2156-9

Summer School in Cosmology

19 - 30 July 2010

Galaxy Formation

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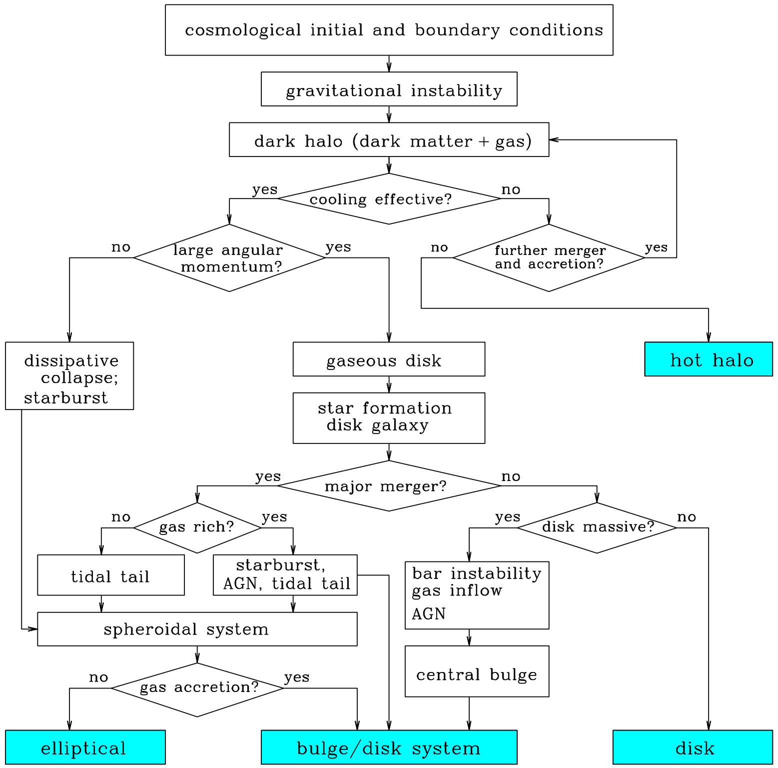
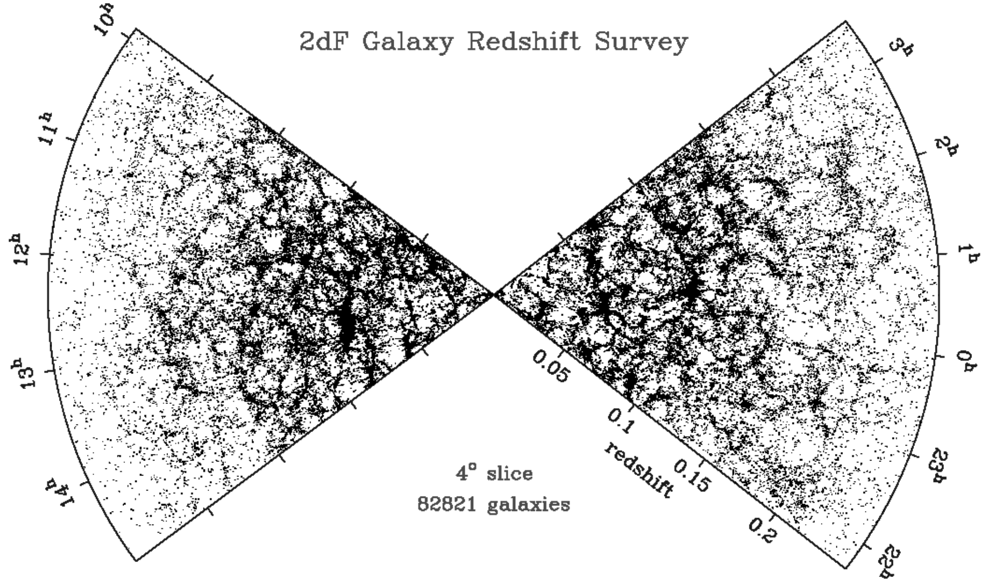
Formation of the galaxy population

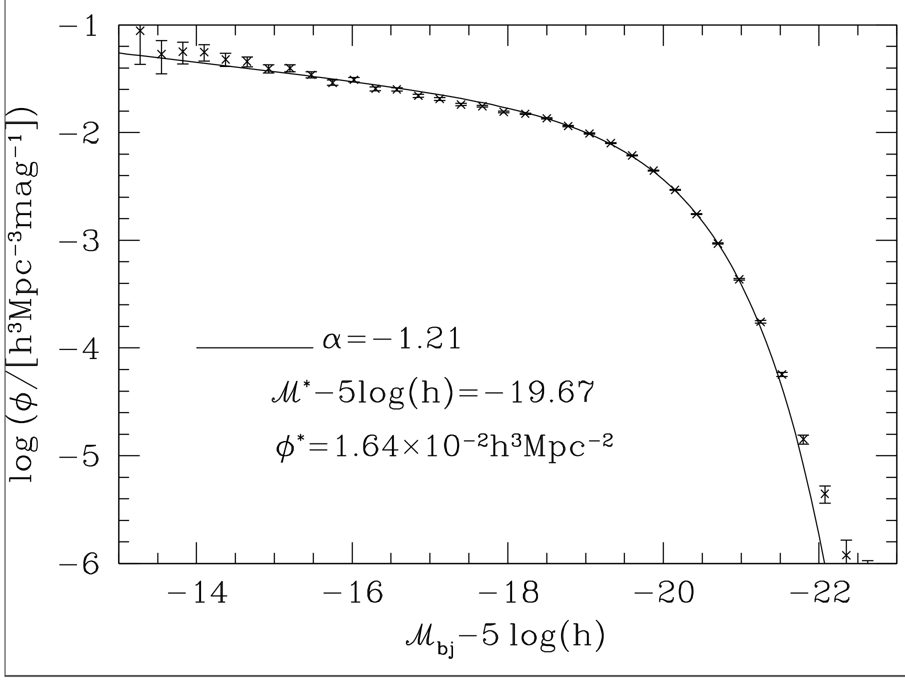
- Cosmology: provides the initial and boundary conditions for galaxy formation
- Gravitational instability: drives large scale structure formation
- Formation of dark matter halos in the cosmic density field
- Formation of galaxies in dark matter halos: gas cooling, heating and accretion; star formation; feedback; galaxy merger
- Galaxy evolution: spectral synthesis; chemical evolution; dynamical evolution
- Galaxy populations: both low and high z

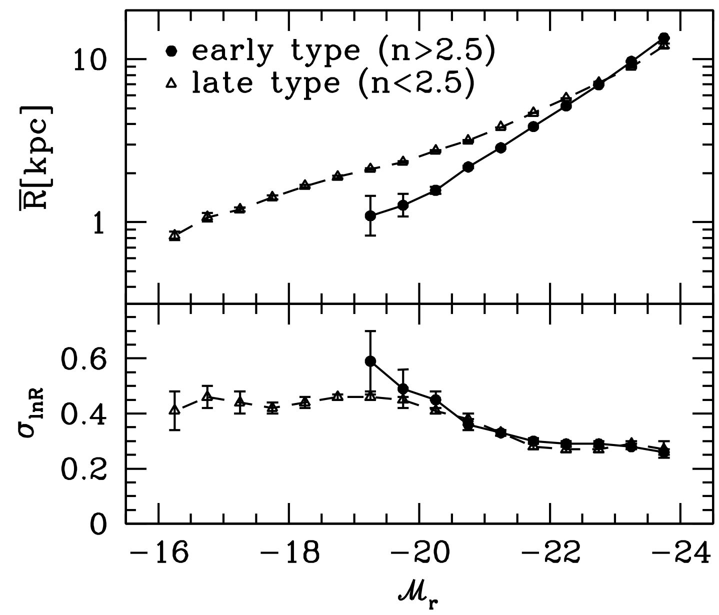


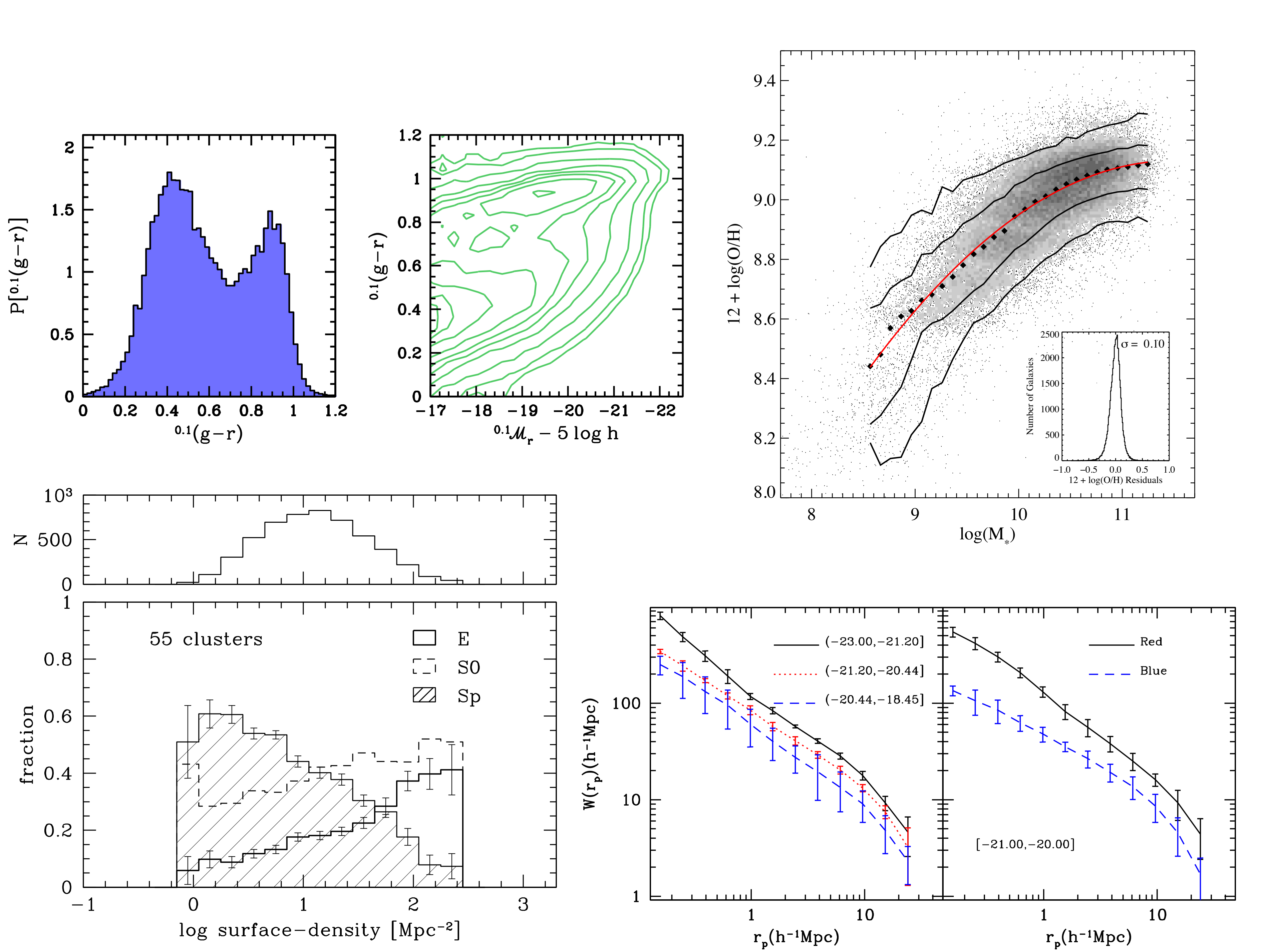
Can we understand the galaxy population in current cosmology?

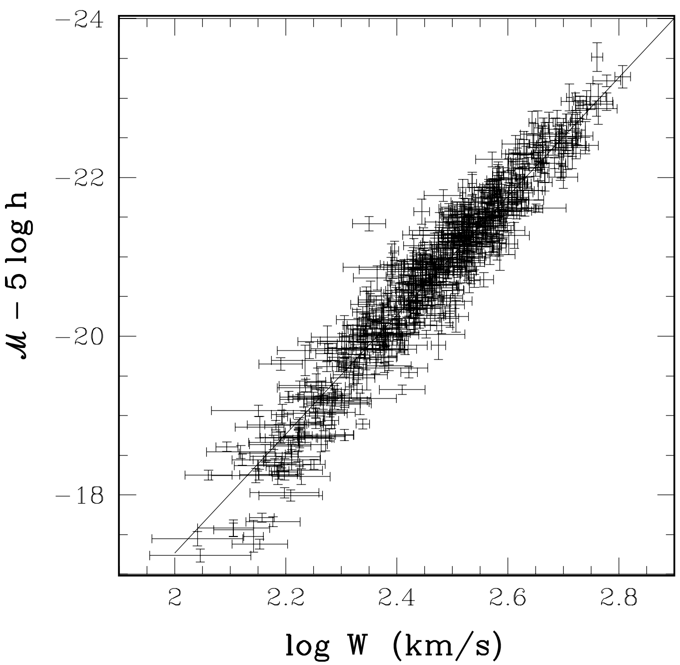
The main observed properties

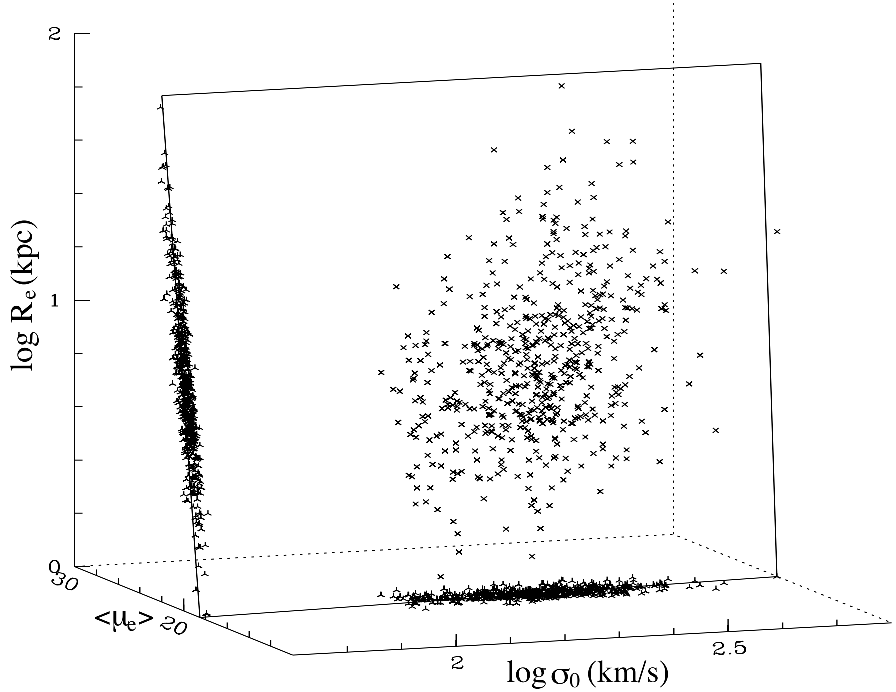






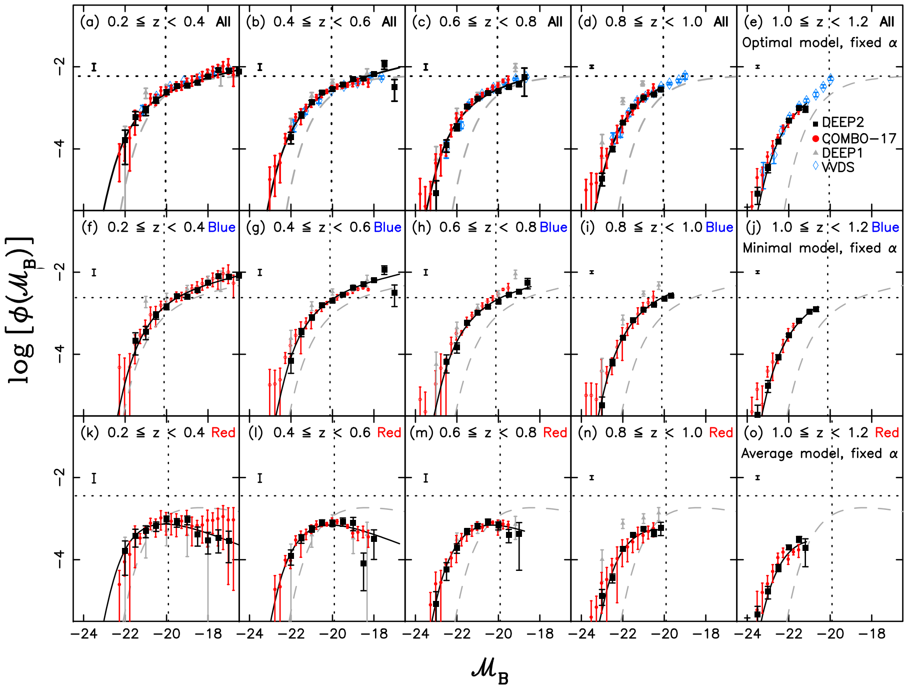

P[0.1(g−r)]
0.1(g−r)
0.1(g−r)
0.1Mr − 5 log h
12 + log(O/H)
log(M*)
Number of Galaxies
σ = 0.10
12 + log(O/H) Residuals
N
fraction
55 clusters
E
S0
Sp
log surface−density [Mpc−2]
W(rp)(h−1Mpc)
(−23.00,−21.20]
(−21.20,−20.44]
(−20.44,−18.45]
rp(h−1Mpc)
Red
Blue
[−21.00,−20.00]
rp(h−1Mpc)



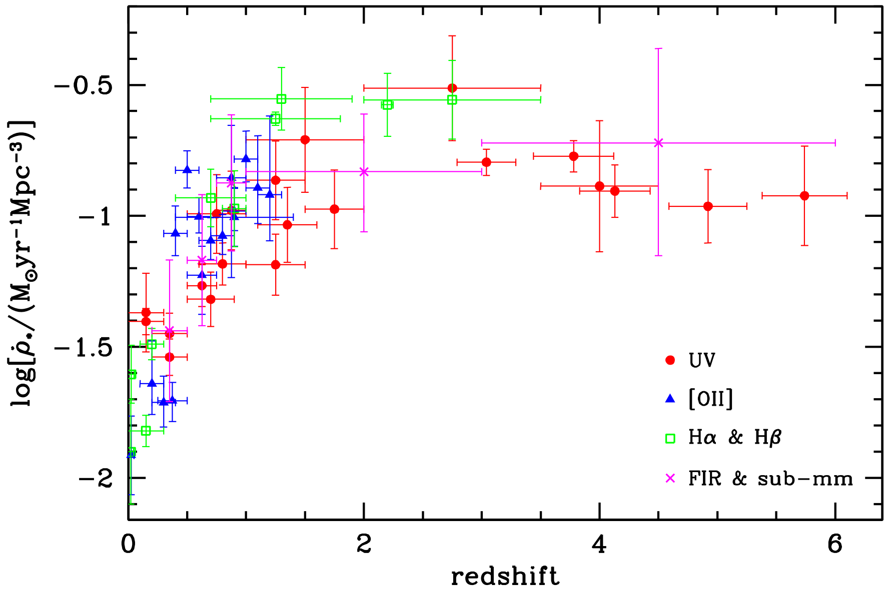


Tully-Fisher relation for spiral galaxies

Fundamental plane for elliptical galaxies



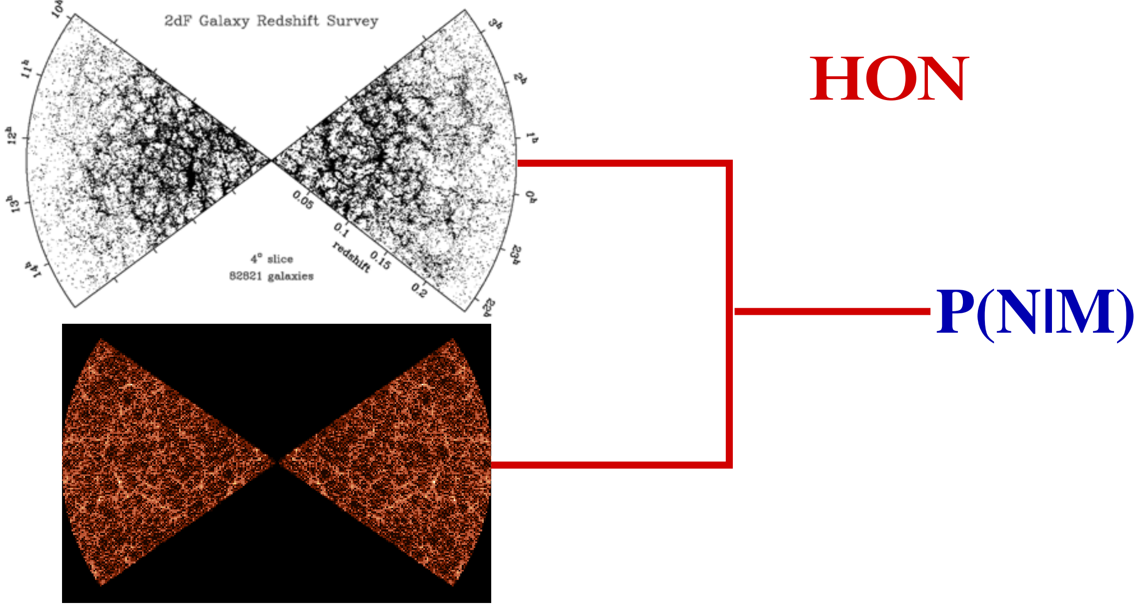
(a) 0.2 ≤ z < 0.4 All
(b) 0.4 ≤ z < 0.6 All
(c) 0.6 ≤ z < 0.8 All
(d) 0.8 ≤ z < 1.0 All
(e) 1.0 ≤ z < 1.2 All
Optimal model, fixed α
DEEP2
COMBO−17
DEEP1
VVDS
(f) 0.2 ≤ z < 0.4 Blue
(g) 0.4 ≤ z < 0.6 Blue
(h) 0.6 ≤ z < 0.8 Blue
(i) 0.8 ≤ z < 1.0 Blue
(j) 1.0 ≤ z < 1.2 Blue
Minimal model, fixed α
(k) 0.2 ≤ z < 0.4 Red
(l) 0.4 ≤ z < 0.6 Red
(m) 0.6 ≤ z < 0.8 Red
(n) 0.8 ≤ z < 1.0 Red
(o) 1.0 ≤ z < 1.2 Red
Average model, fixed α
log [ϕ(ℳ_B)]
ℳ_B



log[ρ̇*/(M⊙yr⁻¹Mpc⁻³)]
redshift
UV
[OII]
Hα & Hβ
FIR & sub−mm

Link galaxies to dark matter halos (Halo population ➡ galaxy population)

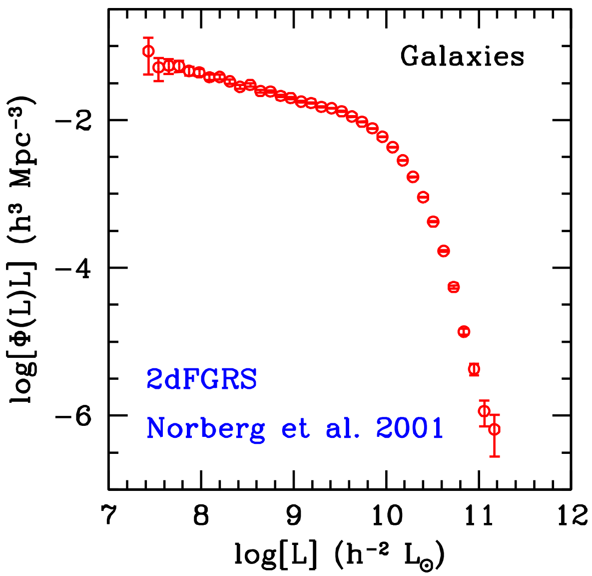
2dFGRS (Peacock et al. 2000)

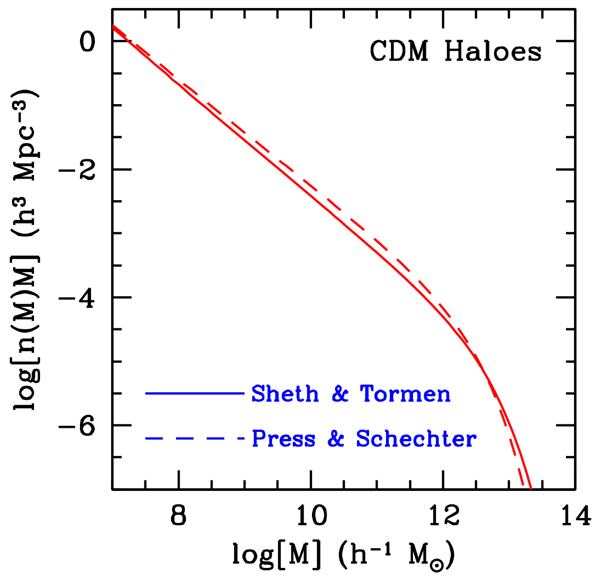


CDM simulation (Virgo consortium)

Halo Occupation Distribution: $P(N|M)$, the probability that a halo of mass M contains N galaxies (of given properties)

Galaxy luminosity function versus halo mass function





We use the Conditional Luminosity Function to link the distributions of galaxies and CDM halos

$\Phi(L|M)\mathrm{d}L$ is average number of galaxies with luminosities in the range L, $L + \mathrm{d}L$ that 'live' in halos of mass M.

Conditional luminosity function

The luminosity function:

$$\Phi(L) = \int_0^\infty \Phi(L|M)\, n(M)\, \mathrm{d}M$$

The average luminosity in a halo of mass M:

$$\langle L\rangle(M) = \int_0^\infty \Phi(L|M)\, L\, \mathrm{d}L$$

Average number of galaxies in a halo of mass M with $L > L_1$:

$$N_M(L > L_1) = \int_{L_1}^\infty \Phi(L|M)\, \mathrm{d}L$$

Clustering properties of galaxies as function of luminosity:

$$\xi_{\rm gg}(r|L) = b^2(L)\, \xi_{\rm dm}(r)$$

$$\bar{b}(L) = \frac{1}{\Phi(L)} \int_0^\infty \Phi(L|M)\, b(M)\, n(M)\, \mathrm{d}M$$

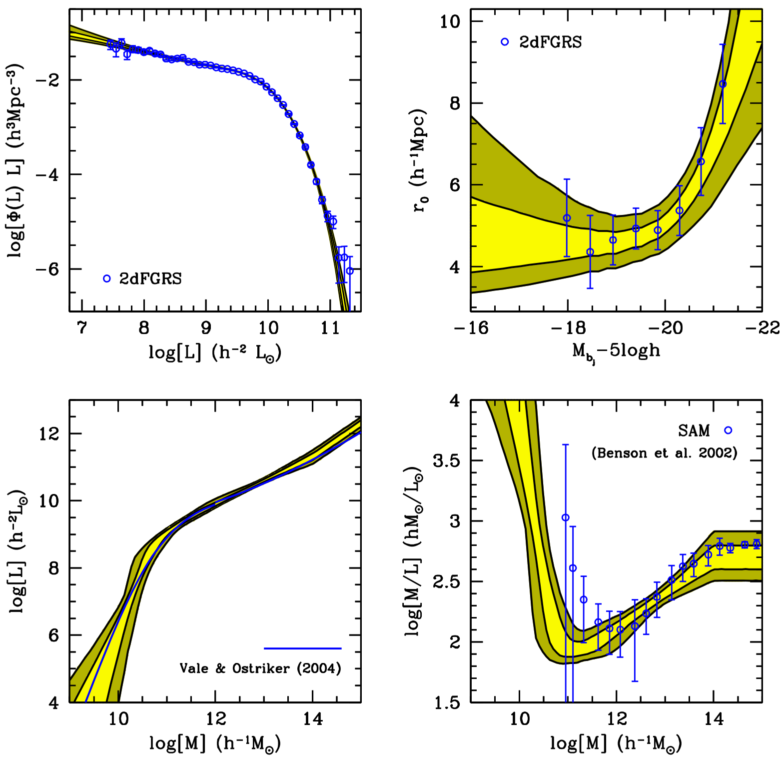
REMINDER: $n(M)$, $b(M)$, $\xi_{\rm dm}(r)$ are well-understood halo properties

The conditional LF is the ideal statistical 'tool' to link
the distributions of dark matter halos and galaxies.

Assuming the CLF also has the Schechter form:

$$\Phi(L|M)\mathrm{d}L = \frac{\tilde{\Phi}^*}{\tilde{L}^*}\left(\frac{L}{\tilde{L}^*}\right)^{\tilde{\alpha}} \exp(-L/\tilde{L}^*)\,\mathrm{d}L.$$

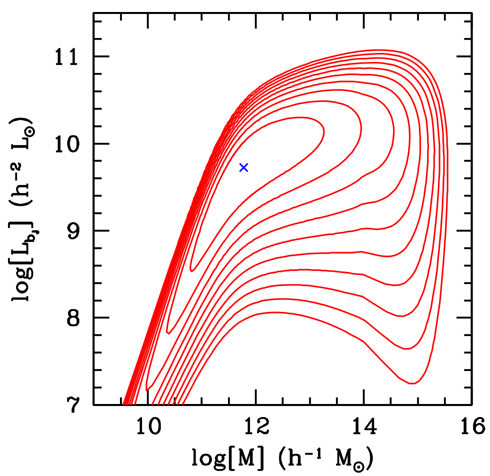
Here $\tilde{\Phi}^*$, $\tilde{L}^*$ and $\tilde{\alpha}$ all depend on M. The forms of these dependencies are parameterized. Monte-Carlo Markov Chain is used to sample posterior distribution of free parameters.

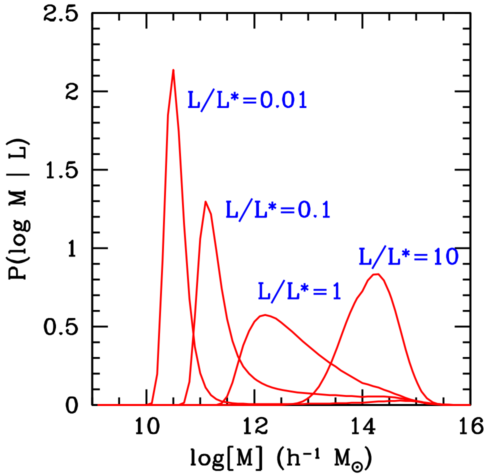


Light distribution in universe

$$P(L,M)\,\mathrm{d}L\,\mathrm{d}M = \frac{1}{\bar{\rho}_L}\,n(M)\,\Phi(L|M)\,L\,\mathrm{d}L\,\mathrm{d}M$$

$$P(M|L)\mathrm{d}M = \frac{\Phi(L|M)\,n(M)\,\mathrm{d}M}{\Phi(L)}$$



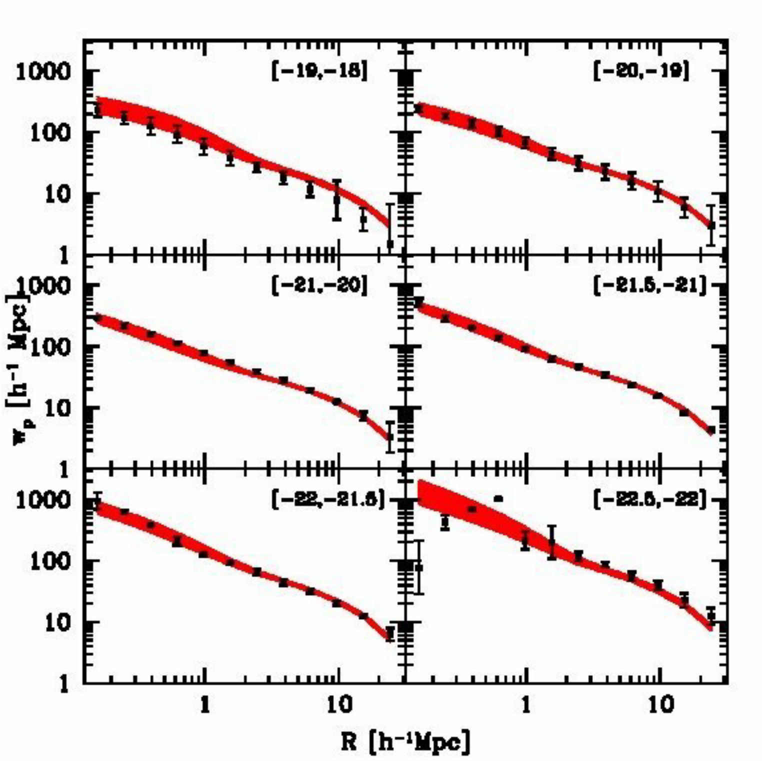


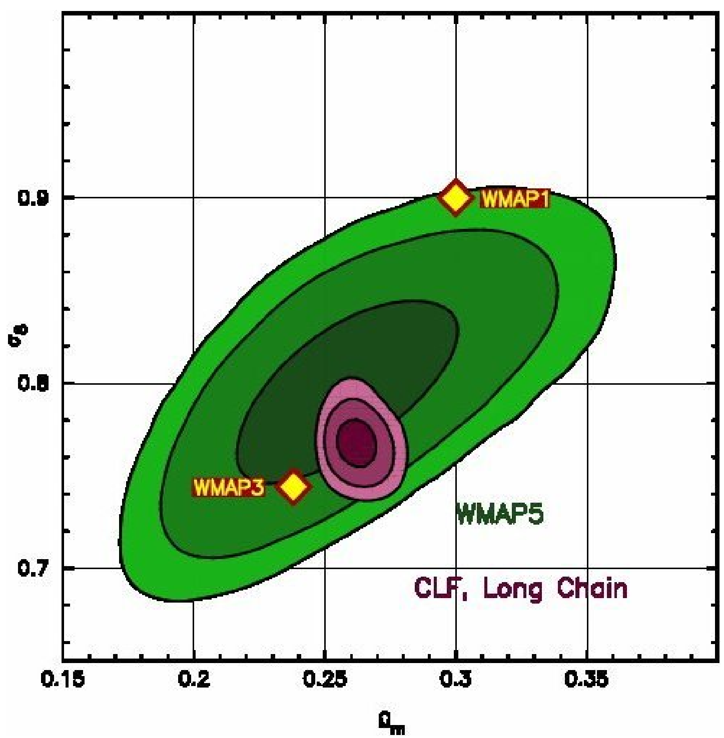
50% of light is produced in halos with $M < 2\times 10^{12} h^{-1}\mathrm{M}_\odot$

Comparison with galaxy-galaxy lensing results

From $\Phi(L|M)$ to obtain $\quad P(M|L) \propto \dfrac{\Phi(L|M)n(M)}{\phi(L)}$.

And asume galaxy distribution in halos follows that of mass.





Semi-analytical model of galaxy formation

- Full numerical simulations: limited by numerical resolution; many processes, such as star formation, feedback have to be treated by uncertain sub-grid prescriptions. Since many of the details are not well understood, the parameter space is too large to be explored numerically.
- Semi-analytical models: processes are modeled as a set of `prescriptions' that carry a number of free parameters. The free parameters in the models are then tuned to reproduce certain observational data of the galaxy population.

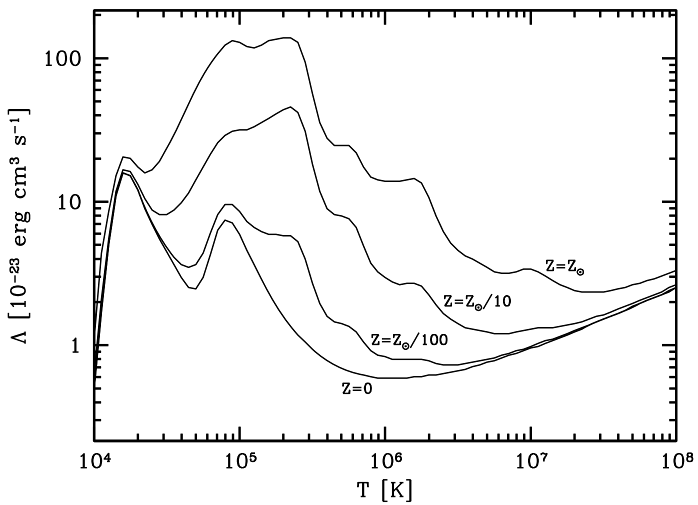
Basic processes

- Hierarchical formation of DM halos (halo merger histories)
- Baryons get shock heated
- Hot gas cools and settles in a disk in the center of the halo potential well
- Cold gas in disk is transformed into stars (star formation)
- Energy output from stars (feedback) reheats some of cold gas
- After haloes merge, galaxies sink to center by dynamical friction
- After halos merge, galaxies sink to center by dynamical friction
- Chemical evolution and stellar population

Some examples of SAM prescriptions

Radiative cooling:

Modeled by cooling function $\Lambda(T,Z)$, $du/dt = \mathcal{C} n_{\rm H}^2 \Lambda$, where u is the internal energy density of the gas.



The cooling timescale:

$$t_{\rm cool} \equiv \frac{\rho \mathcal{E}}{\mathcal{C}} = \frac{3nk_{\rm B}T}{2n_{\rm H}^2\Lambda(T)} \approx 3.3\times 10^9 \frac{T_6}{n_{-3}\Lambda_{-23}(T)} {\rm yr}\,,$$

$\mathcal{E}$: internal energy per unit mass. This should be compared with free-fall time scale of the cloud:

$$t_{\rm ff} = \sqrt{\frac{3\pi}{32G\rho}} = \sqrt{\frac{3\pi f_{\rm gas}}{32Gn\mu m_{\rm p}}} \approx 2.1\times 10^9 f_{\rm gas}^{1/2} n_{-3}^{-1/2} {\rm yr}\,.$$

Cooling is effective if $t_{\rm cool} \ll t_{\rm ff}$.

Define a cooling radius through $t_{\rm cool}(r_{\rm cool}) = t_{\rm age}$, and a free-fall radius through $t_{\rm ff}(r_{\rm ff}) = t_{\rm age}$, the cold gas accretion rate is

$$\dot{M}_{\rm acc} = 4\pi\rho_{\rm gas}(r_{\rm acc}) r_{\rm acc}^2 \frac{{\rm d}r_{\rm acc}}{{\rm d}t}\,, \qquad r_{\rm acc} = \min[r_{\rm cool}, r_{\rm ff}].$$

Uncertainties in choosing $t_{\rm age}$ and in the gas density profile, $\rho_{\rm gas}$.

Star formation prescription

Star formation rate in gaseous disks

$$\dot{M}_* = \epsilon_* \frac{M_{\rm cold}}{\tau_{\rm d}} \,,$$

where $\tau_{\rm d}$ is the dynamical time scale of the disk, and star formation efficiency is parameterized as

$$\epsilon_* = \begin{cases} \alpha_{\rm SF} & V_{\rm vir} \geq V_{\rm SF}; \\ \alpha_{\rm SF} \left(\frac{V_{\rm vir}}{V_{\rm SF}} \right)^{\beta_{\rm SF}} & V_{\rm vir} < V_{\rm SF}, \end{cases}$$

where $\alpha_{\rm SF}$ and $\beta_{\rm SF}$ are parameters and their values are not known a priori. For example, the value of $\beta_{\rm SF}$ ranges from 0 to 2.5 in early models.

Supernova feedback

The SN energy released by a mass of ΔM_* of star formation

$$E_{\rm fb} = \alpha_{\rm SN}\frac{1}{2}\Delta M_* V_{\rm SN}^2 \,,$$

where $V_{\rm SN} = 630{\rm km/s}$ and $\alpha_{\rm SN}$ describes the feedback efficiency.
The effects of feedback:

(i) heating the ISM to hot halo gas;
(ii) ejecting the ISM from the halo;
(iii) driving out hot wind from halo.

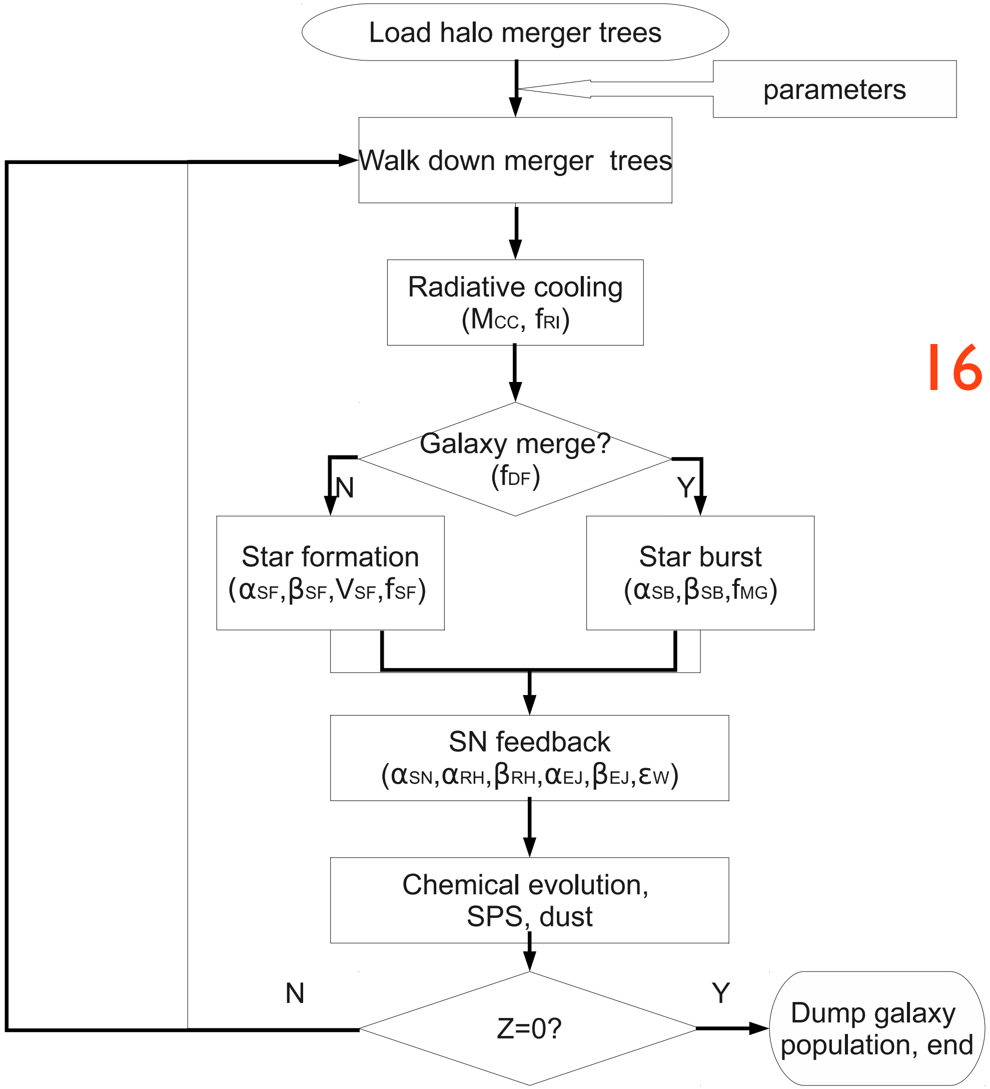
$$E_{\rm fb} = \frac{1}{2}\left(1-f_{\rm ej}\right) f_{\rm rh}\Delta M_* V_{\rm vir}^2 + \frac{1}{2} f_{\rm ej} f_{\rm rh} \Delta M_* v_{\rm esc}^2 + \frac{1}{2}\Delta M_{\rm wind} v_{\rm esc}^2 \,.$$

$$f_{\rm rh} = \alpha_{\rm RH}\left(\frac{V_0}{V_{vir}}\right)^{\beta_{\rm RH}} \;; \qquad f_{\rm ej} = \alpha_{\rm EJ}\left(\frac{V_0}{v_{\rm esc}}\right)^{\beta_{\rm EJ}} \,.$$

$$\Delta M_{\rm wind} = \epsilon_{\rm W}\Delta M_* \left\{\alpha_{\rm SN}\left(\frac{V_{\rm SN}}{v_{\rm esc}}\right)^2 - f_{\rm rh}\left[\left(\frac{V_{vir}}{v_{\rm esc}}\right)^2 + f_{\rm ej}\right]\right\} .$$

All the model parameters are quite uncertain.

A fiducial model family



16 free parameters

How to use SAM to study galaxy formation?

- Early SAM applications: a subset of model parameters is held fixed while other parameters are adjusted to match some observational properties; the goodness of fit is often assessed ``by eye''.
- Problems with this approach:
  (i) many model parameters are uncertain, fixing parameters is equivalent to imposing unsubstantiated priors;
  (ii) no statistically rigorous inference can be made about models.
- Given the uncertainties in models, and the large amounts of observational data, galaxy formation is best studied with the Bayesian inference approach.

The Bayesian Approach

Bayesian Theorem: The posterior probability of a set of parameters Θ in a model (or hypothesis) M for given data D is

$$P(\Theta|D, M) \propto P(\Theta|M)L(D|\Theta, M),$$

where $P(\Theta|M)$ is the prior probability distribution describing the knowledge about the parameters acquired before seeing the data, and $L(D|\Theta, M)$ is the likelihood of data D for the given model parameter set Θ.

This not only allows to derive posterior distributions of model parameters for a given model family, it also allows to compare different model families using Bayesian evidence.

Bayesian Evidence

The normalization of the posterior,

$$P(D|M) = \int P(\Theta|M) L(D|\Theta, M) \mathrm{d}\Theta$$

is the total likelihood of the data for the given model. The probability of the model for the given data is

$$P(M|D) = \frac{P(M)P(D|M)}{P(D)} \,.$$

Thus, for two model families M_1 and M_2, their relative odd for the given data is

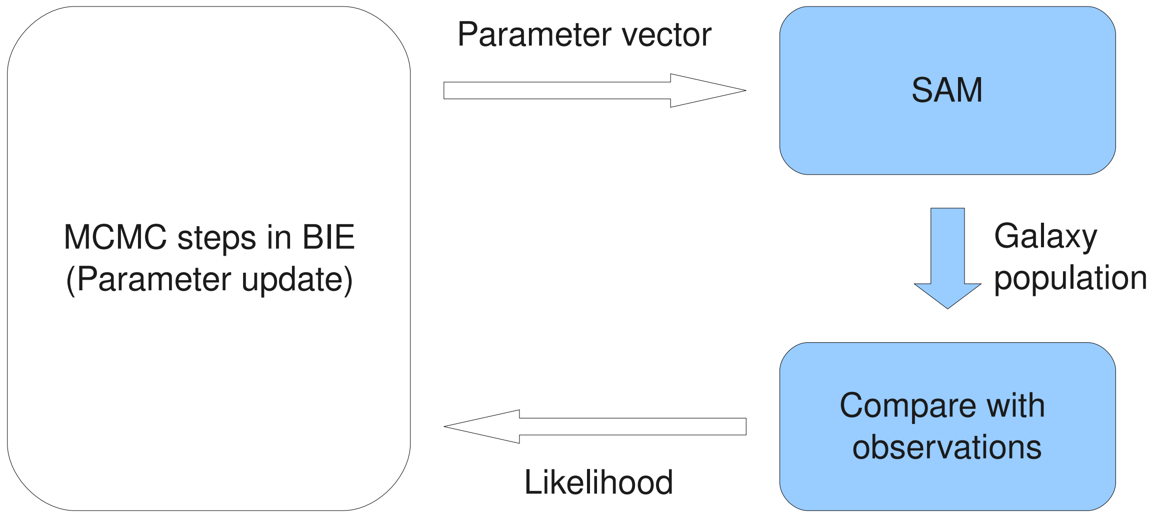
$$\frac{P(M_1|D)}{P(M_2|D)} = \frac{P(M_1)P(D|M_1)}{P(M_2)P(D|M_2)}$$

The ratio $P(M_1)/P(M_2)$ is the relative prior probability, and $P(D|M_1)/P(D|M_2)$ is the Bayesian evidence and can be obtained from the posterior distribution.

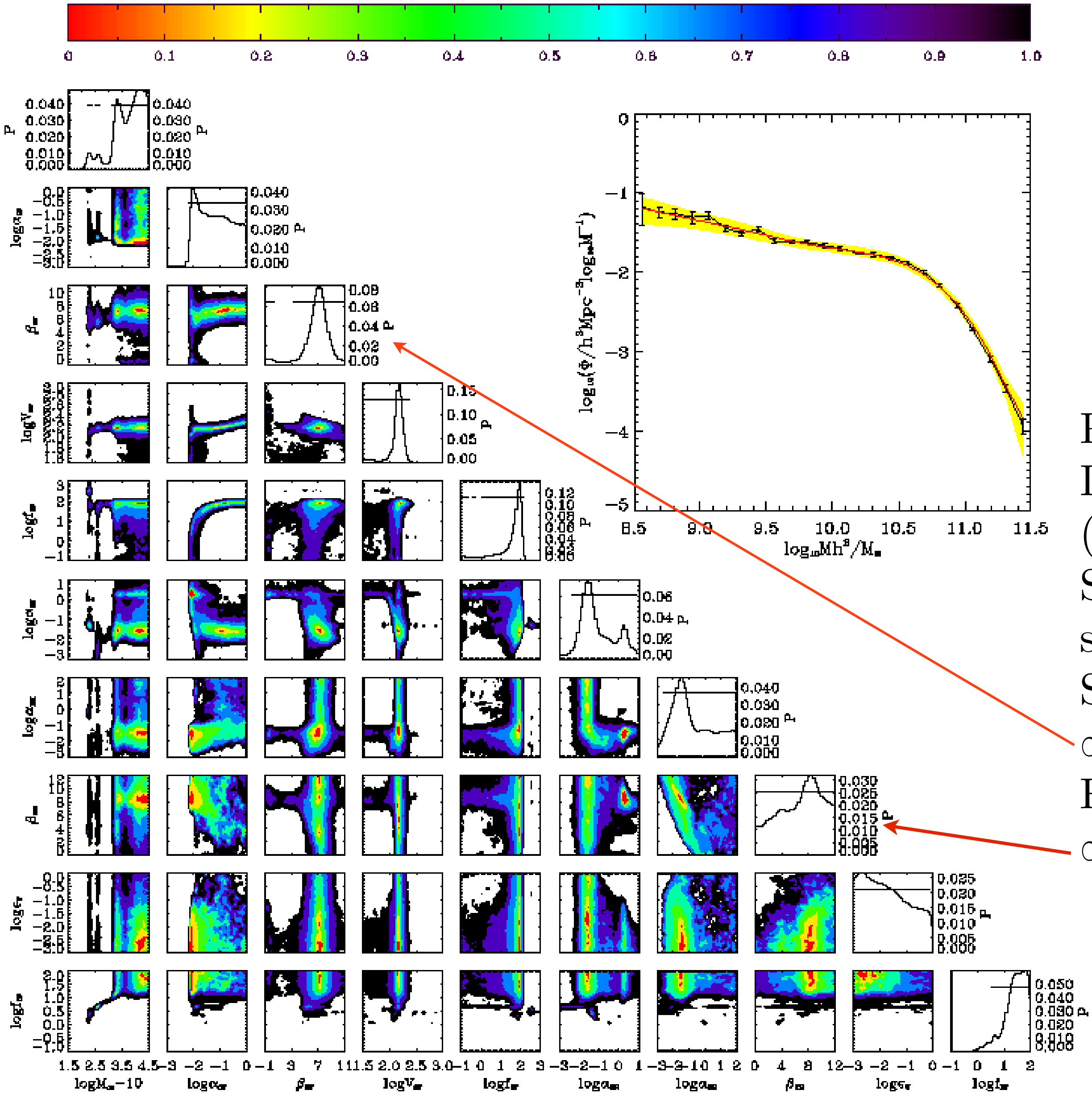
The Markov-Chain Monte-Carlo (MCMC)

- For our problem, it is impossible to derive the posterior probability distribution analytically, A MCMC approach is adopted to sample the posterior.
- Bayesian Inference Engine, a software package, developed at UMass, which includes advanced MCMC algorithms (differential evolution, tempering scheme, etc) and supports parallel computation.

The Bayesian SAM

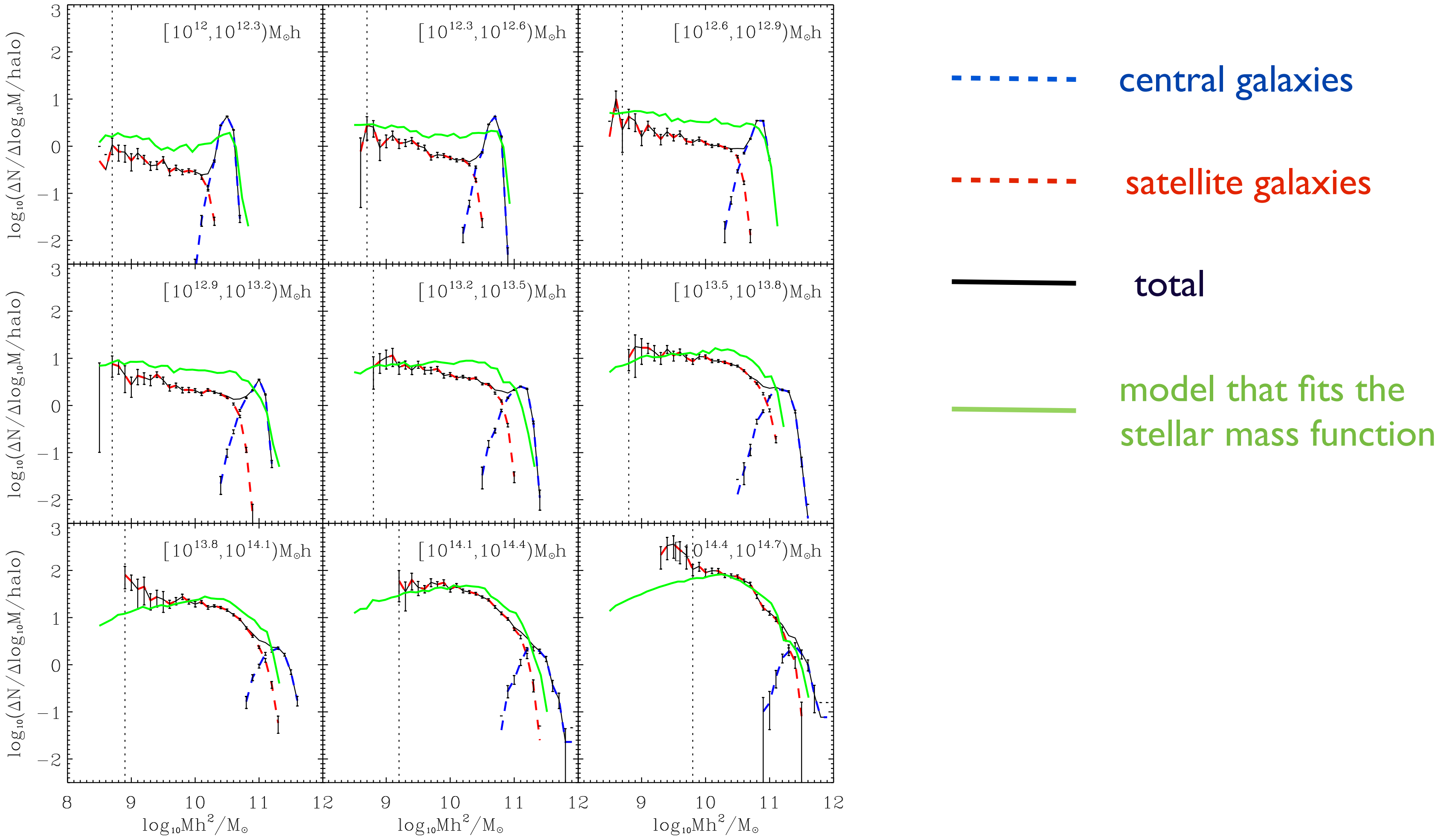


Inference from galaxy stellar mass function



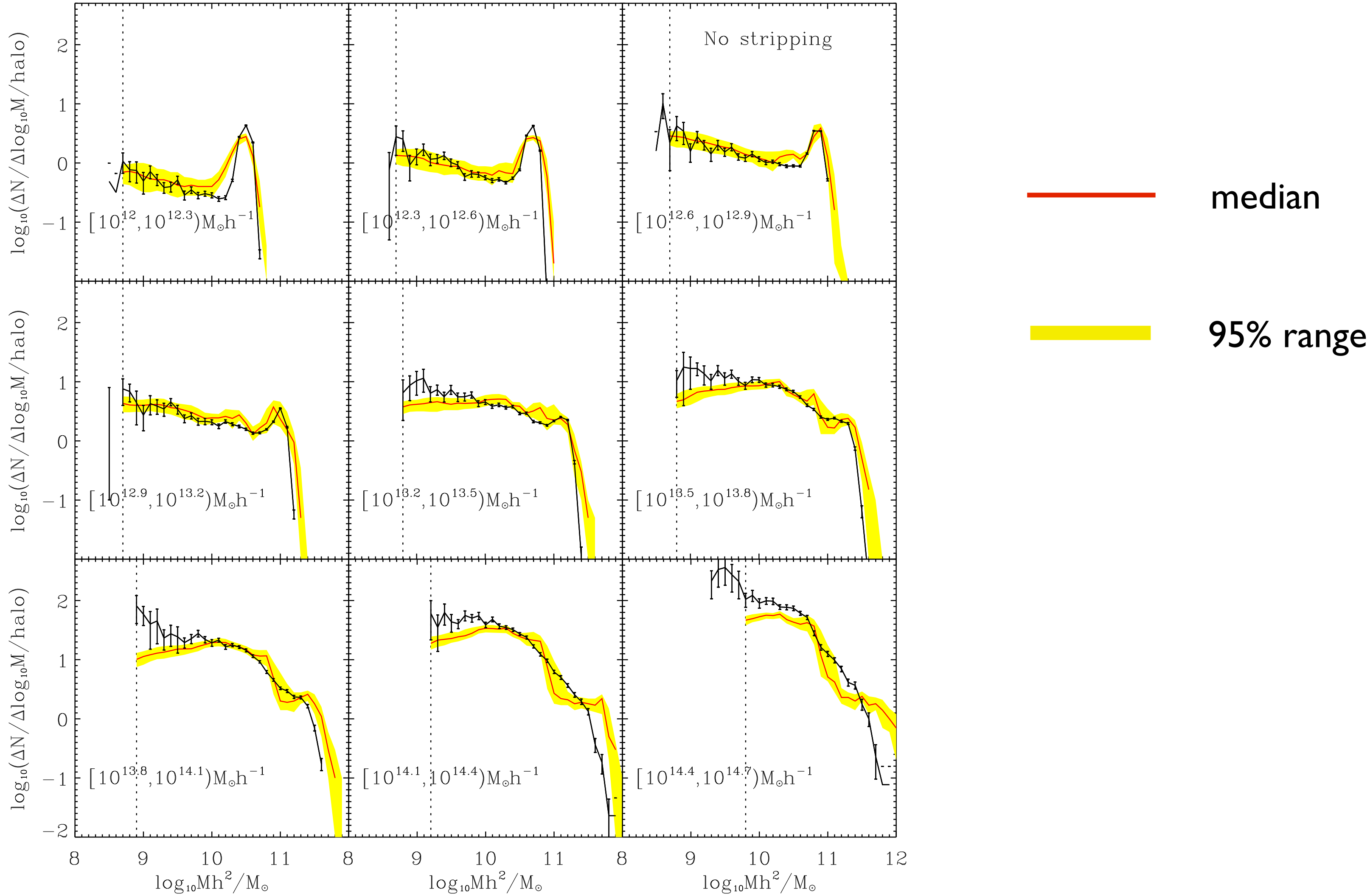
Posterior distribution complex
Degeneracy among parameters (e.g. $\alpha_{\rm SF}$ - $f_{\rm SF}$)
Some parameters extreme, suggesting new physics:
Star formation efficiency, $\propto V_{\rm vir}^{\beta_{\rm SF}}$, $\beta_{\rm SF} \sim 7$;
Feedback efficiency, $\propto V_{\rm vir}^{-\beta_{\rm RH}}$, $\beta_{\rm RH} \sim 8$.

Inference from conditional stellar mass function

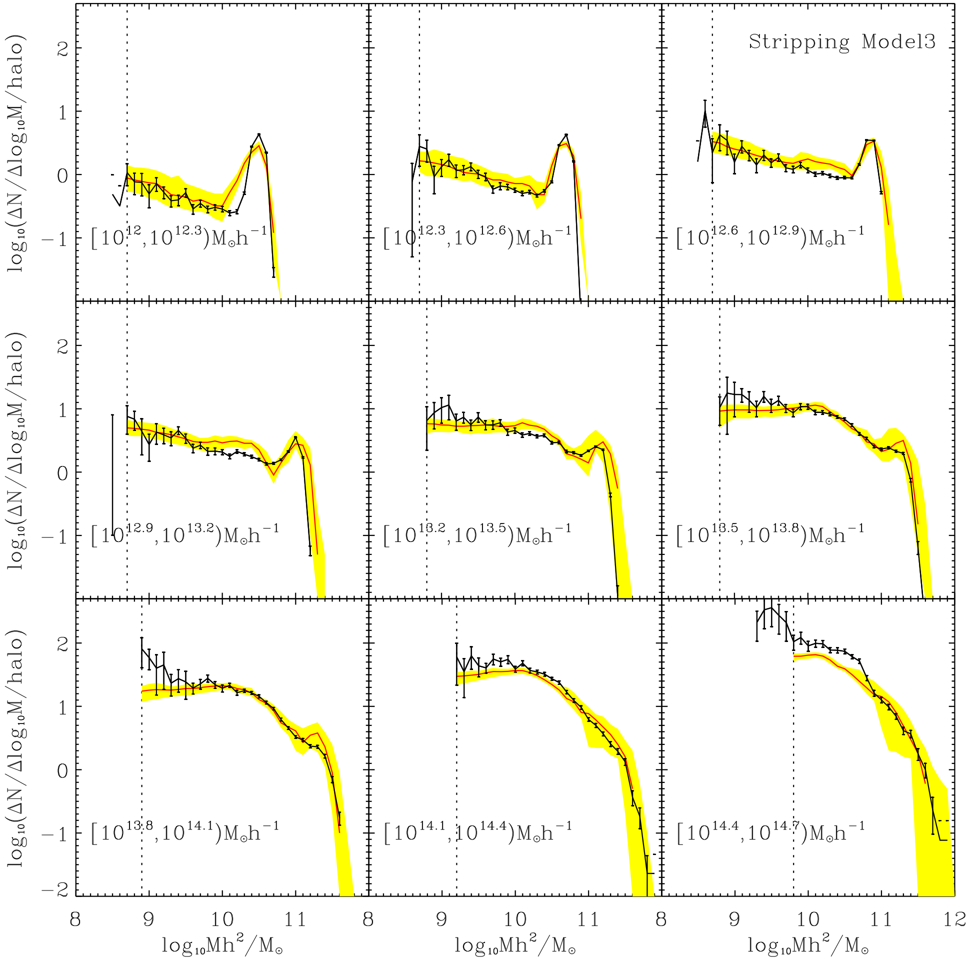


Data: Yang et al (2009)

The fiducial model family



Model including tidal stripping



Bayesian evidence

This model family:

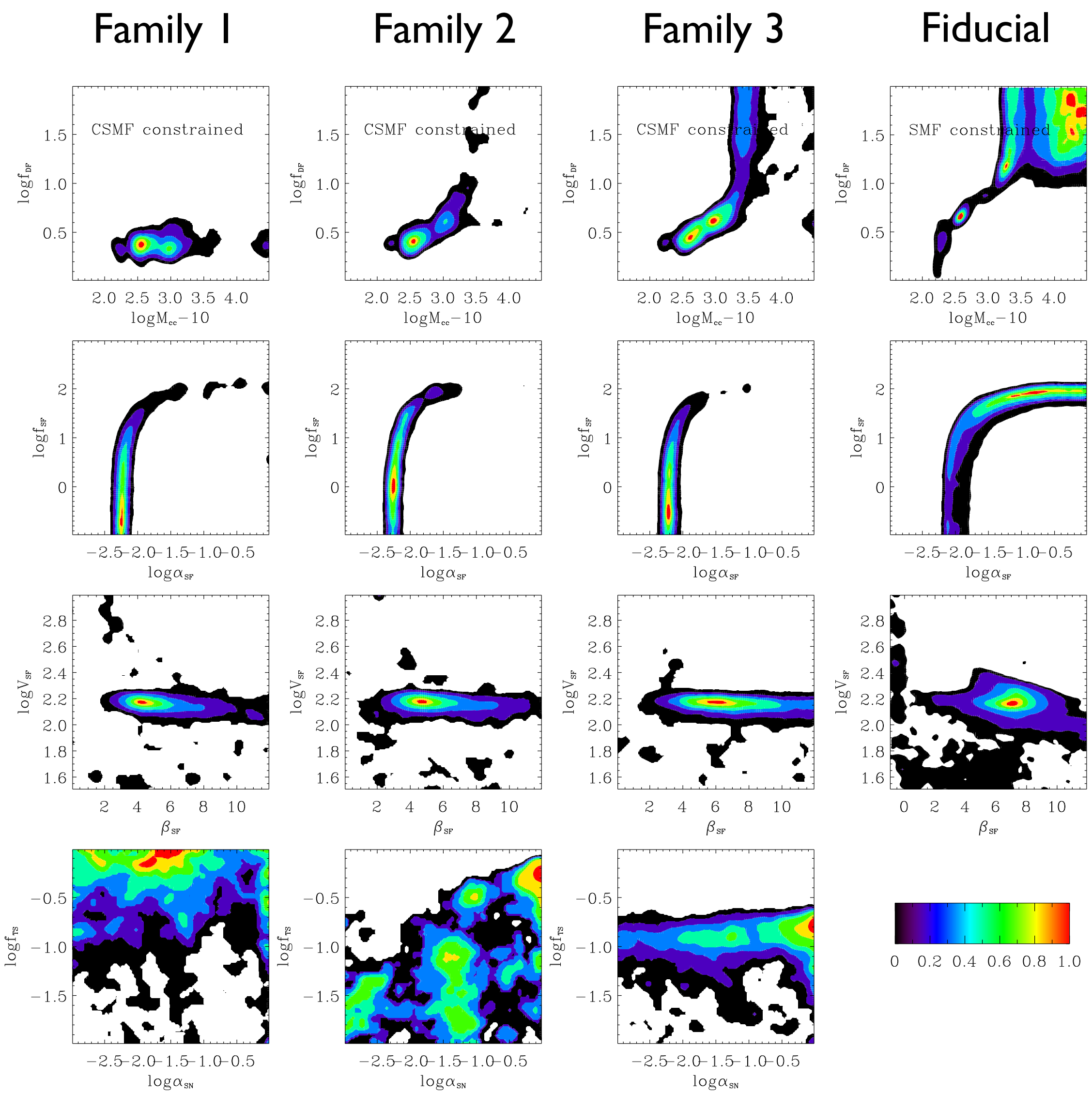
$$\log P(D|M) = -45.6^{+3.40}_{-7.48};$$

Fiducial family (no stripping):

$$\log P(D|M) = -69.15^{+2.19}_{-0.89}.$$

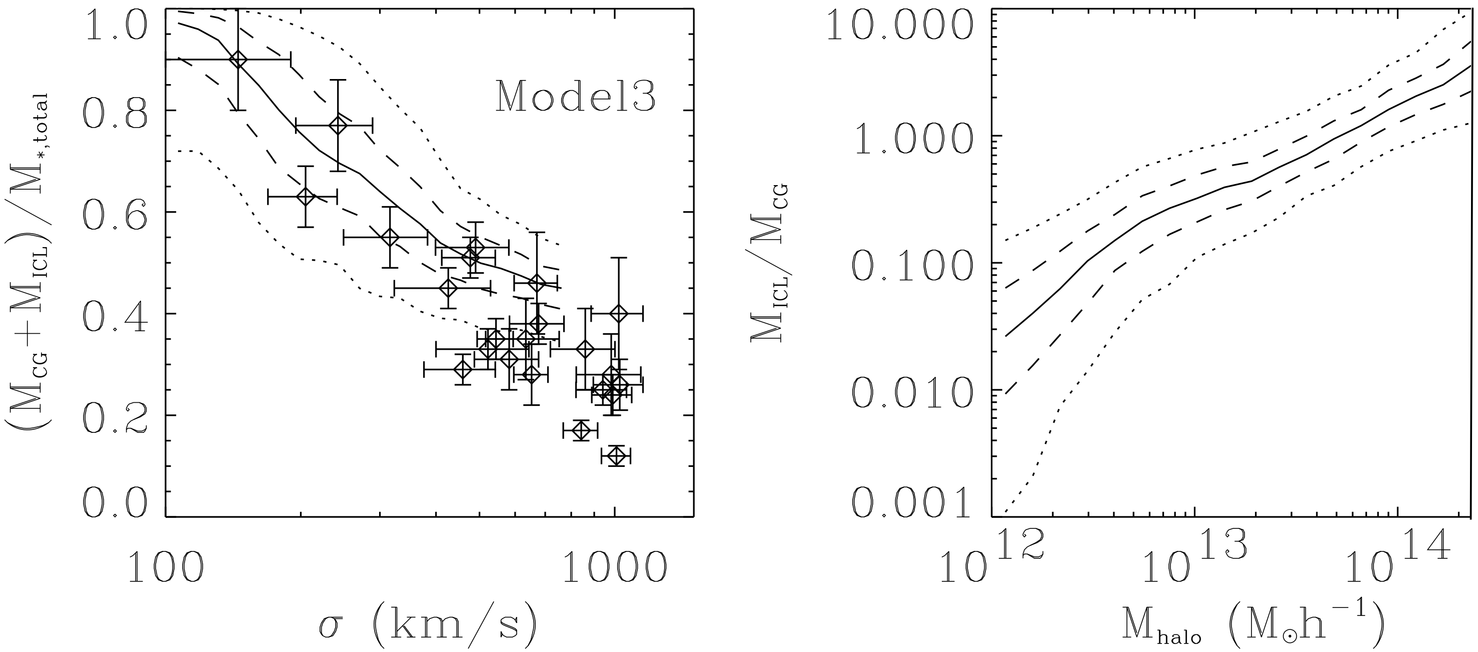
Stripping fraction: $$\mathrm{d}f_\mathrm{s} = \alpha_\mathrm{TS}\frac{\mathrm{dt}}{t_\mathrm{dyn}}$$

Posterior distribution

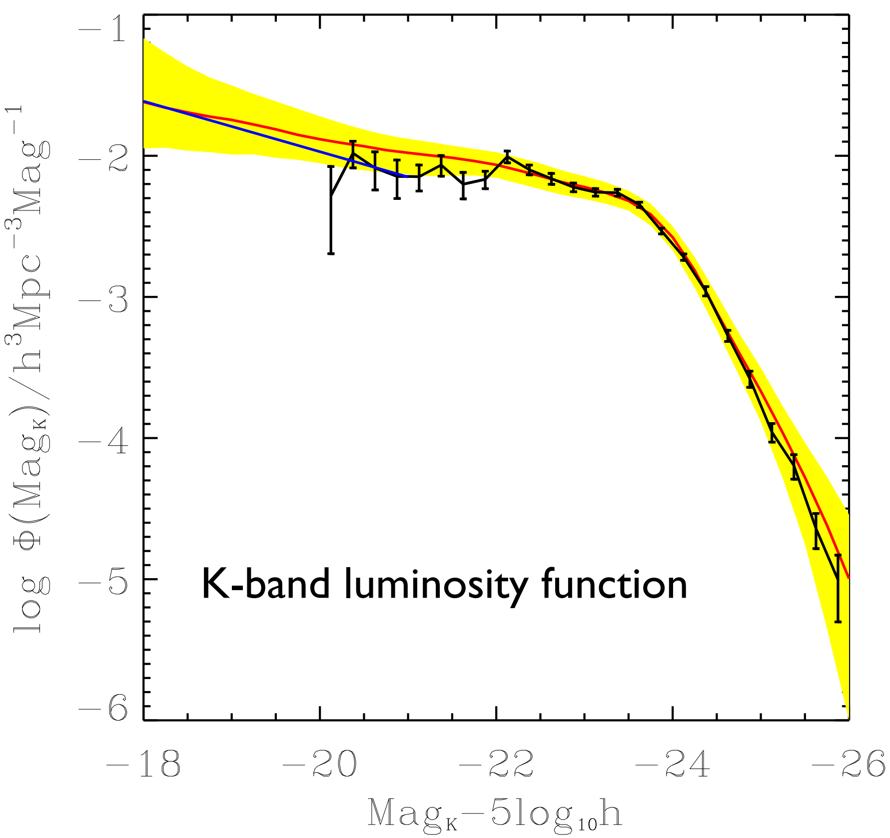


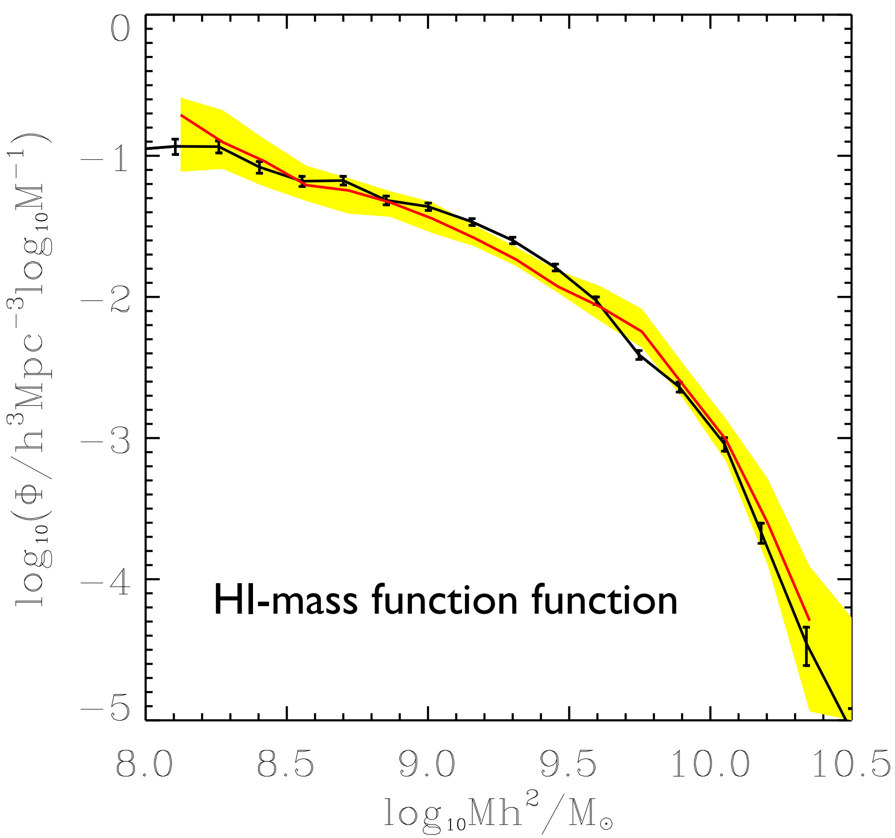
Thursday, July 29, 2010

Intra-cluster stars

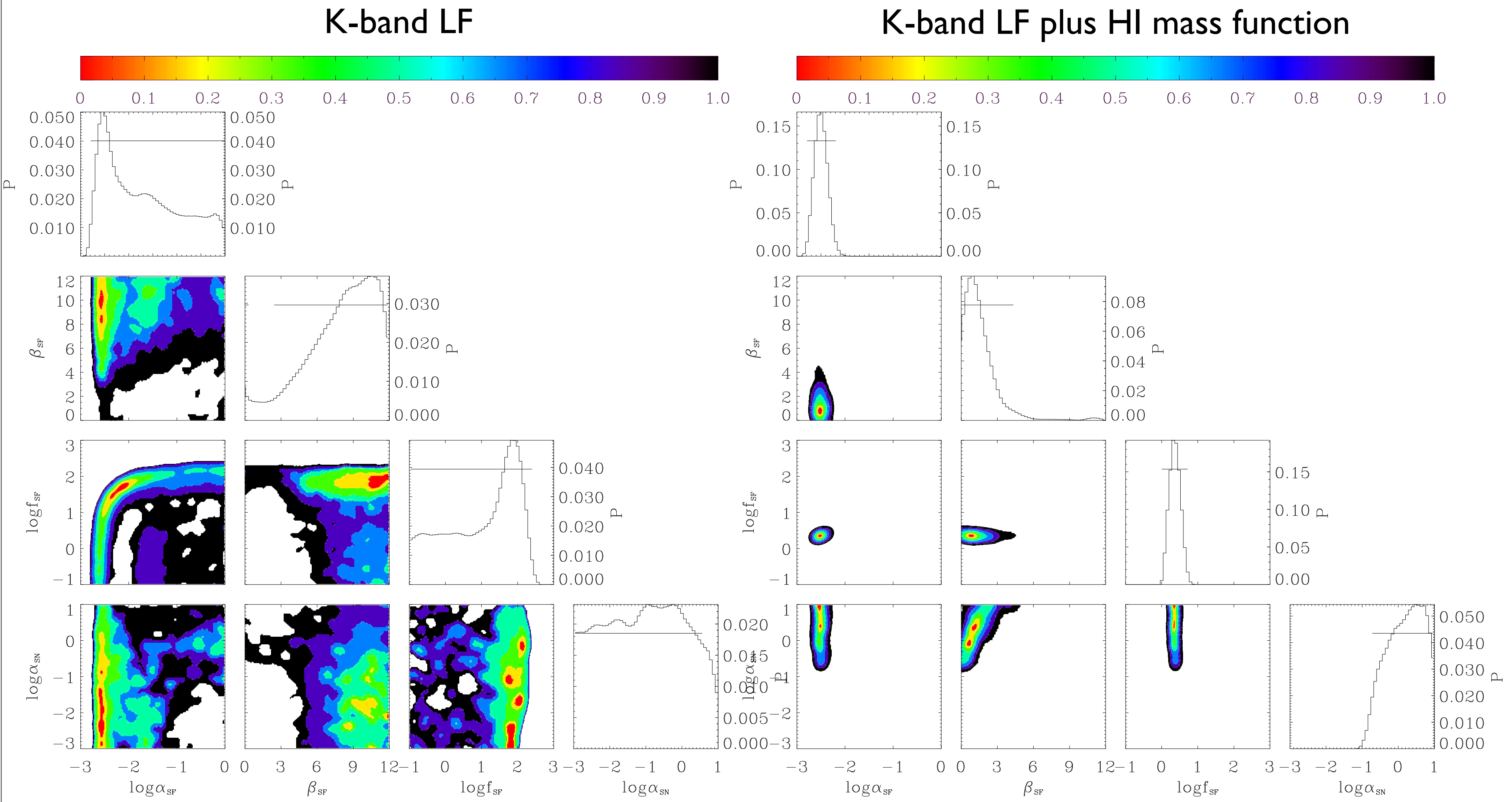


Inference from HI mass function

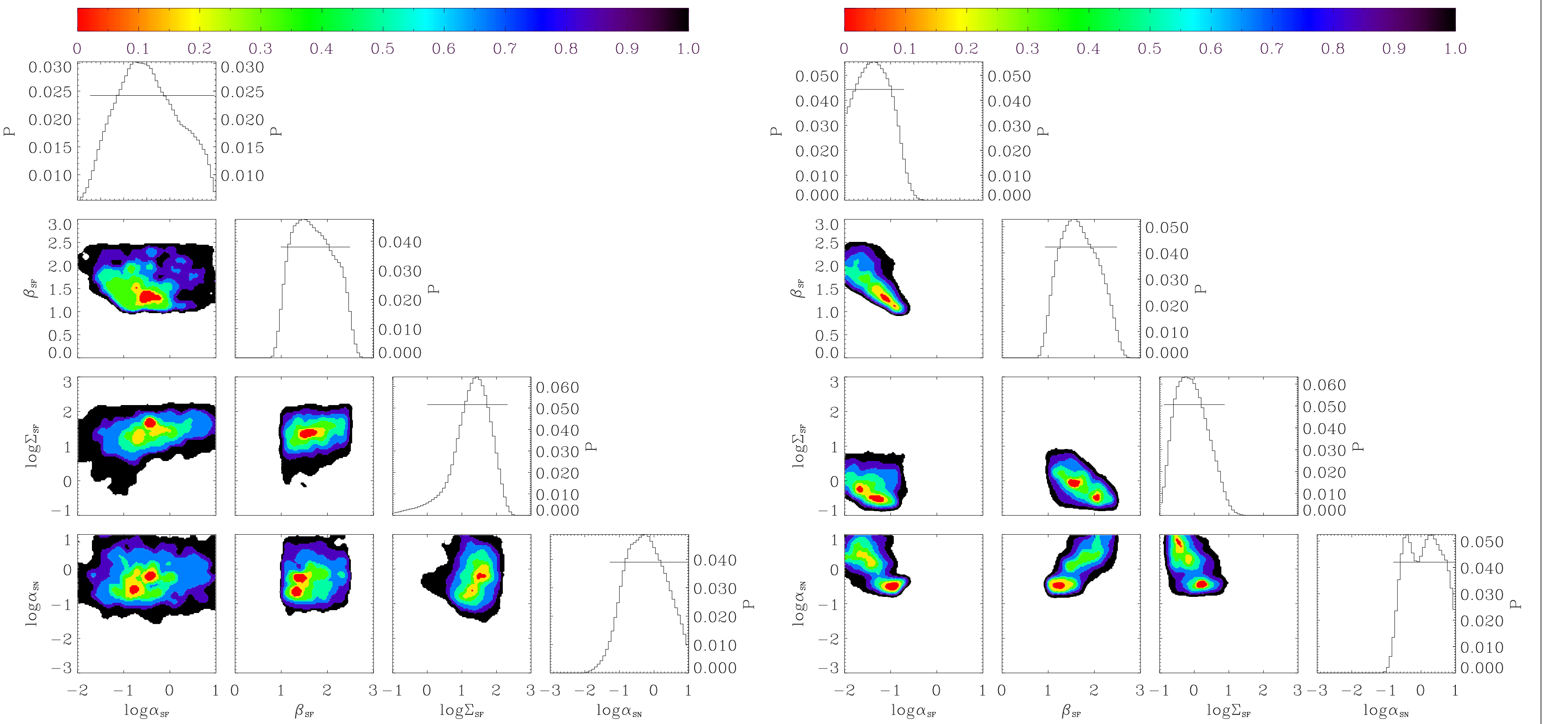




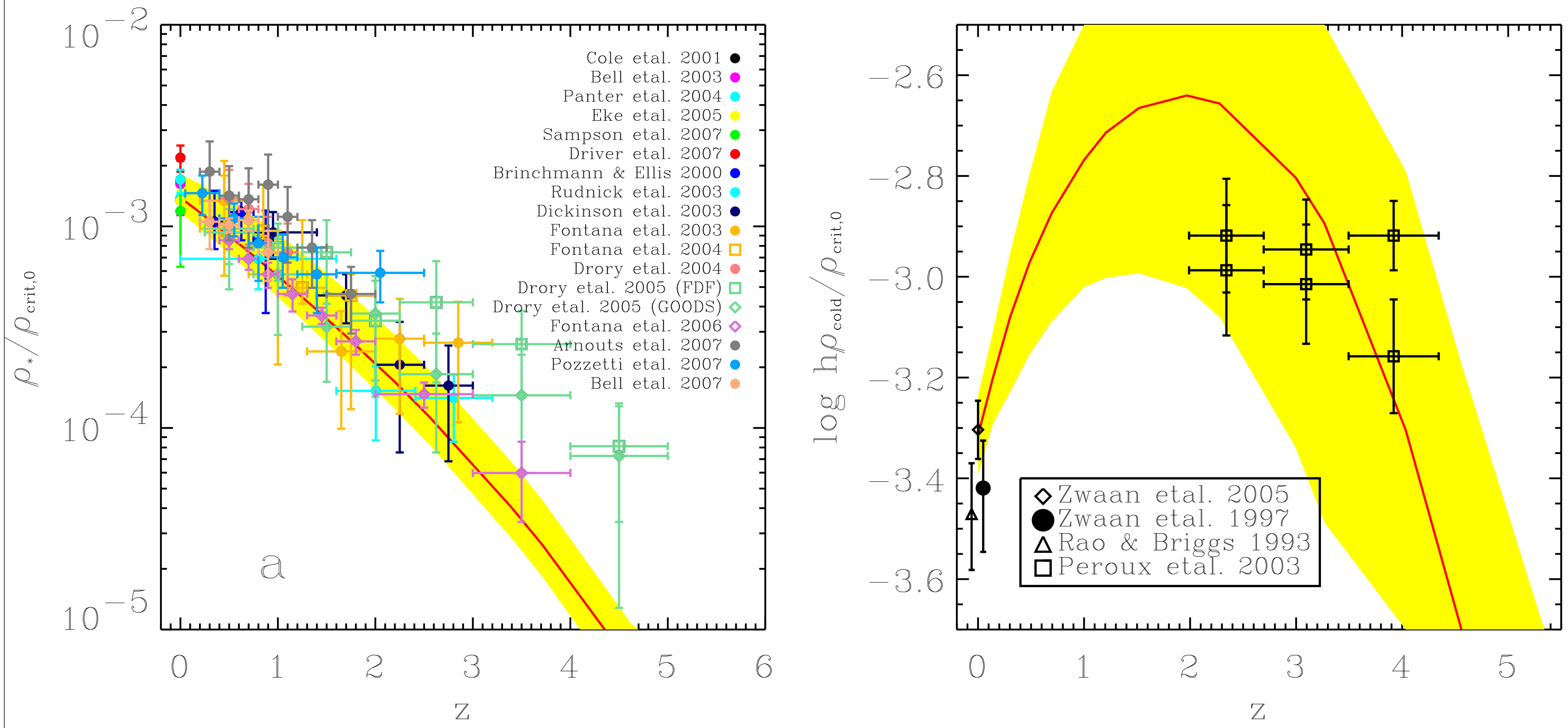
Posterior Distribution



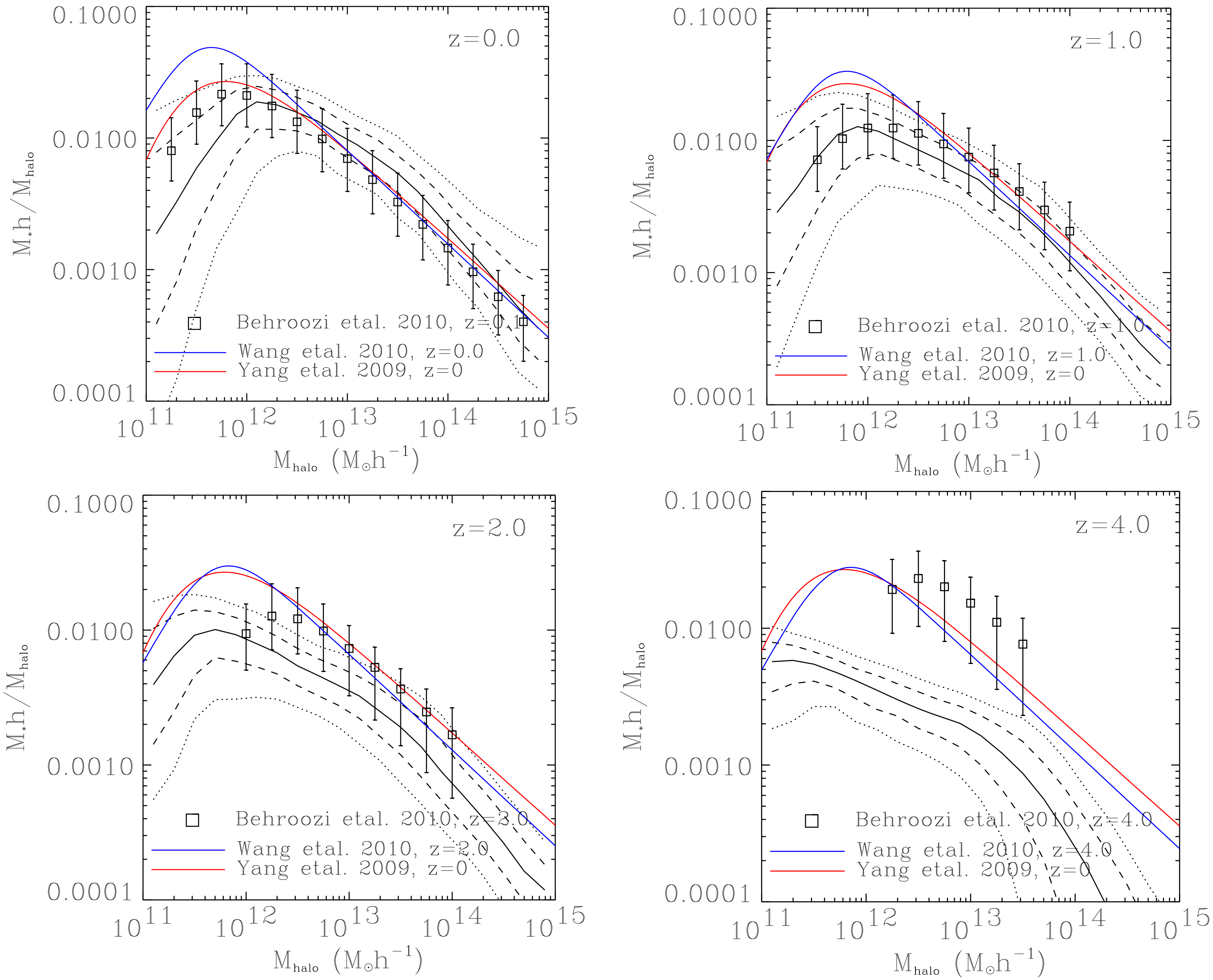
Another model family



Model predictions for high-z galaxies



Stellar mass - halo mass relation



Conclusions

- The cosmological framework for galaxy formation well established.
- Many physical processes affecting galaxy formation, especially those associated with dark matter halos, are well understood, but many others are still poorly understood.
- Copious observational data are available now and in the near future to constrain models.
- A lot of work needs to be done.