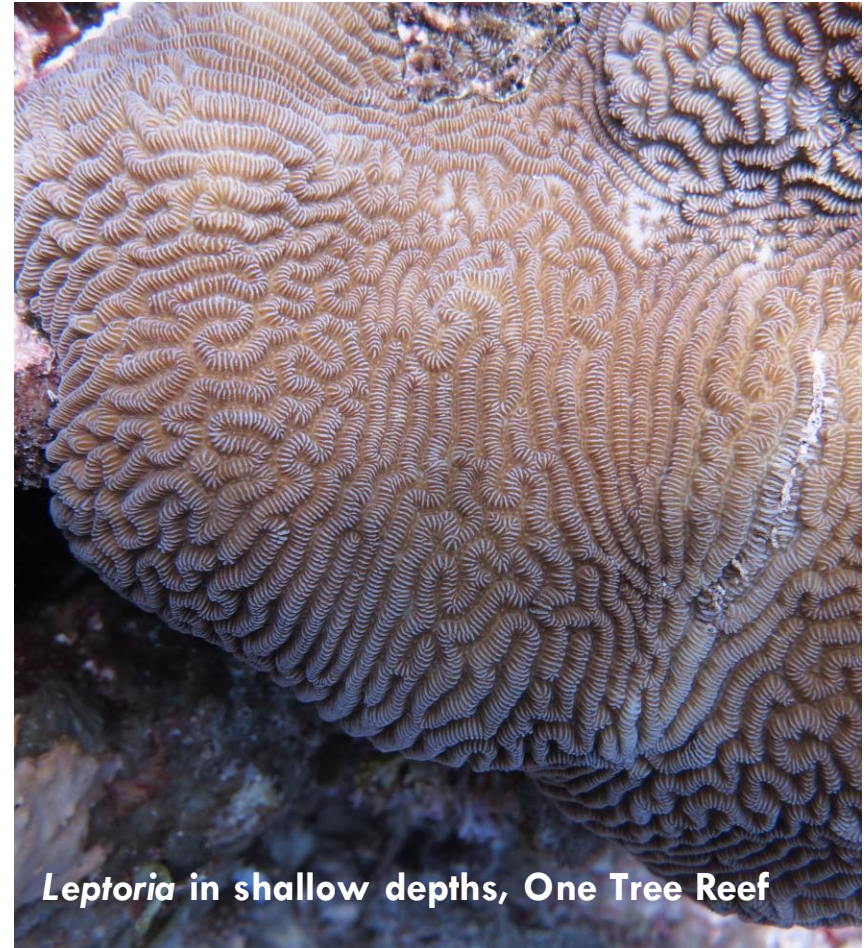


# BayesReef: Bayesian inference for estimation and uncertainty quantification of parameters in geological reef evolution model

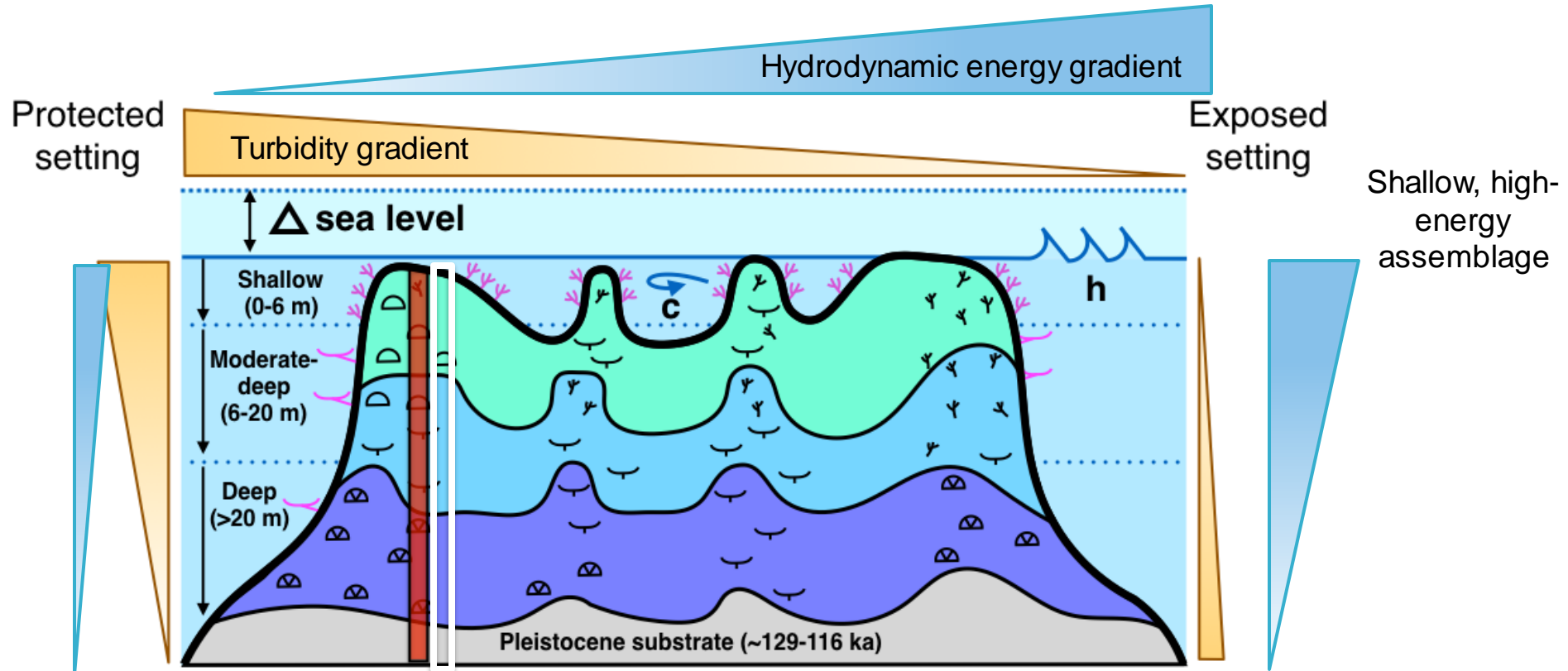
**Rohitash Chandra** and Jodie Pall

1. Geocoastal Research Group, School of Geosciences
2. Centre for Translational Data Science



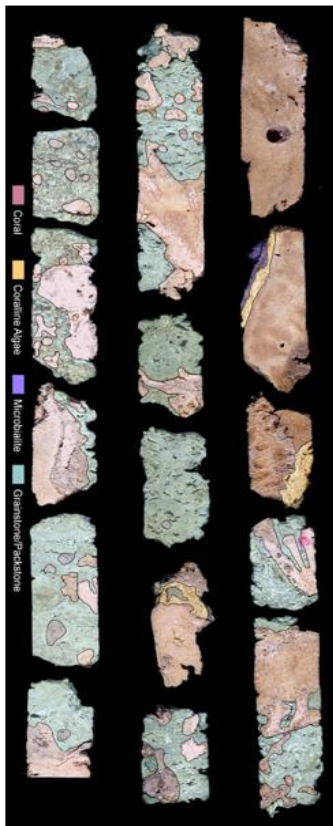
*Leptoria* in shallow depths, One Tree Reef

# Environmental controls on reef growth

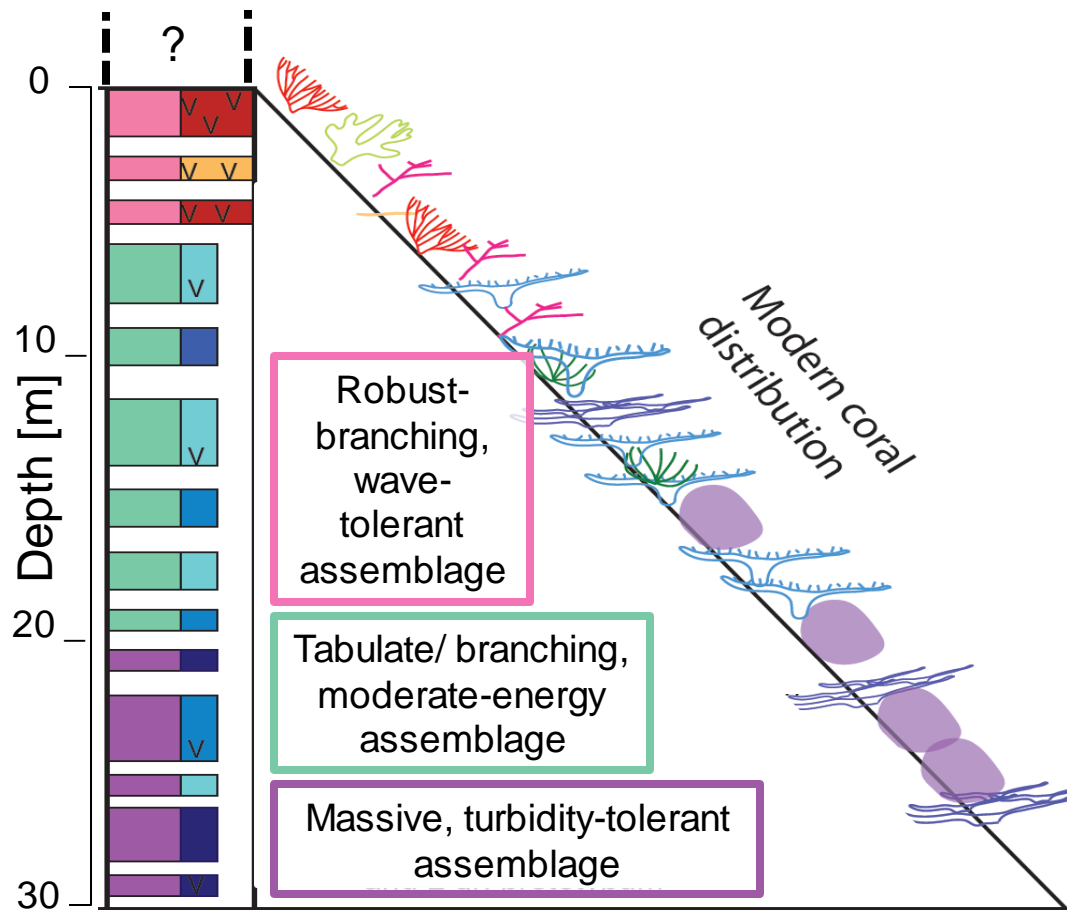


# Geological perspective on reef growth

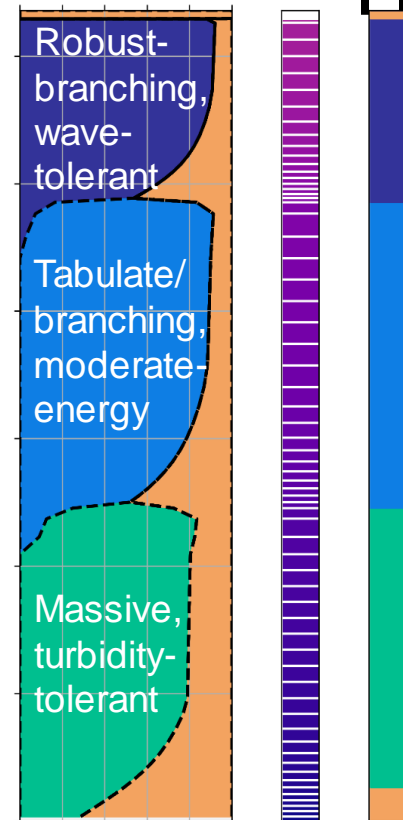
Actual core



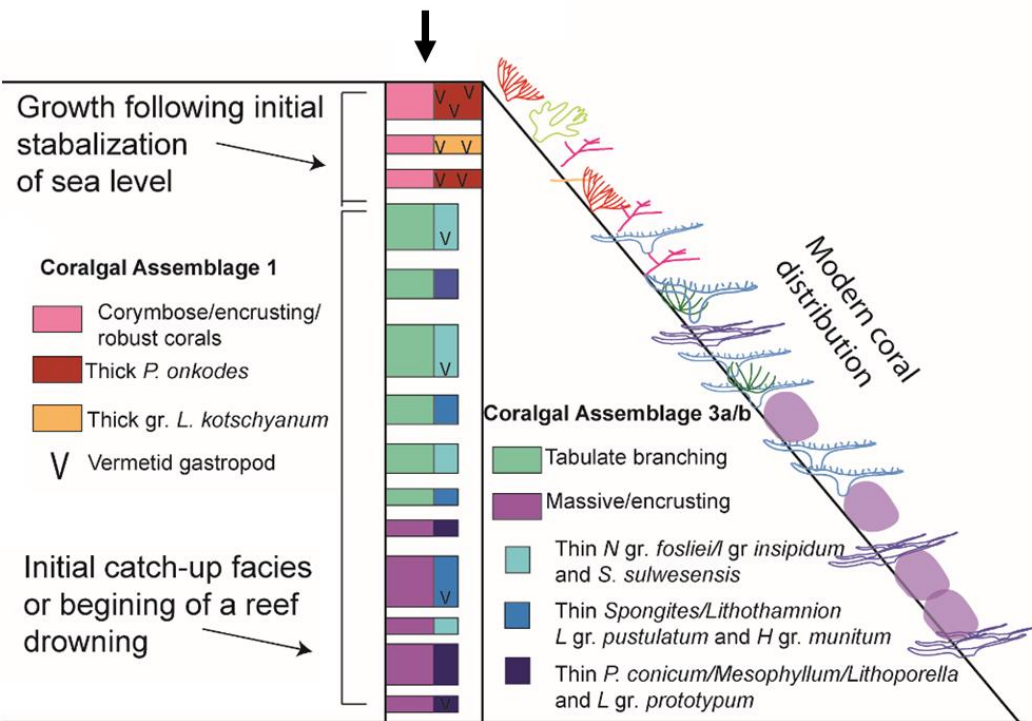
Idealised vertical fossil reef sequence (Dechnik 2016)



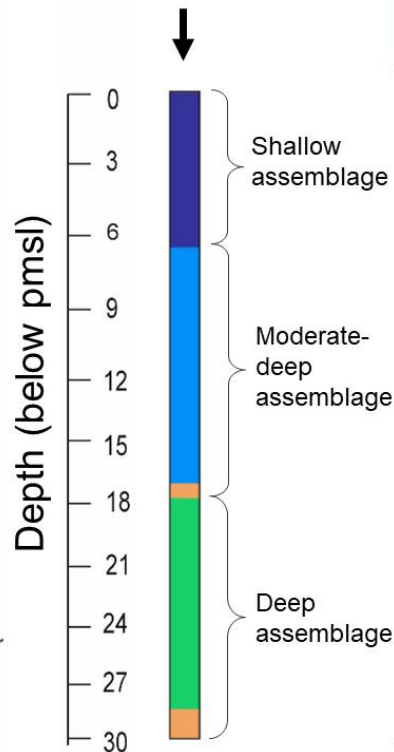
Model core in pyReef-Core



**A.** Idealised, vertical fossil reef sequence,  
exposed margin (Dechnik, 2016)



**B.** Synthetic core  
(this study)

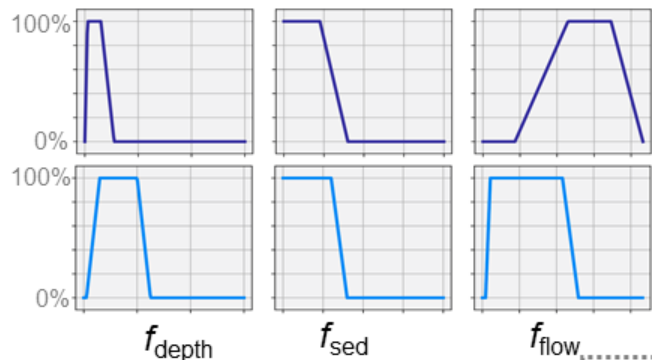


**Assigned Numerical IDs**

Depth interval [m]	Assemblage	Num. ID
0	Shallow, exposed	0.143
...	...	...
3	...	...
...	...	...
4	Shallow, exposed	0.143
6	Mod-deep, exposed	0.286
...	...	...
9	...	...
...	...	...
12	...	...
...	...	...
15	Mod-deep, exposed	0.286
16	Carbonate sediment	0.581
18	Deep, exposed	0.429
...	...	...
21	...	...
...	...	...
24	...	...
...	...	...
27	Deep, exposed	0.429
30	Carbonate sediment	0.581

Assemblage 2 Assemblage 1

Environmental tolerance threshold functions for each assemblage



Community Interaction Matrix

$$A = \begin{bmatrix} \alpha_{ii} & \alpha_{i+1,i} \\ \alpha_{i,i+1} & \alpha_{ii} \end{bmatrix} \quad -1 < a_{ij} < 0$$

$$\min\{f_{\text{depth}}, f_{\text{sed}}, f_{\text{flow}}\} = f_{\text{env}}$$

$$f_{\text{env}}^1$$

$$0 < f_{\text{env}} < 100\%$$

$$f_{\text{env}}^2$$

$$\times$$

Malthusian Parameter  $\epsilon$

if population = 0 :  
if  $f_{\text{env}}^i > 0.5$  :  
begin growth

$$0 < \epsilon < 1$$

GLV Equations

Community Populations

Carbonate Production

Population growth limited by environmental factor

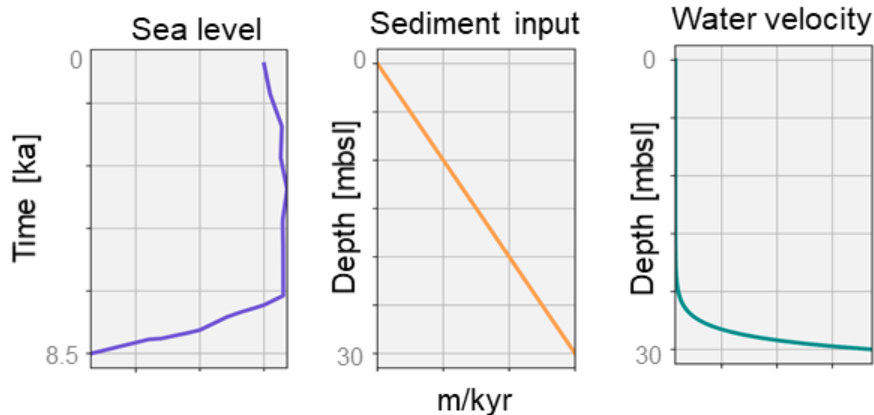
$$t_{\text{fin}} = 0$$

...

Simulation time

Time layers

Modelled core



Repeat for each 0.25 yr timestep from 8500 yrs to present

$$t_0 = 8500$$



# pyReef-Core output

Depth [m]

Shallow assemblage

~6 m -

?

Moderate-deep assemblage

~20m -

?

?

Deep assemblage

~30 m -

?

?

Predator-prey model

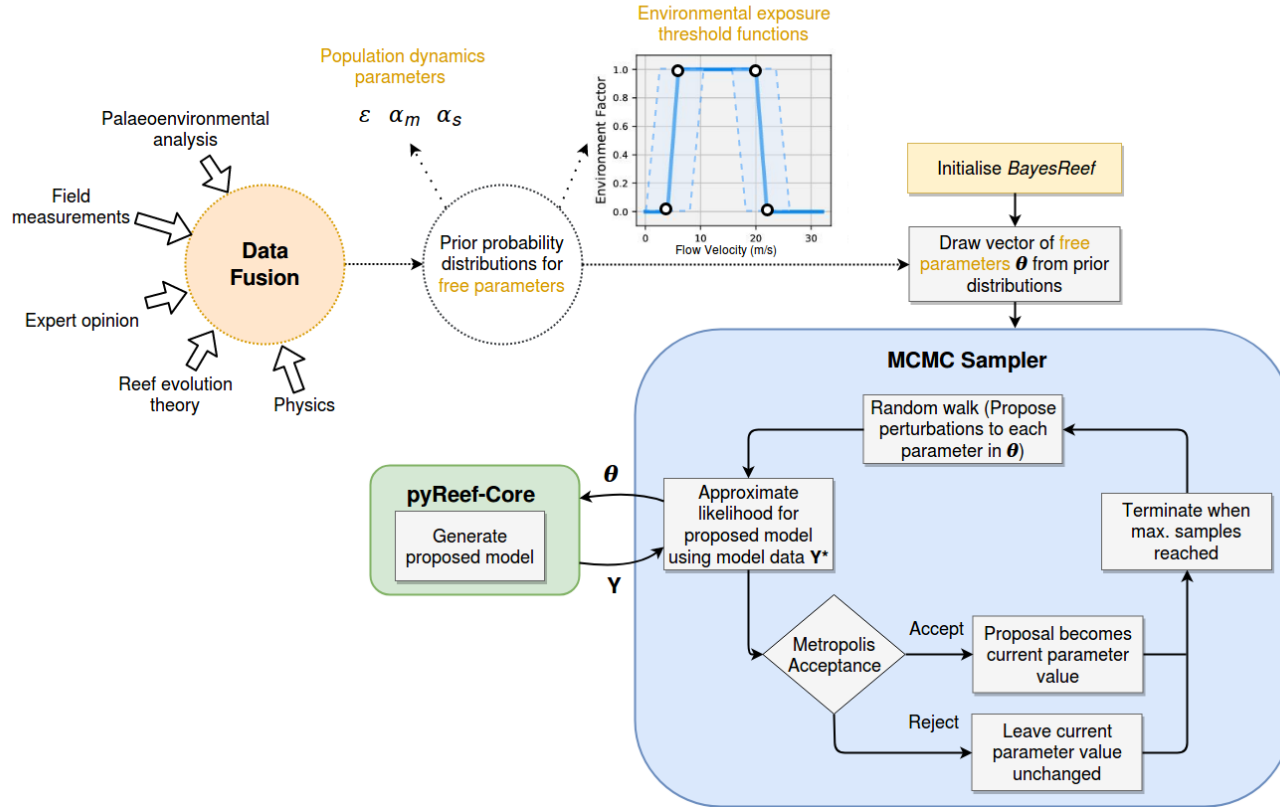
Ecological Dynamics

Sediment input

Hydrodynamic energy  
Accommodation

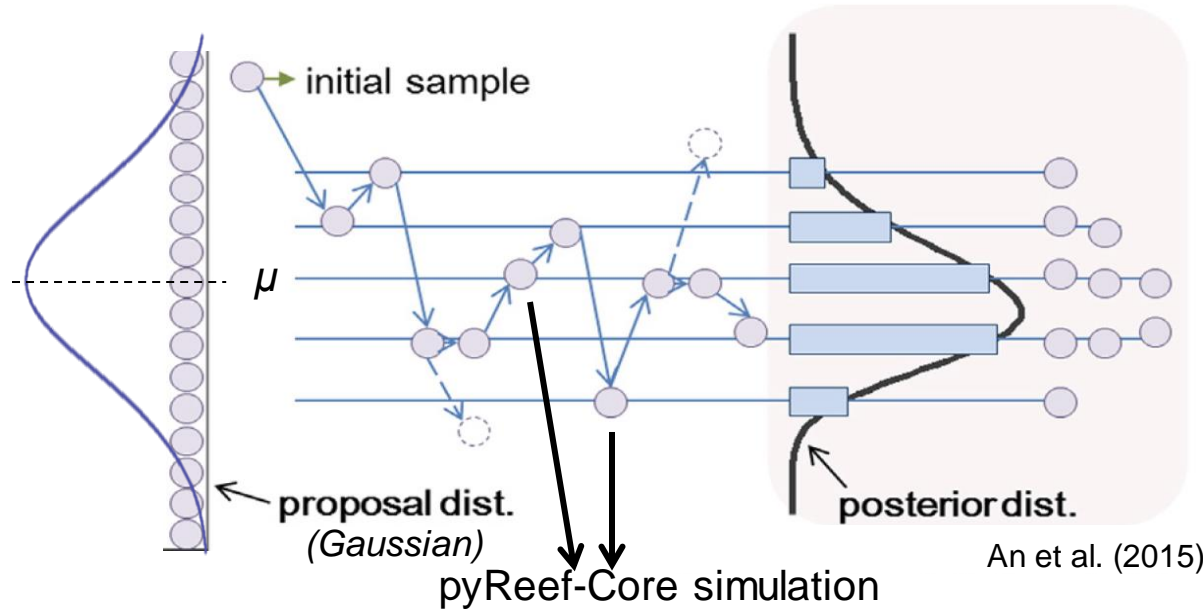
- Markov Chain Monte Carlo (MCMC) is a **Bayesian Inference method** that accommodates complex models and missing data problems.
- **BayesReef** uses MCMC methods to
  1. calibrate models to core data;
  2. quantify uncertainty in models; and
  3. estimate model parameters.

## Data Fusion and Bayesian inference in *BayesReef*



# BayesReef

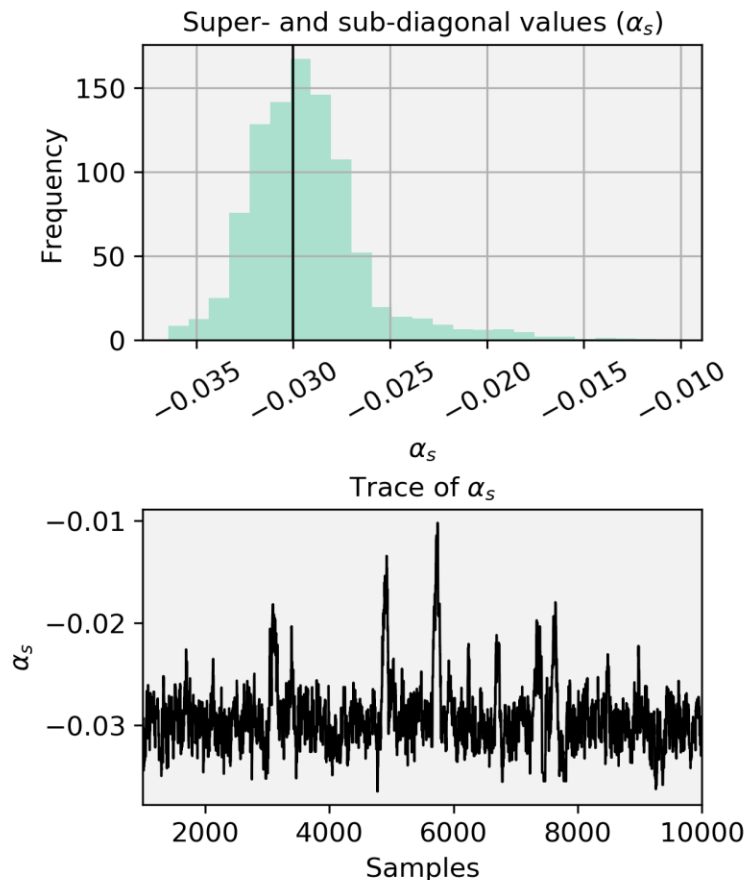
Using Monte Carlo Markov Chain ( $\text{MCMC}_{\text{PL}}$ )

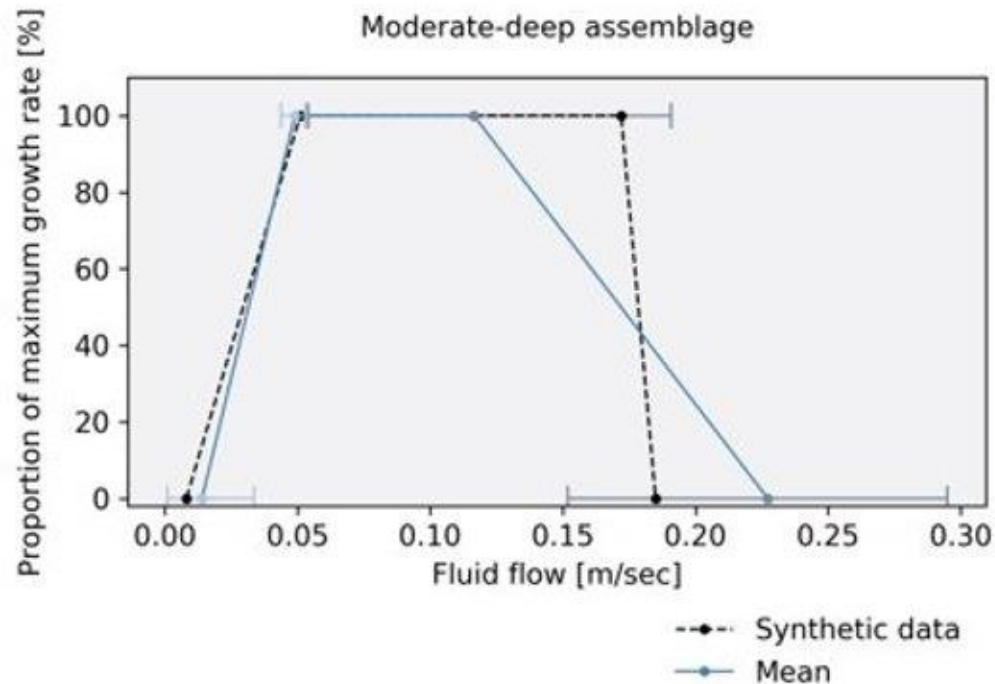
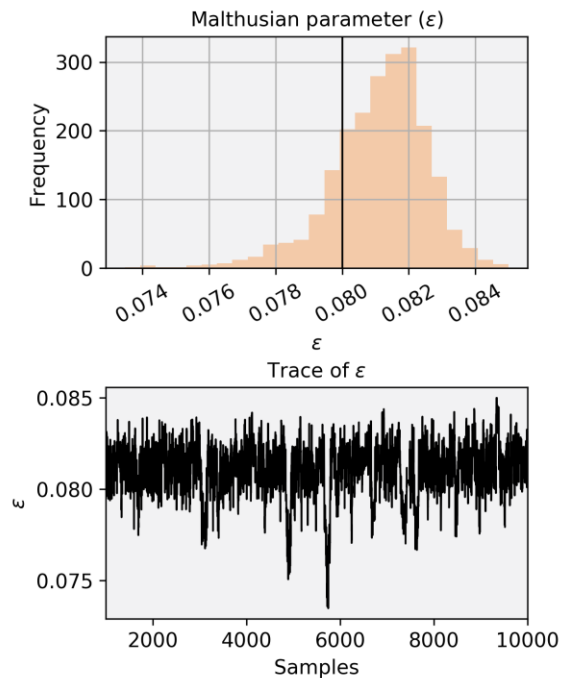


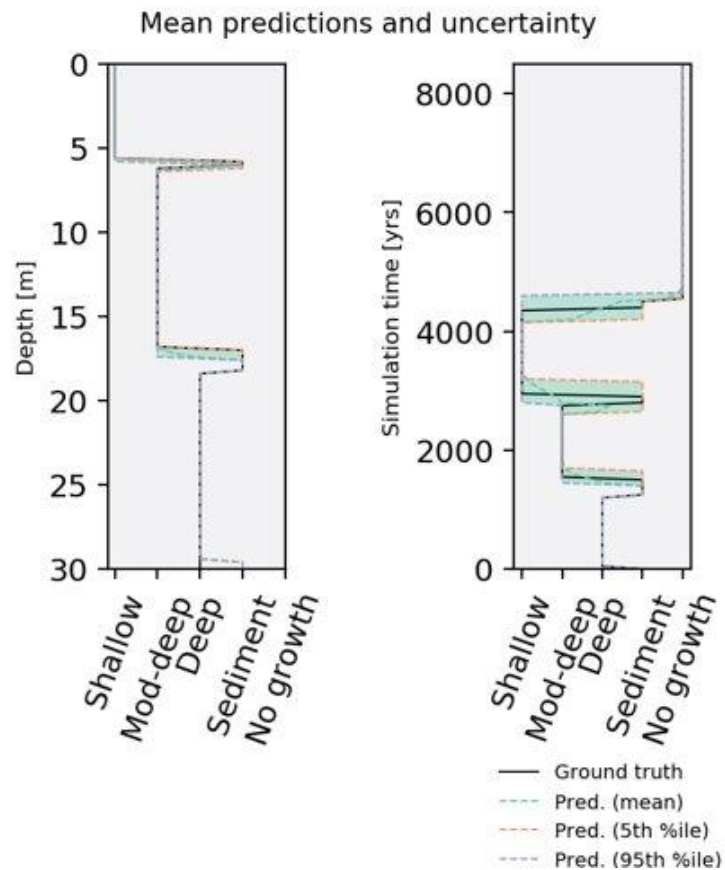
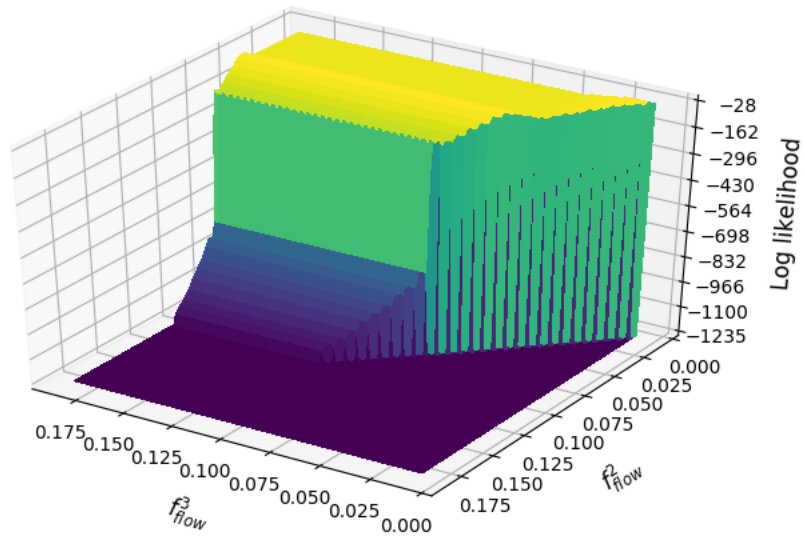


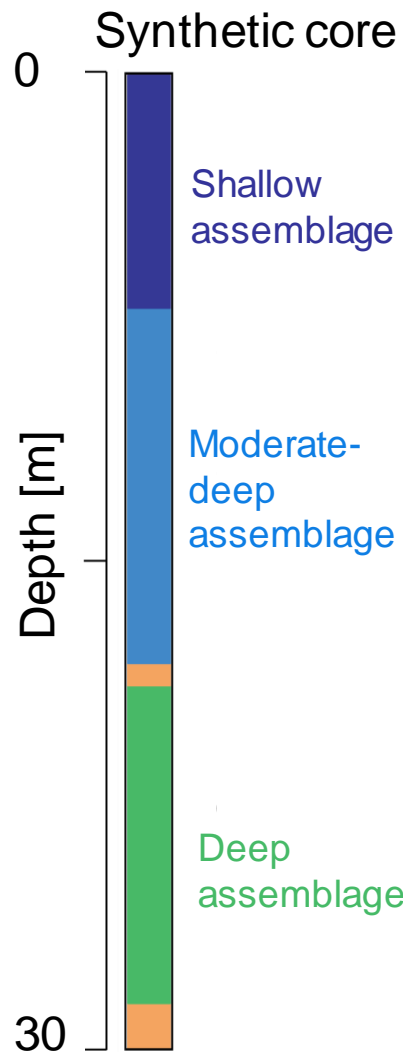
# Synthetic reef-core experiments (Part 1)

- Tested for ability of py-Reef-core to predict synthetic core.
- 4 ‘free parameters’
  - Community Matrix – Super and Sub-diagonals
  - Malthusian parameter
- Ran chains 10,000 samples long ( $\sim 1$  day)
- Use Multinomial Likelihood in MCMC



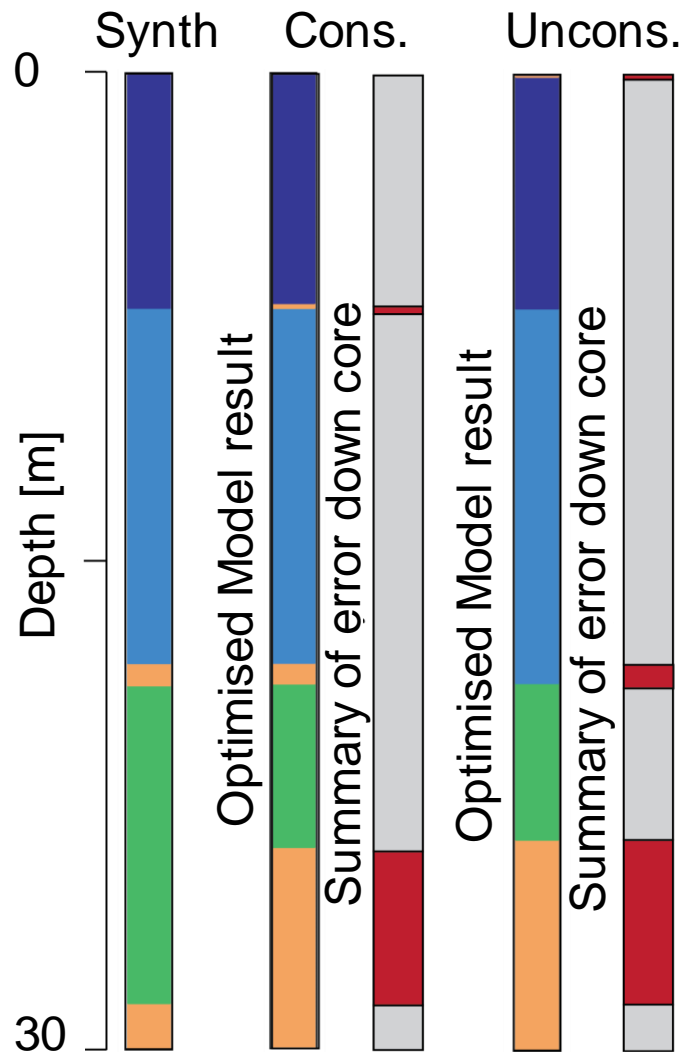






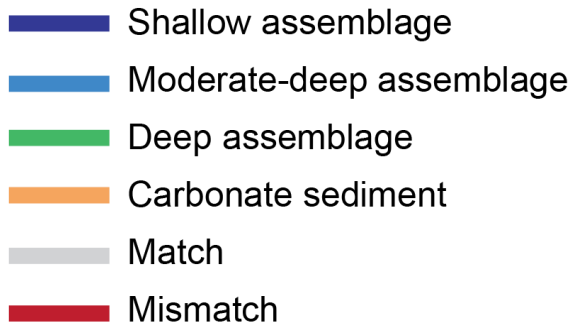
## Synthetic reef-core experiments (Part 2)

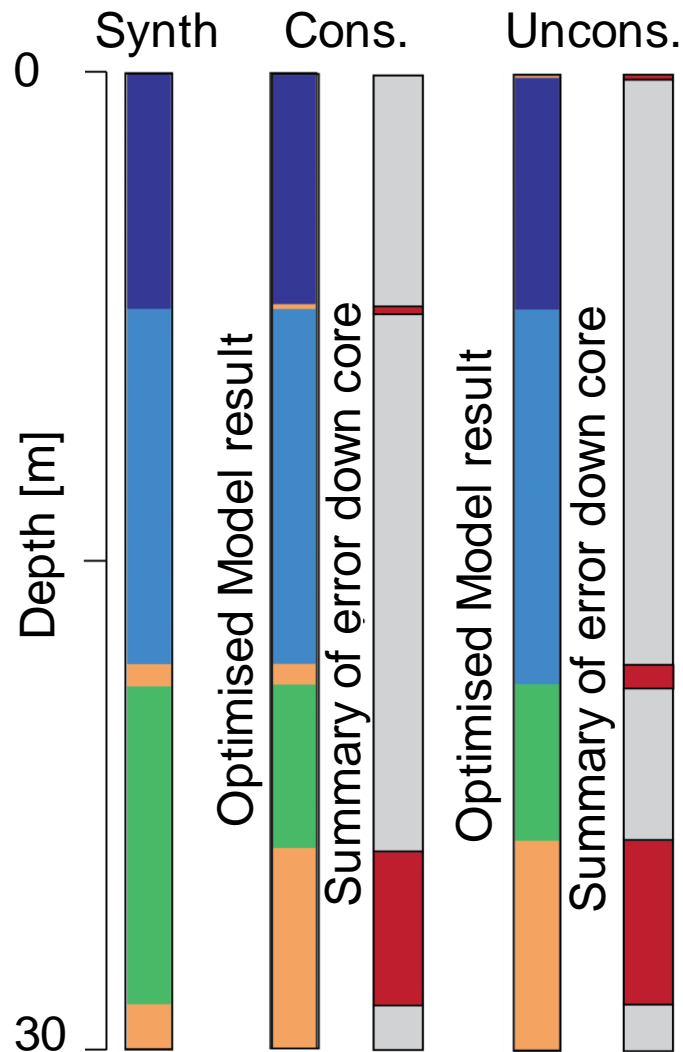
- Tested for ability to predict (converge on) synthetic core.
- 15 vs 27 ‘free parameters’
  - Exposure thresholds of assemblages
  - Assemblage interactions
- Ran chains 50,000 samples long ( $\sim 5$  days)
- Use Gaussian Likelihood in MCMC



## Results regarding accuracy

- Both cores fit synthetic data well.

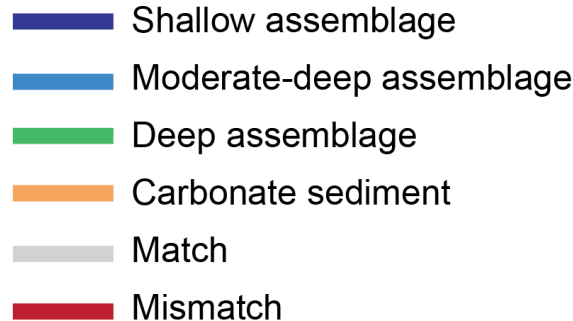




## Results regarding accuracy

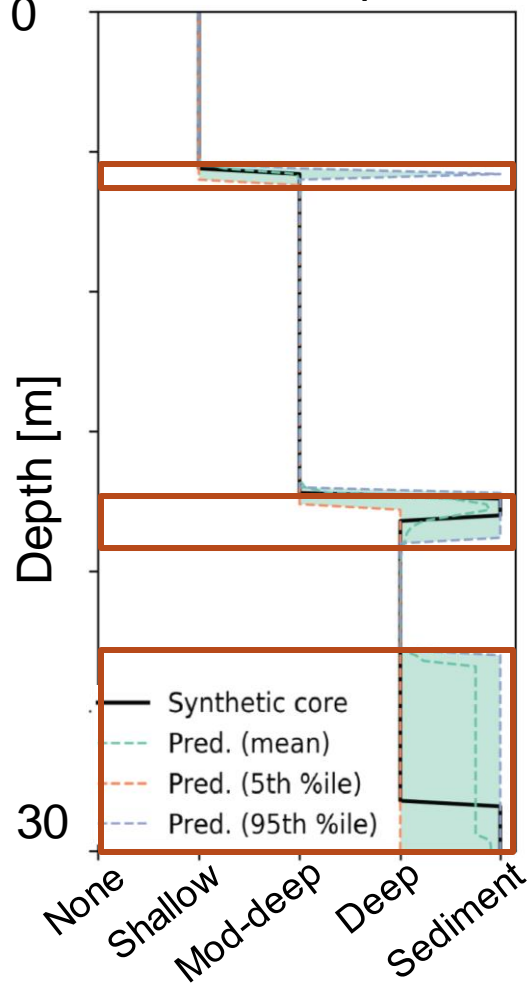
- Both cores fit synthetic data well.
- Constrained experiment converged marginally better model prediction.

	Constrained experiment	Unconstrained experiment
No. of free parameters	15	27
RMSE	0.066	0.076

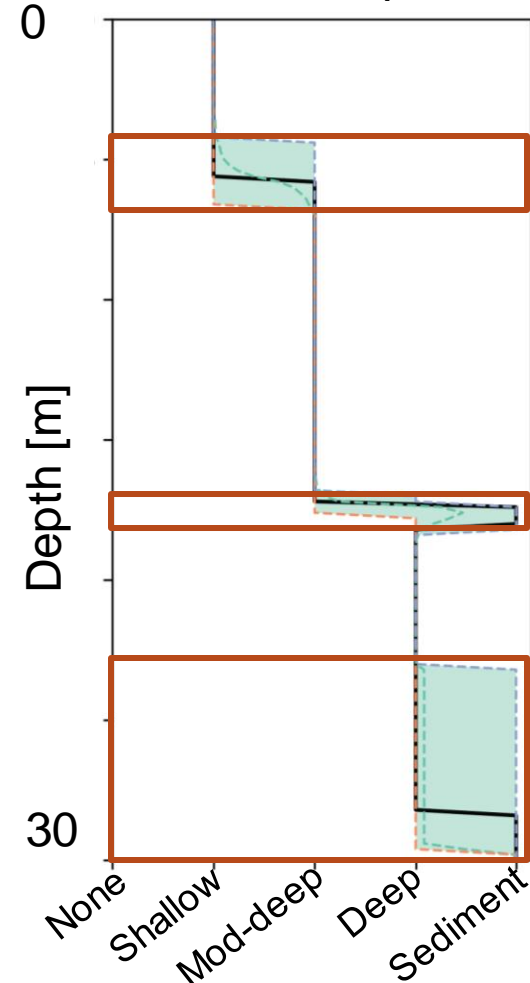




Constrained experiment



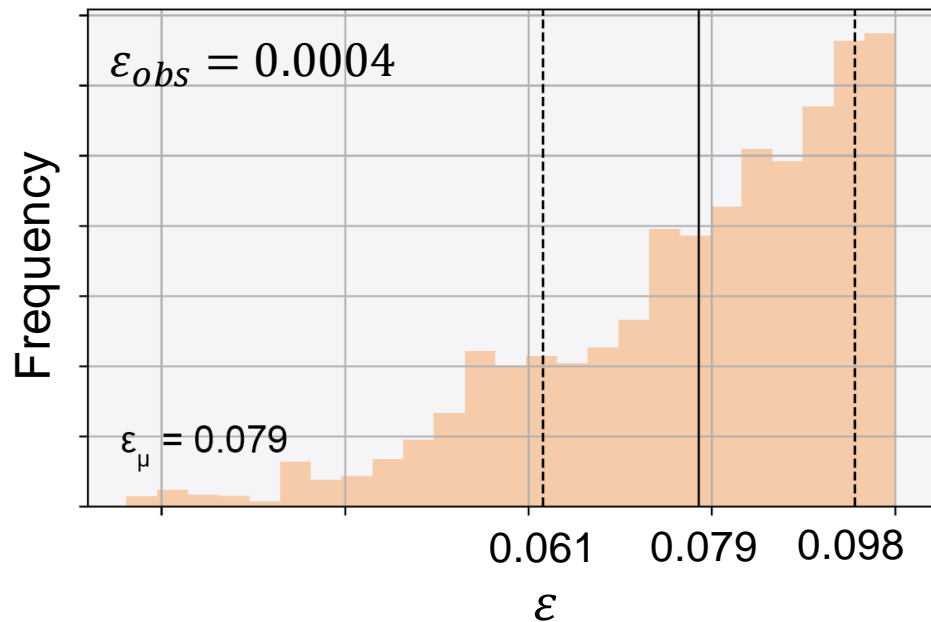
Unconstrained experiment



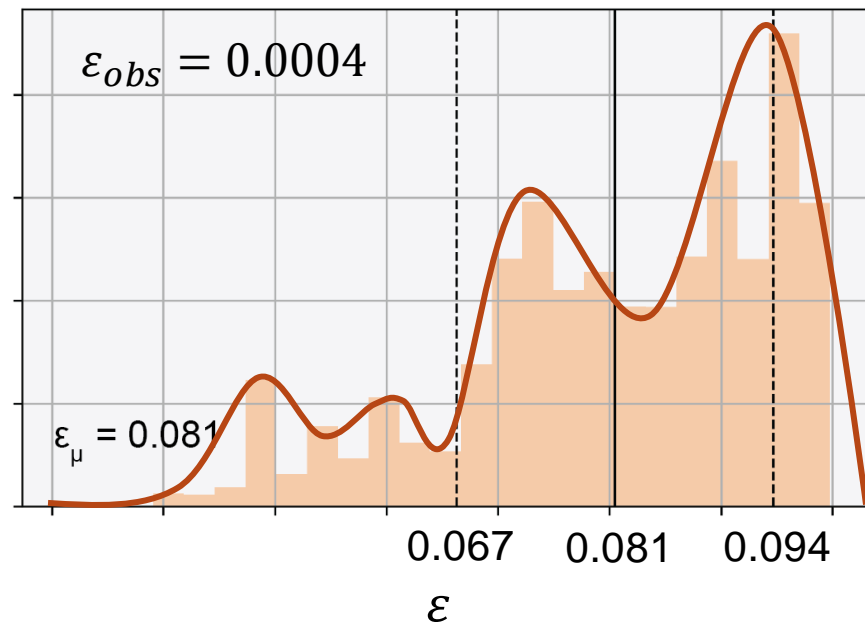
## Results regarding uncertainty

- Uncertainty focused at assemblage transitions.
- Comparable level of uncertainty.

Constrained experiment



Unconstrained experiment



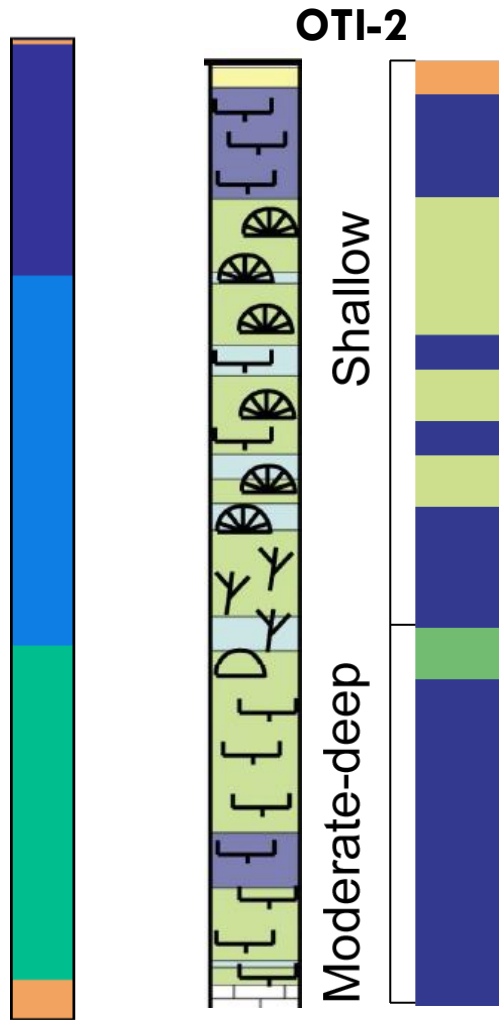
### Results regarding parameter estimation

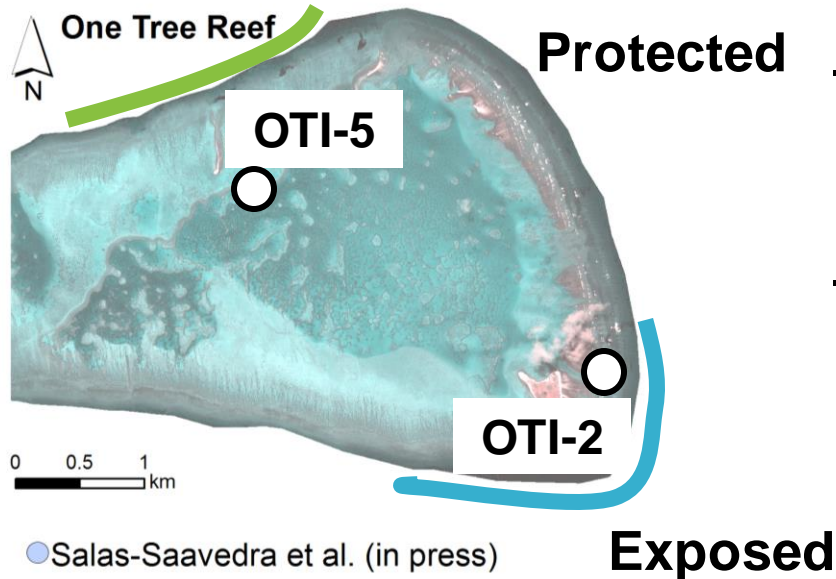
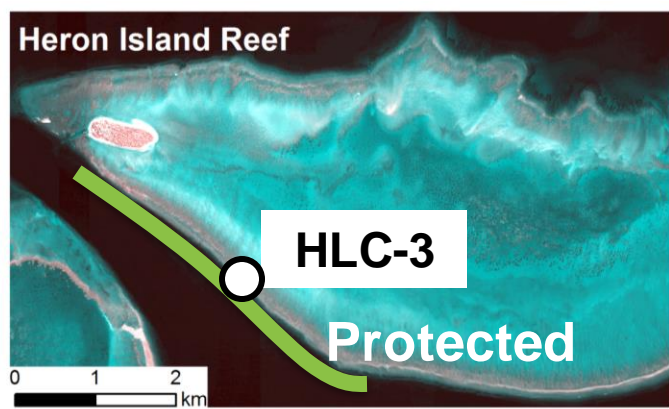
- Observed parameter not within credible interval of point-estimate values.
- Multi-modal distributions

*Model predictions approximate the data well, but not the parameters.*

# Preliminary experimental results for real world reef-core simulations

- Real-world reef development is far more complex than synthetic case.
- **Objectives:**
  - Using **BayesReef** on noisy data, predict exposure threshold of assemblages to:
    - Hydrodynamic energy
    - Sediment input





● Salas-Saavedra et al. (in press)

● Marshall and Davies (1982)

- Three reef cores selected from exposed and sheltered margins of **One Tree** and **Heron Island Reefs**.
- Both cores exhibit similar coralgal assemblages (Dechnik, 2016; Dechnik, unpublished)
- **Experiment:** Run MCMC chain of 50,000 samples using BayesReef to calibrate model to core data.

Model



HLC-3



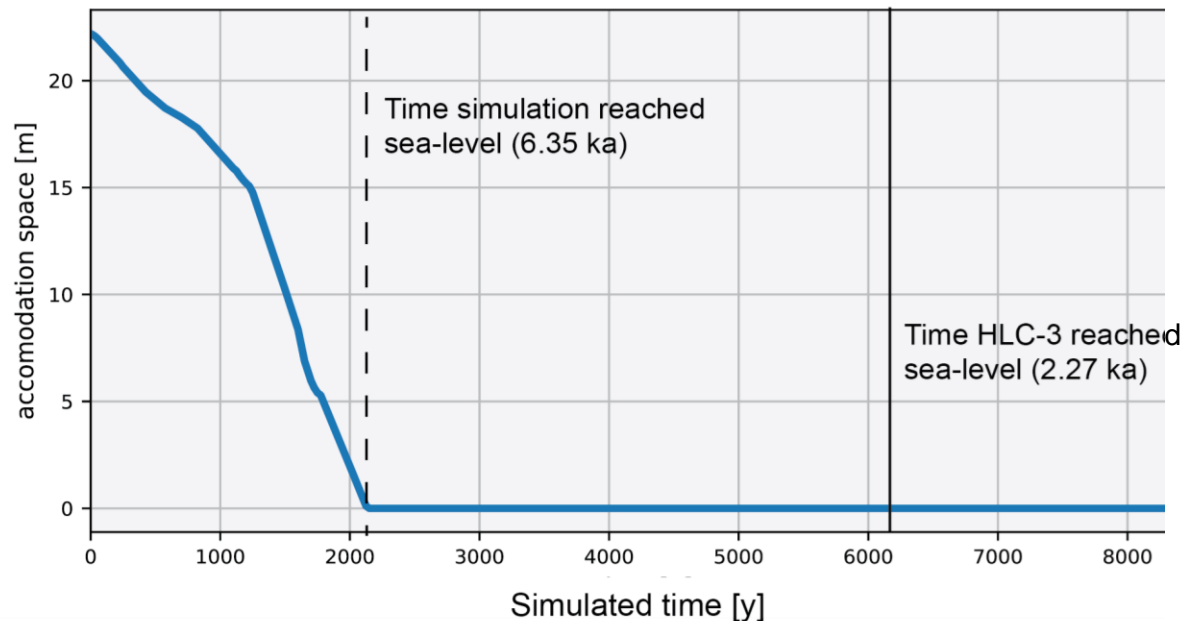
Summary of error down core



RMSE = 0.09

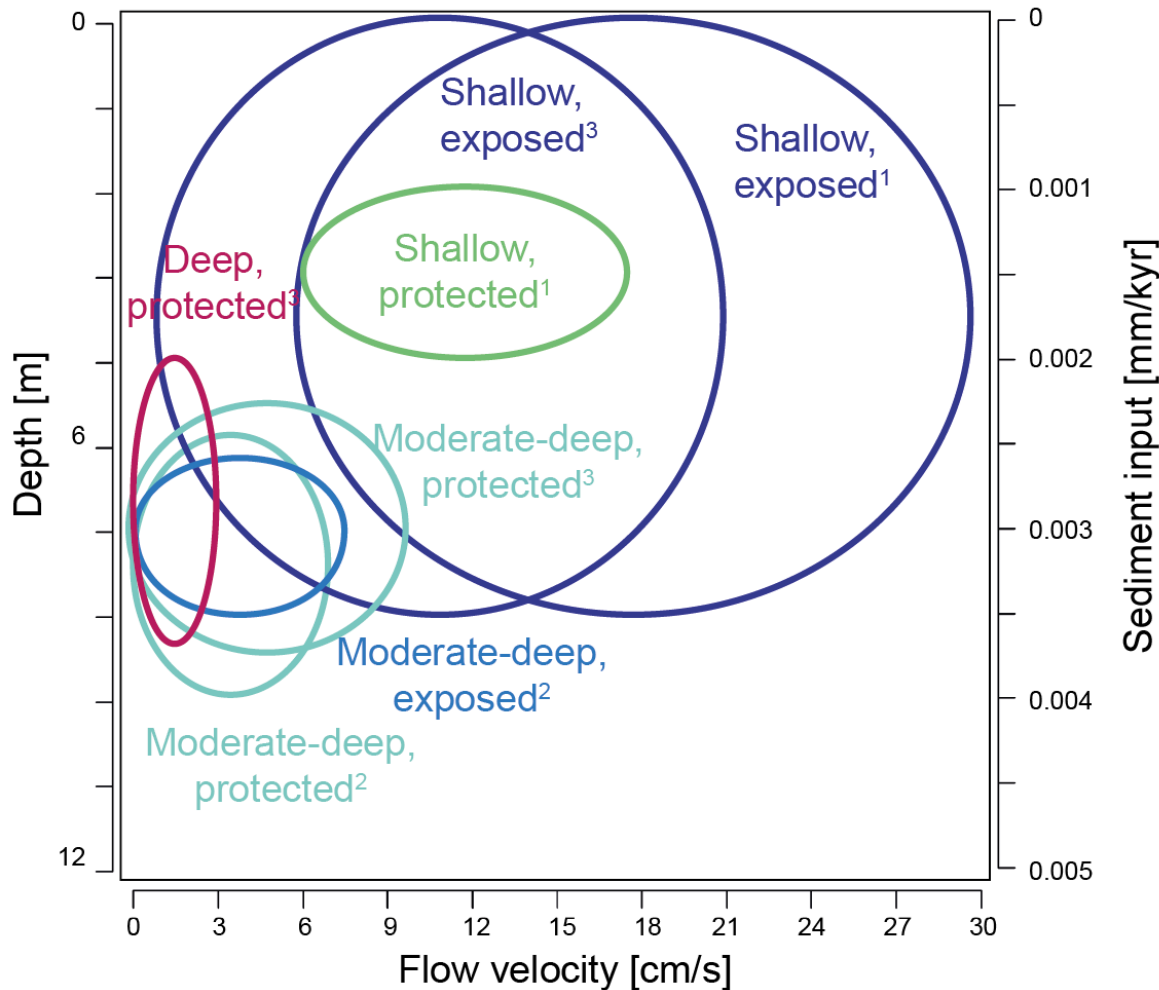
- Shallow, high-energy assemblage
- Moderate-deep, low-energy assemblage
- Deep, low-energy assemblage
- Carbonate sediment
- Match
- Mismatch

Accommodation space evolution through time



## Results

- Very good fit with data
- Reached sea-level  $\sim 4$  ky sooner than actual core

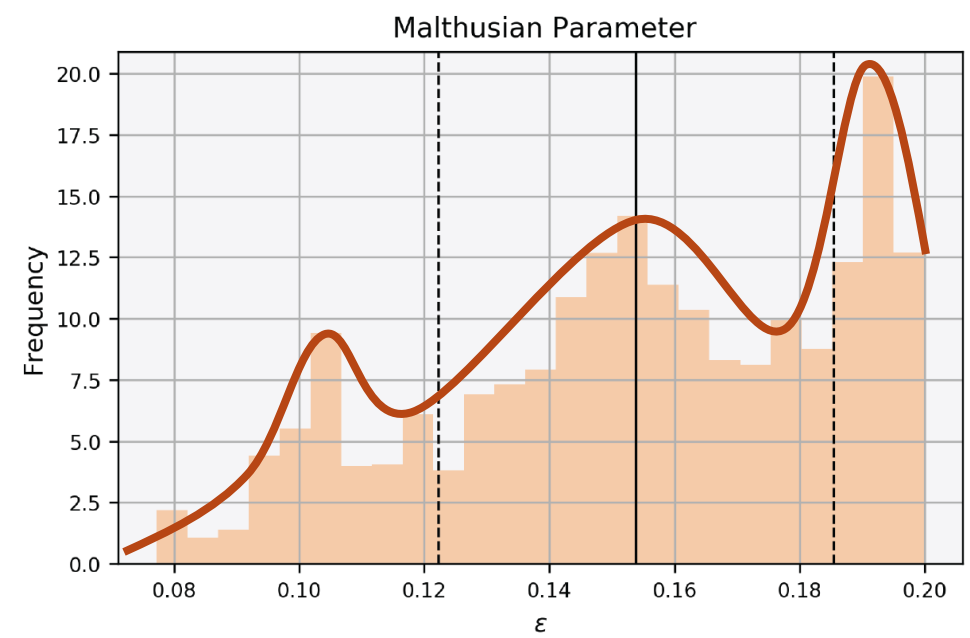


## Palaeo-environmental analysis

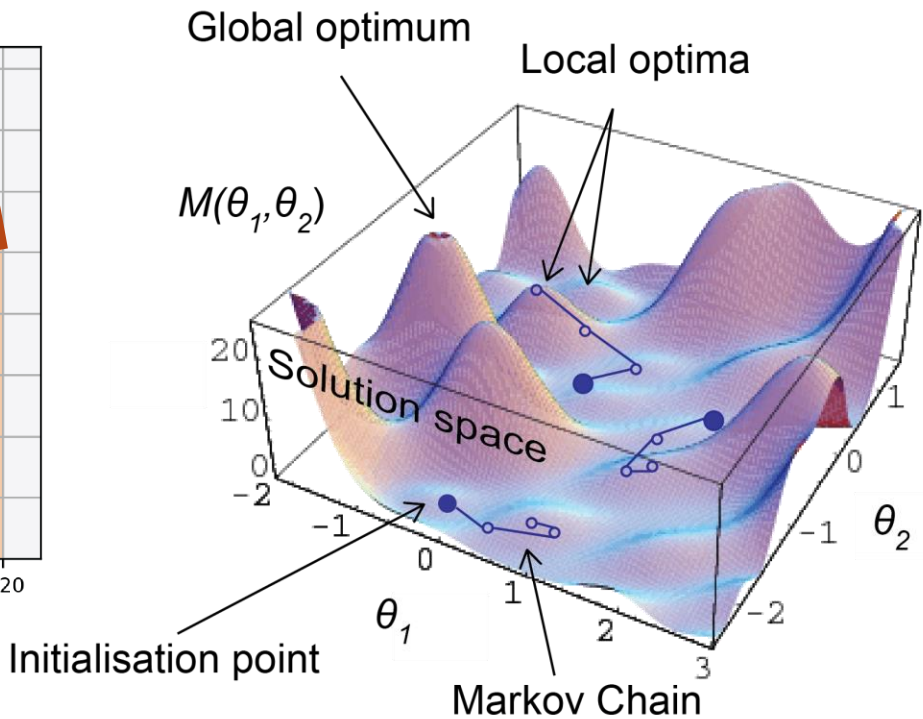
- Shallow, exposed assemblages are relatively insensitive to sediment input and flow velocity.
- Deeper assemblages have tighter environmental niches



# Multi-modal distributions

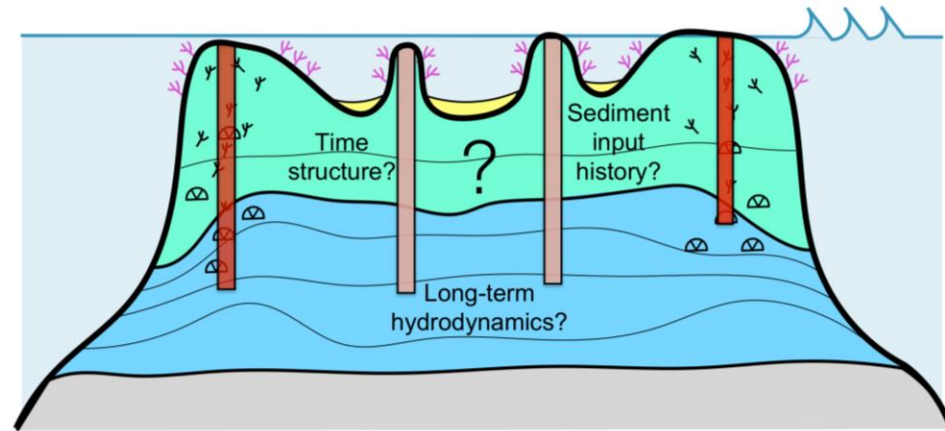


## The multi-modal solution space



# Conclusions and future work

1. The MCMC sampler in BayesReef is accurate, robust and efficient with fewer free parameters, but less so when calibrating models to noisy data.
2. Current work focuses on BayesReef for high performance computing and parallel tempering for sampling multi-modal distributions
3. Future work will feature BayesReef for 3D Reef-Core and for the Great Barrier Reef Model (T. Salles, 2018)



# Questions welcome

- Acknowledgements

Jodie Pall, Tristan Salles, Sally Cripps, and Jody Webster

- Technical Report:

Jodie Pall, **Rohitash Chandra**, Danial Azam, Tristan Salles, Jody M. Webster, Sally Cripps: BayesReef: A Bayesian inference framework for modelling reef growth in response to environmental change and biological dynamics, <https://arxiv.org/abs/1808.02763>

- Github:

<https://github.com/pyReef-model/BayesReef>  
<https://github.com/pyReef-model/pt-BayesReef/settings/collaboration>



*Acropora* at 2 m depth, One Tree Reef