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BAYESIAN TOOLS IN MODELLING PRIMARY PRODUCTION

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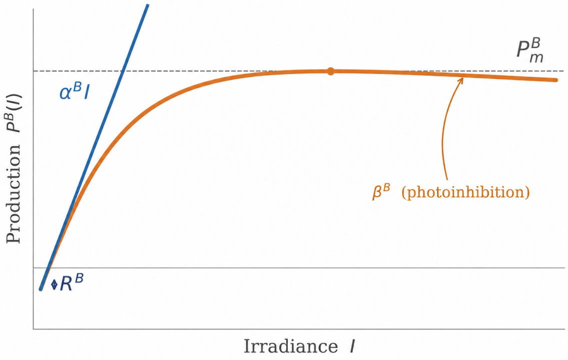
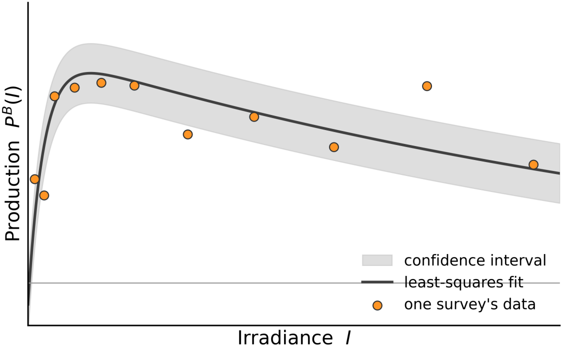
The photosynthesis-irradiance (P-I) curve



Four parameters, each with a physical meaning.

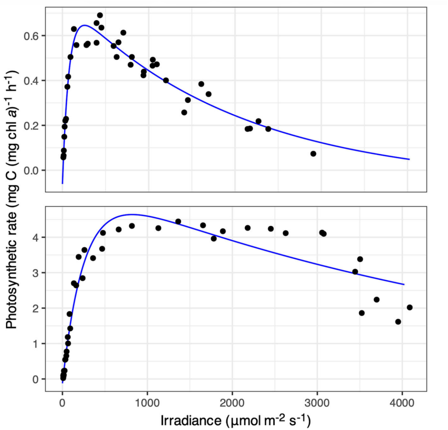
$$p^B(I) = P_m^B \left(1 - \exp\left(-\frac{\alpha^B I}{P_m^B}\right)\right) \exp\left(-\frac{\beta^B I}{P_m^B}\right) - R^B$$

How the parameters are estimated today



Least squares, *one curve at a time*. Uncertainty as an afterthought.

The functional form matters - Amirian et al. (2025)

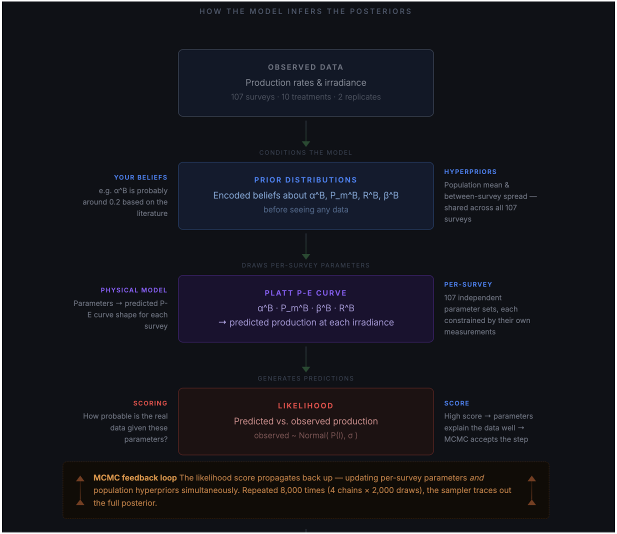


1808 P–I curves · 16 photoinhibition models · parameters differ up to 40%.

So what can a Bayesian approach give us?

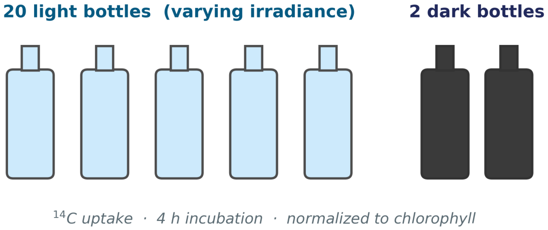
Fit all surveys together. Carry the full uncertainty.

The Bayesian idea



Hierarchy: surveys share strength. **Uncertainty comes built in**, not added afterward.

The data: Bedford Basin



1975–76 · replicated ^{14}C incubations · ∼100 surveys · a built-in benchmark.

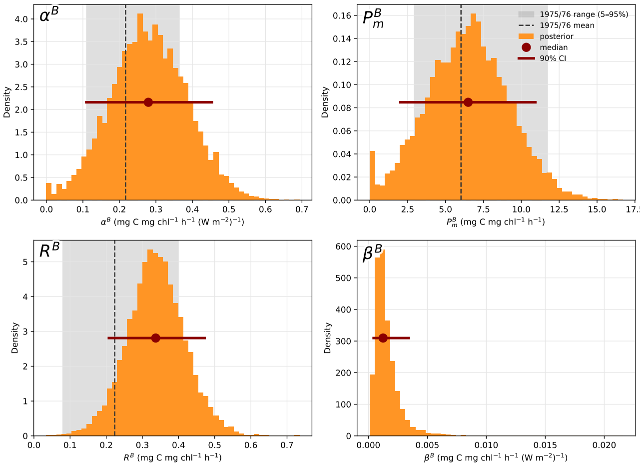
Model diagnostics

Progress	Draws	Divergences	Step size	Grad evals	Sampling Speed	Elapsed	Remaining
	4000	0	0.02	255	19.11 draws/s	0:03:29	0:00:00
	4000	0	0.03	127	26.20 draws/s	0:02:32	0:00:00
	4000	0	0.03	255	22.35 draws/s	0:02:58	0:00:00
	4000	0	0.03	255	22.59 draws/s	0:02:57	0:00:00

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
α group	0.280	0.104	0.087	0.476	0.001	0.001	11550.0	5570.0	1.0
Pmax group	6.475	2.699	1.218	11.478	0.023	0.033	13907.0	5879.0	1.0
R group	0.338	0.080	0.185	0.491	0.001	0.001	13607.0	5475.0	1.0
β avg	0.002	0.001	0.000	0.003	0.000	0.000	10948.0	5447.0	1.0

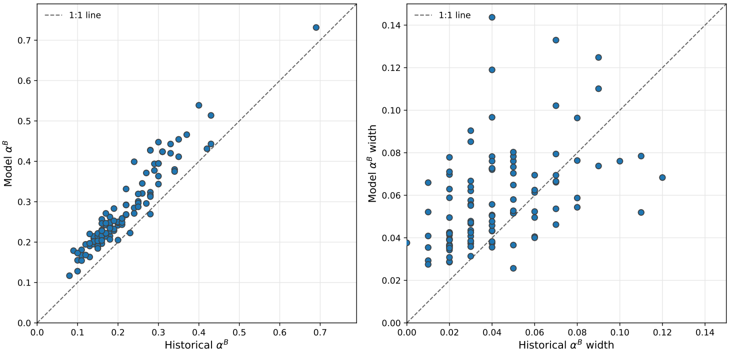
4 chains · 2,000 draws · 0 divergences · $\hat{R} = 1.0$ for all parameters · ESS $> 5{,}000$.

Results: every parameter is a distribution



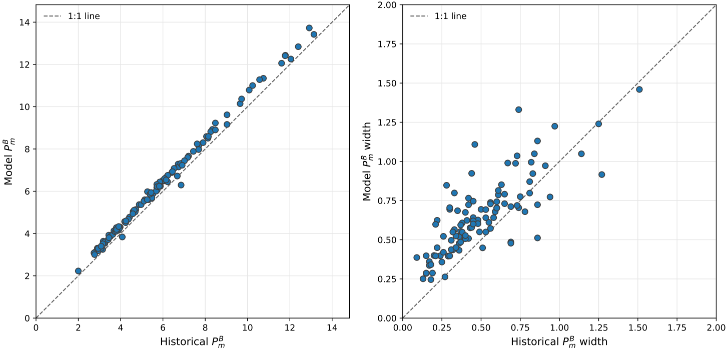
α^B, P_m^B, R^B sharp; β^B near zero means weak photoinhibition.

Results: model vs. historical, survey by survey



Left: we recover the classical values. Right: pooling reins in the blown-up intervals.

Results: model vs. historical, survey by survey



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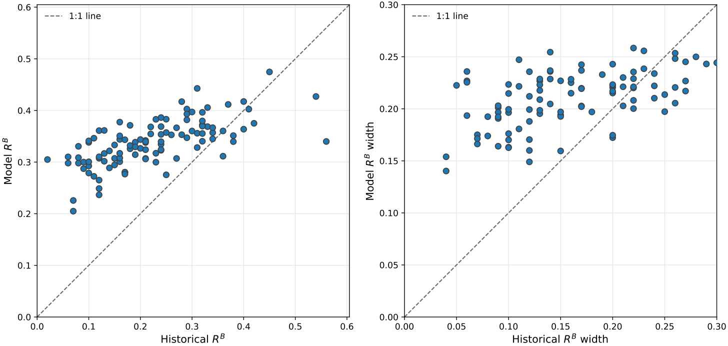
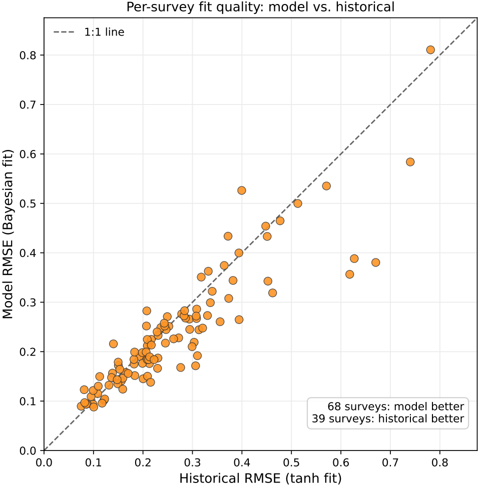


Left: we recover the classical values. Right: pooling reins in the blown-up intervals.

Results: and it fits better



Better in 68 of 107; mean RMSE 0.237 vs 0.261. Losses concentrated in handful of surveys; median difference negligible.

① WHAT WE HAVE NOW

Full posterior distributions for every parameter

Not point estimates — complete probability distributions, per survey

SAMPLE THOUSANDS OF PARAMETER SETS

② KOVAČ ET AL. (2016) — DEPTH & TIME INTEGRATION

Run each parameter sample through the water-column model

$$W(z, t) = \int P^B(I(z,t)) \cdot Chl(z)\, dz \leftarrow \text{per sample}$$

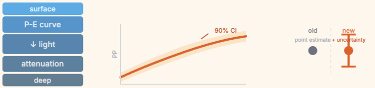
$$PP_{day} = \int W(z, t)\, dt \leftarrow \text{daily integral}$$

Each of the 8,000 posterior samples → one depth-integrated daily production value

8,000 RUNS → FULL OUTPUT DISTRIBUTION

③ OUTPUT — HONEST UNCERTAINTY ON WATER-COLUMN PRODUCTION

Daily primary production with full propagated uncertainty



depth profile integrated

seasonal cycle with uncertainty band

honest error bars not available before

Bayesian tools **recover** the classical answers,

quantify uncertainty that was rarely quantified,
and **fit better**.

THANK YOU!