Scaling laws in Star & Structure formation:

Density Models fitted to Observational Data

Marco Lombardi, University of Milan

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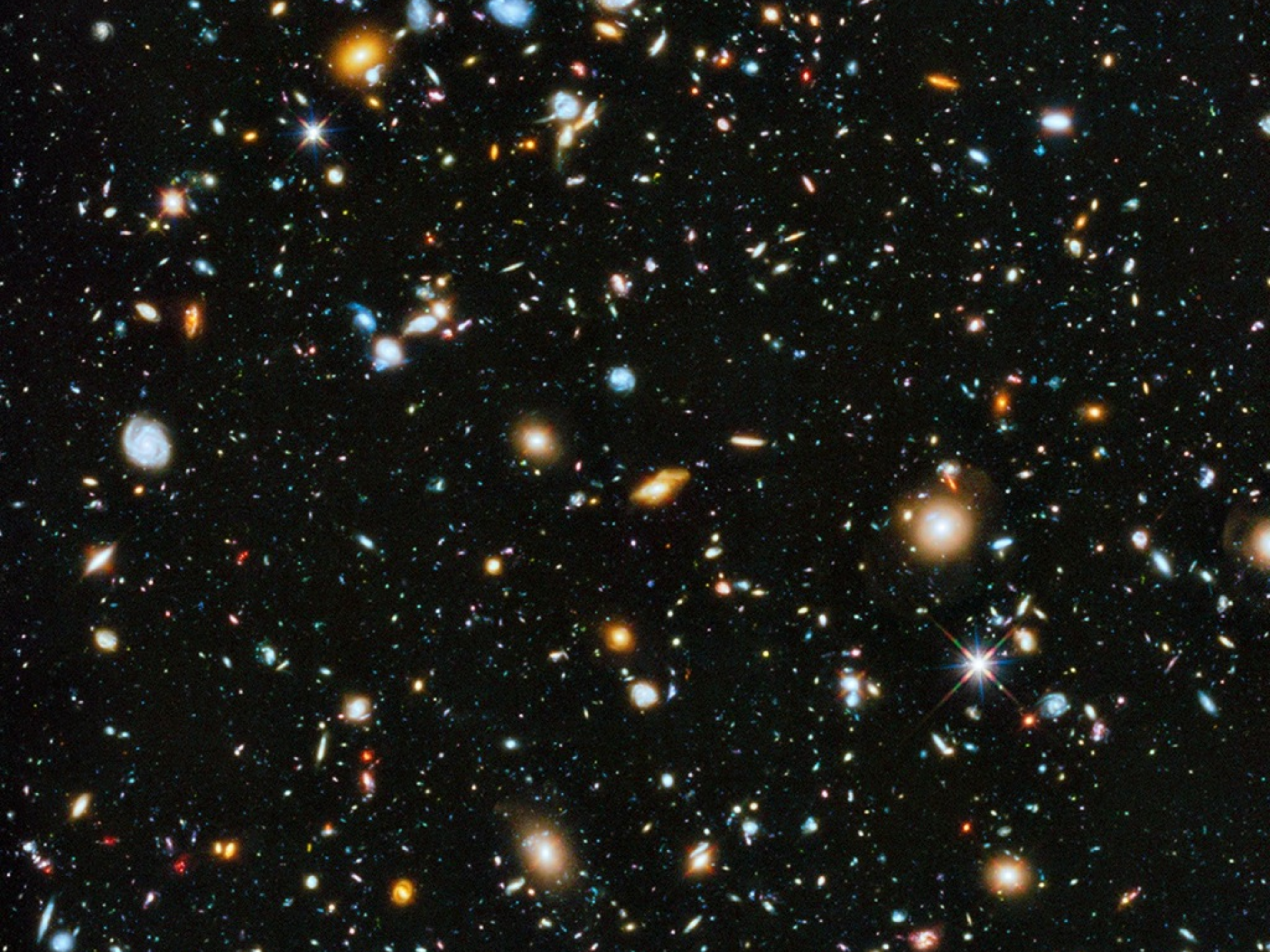
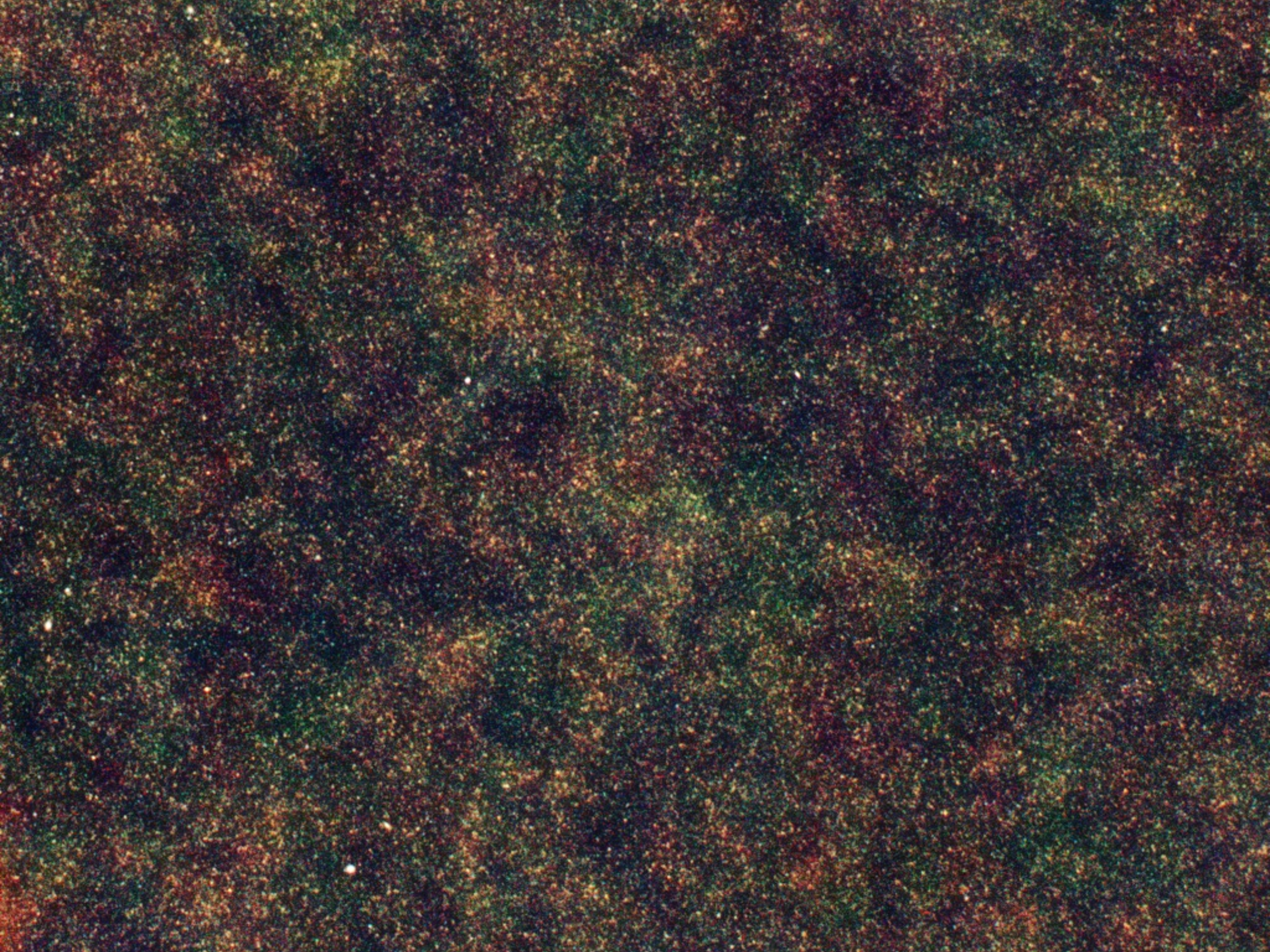
Density Models fitted to Observational Data

Marco Lombardi, University of Milan

with:
Charles Lada, CfA, Harvard
Joao Alves et al., University of Vienna





Pillars of star formation

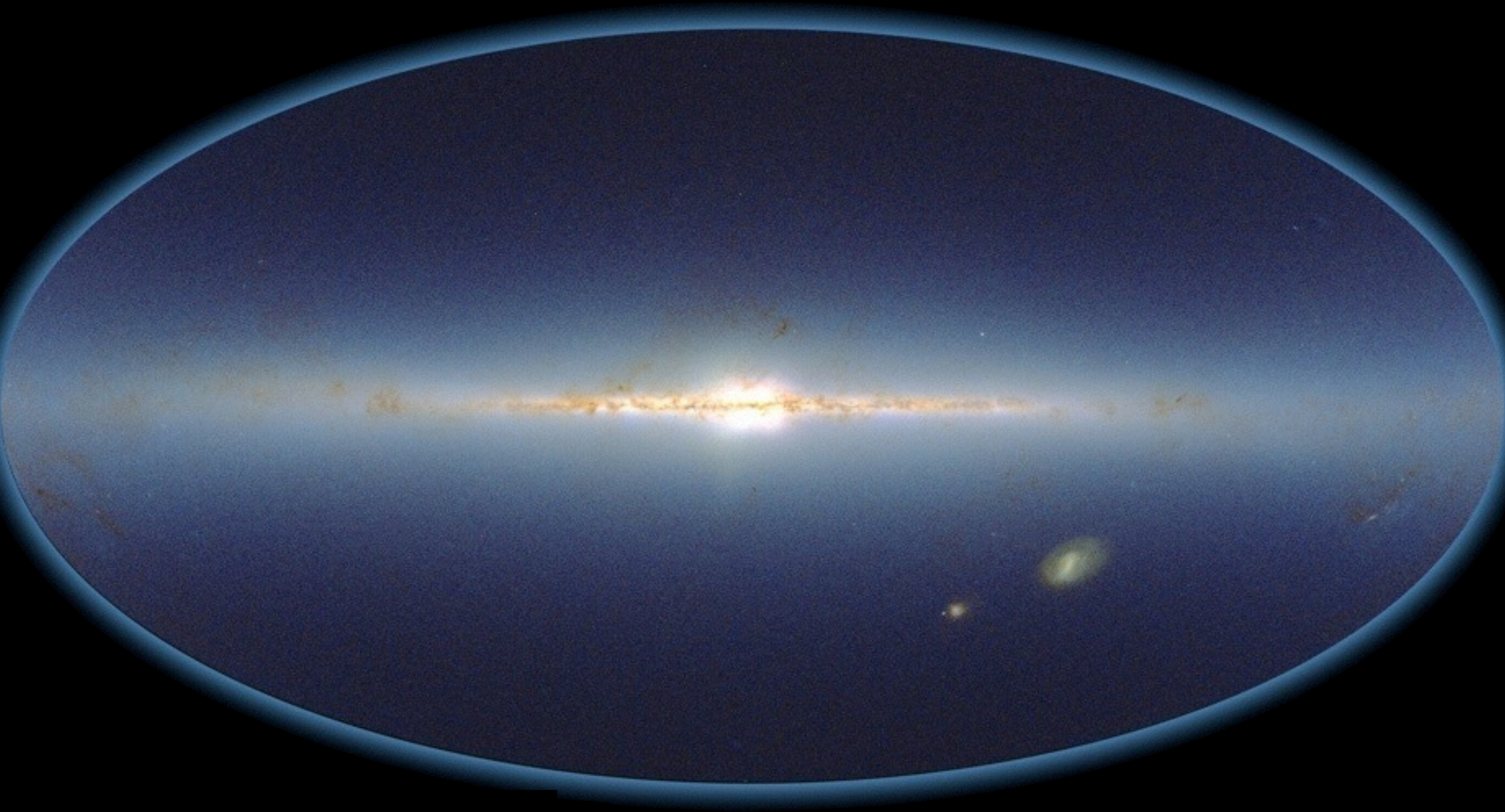
1. Stars form within dense molecular clouds
2. Star formation is a complex process
3. Different clouds have different star formation efficiencies
4. Molecular clouds have peculiar structures
5. Scaling laws play a fundamental role in SF

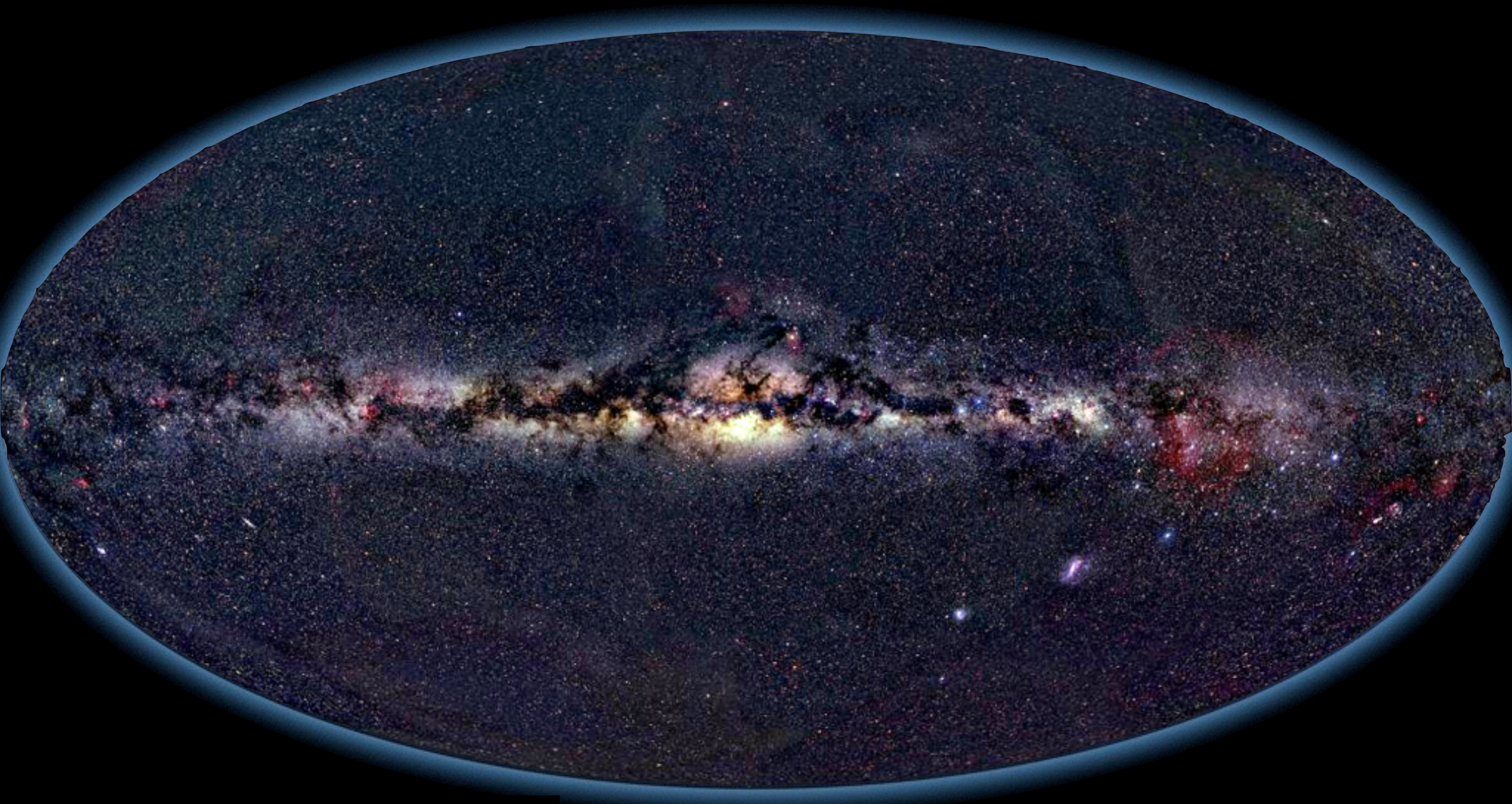
Fact 1

Stars form within dense molecular clouds

Fact 2
Star formation is a complex process

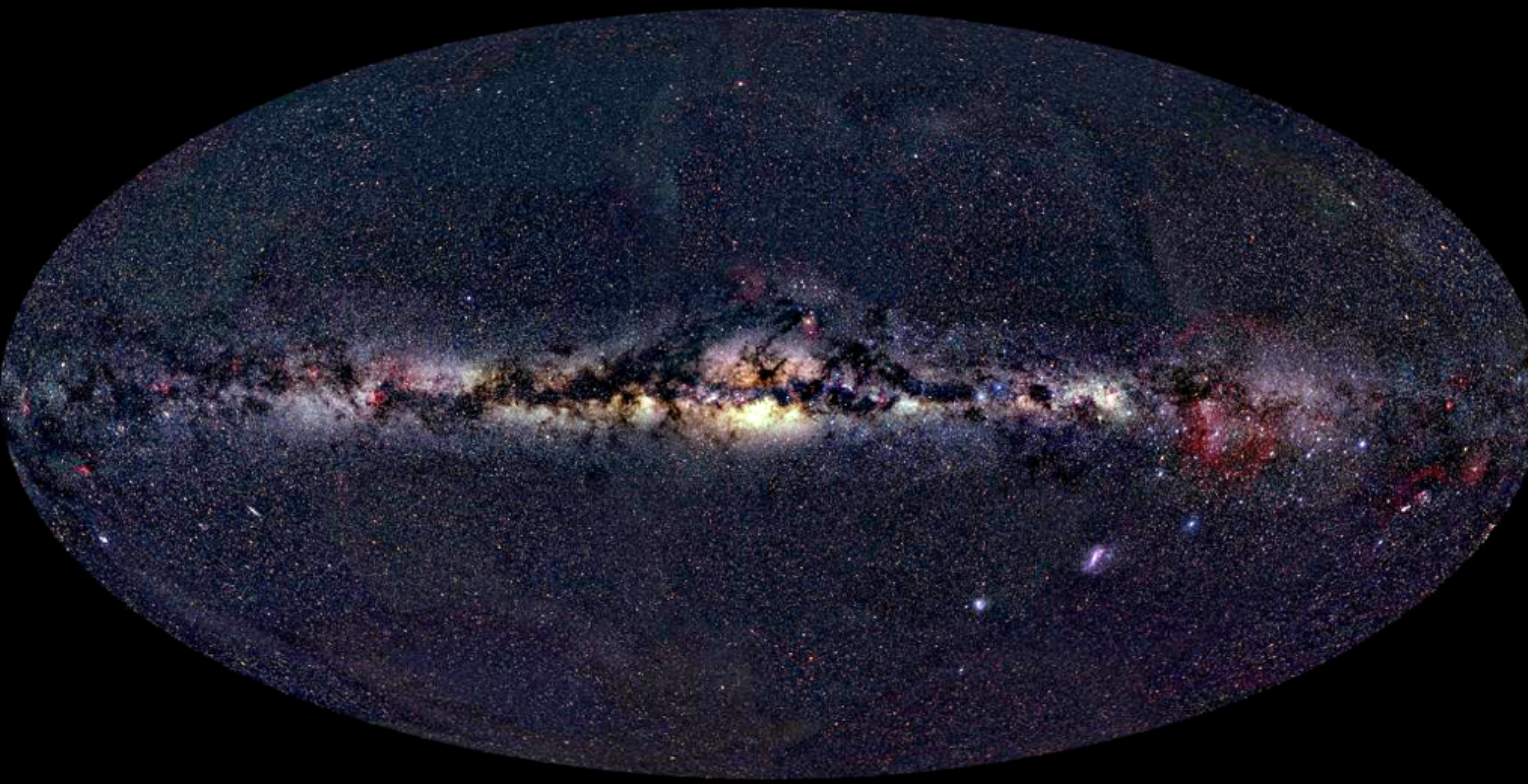
Molecular clouds in the Milky Way


2MASS



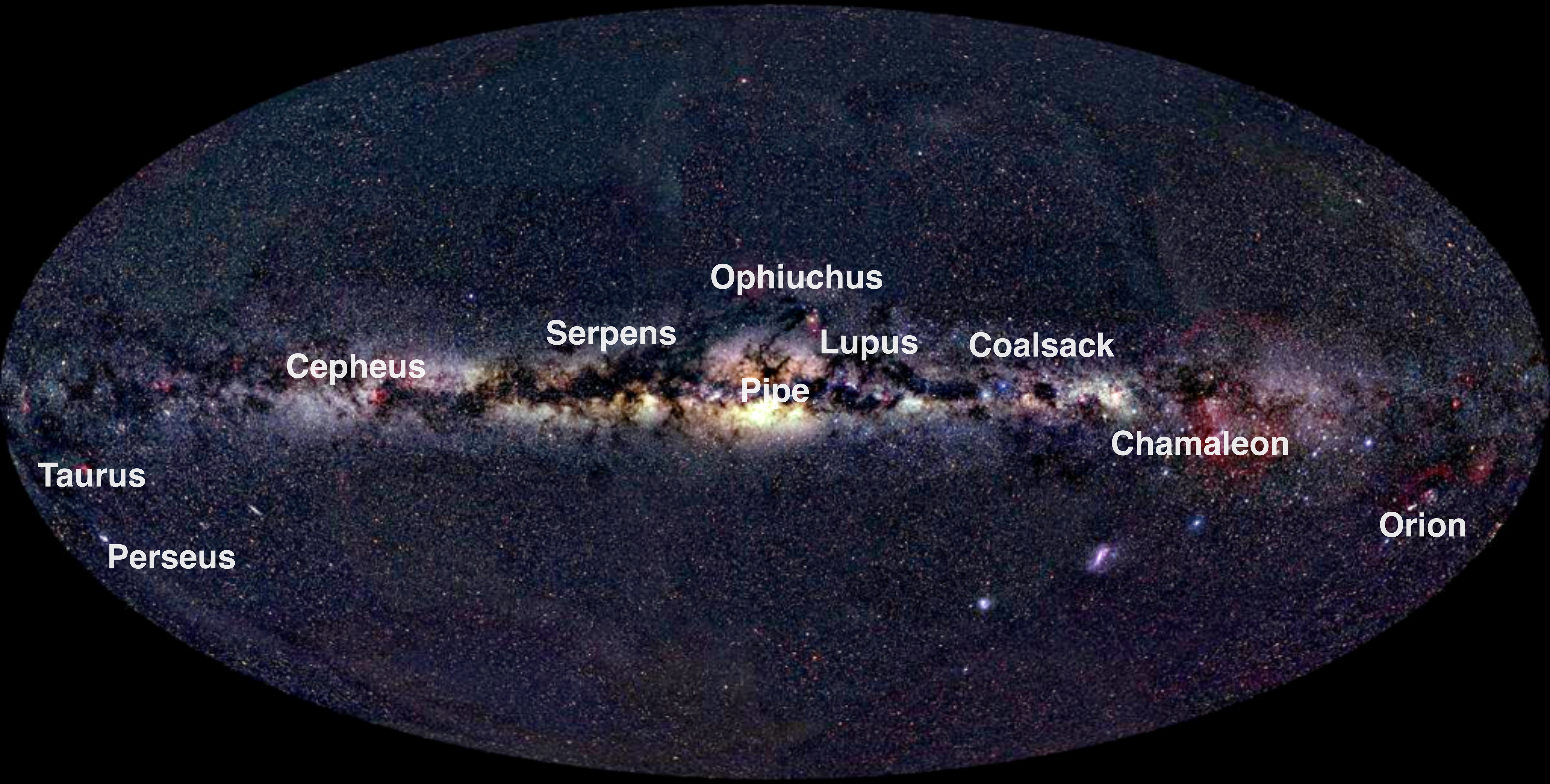
A. Mellinger

Gould belt



A. Mellinger

Gould belt



A. Mellinger

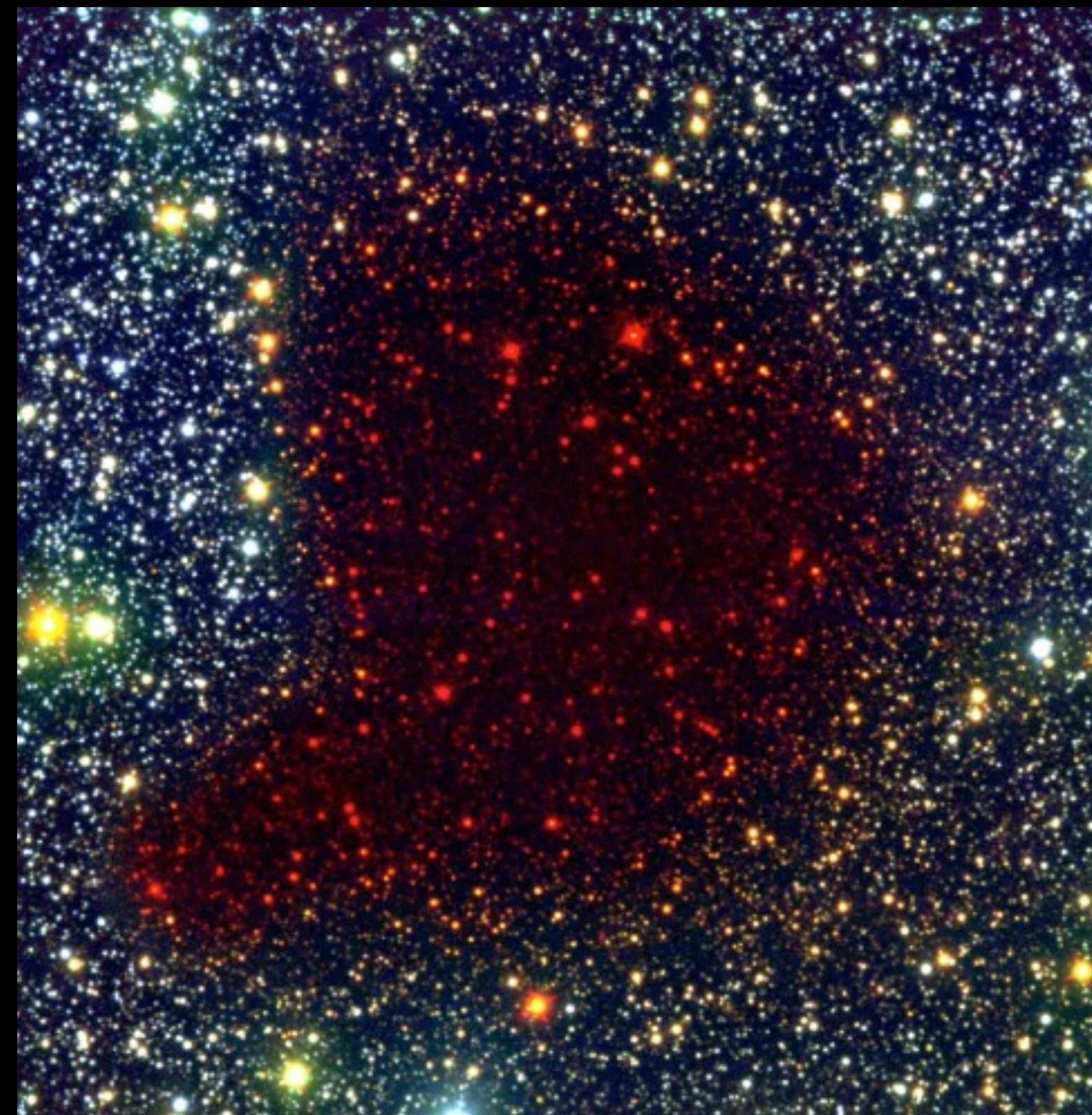
Extinction

Extinction

Alves et al. (2000)

Extinction

VLT (BVI)

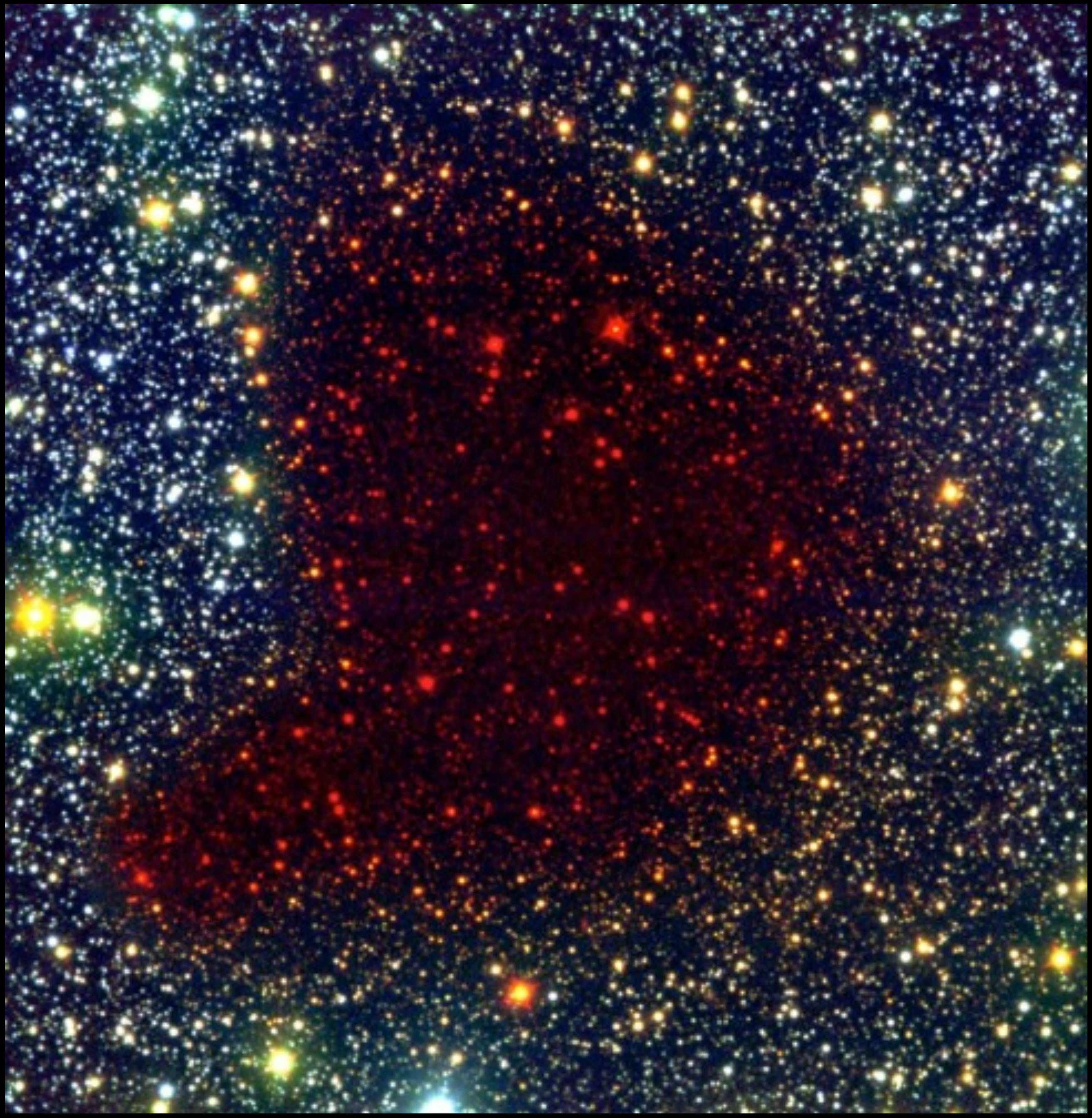


VLT + NTT (BIK)

Alves et al. (2000)

NICE(R)

VLT (BVI)

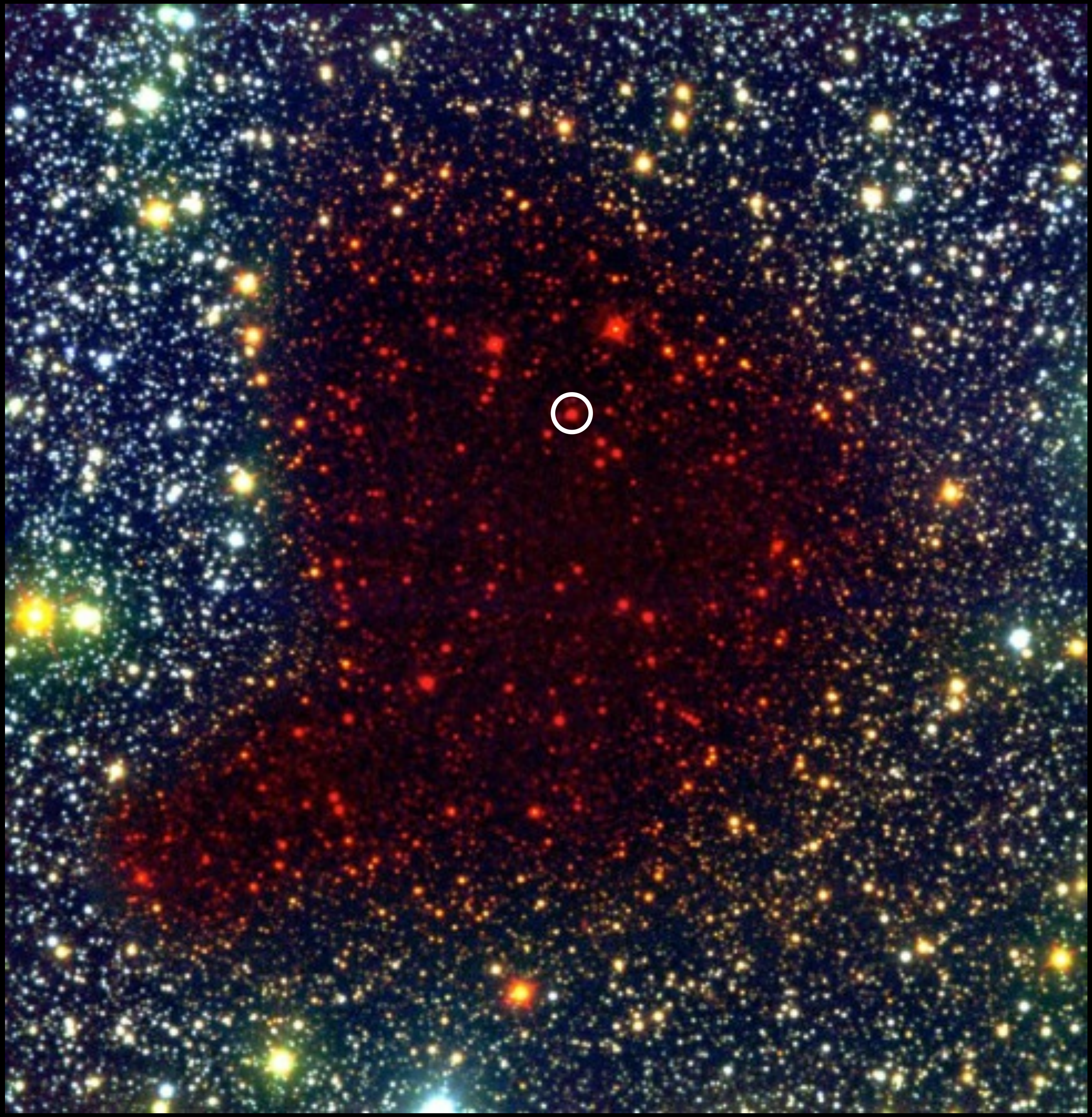


VLT + NTT (BIK)

Alves et al. (2000)

NICE(R)

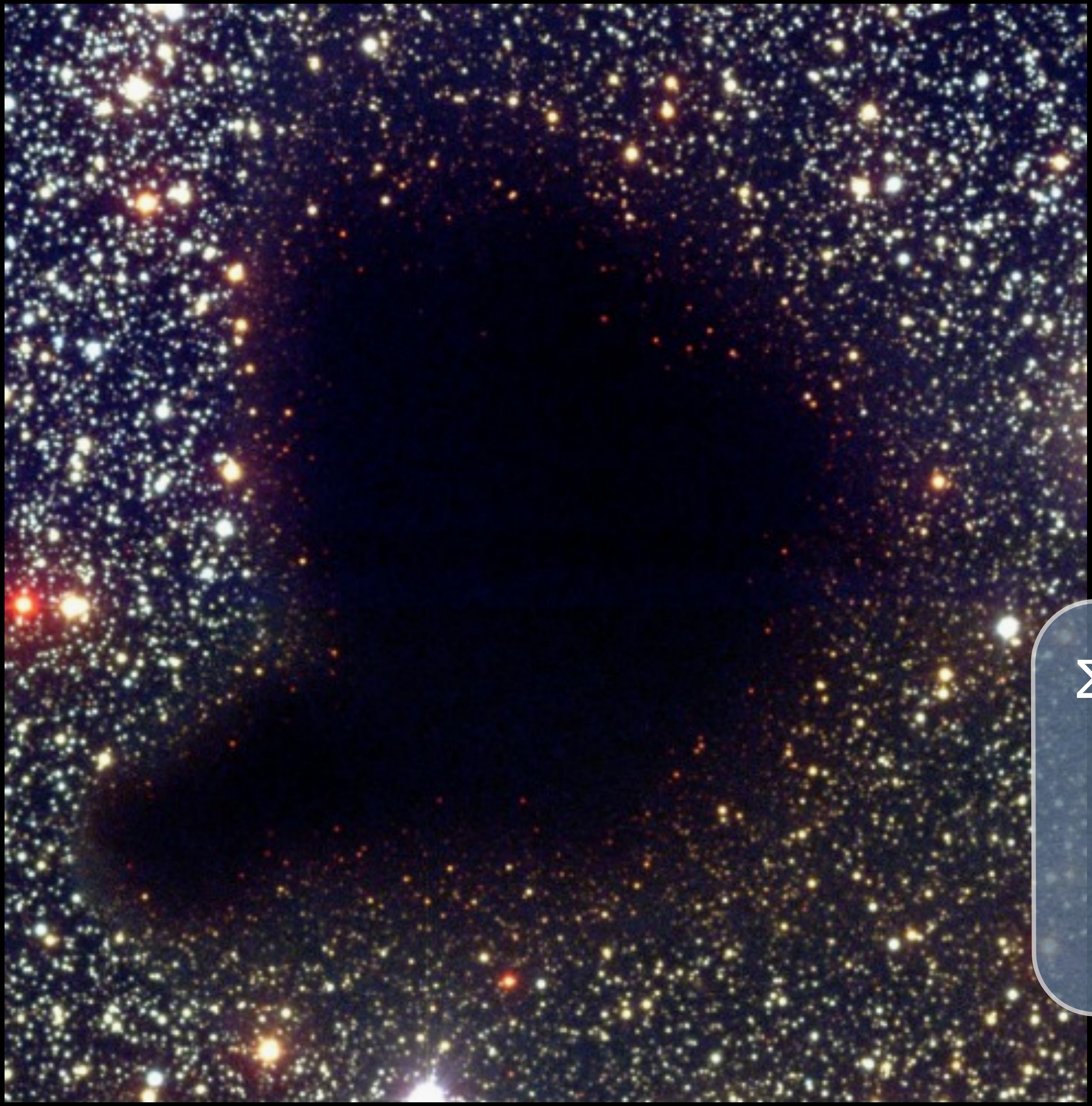
VLT (BVI)



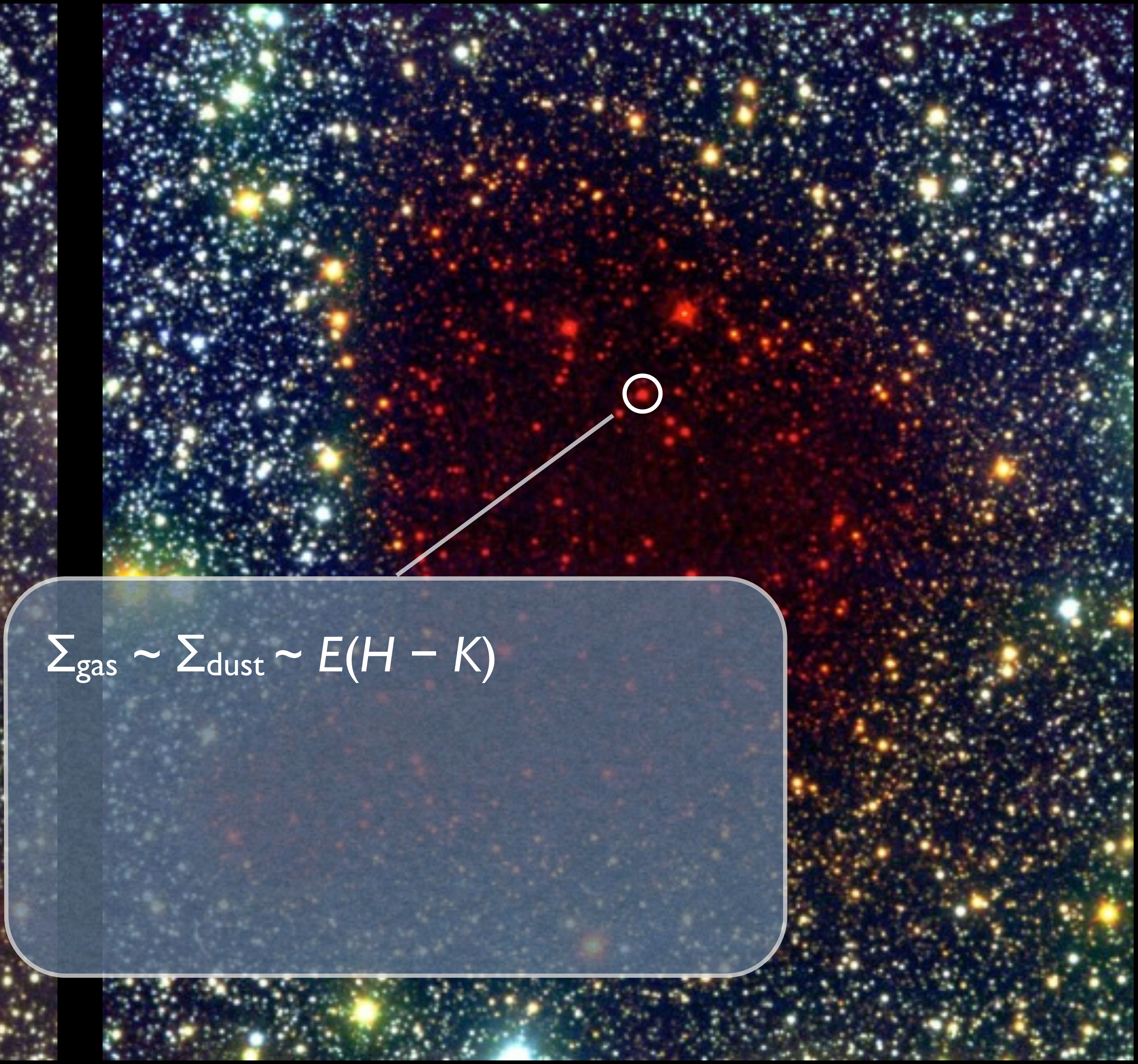
VLT + NTT (BIK)

Alves et al. (2000)

NICE(R)



VLT (BVI)

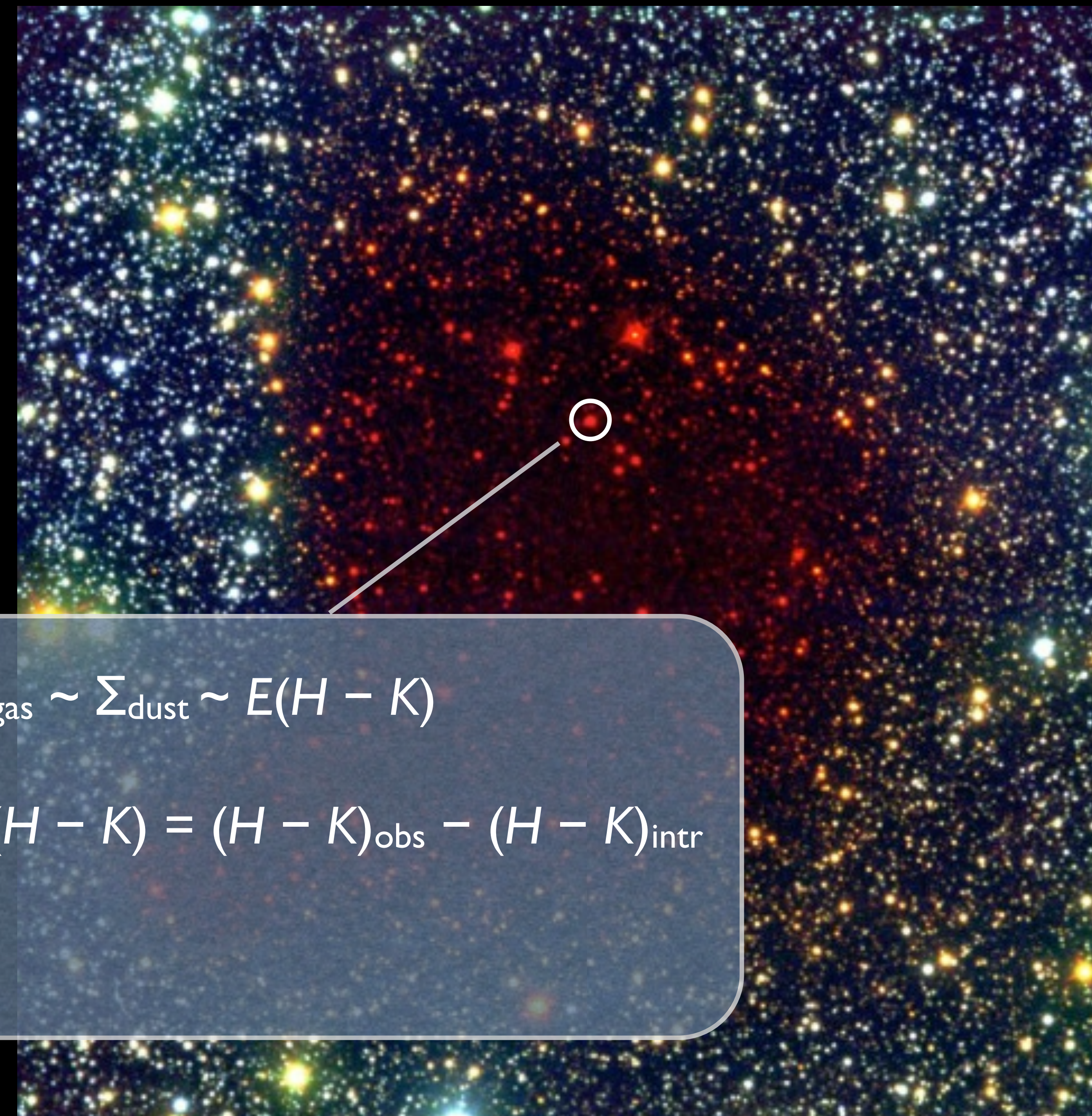


VLT + NTT (BIK)

Alves et al. (2000)

NICE(R)

VLT (BVI)



$$\Sigma_{gas} \sim \Sigma_{dust} \sim E(H-K)$$

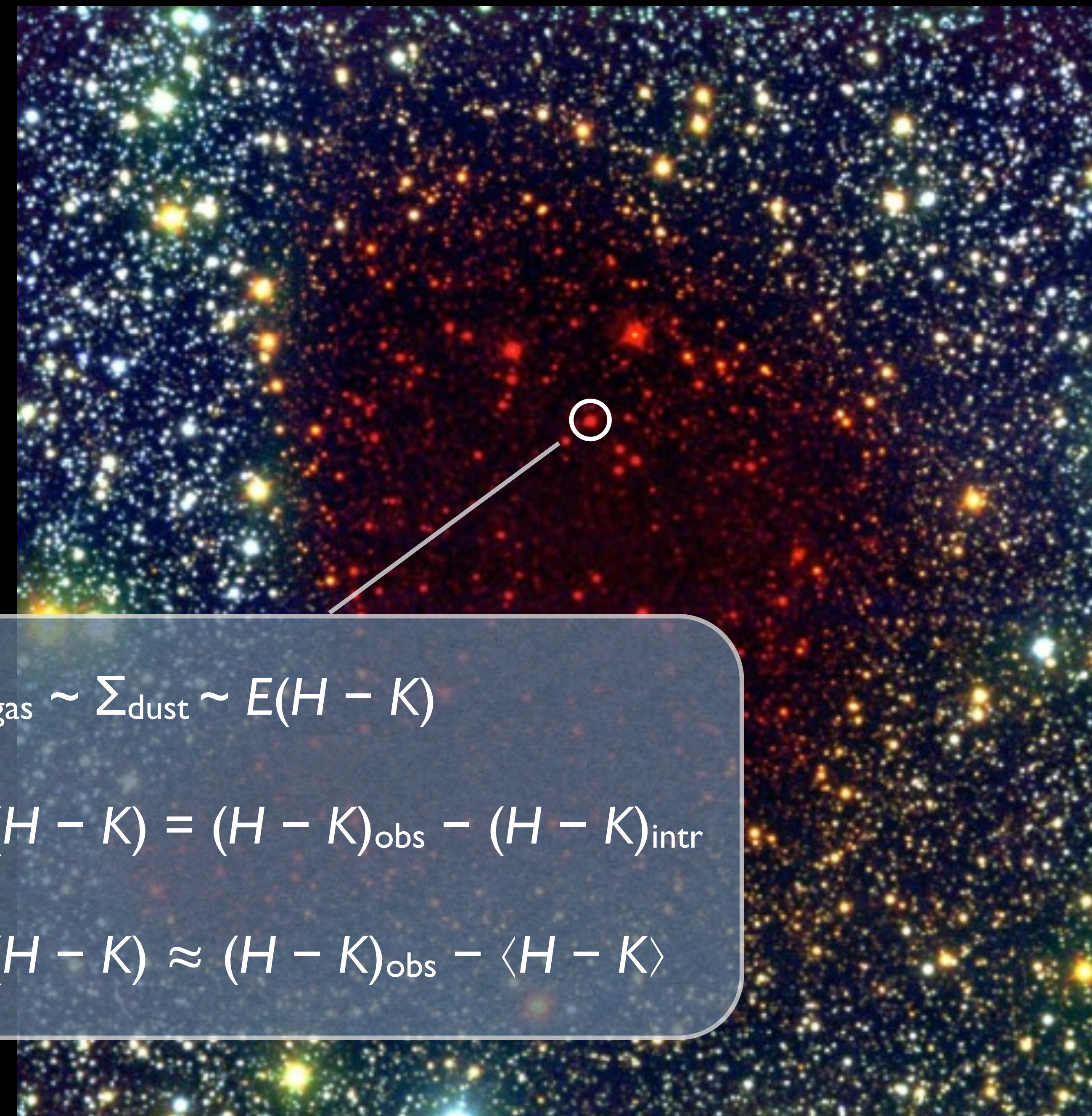
$$E(H-K) = (H-K)_{obs} - (H-K)_{intr}$$

VLT + NTT (BIK)

Alves et al. (2000)

NICE(R)

VLT (BVI)



VLT + NTT (BIK)

$$\Sigma_{gas} \sim \Sigma_{dust} \sim E(H - K)$$

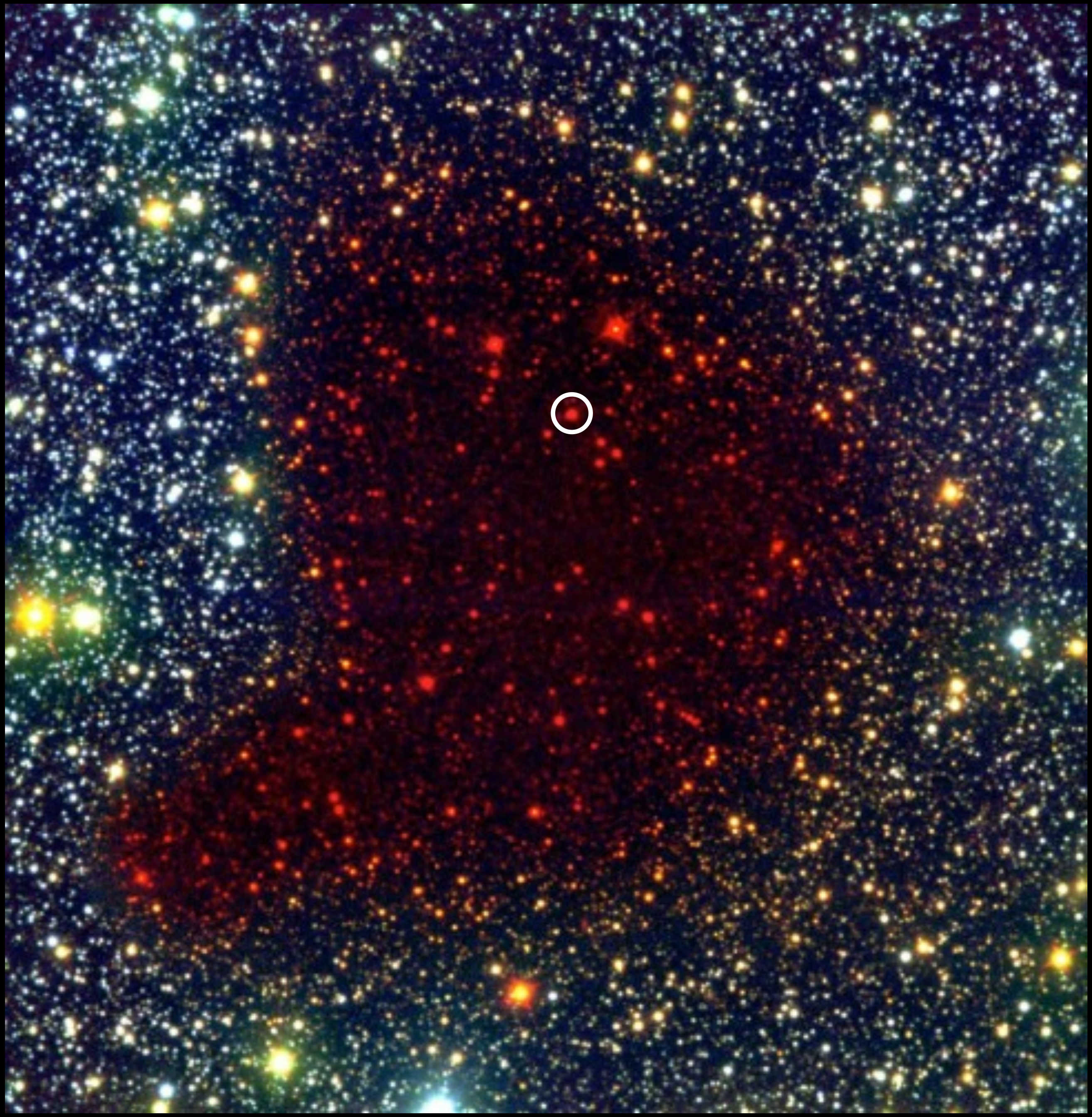
$$E(H - K) = (H - K)_{obs} - (H - K)_{intr}$$

$$E(H - K) \approx (H - K)_{obs} - \langle H - K \rangle$$

Alves et al. (2000)

NICE(R)

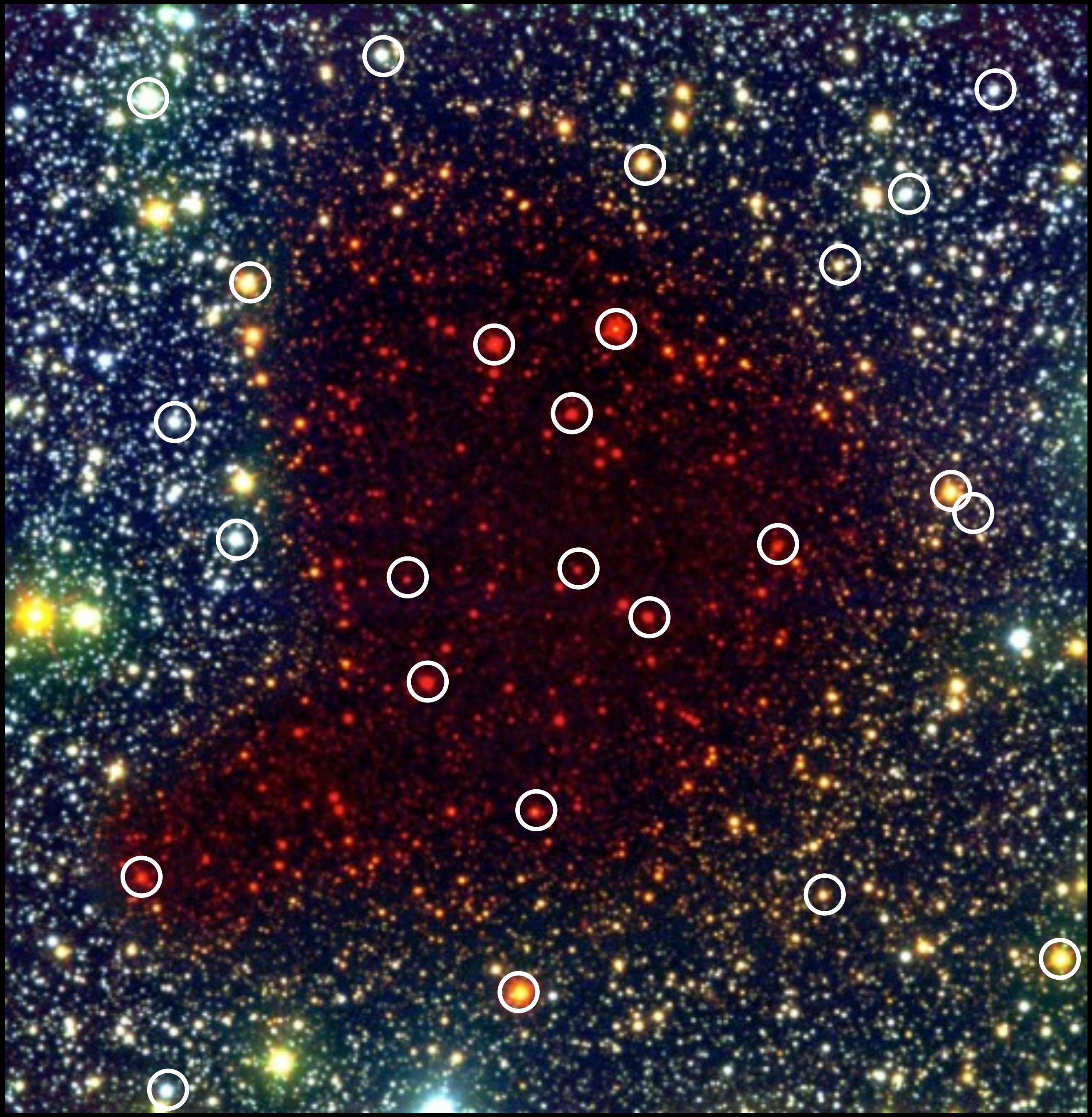
VLT (BVI)



VLT + NTT (BIK)

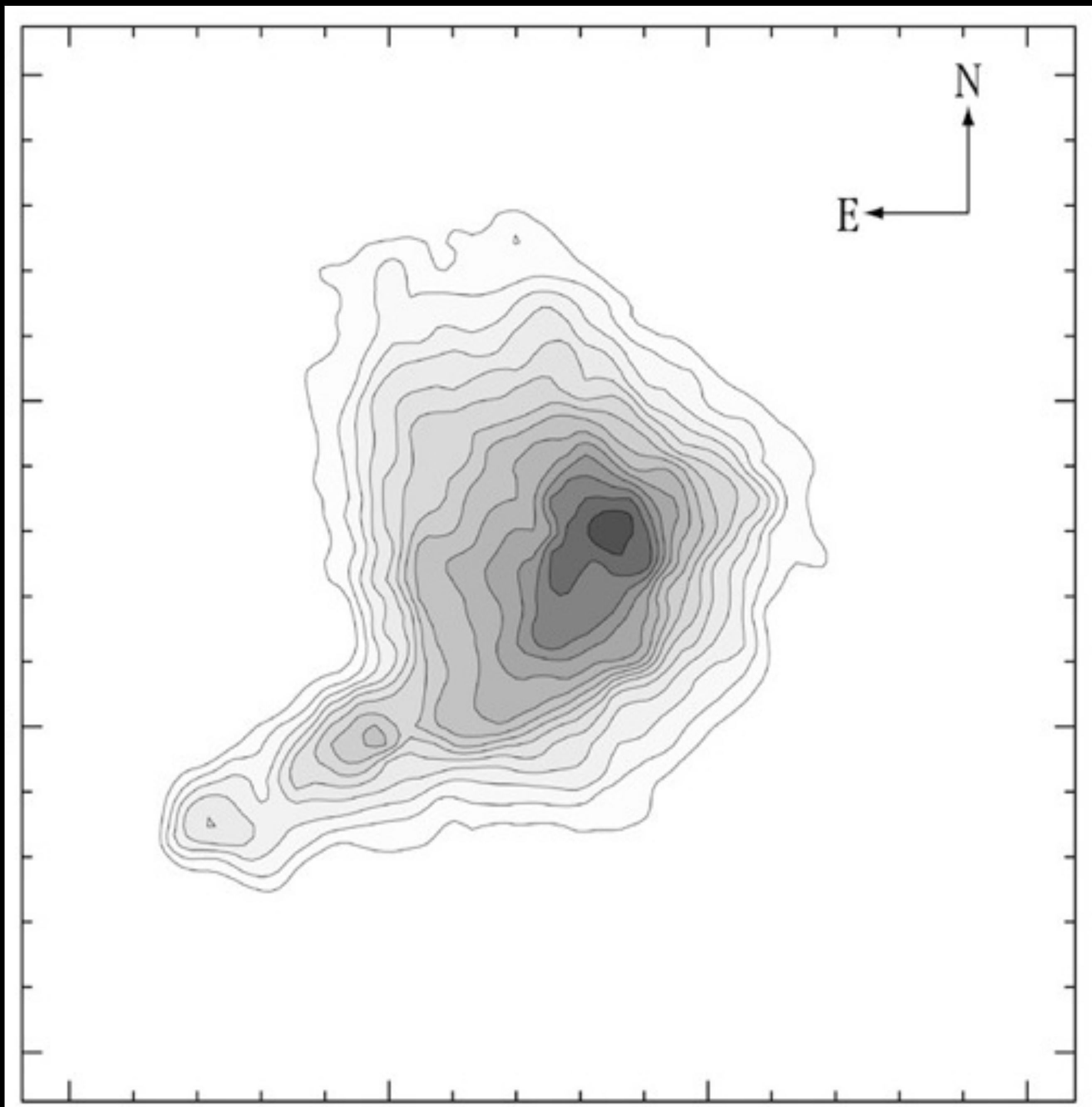
Alves et al. (2000)

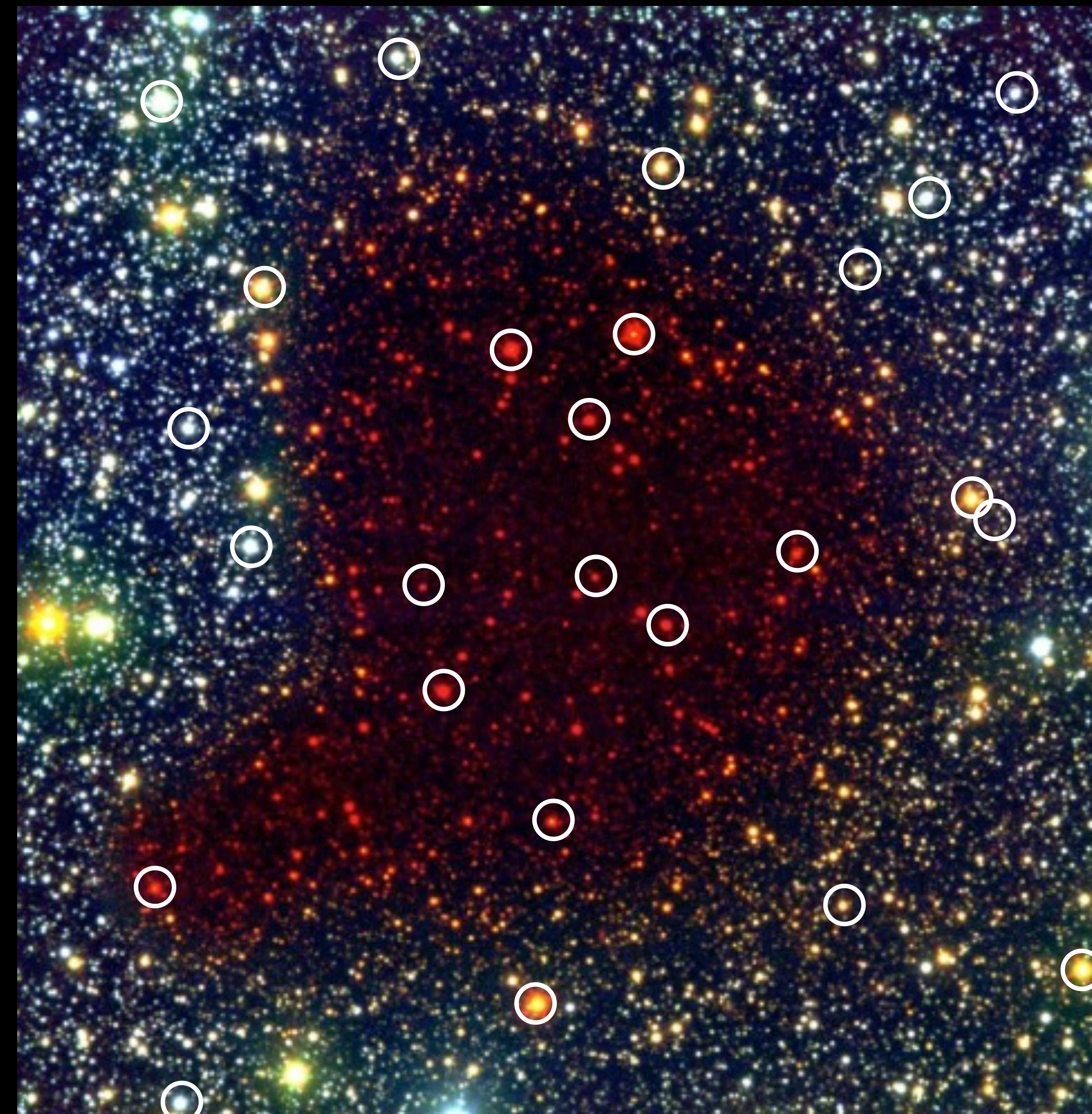
NICE(R)



Alves et al. (2000)

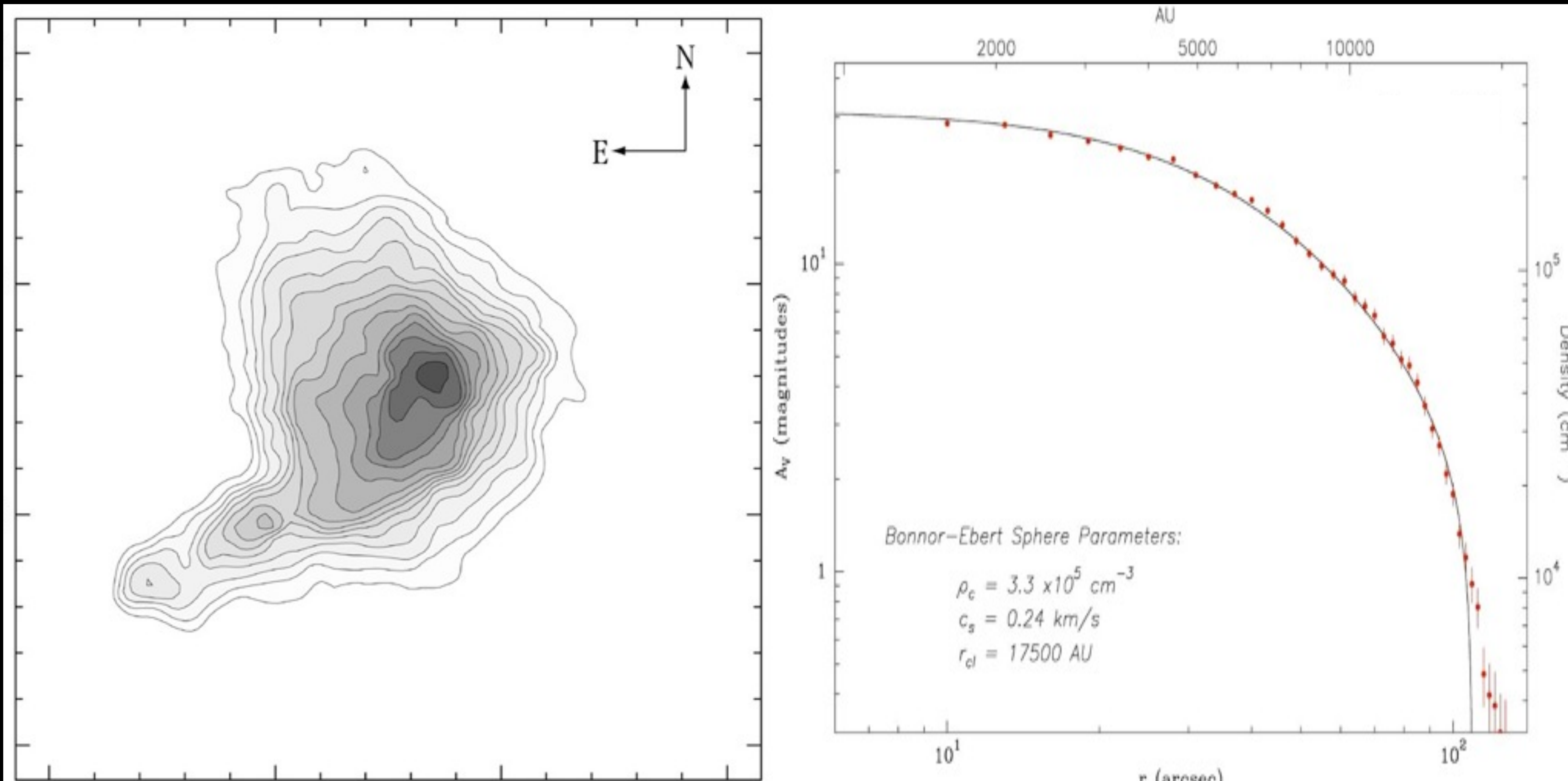
NICE(R)





Alves et al. (2000)

NICE(R)



Alves et al. (2000)

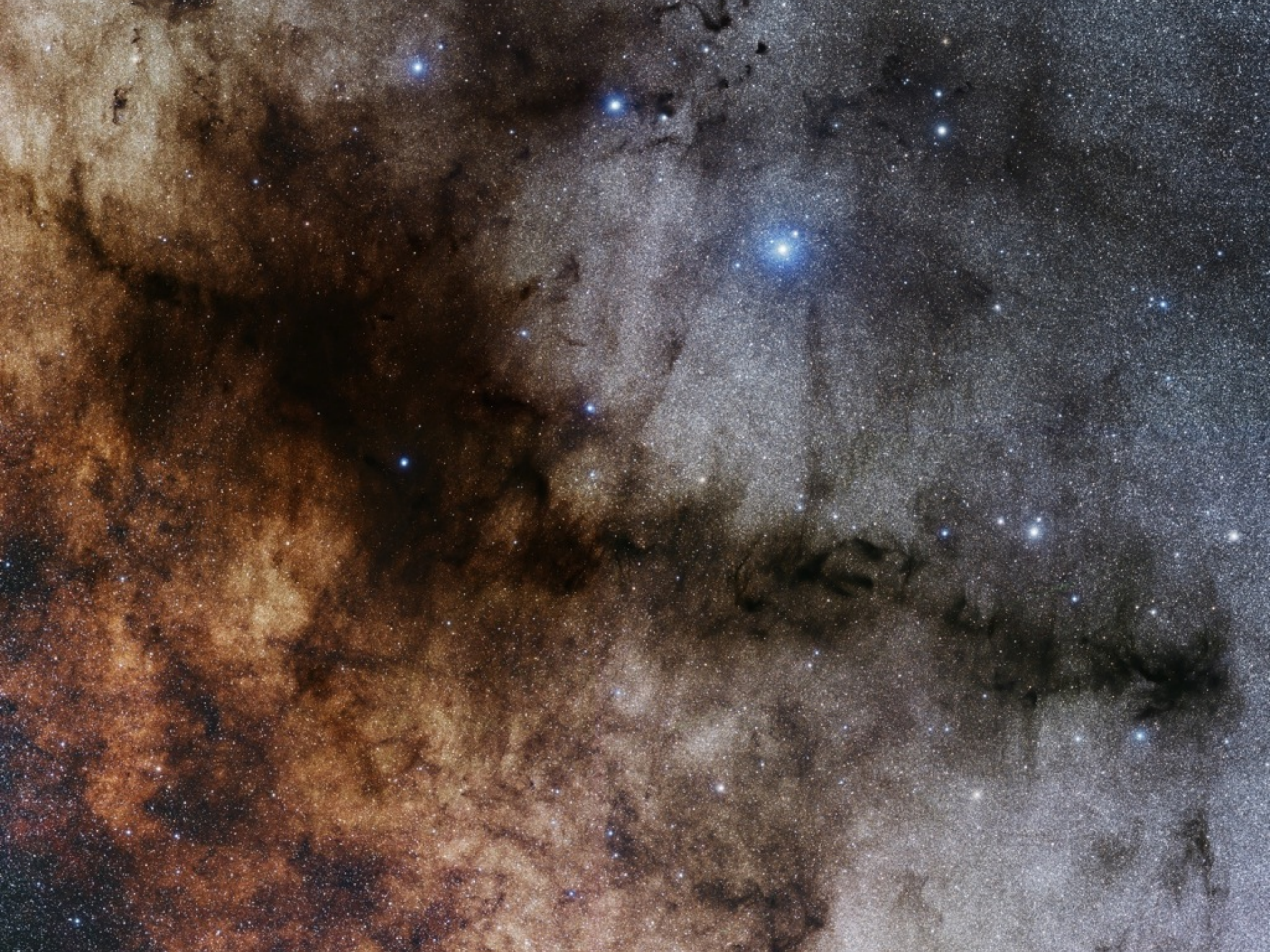
Barnard 68

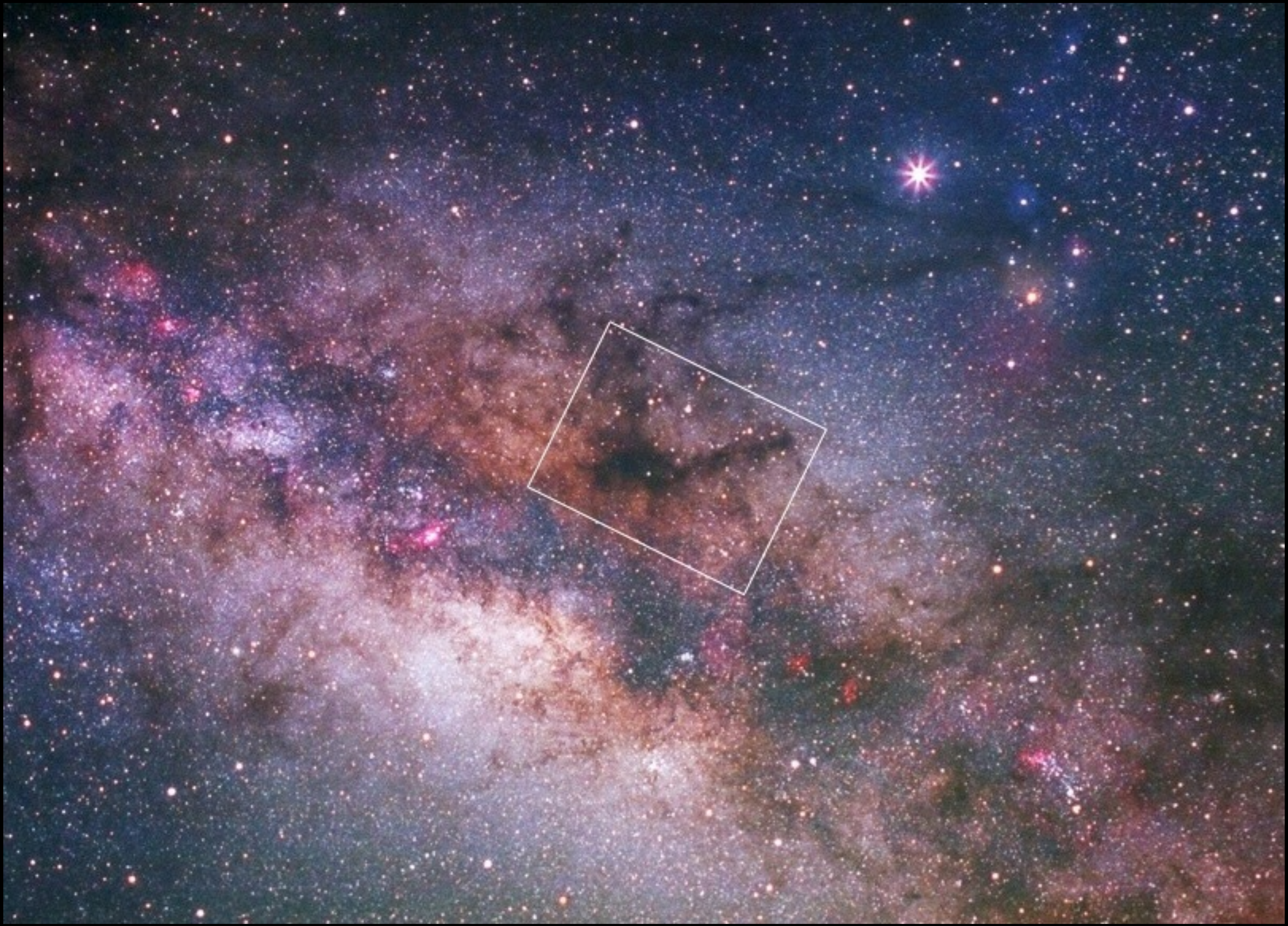
Alves et al. (2000)

Barnard 68

Alves et al. (2000)

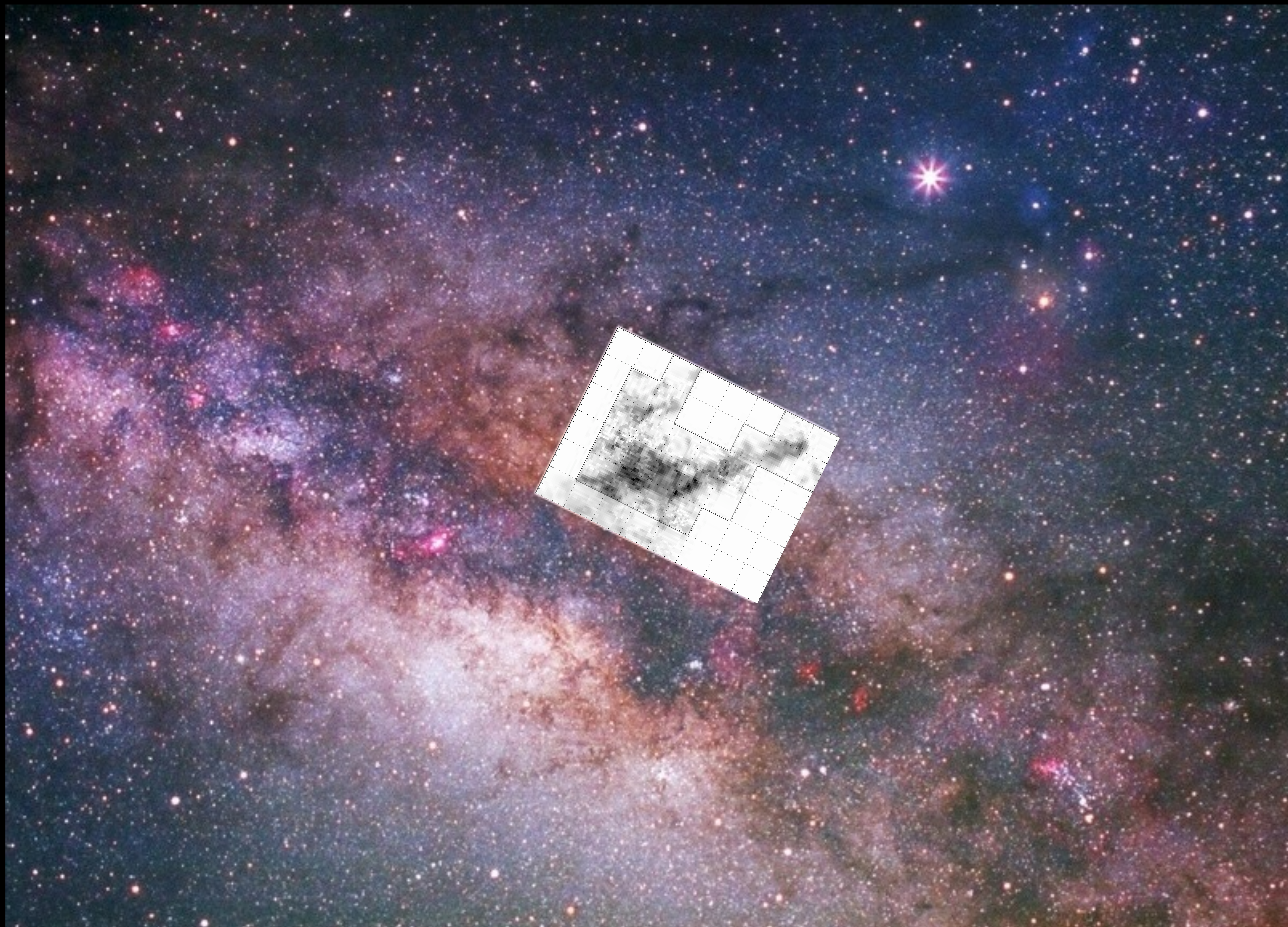

Ceci n'est pas une pipe.





The Pipe Nebula

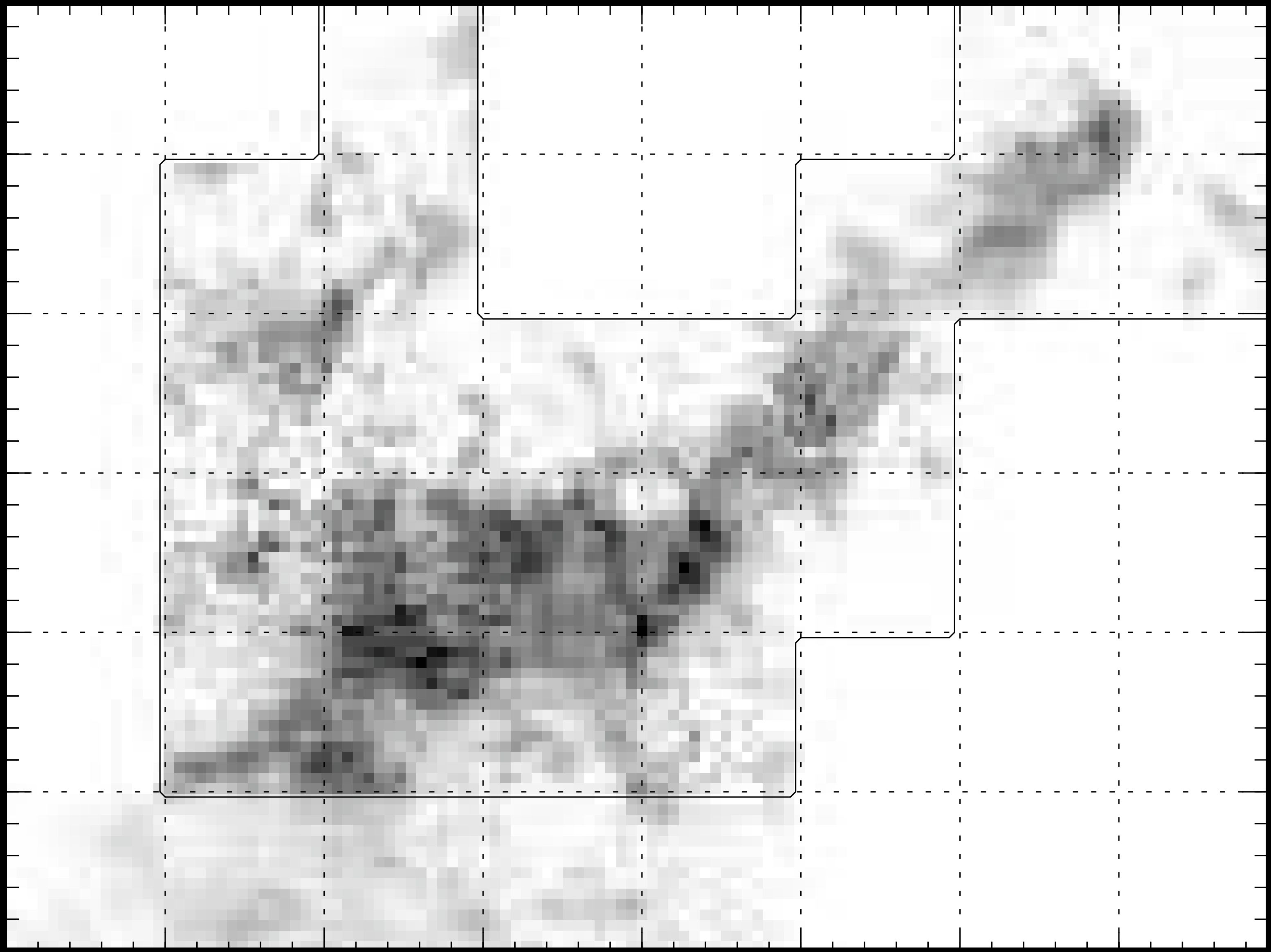
Lombardi et al. (2006)



The Pipe Nebula

Lombardi et al. (2006)

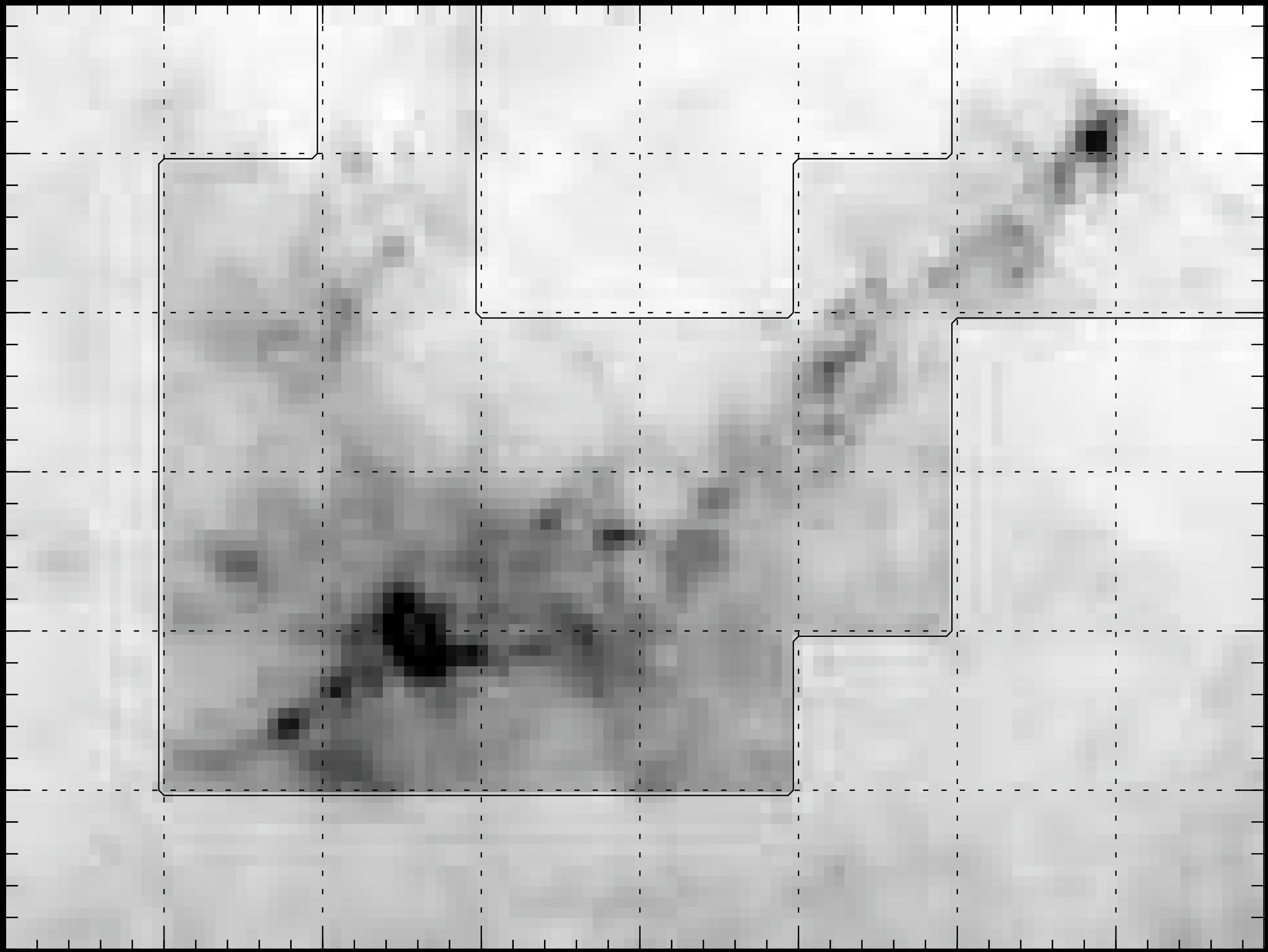
CO vs. dust



^{12}CO: Onishi et al. (1999), M=6500 $M_\odot$

Lombardi et al. (2006)

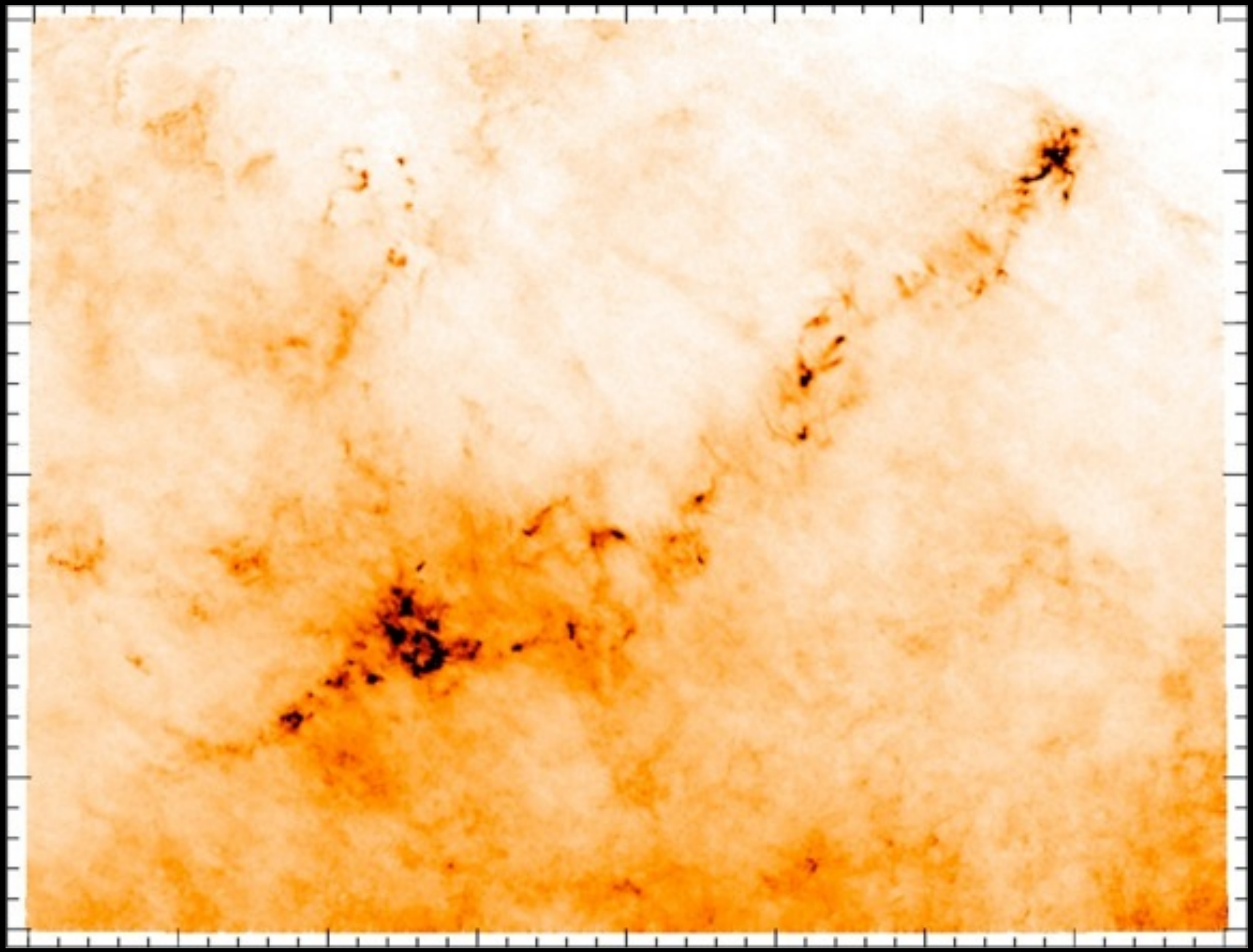
CO vs. dust



NICER: Lombardi et al. (2006), M=11000 $M_\odot$

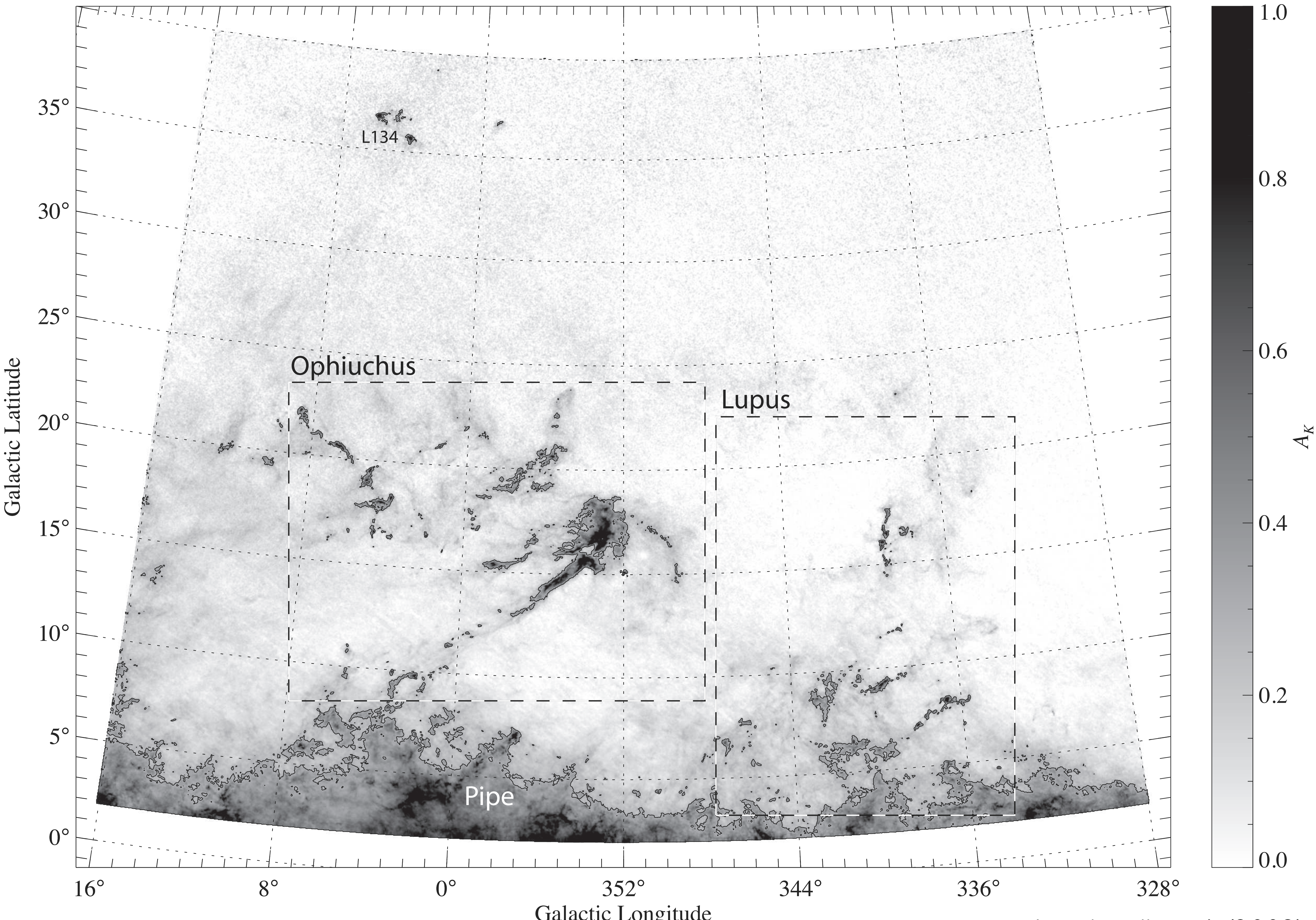
Lombardi et al. (2006)

CO vs. dust



NICER: full resolution (1 arcmin)

Lombardi et al. (2006)



Lombardi et al. (2009)

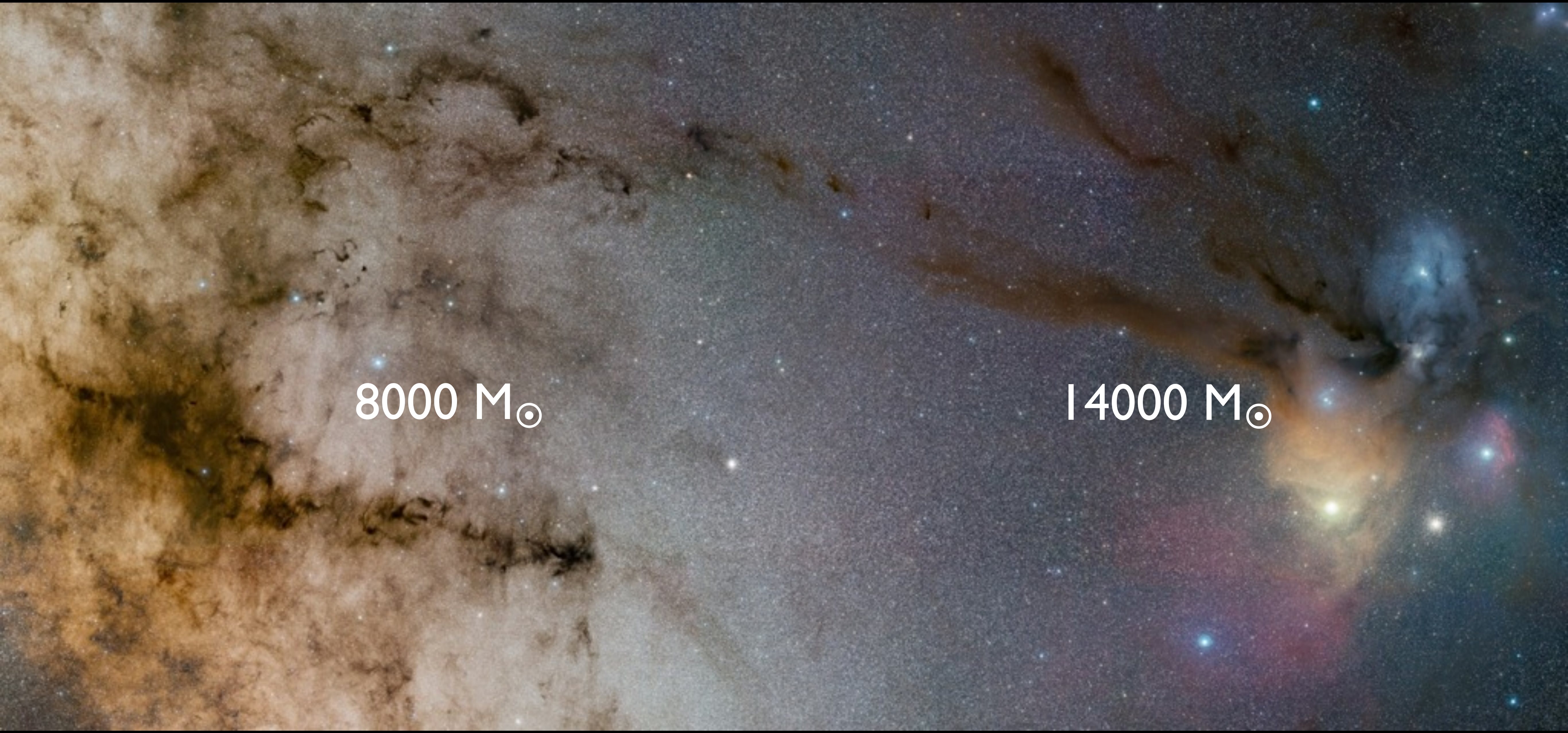
Fact 3
Different molecular clouds have different SFRs

Pipe nebula

ρ Ophiuchi cloud

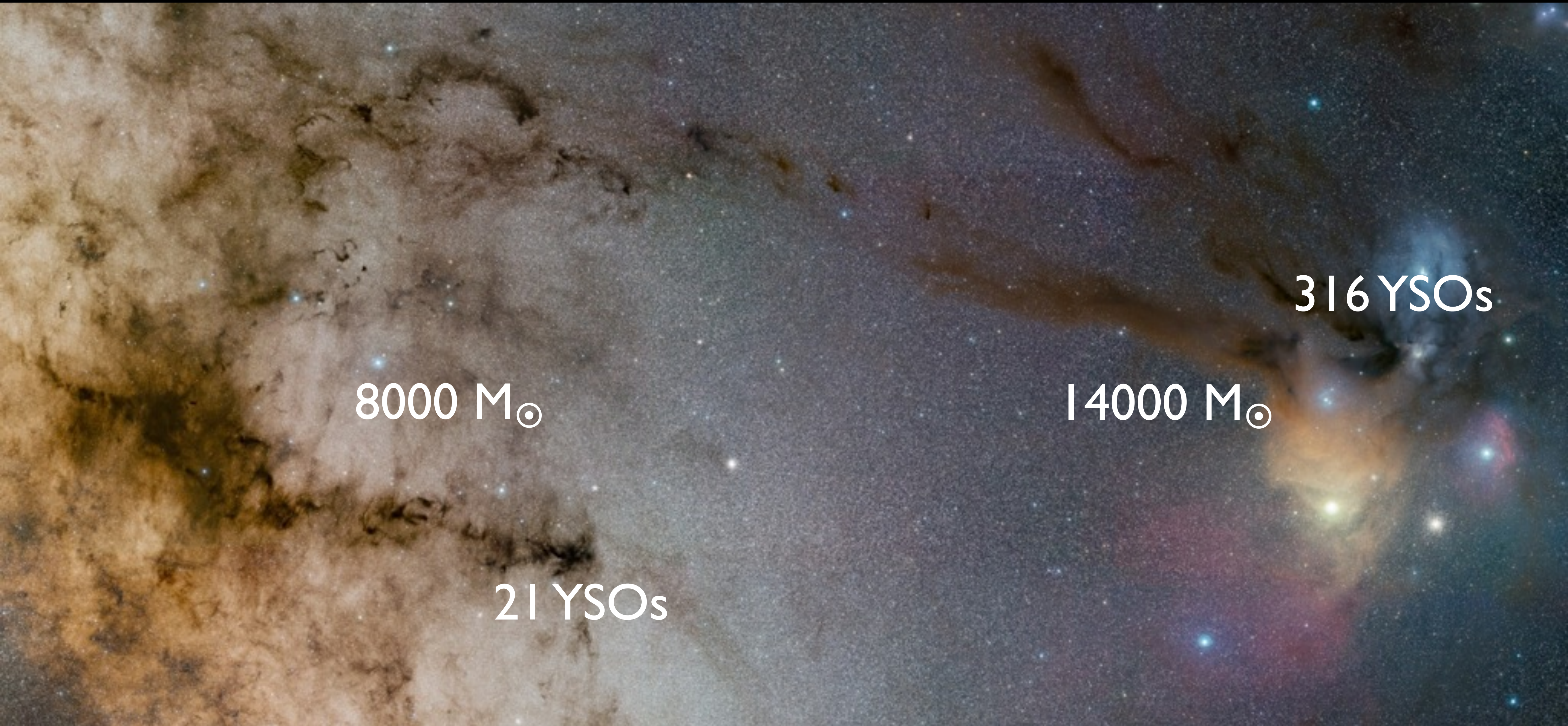
$\Sigma_{Pipe} = 50\ M_\odot\ pc^{-2}$

$\Sigma_{Oph} = 40\ M_\odot\ pc^{-2}$



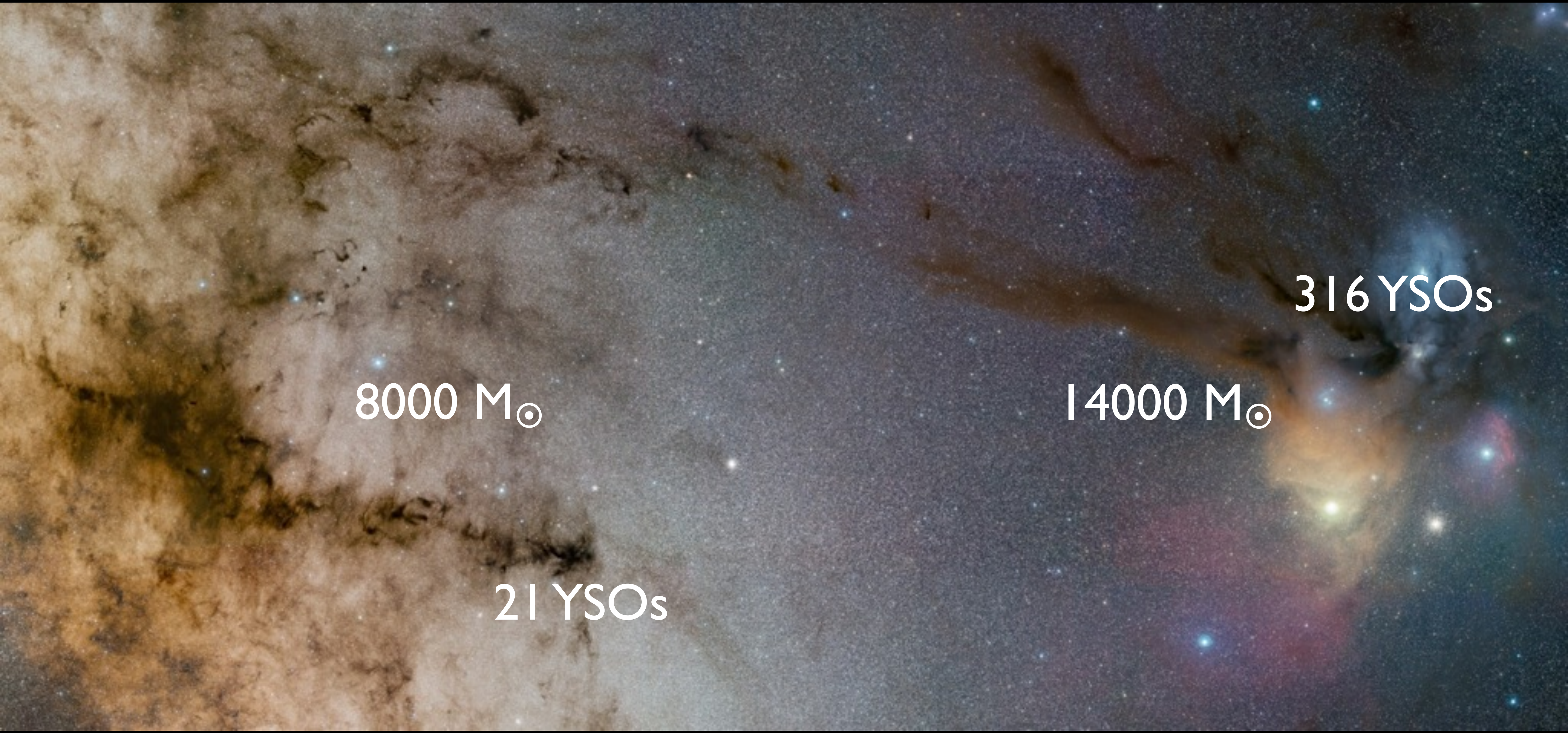
$\Sigma_{Pipe} = 50\ M_{\odot}\ pc^{-2}$

$\Sigma_{Oph} = 40\ M_{\odot}\ pc^{-2}$



$\Sigma_{Pipe} = 50\ M_\odot\ pc^{-2}$

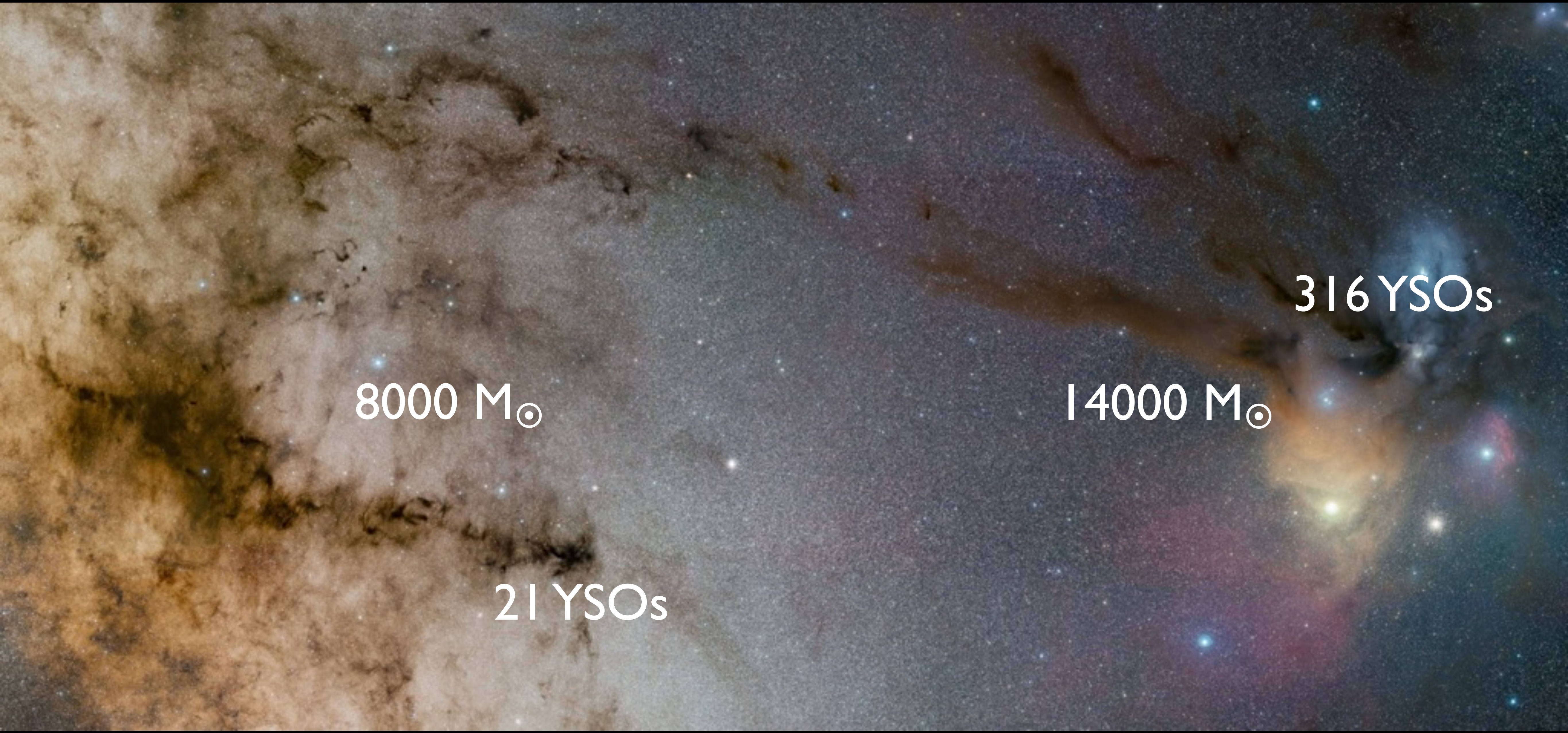
$\Sigma_{Oph} = 40\ M_\odot\ pc^{-2}$



$$SFR_{Oph} = 15 \times SFR_{Pipe}$$

$\Sigma_{Pipe} = 50\ M_\odot\ pc^{-2}$

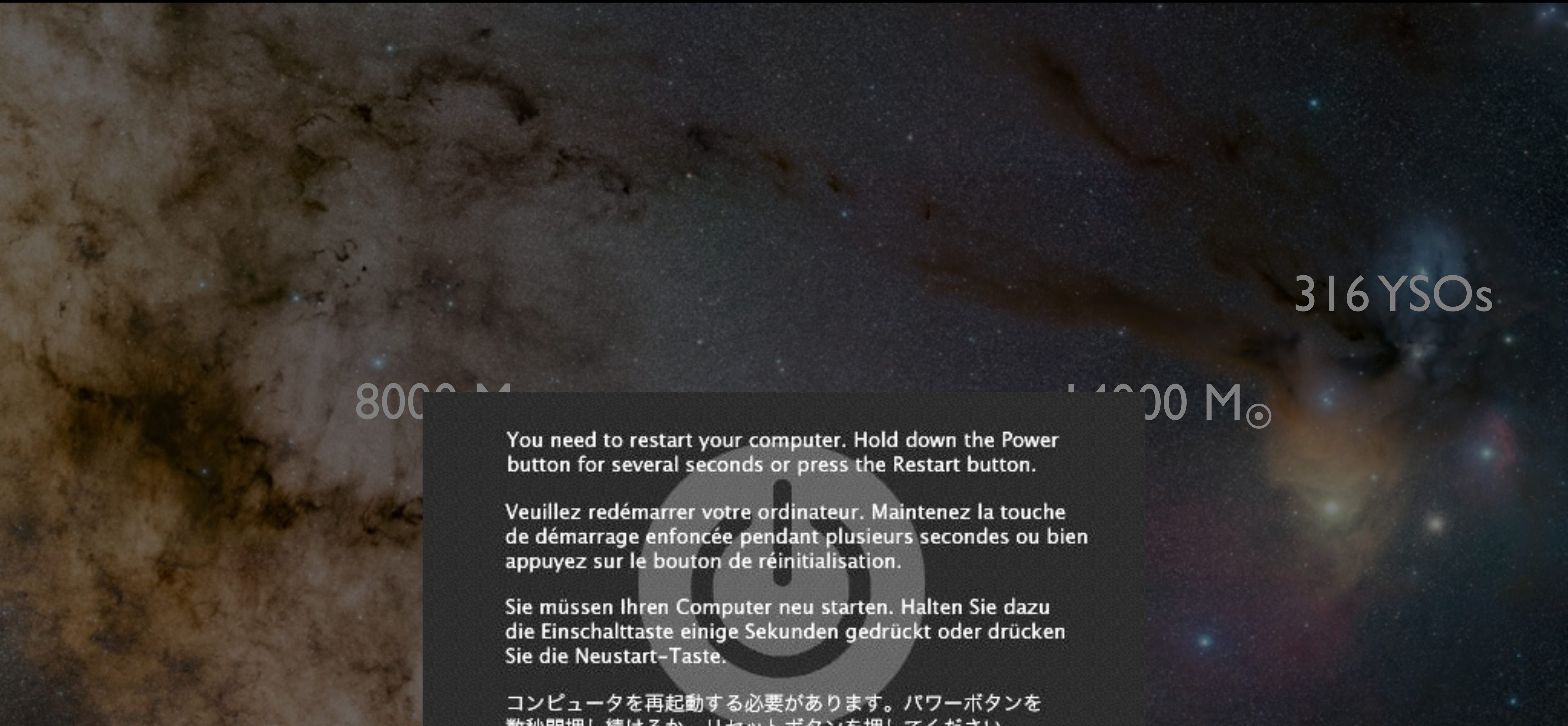
$\Sigma_{Oph} = 40\ M_\odot\ pc^{-2}$



$$\mathrm{SFR}_{\mathrm{Oph}} = 15 \times \mathrm{SFR}_{\mathrm{Pipe}}$$

$\Sigma_{\mathrm{Pipe}} = 50\ M_\odot\ \mathrm{pc}^{-2}$

$\Sigma_{\mathrm{Oph}} = 40\ M_\odot\ \mathrm{pc}^{-2}$



You need to restart your computer. Hold down the Power button for several seconds or press the Restart button.

Veuillez redémarrer votre ordinateur. Maintenez la touche de démarrage enfoncée pendant plusieurs secondes ou bien appuyez sur le bouton de réinitialisation.

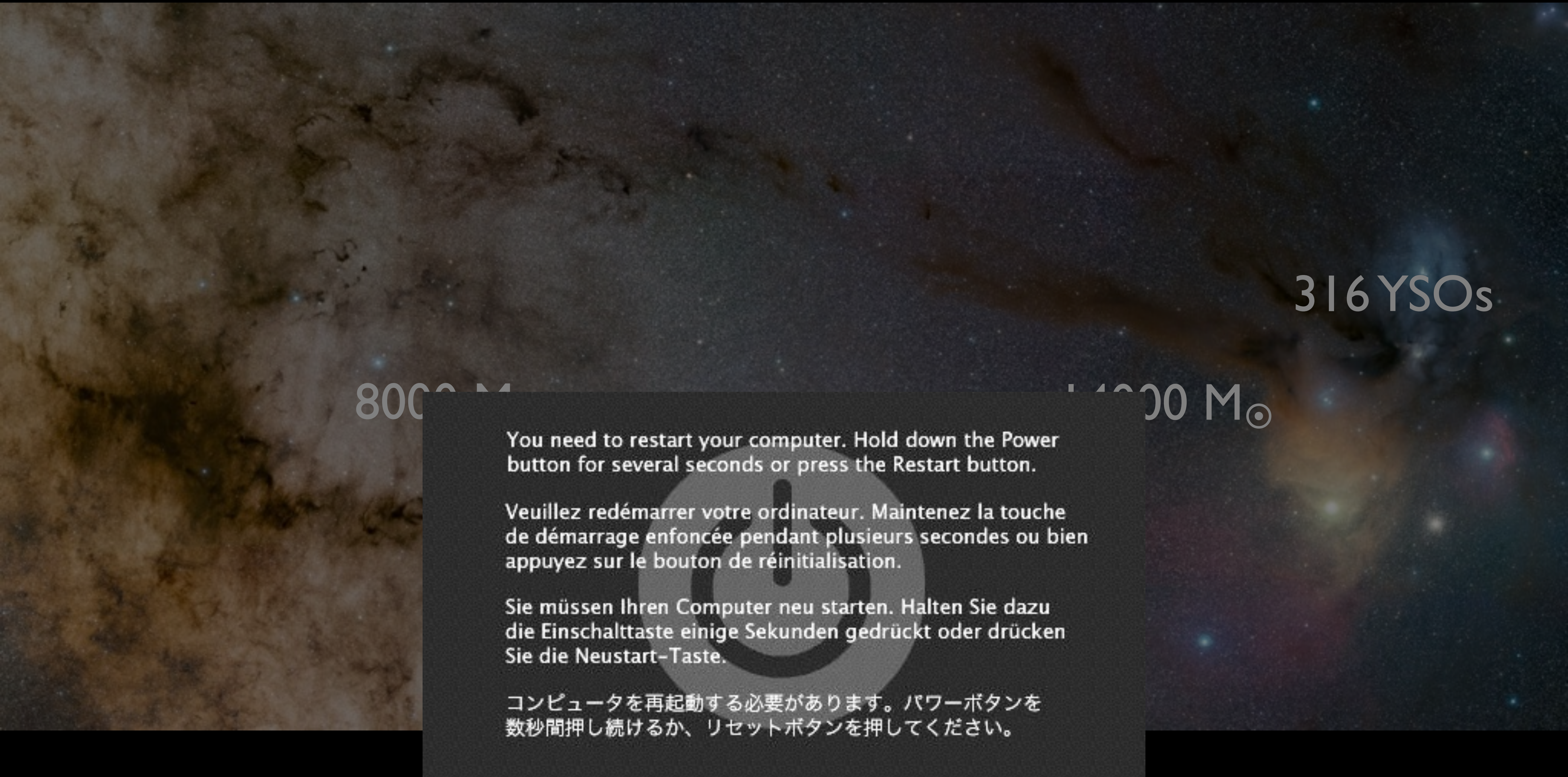
Sie müssen Ihren Computer neu starten. Halten Sie dazu die Einschalttaste einige Sekunden gedrückt oder drücken Sie die Neustart-Taste.

コンピュータを再起動する必要があります。パワーボタンを数秒間押し続けるか、リセットボタンを押してください。

$$SFR_{Oph} = 15 \times SFR_{Pipe}$$

$\Sigma_{Pipe} = 50\ M_\odot\ pc^{-2}$

$\Sigma_{Oph} = 40\ M_\odot\ pc^{-2}$



$$SFR_{Oph} = 15 \times SFR_{Pipe}$$

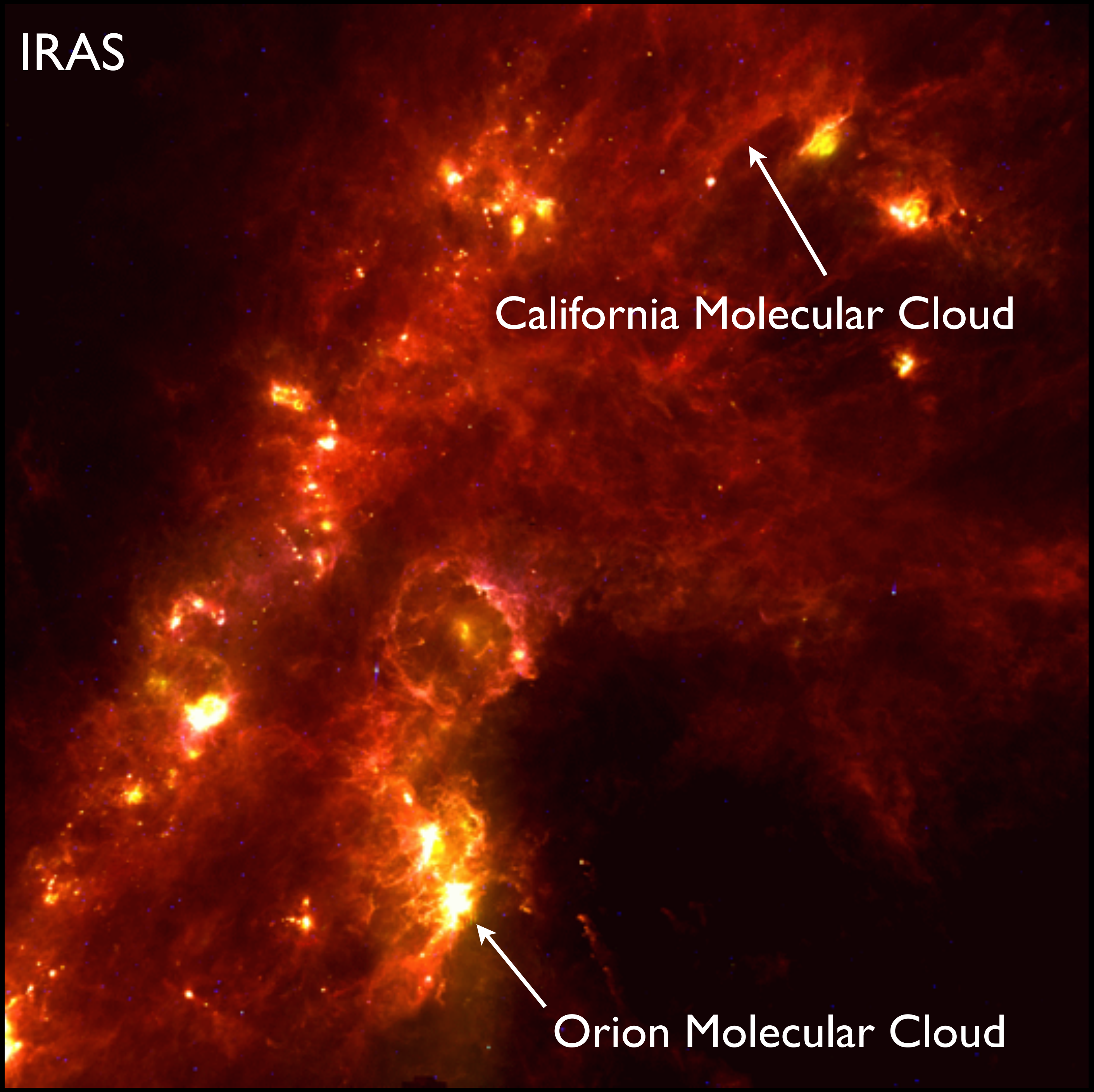
Ceci n'est pas une exception.

$\Sigma_{Pipe} = 50\ M_{\odot}\ pc^{-2}$

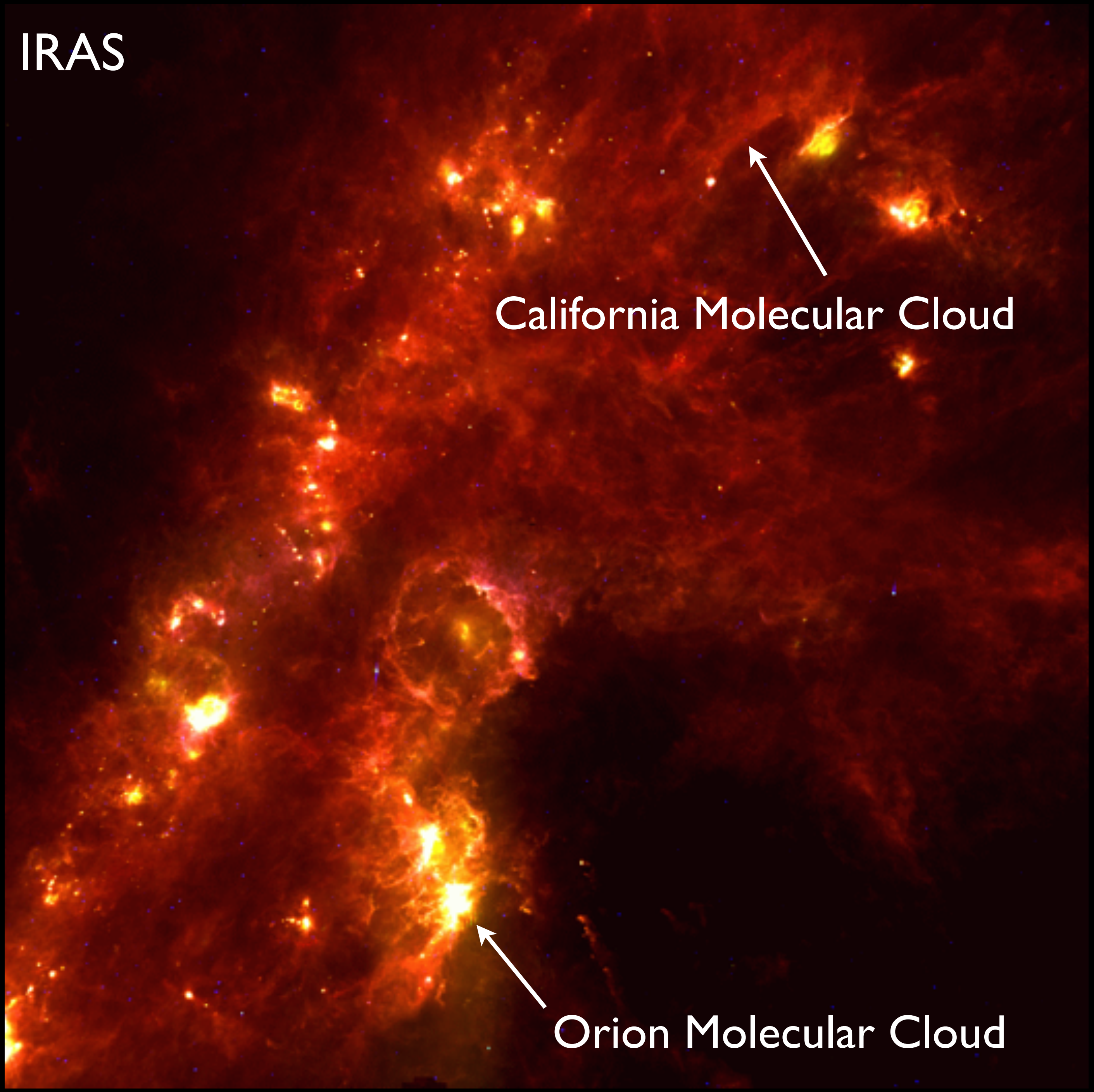
$\Sigma_{Oph} = 40\ M_{\odot}\ pc^{-2}$

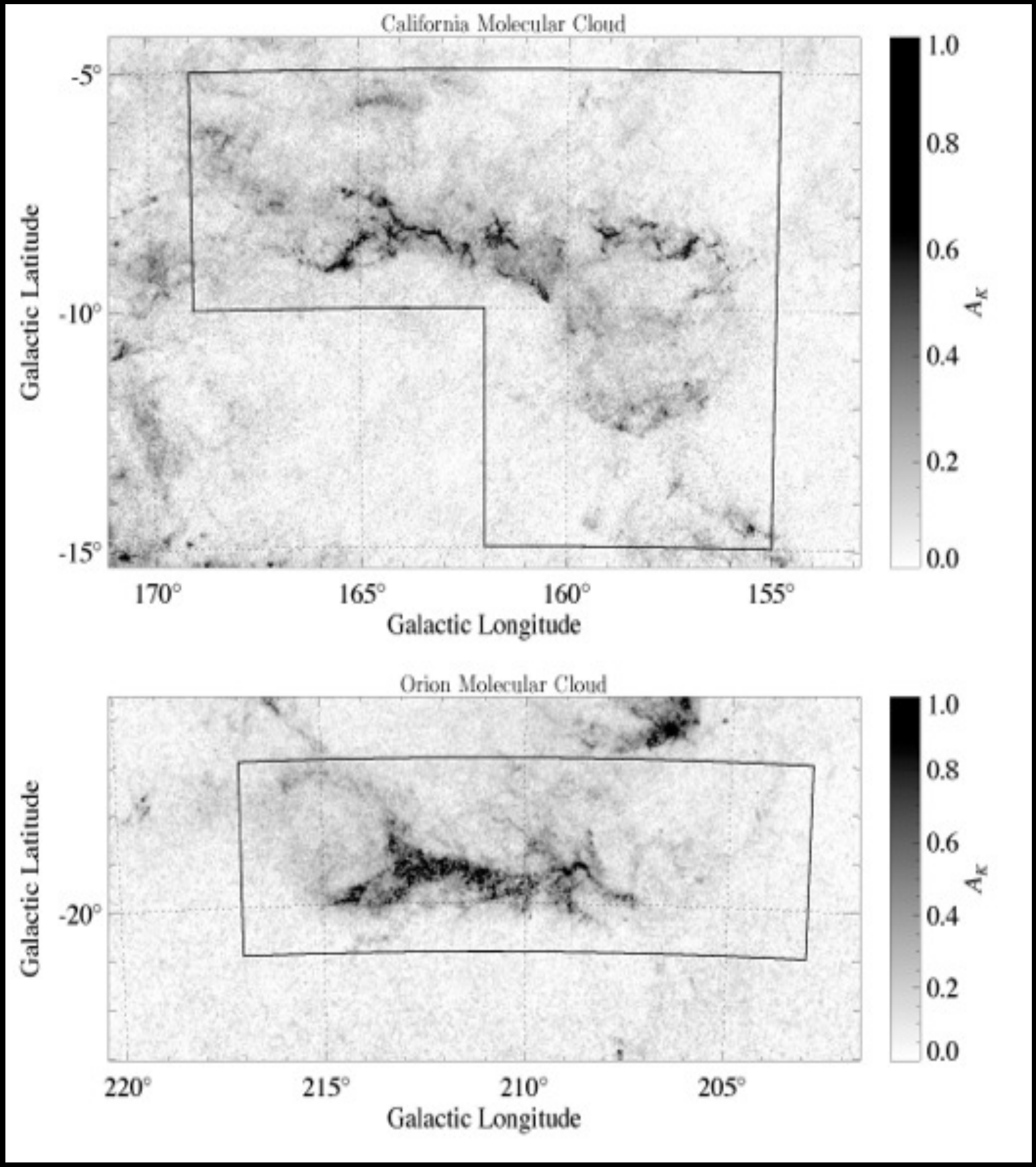
Ceci n'est pas une exception.

Ceci n'est pas une exception.

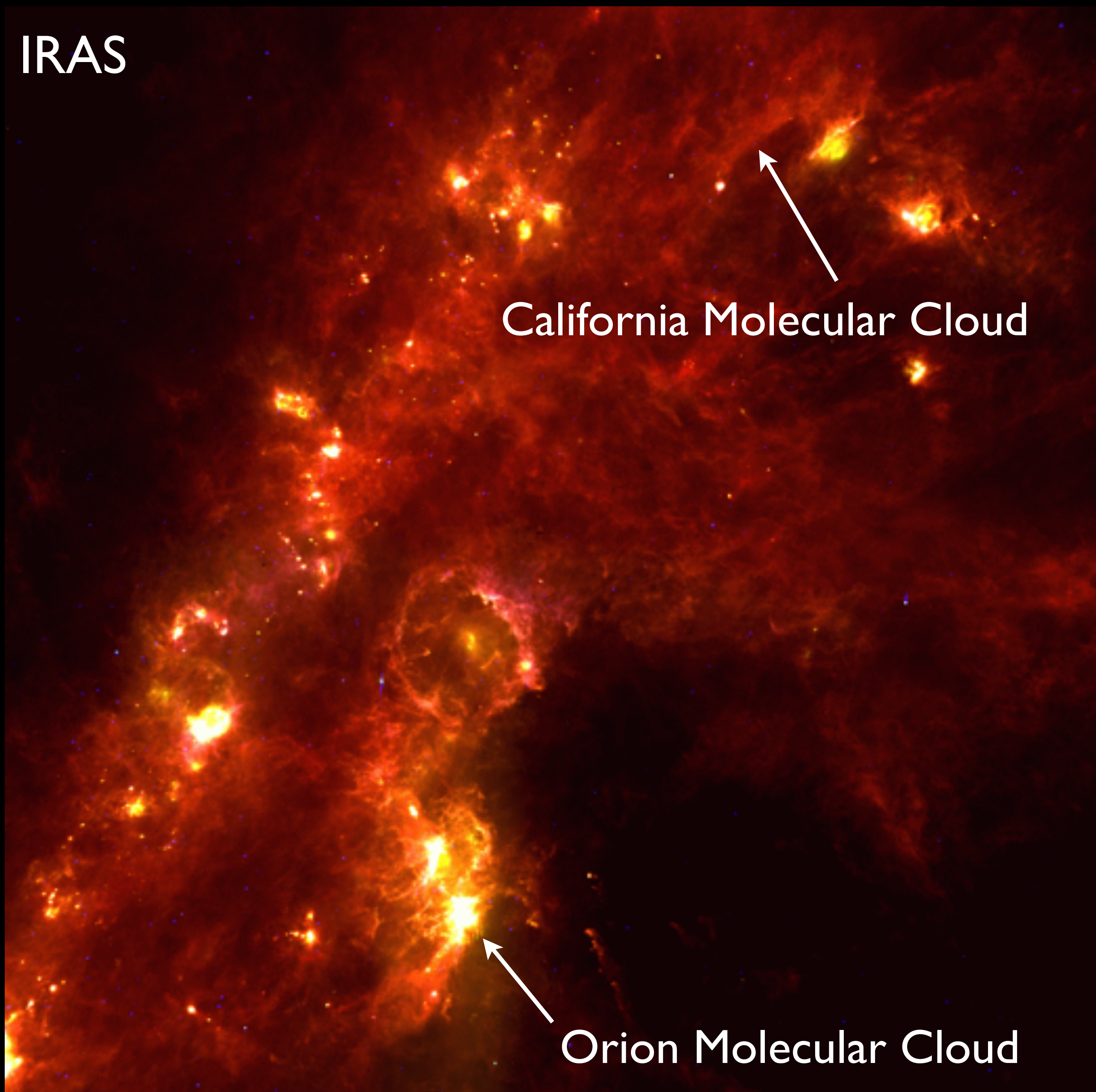


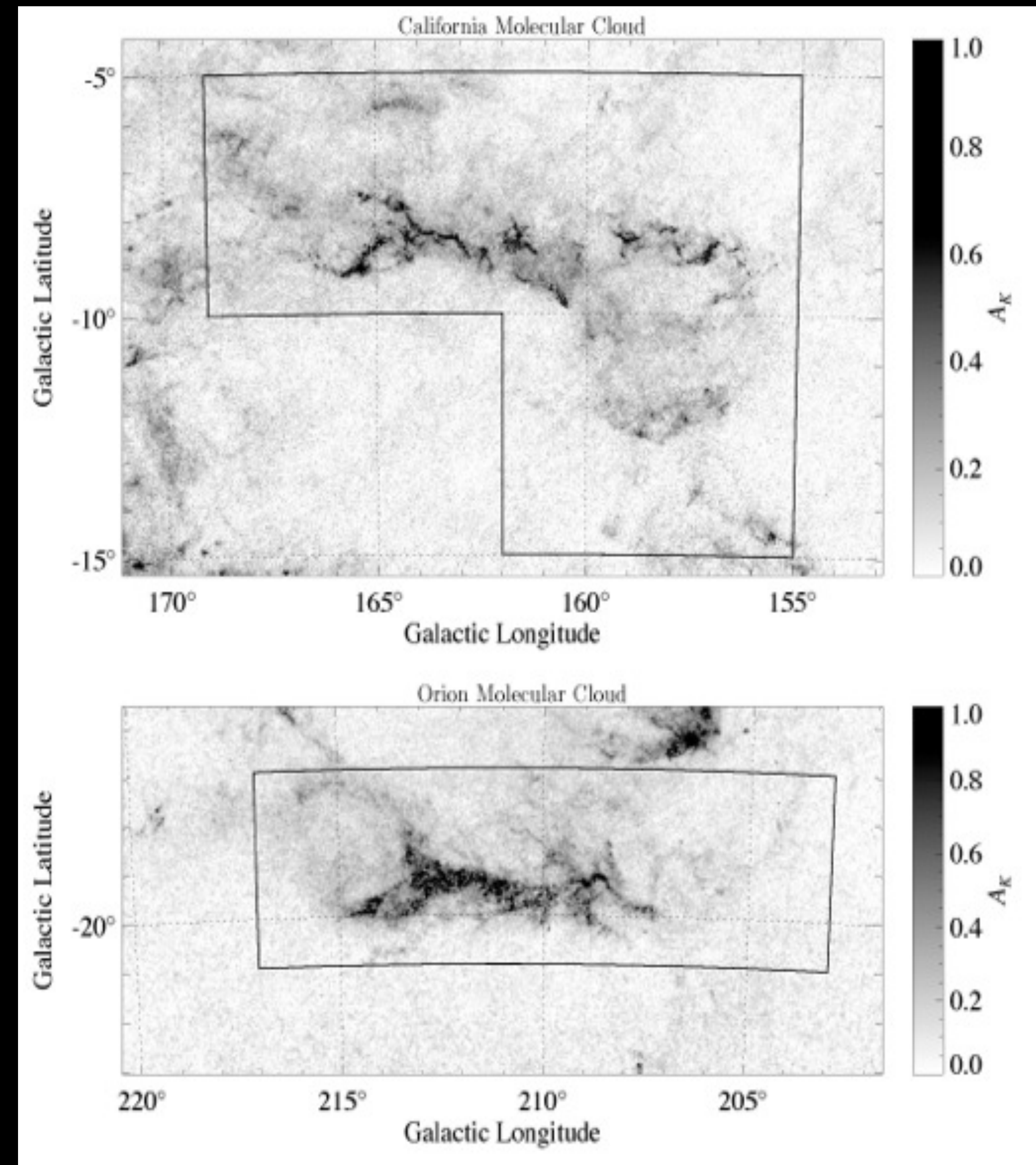
Ceci n'est pas une exception.





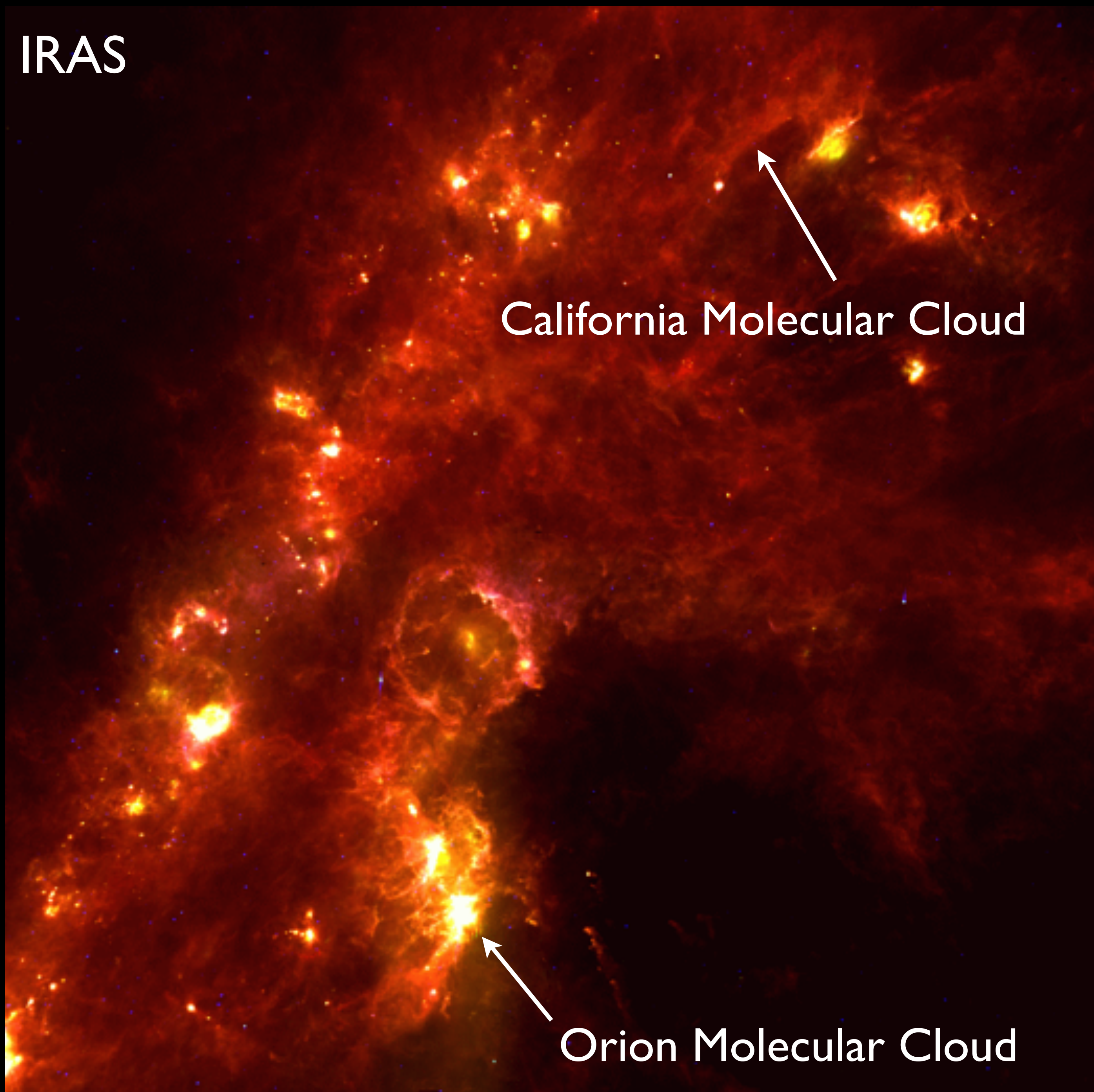
Ceci n'est pas une exception.

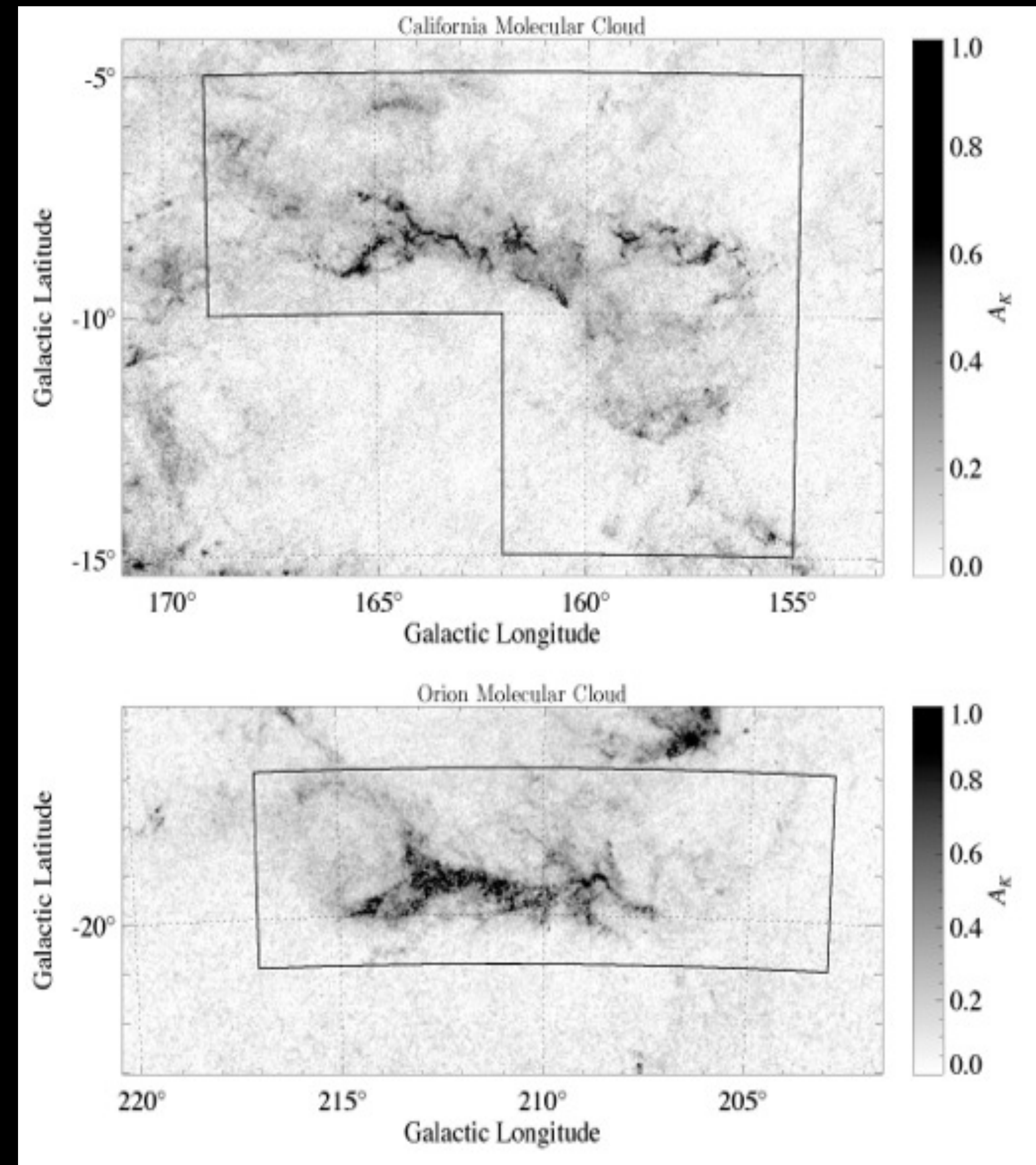




$SFR_{Orion} = 10 \times SFR_{California}$

Ceci n'est pas une exception.



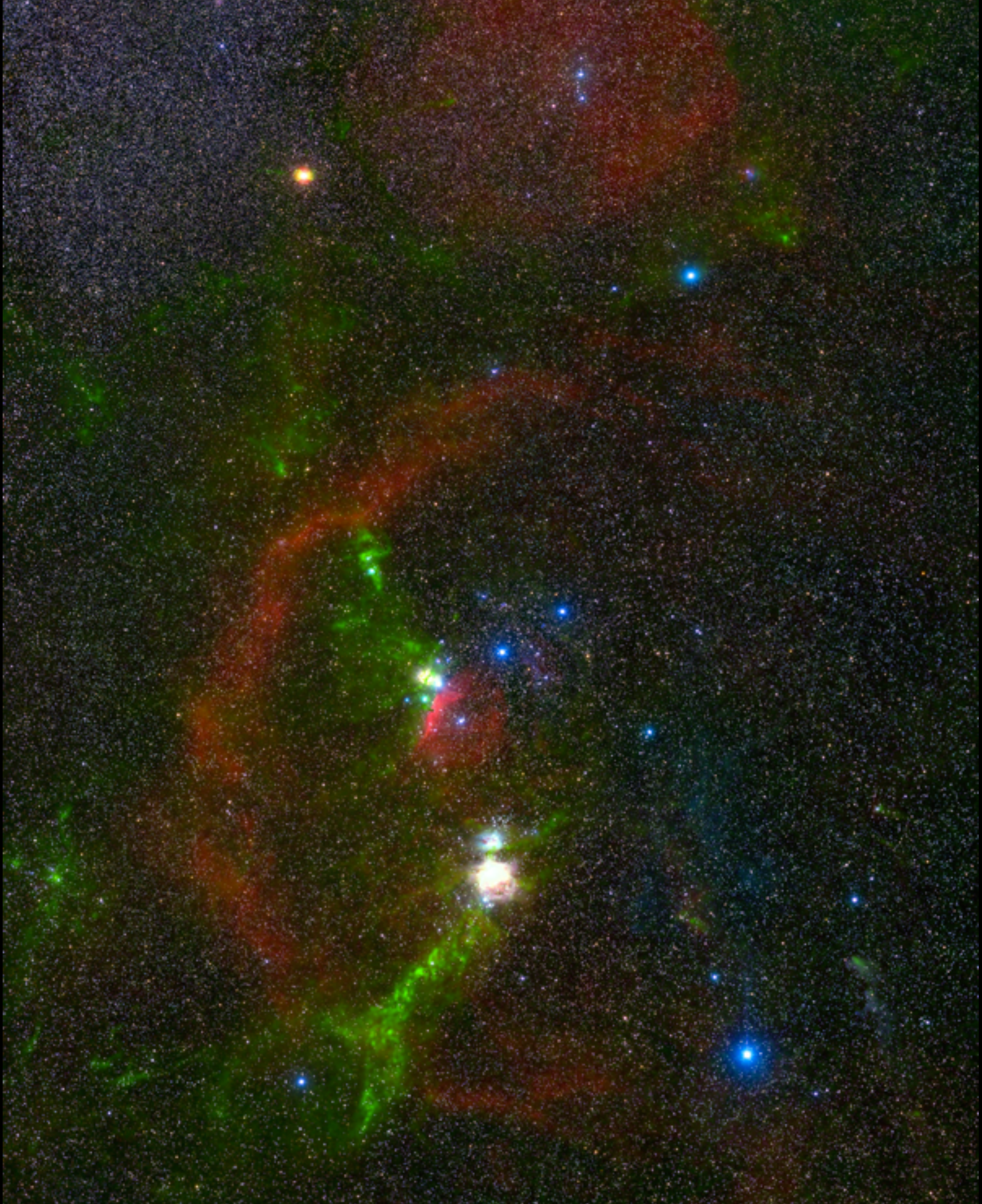


$SFR_{Orion} = 10 \times SFR_{California}$ Clouds identical in mass & size

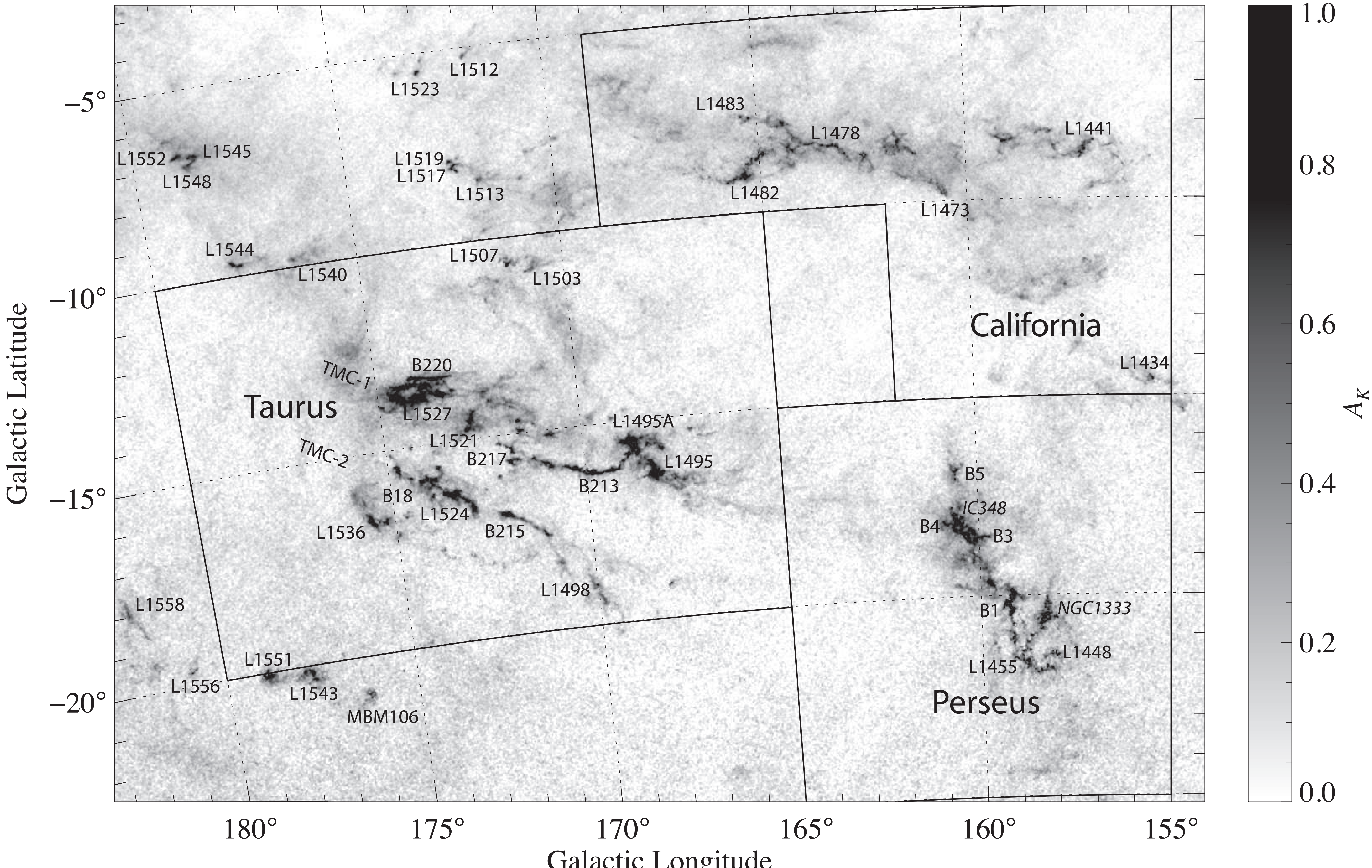
Inventory of Local Star Formation Activity

Infrared extinction and cloud masses

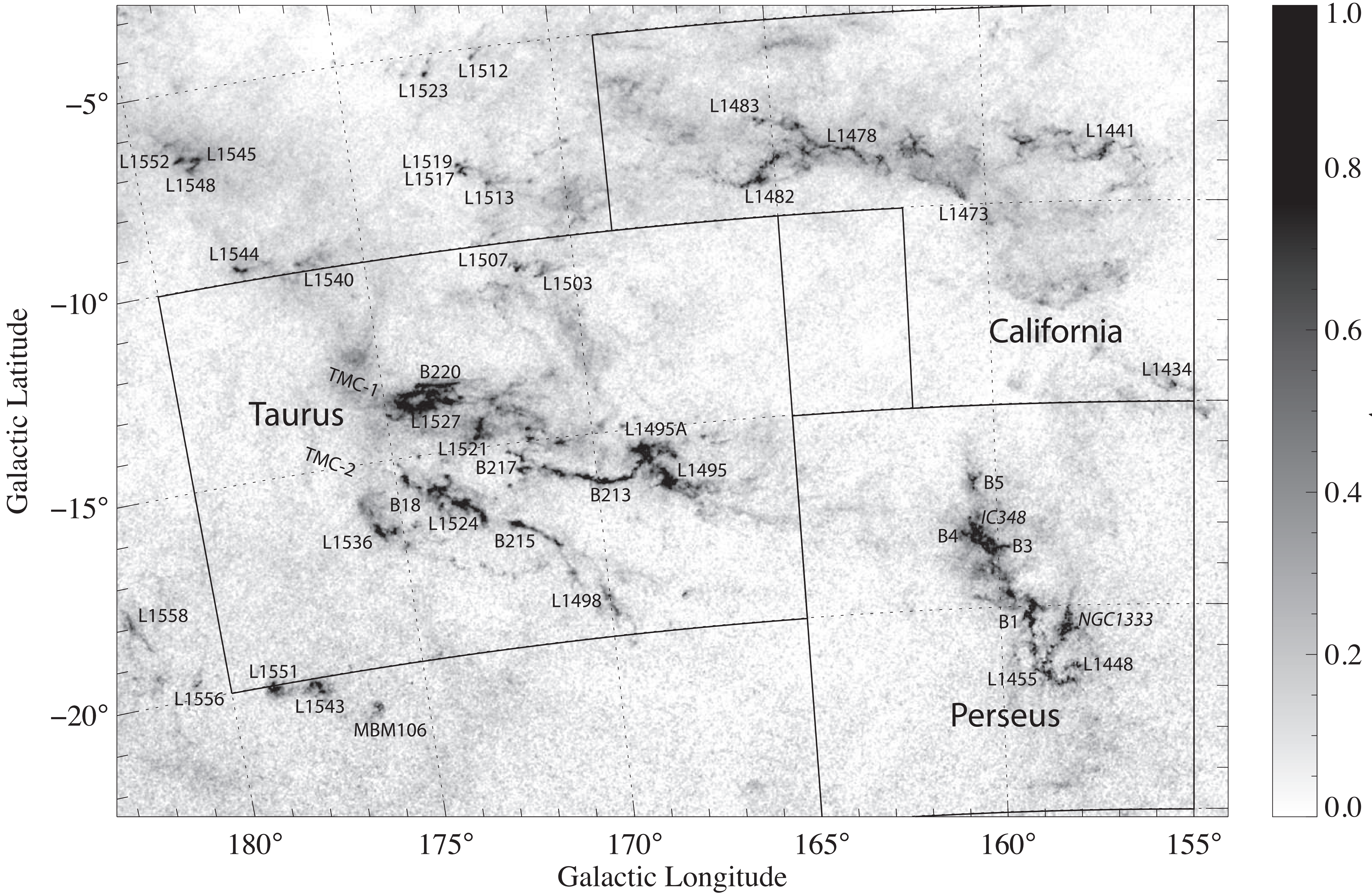
Lombardi et al. (2011)



Lombardi et al. (2011)



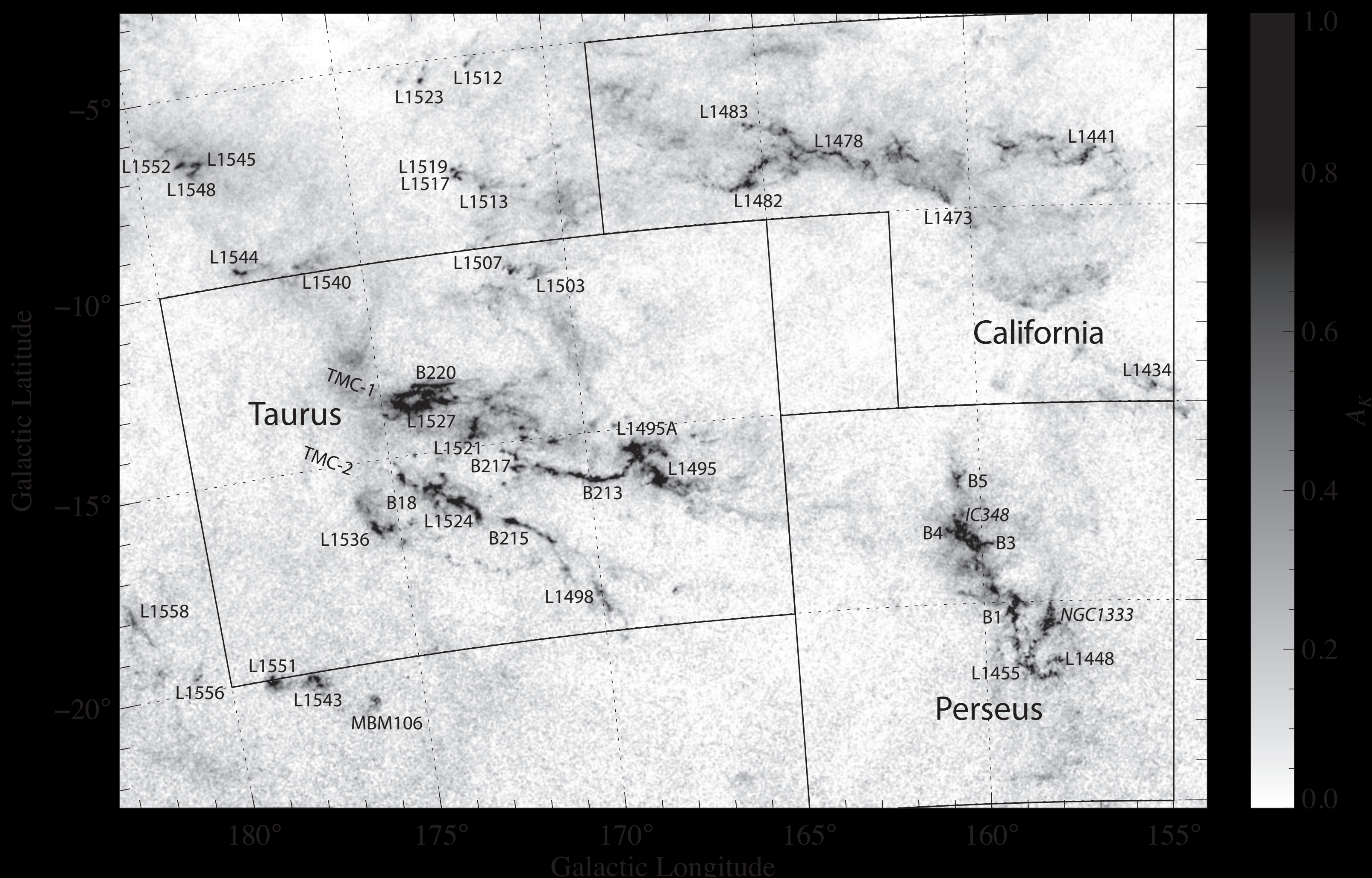
Lombardi et al. (2010)



L1512
L1523
L1483
L1478
L1441
L1552
L1545
L1548
L1519
L1517
L1513
L1482
L1473
L1544
L1540
L1507
L1503
California
L1434
B220
TMC-1
Taurus
L1527
L1495A
L1521
TMC-2
B217
L1495
B213
B5
IC348
B4
B3
B18
L1524
L1536
B215
L1498
L1558
B1
NGC1333
L1448
L1455
L1551
L1556
L1543
MBM106
Perseus
−5°
−10°
−15°
−20°
180°
175°
170°
165°
160°
155°
Galactic Latitude
Galactic Longitude
A_K
1.0
0.8
0.6
0.4
0.2
0.0

Inventory of Star Formation Activity: Molecular Clouds

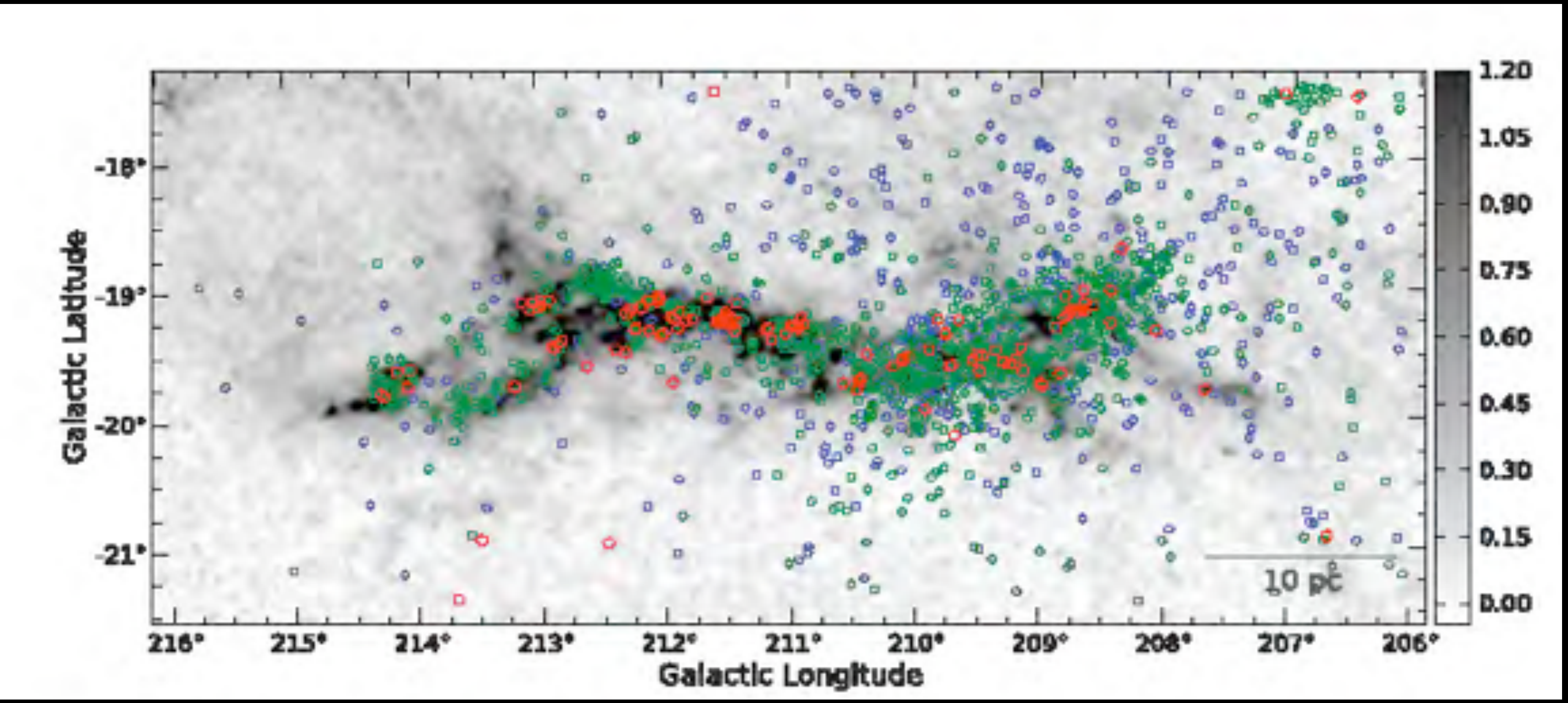
Cloud sample: wide field 2MASS/NICER extinction survey of 21 local modelcular clouds



Cloud	Mass (10
Orion A	6.77
Orion B	7.18
California	9.99
Perseus	1.84
Taurus	1.49
Ophiuchus	1.41
RCrA	0.11
Pipe	0.79
Lupus 1	0.22
Lupus 3	0.14
Lupus 4	0.08

Inventory of Star Formation Activity: Young Stellar Objects (YSOs)

Mining the literature: mostly IR data (SPITZER)

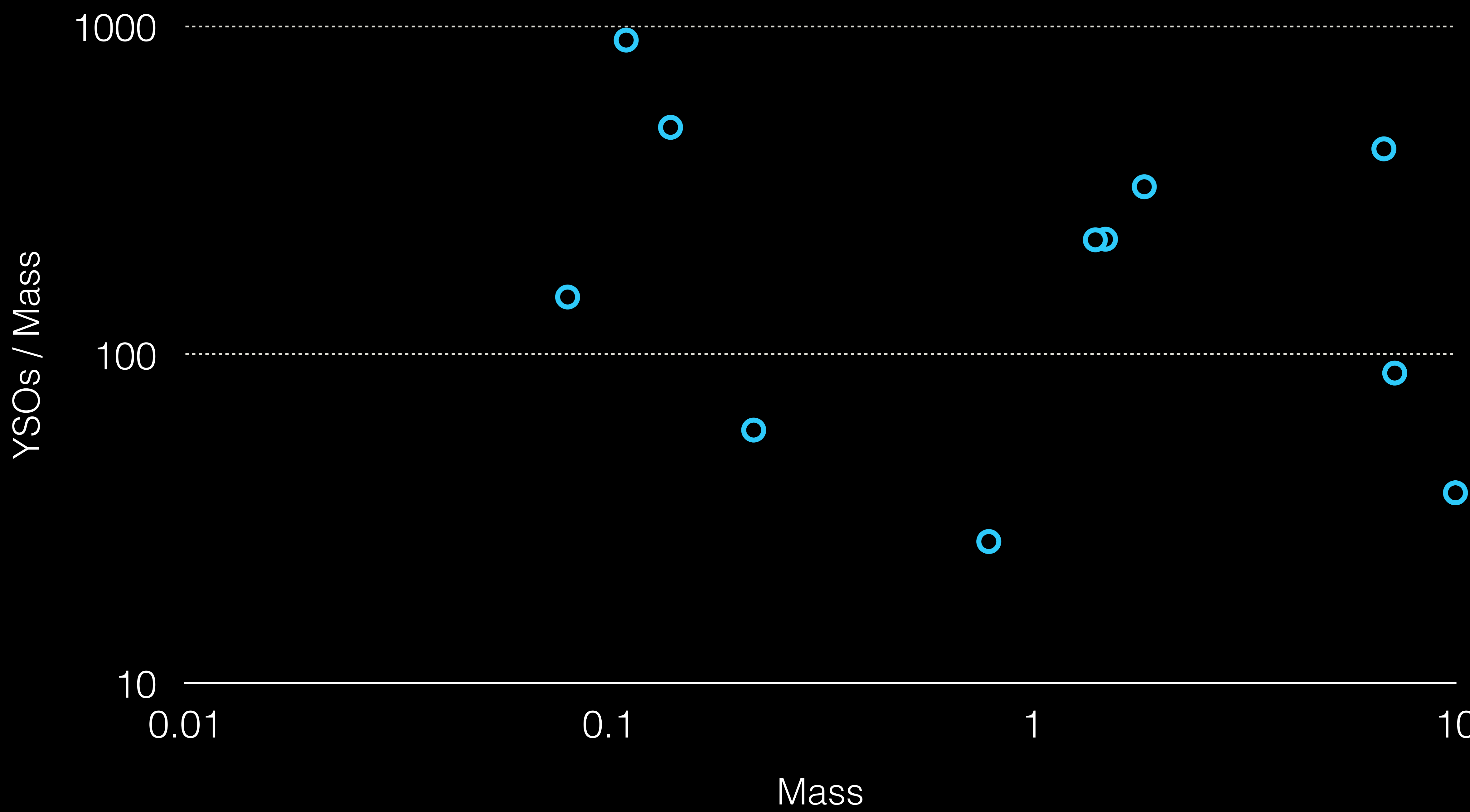


Cloud	YSOs
Orion A	2862
Orion B	635
California	279
Perseus	598
Taurus	335
Ophiuchus	316
RCrA	100
Pipe	21
Lupus 1	13
Lupus 3	69
Lupus 4	12

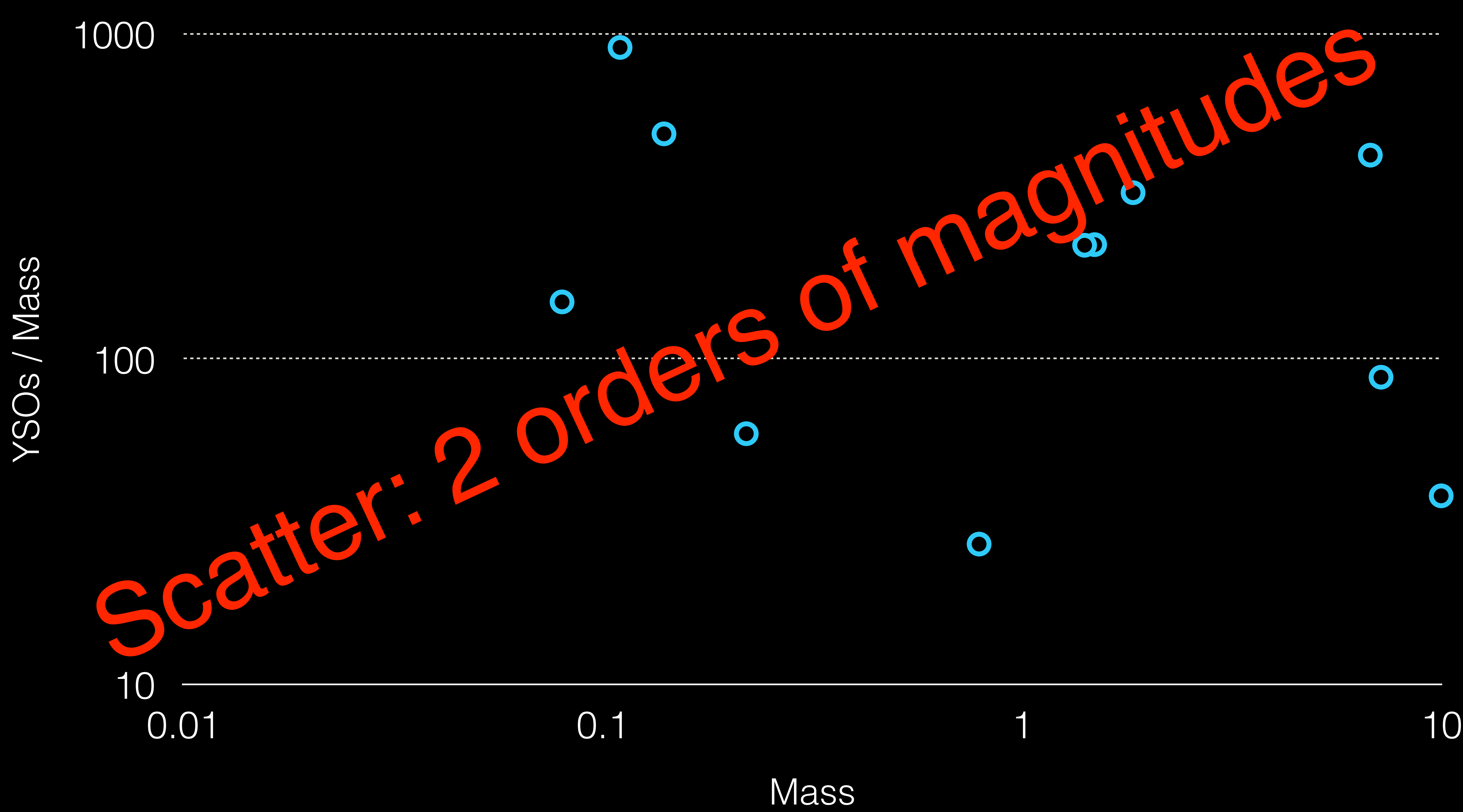
Inventory of Star Formation Activity: Young Stellar Objects (YSOs)

Cloud	Mass (10	YSOs	YSOs / Mass
Orion A	6.77	2862	424
Orion B	7.18	635	88
California	9.99	279	38
Perseus	1.84	598	325
Taurus	1.49	335	225
Ophiuchus	1.41	316	224
RCrA	0.11	100	909
Pipe	0.79	21	27
Lupus 1	0.22	13	59
Lupus 3	0.14	69	493
Lupus 4	0.08	12	150

Inventory of Star Formation Activity: Young Stellar Objects (YSOs)

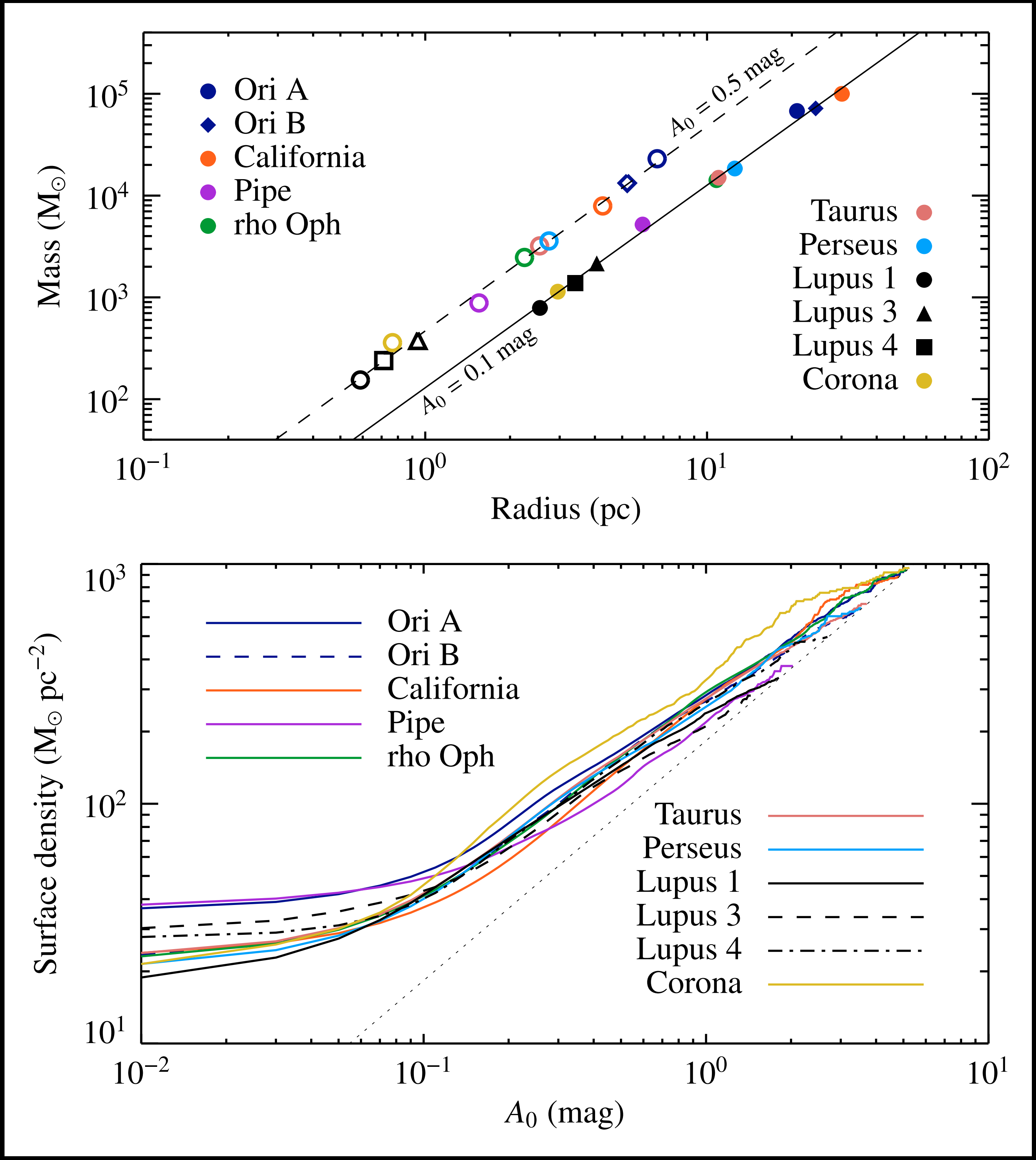


Inventory of Star Formation Activity: Young Stellar Objects (YSOs)



Fact 4
Molecular clouds have a peculiar structure

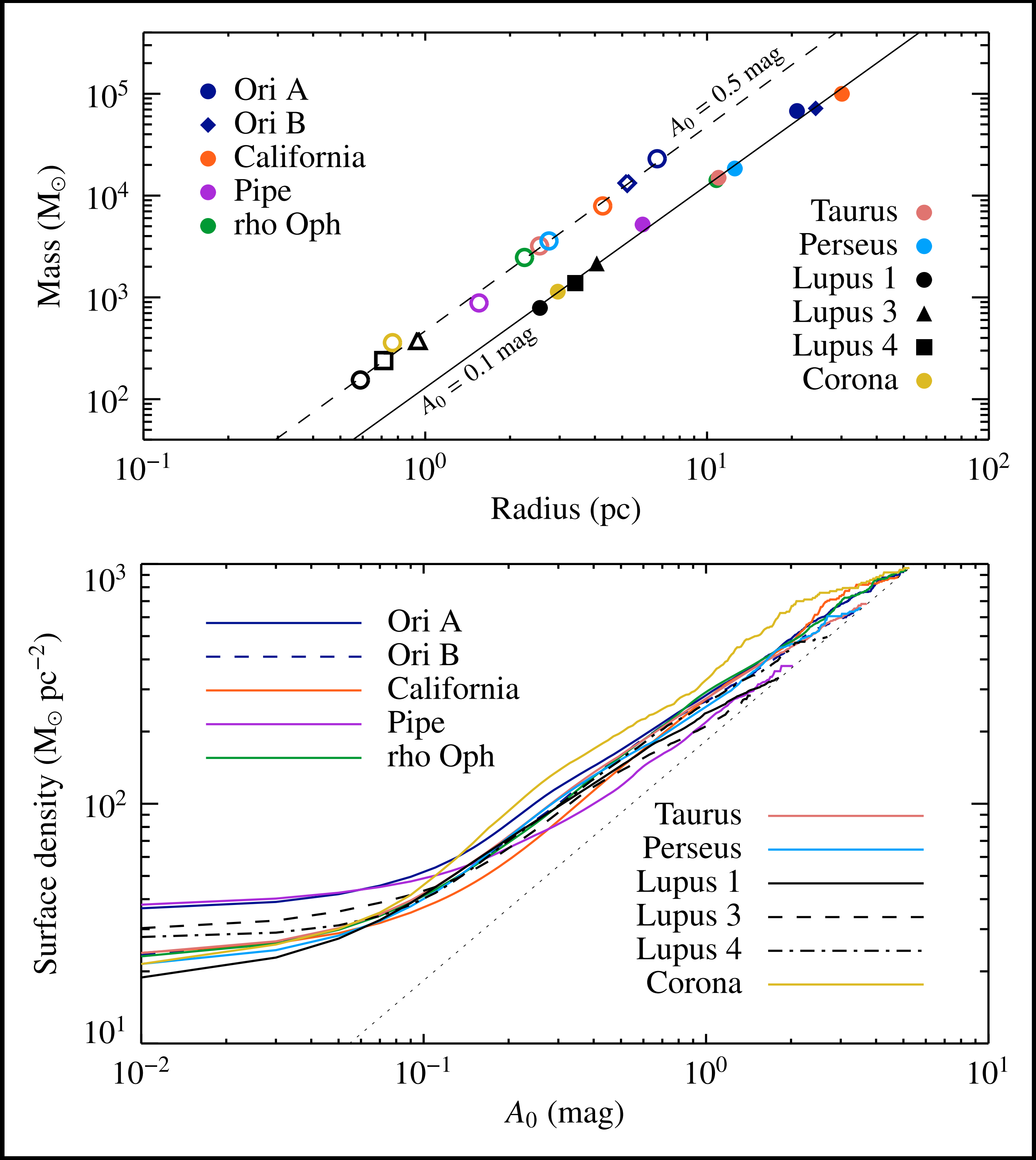
The structure of molecular clouds



Lombardi et al. (2010)

The structure of molecular clouds

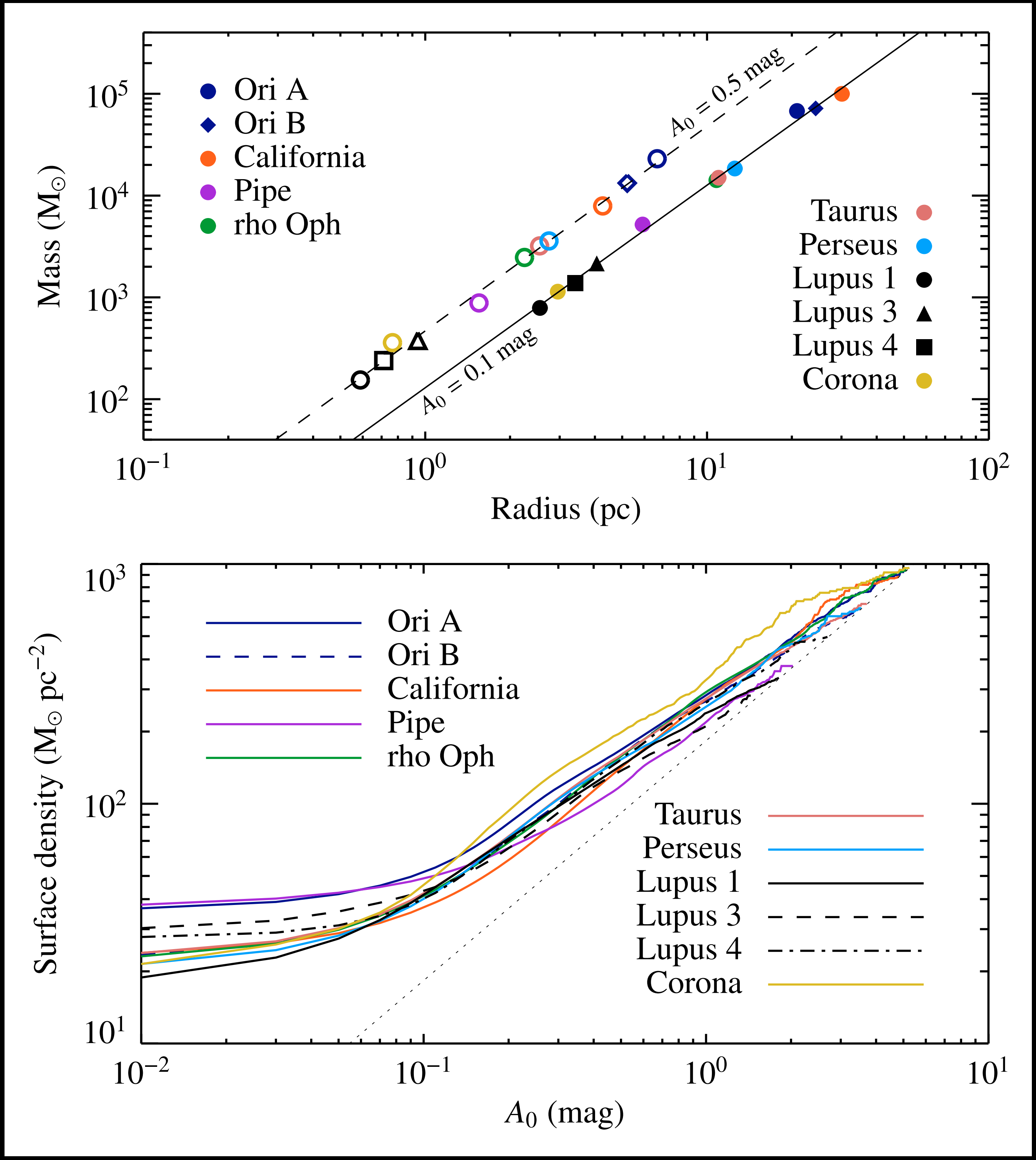
- Different molecular clouds show consistent structure



Lombardi et al. (2010)

The structure of molecular clouds

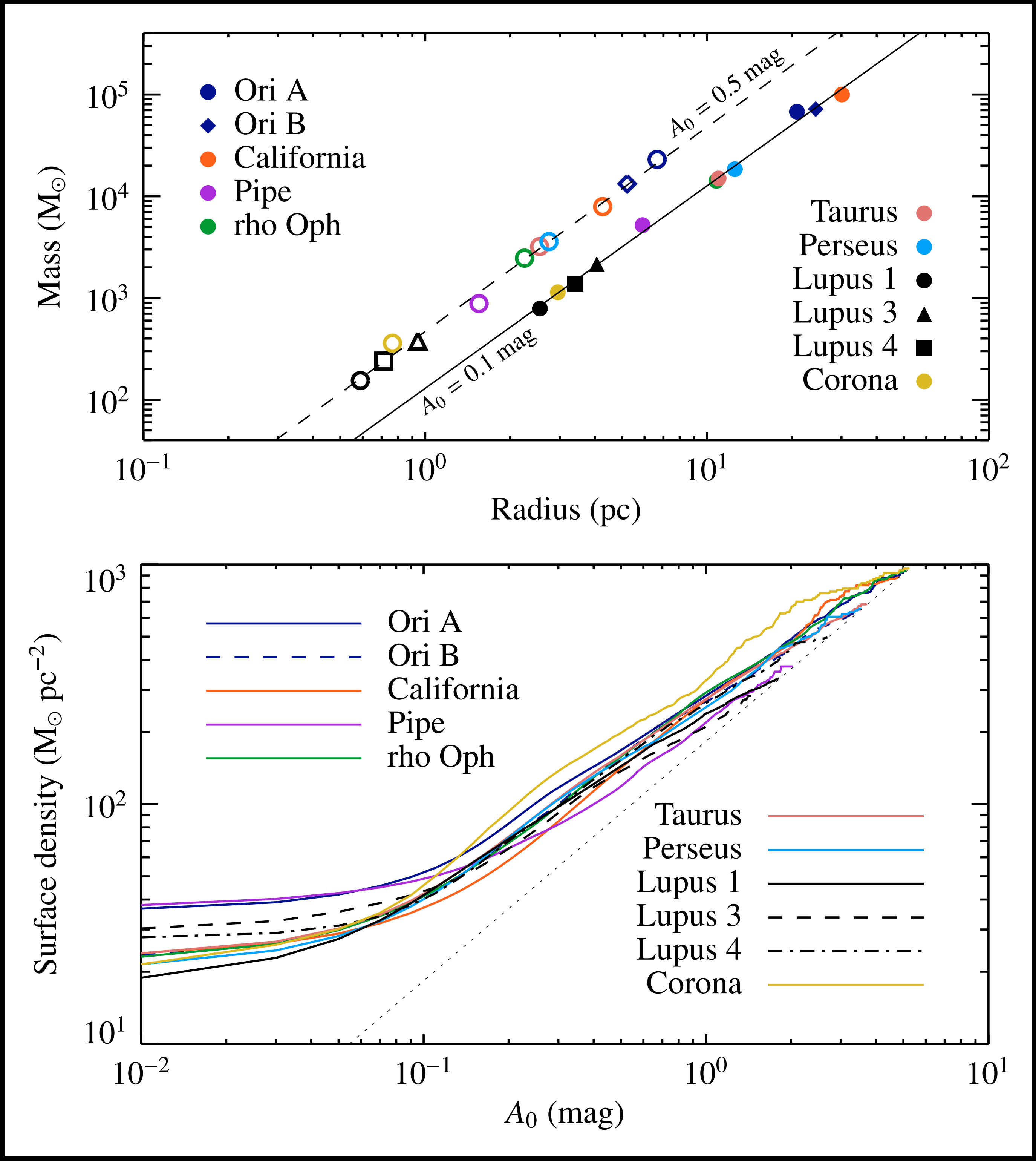
- Different molecular clouds show consistent structure
  - Same average density above threshold value (as predicted by WDM)



Lombardi et al. (2010)

The structure of molecular clouds

- Different molecular clouds show consistent structure
  - Same average density above threshold value (as predicted by WDM)
  - Same probability distribution for Σ (log-normal)



Lombardi et al. (2010)

The structure of molecular clouds

- Different molecular clouds show consistent structure
  - Same average density above threshold value (as predicted by WDM)
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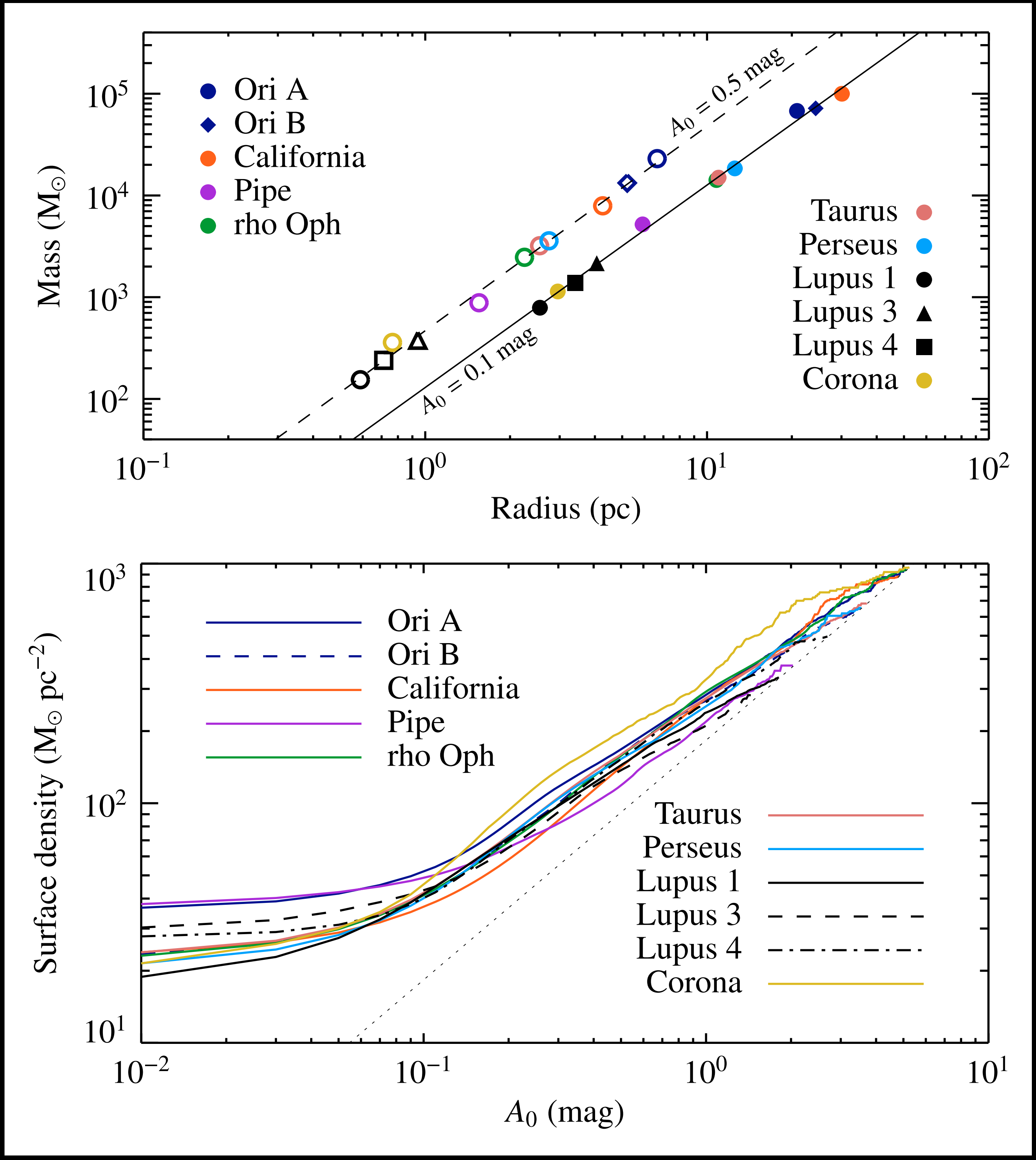
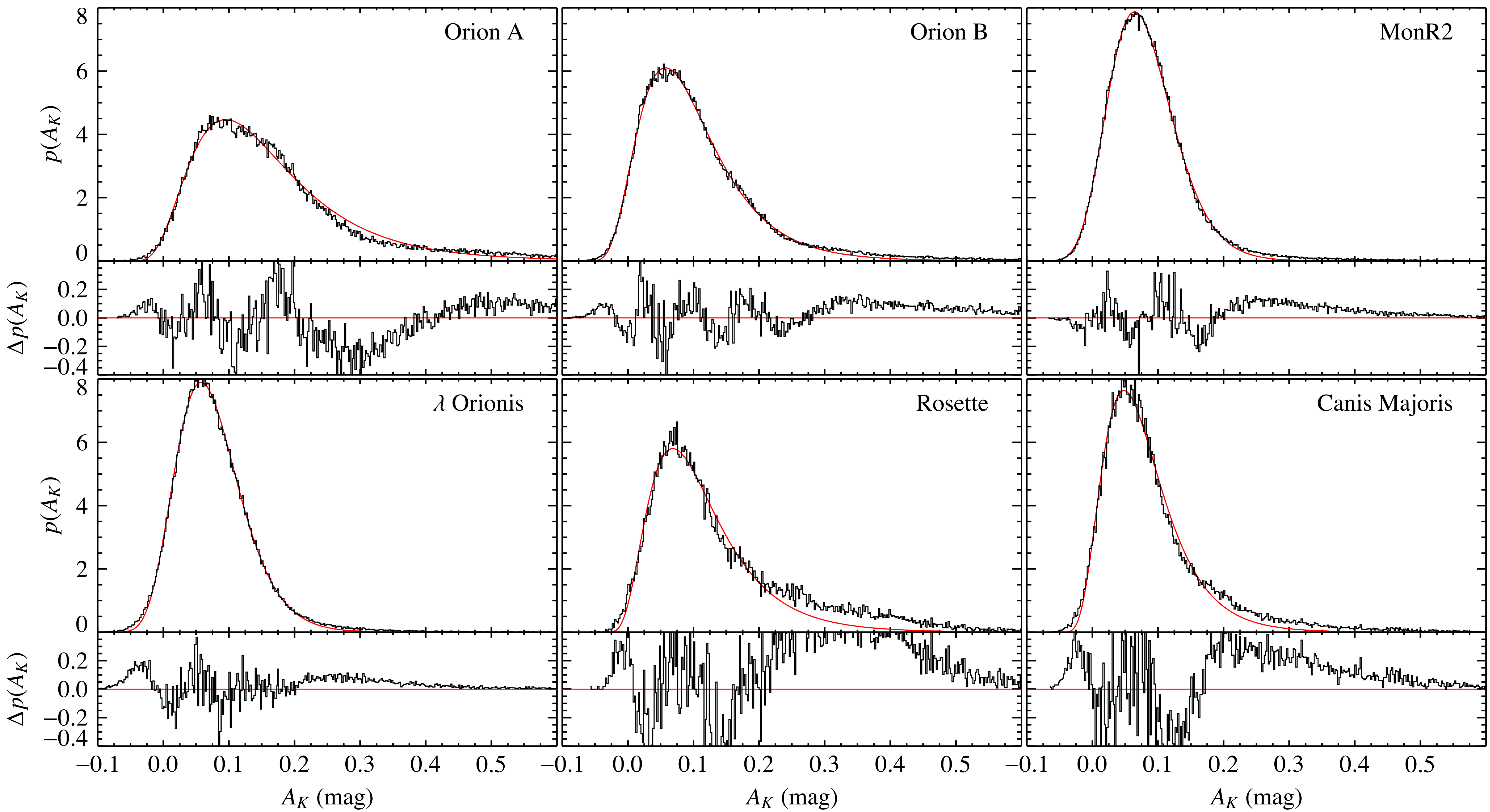


Lombardi et al. (2010)

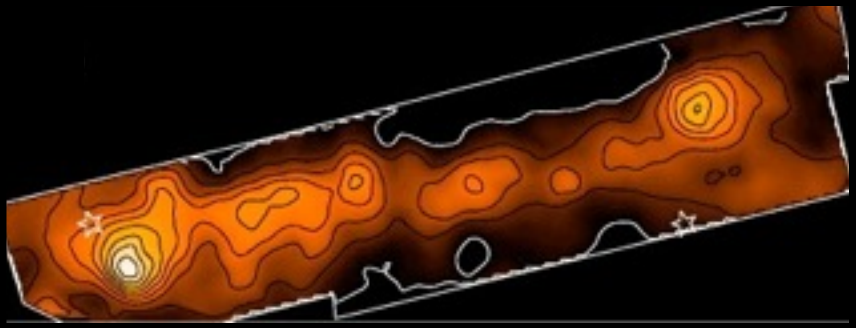
Log-normal fits to cloud projected density distributions

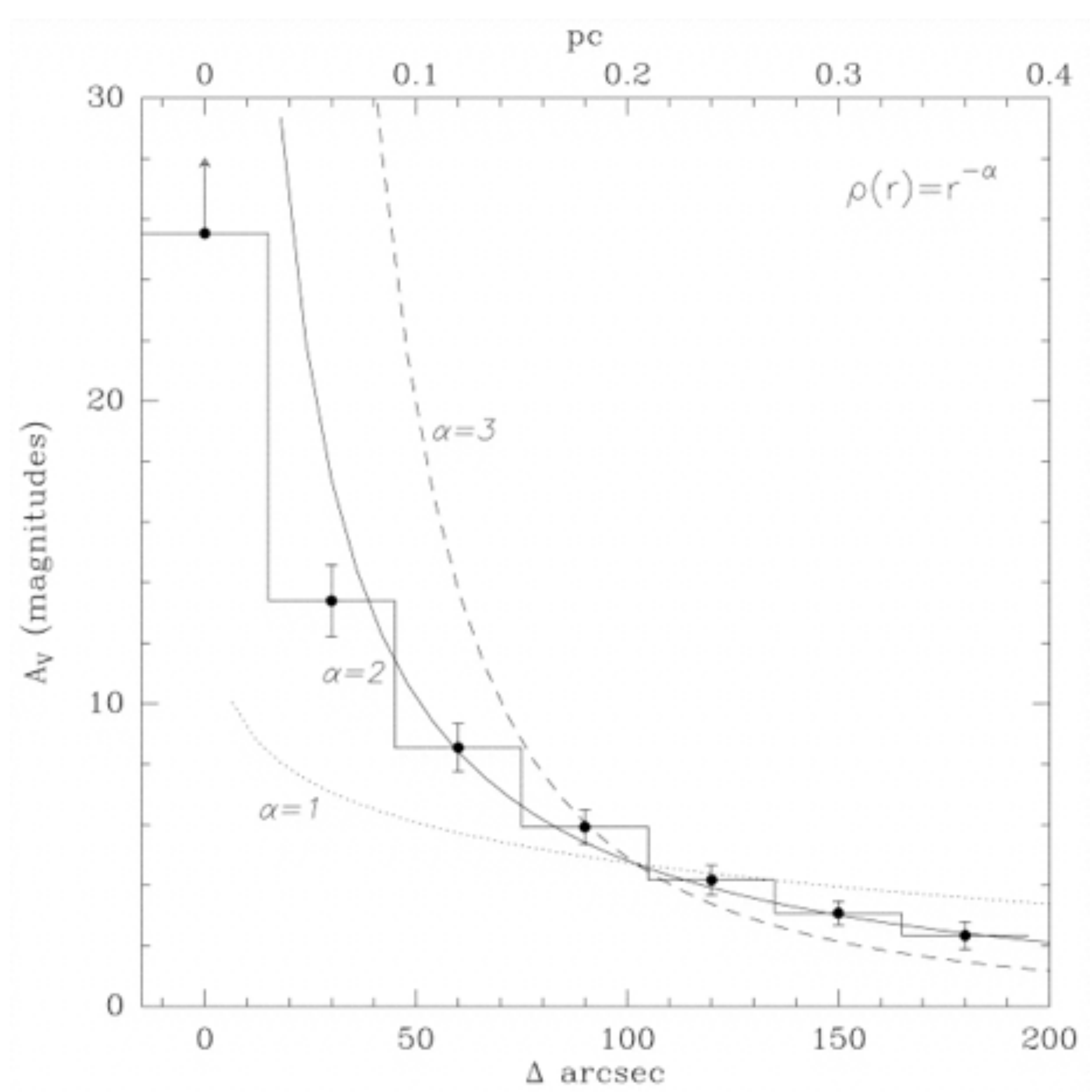


Lombardi et al. (2011)

A Σ-ρ relation for molecular clouds

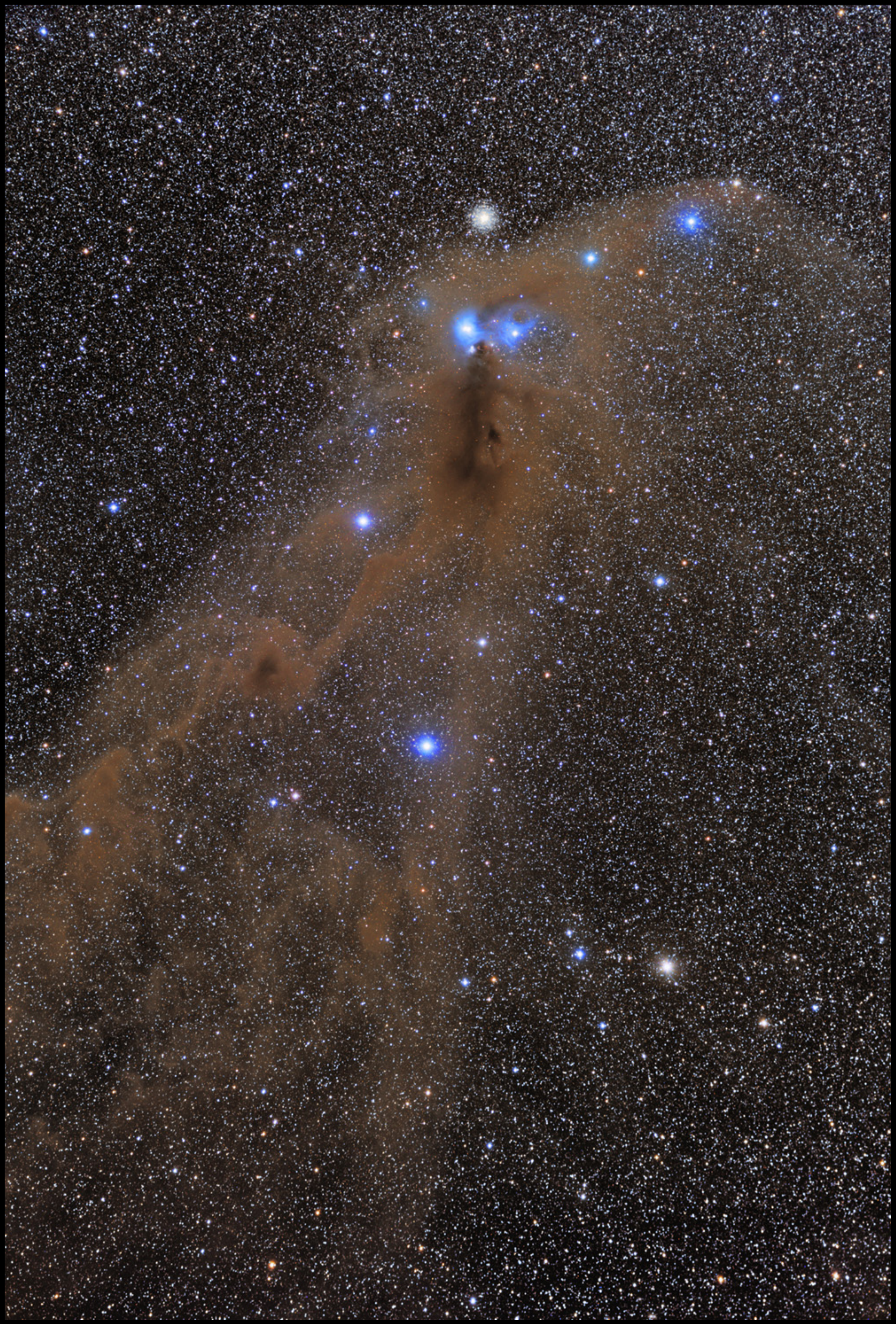
- Different Molecular clouds show consistent structure
  - Same average density above threshold value (as predicted by WDM)
  - Same probability distribution for Σ (log-normal)
  - Similar stratification of surface density contours





Lada, Alves, Lada (1999)

Log-normals? Think it twice



Alves et al. (2014)

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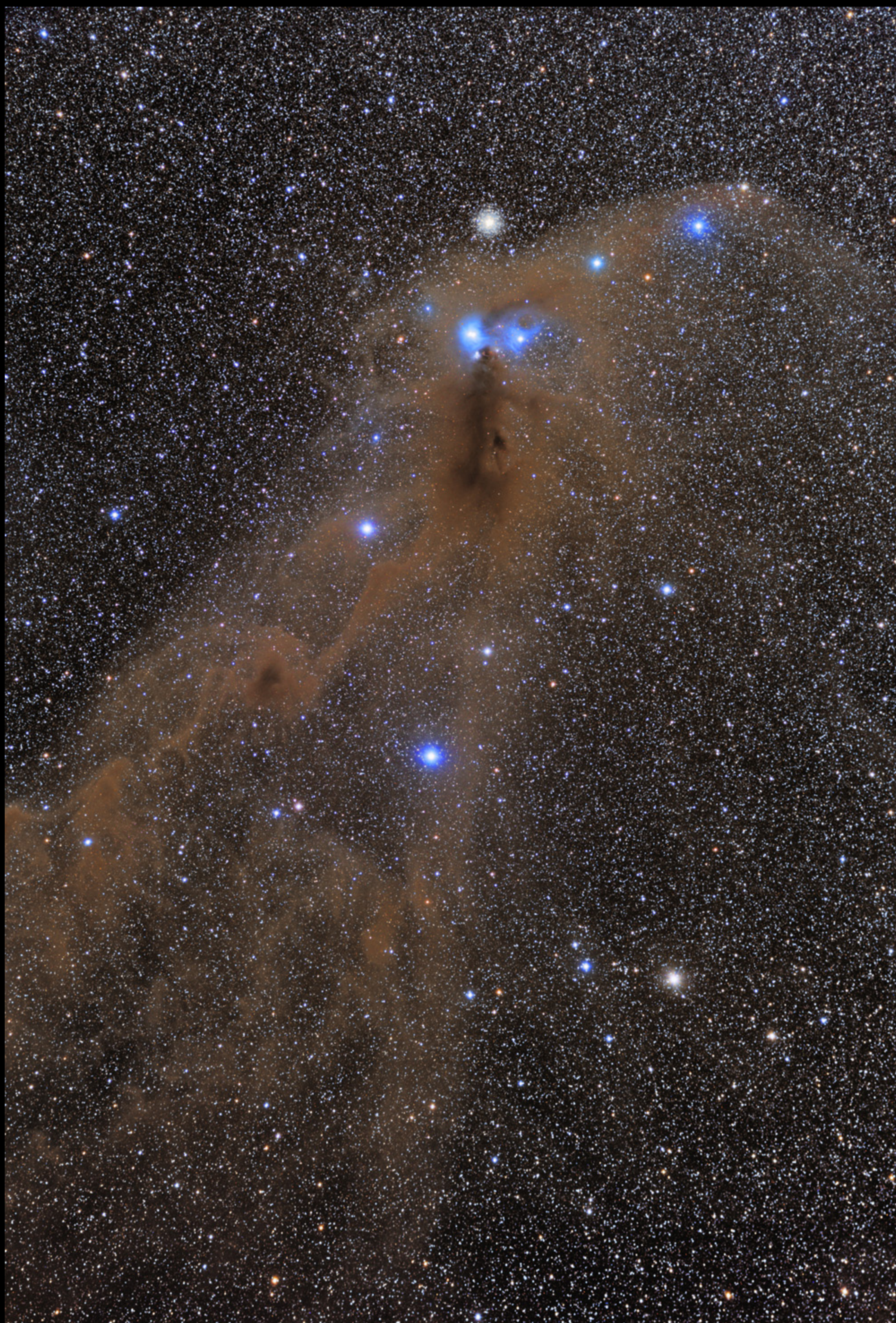

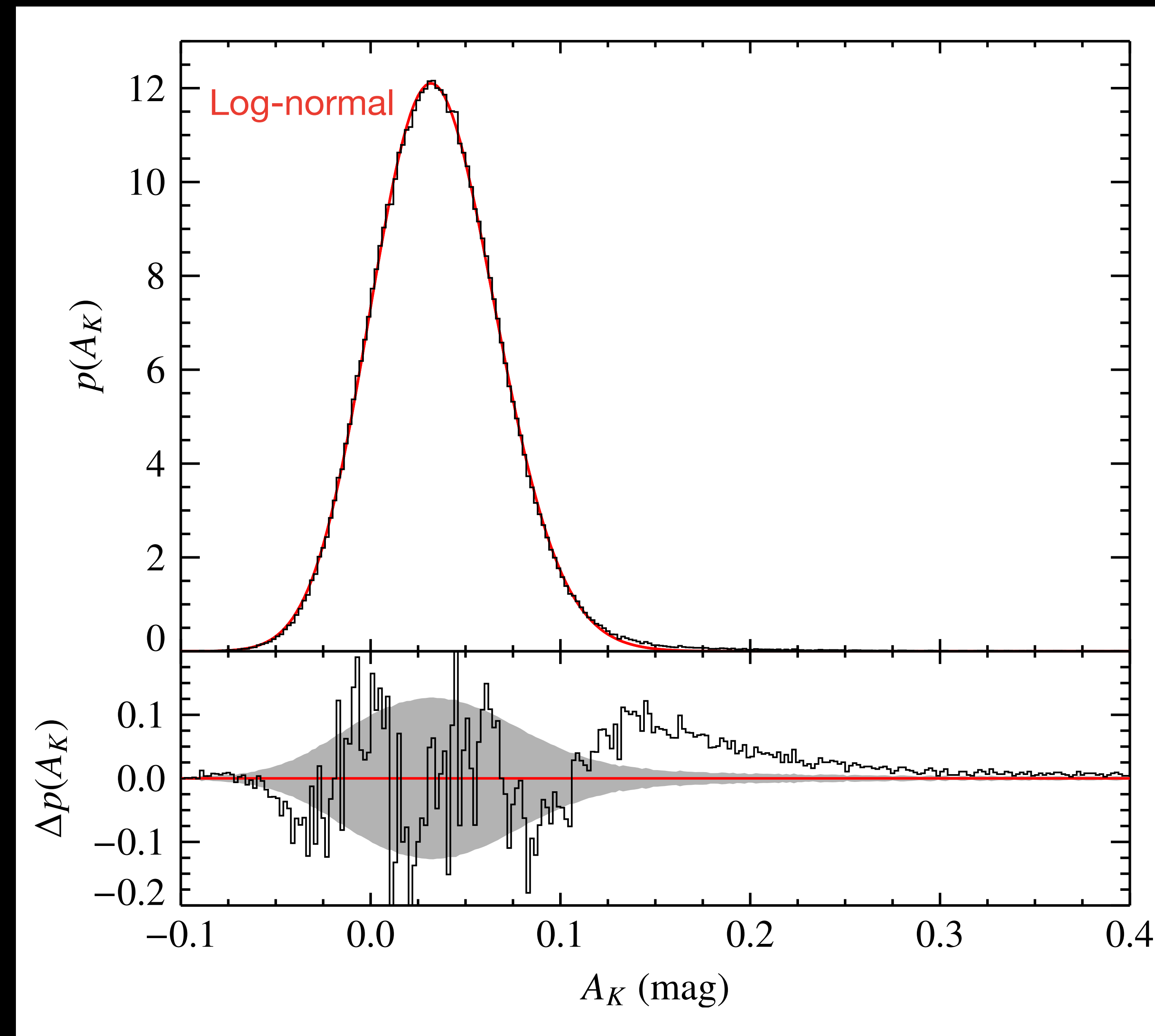

Systematic residuals in the entire fitting region!

Alves et al. (2014)

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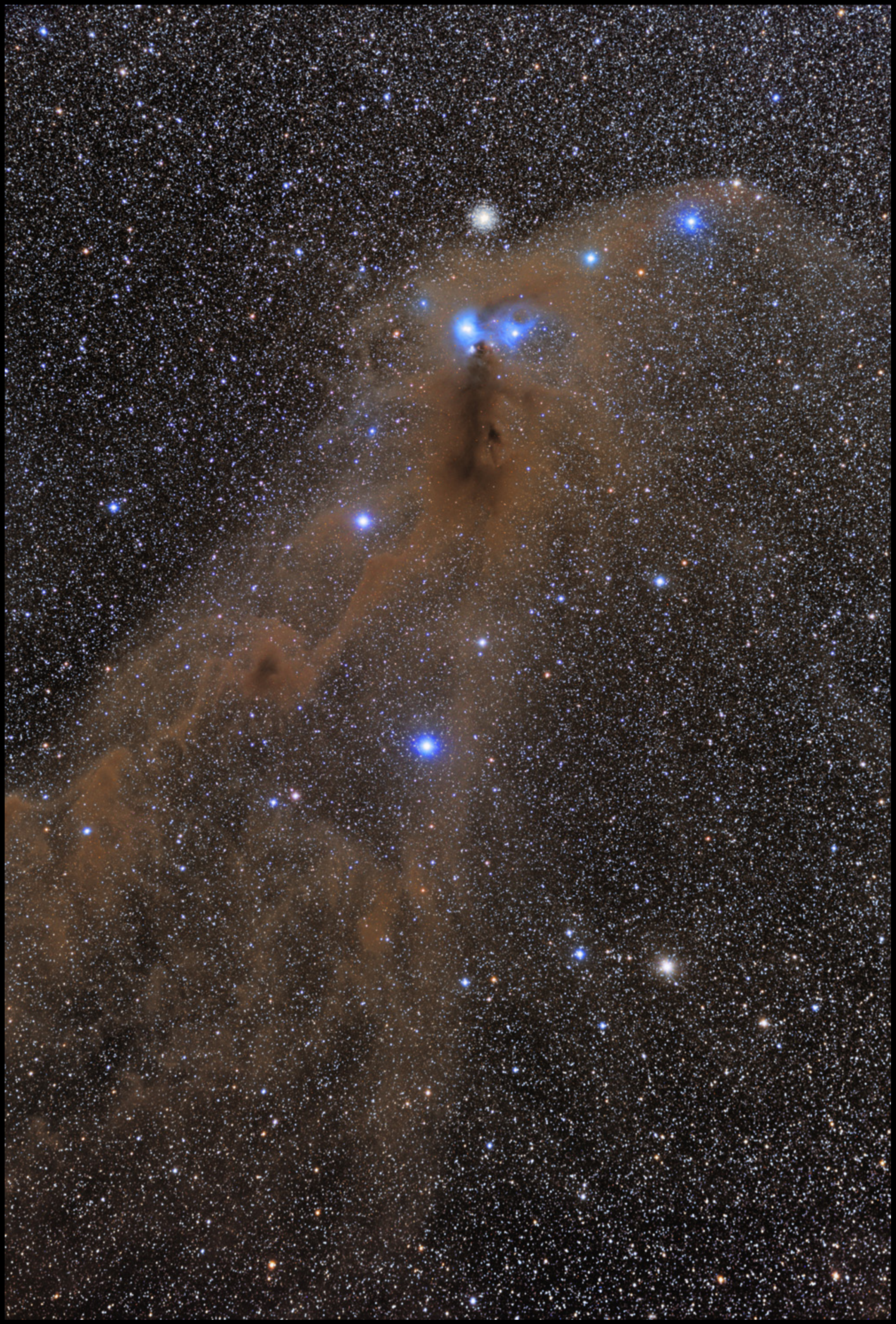

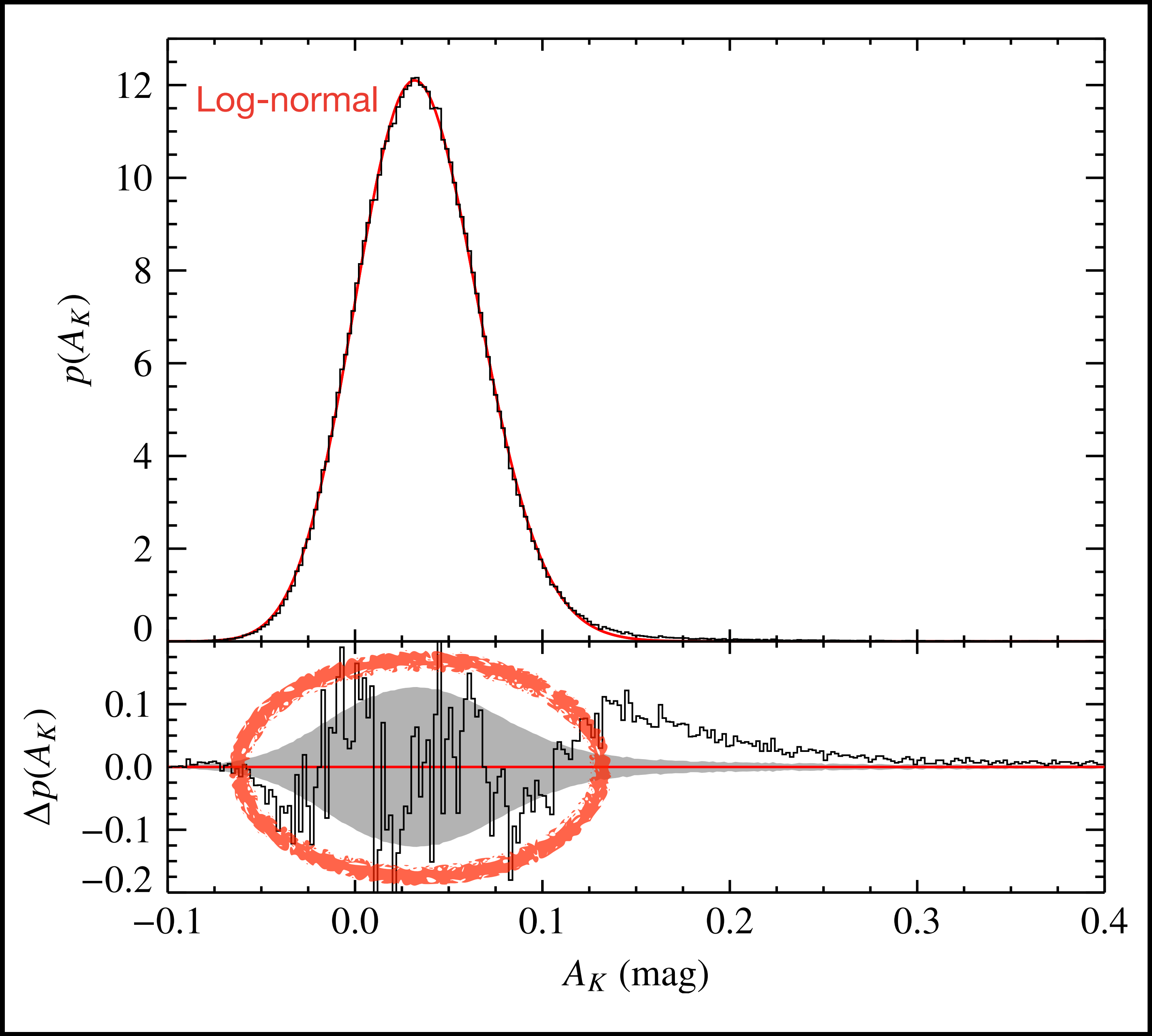

Systematic residuals in the entire fitting region!

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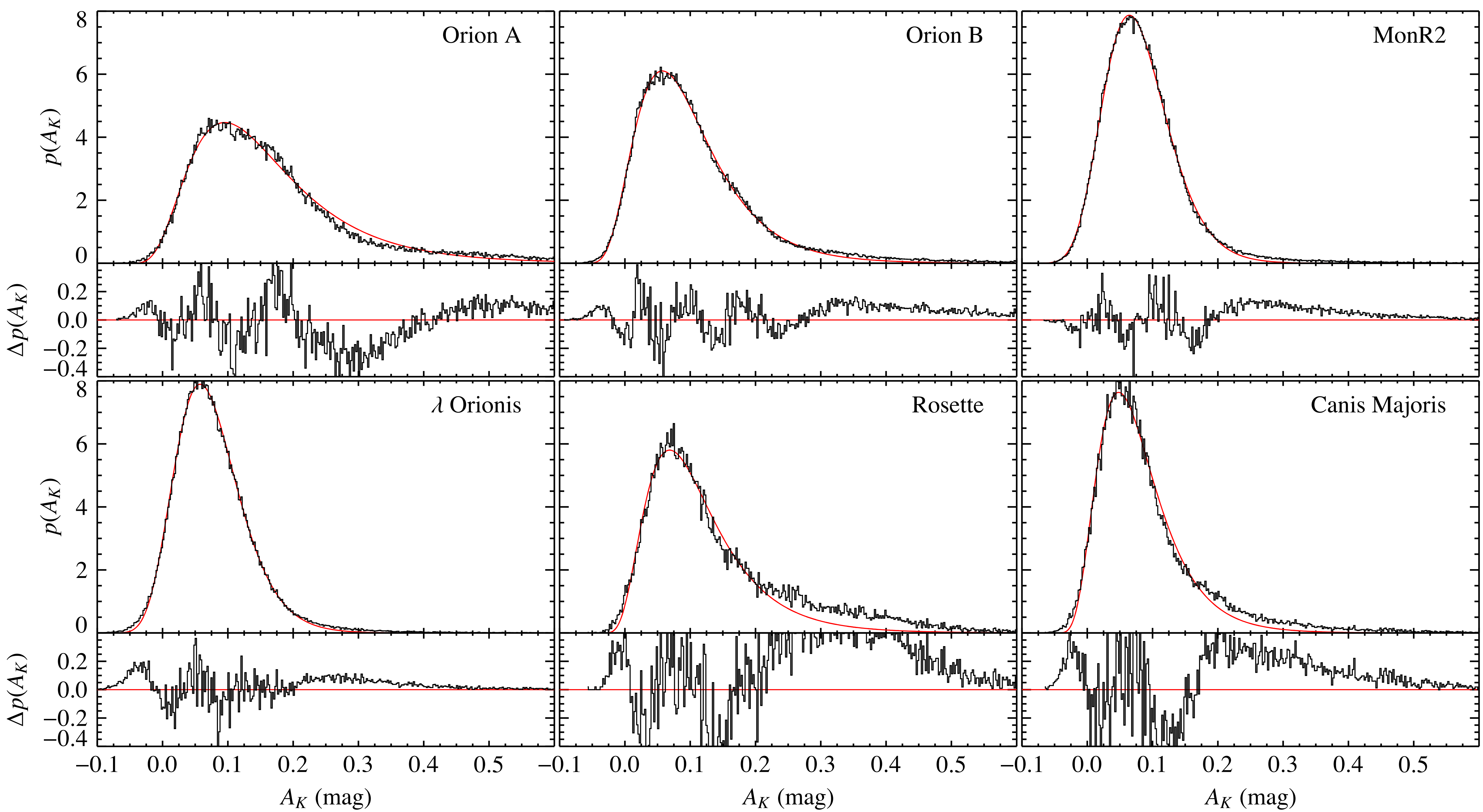
All log-normal fits show systematic residuals



Lombardi et al. (2011)

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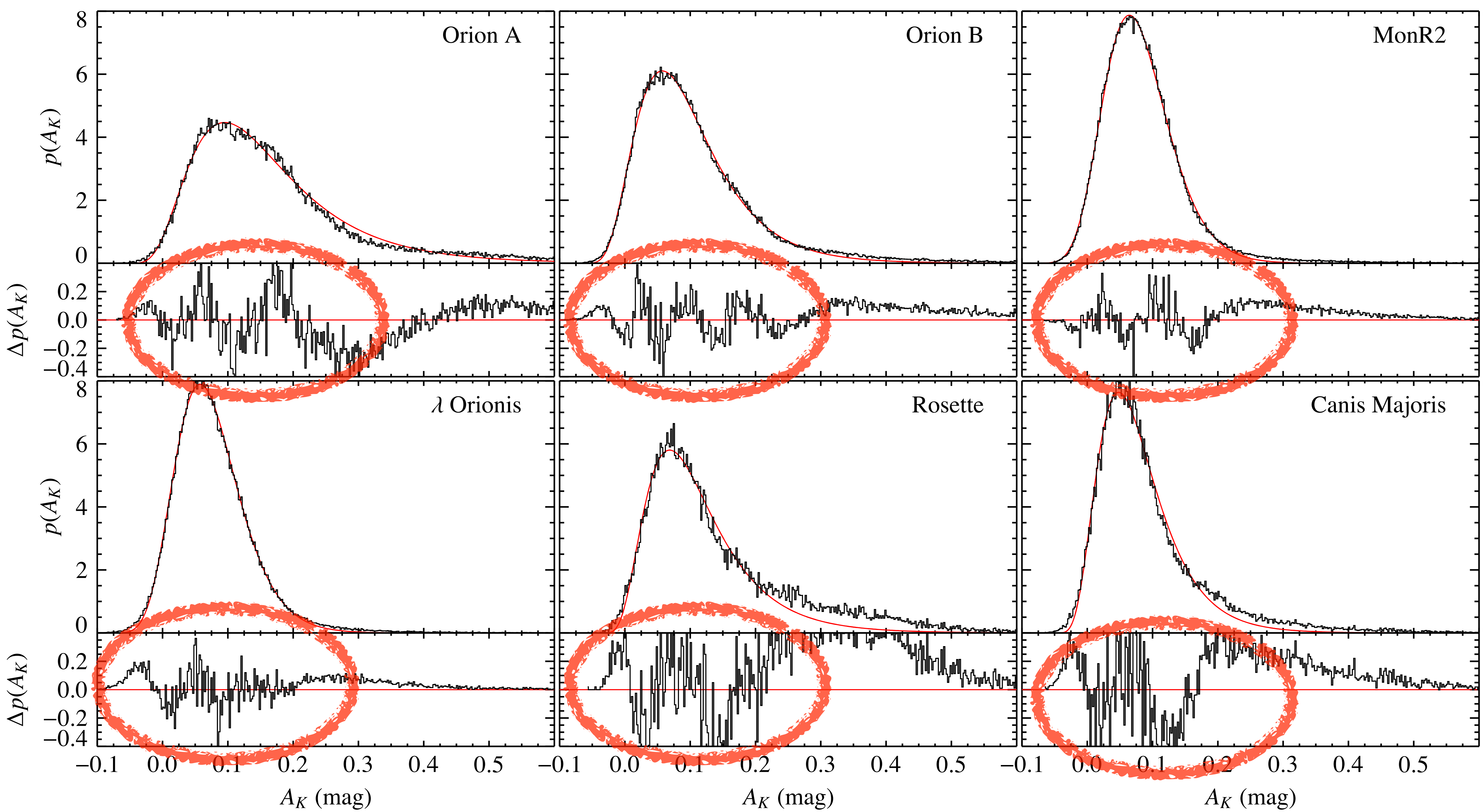

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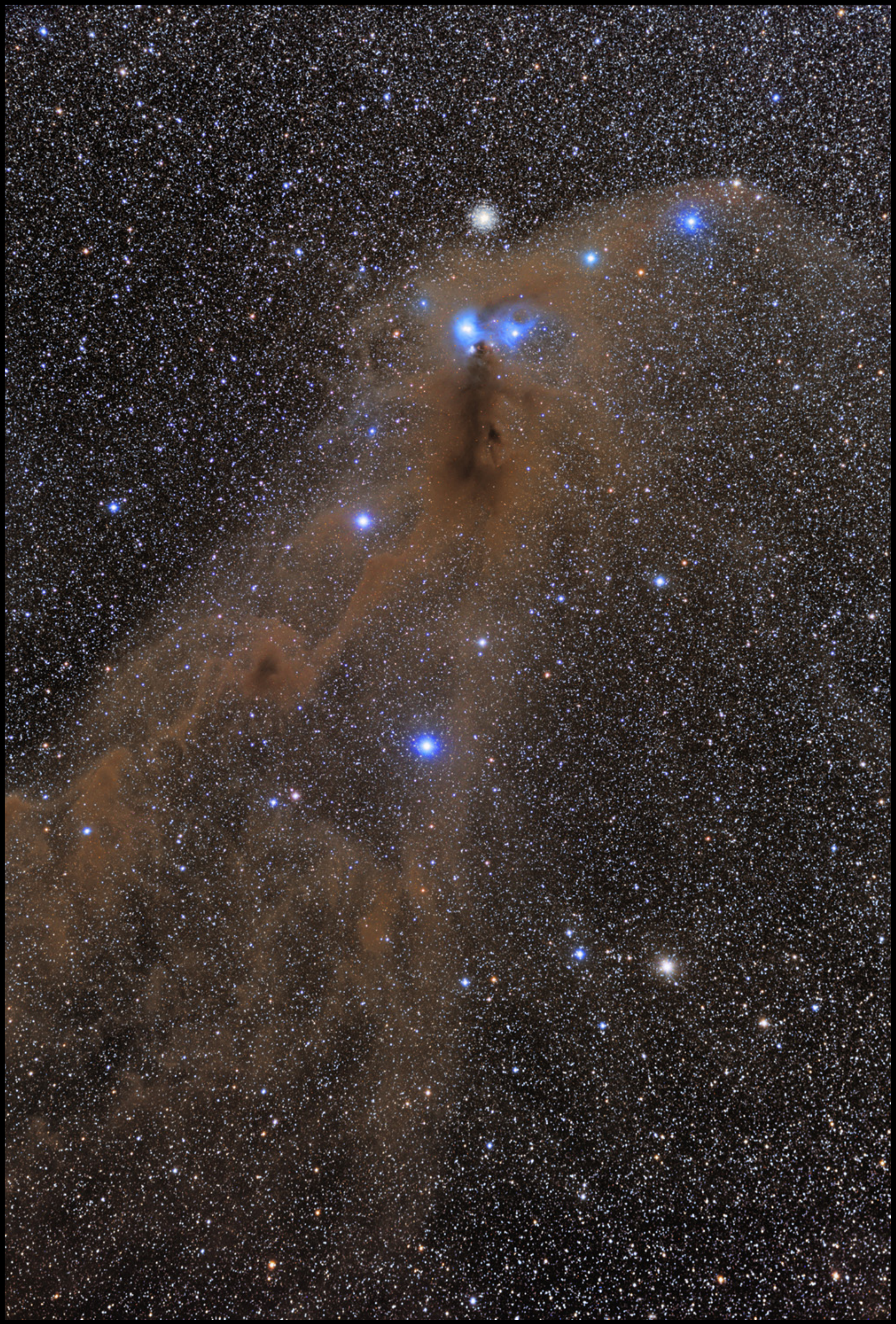

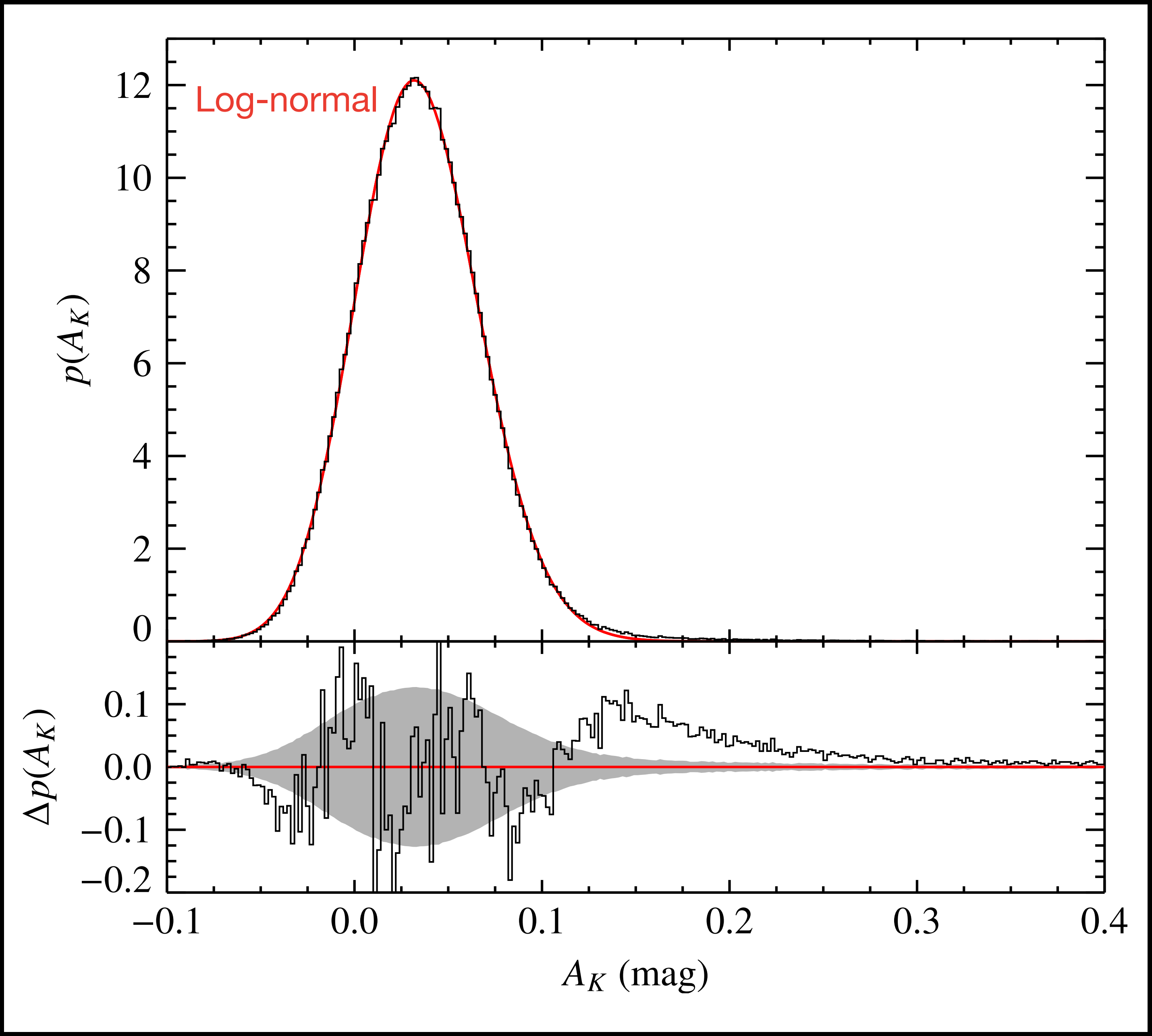

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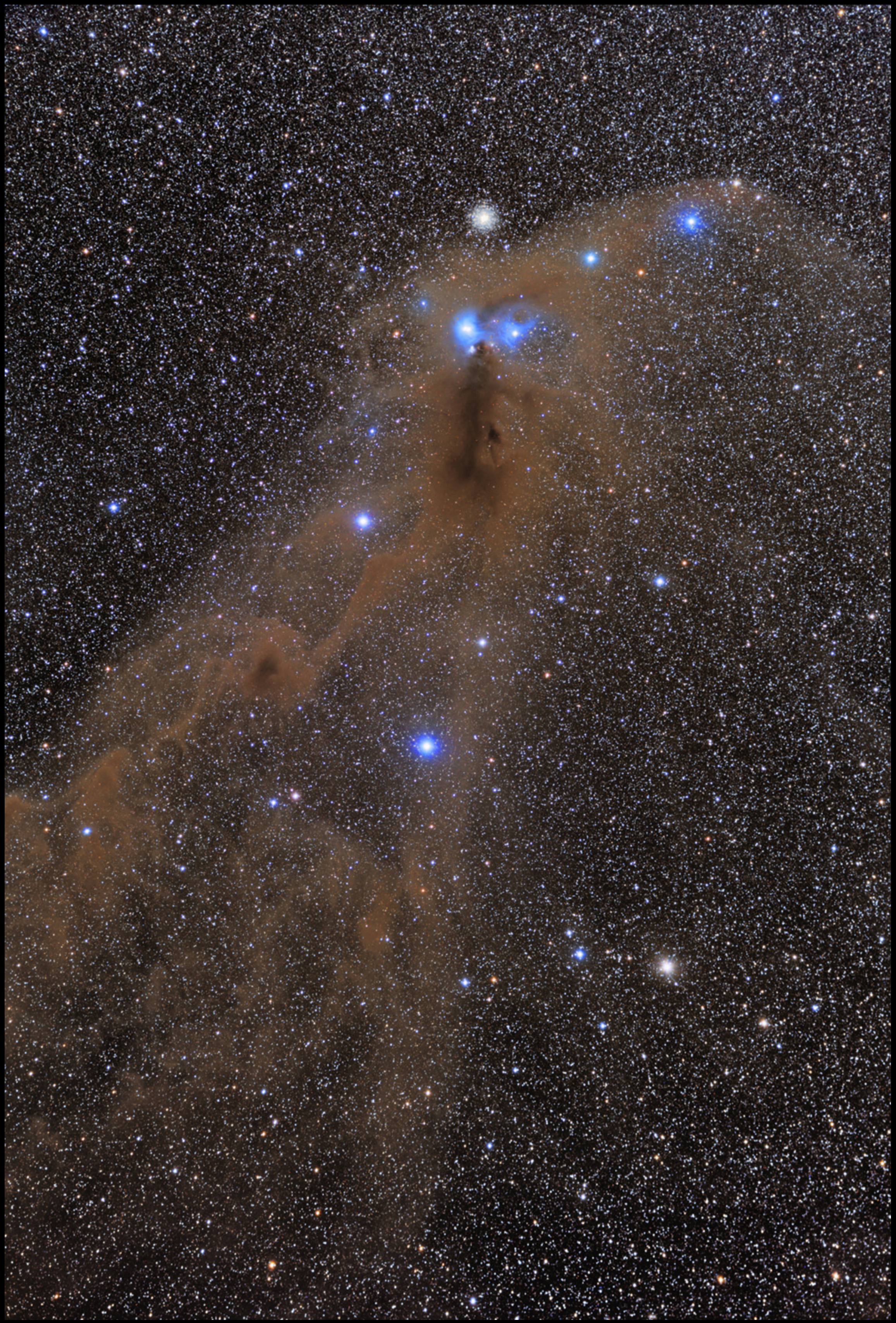

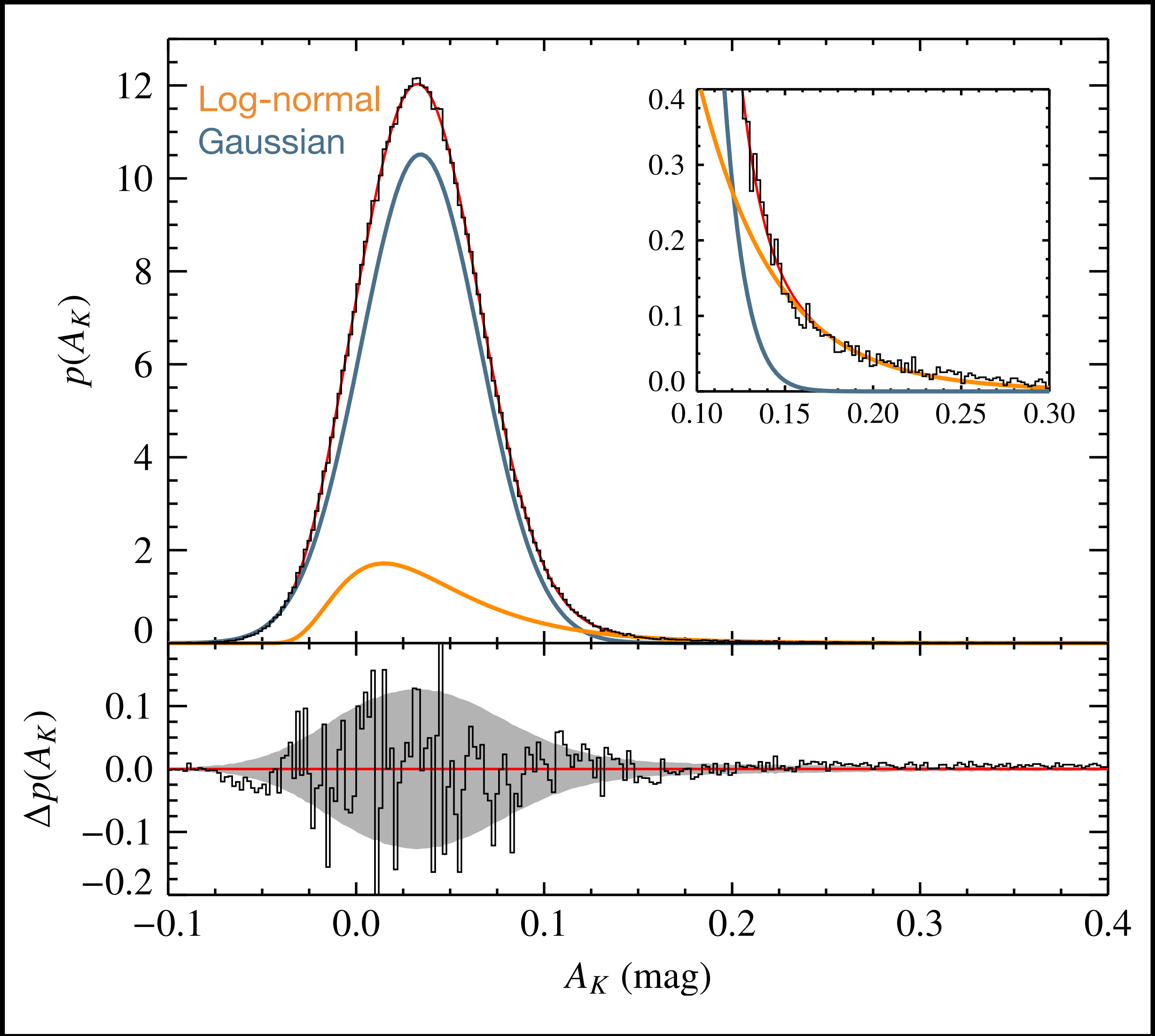

Residuals disappear when fitting a Gaussian + Log-normal.

Alves et al. (2014)

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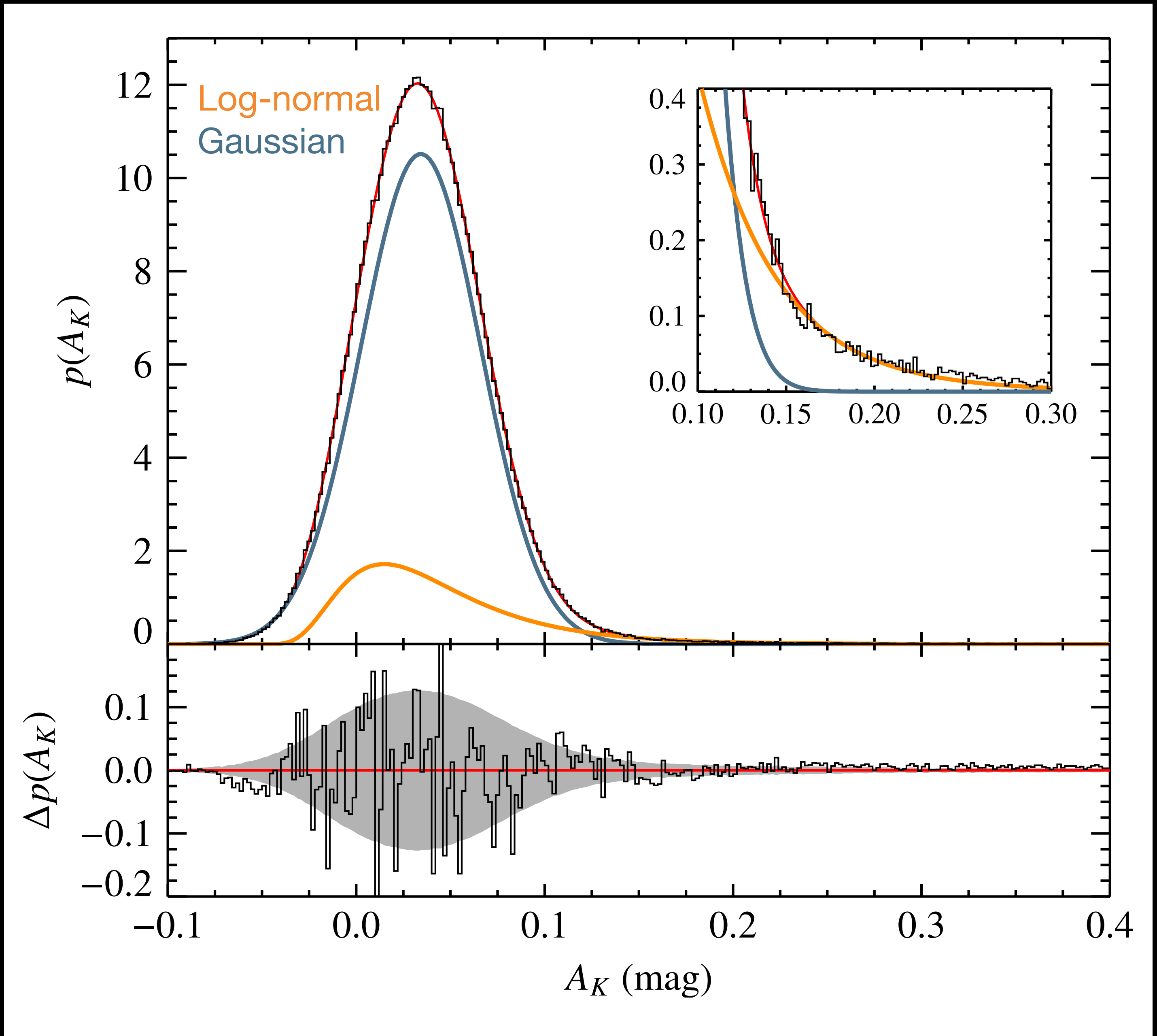

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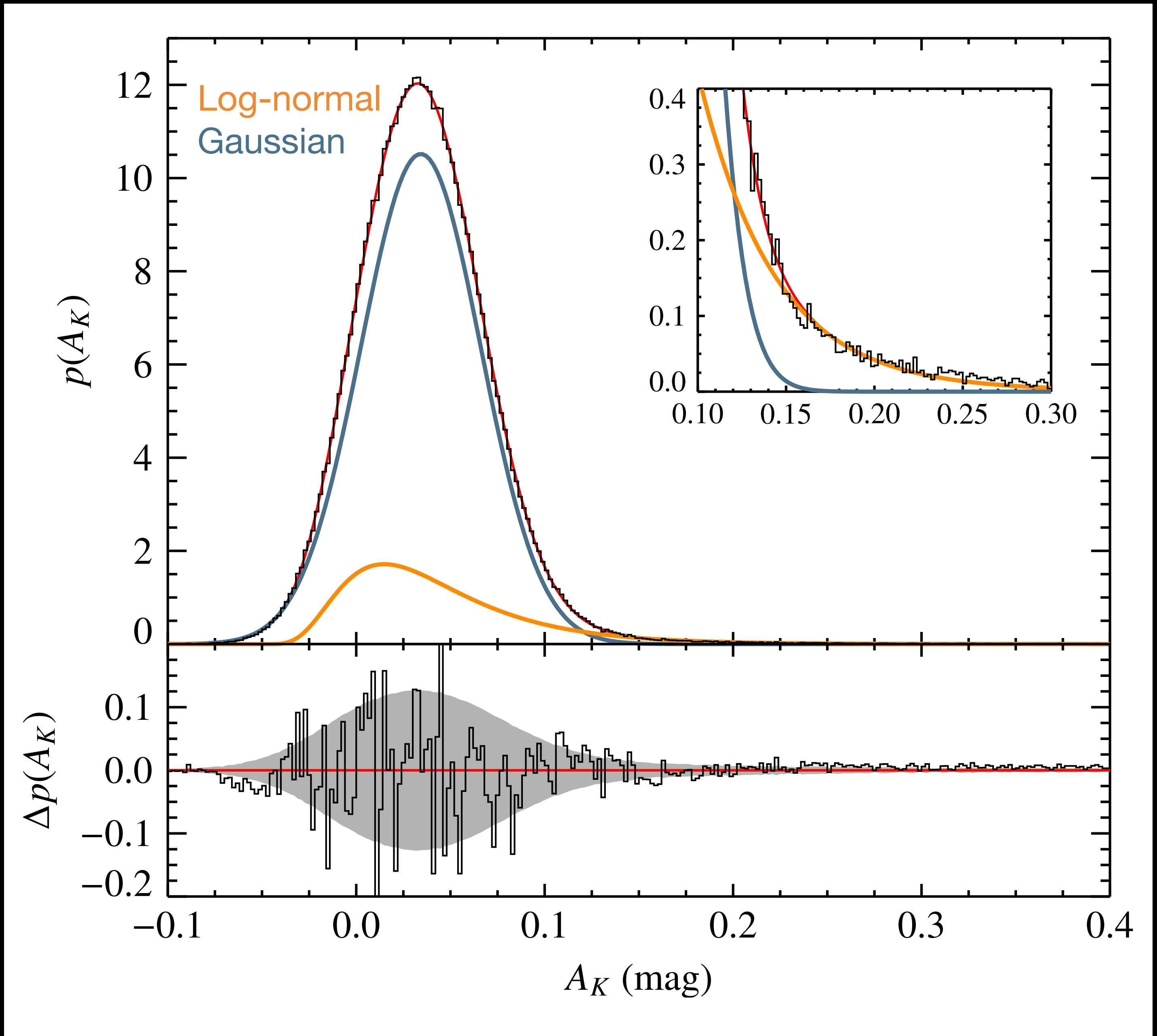

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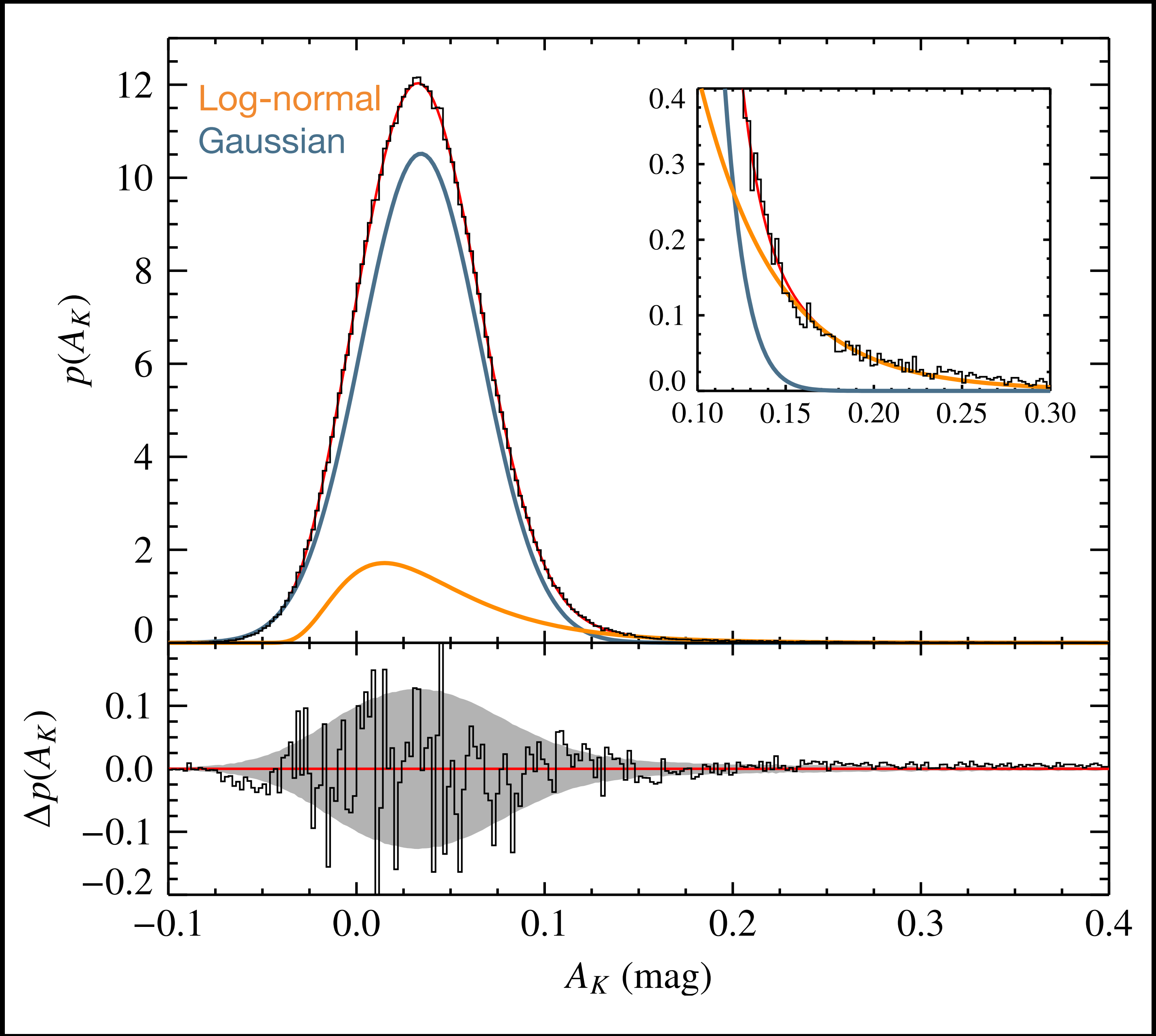

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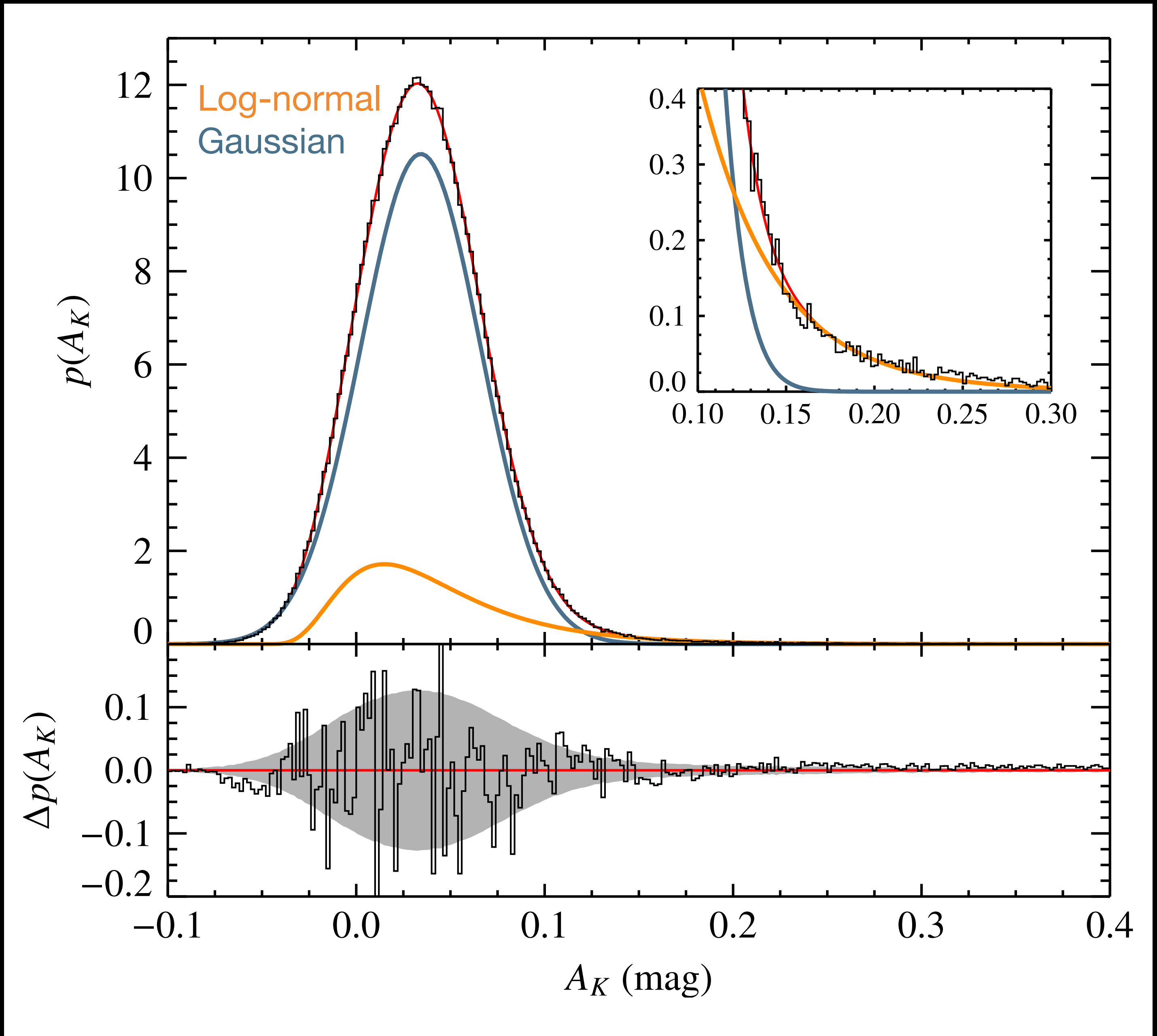

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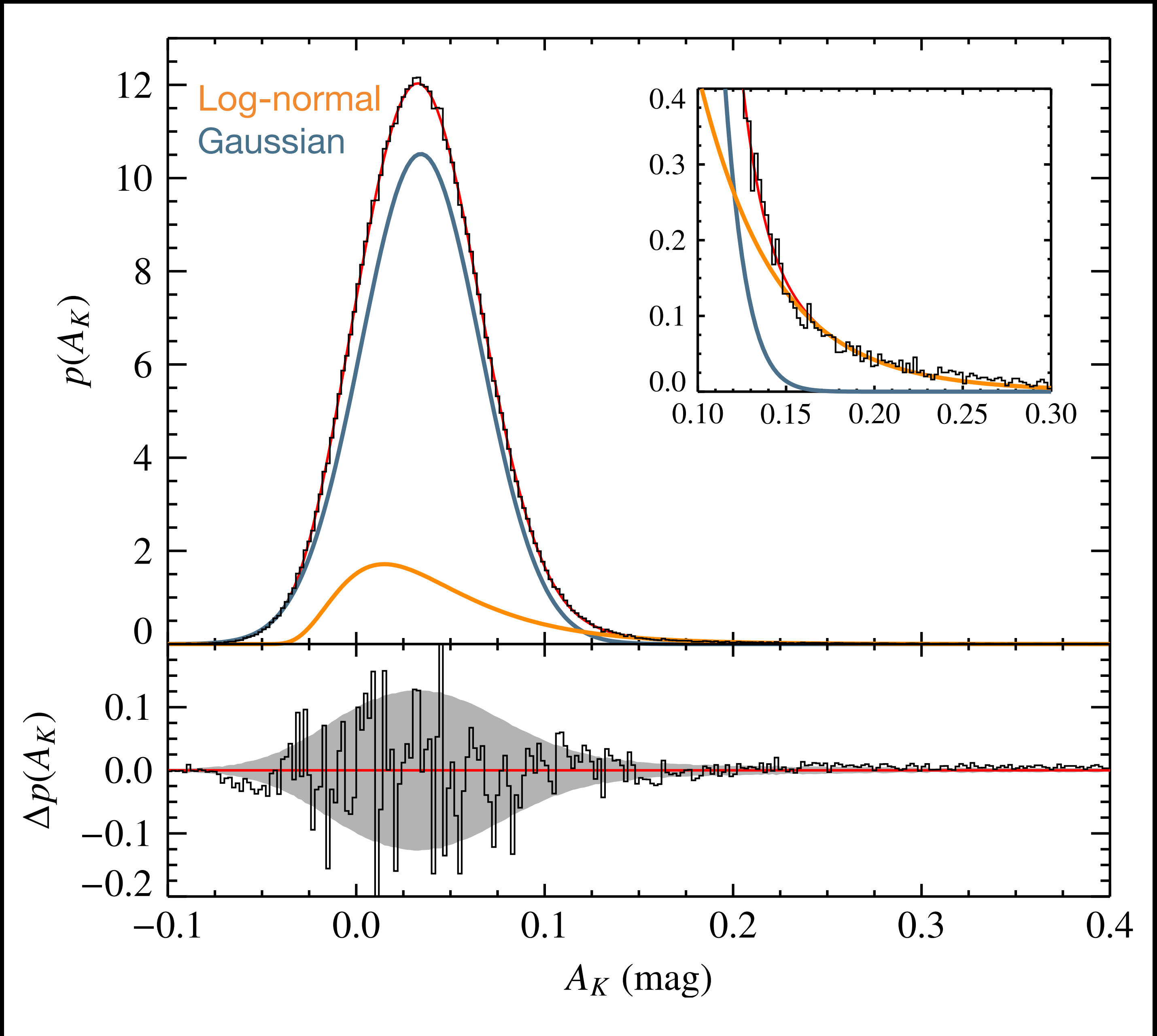

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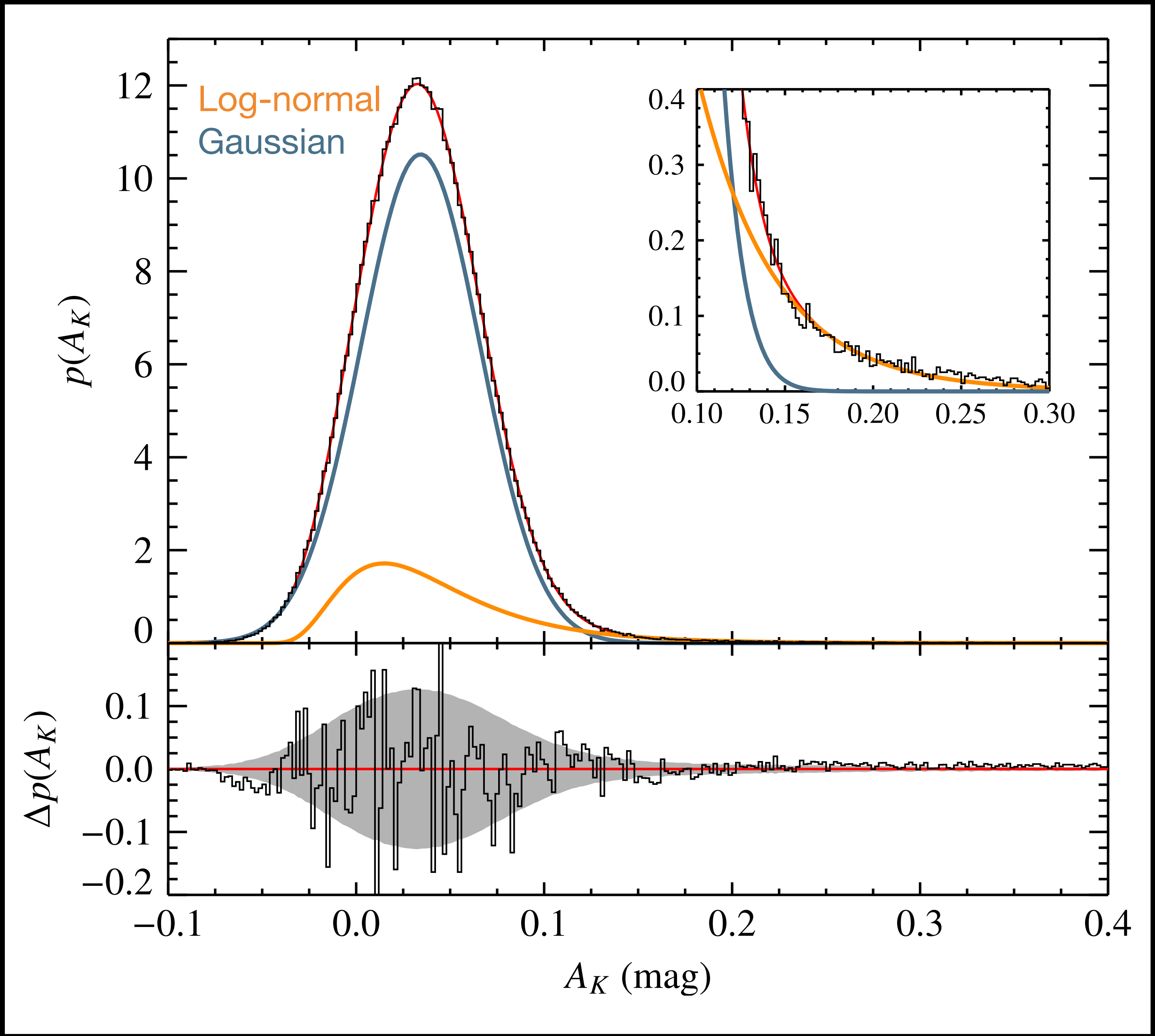

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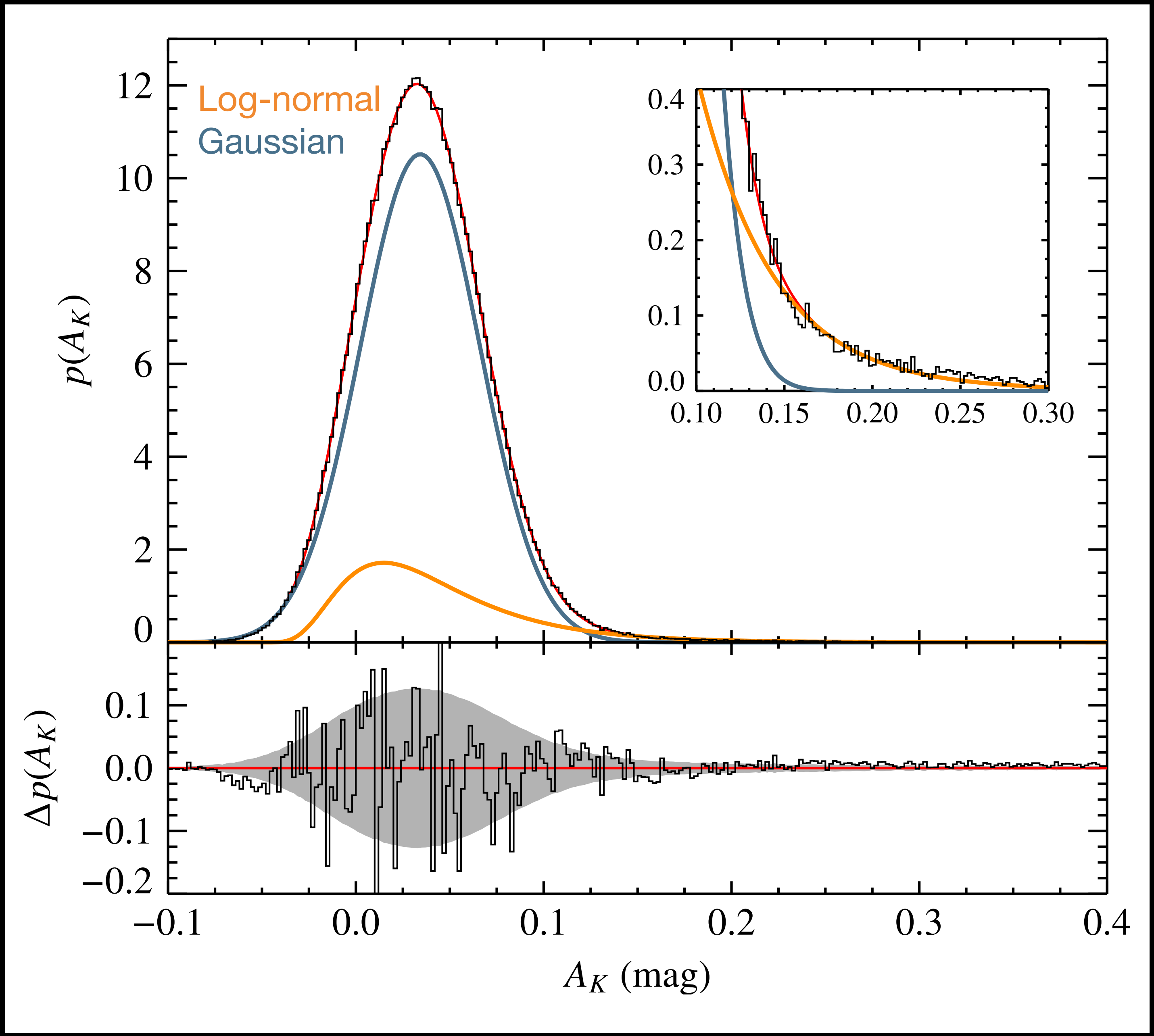

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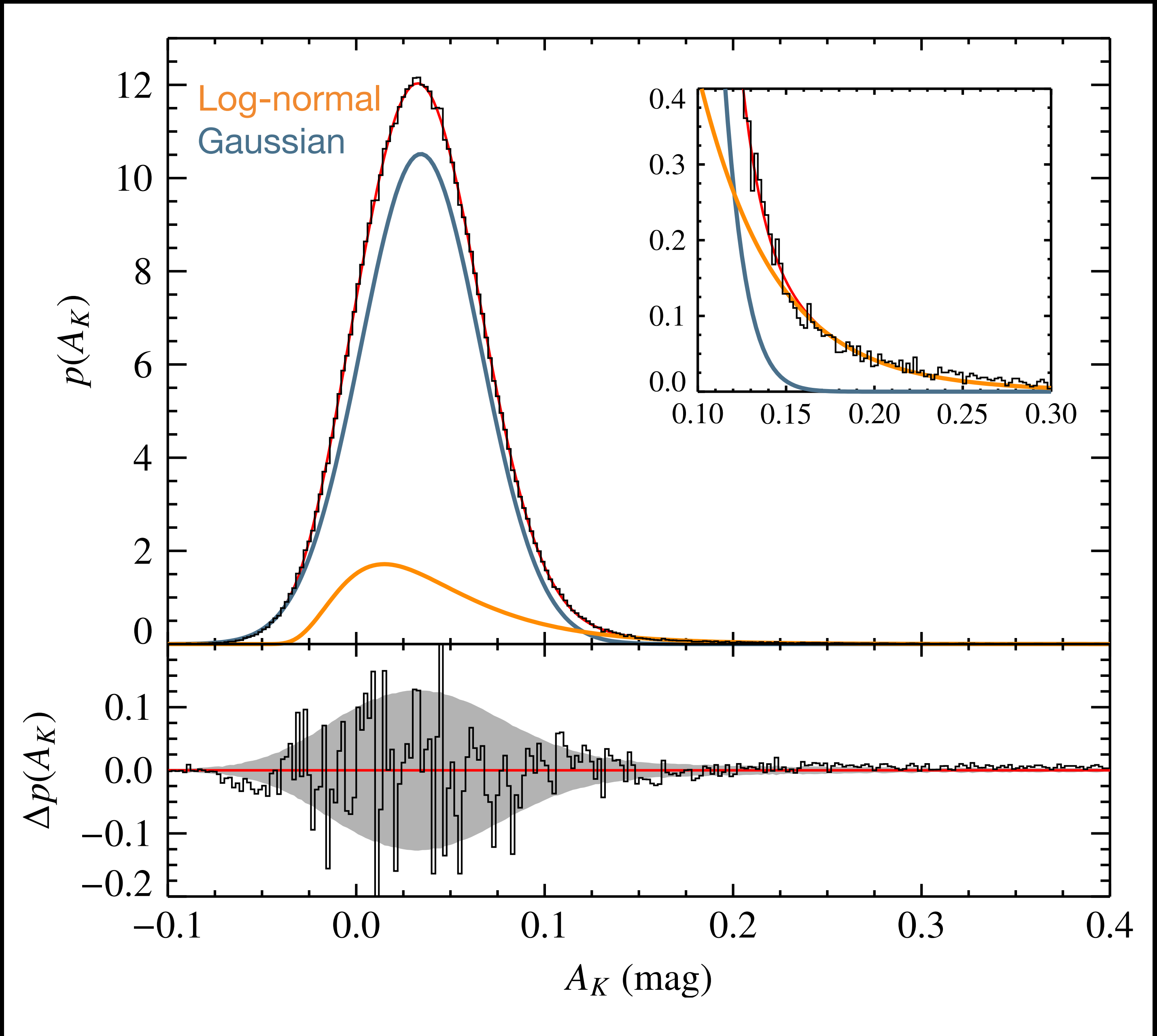

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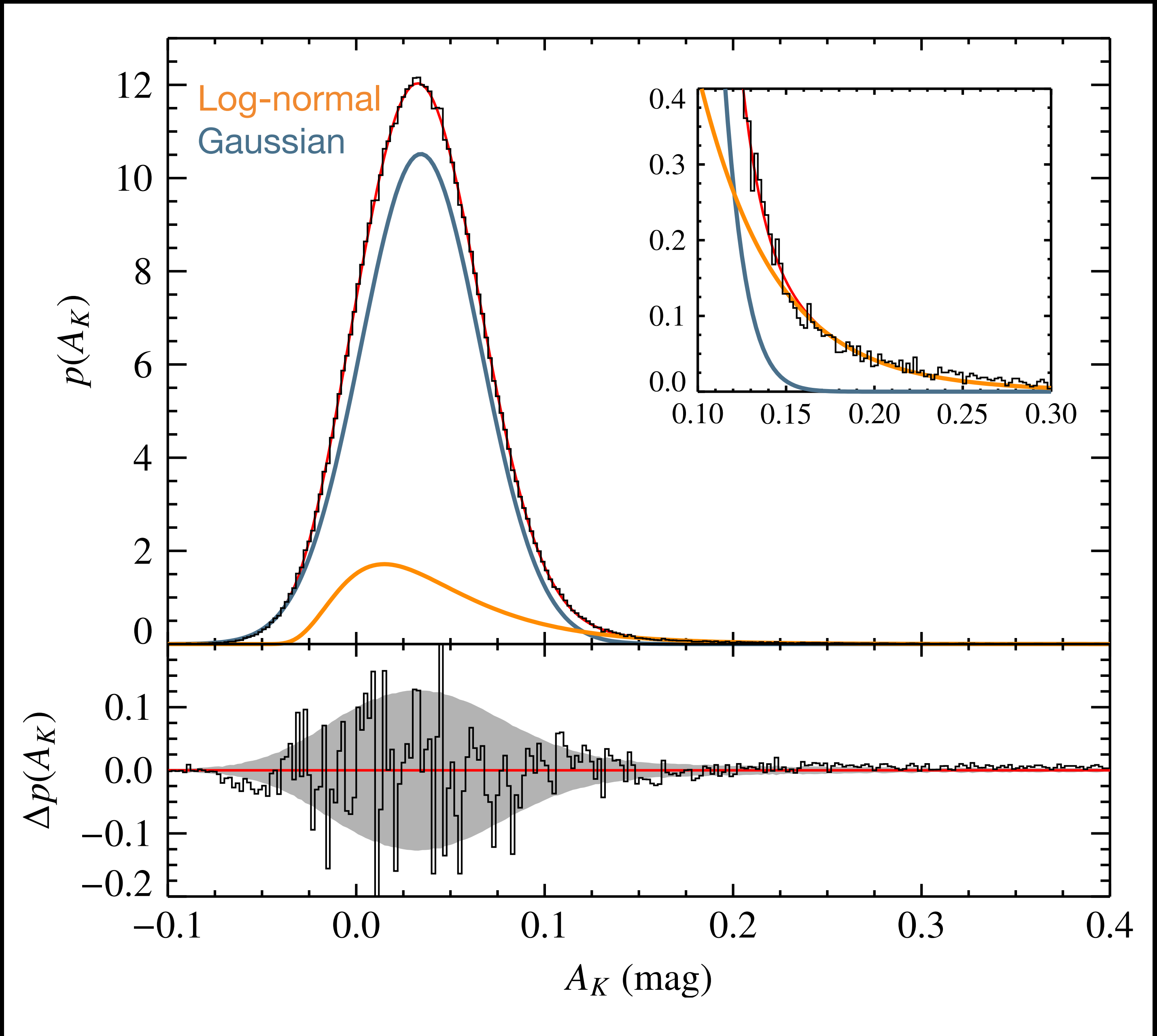
- Log-normals: are they real?



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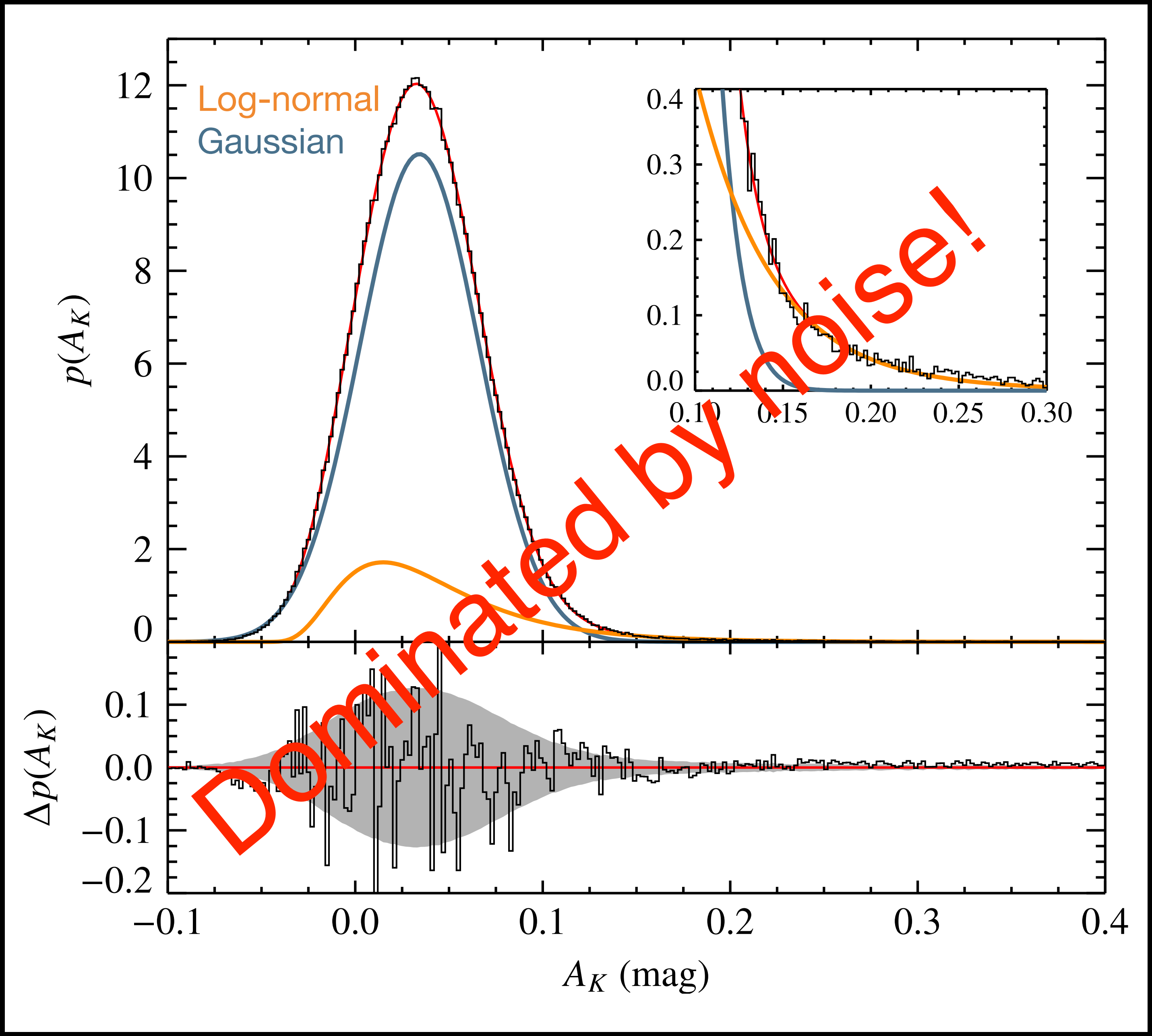
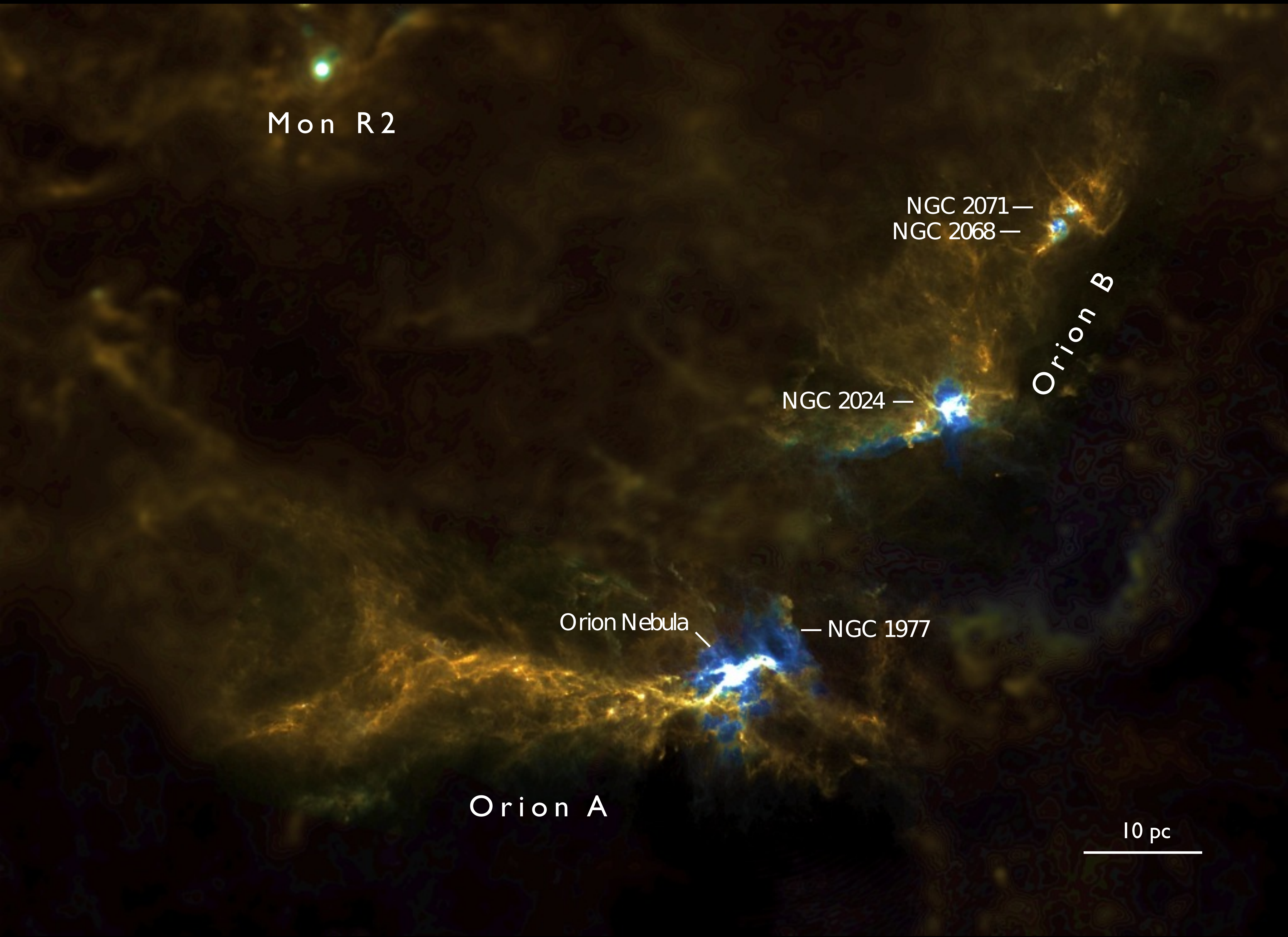


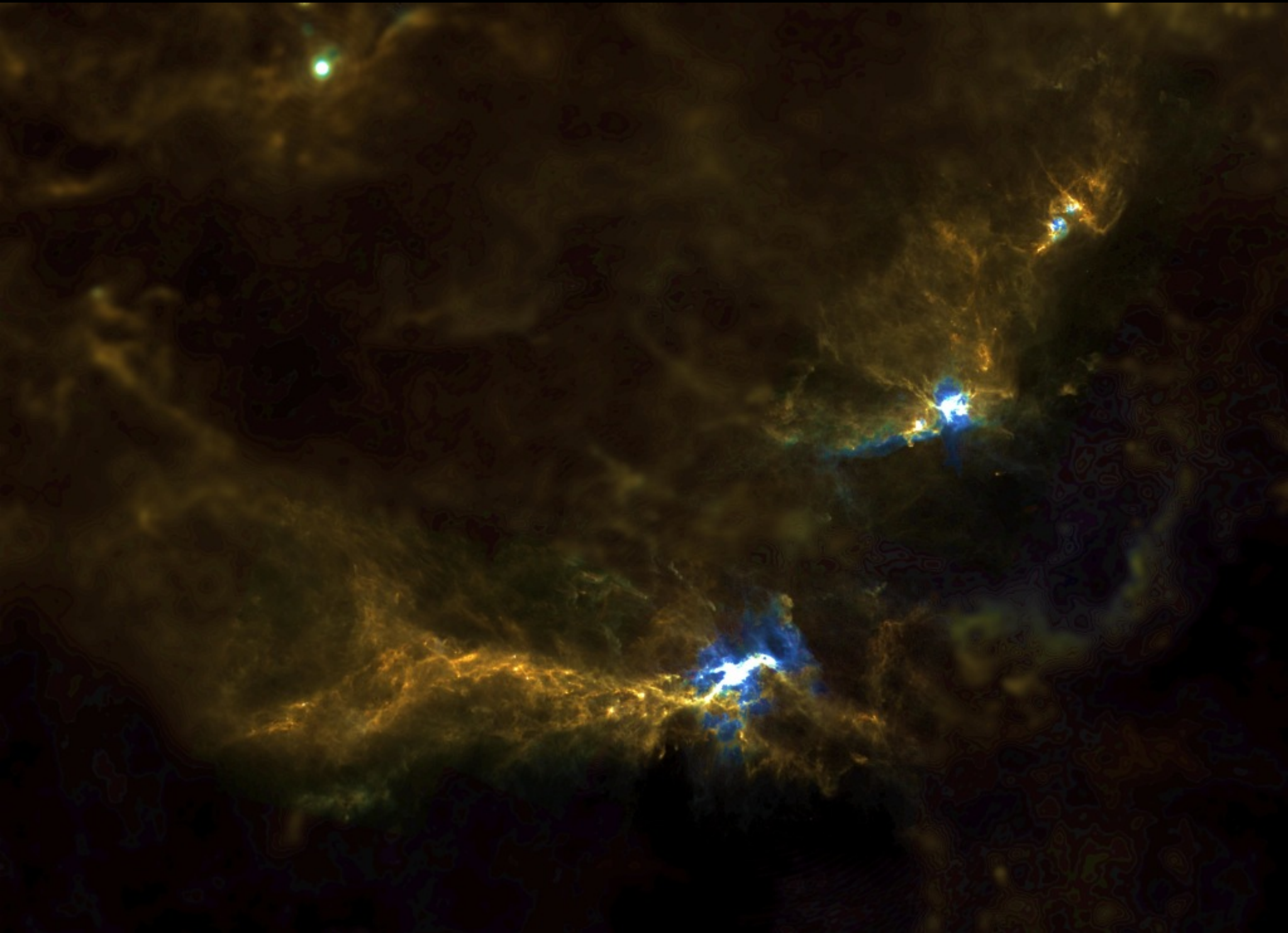
Residuals disappear when fitting a Gaussian + Log-normal.

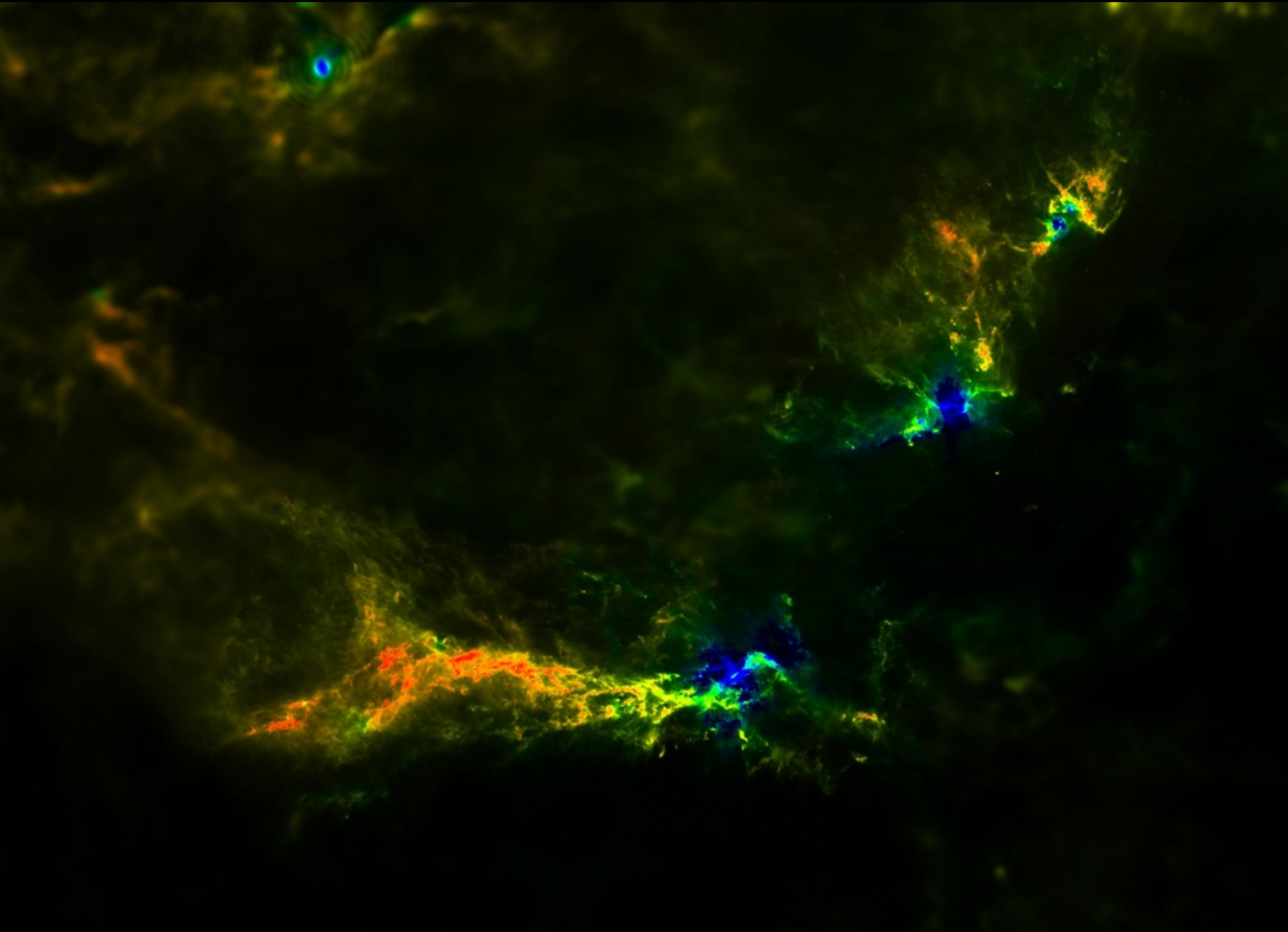
Alves et al. (2014)

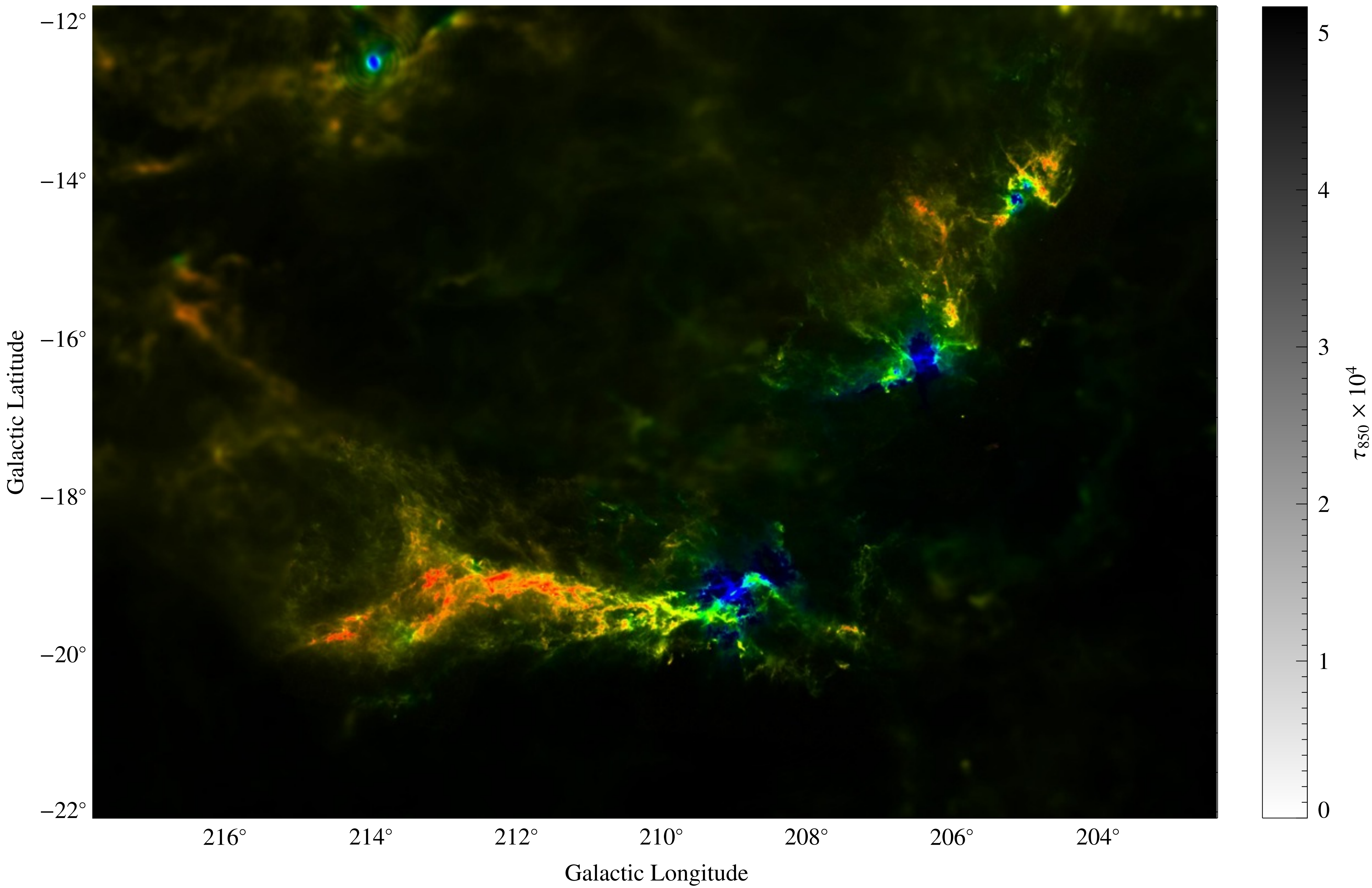
We need high-resolution, low-noise density maps of molecular clouds

i.e., Herschel data…


Mon R2
NGC 2071
NGC 2068
Orion B
NGC 2024
Orion Nebula
NGC 1977
Orion A
10 pc







−12°
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Galactic Latitude
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Galactic Longitude
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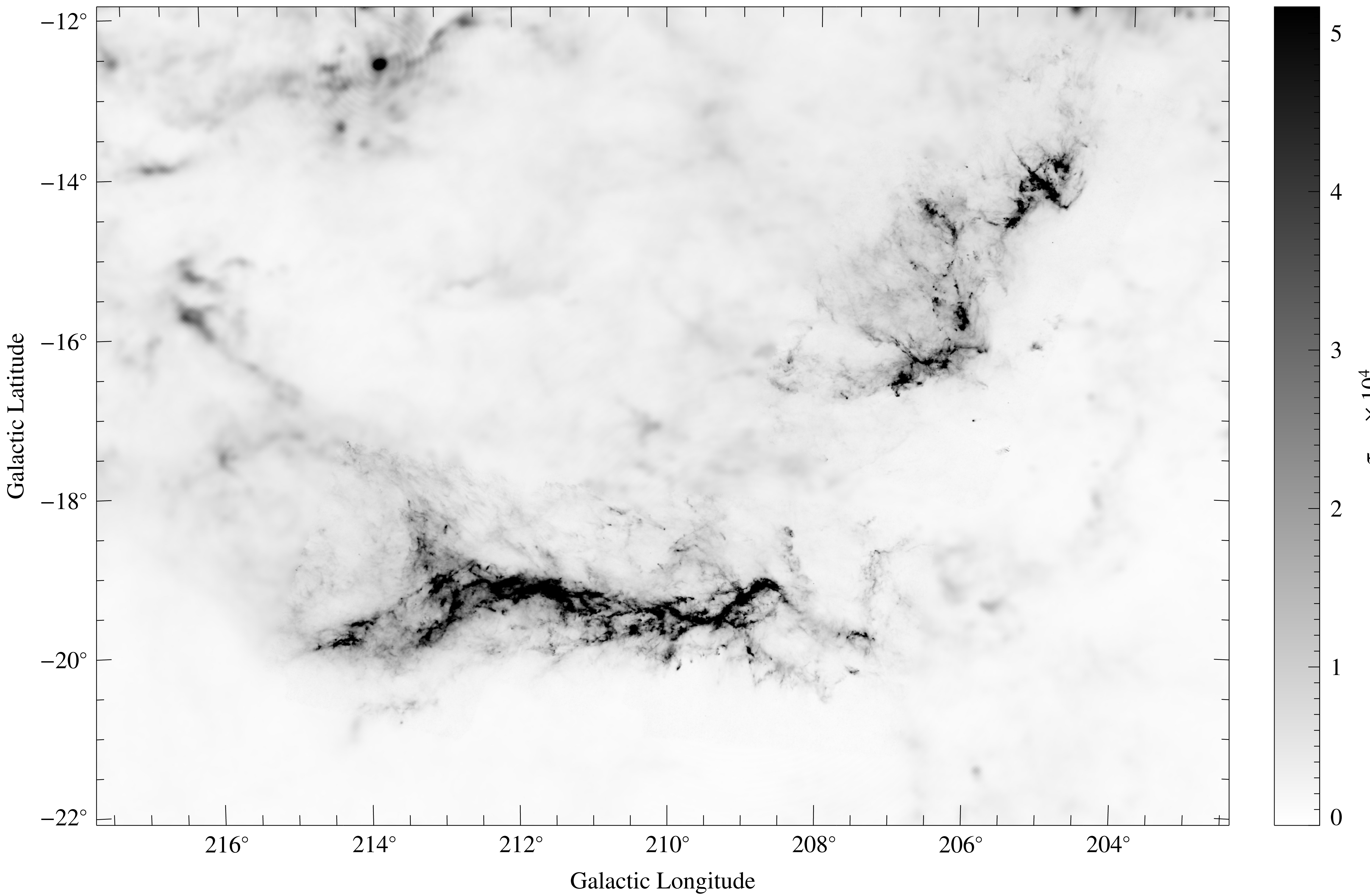
$\tau_{850} \times 10^4$



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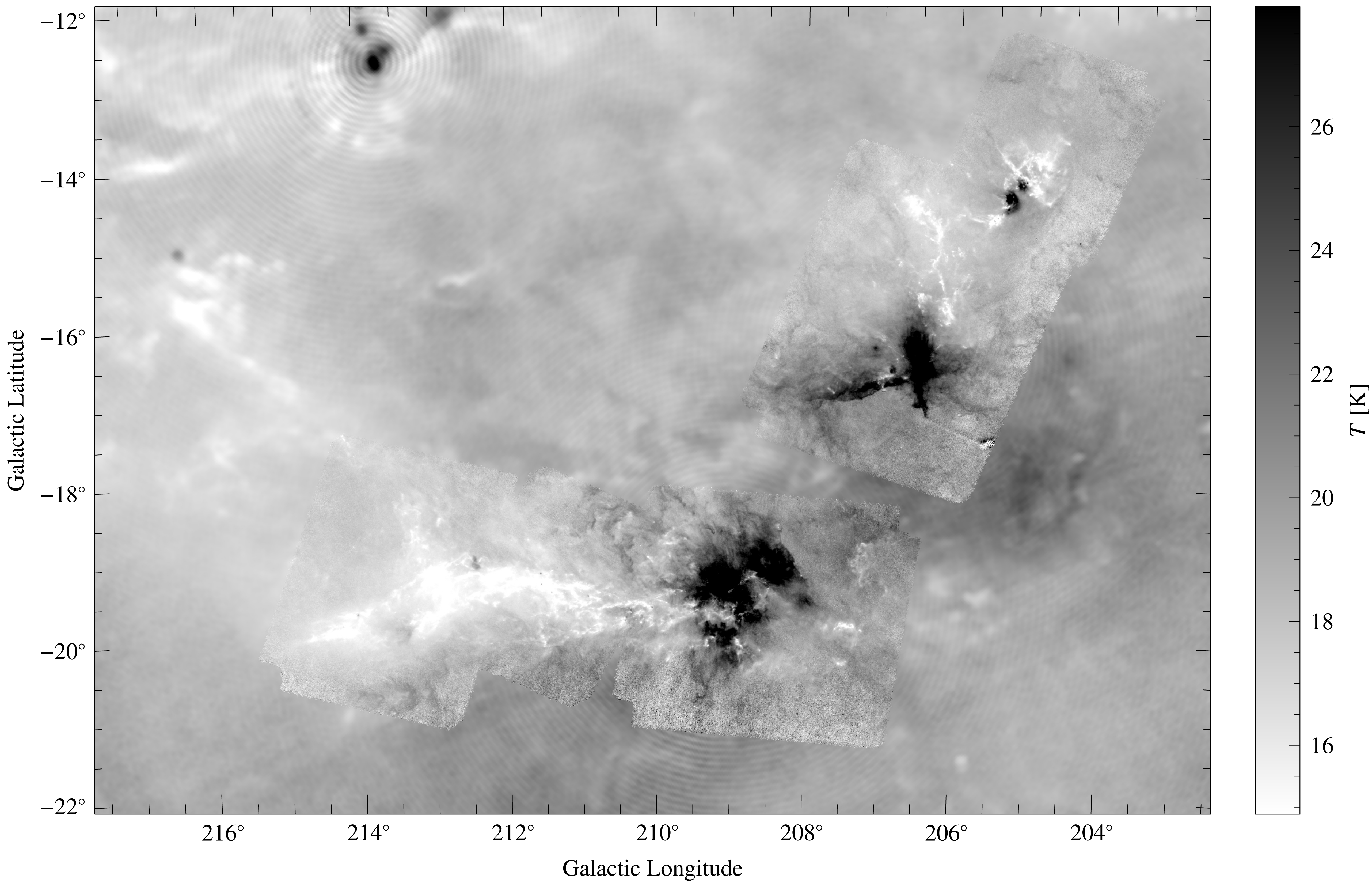

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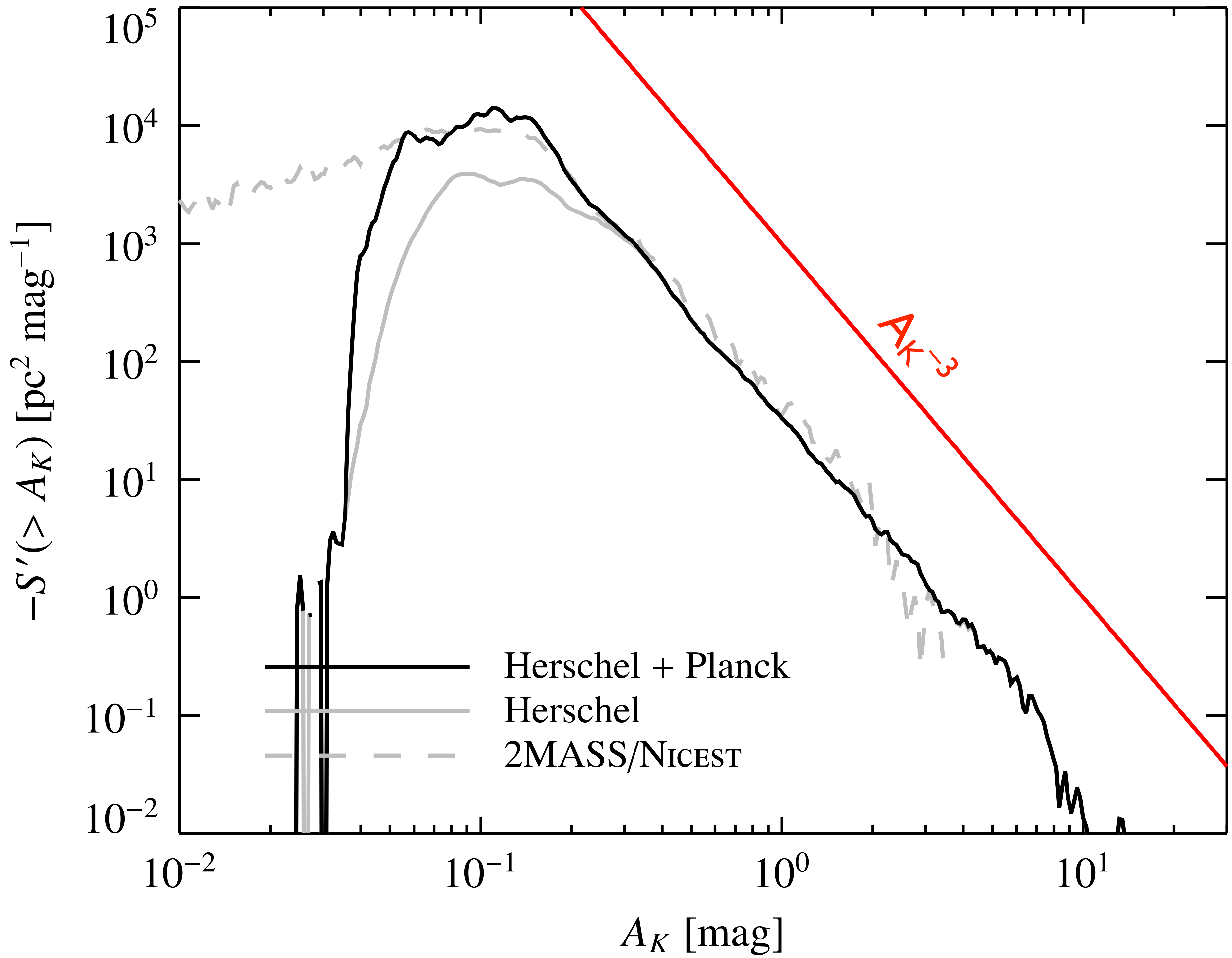
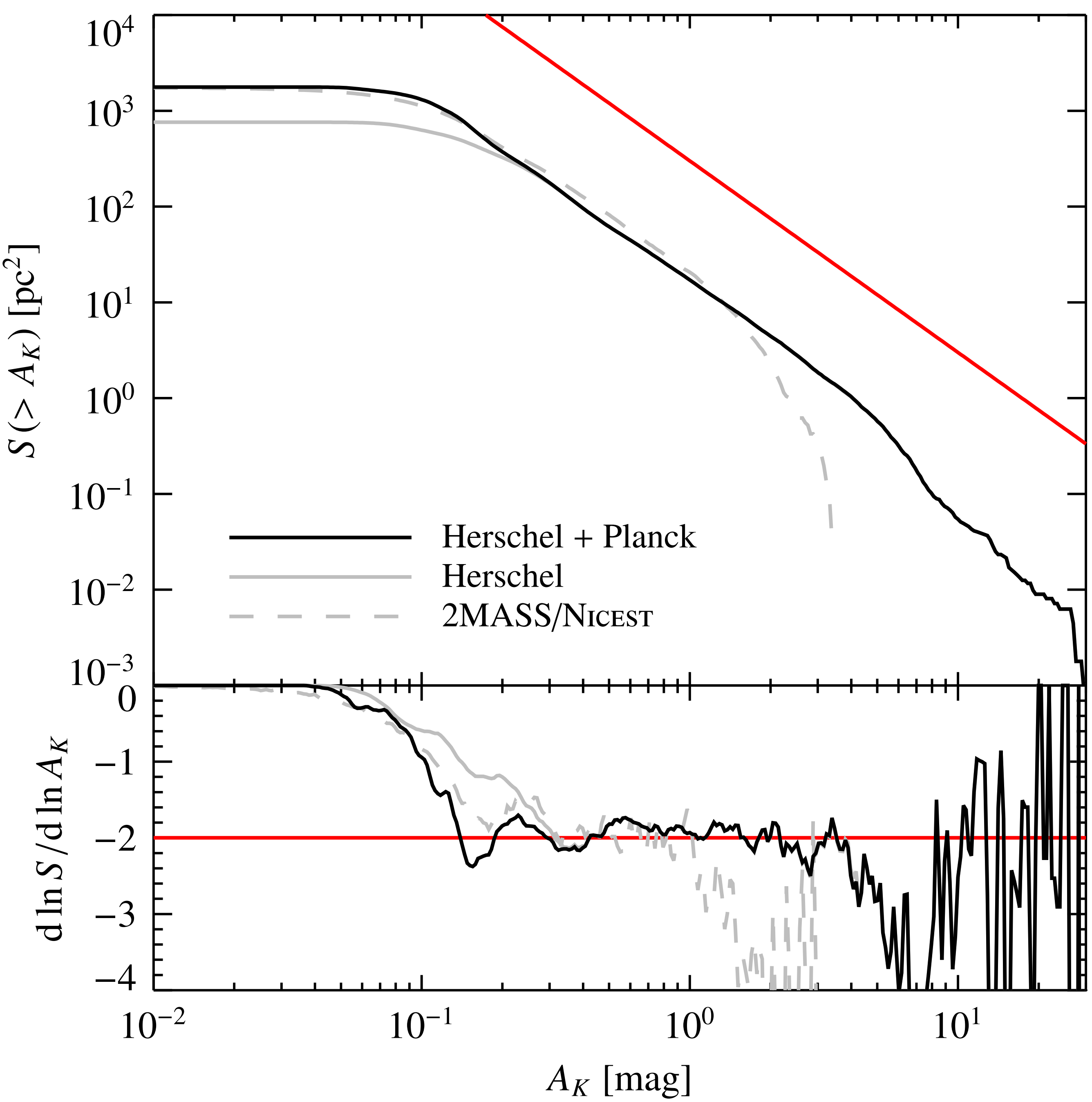
Herschel PDF for Orion B



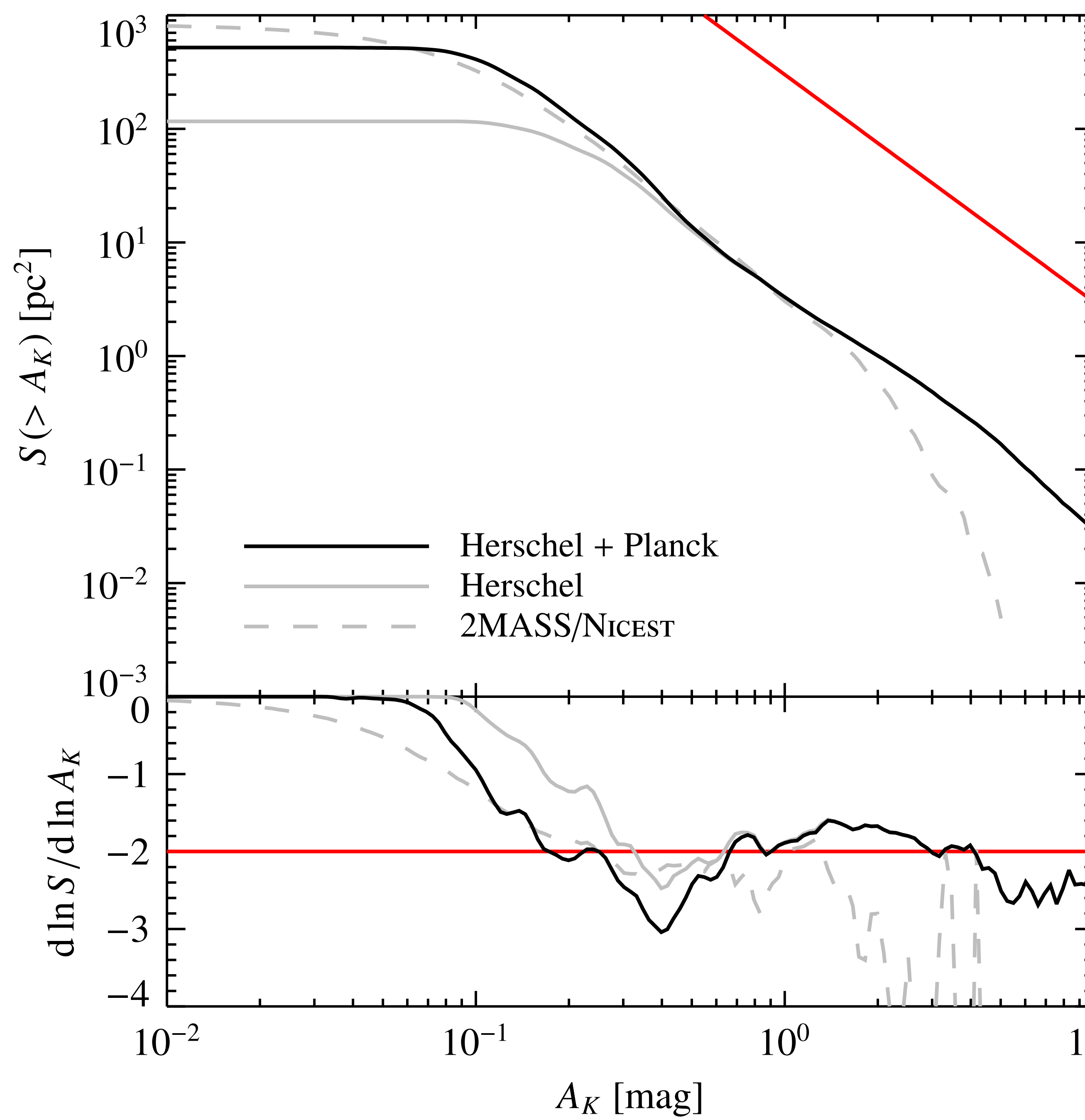
Lombardi et al. (2014)

Fact 5
Scaling laws play a fundamental role in SF

Area functions (integrals of PDFs)

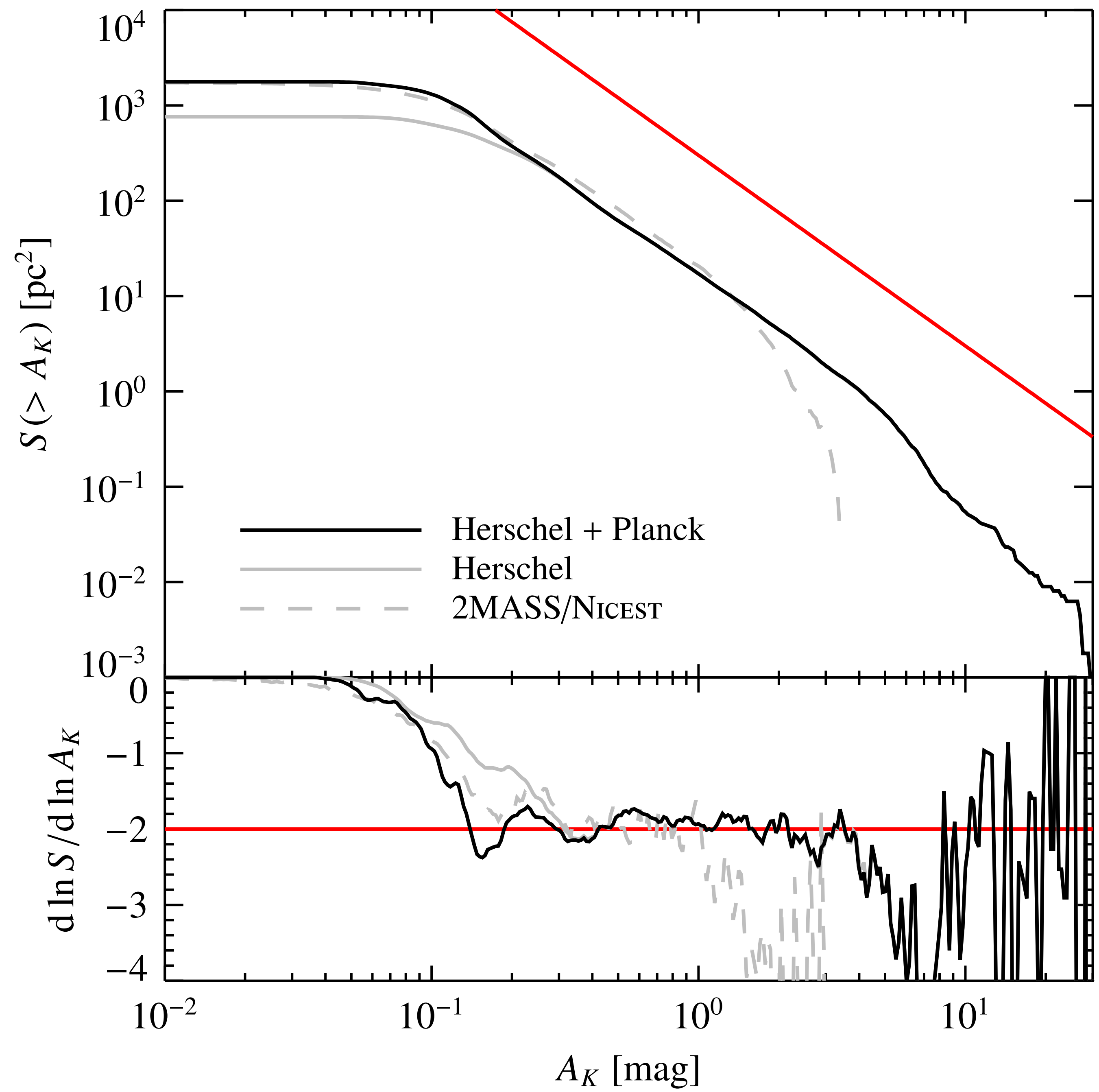


Lombardi et al. (2014)



Alves et al. (2014)

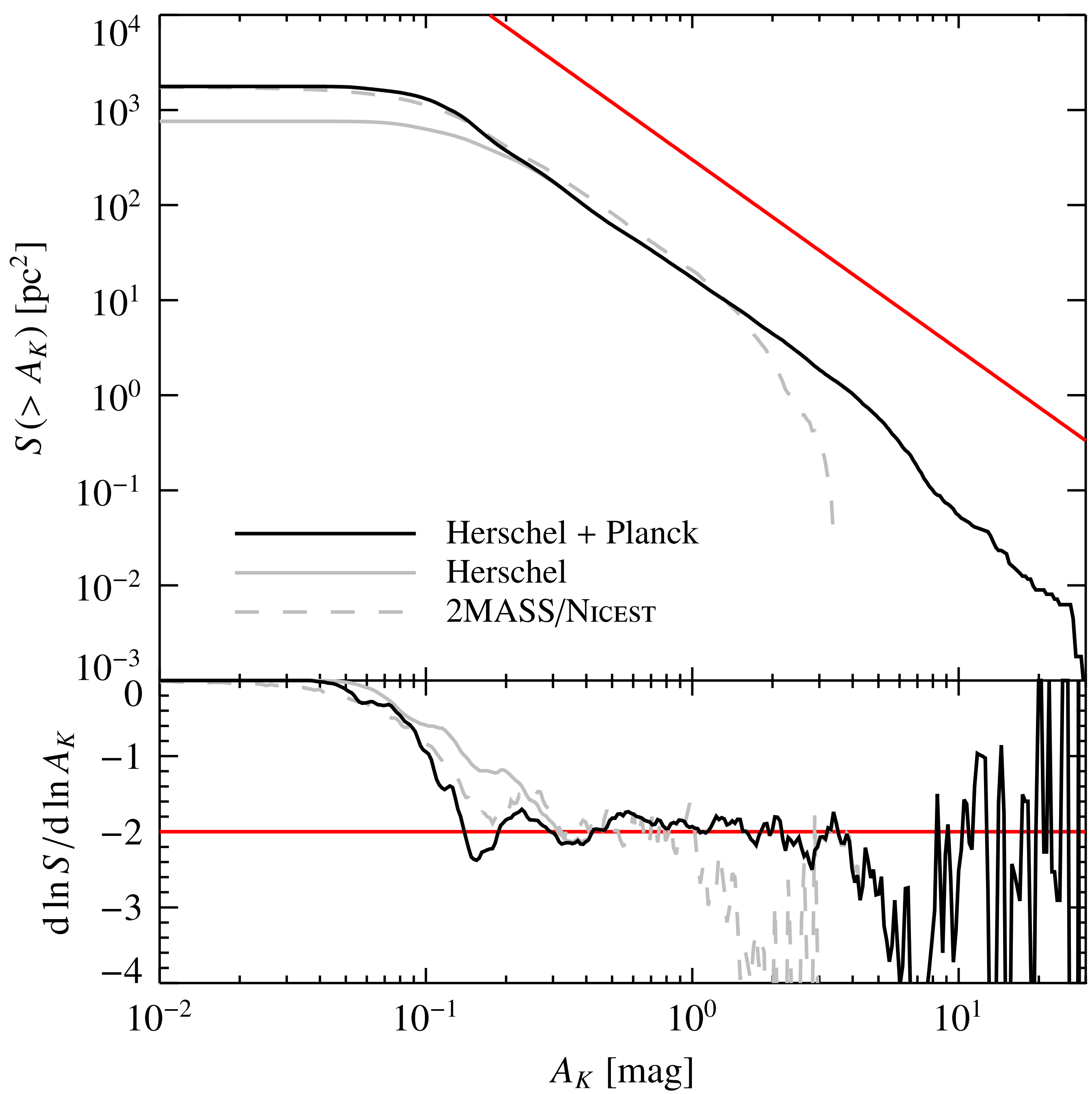
Toy model



Lombardi et al. (2014)

Toy model

Consider an isothermal sphere:



Lombardi et al. (2014)

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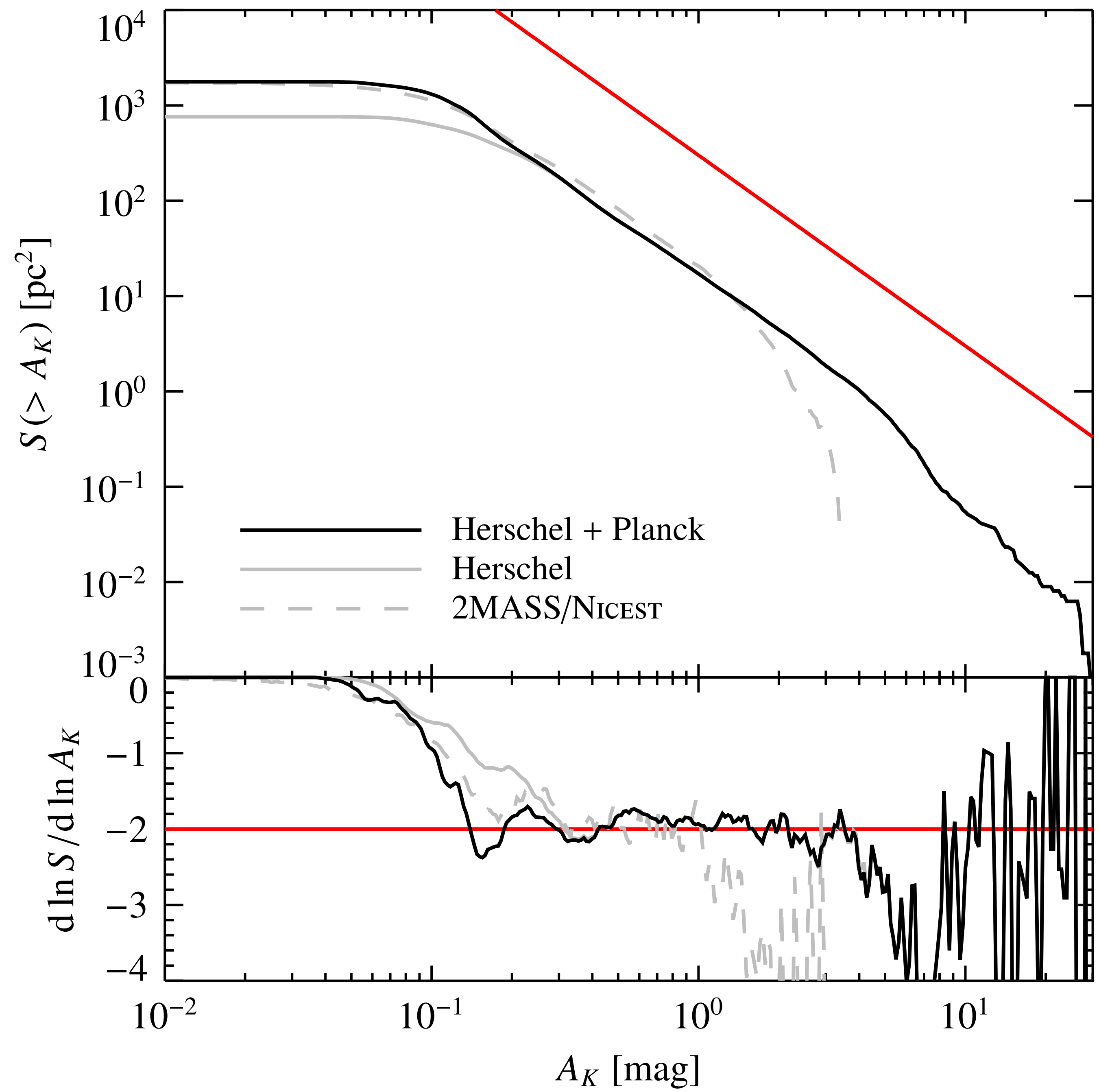
Consider an isothermal sphere:

$\rho \sim R^{-2}$



Lombardi et al. (2014)

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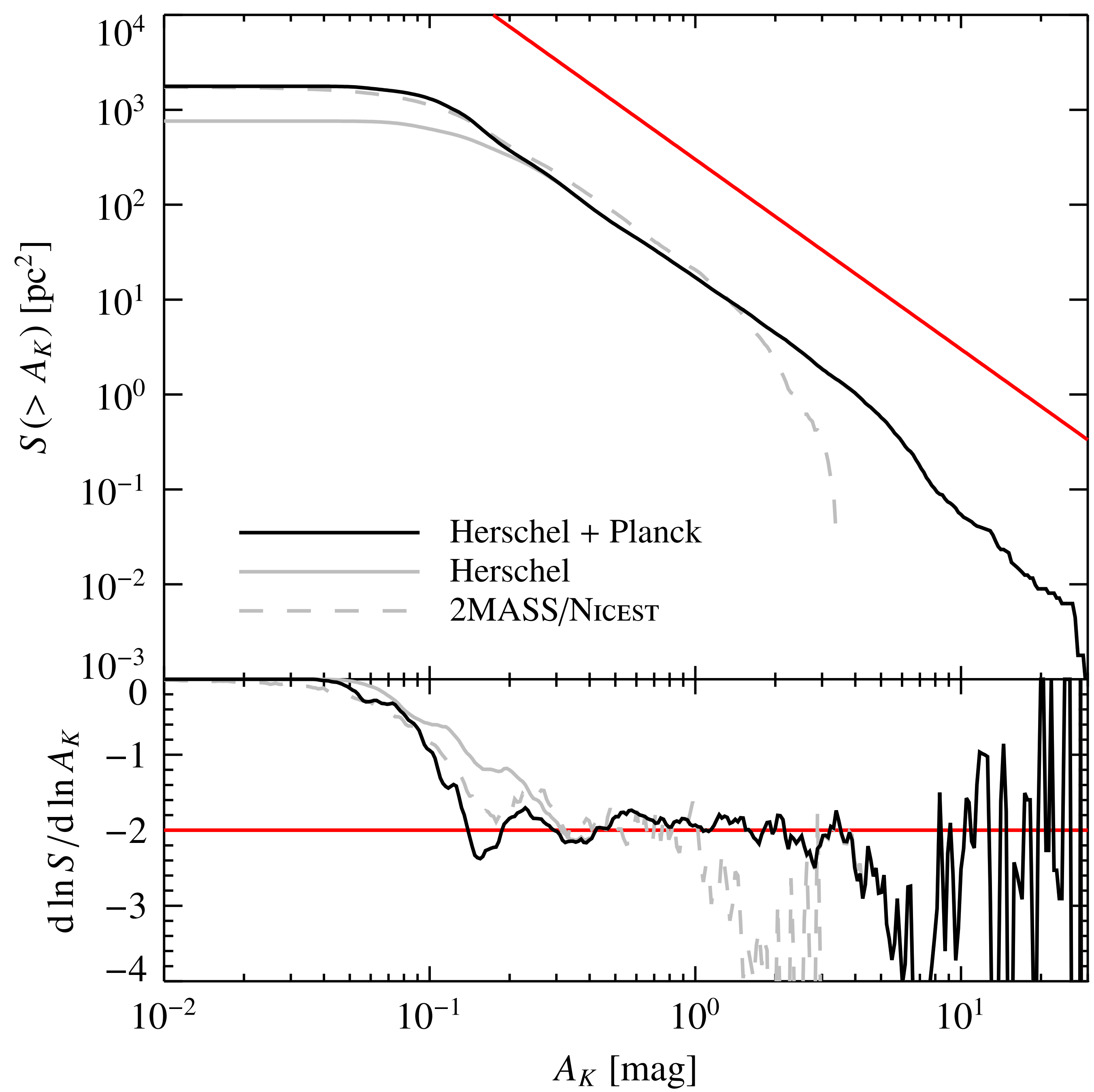

Lombardi et al. (2014)

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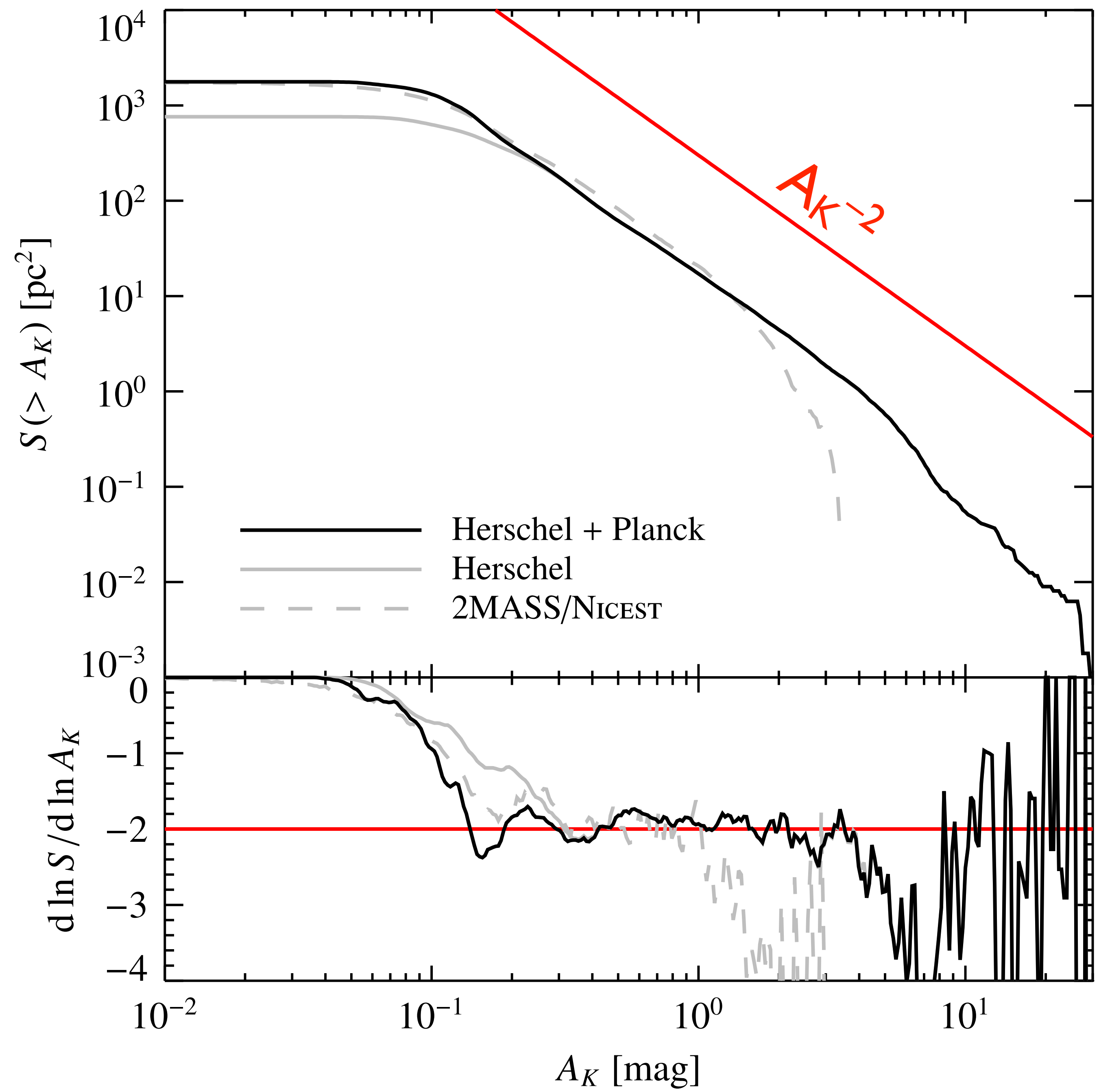

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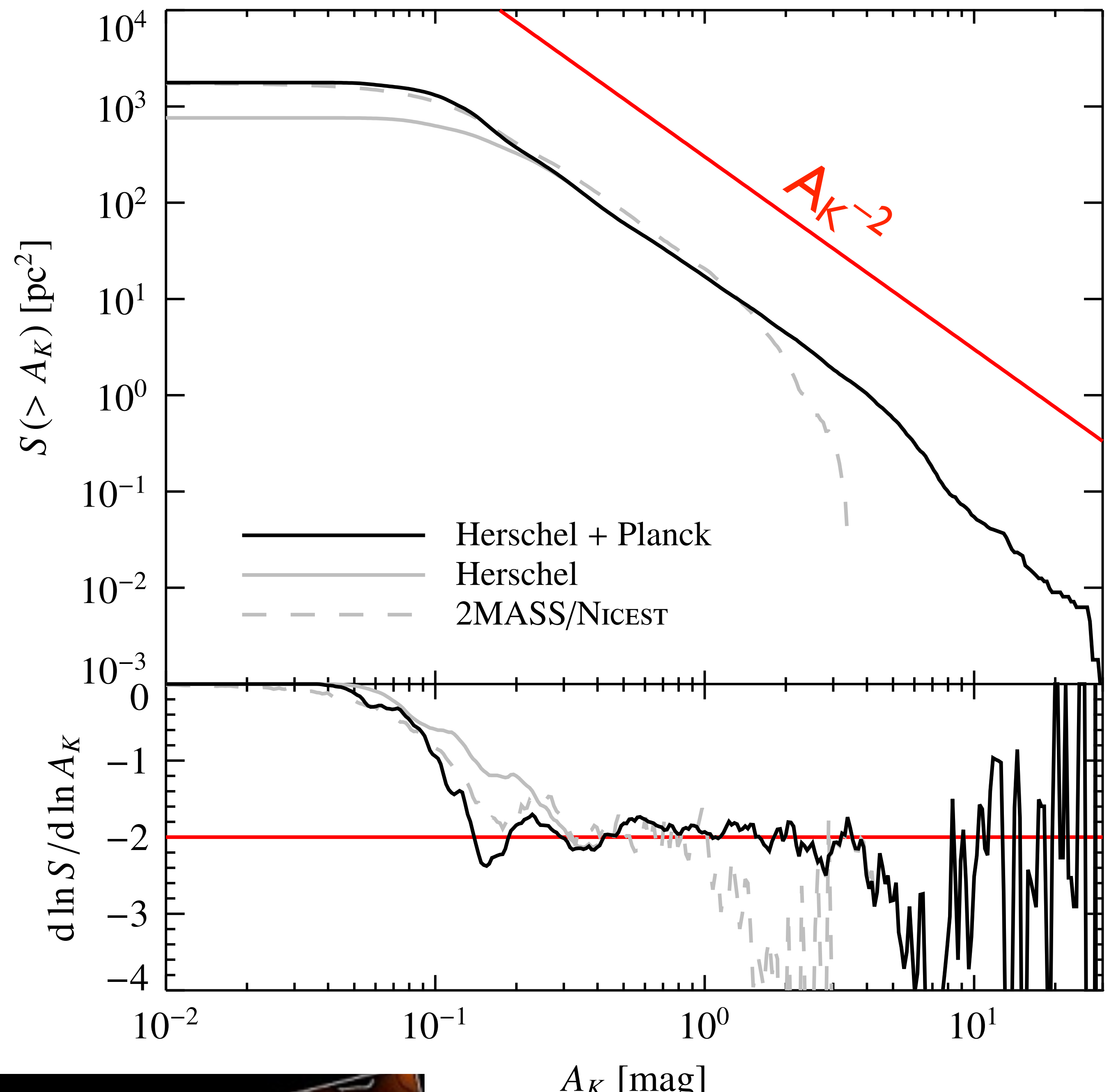
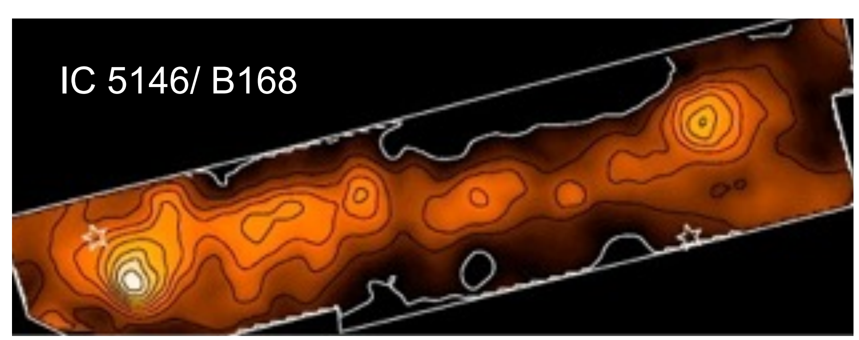
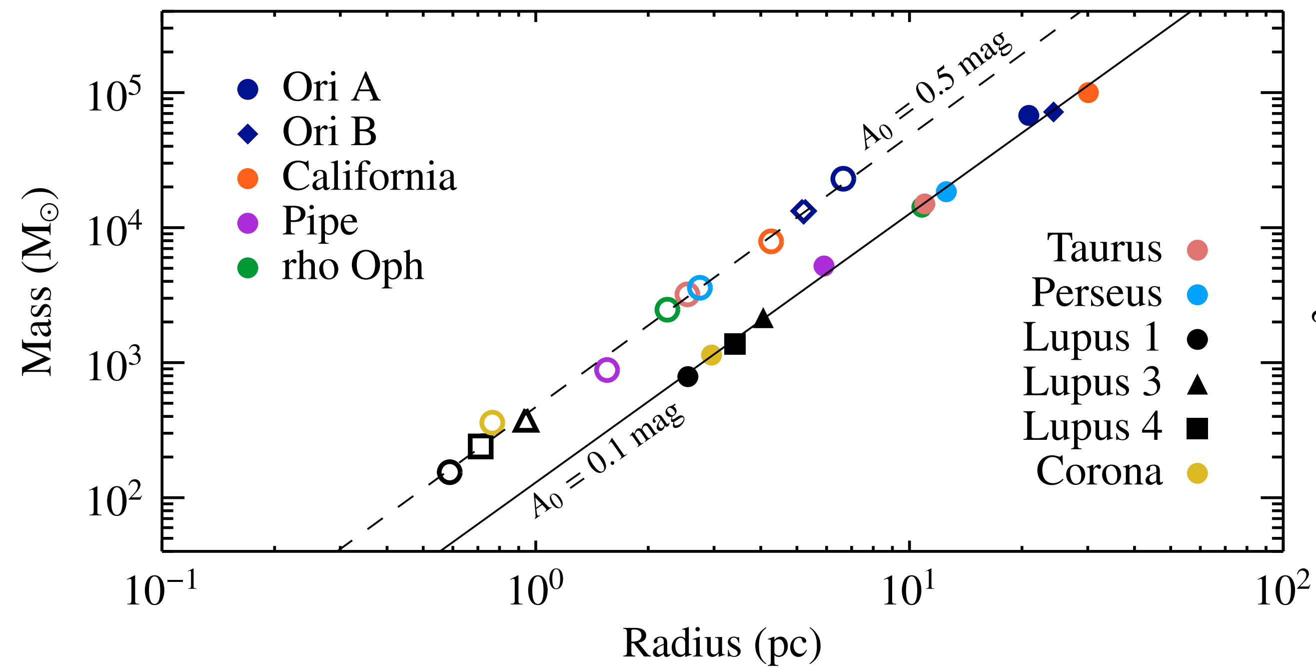
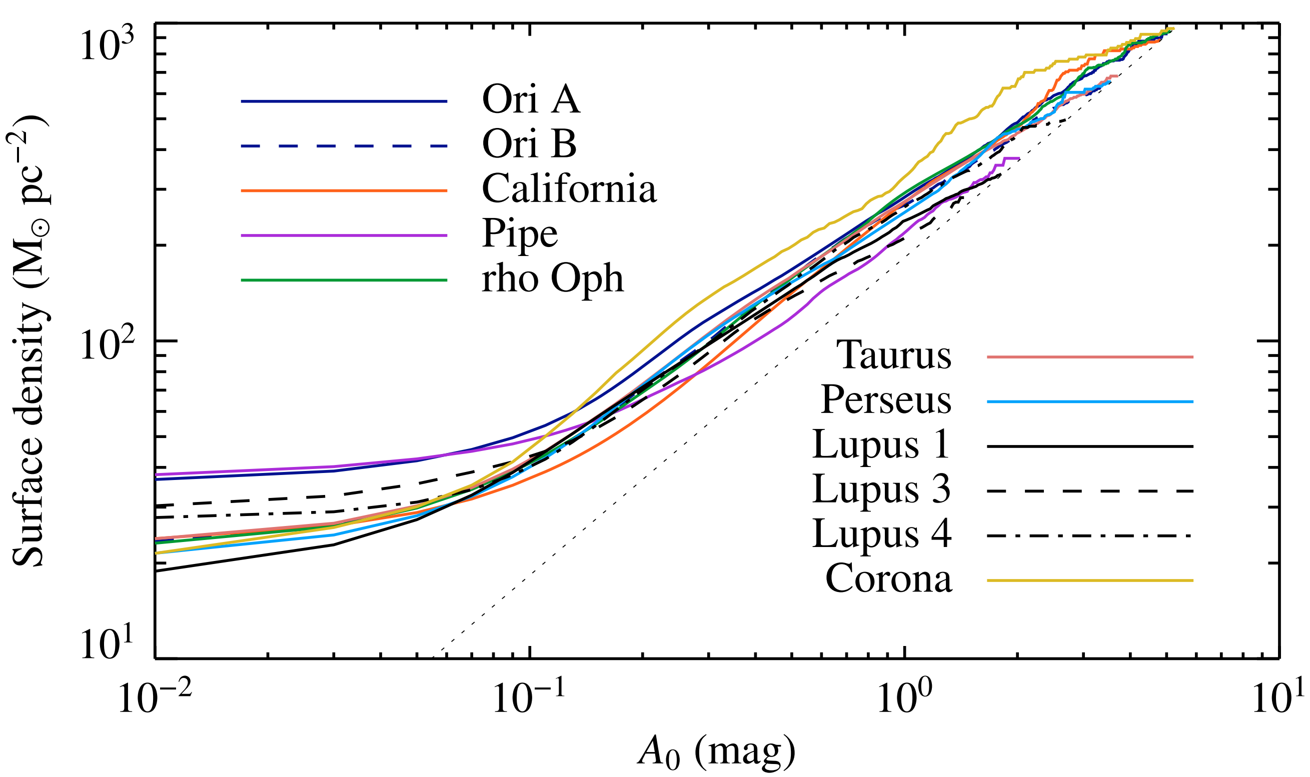


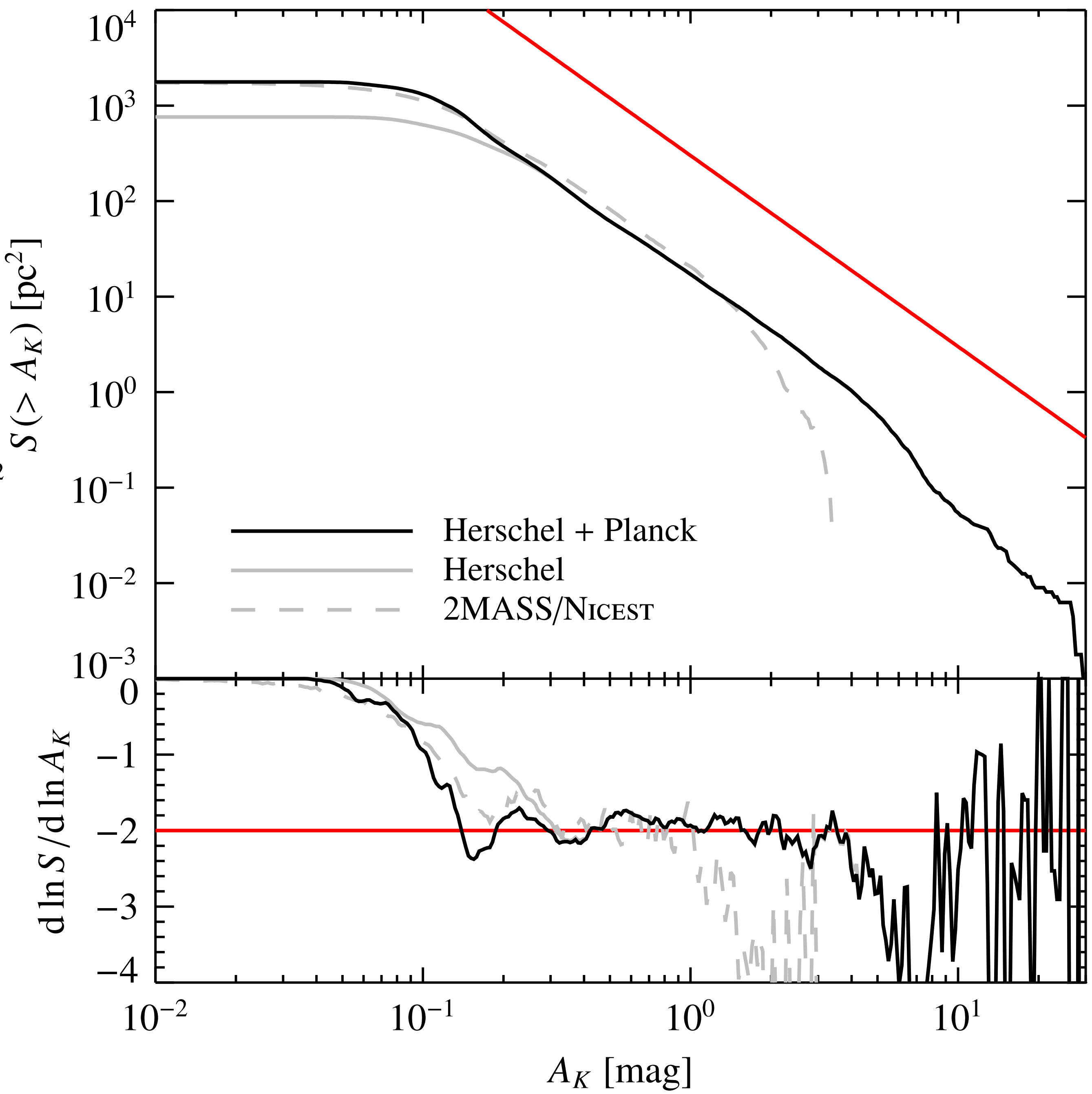


Lombardi et al. (2014)

3rd Larson's law







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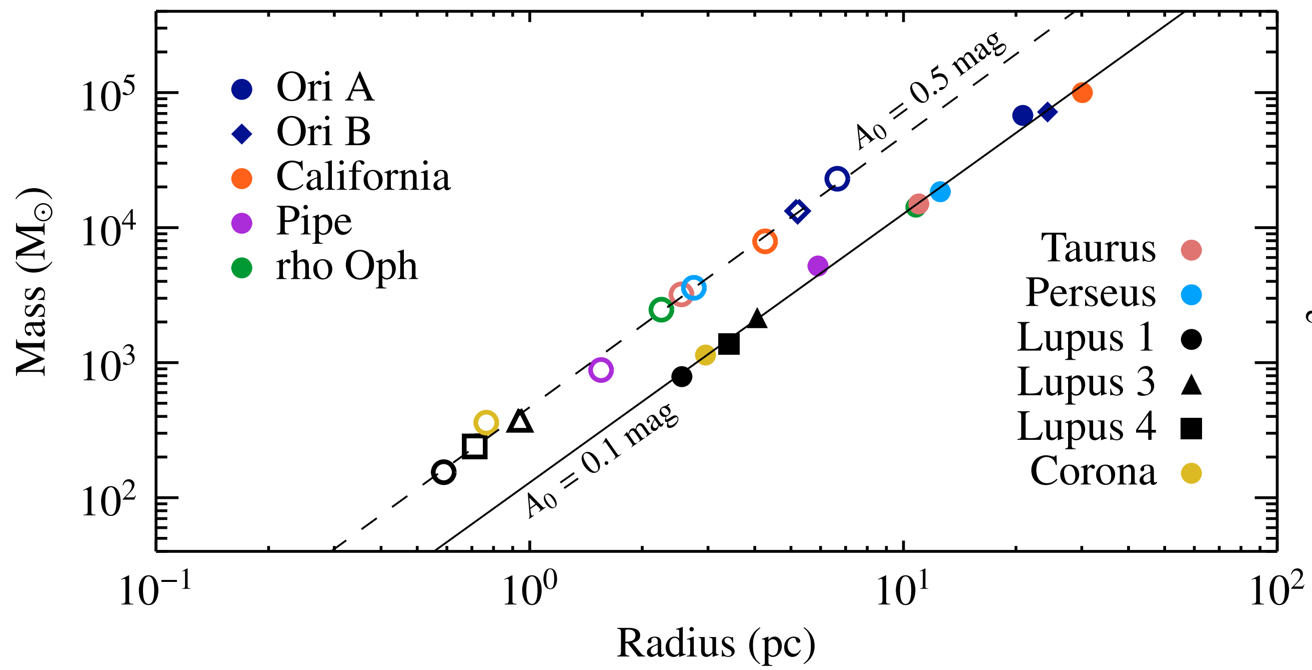
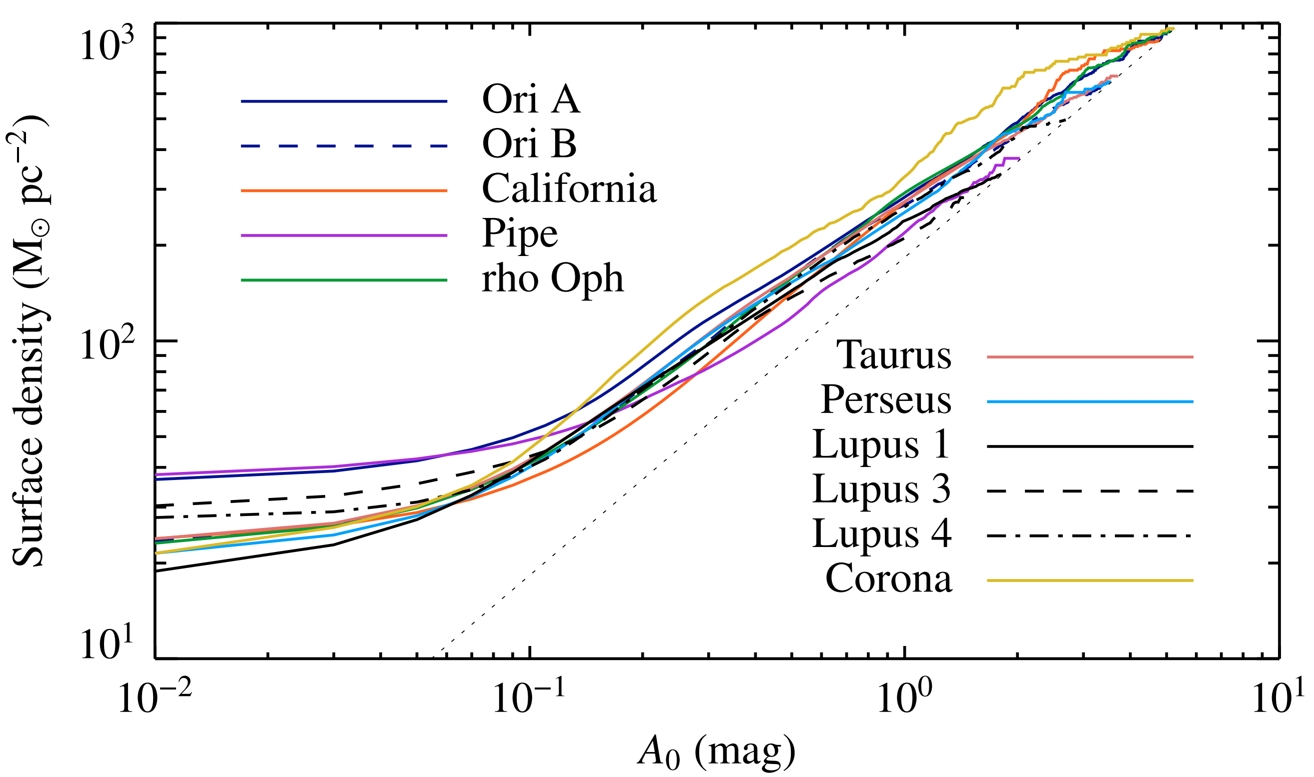
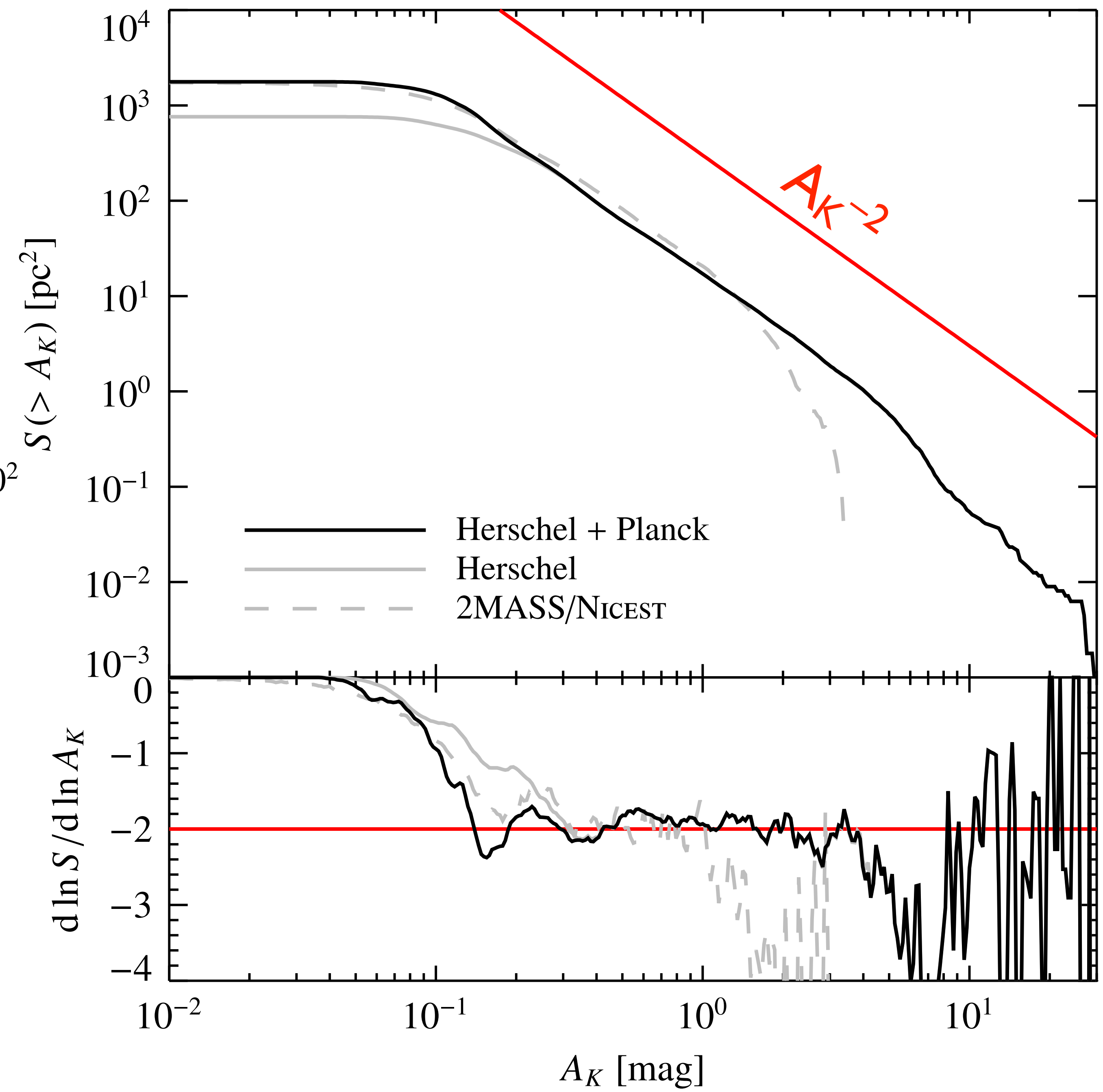
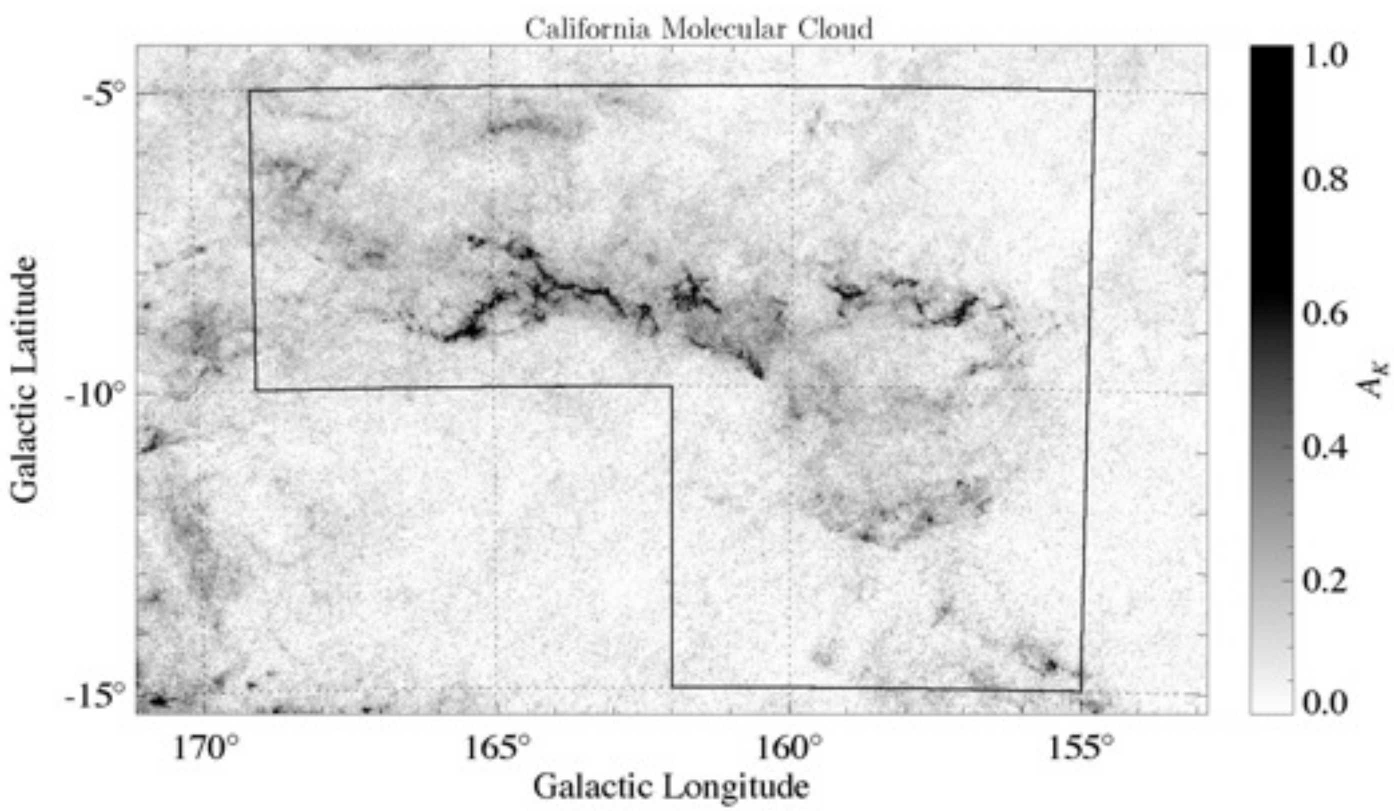


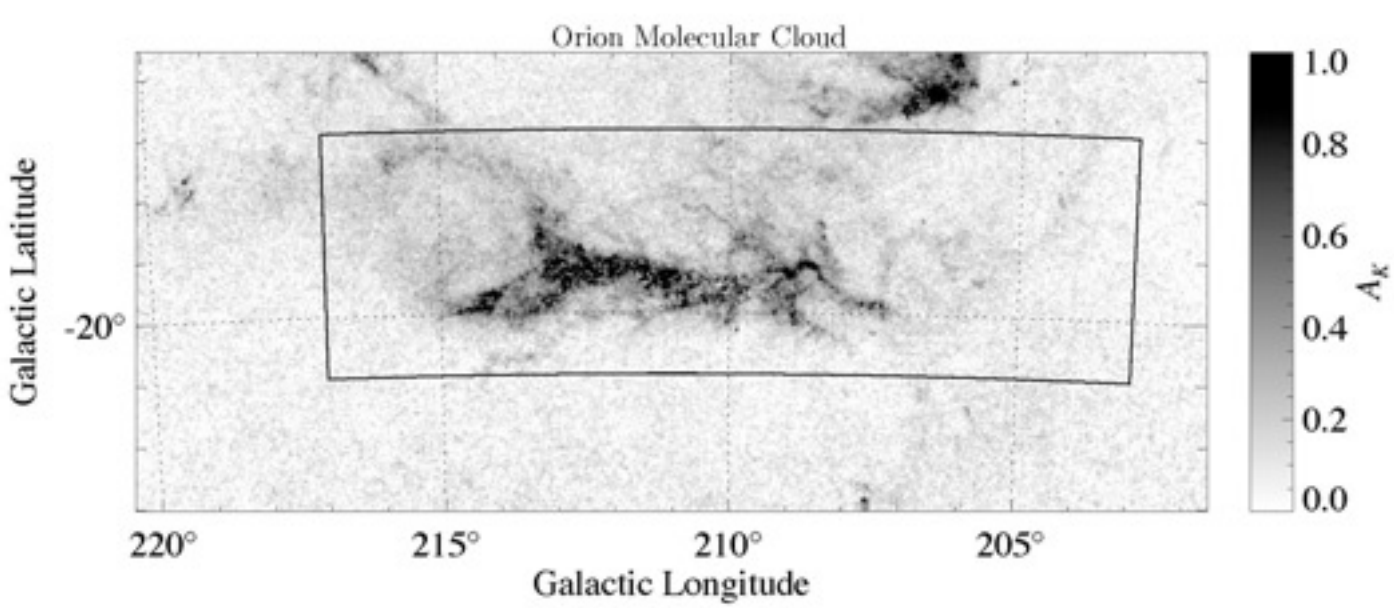




Lombardi et al. (2014)

SFRs in the California and Orion molecular clouds





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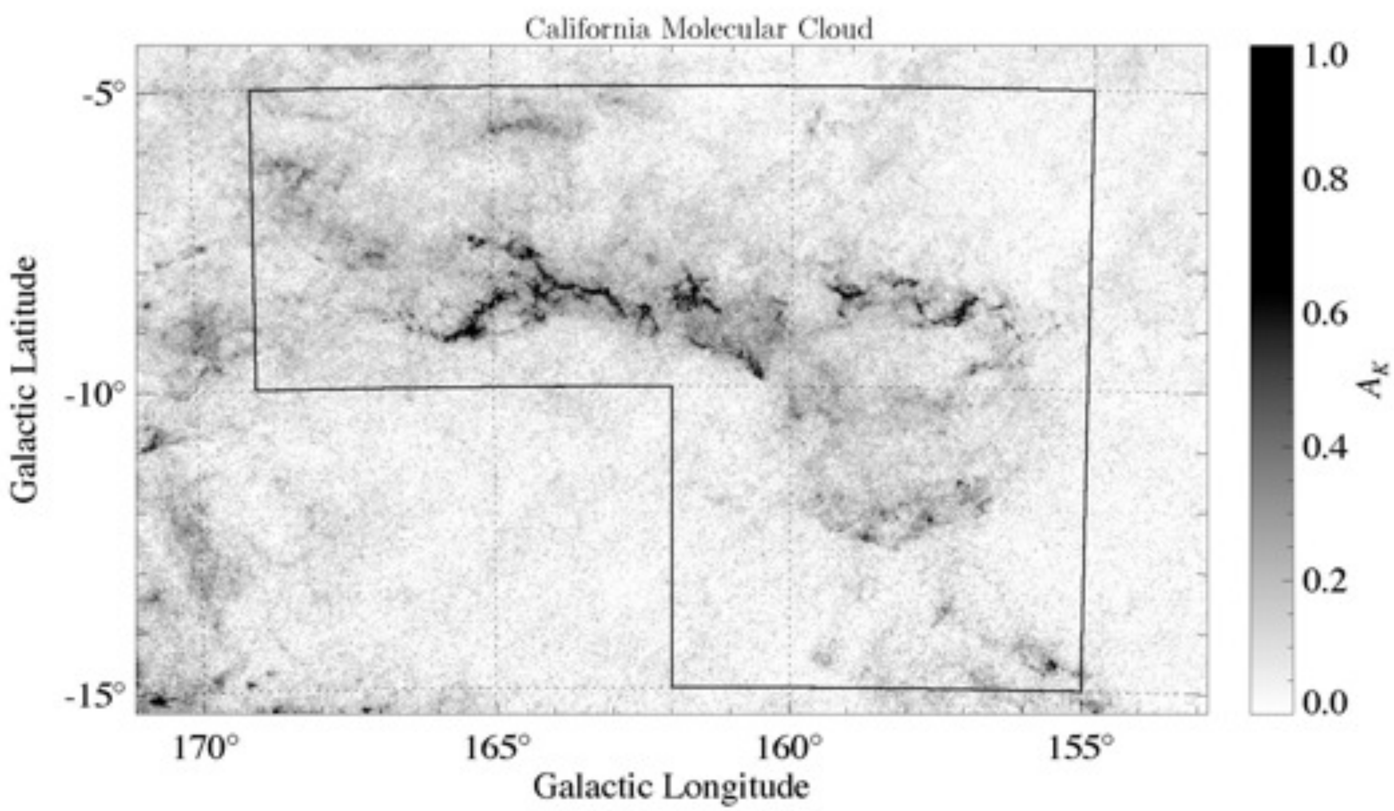

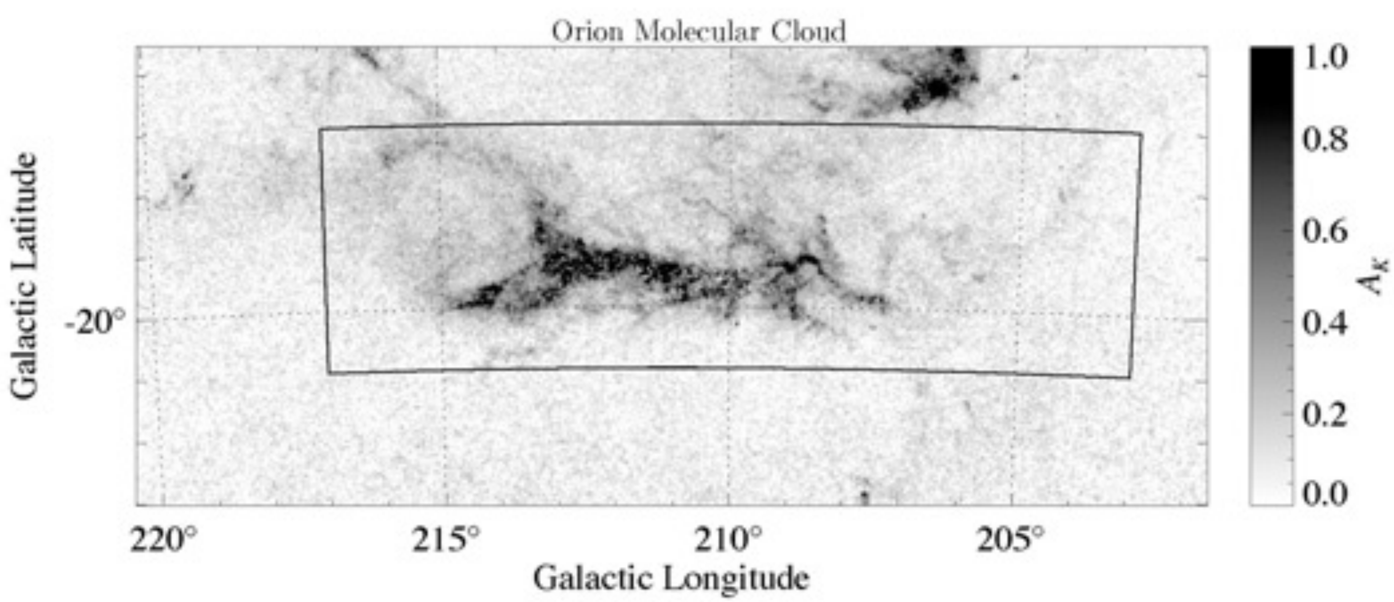

Nearly identical shapes & sizes, but

YSOs(Orion) > 10 × YSOs(California)

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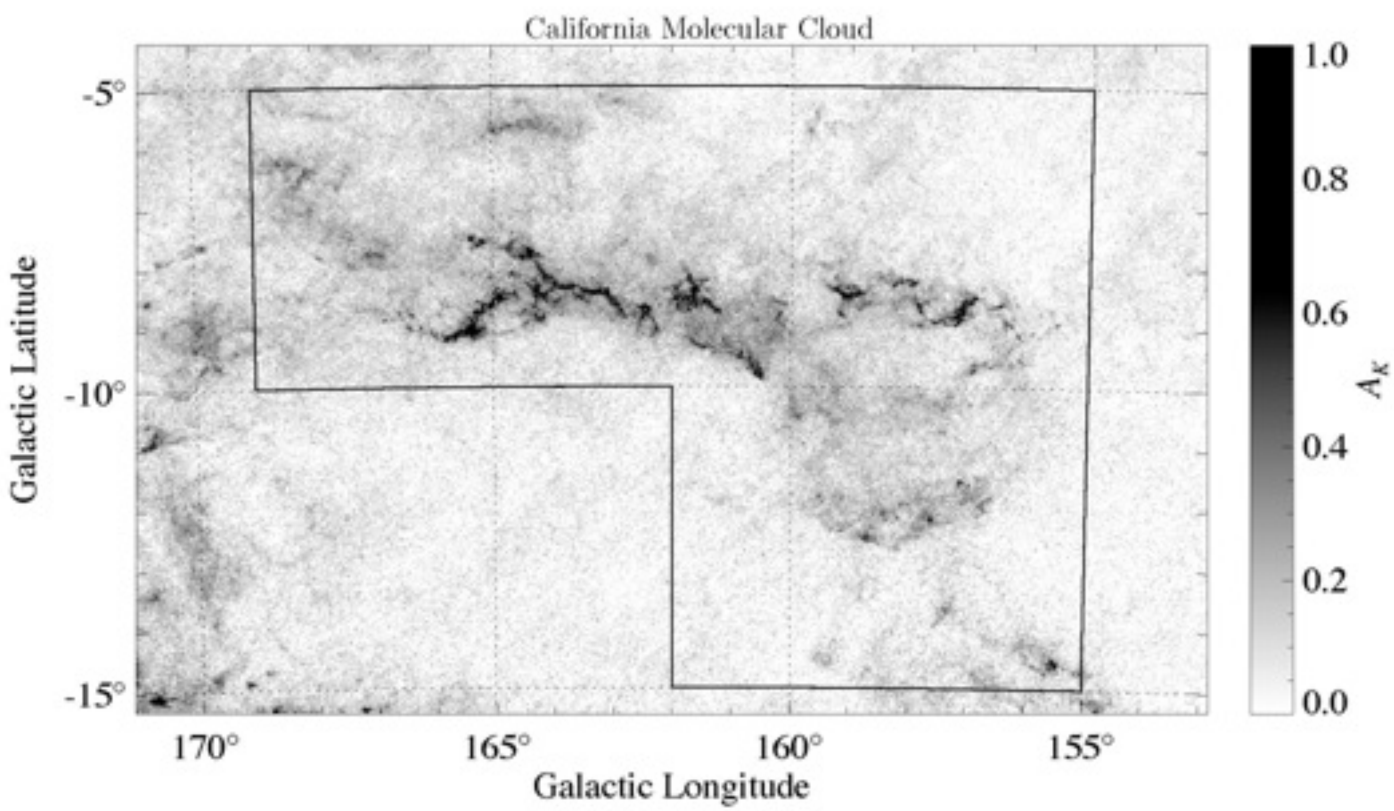

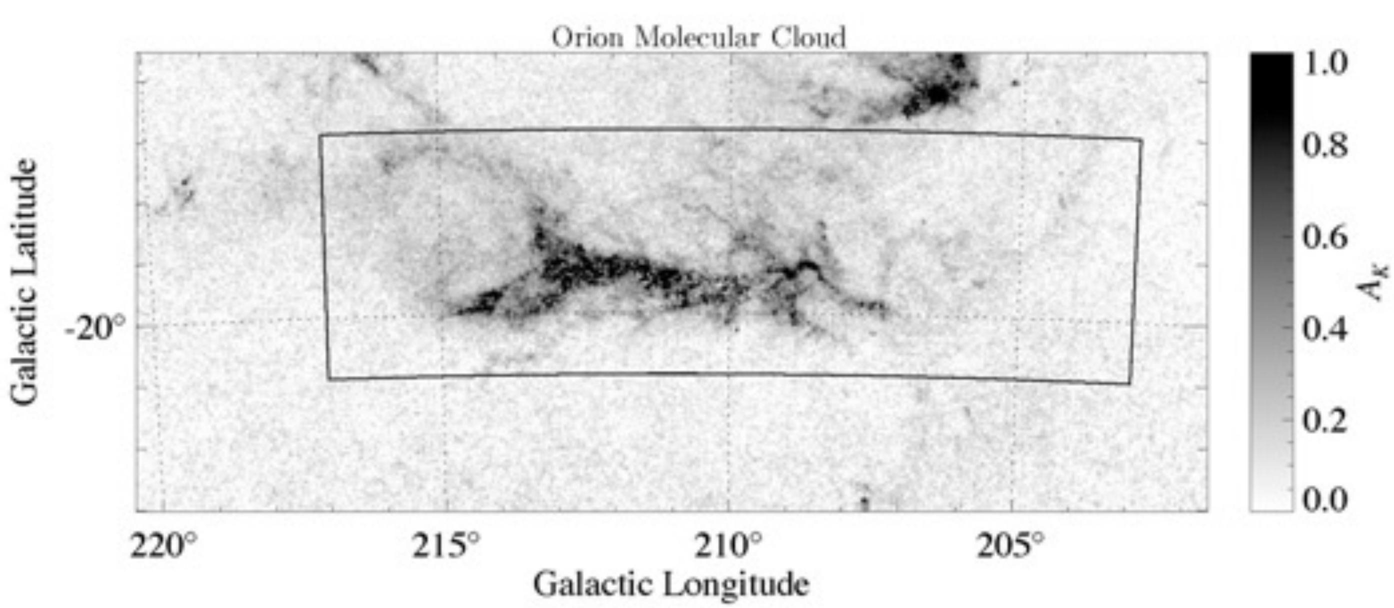

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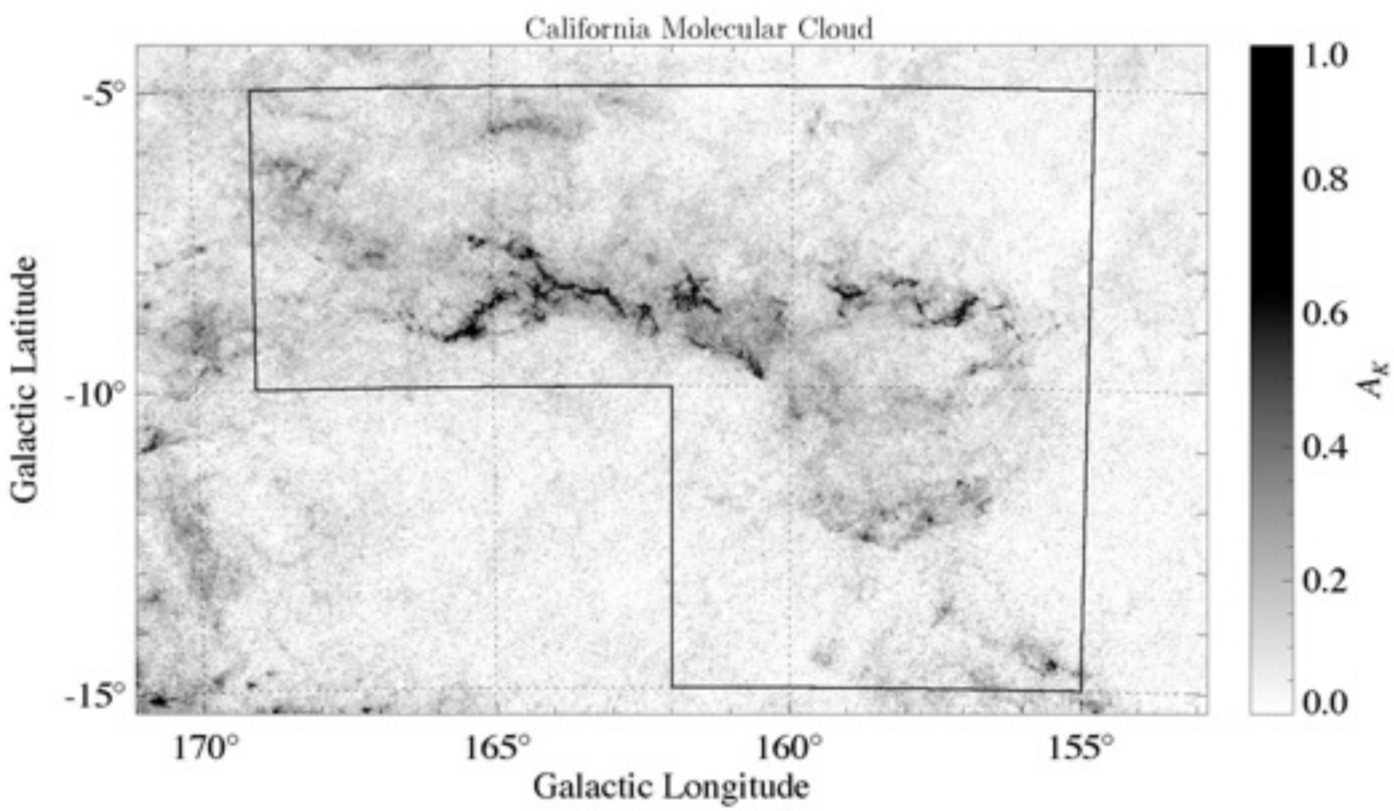

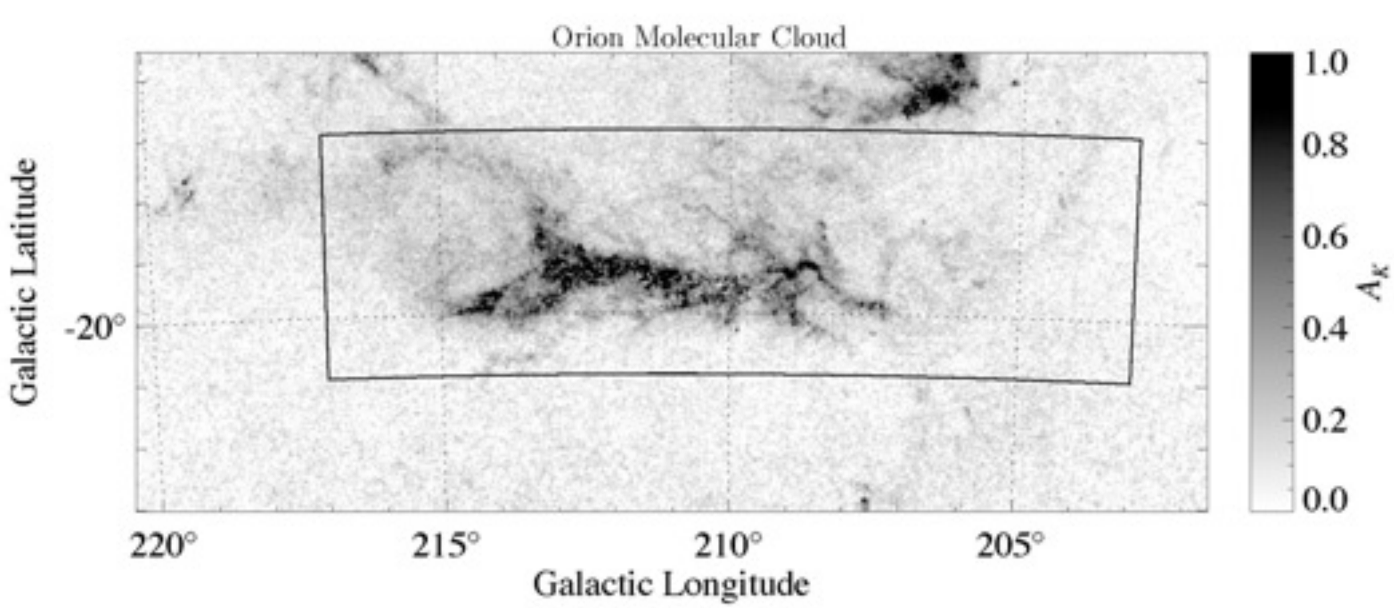

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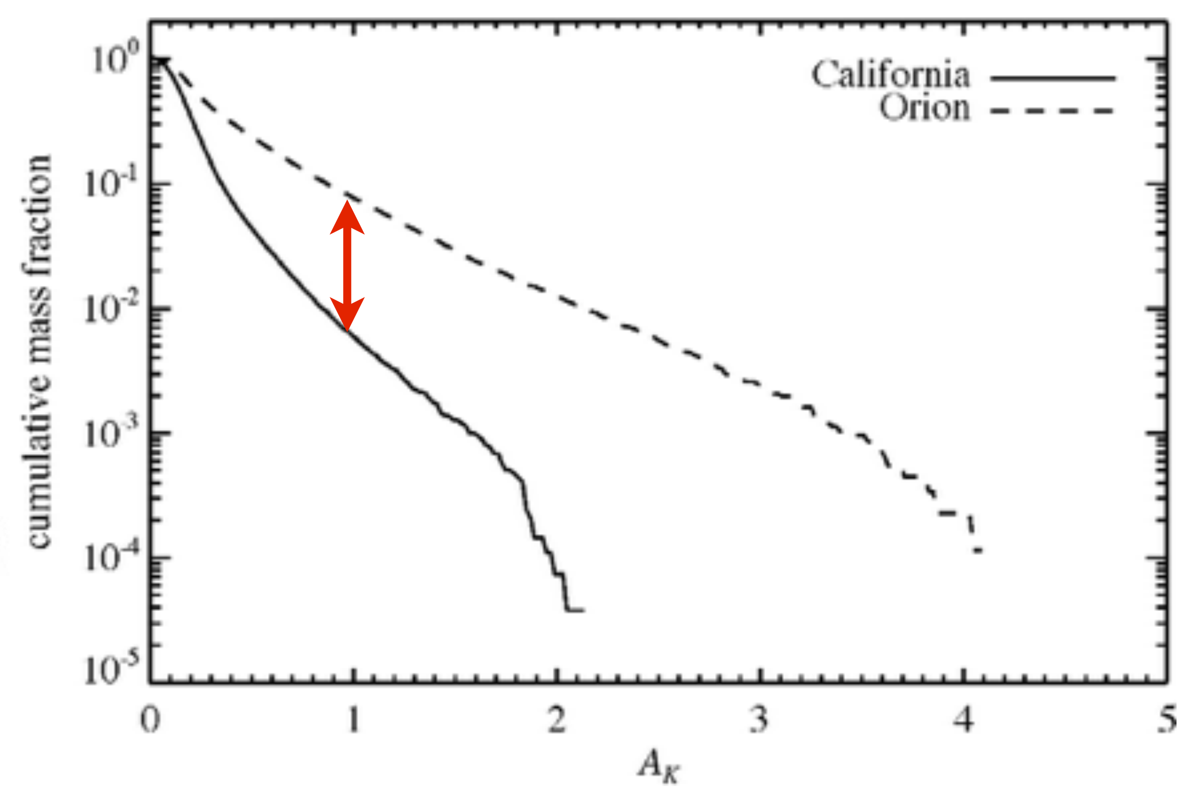

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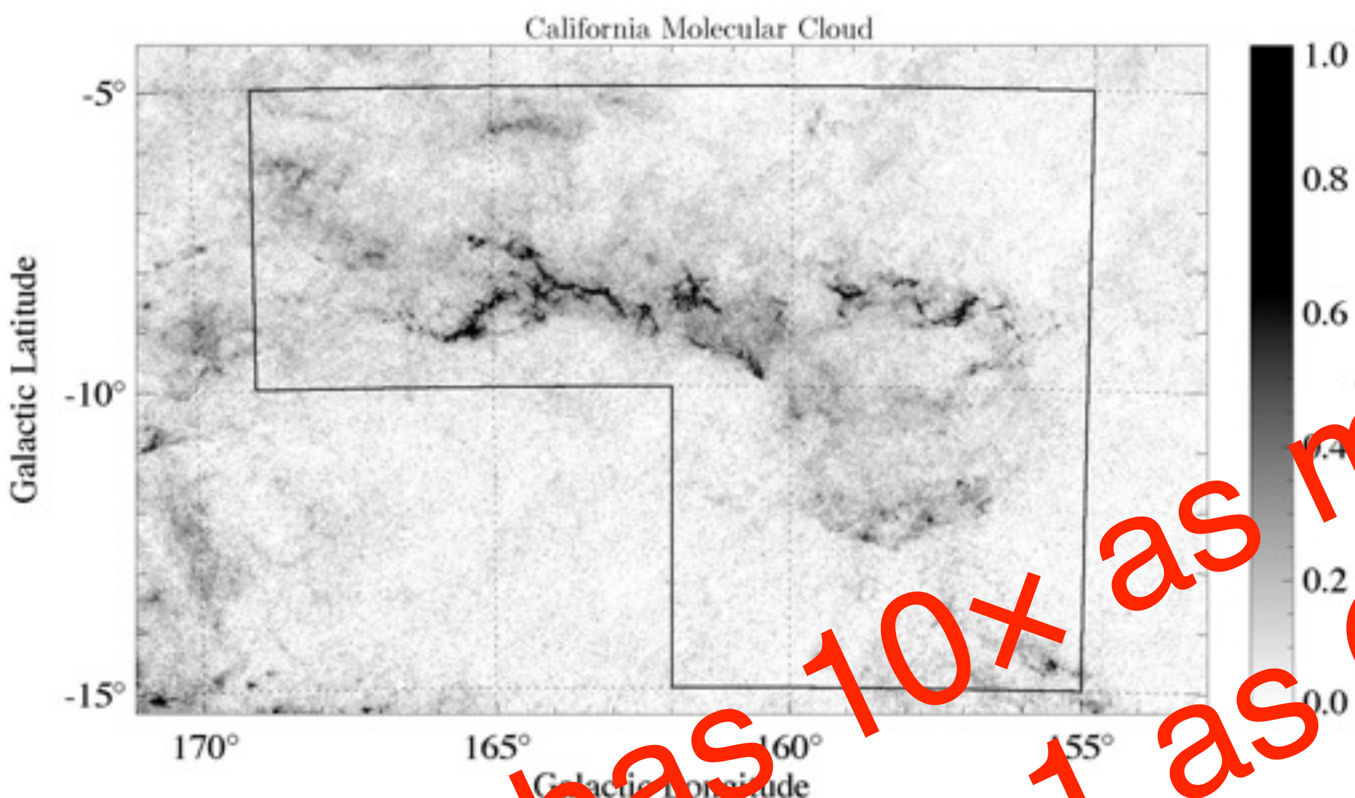
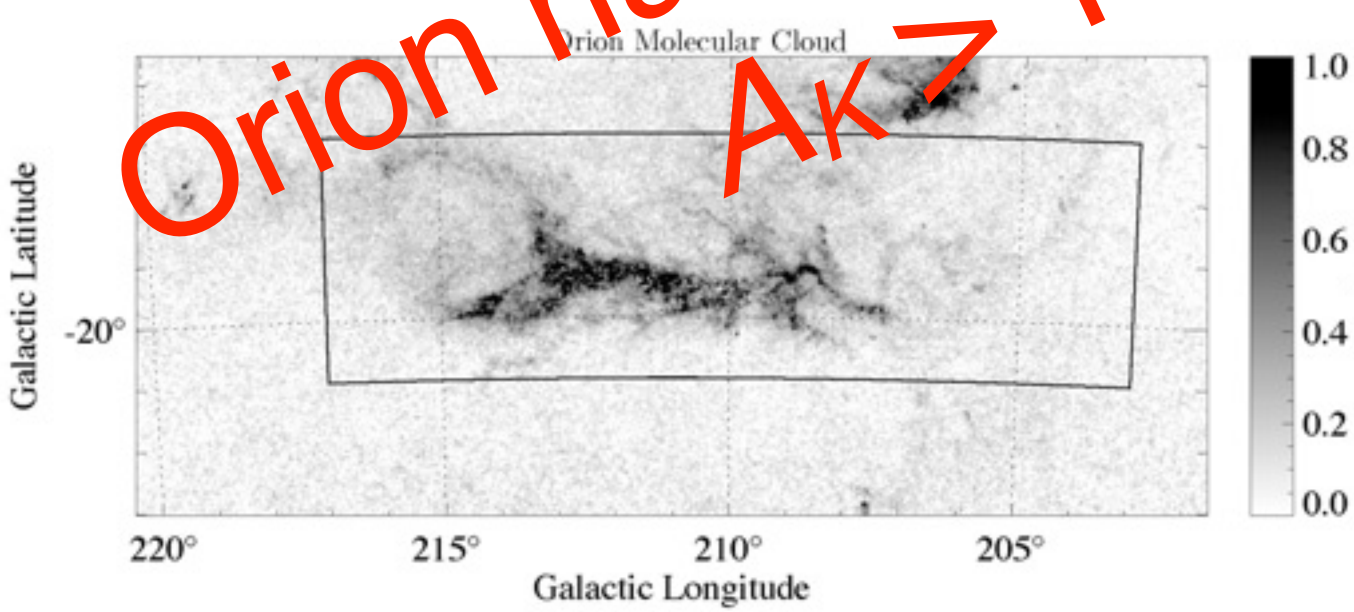
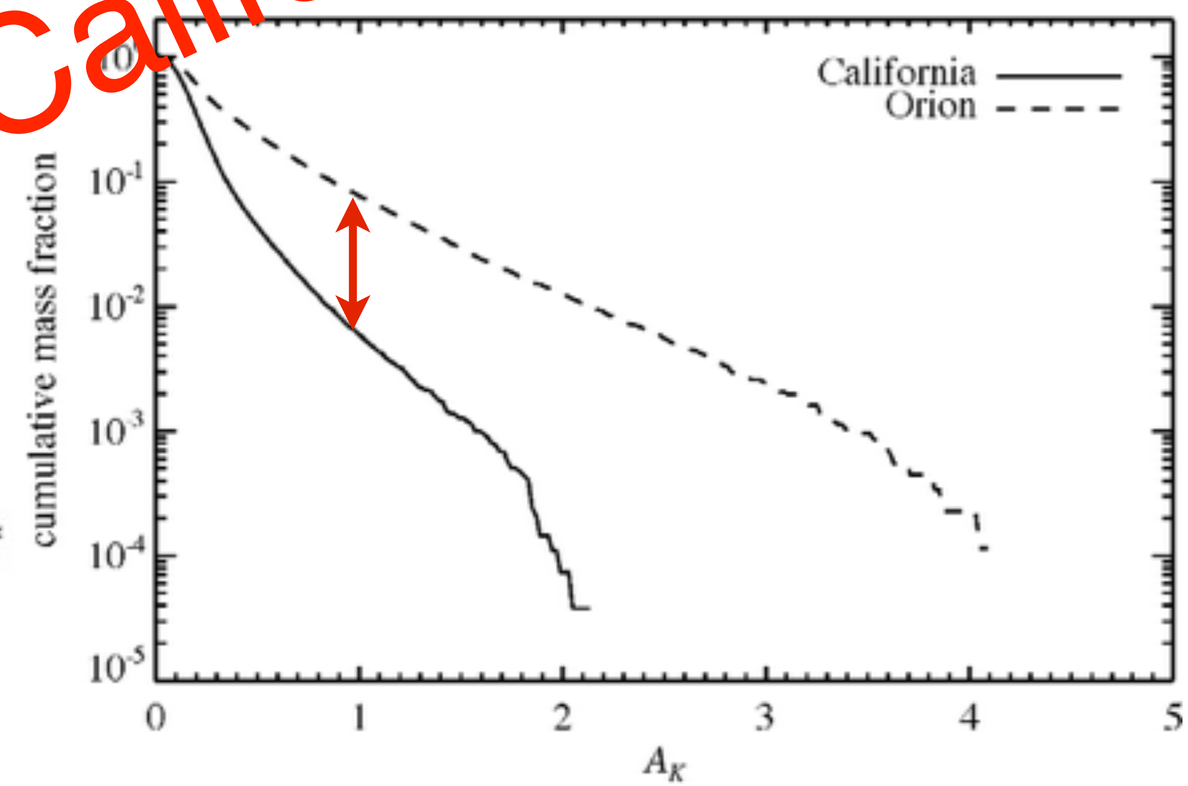
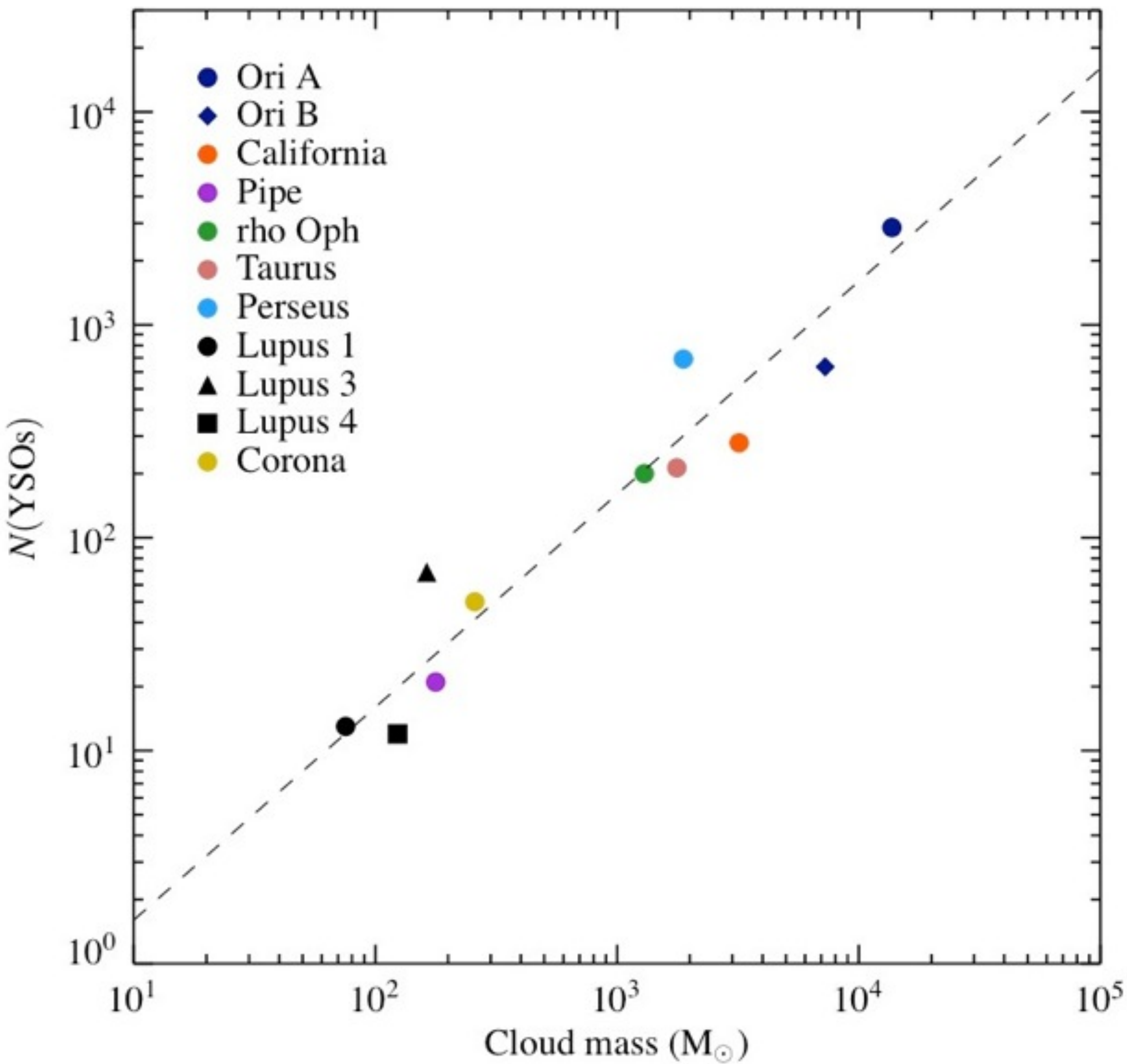






Orion has 10× as much material at $A_K > 1$ as California

SFR directly proportional to mass above $A_K > 0.8$ mag ($\Sigma > 116\ M_\odot\ pc^{-2}$)



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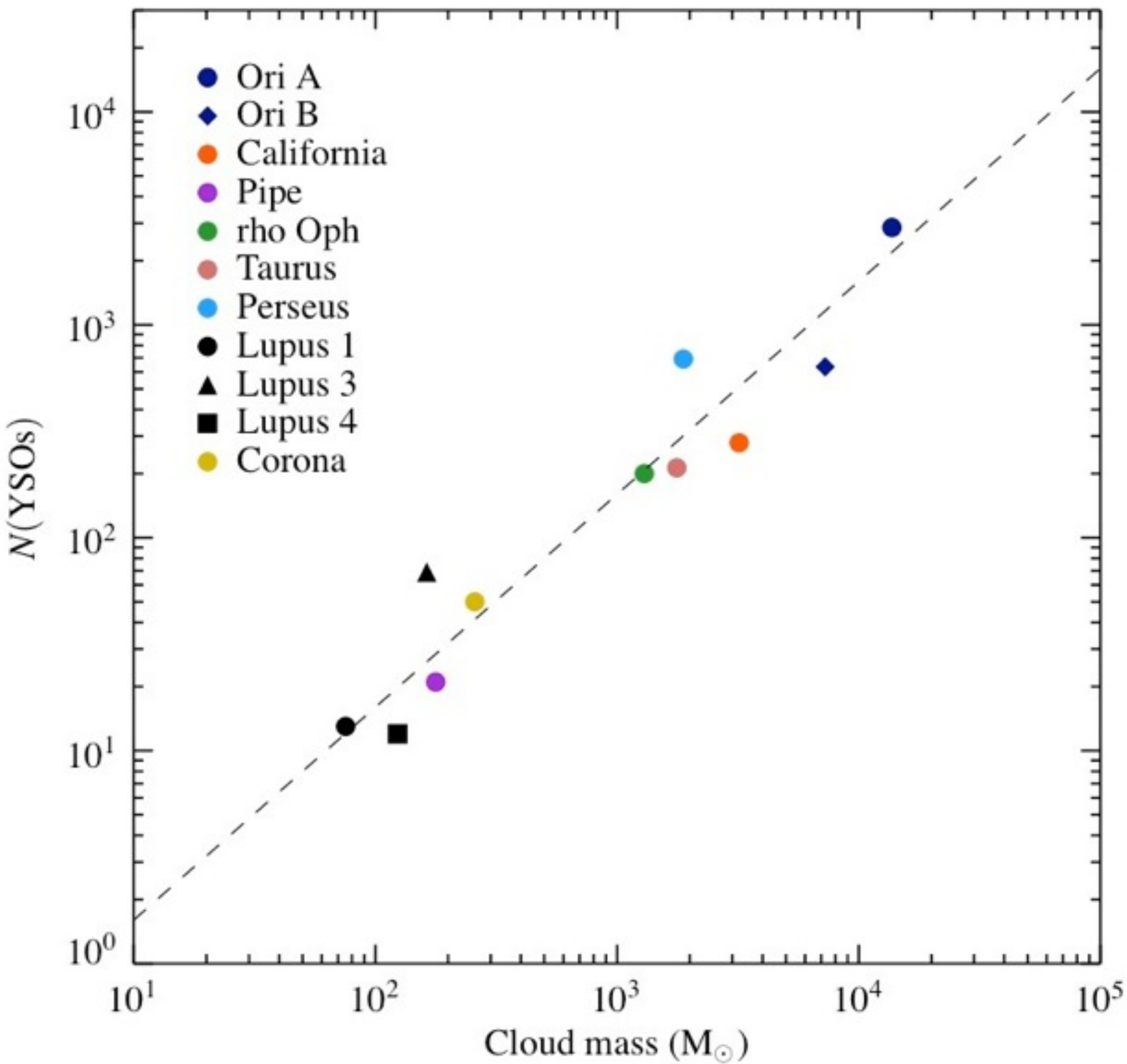

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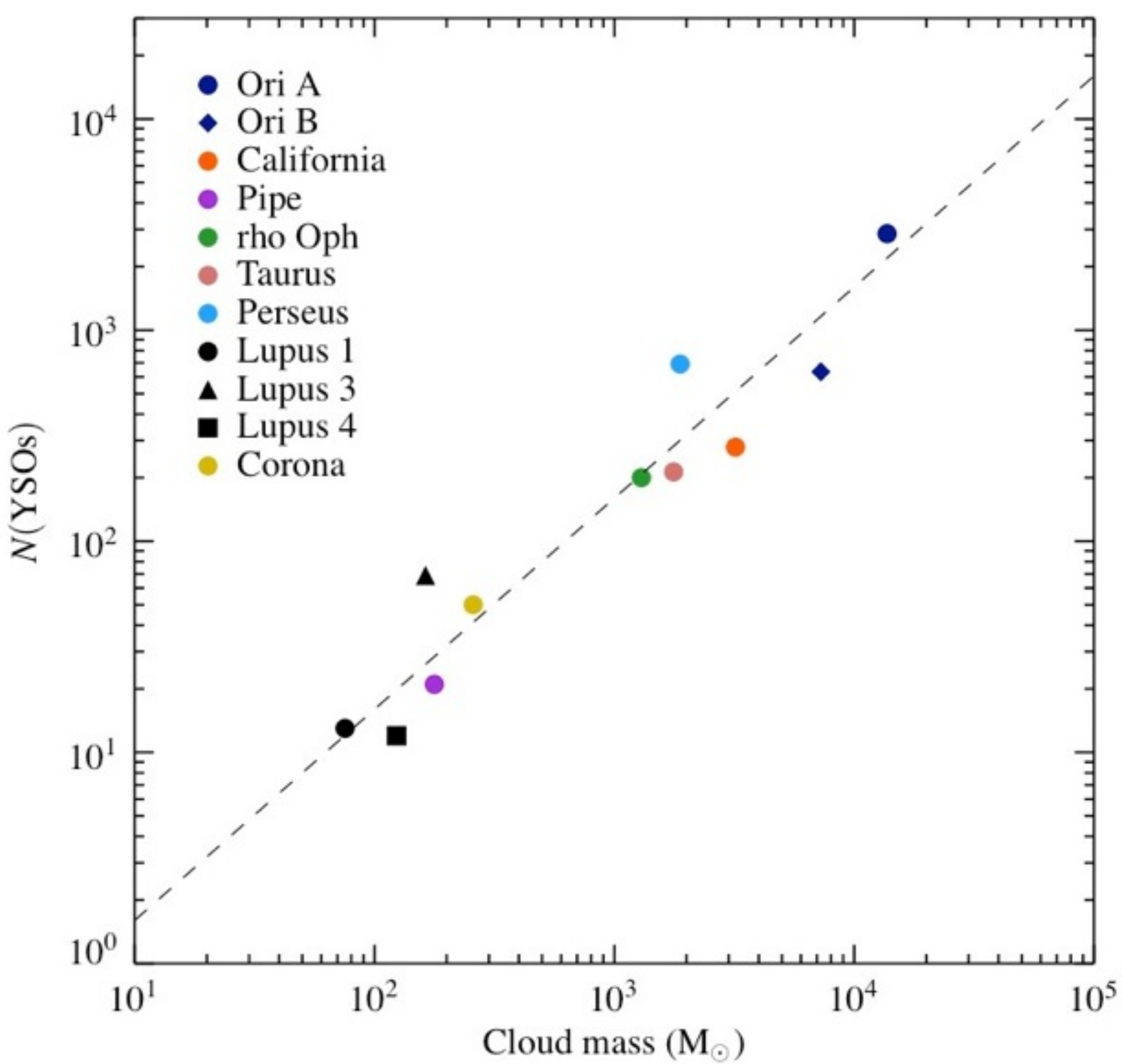

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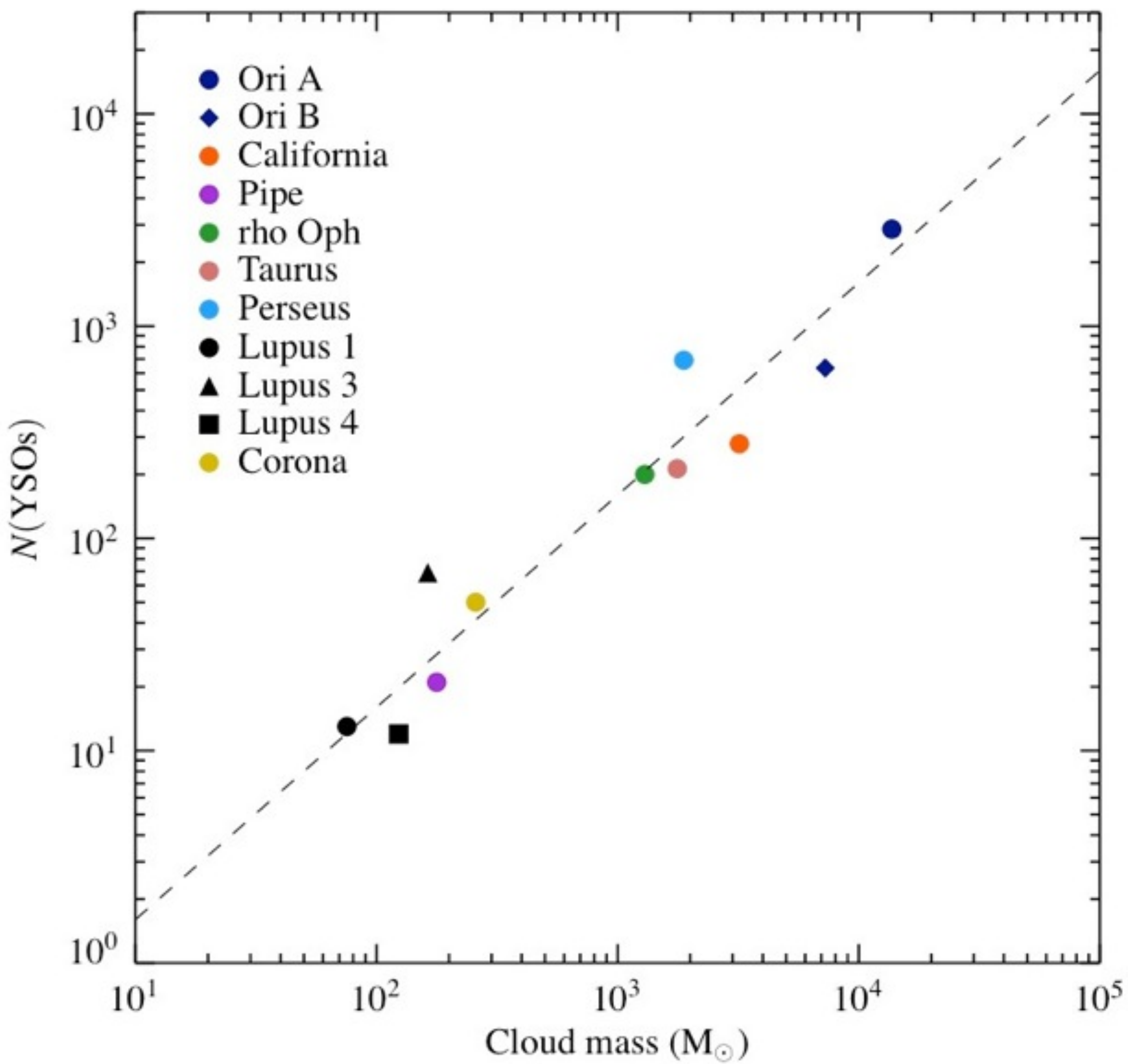

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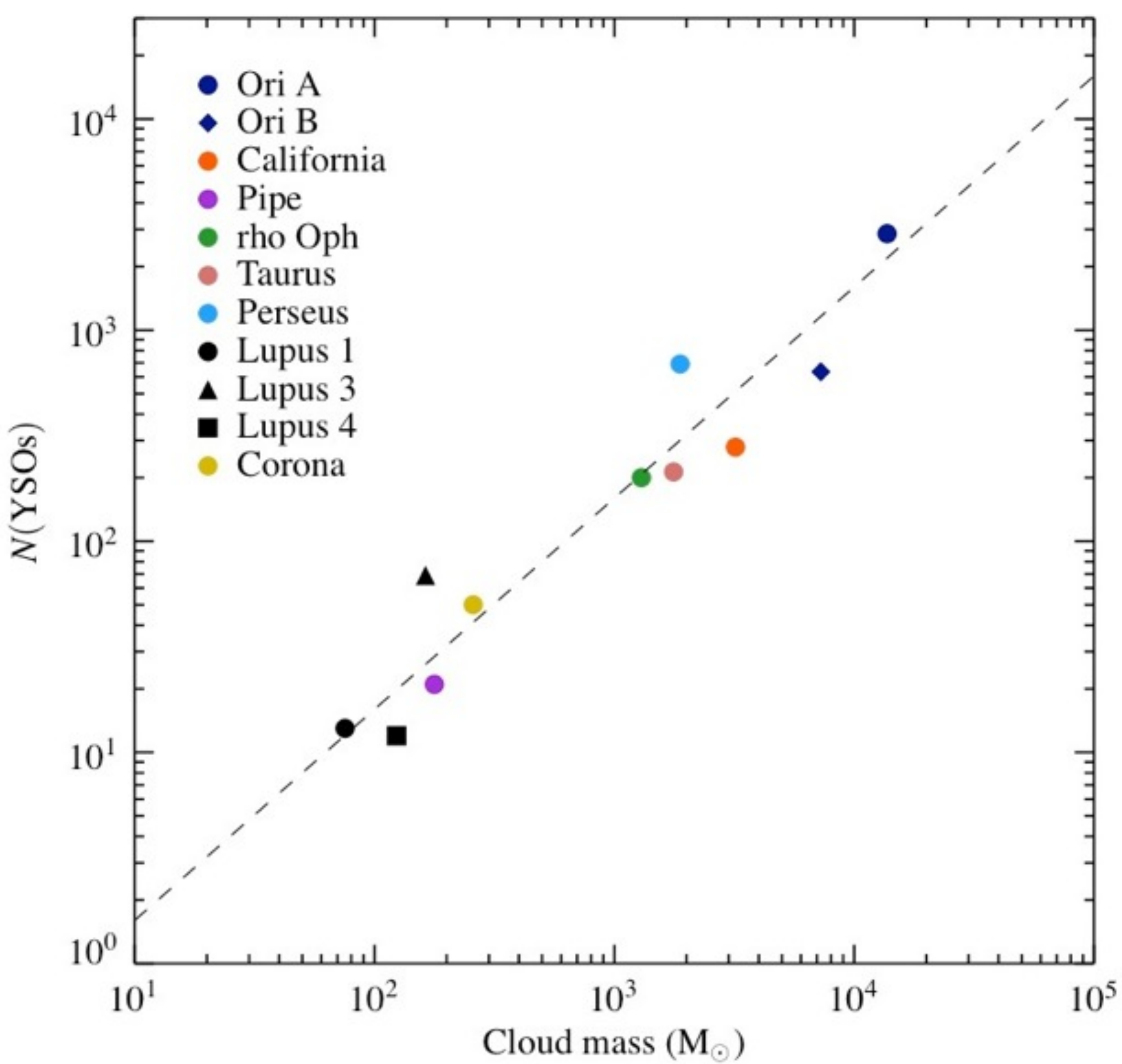

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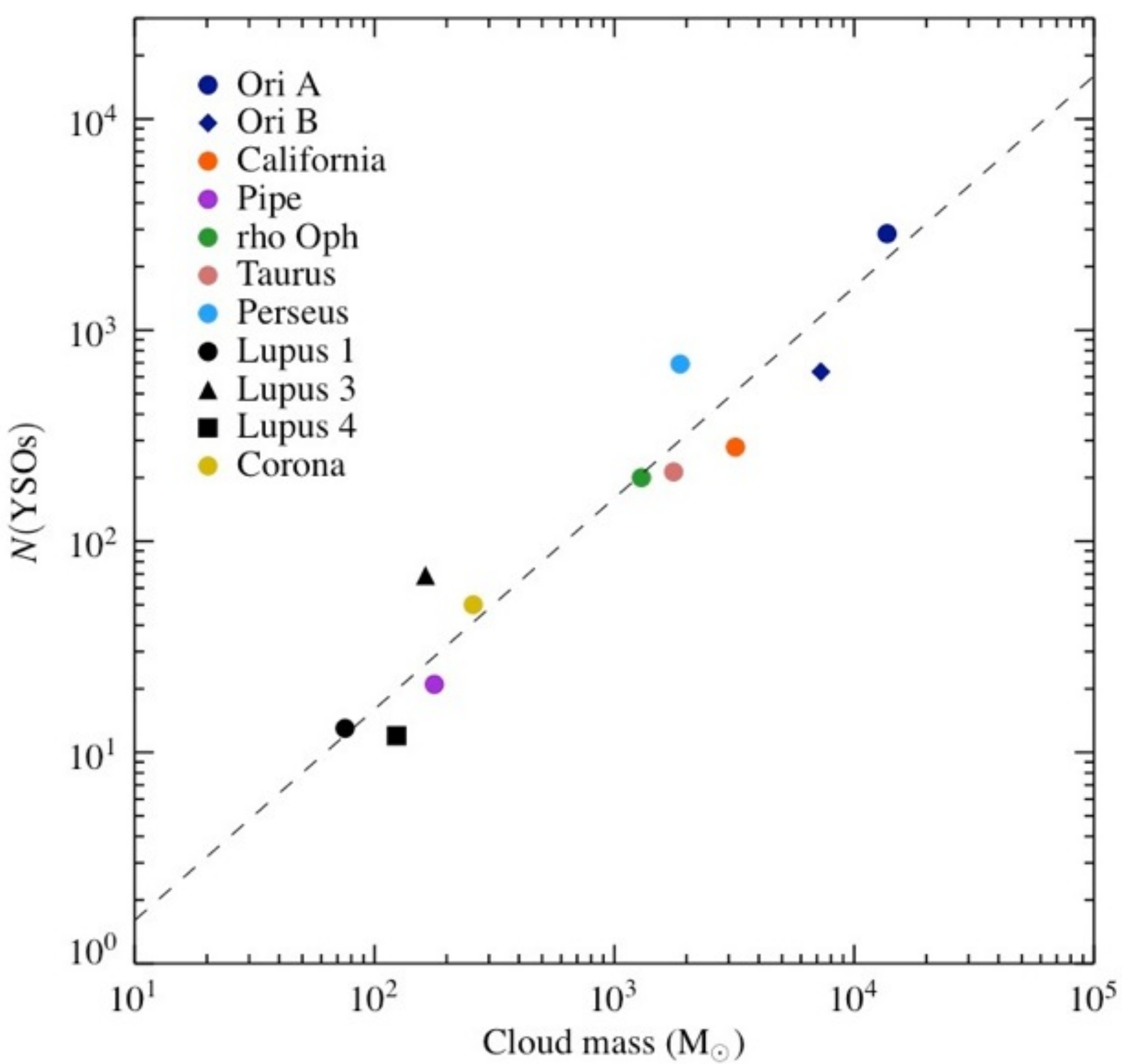


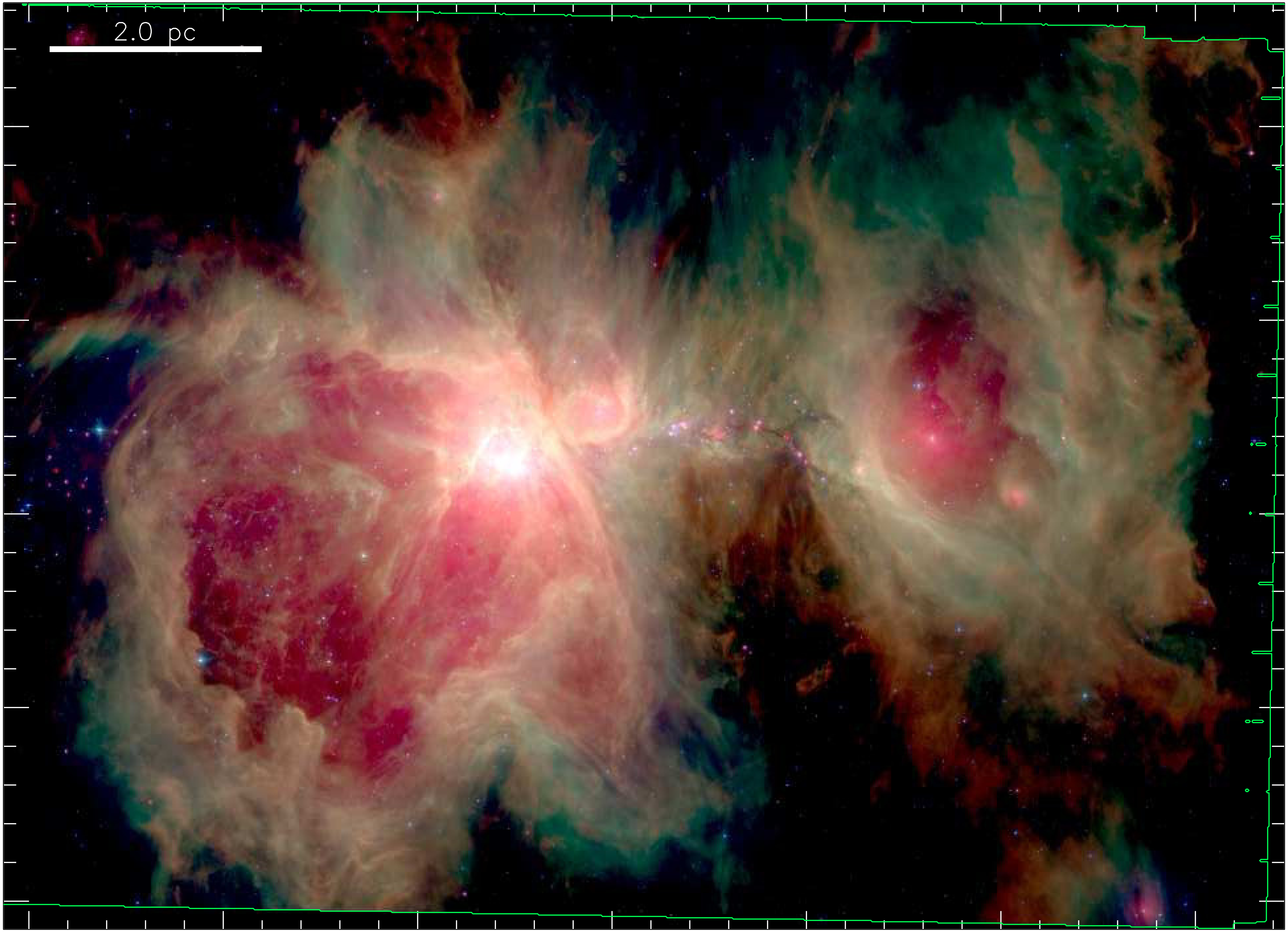
What is the meaning of the slope of this relation?

$$SFR = \varepsilon M_{0.8}/\tau_{sf}$$

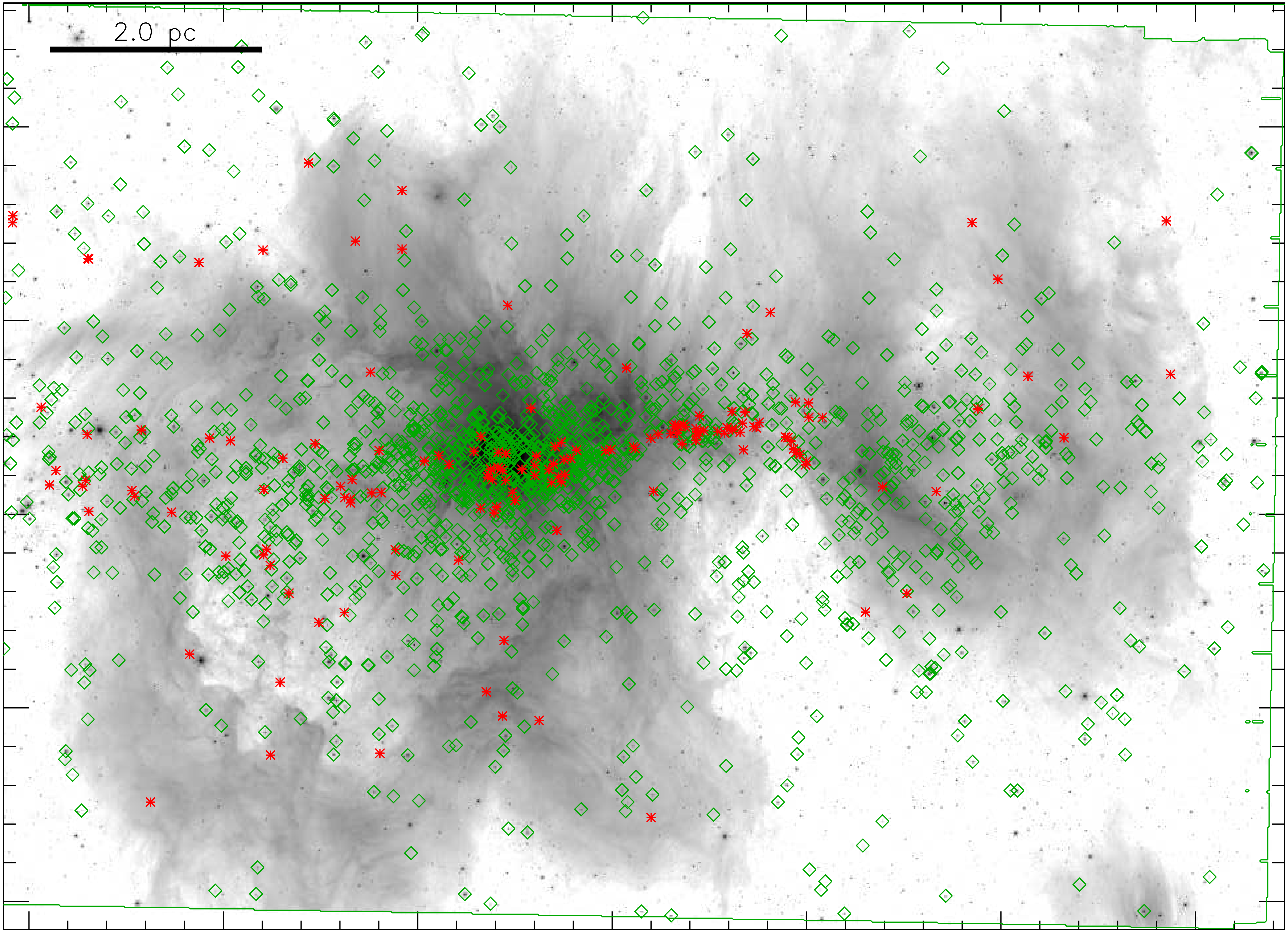
$$\tau_{sf} \simeq 2 \times 10^6\ yr$$

$$\varepsilon = SFE \simeq 0.10$$

One step further:
the *local* Schmidt law



Megeath et al. (2012)



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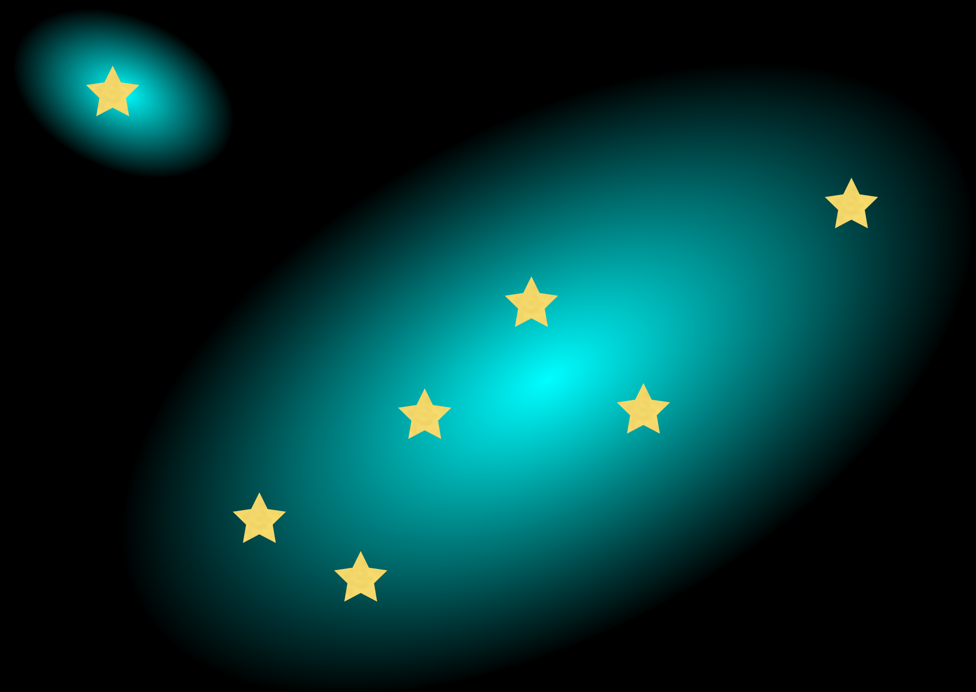
Fitting random spatial data

Fitting random spatial data

(Sarazin 1980, Lombardi et al. 2013)

Fitting random spatial data

Problem 1: check if a set of points is a likely realization of a 2D density



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Fitting random spatial data

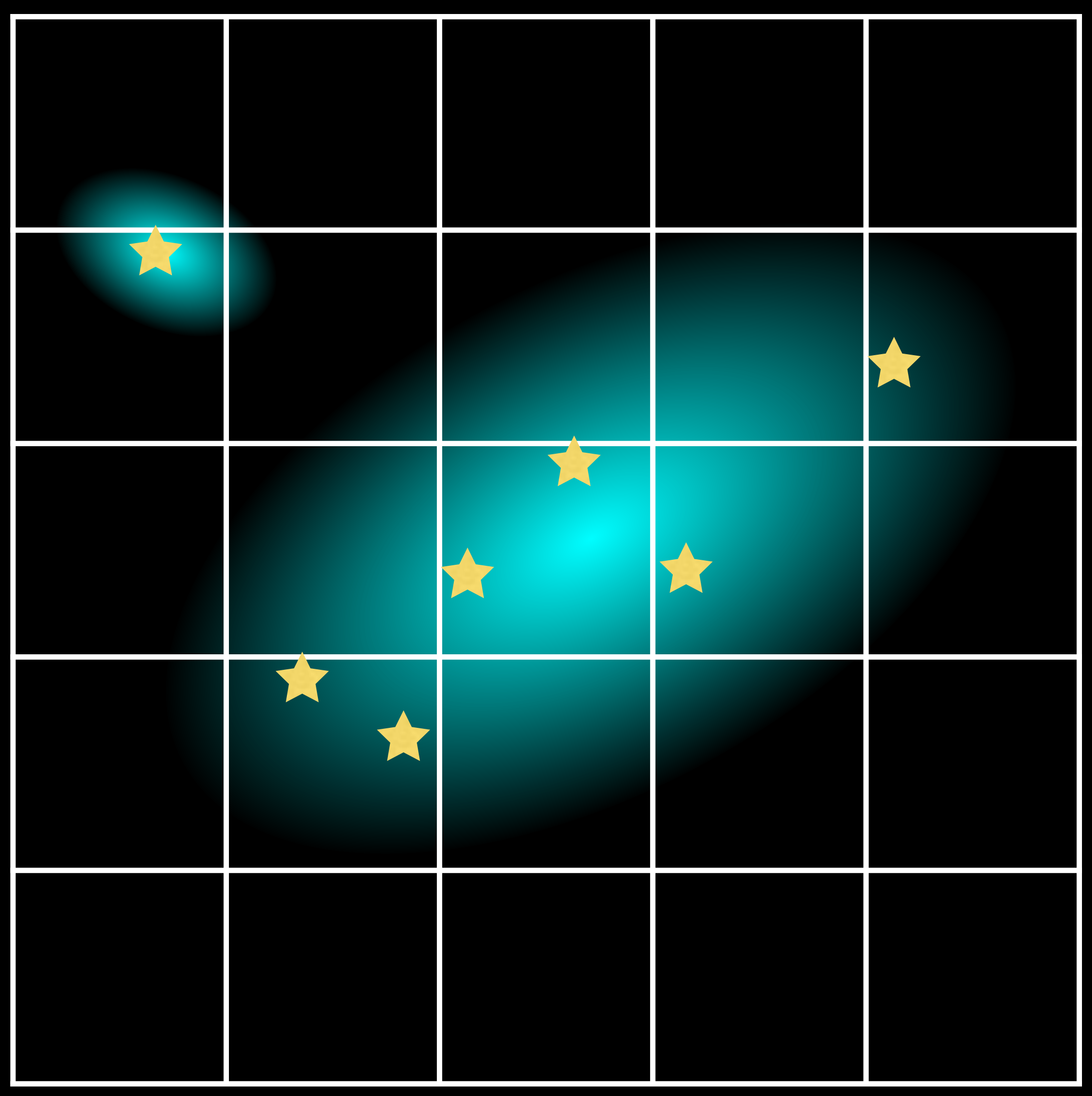
Problem 1: check if a set of points is a likely realization of a 2D density

Solution: bin the data and apply a Poisson statistics

$$P(N_i) = \mathrm{e}^{-\mu_i} \frac{\mu_i^{N_i}}{N_i!}$$

$$\mu_i = \int_{\square_i} \Sigma(x) \, \mathrm{d}^2 x$$

$$P_{\mathrm{tot}} = \prod_i P(N_i)$$



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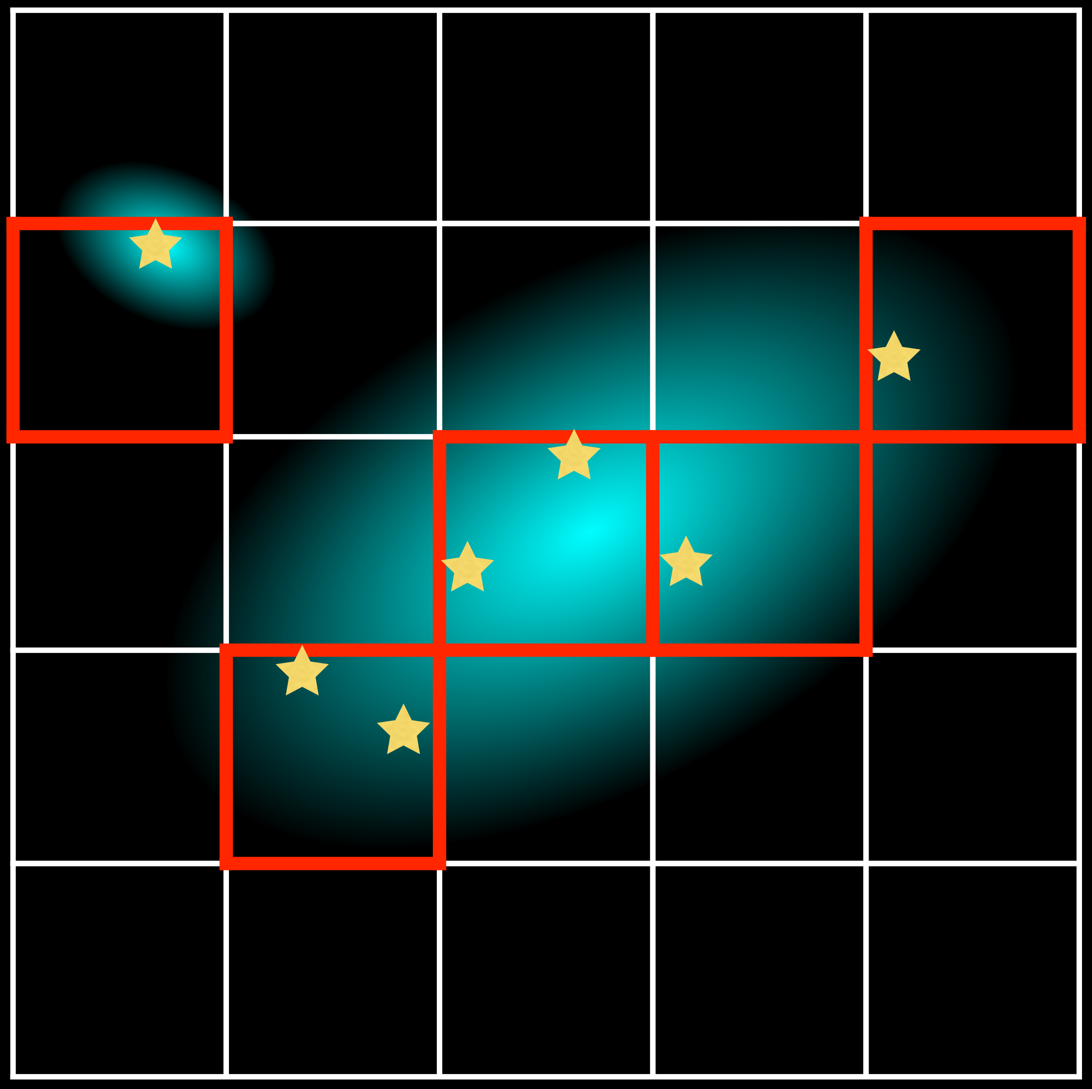

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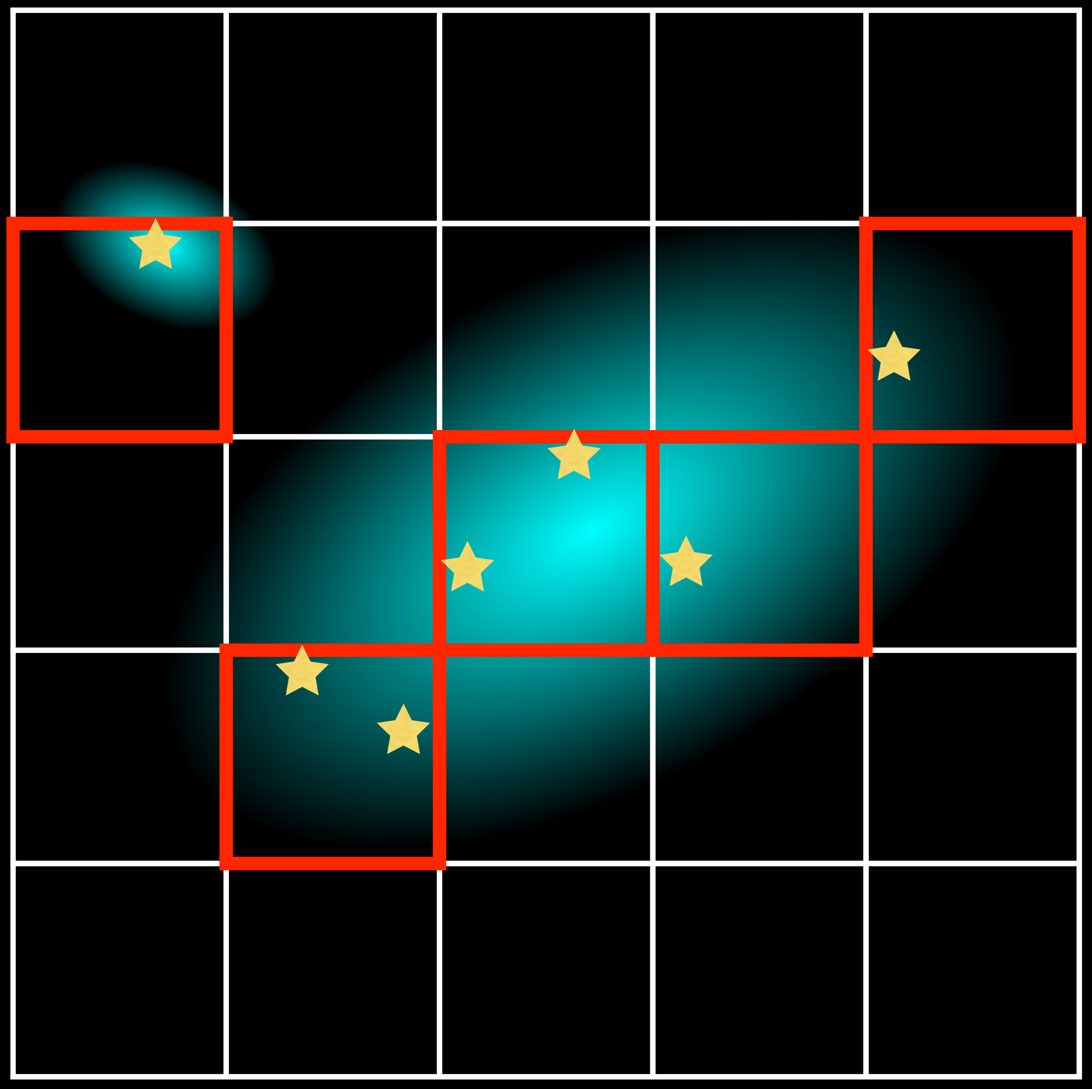
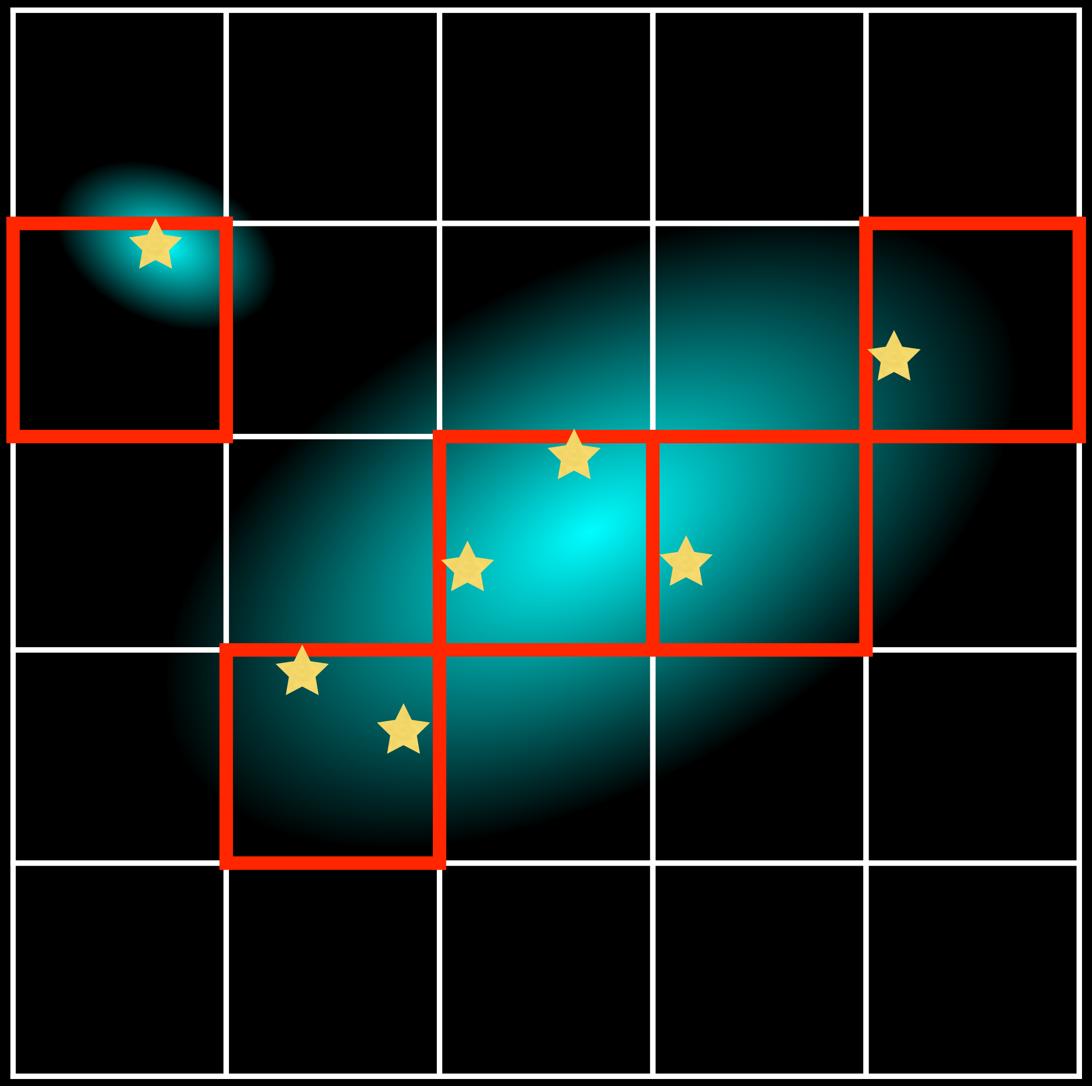


Fitting random spatial data

Problem II: how should we bin the data?



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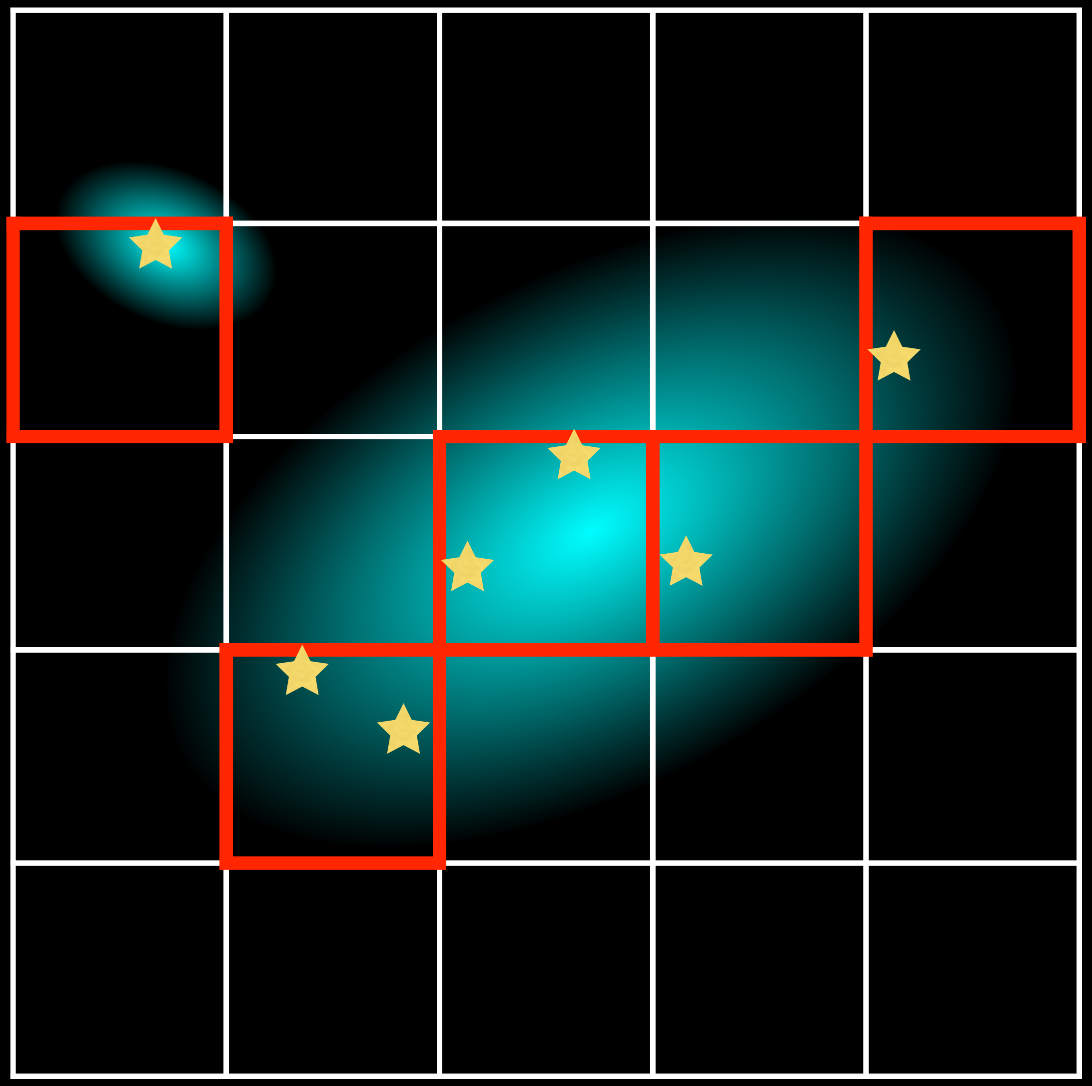
Solution: use infinitesimal bins (easier math, optimal test)



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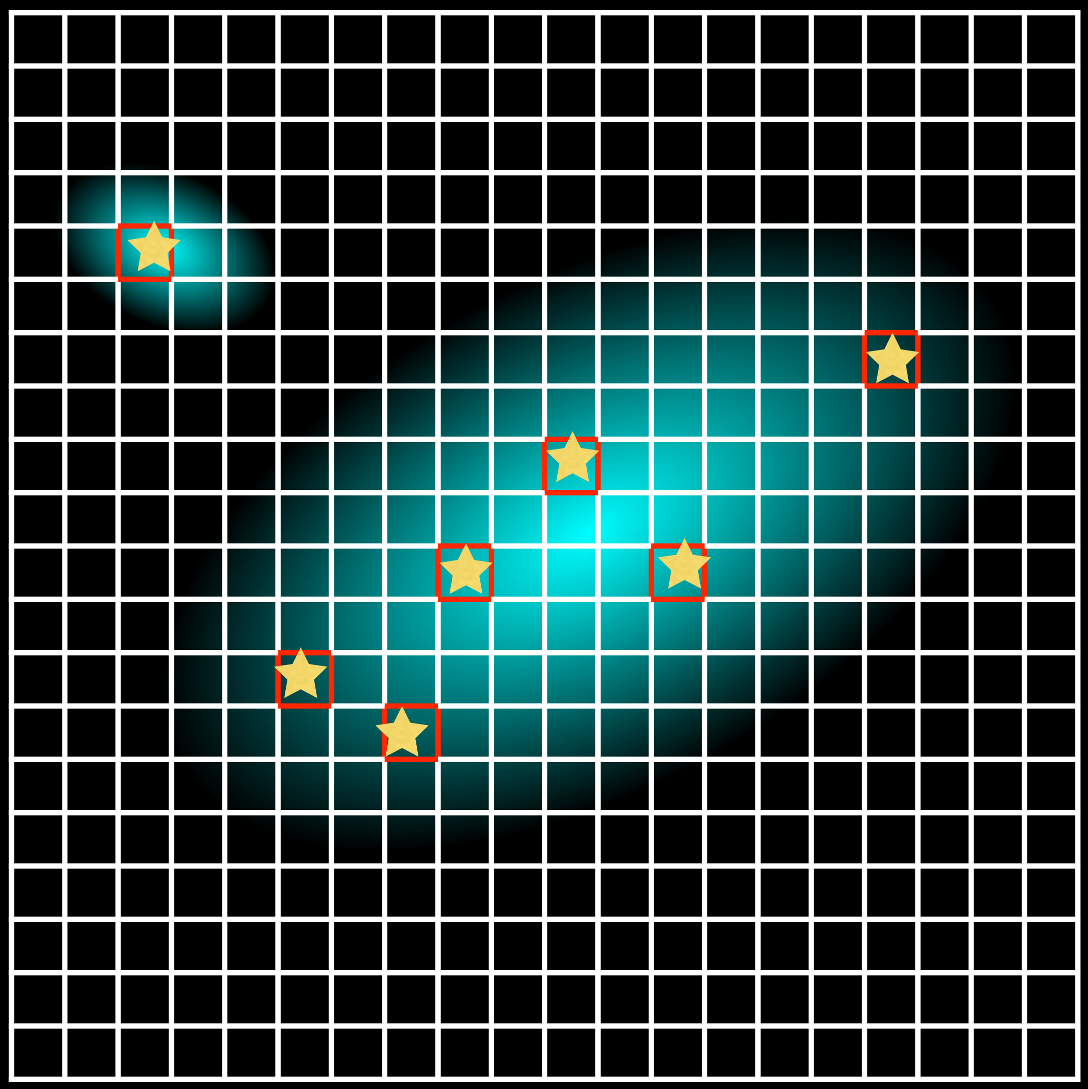

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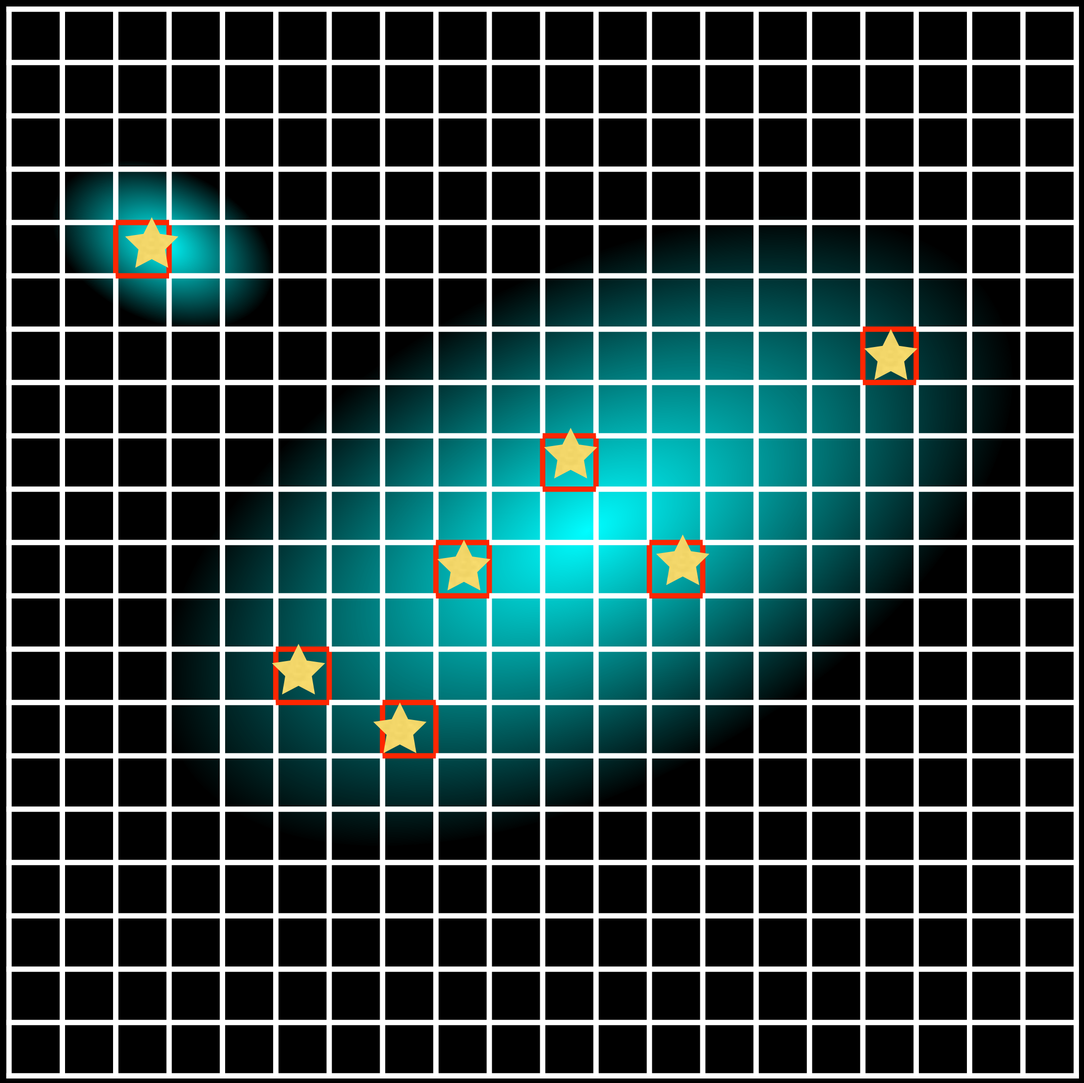


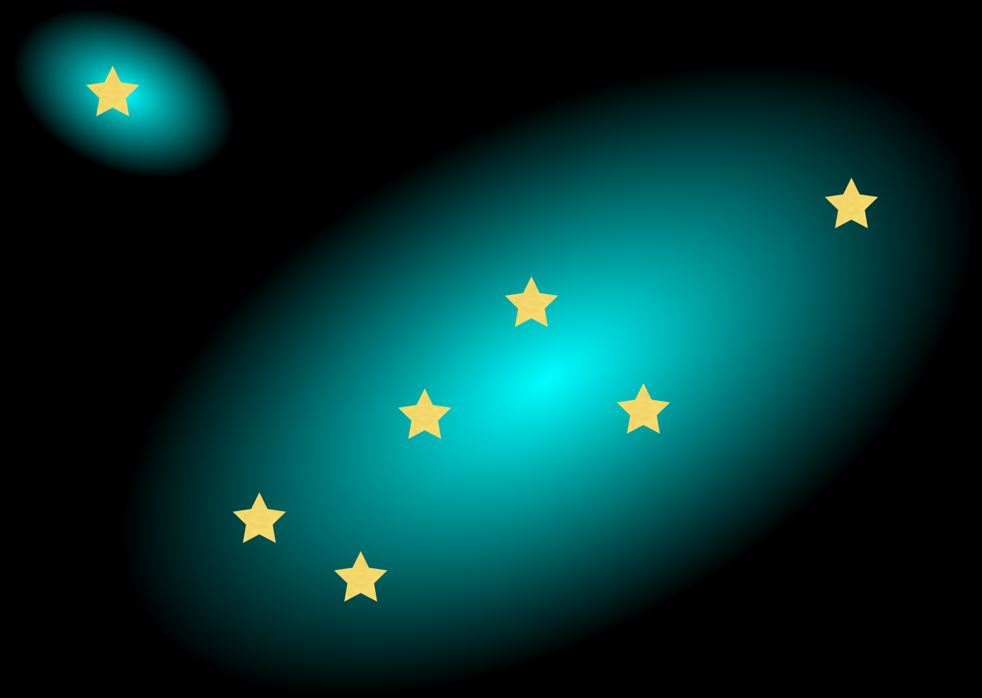
The final solution is best expressed using logarithms

$$\ln P_{\rm tot} \equiv L = \sum_i \ln \Sigma(x_i) - \int \Sigma(x)\, \mathrm{d}^2 x$$

Fitting random spatial data

Fitting random spatial data

Problem III: which density fits best the data?



Fitting random spatial data

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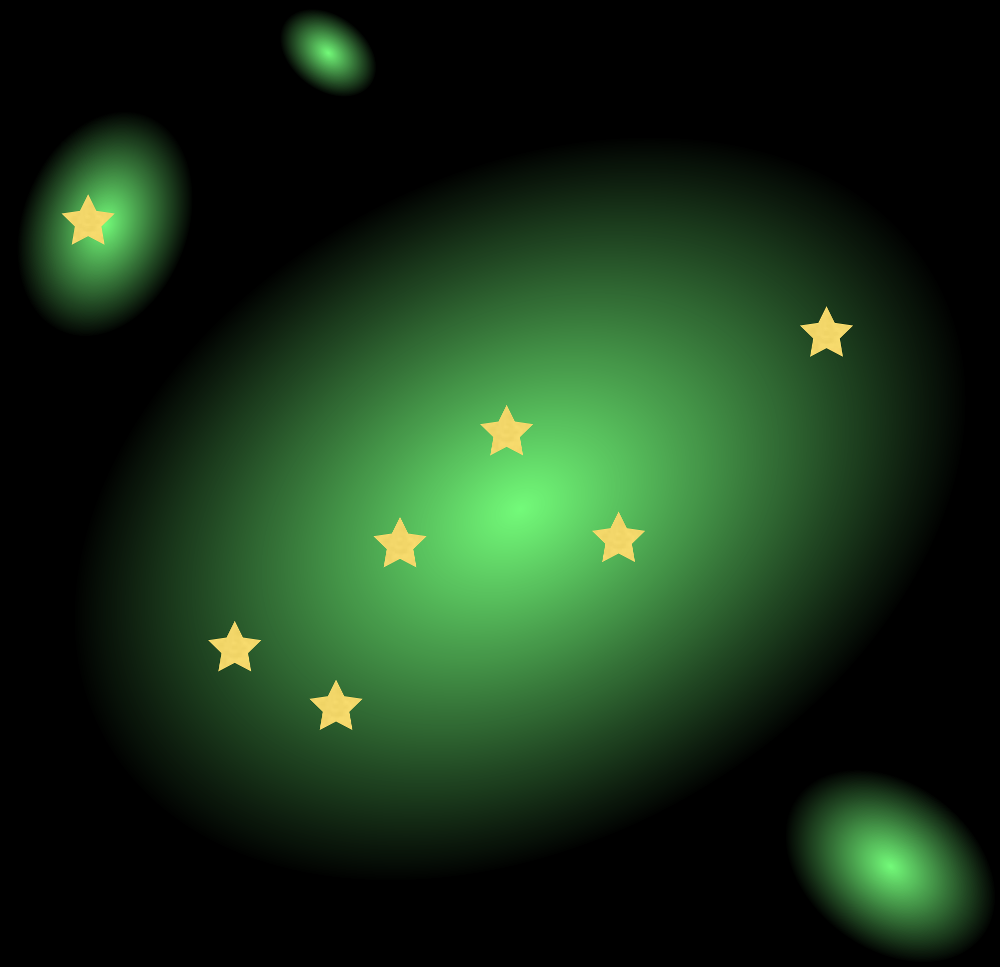

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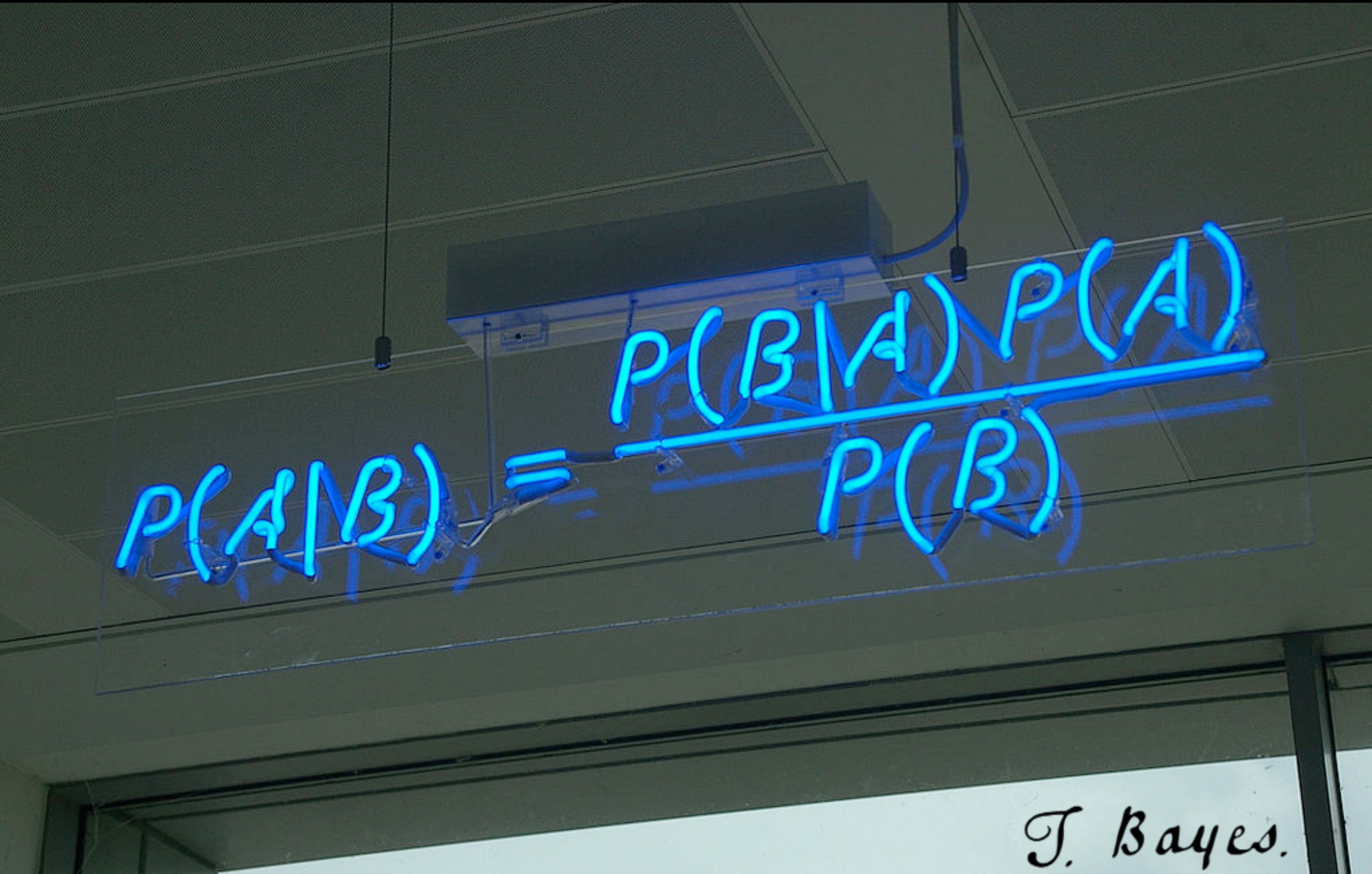
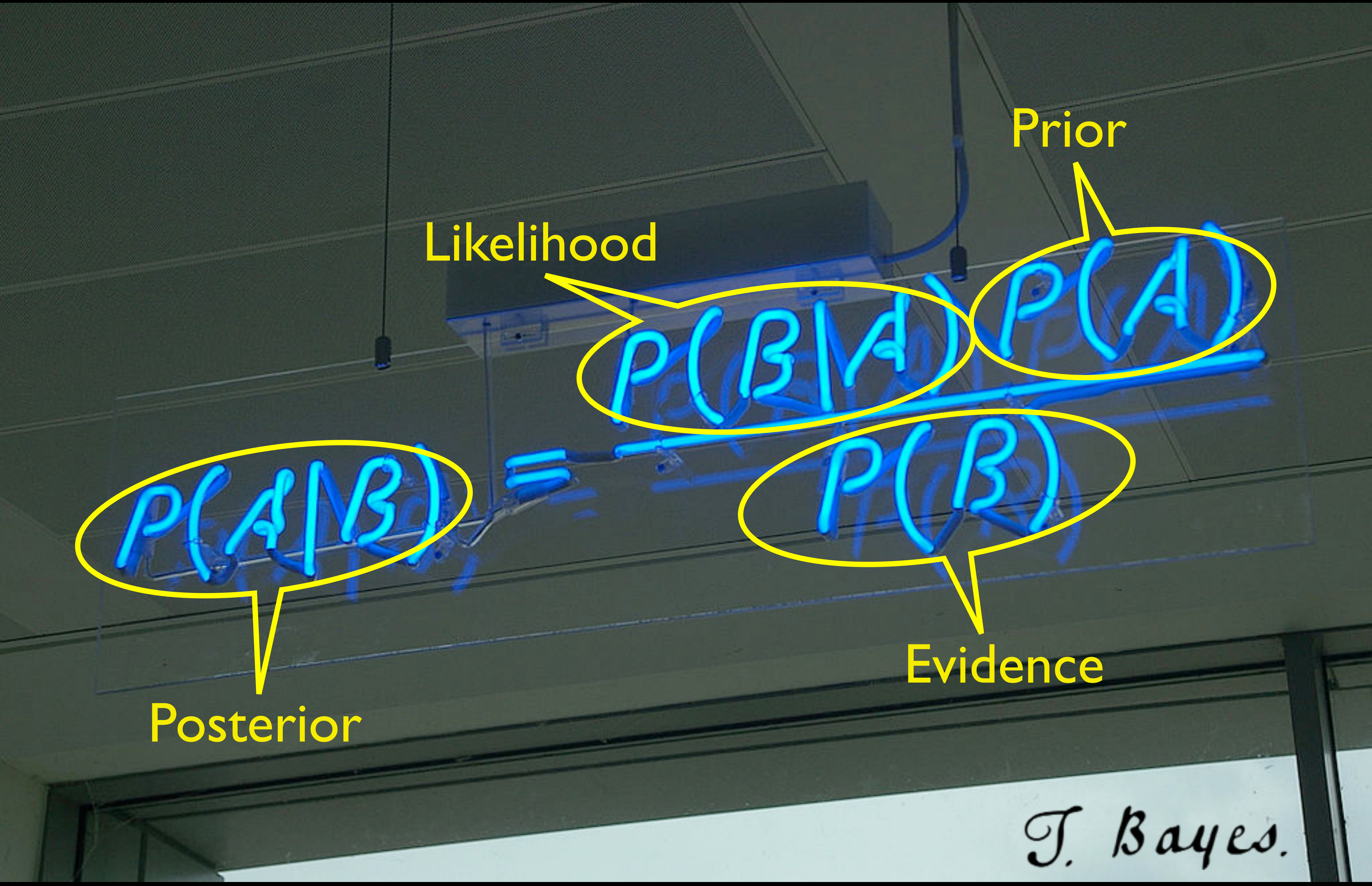


$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$
T. Bayes.


Prior
Likelihood
P(B|A) P(A)
P(A|B) =
P(B)
Evidence
Posterior
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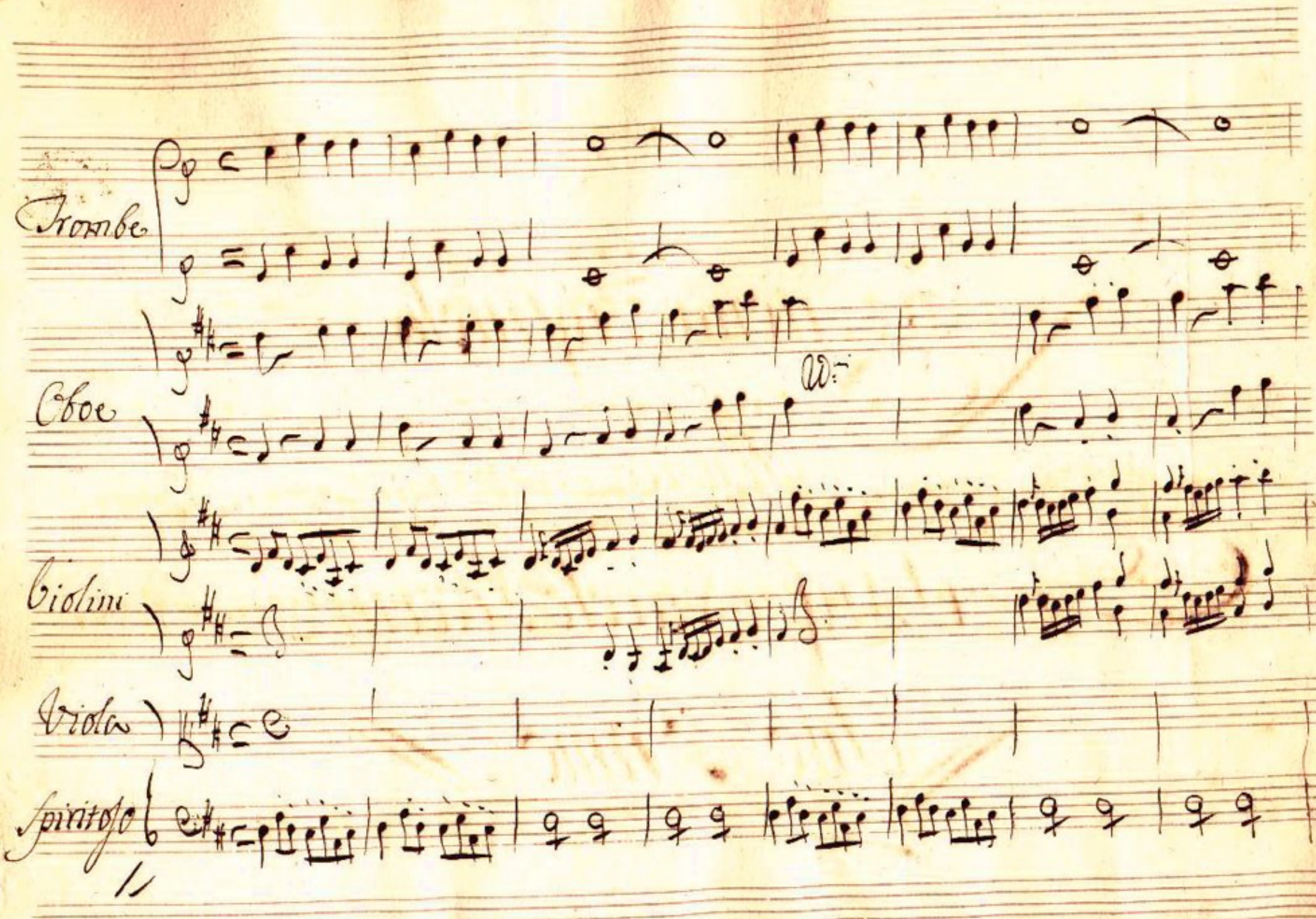
Trombe
Oboe
Violini
Viola
Spiritoso

The local Schmidt law

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- Include other possible effects:
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  - The diffusion of the stars from the cloud (σ)
  - [Contamination by spurious sources…]

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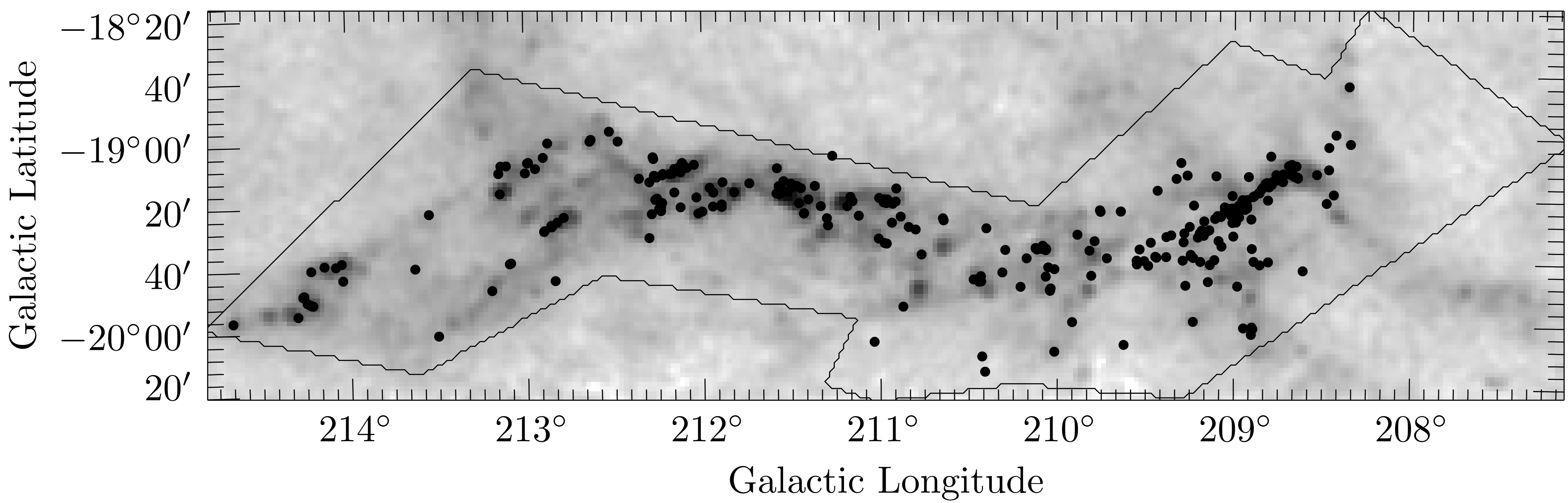
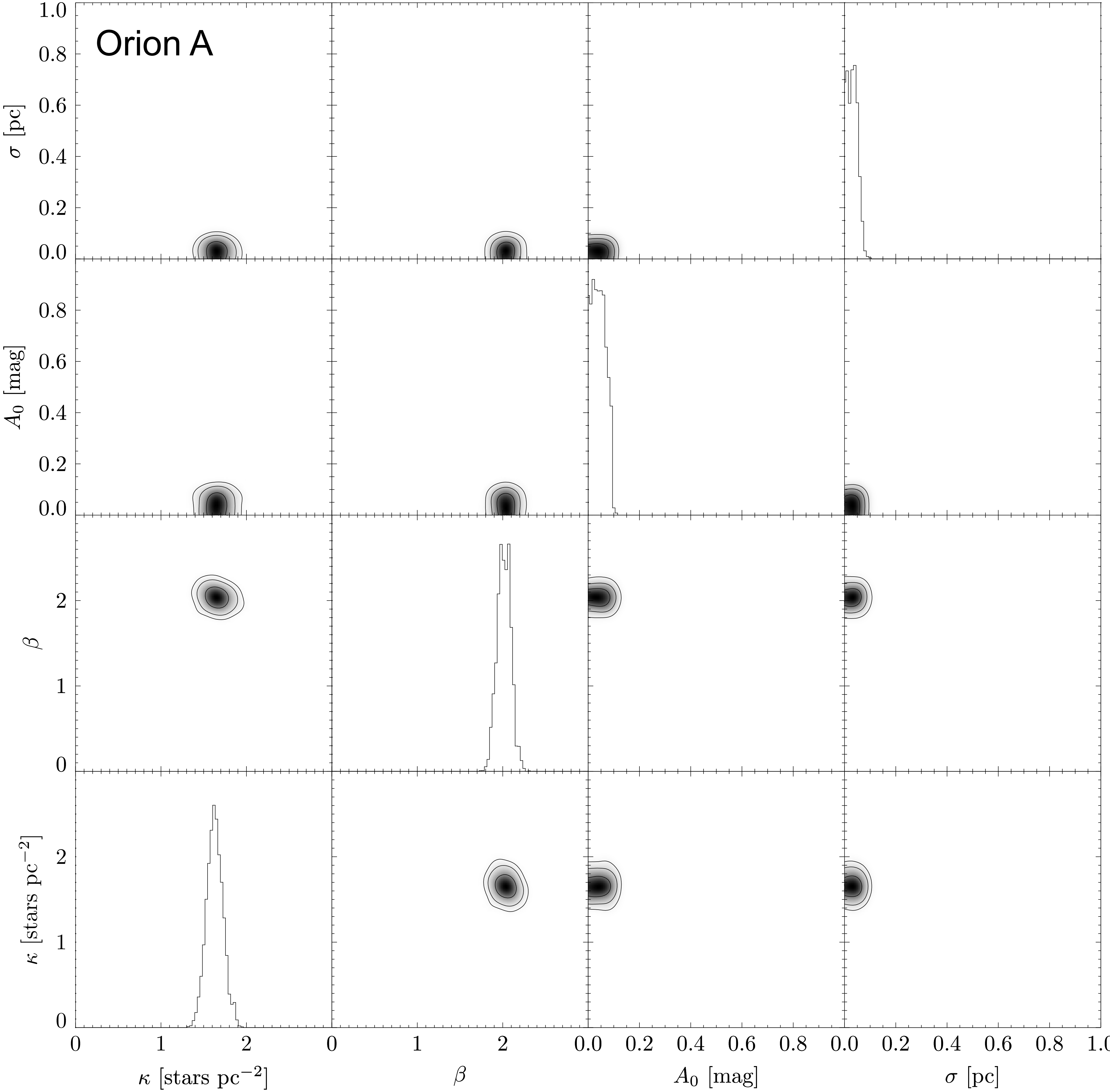
- Data: 2MASS/Nicer extinction maps and Spitzer catalogues of YSOs

Orion A

(Lombardi et al. 2011, Megeath et al. 2012)



- 329 Class I protostars in Orion A
- Posterior distribution sampled with MCMC
- Credible intervals inferred for 4 parameters



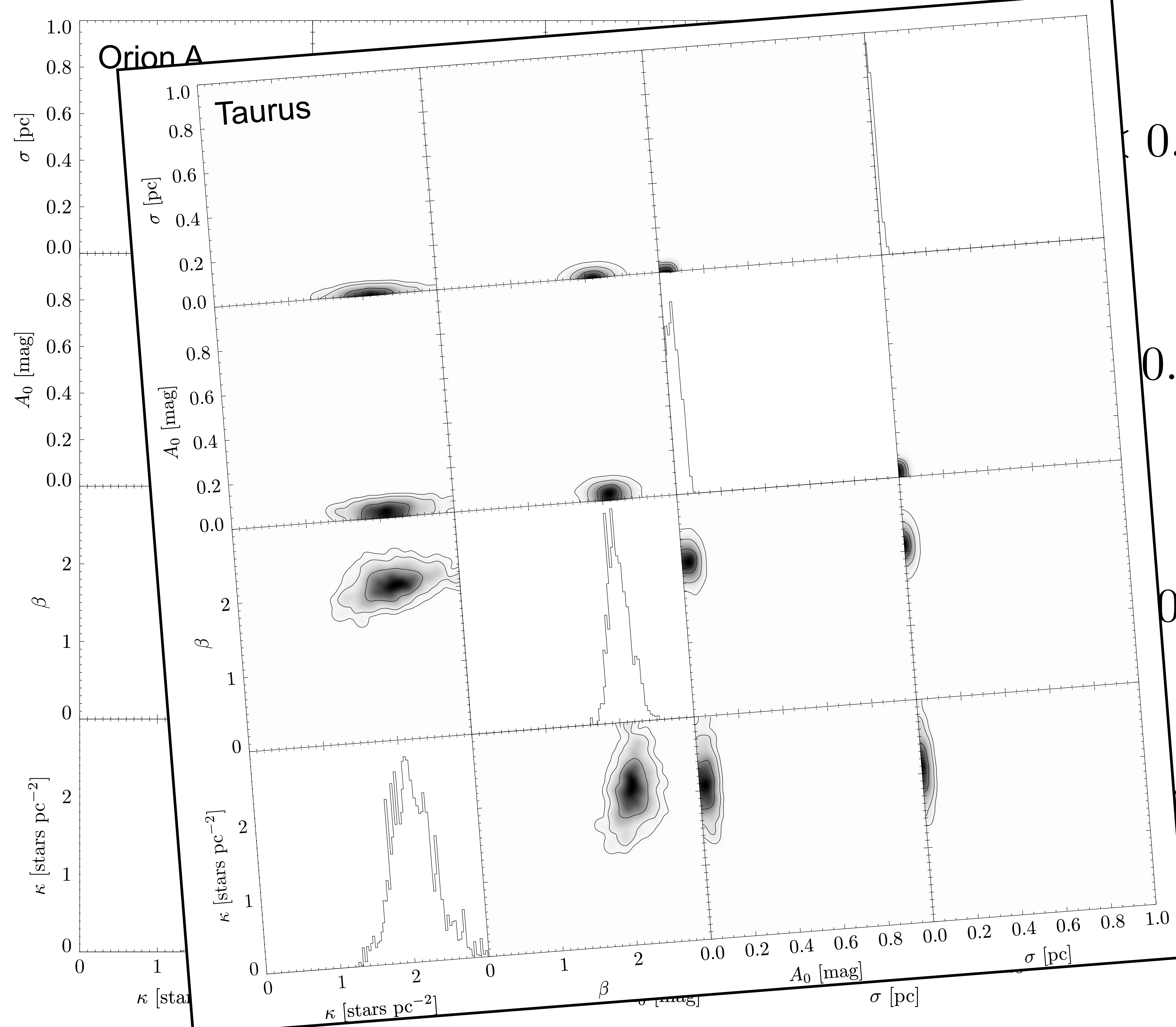
$$\sigma < 0.05 \text{ [pc]}$$

$$A_0 < 0.07 \text{ [mag]}$$

$$\beta = 2.03 \pm 0.15$$

$$\kappa = 1.64 \pm 0.09$$

$$[\text{stars pc}^{-2}]$$



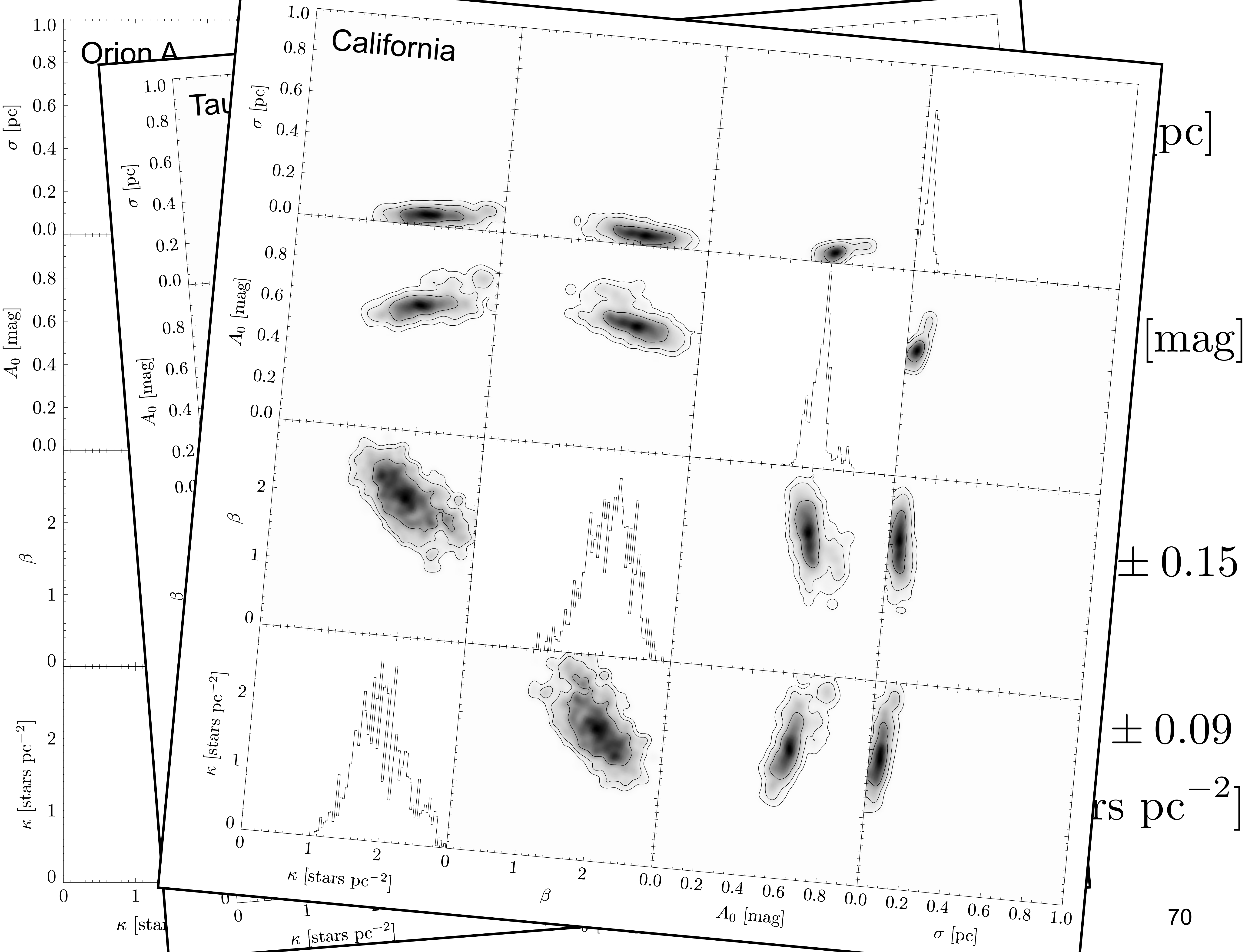
< 0.05 [pc]

0.07 [mag]

03 ± 0.15

4 ± 0.09

$\mathrm{rs\ pc}^{-2}]$


California
Orion A
Tau
σ [pc]
A_0 [mag]
β
κ [stars pc^{-2}]
[pc]
[mag]
$\pm\,0.15$
$\pm\,0.09$
rs pc^{-2}]

A consistent picture

- The local Schmidt law holds: SFR ~ Σ^2
- Clouds are self-similar above a threshold, with isothermal profiles $S(> \Sigma) \sim \Sigma^{-2}$
  - 3rd Larson's law holds: identical Σ above threshold
- Stars form in dense regions of molecular clouds
  - "protected" environment: cold gas, no UV radiation, Jeans/Bonnor-Ebert instability
  - SFR proportional to the amount of mass above a (projected) density threshold, SFR ~ M_{dense}

SUMMARY

1. Scaling laws are ubiquitous in molecular cloud physics (local Schmidt law, Larson's law, power-laws for PDFs)

2. Large differences in the properties of molecular clouds might be confined to the low-density, peripheral areas

3. Current observations show that clouds have self-similar structures