

# Adaptive model-based dose selection methods



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NCS 2008, Leuven, 24 Sept. 2008



# Outline

## **Adaptive modelling strategy**

Background and example

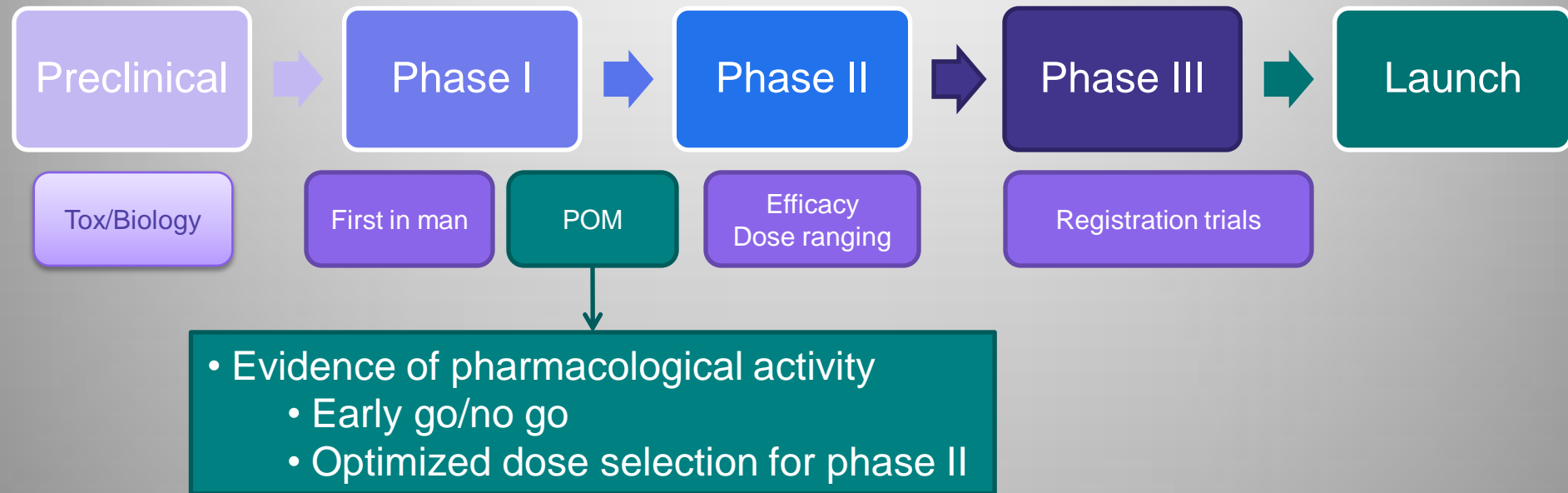
Principles and components

Analysis of a case study

Conclusions



# Proof of mechanism

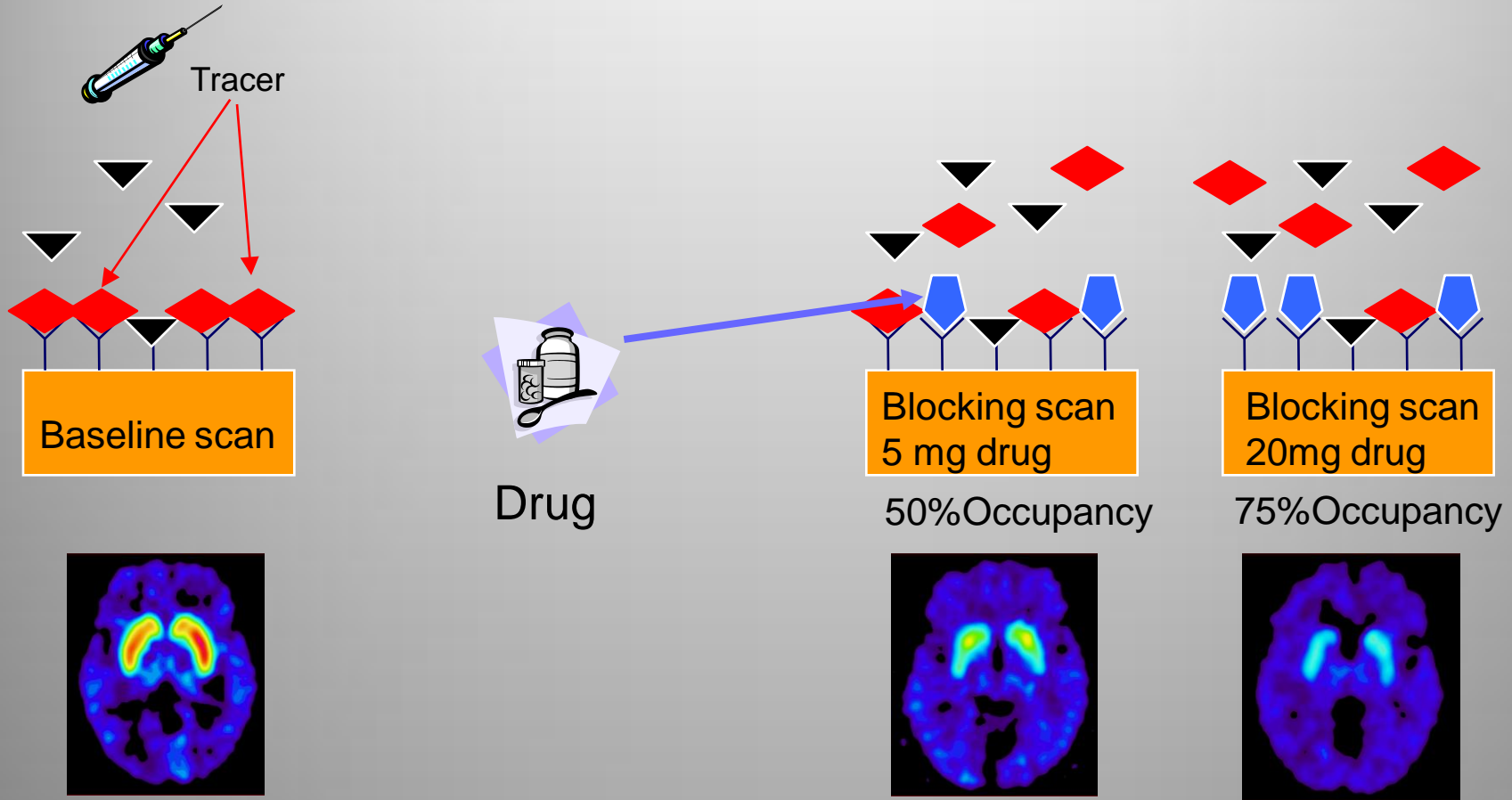


- **Challenges:**

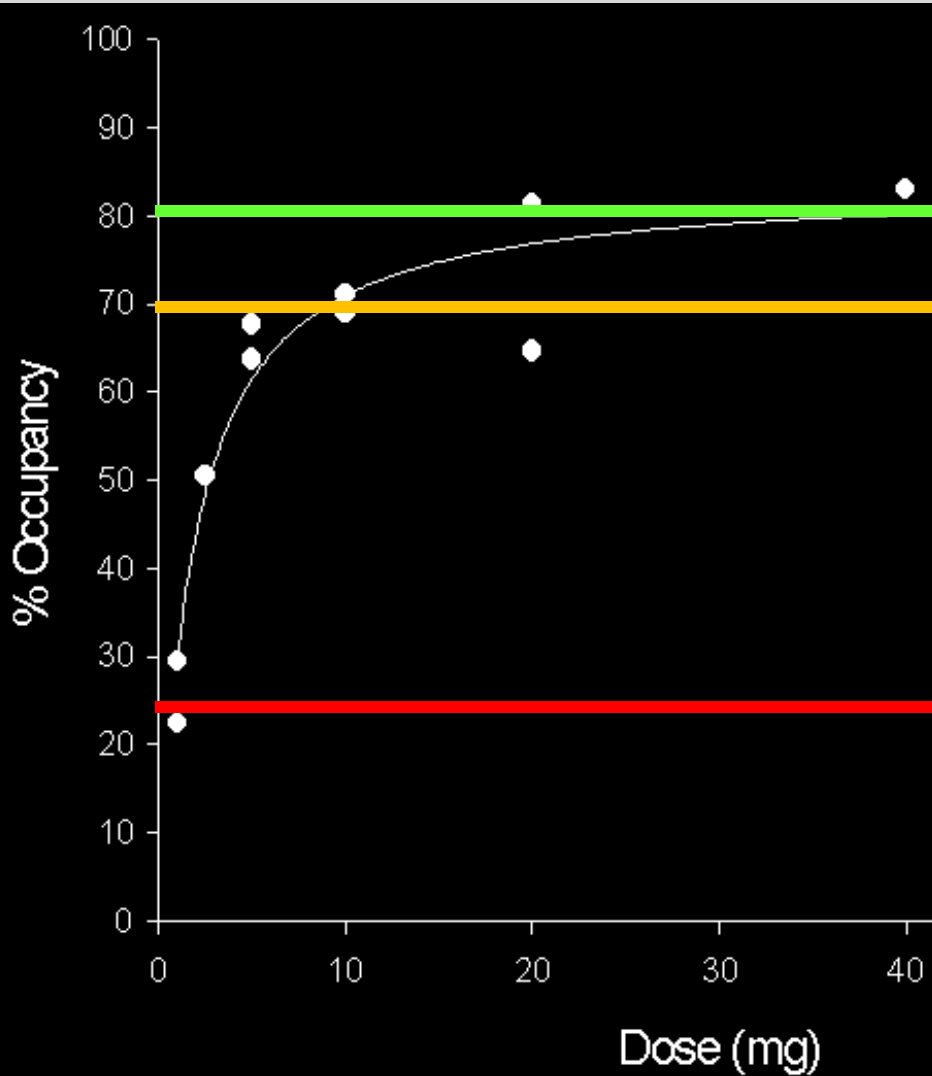
- *Availability of a validated biomarker*
- Cost effectiveness
- Predictivity



# Example: Receptor Occupancy PET



# Dose-Occupancy Relationship

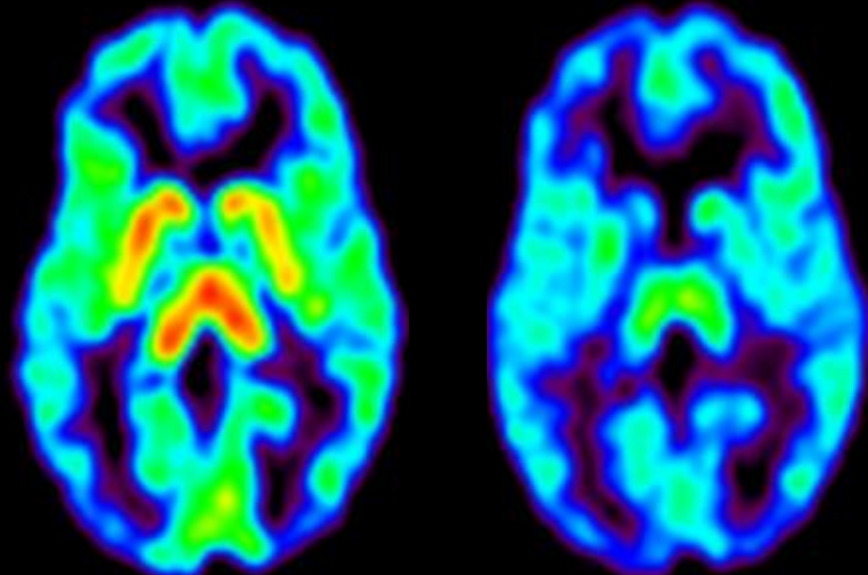


No occupancy :

❖ Quick kill

Dose selection:

❖ Quantiles of dose-response



*J. Meyer et al., [C-11]DASB uptake before and after SSRI, Toronto.*



# Adaptive Modelling Strategy

- Parametric dose-response model

$$RO = f(dose, \theta)$$

- E.g., Emax model or 4PL

- Bayesian inference

$$p(\theta | RO) \propto p(\theta)L(RO | \theta)$$

- Uses available prior information  $p(\theta)$  from preclinical assays or competitors.
- Posterior update possible after every subject



# Adaptive Modelling Strategy (II)

- Adaptive dose selection during study:
  - Select next dose **dz** that optimizes a property of  $p(\theta | RO_{hist}, RO_{dz})$
  - E.g., D-optimal design:  $\min |\text{Var}(\theta)|$
- Decision to stop POM trial
  - Stop enrolment when
    - Precision around  $f(\text{dose}, \theta)$  is sufficient, or
    - For futility, when, eg:  $\Pr[f(\text{dose}, \theta) > 50\%] < 5\%$ .



# Adaptive Modelling Strategy (III)

- Predicting relevant doses for phase II:
  - Based on posterior predictive distribution:

$$p(RO_{\text{patient}} | RO_{\text{POM}}) = \int p(RO_{\text{patient}} | \theta, RO_{\text{POM}}) p(\theta | RO_{\text{POM}}) d\theta$$

– E.g.:

$$p(RO_{\text{patient}} > 70\% | RO_{\text{POM}}) > 90\%$$

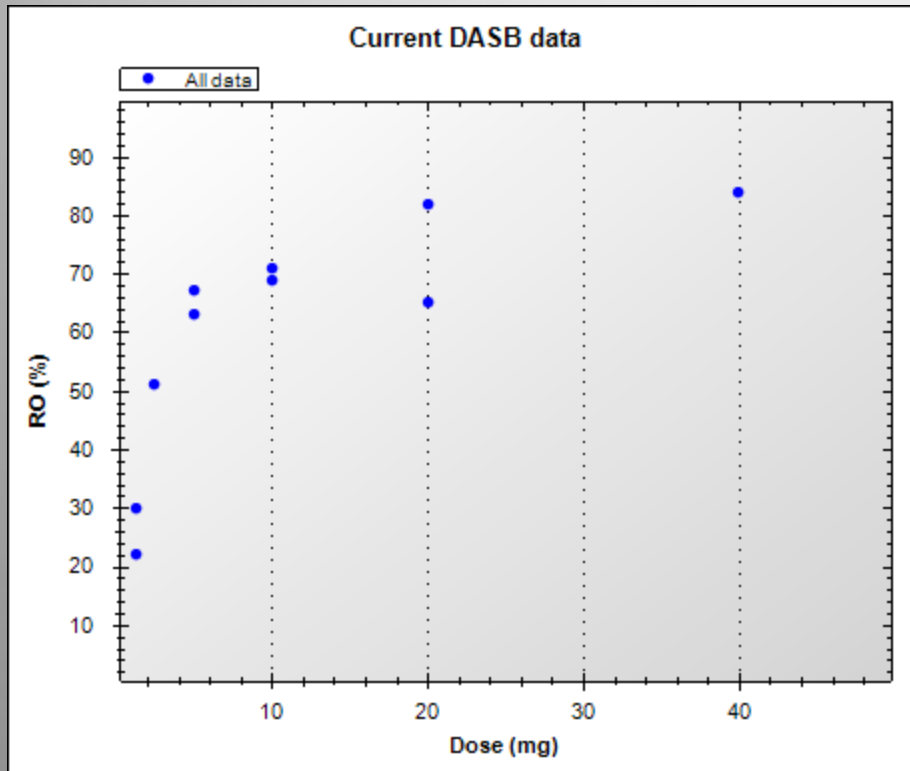
$$p(RO_{\text{patient}} > 70\% | RO_{\text{POM}}) \approx 50\%$$

$$p(RO_{\text{patient}} > 70\% | RO_{\text{POM}}) < 10\%$$





# DASB Case Study



Design and analysis settings:

- ❖ Emax model (flat priors)
- ❖ Next dose: D-optimal
- ❖ Stop study if
  - ❖  $CV(ED_{50}) < 30\%$  or
  - ❖  $Pr[Emax < 50\%] > 95\%$ .
- ❖ Phase II doses based on  $PP(RO > 70\%)$





# Emax model and Priors

Define model parameters

Preview model...

## Define model parameters

1. Select a model    2. Define model parameters

MCMC parameters

Seed:  random     specify:

Size of burn-in:     Number of chains:

Size of simulation after burning:     Thin:

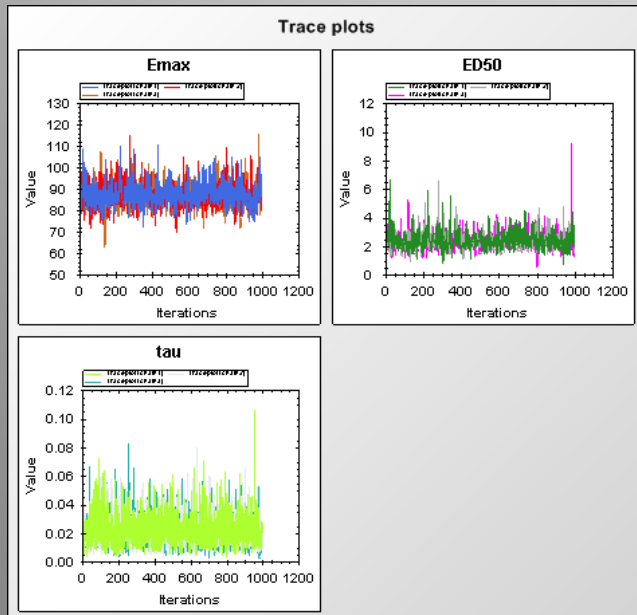
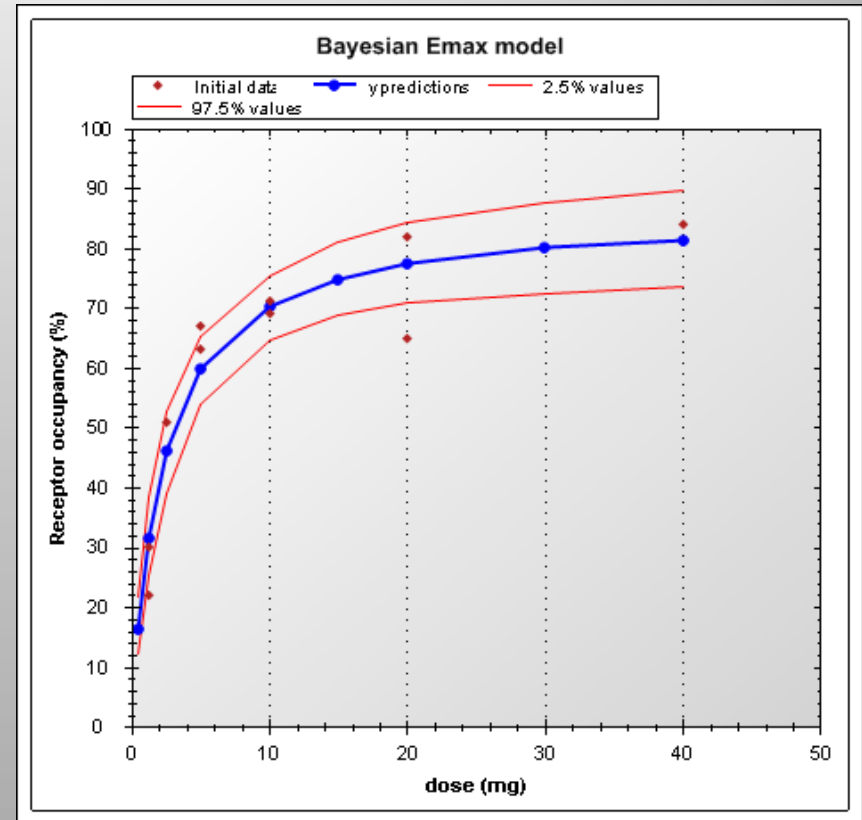
**Model parameters :**

Name	Description	InitialValue	Constant	Distribution	Description	p1	p2	p3	Notes
E0	response at x=0	0	<input checked="" type="checkbox"/>						
E <sub>max</sub>	maximum change from E0	100	<input type="checkbox"/>	dflat	constant value; not a proper di...				
ED50	x value producing 50% of E <sub>max</sub>	10	<input type="checkbox"/>	dflat	constant value; not a proper di...				
gamma	Sigmoidal parameter	1	<input checked="" type="checkbox"/>						
tau	precision (1/sigma <sup>2</sup> )	1	<input type="checkbox"/>	dgamma	Gamma[rate; mu]	0.0001	0.0001		



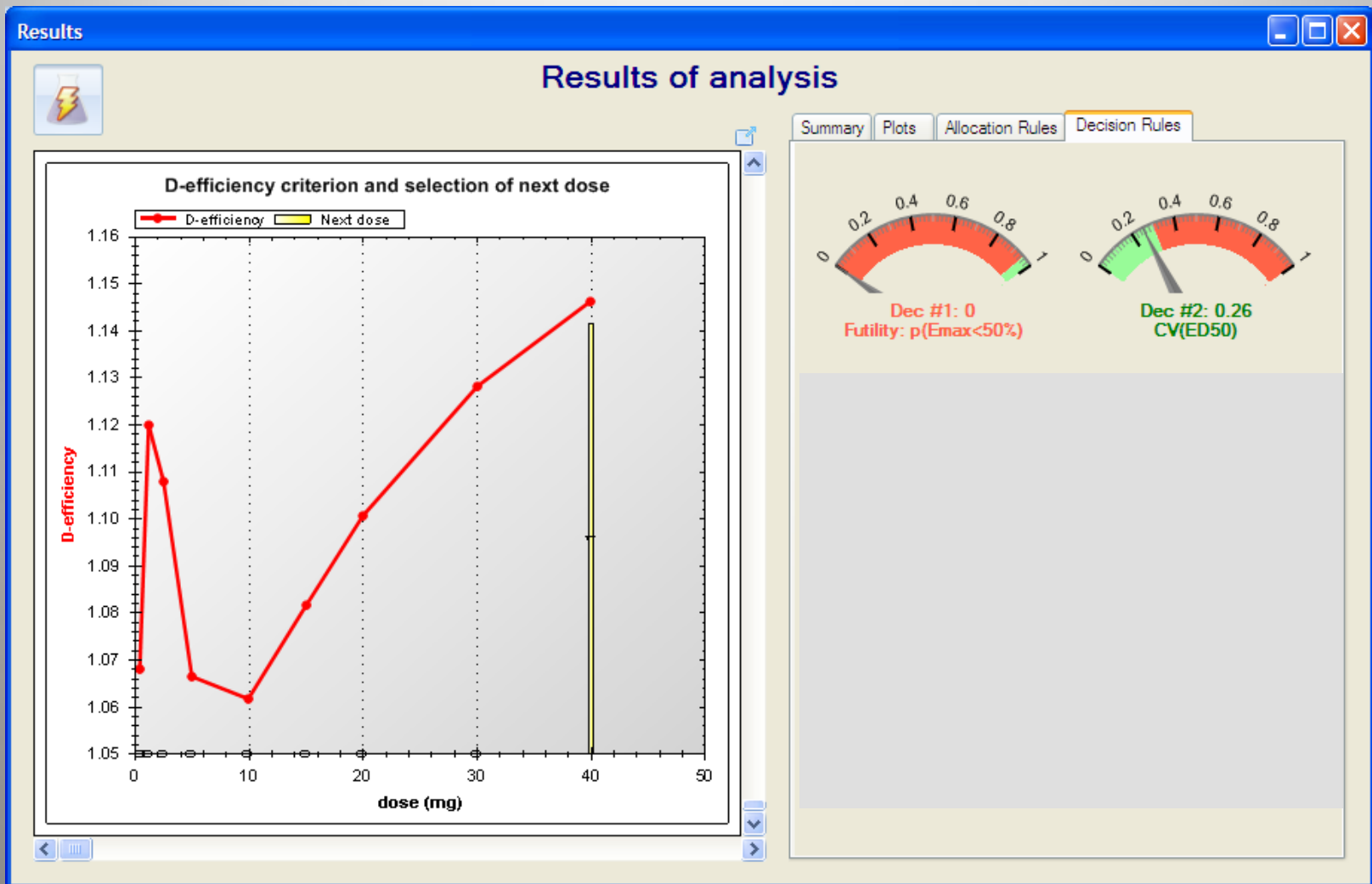
# Bayesian Emax model fit

Param	mean	sd	2.5%	median	97.5%
Emax	85.82	5.191	76.54	85.47	97.06
ED50	2.199	0.539	1.39	2.154	3.398
tau	0.022	0.011	0.006	0.021	0.046



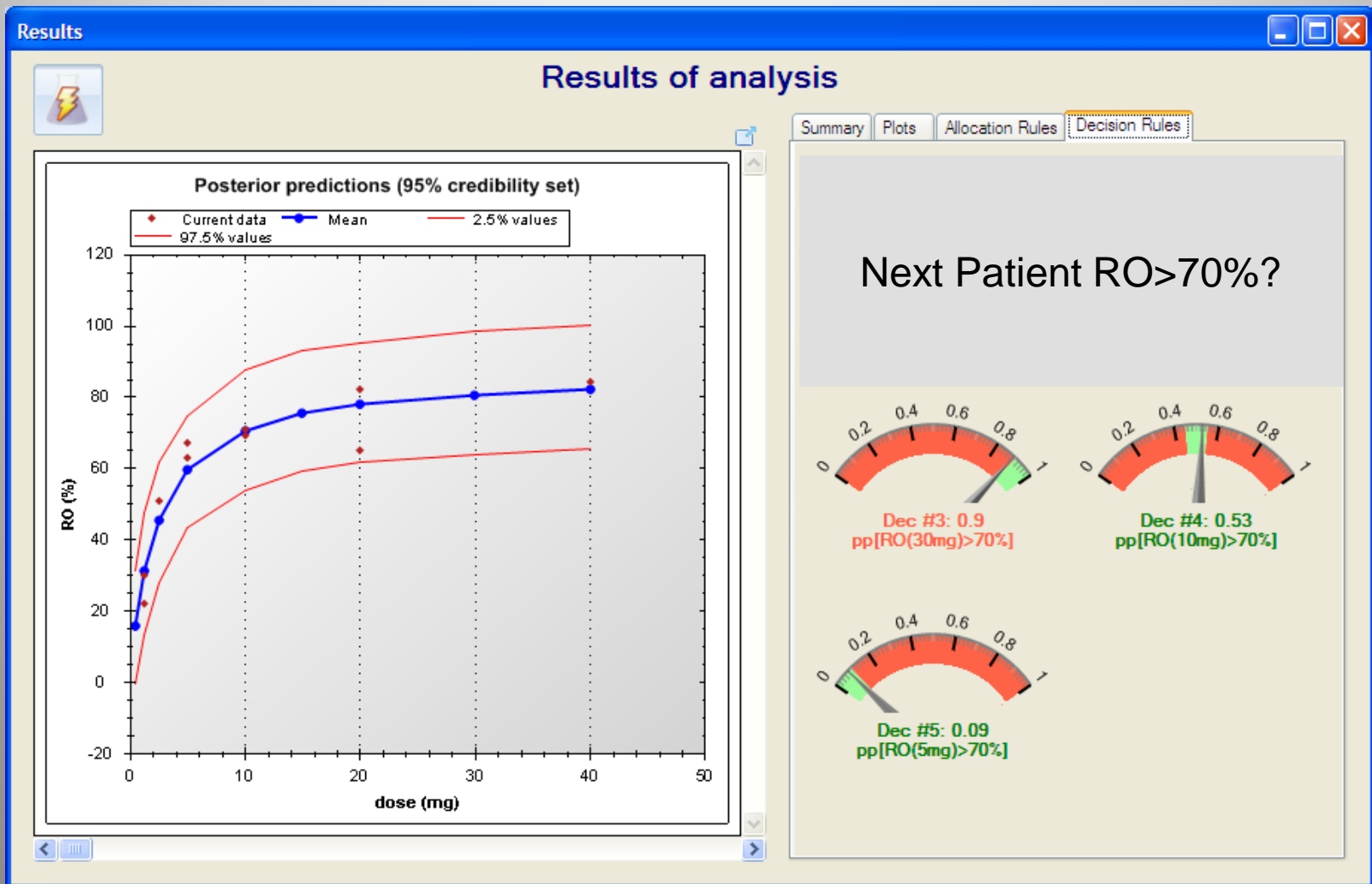


# Next dose and stopping rules





# Dose selection for Phase II





# Conclusions

- Adaptive modelling strategy permits quantitative, data-driven decisions:
  - Within study:
    - Dose selection
    - Trial termination
  - Across drug development:
    - Probability of failure (success) drives go/no go decisions
    - Summary of all historical data
    - Prediction of future patient responses
- Technical challenges when using quantitative methods:
  - More work upfront on definition of decision tree.
  - Trial simulations to validate strategy.
  - Software availability as a key enabler.

Thank you!

Any Question?

