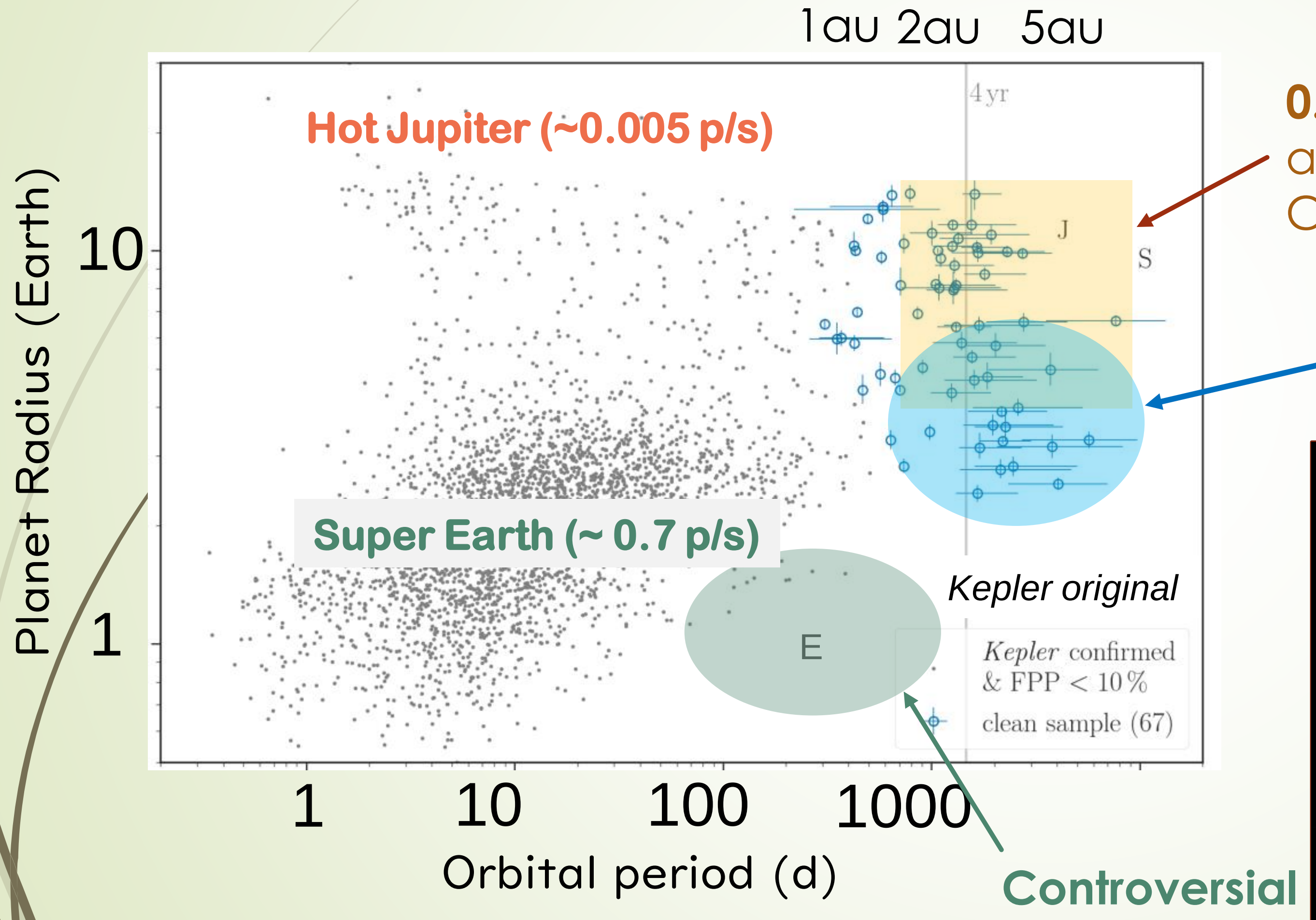
Long-period planet in *Kepler*



Kepler prime mission
Kawahara and Masuda (2019)

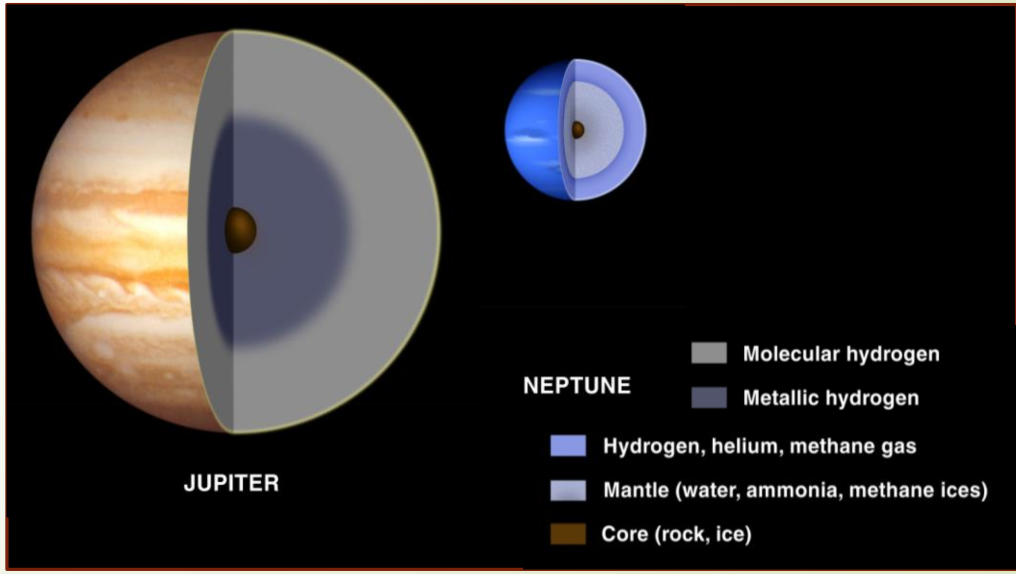
Basic

Exoplanet landscape (solar-type star)



0.39+-0.07 planets/star
assuming 100% completeness
Consistent with RV

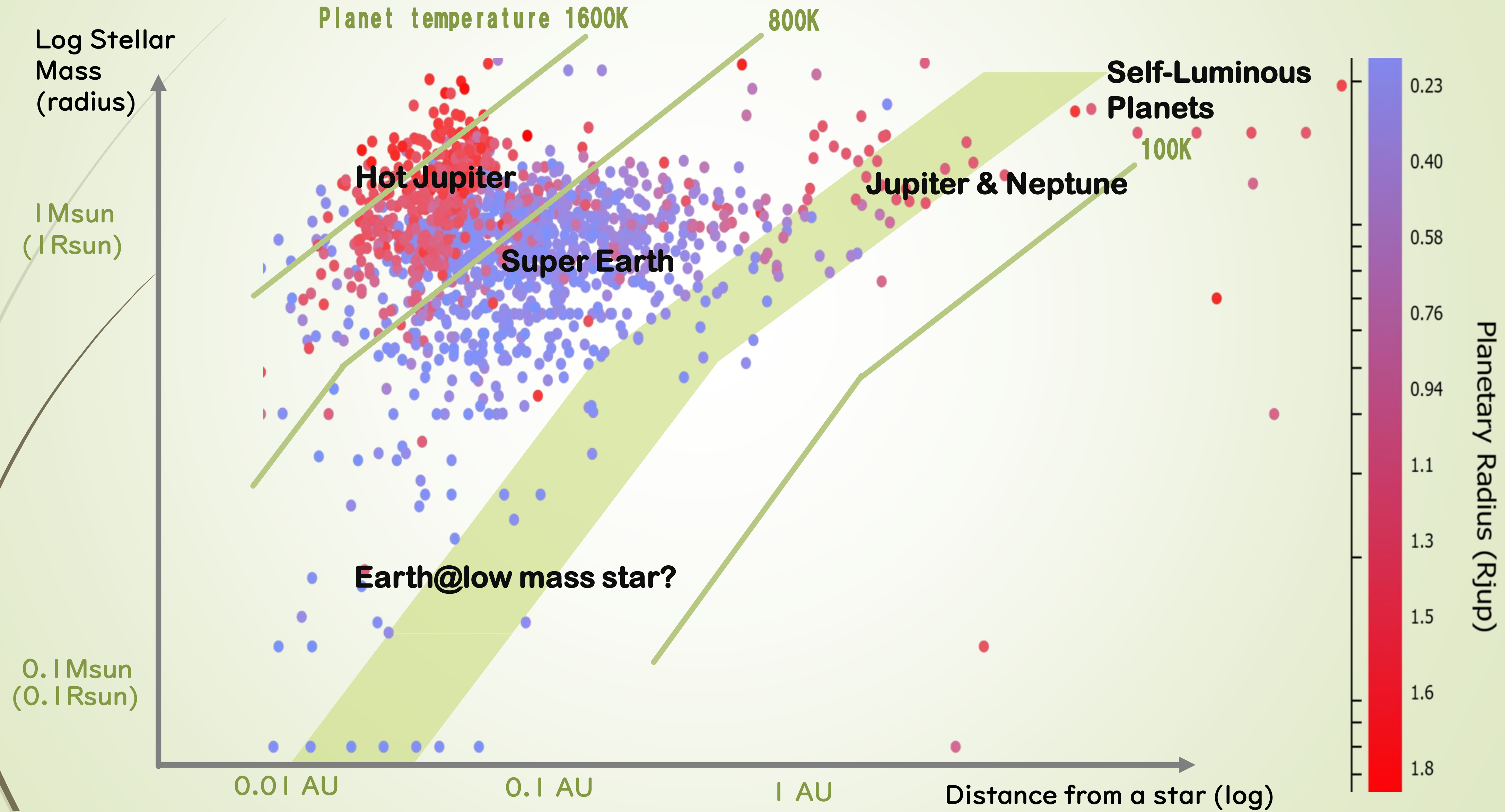
Neptune-sized Planets are common at Jupiter position (>~0.5 p/s)



Kepler prime mission
Kawahara and Masuda (2019)

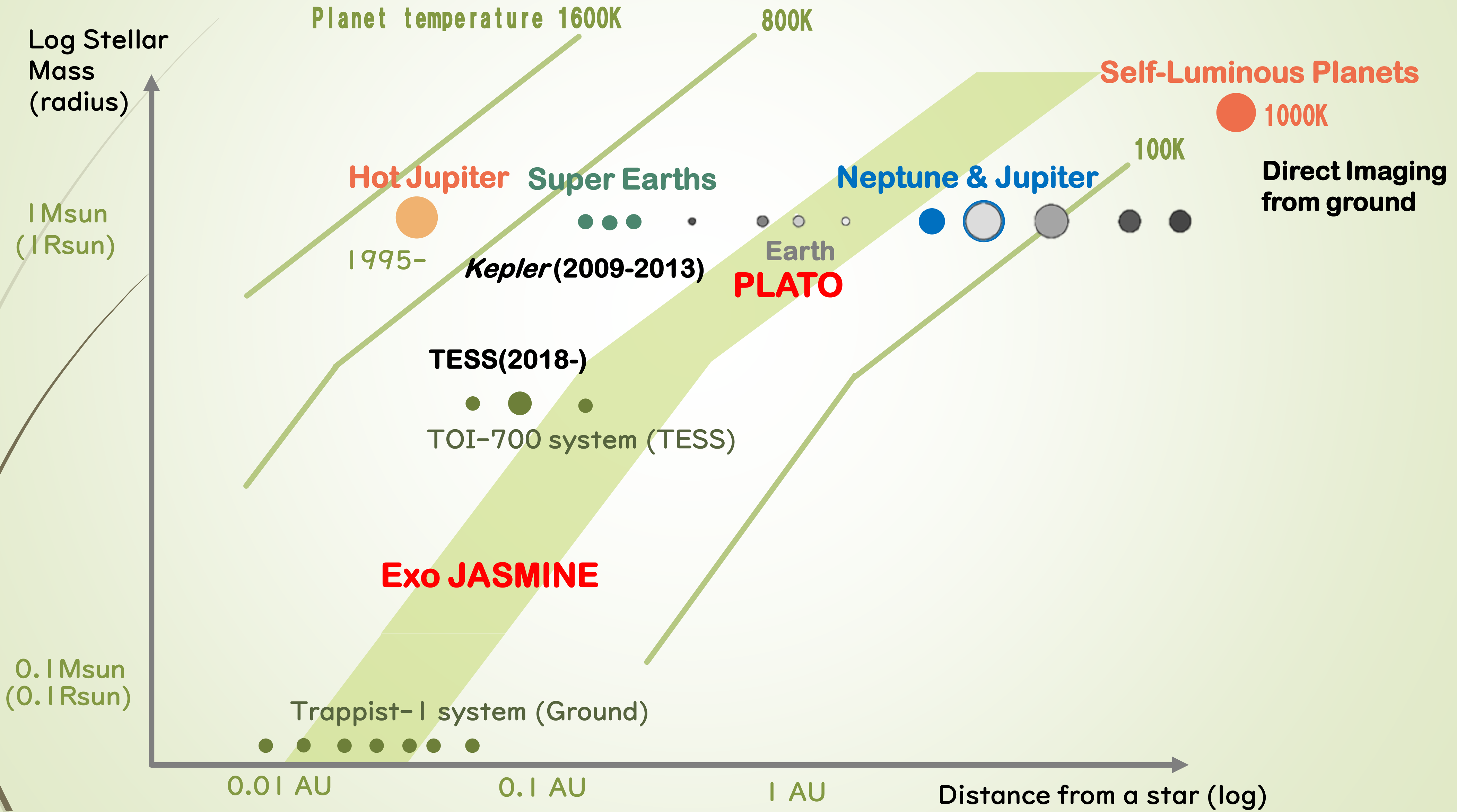
Basic

Exoplanet landscape



Basic

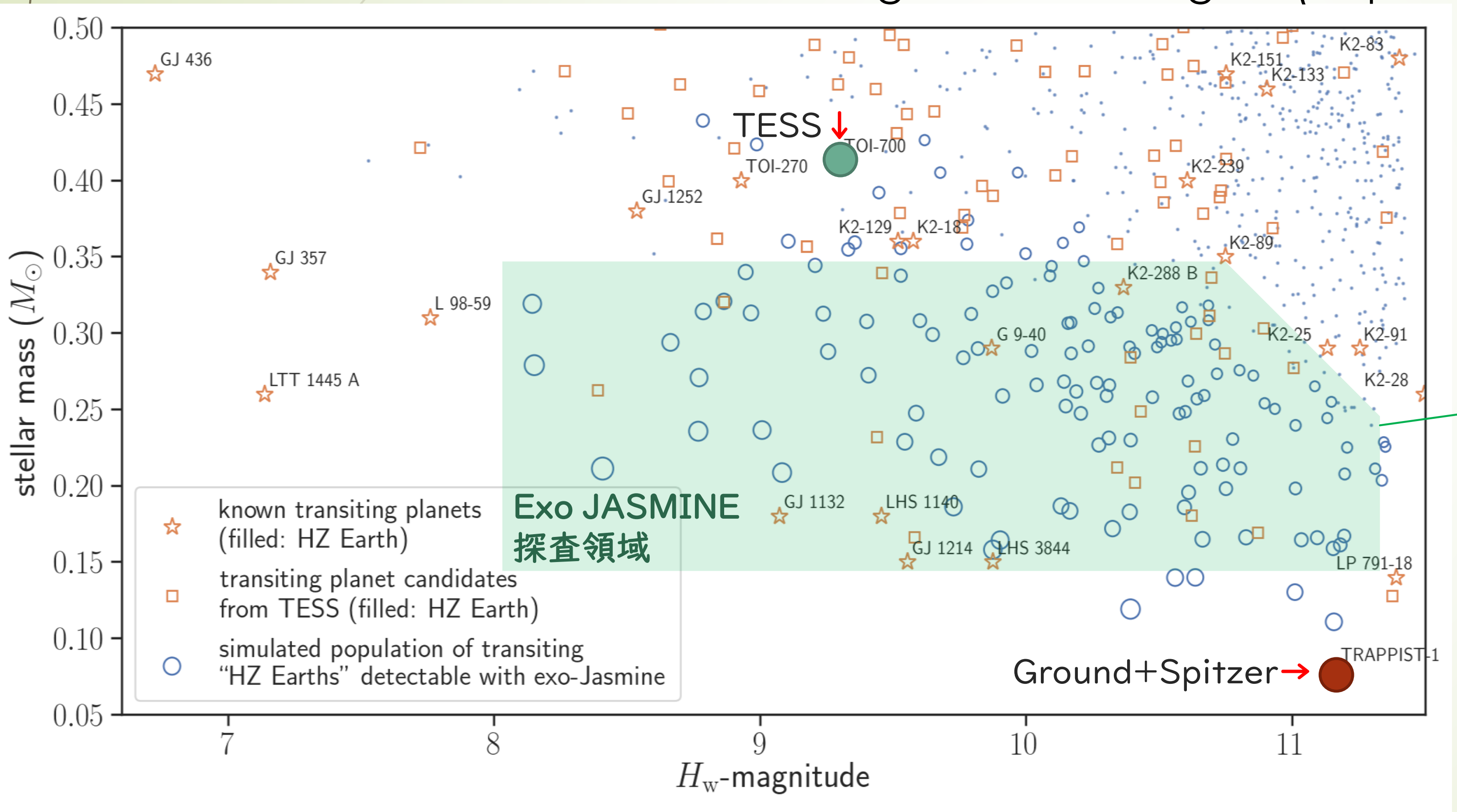
Exoplanet landscape (schematic)



Advanced

Fill a gap by Exo JASMINE

TOI-700: Bright but small signal (depth=0.05%)



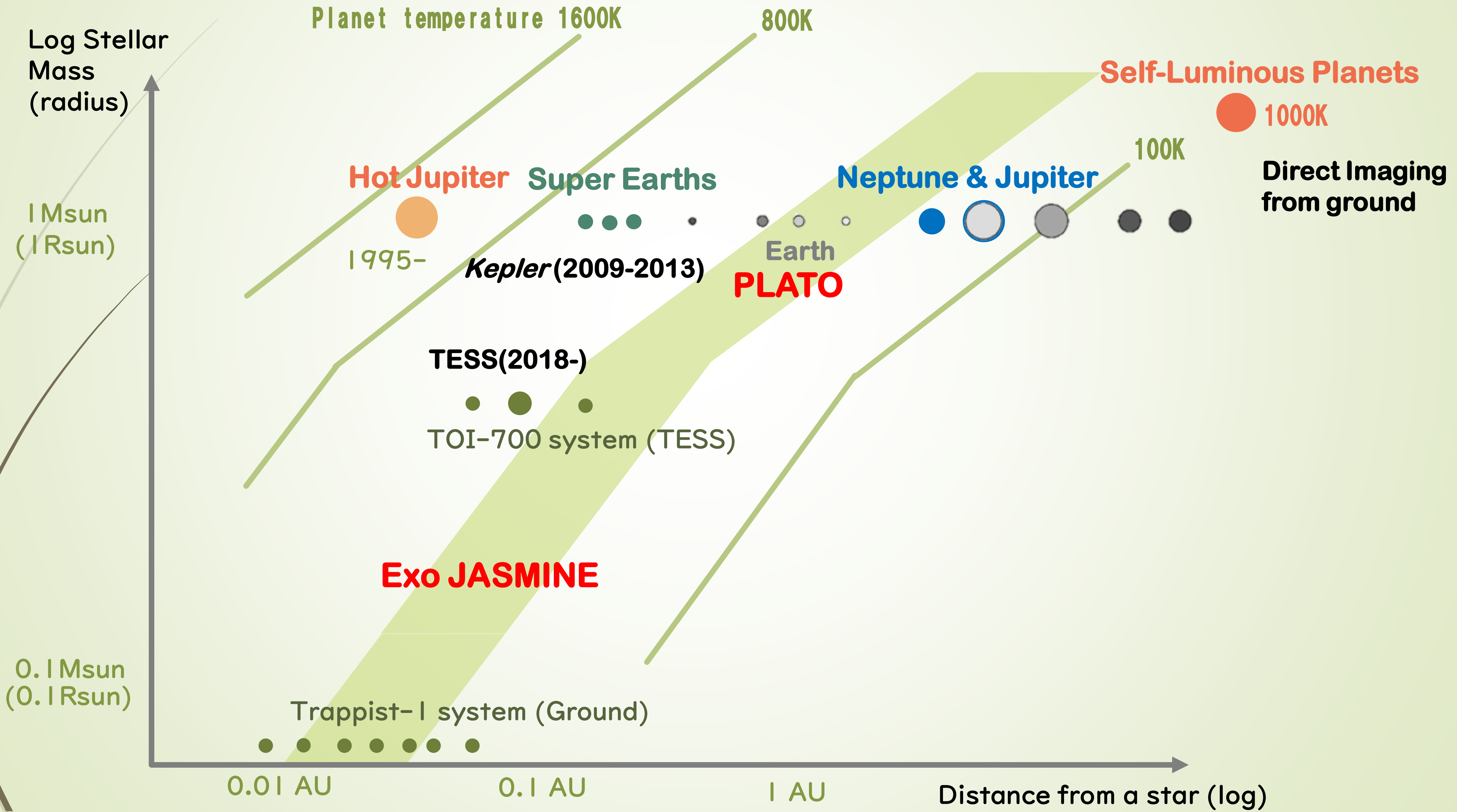
TESS 0.6-1.0 um 10cm all-sky
Exo JASMINE 1.1-1.7um 30cm
Grounds <0.9um 1m class

Depth=0.3 – 0.1 %
Mag = 8 - 11

Trappist system
Large signal (depth=1%)
but faint

Basic

Exoplanet landscape (schematic)



Short Summary

Exoplanet landscape

- Jupiter in solar system is universal.
  Super Earth < 1 AU and cool Neptune @ several AU, which do not exist in solar system, are also common.

- Current astronomers are trying to cheat with Earths around low-mass stars or young self-luminous planets because it's easy to observe.

- **Earth not yet**

Basic

Transit or directly-imaged planet exists. So next?

Radius/mass

HD XXXXXX b

If we find exo-Earths, we want to know

Molecules in atmosphere
$H2O$ or $O2$ (biosignature)

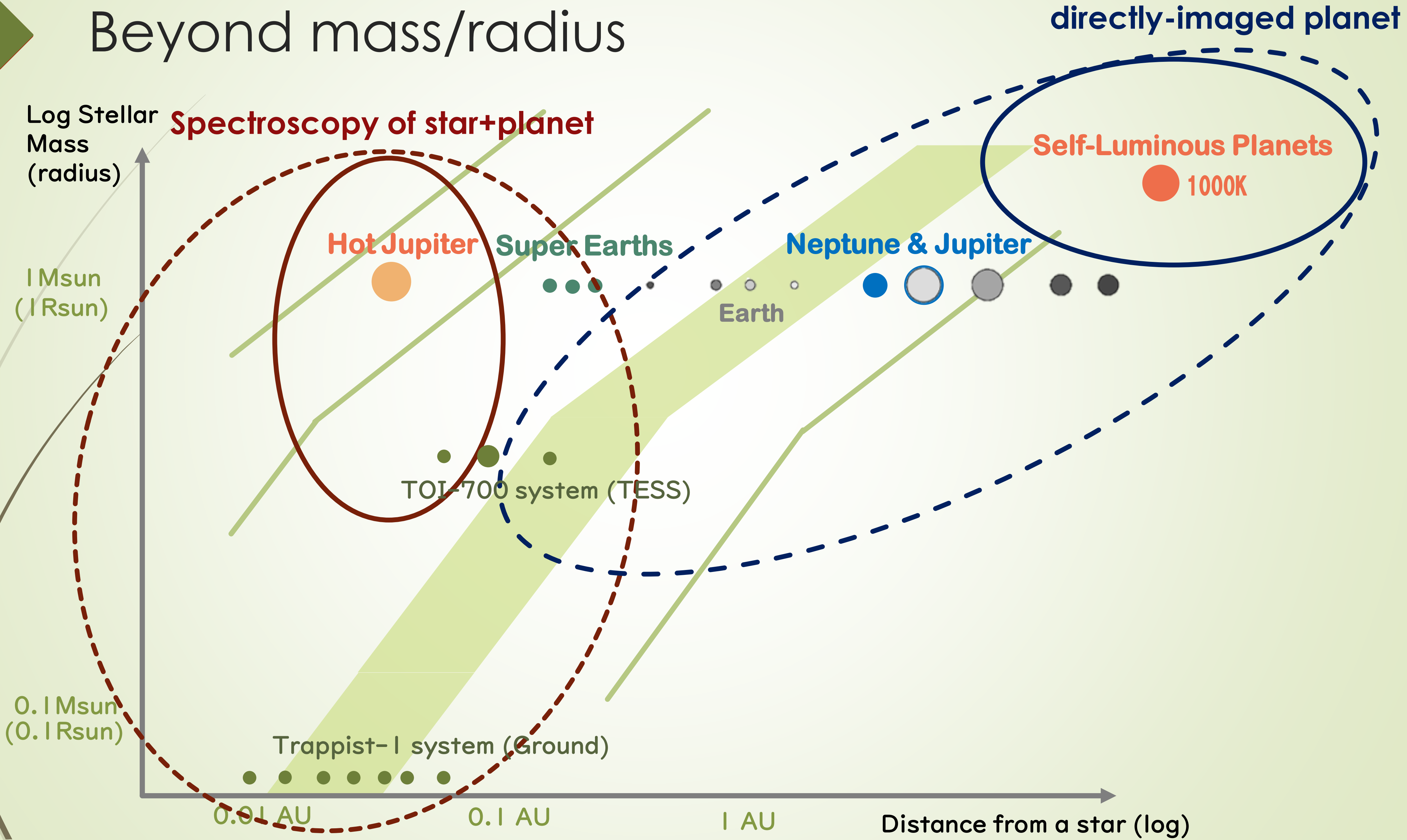
Surface environment
Atmosphere, climate
Continents/ocean

Exo Earth not yet.
Lesson using other exoplanets

Hot Jupiters and self-luminous planets are mainly used in reality

Basic

Beyond mass/radius



Basic

History/Future of Characterization by Transit Exoplanets

Low-Res Spectroscopy (space)

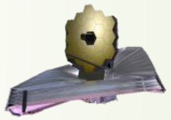
2001
HD209458b
Detection of **Na**

K, H2O

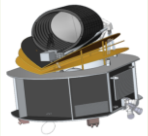
2014
Clouds/haze
in Hot Planets
HST, 26 ppm
Spitzer 15 ppm

2017 - 2020
Trappist-1
7 rocky planets

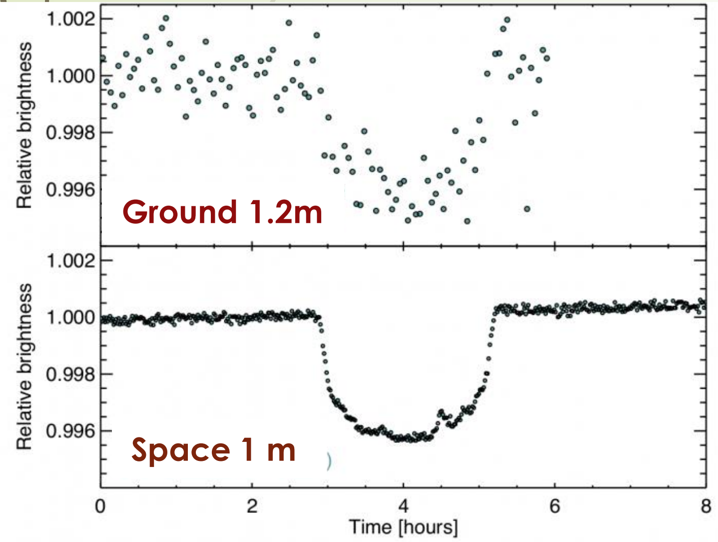
JWST 6.5m
(2021)



ARIEL ~1m
(2028)



OST・LUVOIR?



Heng and Winn

High-Res Spectroscopy (ground)

CO, H2O, TiO, Metals, HCN, CH4

Transit Survey

2009
Kepler

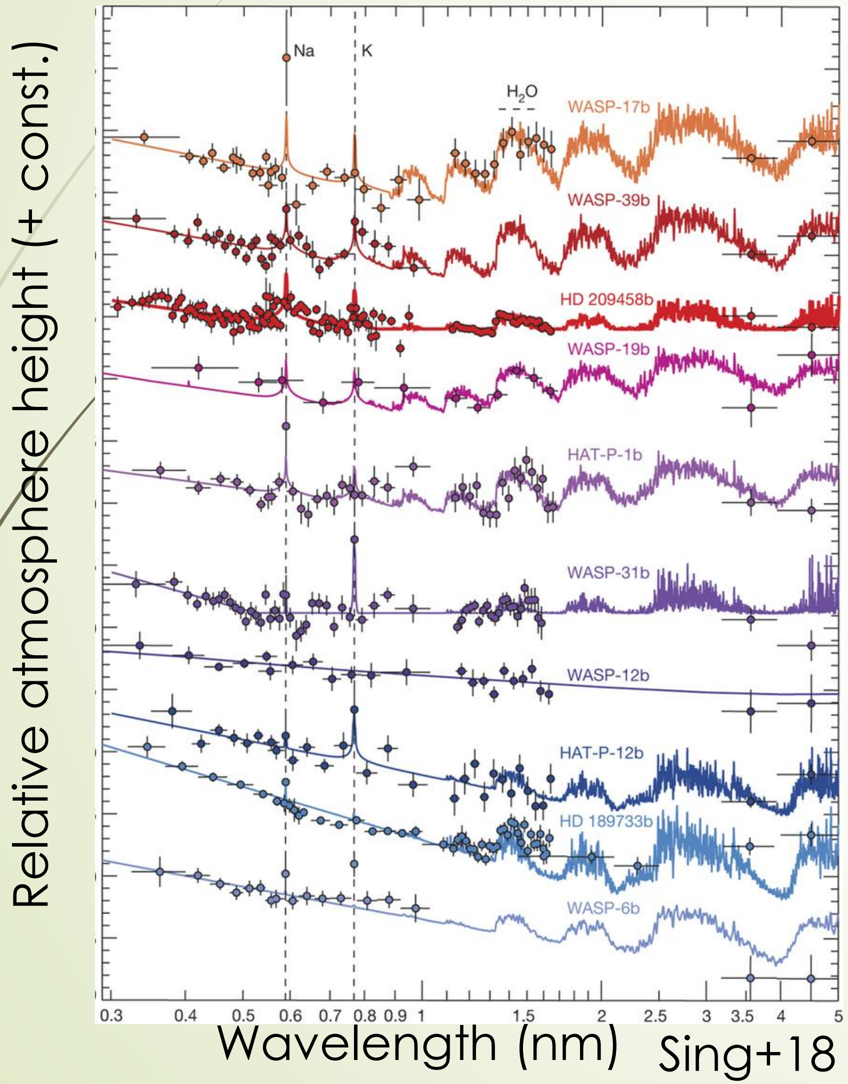
2018
TESS
(CHEOPS)

Late 2020-2030
PLATO
(Exo JASMINE)

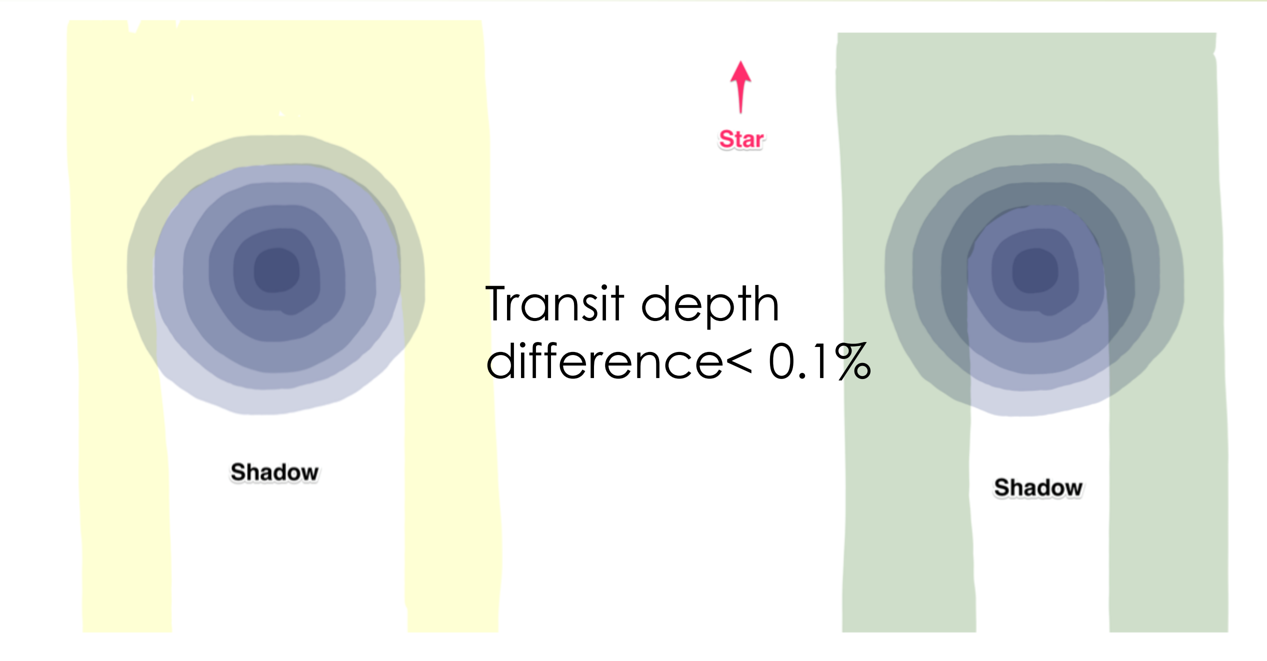
Basic

Low-R Spectroscopy from space (transmission)

Hot Jupiters Transmission



Sing+18



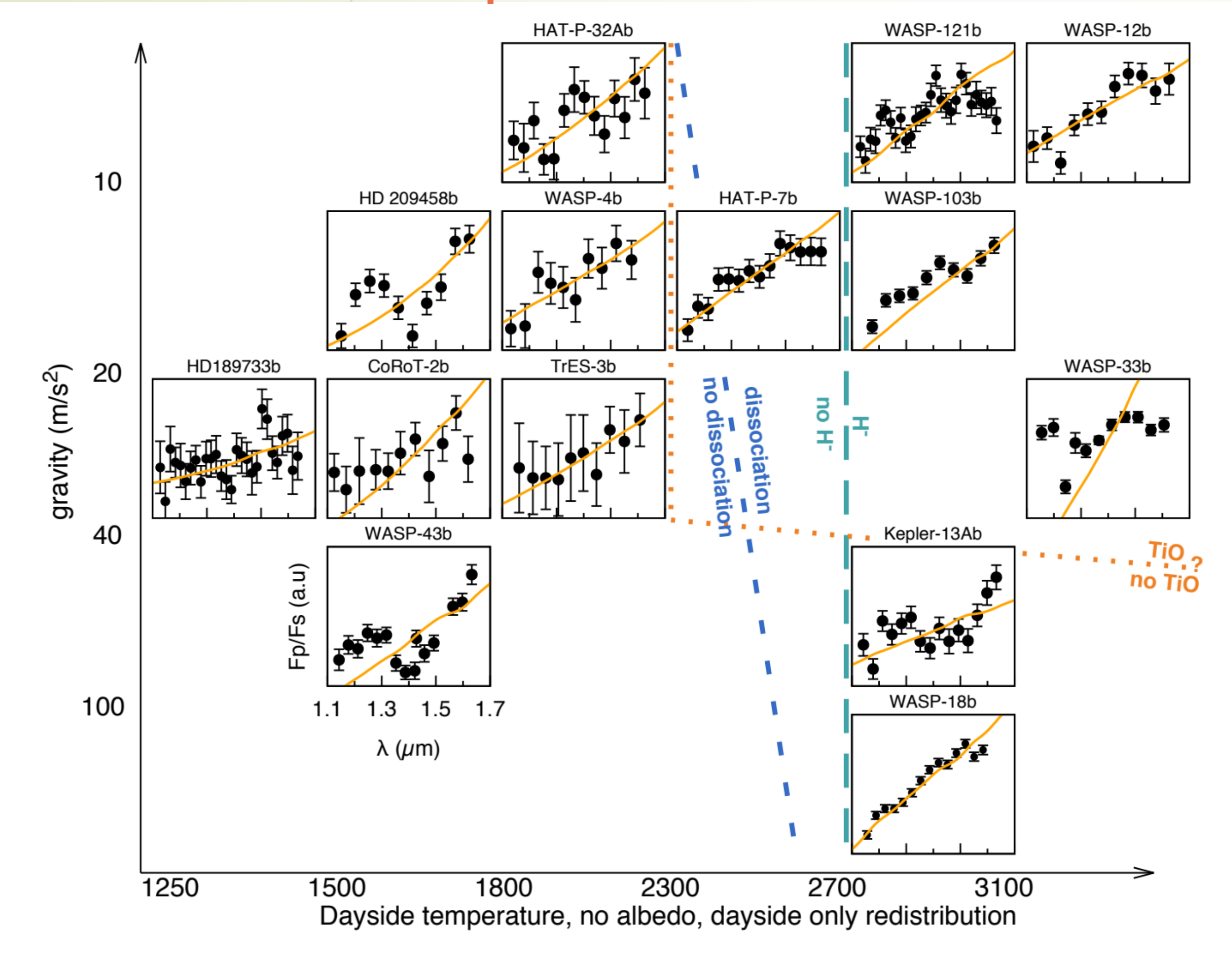
Transit depth difference< 0.1%

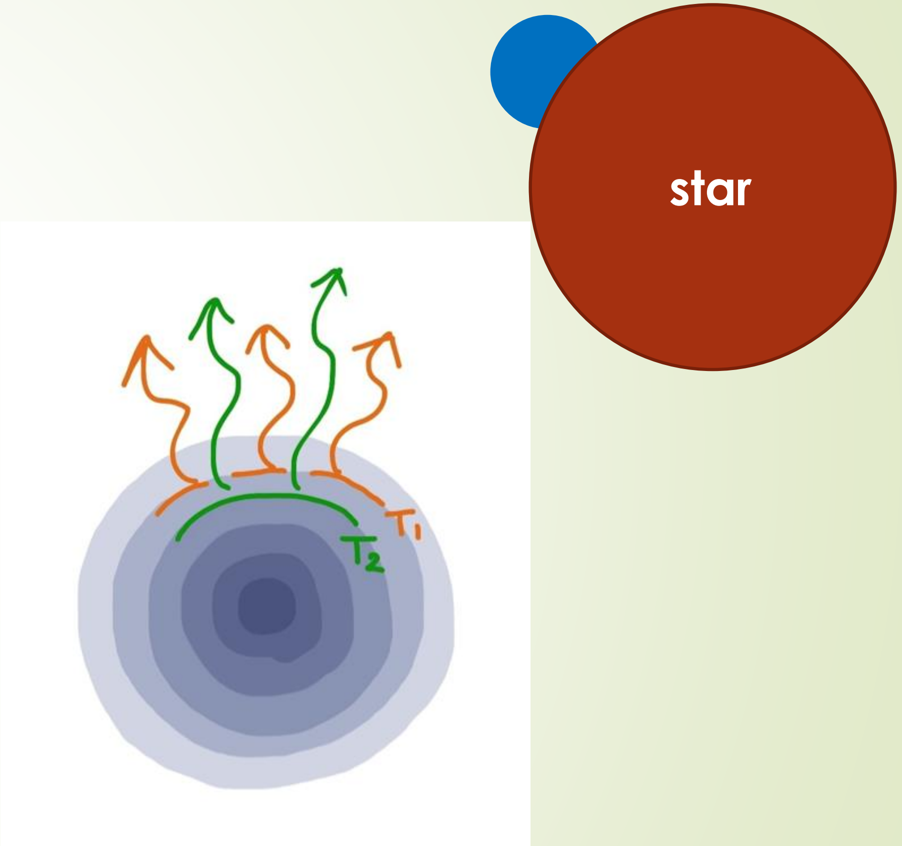
Insensitive to temperature structure
Sensitive to molecules at higher atmosphere
Total modeling required

Basic

Low-R Spectroscopy from space (emission)

Hot Jupiters Emission





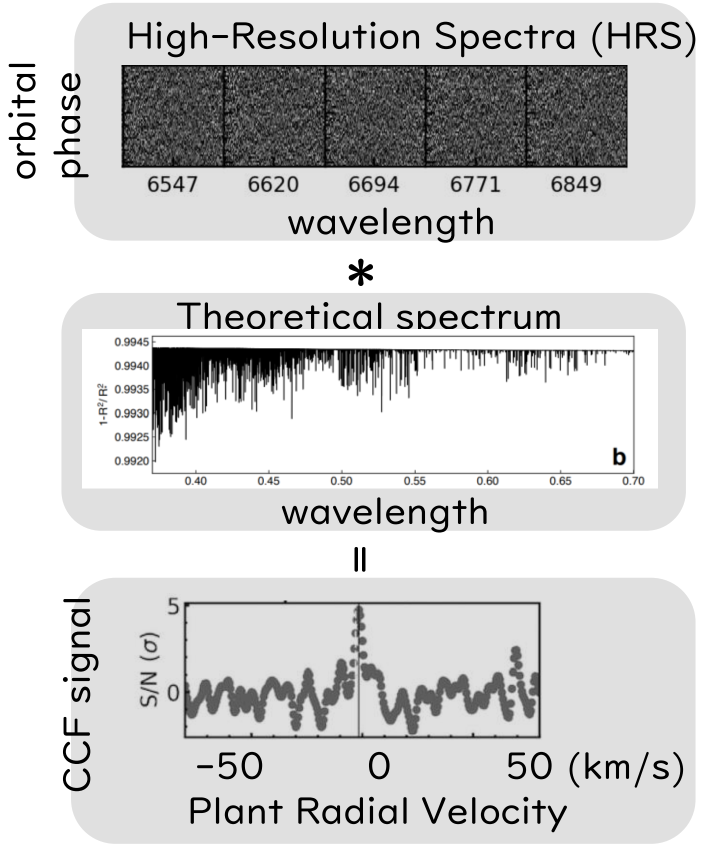
Integrated blackbody
Sensitive to temperature structure
Sensitive to molecules at mid atmosphere

Parmentier+18

Basic

Atoms/Molecules detection using High-R Spectroscopy

R = λ/Δλ ~ 100,000, Δλ ~ linewidth



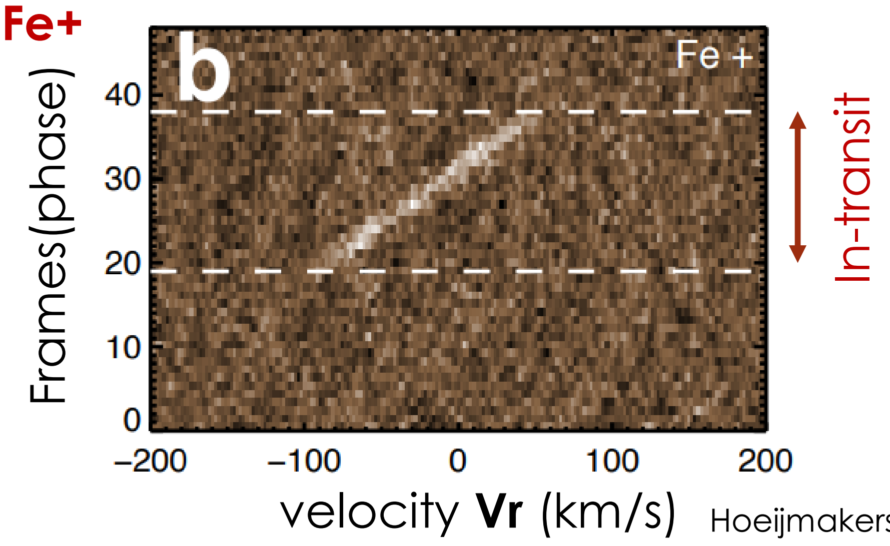
Stellar : Planet
~ 1000 : 1

Molecule-by-Molecule detection

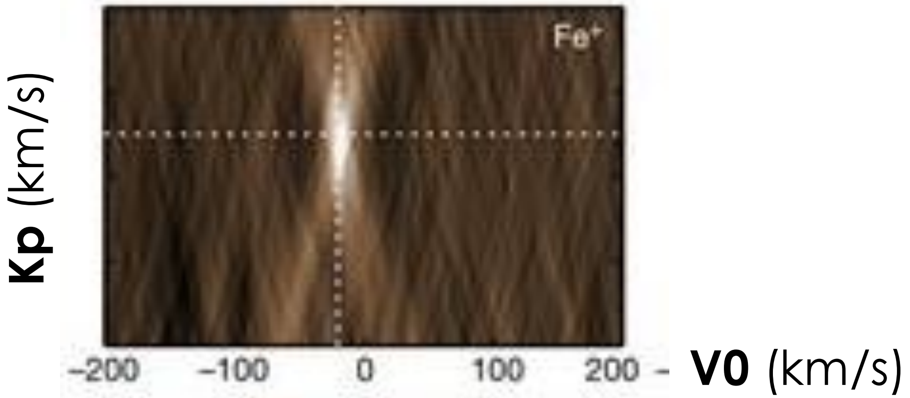
Planetary wind
(a few km/s) can be detectable

Pro: High-frequency signal is stable even for ground-based observation

The best one so far. Hot Jupiter KELT9b

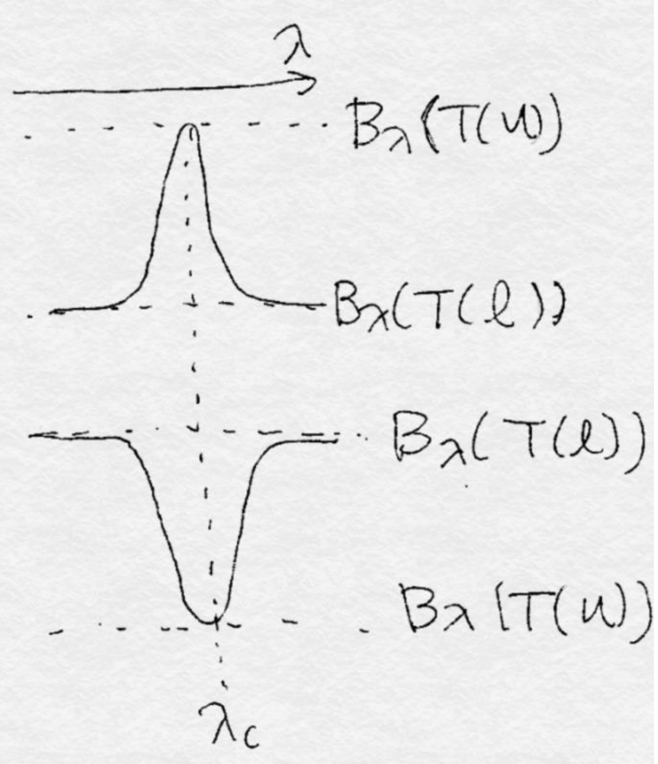


Vr = Kp cos(phase) + V0

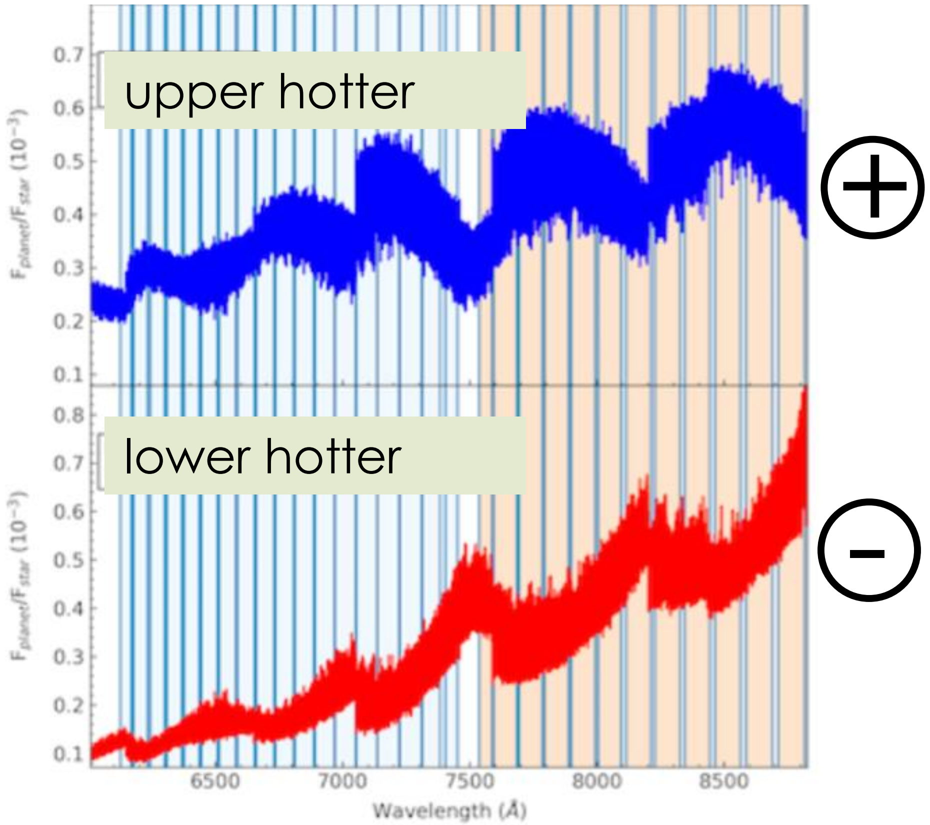


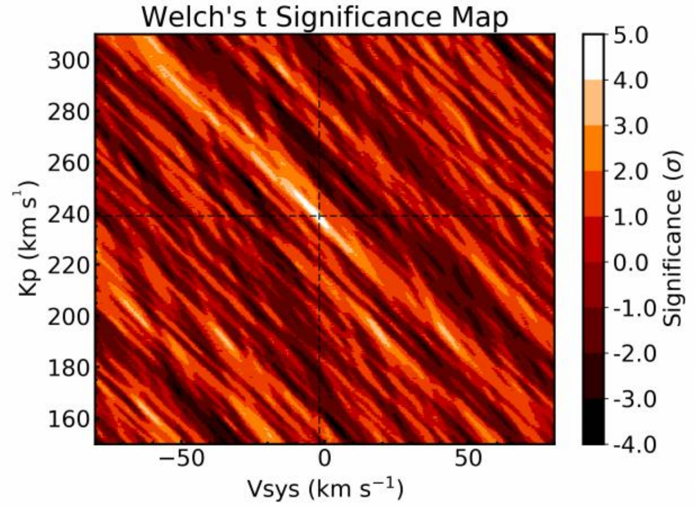
HRS Thermal Inversion by Titanium Oxide

WASP33b emission using Subaru/HDS = star : planet ~ 1000 : 1



Intensity at the line center
comes from upper atmosphere





Nugroho, H.K.+ 2017, AJ
Ishizuka, H.K.+ in prep

Titanium oxide absorbs blue light and heats the upper atmosphere, like O3 on Earth.

Short Summary

LRS from space: **metals, H_2O, haze, scattering, black body**
Pros: intuitive, can detect continuum (haze, clouds, scattering)
Cons: Total modeling required -> weak for systematics
Toward exo Earth:
JWST will try to detect molecules in terrestrial planets @ late-M
Larger telescope is justice (LUVIOR…)

HRS from ground: **CO, H_2O, TiO, HCN, CH_4, metals, ions, T-P structure**
Pros: molecules even with many lines, no need of total modeling
Cons: connection with model is much more difficult
Toward exo Earth:
Applicable to water detection(many lines).
Larger telescope is justice (TMT, E-ELT)

Basic

History and future of direct imaging

1st gen
(AO only)

2nd gen
(ExAO+coronagraph)

Ground

Space

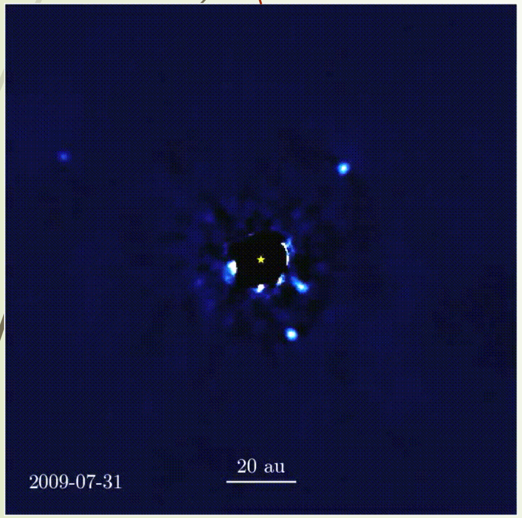
2007
HR8799

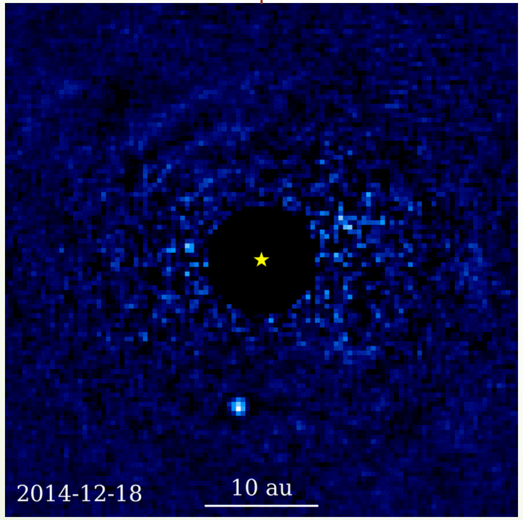
2014
51 Eri b

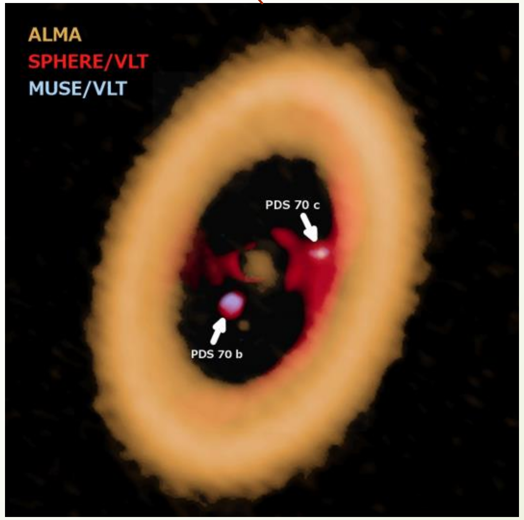
2018
PDS70 b

2025
Roman telescope

2035-45
HabEx or LUVOIR







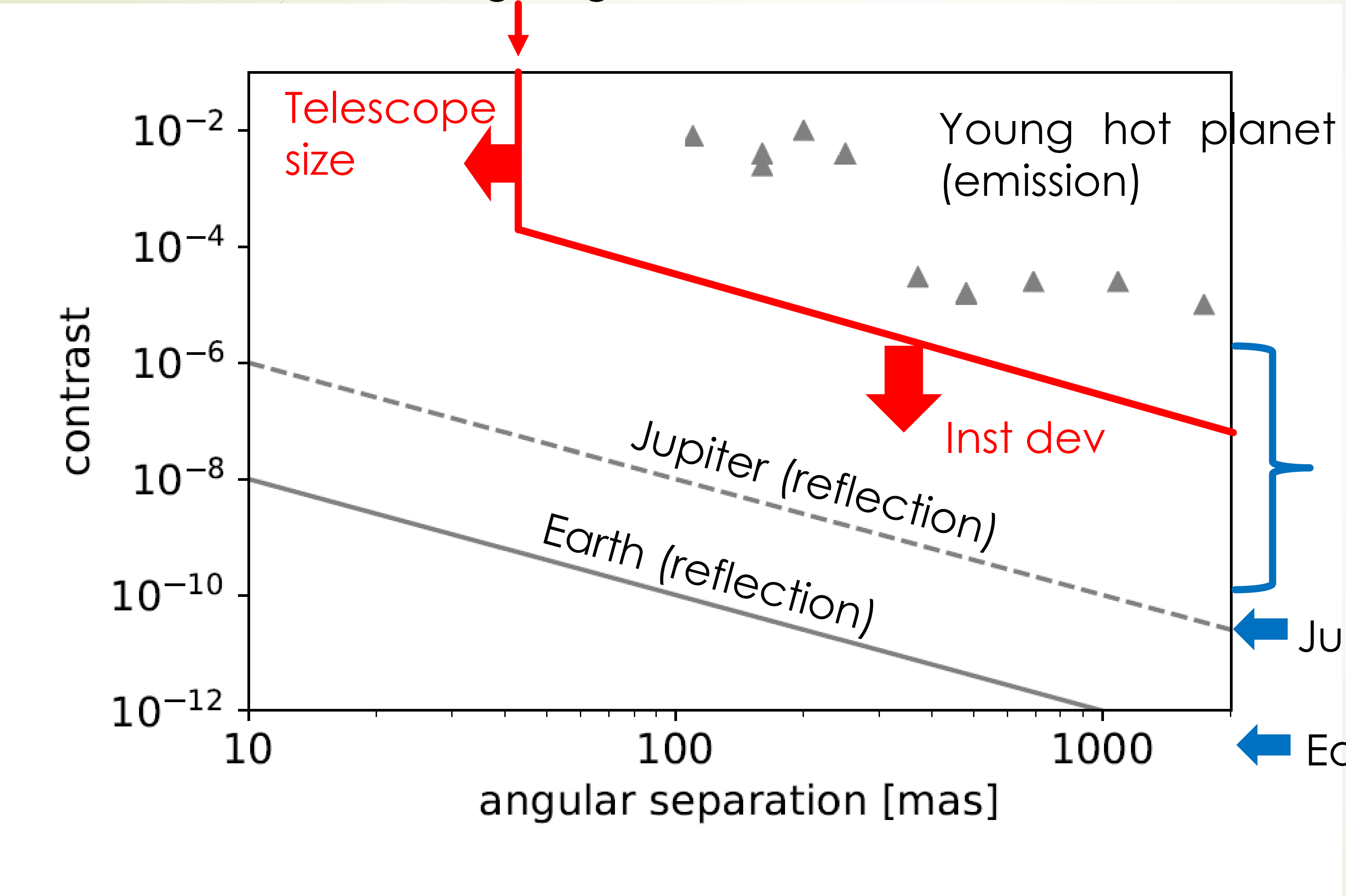
Planets by reflection light

Self-luminous young planets (T ~ 1000 K)

Basic

Why is the detection limited so far?

Inner Working Angle ∝ λ/D



Almost no signal

Jupiters to be detectable at any

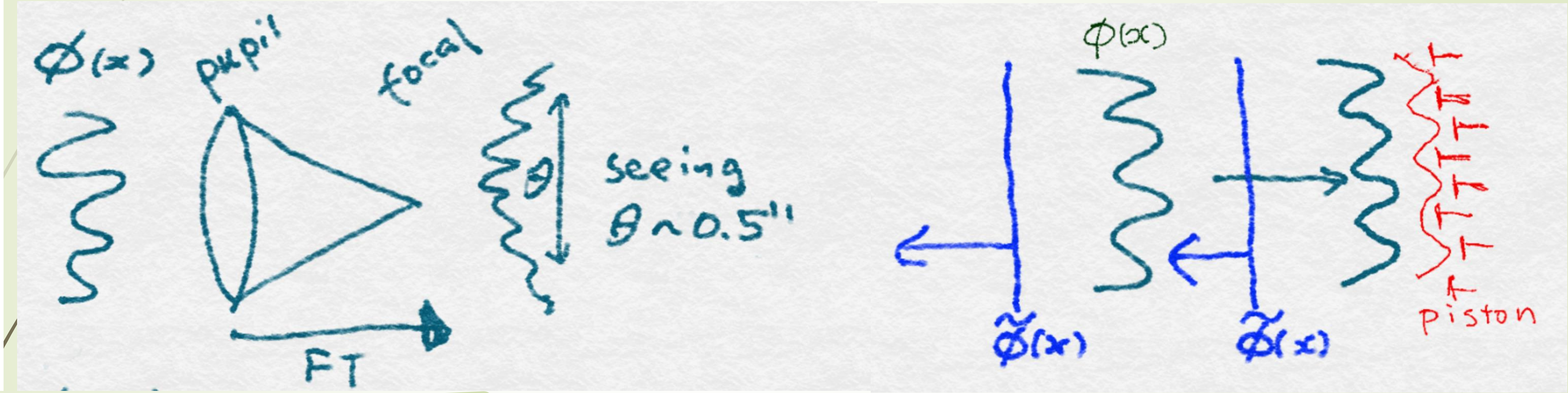
Earths to be detectable at any

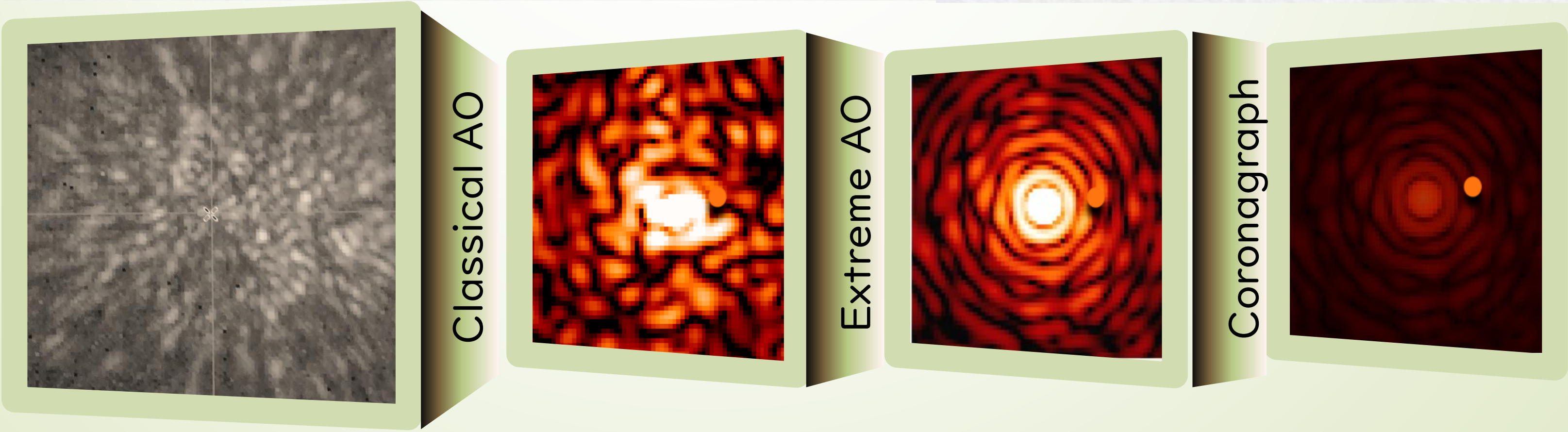
Sudden open like gravitational waves (my hope, not yet)

2nd gen: Adaptive Optics, Coronagraph

Phase correction @ pupil
by a deformable mirror

Complex amplitude:
$A(x) = a\, e^{\Phi(x)}$



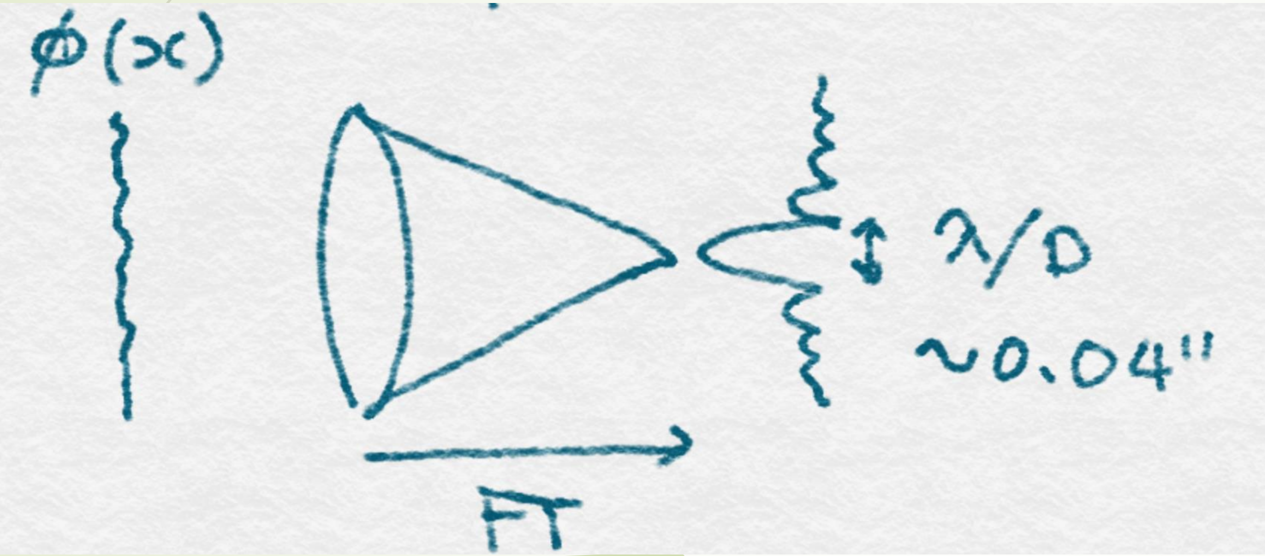


Basic

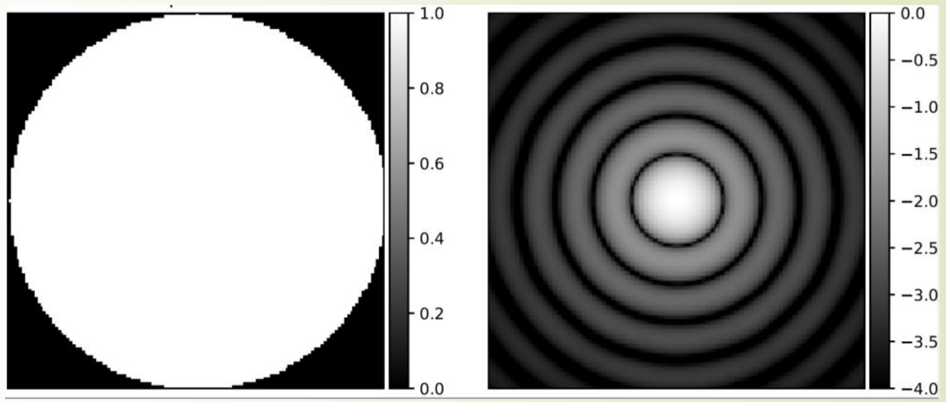
2nd gen: Adaptive Optics, Coronagraph

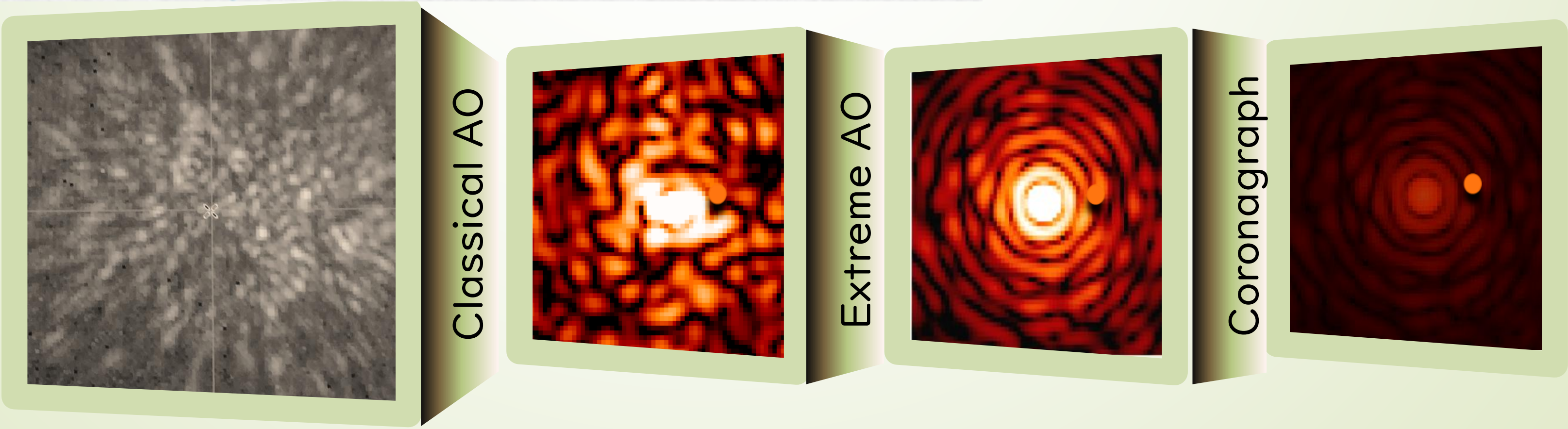
Complex amplitude:
$A(x) = a\,e^{\Phi(x)}$

pupil Focal plane



pupil Focal plane





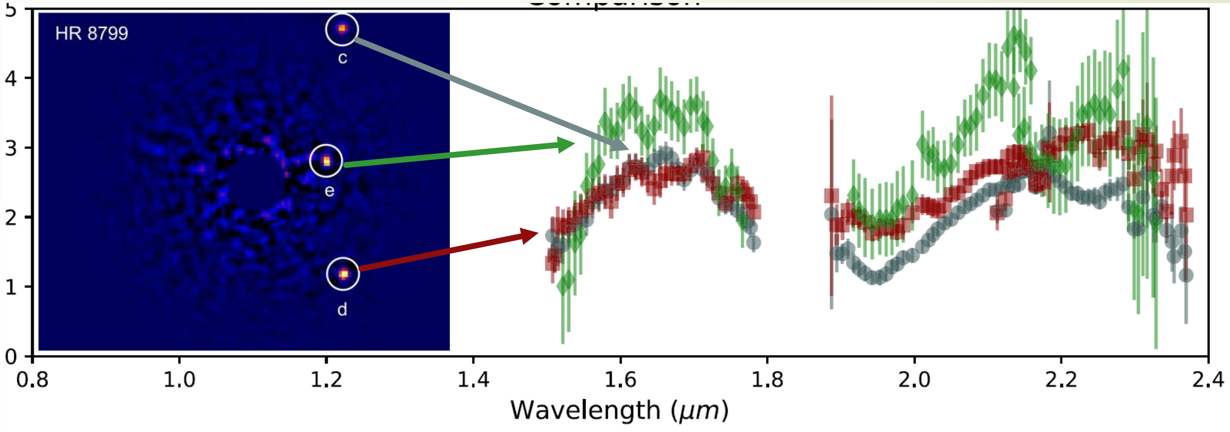
Basic

Why is direct imaging worth?

Spectrum

Molecules, dynamics, atmospheric structure
Biosignature in future

Greenbaum+2018



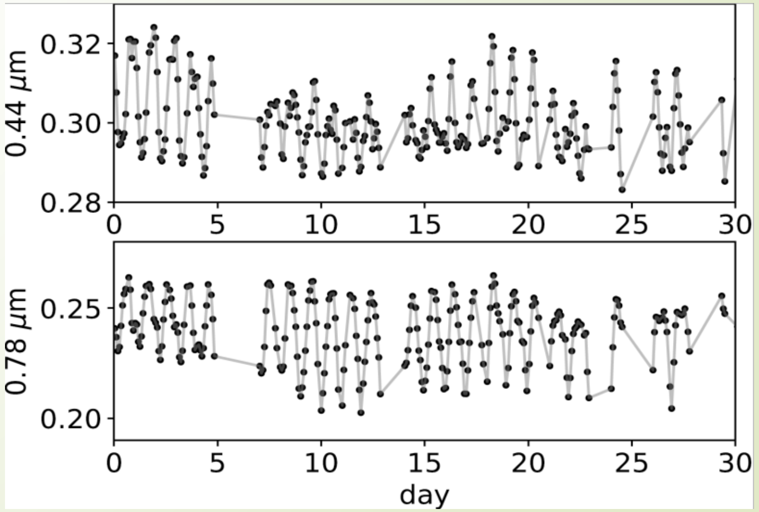
Photometric variability

Planet Spin/Tilt

Surface Composition, Continents, Ocean in future

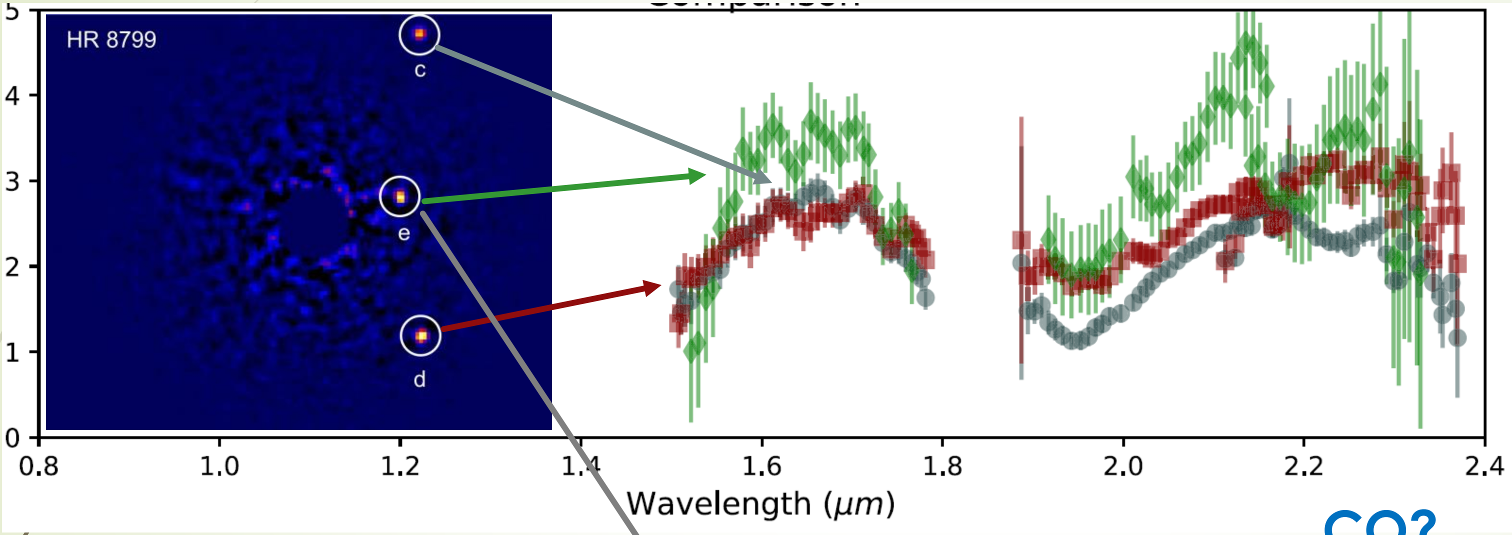
現代の天文学（原稿）

Real light curve of Earth by DSCOVR



Basic

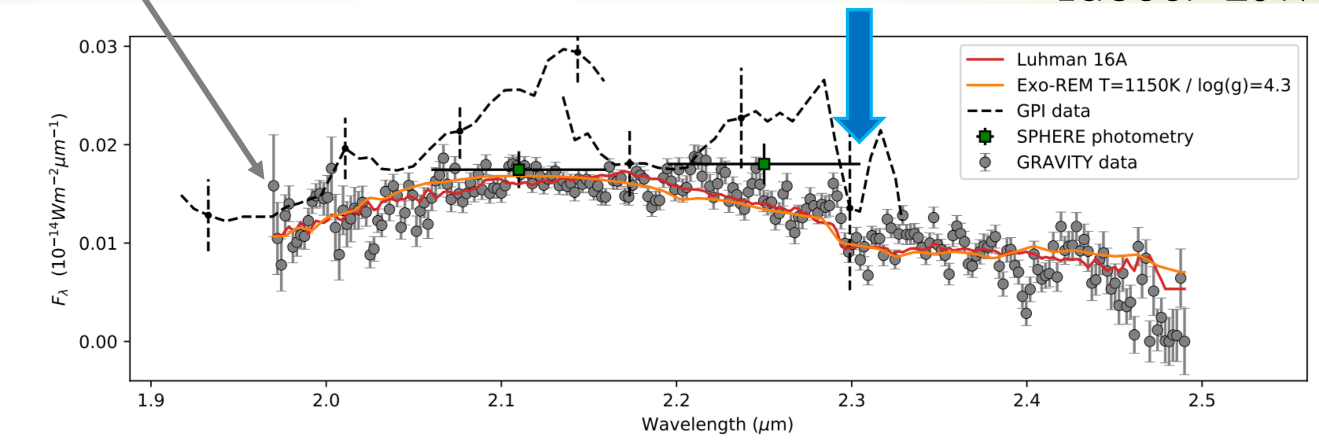
Low-Resolution Spectroscopy



Greenbaum+2018

CO?

Lacour+2019

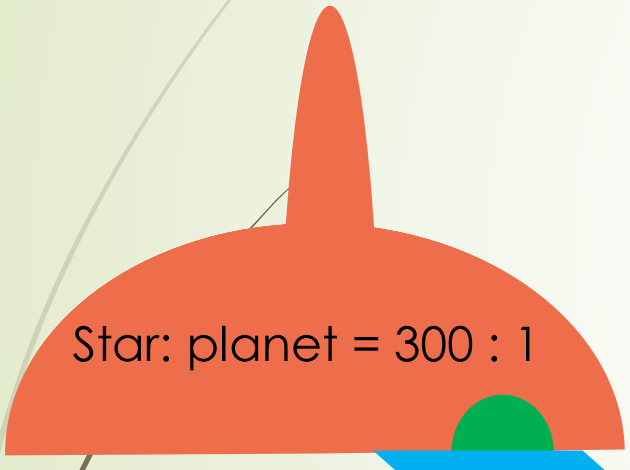


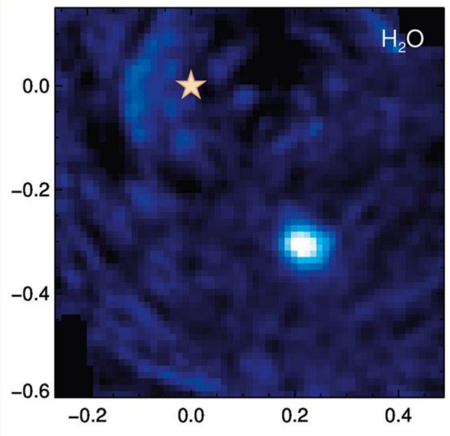
Late L Brown Dwarf model well fitted? (covered by clouds)

Advanced

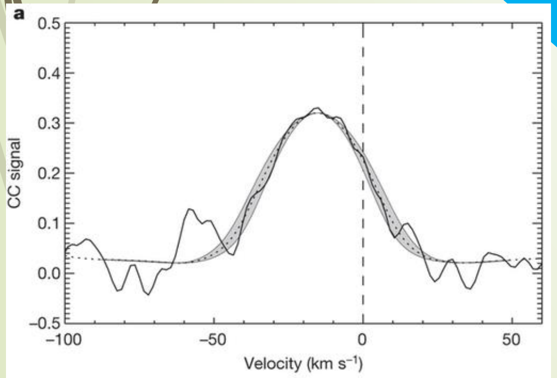
High-Dispersion Coronagraphy

Classical HRS for direct imaging
(Snellen+14, Hoeijimakers+18)





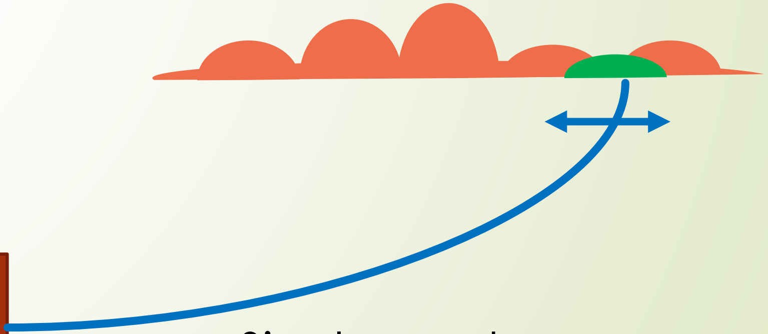
CCF map of water
(Hoeijimakers+18)



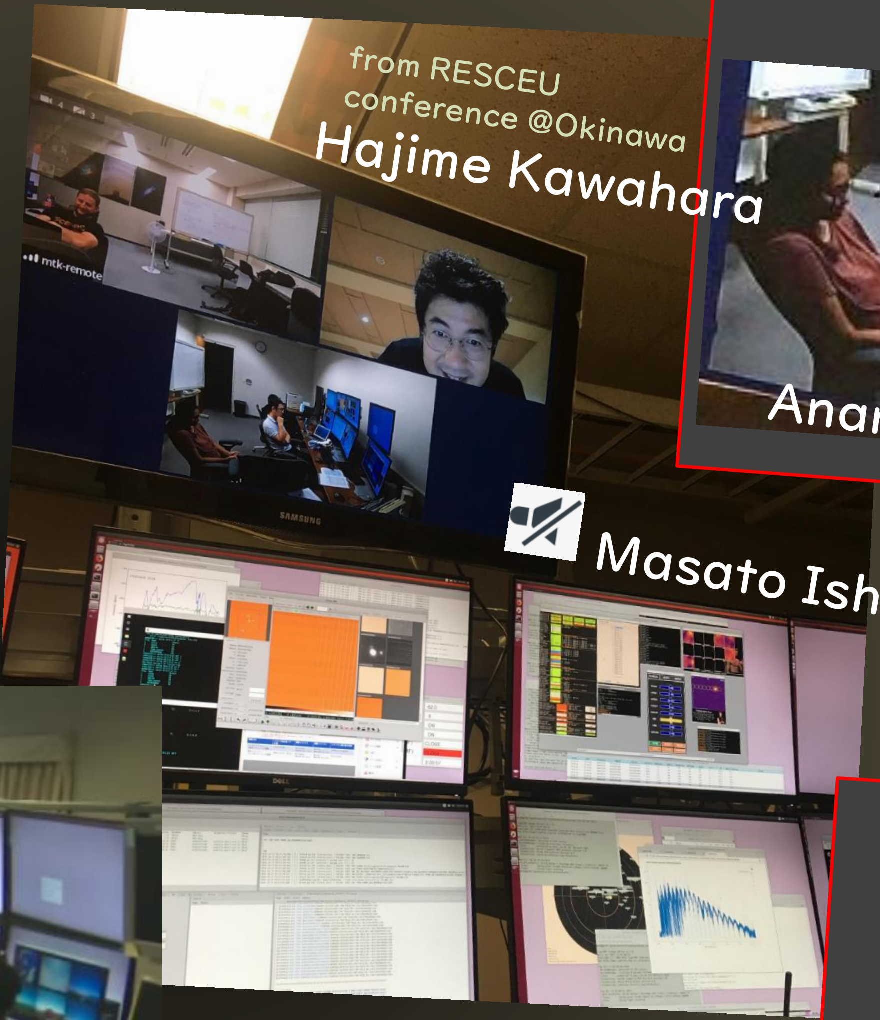
CCF of CO (Snellen+18)

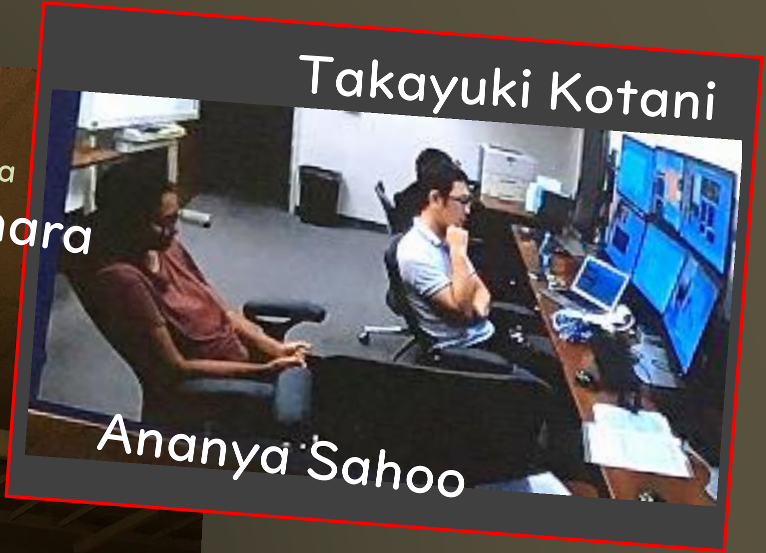
HRS + ExAO + Coronagraph
= High-Dispersion Coronagraphy
(Kawahara+14, Snellen+15, Wang+17)

REACH on Subaru (Y,J,H)
KPIC on Keck (K,L,M)
HiRISE on VLT (planned, H,K)

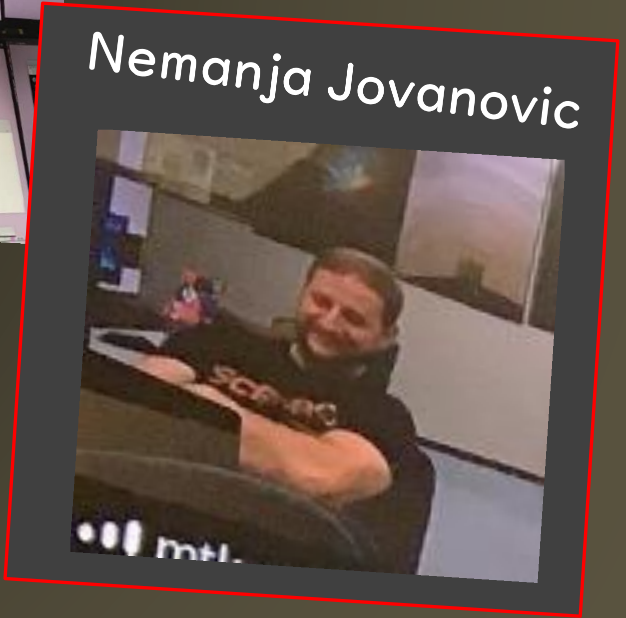


REACH collaboration





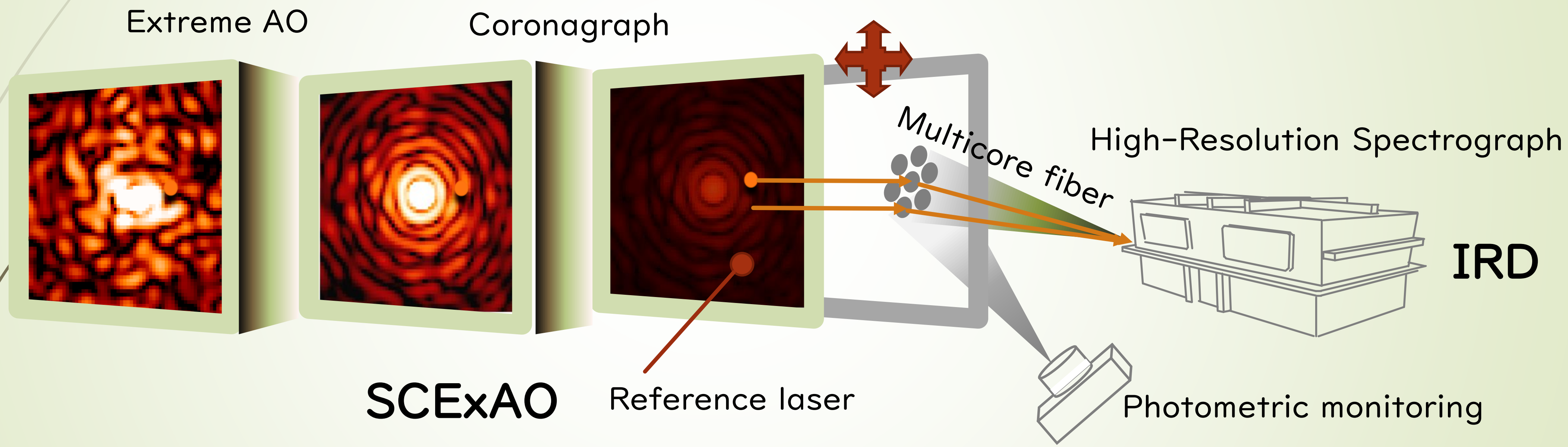
The first real spectrum by REACH in Oct 16th (2019)



Advanced

High-Dispersion Coronagraphy on Subaru

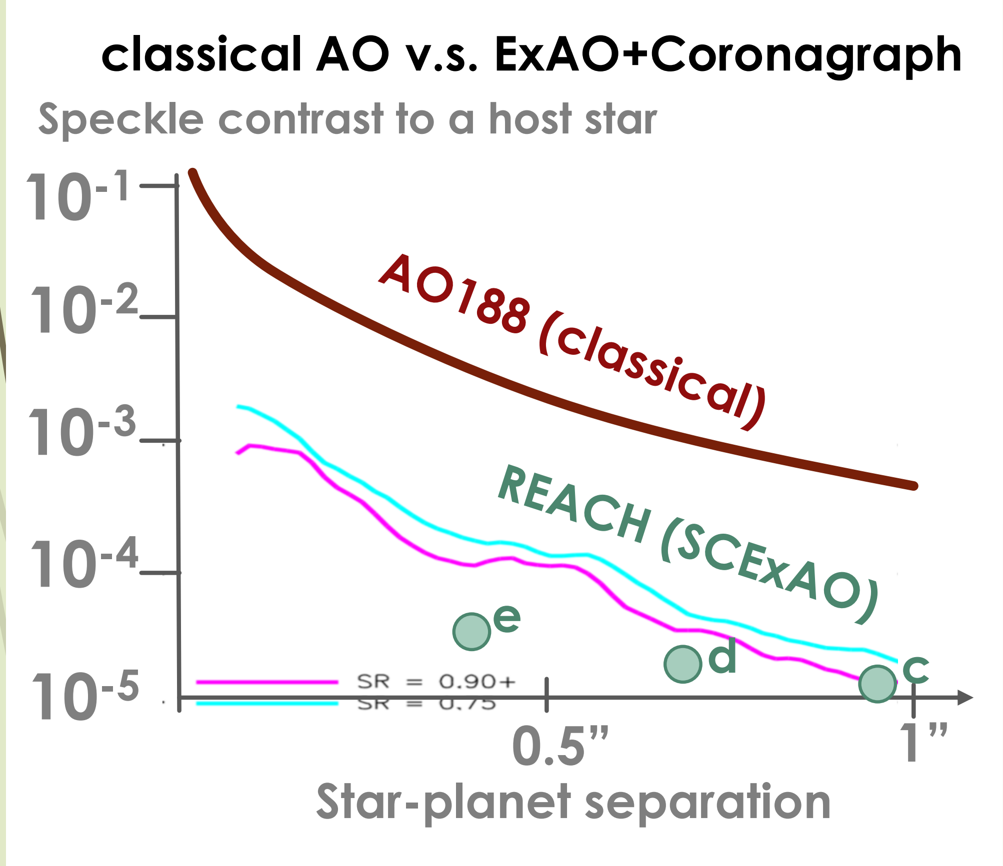
REACH on Subaru telescope

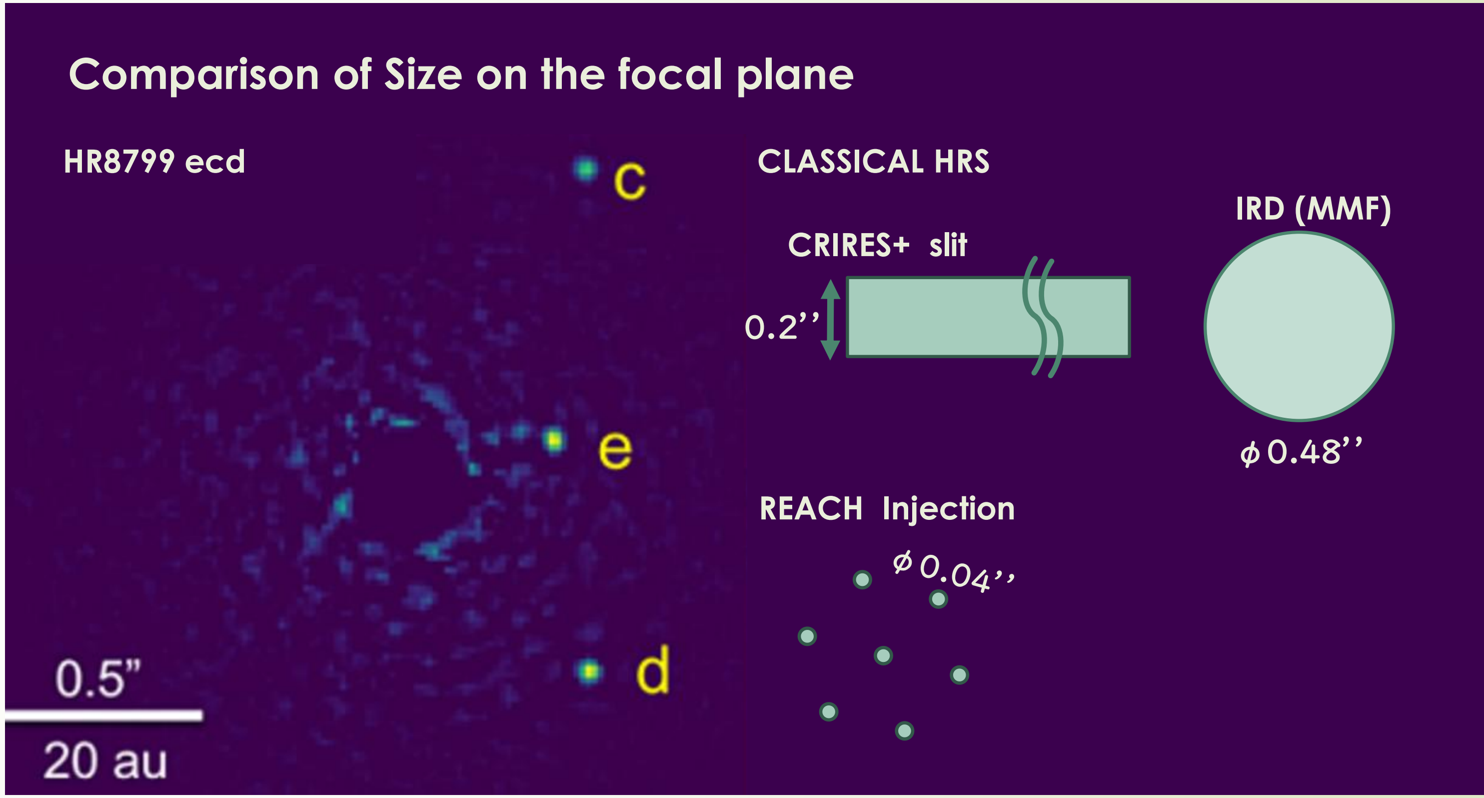


2014 idea (Kawahara+2014)
2015-2017 **Supported by RESCEU**
2019 first light (engneering), open use (since S20B)
2020 Kiban A, first science obs (Aug 1-6 2020)

Advanced

HDC significantly improves S/N

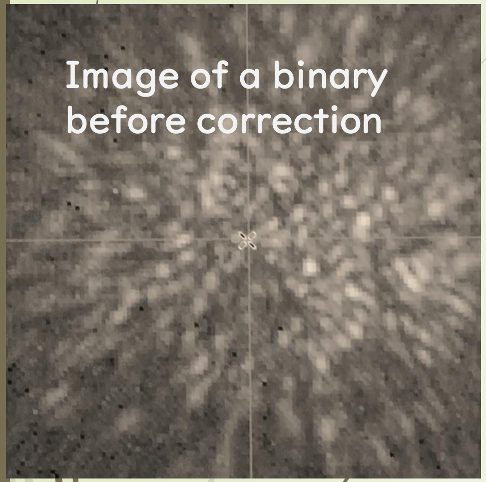


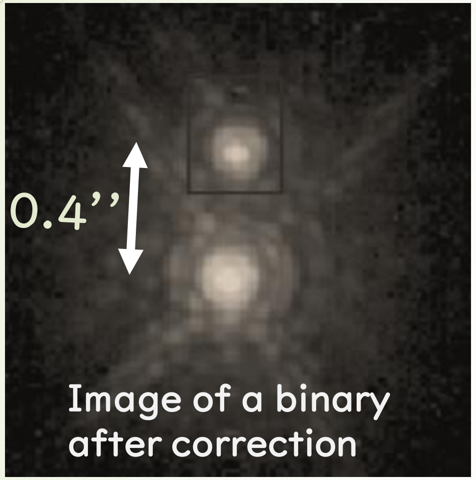


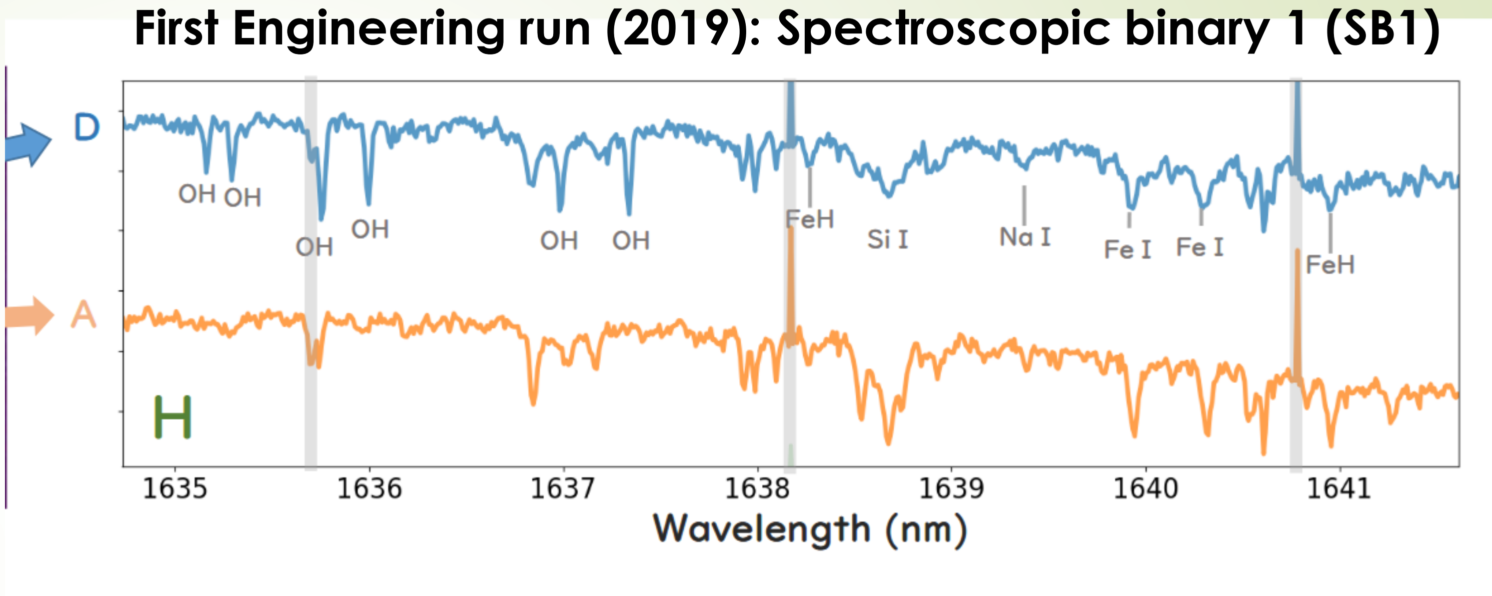
ExAO + Coronagraph + Small Injection can significantly increase planet signal in R=100,000 spectrum (0.95-1.75 um)

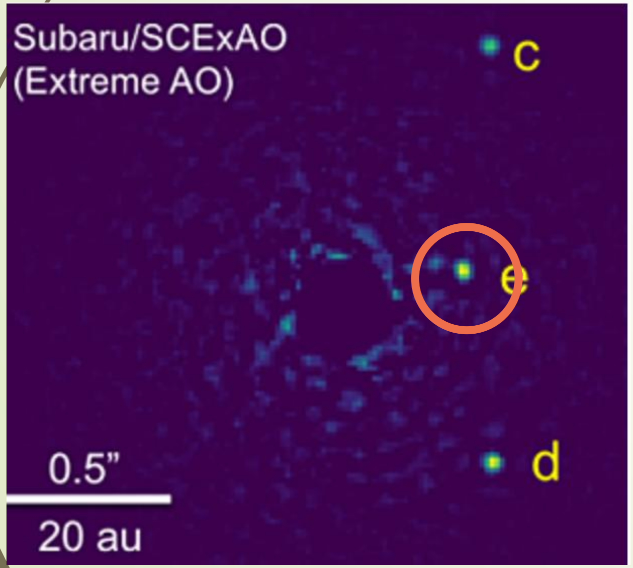
Advanced

Power of REACH









First science run (this month!) HR8799e

5.5 hours pilot data. Now processing, we'll see…

Contrast = **3×10^{-4}** -> planet : star = 1 : 10

S21A proposal welcome!

Short Summary

Direct imaging Ground: self-luminous planets so far

Pros: cutting-edge technique can be tested by a small group.
Cons: It will not reach Earth@solar-type star
Toward exo Earth: 30-40 m class telescope will try to detect water/oxygen in terrestrial planets @ late-M

Direct imaging from space: not yet. Roman will open, HabEx, LUVIOR

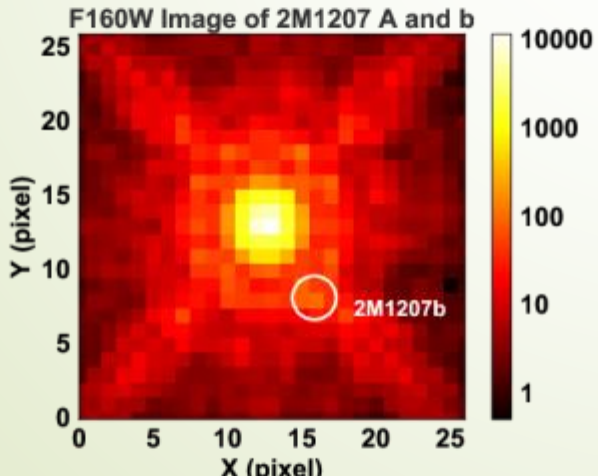
Pros: No ExAO needed, it can reach Earth@solar-type star, it can detect oxygen, water.
Cons: dev by a small group with try-and-error is almost impossible
It's not clear except for low-res spectroscopy
-> Methodology for space DI should be explored more.

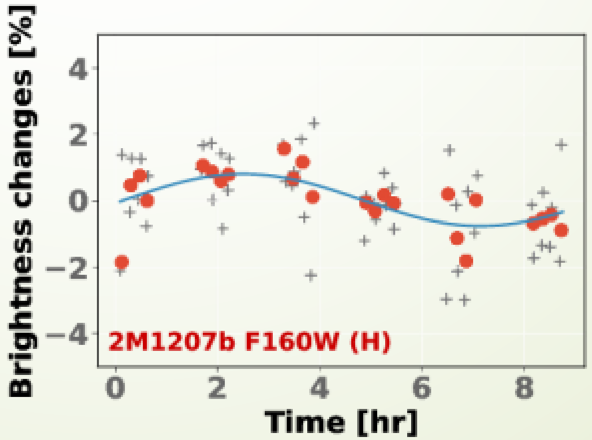
Basic

Photometric variability as a new probe of exoplanets

Space Direct Imaging: Roman 2025-, HabEx/LUVOIR 203X-
Reflection light from exoplanets around solar-type stars will be available

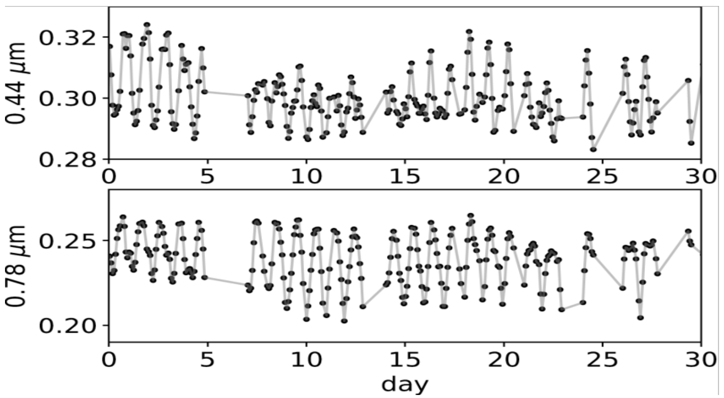
- Low resultion spectroscopy
- Time-series analysis





Variability of 2M1207b by HST (Zhou+ 2016)

How do we disentangle spatial and spectral information from time-series data?



Spin-Orbit Tomography

given — given — albedo map (we want to know)

$$d(t) = \int W(\mathrm{t}, \Omega)\, \mathrm{a}(\Omega) \mathrm{d}\Omega$$

Spin-Orbit Unmixing

$$d(t,\lambda) = \int\int W(\mathrm{t}, \Omega)\, \mathrm{A}(\Omega, k)\, \mathrm{X}(k, \lambda) \mathrm{d}\lambda \mathrm{d}\Omega$$

Map of k-th component

k-th component spectrum

Dynamic Mapping

$$d(t) = \int W(\mathrm{t}, \Omega)\, \mathrm{A}(\mathrm{t}, \Omega) \mathrm{d}\Omega$$

Time-dependent albedo

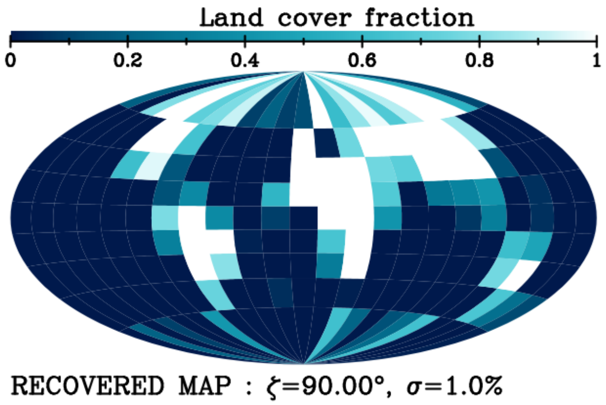
Dynamic Unmixing

Not Solved Yet

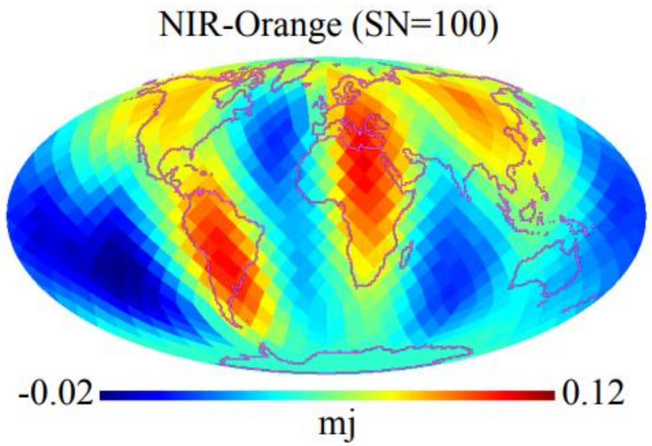
$$d(t,\lambda) = \int\int W(\mathrm{t}, \Omega)\, A(\mathrm{t}, \Omega, k)\, \mathrm{X}(k, \lambda) \mathrm{d}\lambda \mathrm{d}\Omega$$

Gallery

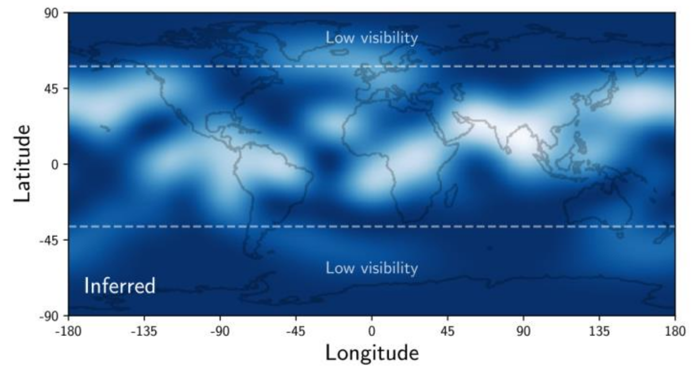
2010 Cloudless simulation
Kawahara & Fujii 2010



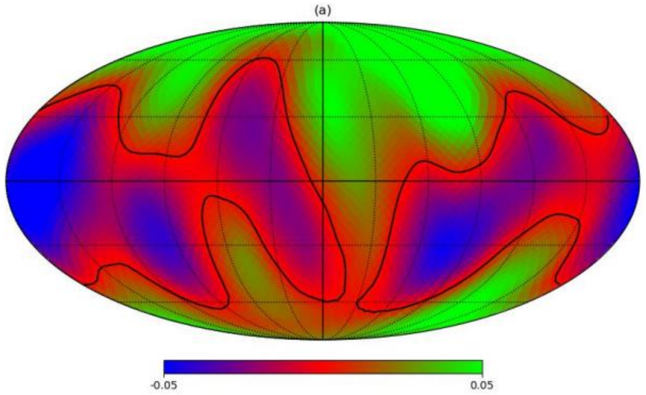
2012 full simulation
K&F 2011, F&K 2012



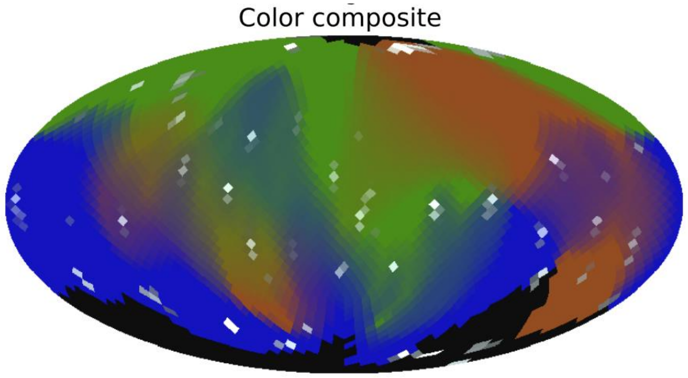
2019 REAL EARTH single band (TESS)
Luger+2019



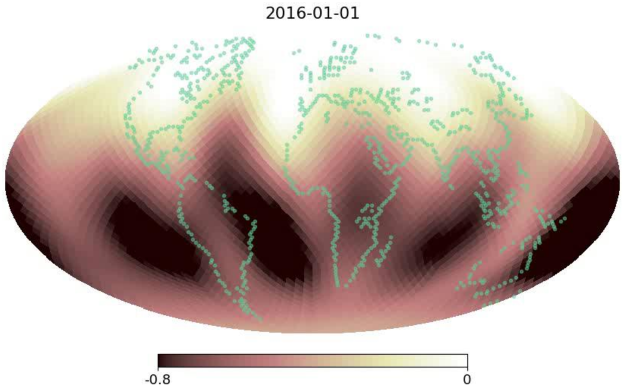
2019 REAL EARTH (L2/PCA)
Fan+2019



2020 REAL EARTH (NMF)
Kawahara 2020



2020 REAL EARTH (clouds)
Kawahara & Masuda 2020



Basic

Linear Inverse Problem

$$d(t) = \int W(t,\Omega)\, a(\Omega) d\Omega \;\rightarrow\; \boldsymbol{d} = W\boldsymbol{a}$$

Singular Value Decomposition $W = U^T \Lambda V$

Moore-Penrose Matrix $W^{-g} = V \Lambda^{-1} U^T$

U, V: orthoaonal matrix

$$\Lambda = \begin{pmatrix} \Lambda_p & 0 \\ 0 & 0 \end{pmatrix}$$

$$\Lambda_p \equiv diag(\kappa_1, .., \kappa_p)$$

$$\boldsymbol{a}^{\text{est}} = W^{-g}\boldsymbol{d} = \sum_{i=1}^{p} \frac{(\boldsymbol{u}_i^T \boldsymbol{d})}{\kappa_i} \boldsymbol{v}_i$$

Very unstable for small singular value κ_i

Tikhonov regularization

$$\boldsymbol{a}^{\text{est}} = V\Sigma_\lambda U^T \boldsymbol{d}^{\text{obs}} = \sum_{i=1}^{\min(N,M)} \frac{\kappa_i}{\kappa_i^2 + \lambda^2} (\boldsymbol{u}_i^T \boldsymbol{d}) \boldsymbol{v}_i \Leftrightarrow$$

"L2" norm regularization

minimize $Q_\lambda = |W\boldsymbol{a} - \boldsymbol{d}|^2 + \lambda^2 |\boldsymbol{a}|^2$

The math structure is clear, but needs to determine an arbitrary parameter.

Basic

Bayesian LIP

Tarantra 2005, Bishop 2006, Farr+2018
Kawahara and Masuda 2020

Linear Inverse Problem with known covariance matrices

likelihood $p(\boldsymbol{d}|\boldsymbol{a}) = \mathcal{N}(\boldsymbol{d}|W\boldsymbol{a}, \Sigma_{\boldsymbol{d}})$

prior $p(\boldsymbol{a}) = \mathcal{N}(\boldsymbol{a}|\boldsymbol{0}, \Sigma_{\boldsymbol{a}}),$

$$\mathcal{N}(\boldsymbol{x}|\boldsymbol{\mu}, \Sigma) = \frac{1}{(2\pi)^{N/2}(\det \Sigma)^{1/2}} e^{-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^T \Sigma^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$$

Posterior: $p(\boldsymbol{a}|\boldsymbol{d}) = \dfrac{p(\boldsymbol{d}|\boldsymbol{a})p(\boldsymbol{a})}{p(\boldsymbol{d})} = \mathcal{N}(\boldsymbol{a}|\boldsymbol{\mu}, \Sigma_{\boldsymbol{a}|\boldsymbol{d}})$

$$\begin{cases} \boldsymbol{\mu} = (W^T \Sigma_{\boldsymbol{d}}^{-1} W + \Sigma_{\boldsymbol{a}}^{-1})^{-1} W^T \Sigma_{\boldsymbol{d}}^{-1} \boldsymbol{d} \\ \Sigma_{\boldsymbol{a}|\boldsymbol{d}} = (W^T \Sigma_{\boldsymbol{d}}^{-1} W + \Sigma_{\boldsymbol{a}}^{-1})^{-1}. \end{cases}$$

In general: Nonlinear parameters (**NLPs**) in $W = W(\boldsymbol{g})$: axial tilt, spin rate
Covarianceare modeled through a Gaussian process with hyperparameters:

$$\begin{cases} \Sigma_{\boldsymbol{a}} = K_S(\boldsymbol{\theta_a}) \\ \Sigma_{\boldsymbol{d}} = K_D(\boldsymbol{\theta_d}) \end{cases}$$

$$p(\boldsymbol{a}|\boldsymbol{d}, \boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}) = \frac{p(\boldsymbol{d}|\boldsymbol{a}, \boldsymbol{\theta_d}, \boldsymbol{g})p(\boldsymbol{a}|\boldsymbol{\theta_a})}{p(\boldsymbol{d}|\boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g})} \rightarrow p(\boldsymbol{d}|\boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}) = \mathcal{N}(\boldsymbol{d}|\boldsymbol{0}, \Sigma_{\boldsymbol{d}} + W\Sigma_{\boldsymbol{a}}W^T)$$

Posterior of NLPs given by MCMC: $p(\boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}|\boldsymbol{d}) \propto p(\boldsymbol{d}|\boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g})p(\boldsymbol{\theta_a})p(\boldsymbol{\theta_d})p(\boldsymbol{g})$

Posterior of a map:

$$p(\boldsymbol{a}|\boldsymbol{d}) = \int d\boldsymbol{\theta_a} \int d\boldsymbol{\theta_d} \int d\boldsymbol{g}\, p(\boldsymbol{a}, \boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}|\boldsymbol{d})$$

$$= \int d\boldsymbol{\theta_a} \int d\boldsymbol{\theta_d} \int d\boldsymbol{g}\, p(\boldsymbol{a}|\boldsymbol{d}, \boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}) p(\boldsymbol{\theta_a}, \boldsymbol{\theta_d}, \boldsymbol{g}|\boldsymbol{d}) \approx \frac{1}{N_s} \sum_{n=0}^{N_s-1} p(\boldsymbol{a}|\boldsymbol{d}, \boldsymbol{\theta_a}^\dagger, \boldsymbol{\theta_d}^\dagger, \boldsymbol{g}^\dagger)$$

Sampled NLPs

Advanced

Linear Inverse Problem + Matrix Factorization

Kawahara 2020

$$d(t,\lambda) = \int\int W(t,\Omega)\, A(\Omega,k)\, X(k,\lambda) d\lambda d\Omega \longrightarrow D = WAX$$

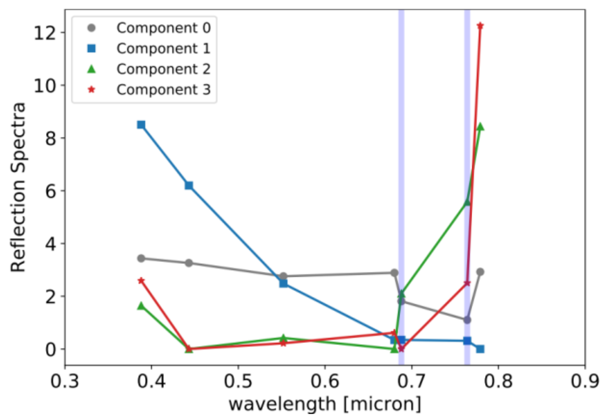
$$\boxed{A \leftarrow AG^{-1} \quad X \leftarrow GX}$$

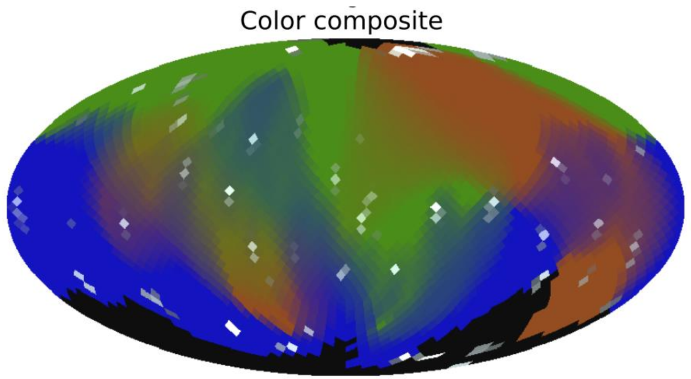
$$\text{minimize} \;\; Q = \frac{1}{2}||D - WAX||_F^2 + R(A,X) \longrightarrow R(A,X) = \frac{\lambda_A}{2}||A||_F^2 + \frac{\lambda_X}{2}\det(XX^T)$$

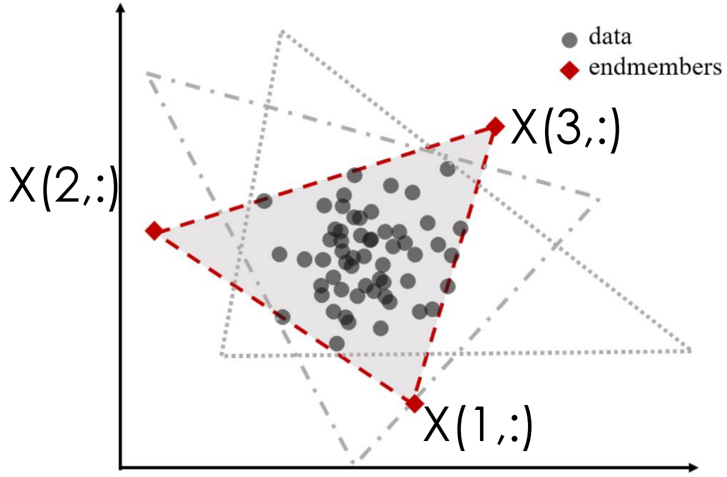
$$\text{subject to } A_{jk} \geq 0, X_{kl} \geq 0.$$

Nonnegative MF

Volume Regularization



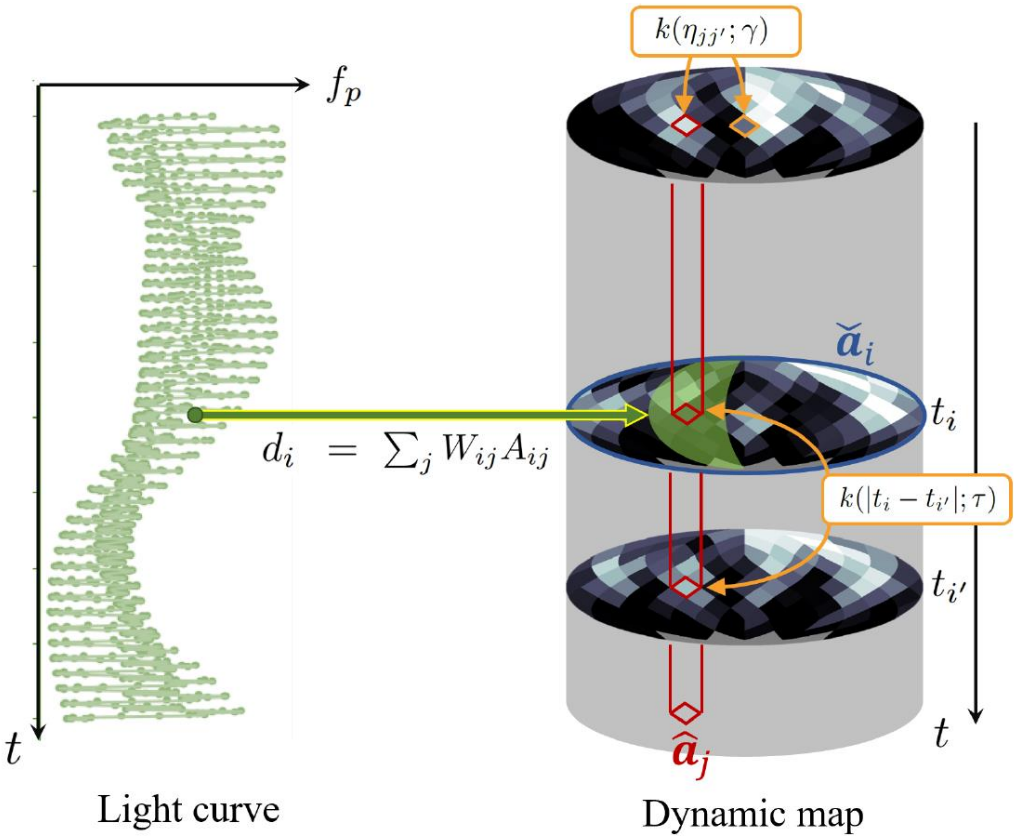




Advanced

Dynamic Mapping

Kawahara and Masuda 2020



Data
N~1,000

Model
M~1,000,000

$$d_i = \sum W_{ij} A_{ij} \quad \Rightarrow \quad \boldsymbol{d} = \tilde{W} \boldsymbol{a}.$$

$$\tilde{W} = \left(\mathcal{D}(\boldsymbol{w}_0) \quad \mathcal{D}(\boldsymbol{w}_1) \quad \cdots \quad \mathcal{D}(\boldsymbol{w}_{N_j-1}) \right) \qquad \boldsymbol{a} = \mathrm{vec}(A)$$

$\boldsymbol{\omega}_i$: i-th column of $\tilde{W}$ $\quad$ $\mathcal{D}(\boldsymbol{y})$: Diagonal matrix from a vector $\boldsymbol{y}$

Remark: We know a posterior of $\boldsymbol{a}$. But, we need to reduce memory size and computational complexity.

The Kronecker-product type kernel $K = \alpha K_S \otimes K_T$ and isomorphic transformation enable us to do that.

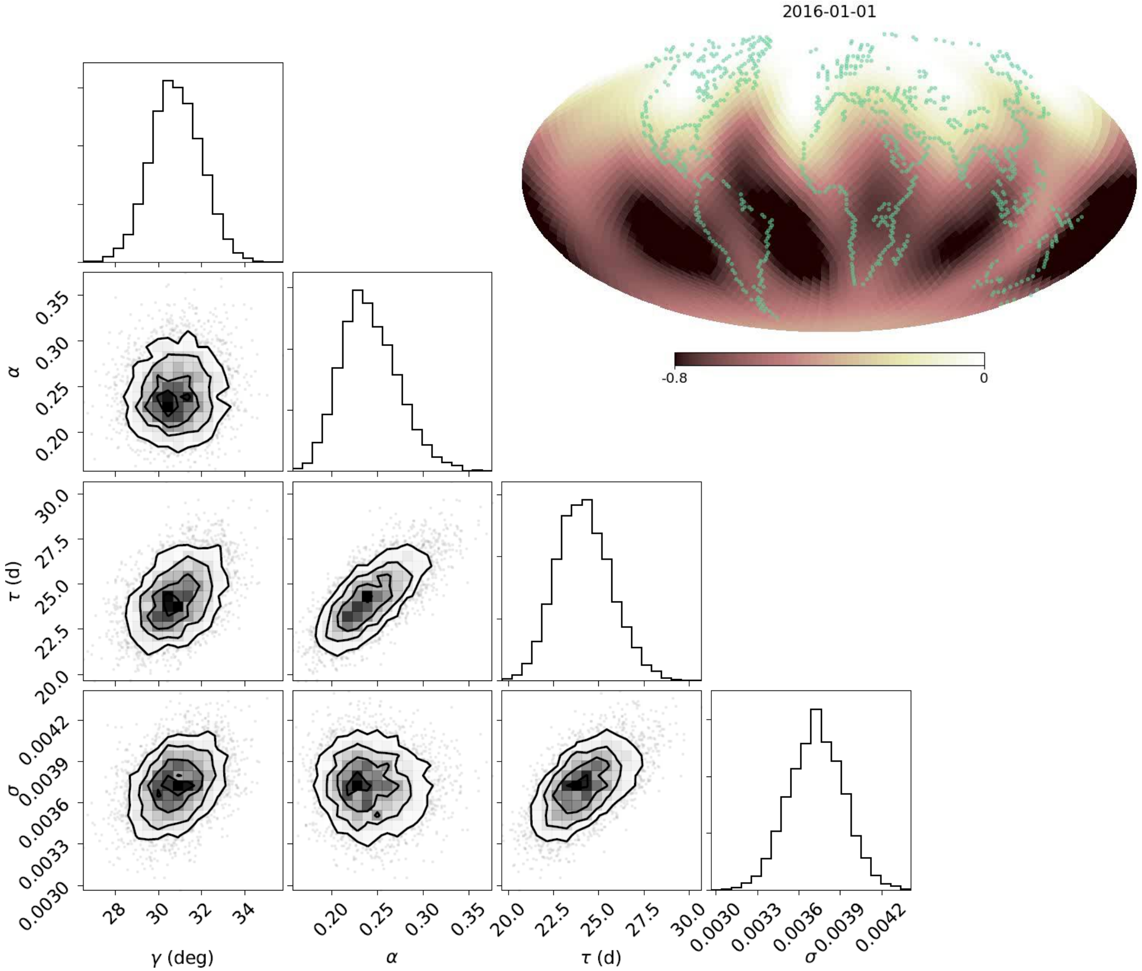
Example: mean of a posterior of A

$$A^* = \alpha K_T \mathcal{D}(\boldsymbol{y}) W K_S$$
$$\boldsymbol{y} \equiv (I + \Pi_{\boldsymbol{d}} K_W)^{-1} \Pi_{\boldsymbol{d}} \boldsymbol{d}$$
$$K_W \equiv \alpha K_T \odot (W K_S W^T).$$

$\odot$= element-wise product

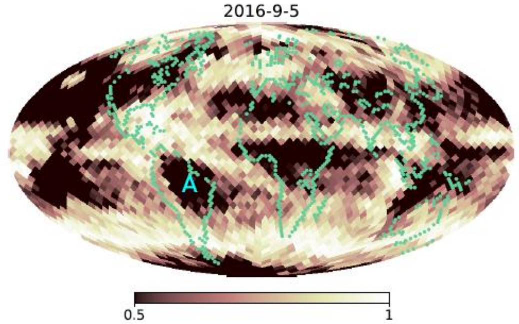
Advanced

Dynamic Mapping of Real data

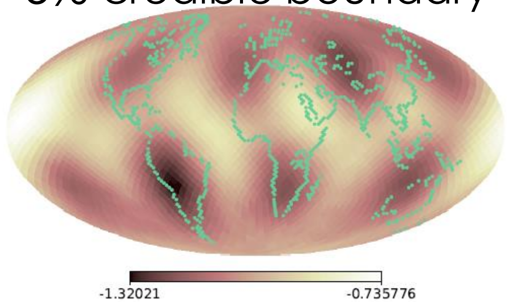


correlation spatial scale | Kernel intensity | correlation time scale | Noise level

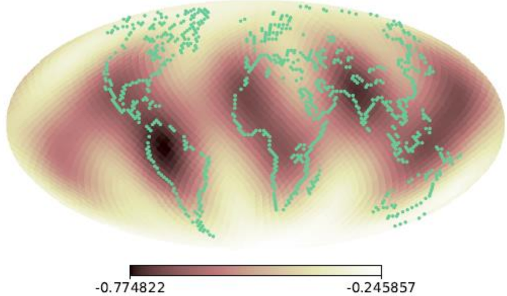
Cloud fraction in September 2016



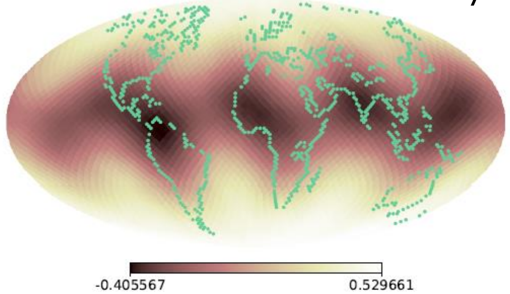
5% credible boundary



median



95% credible boundary



Summary

Landscape to characterization