

Ca²⁺ modelling and TMS variability



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Outline

- Neural field modelling
 - Of calcium
- Modelling MEPs from a neural field scheme
- Consequences for variability

Neural field modelling of Calcium

$$V_a(t) = \sum_b V_{ab}(t),$$

$$Q_a(V_a) = \frac{Q_a^{\max}}{1 + e^{-(V_a - \theta_a)/\sigma_a}},$$

$$\left(\frac{1}{\gamma_{ab}} \frac{d}{dt} + 1\right)^2 \phi_{ab}(t) = Q_{ab}(t),$$

$$\left(\frac{1}{\alpha_{ab}} \frac{d}{dt} + 1\right) \left(\frac{1}{\beta_{ab}} \frac{d}{dt} + 1\right) V_{ab}(t) = v_{ab}(t) \phi_{ab}(t - \tau_{ab})$$

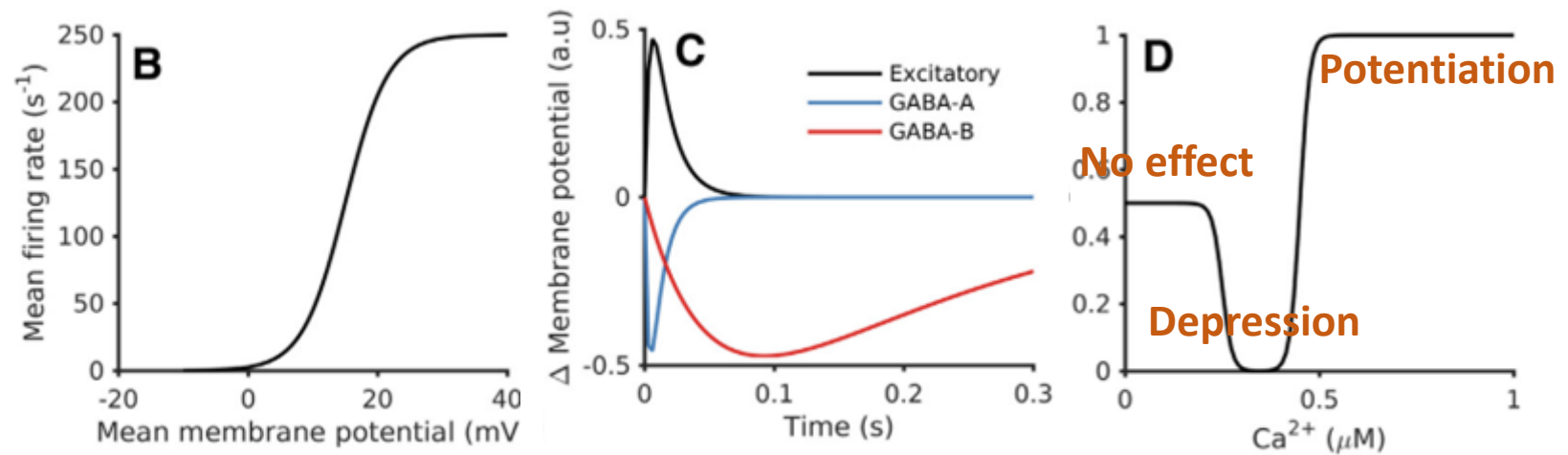
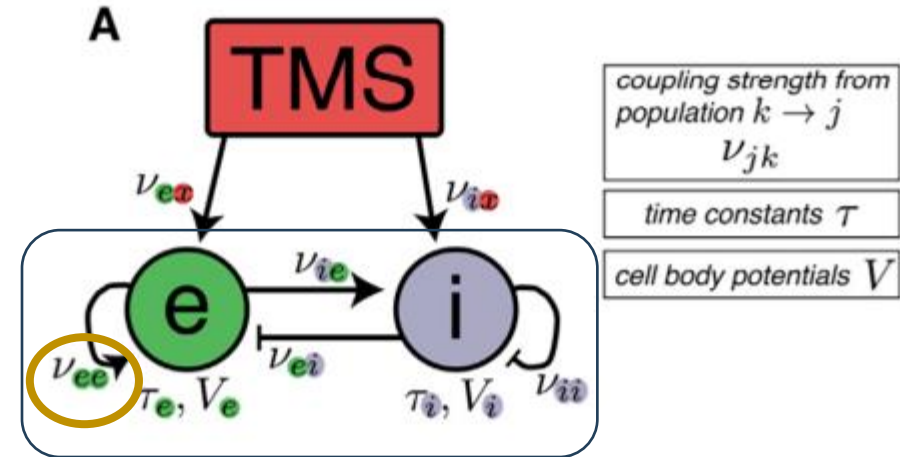
$$\frac{d\bar{v}_{ee}}{dt} = \eta([Ca^{2+}]_e) \left(v_{\max} \Omega([Ca^{2+}]_e) - \bar{v}_{ee} \right)$$

$$\frac{d[Ca^{2+}]_e}{dt} = gB([glu])H(V) - \frac{[Ca^{2+}]_e}{\tau_{Ca}},$$

$$\frac{d[glu]}{dt} = \lambda_{glu} \phi_{ee} - \frac{[glu]}{\tau_{glu}},$$

$$\frac{dg}{dt} = \frac{1}{\tau_{rec}} (g_0 - g) - \frac{g_0}{\tau_{BCM}} \left(\frac{\bar{v}_{ee}}{v_{ee}} - 1 \right)$$

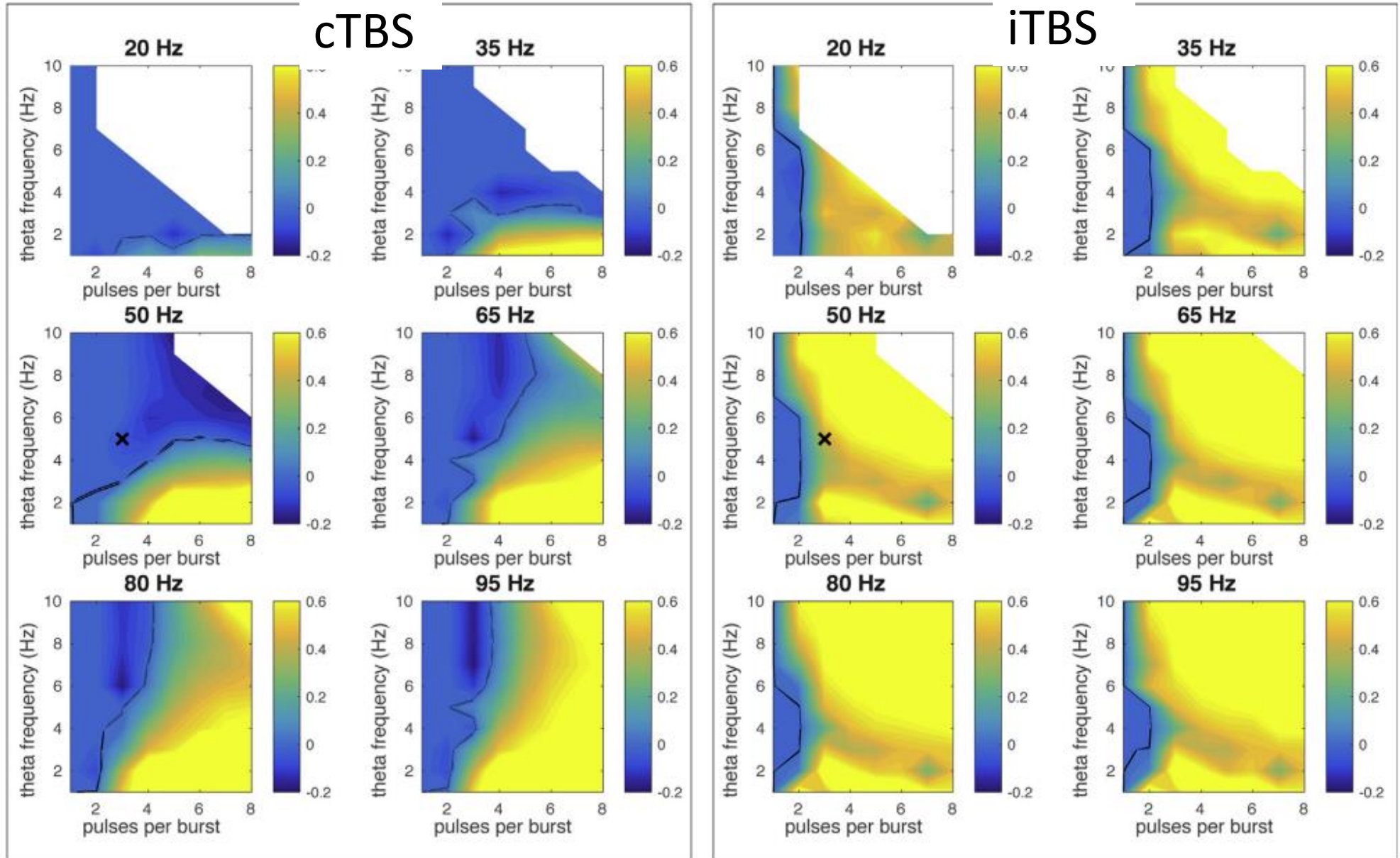
$$\left(z \frac{d}{dt} + 1\right)^2 v_{ee} = \bar{v}_{ee}.$$



M.T. Wilson et al. *Clinical Neurophysiology* 129 (2018) 1230–1241, Figure 1

What can we do? Vary protocols

How does v_{ee} change?



M.T. Wilson et al. *Clinical Neurophysiology* 129 (2018) 1230–1241, Figure 4

Consequences for variability

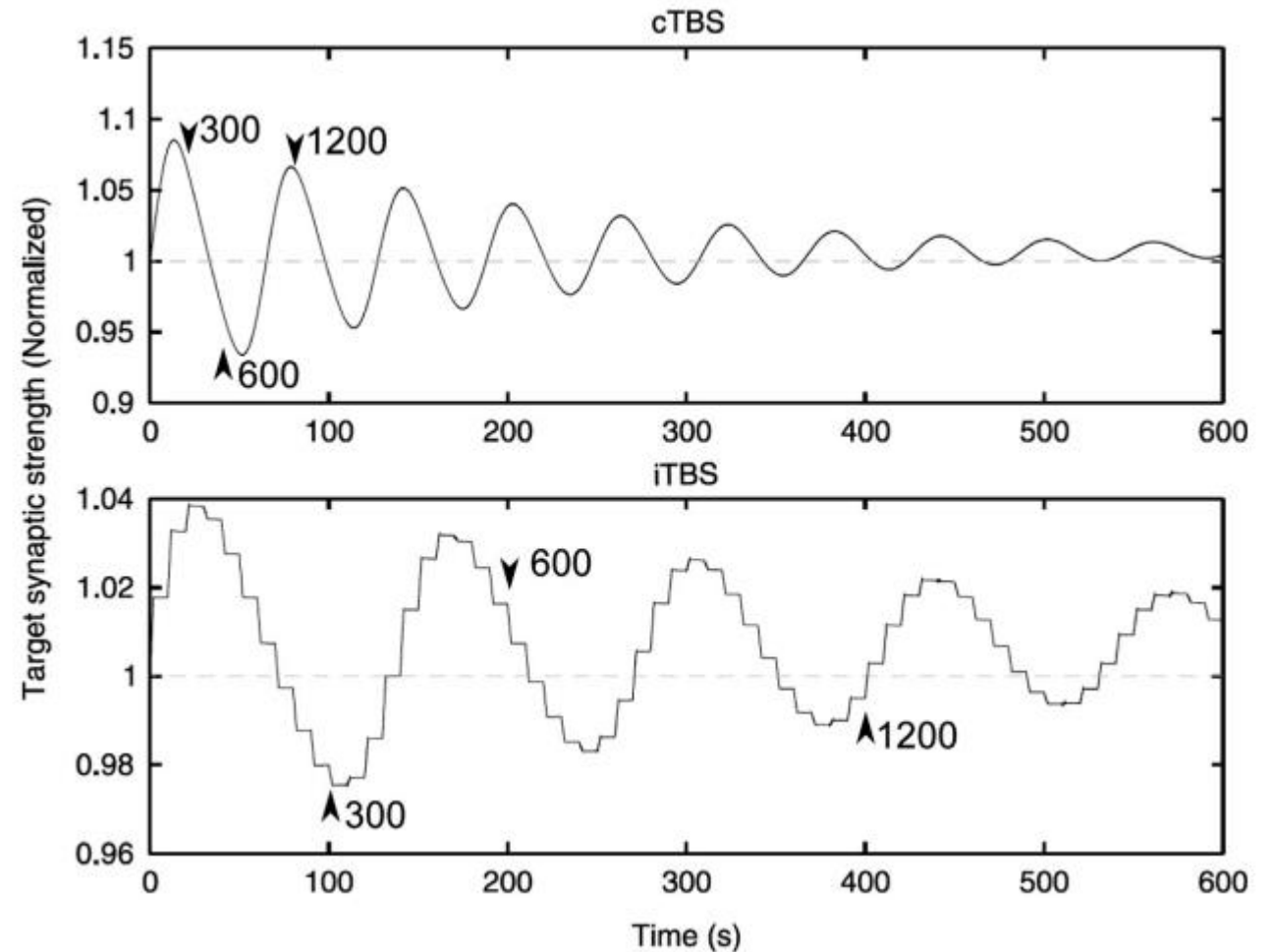
- Responses are variable because...

What you do

- Ultimate synaptic strength can **oscillate with number of pulses**
- Ultimate synaptic strength **varies with strength of application**

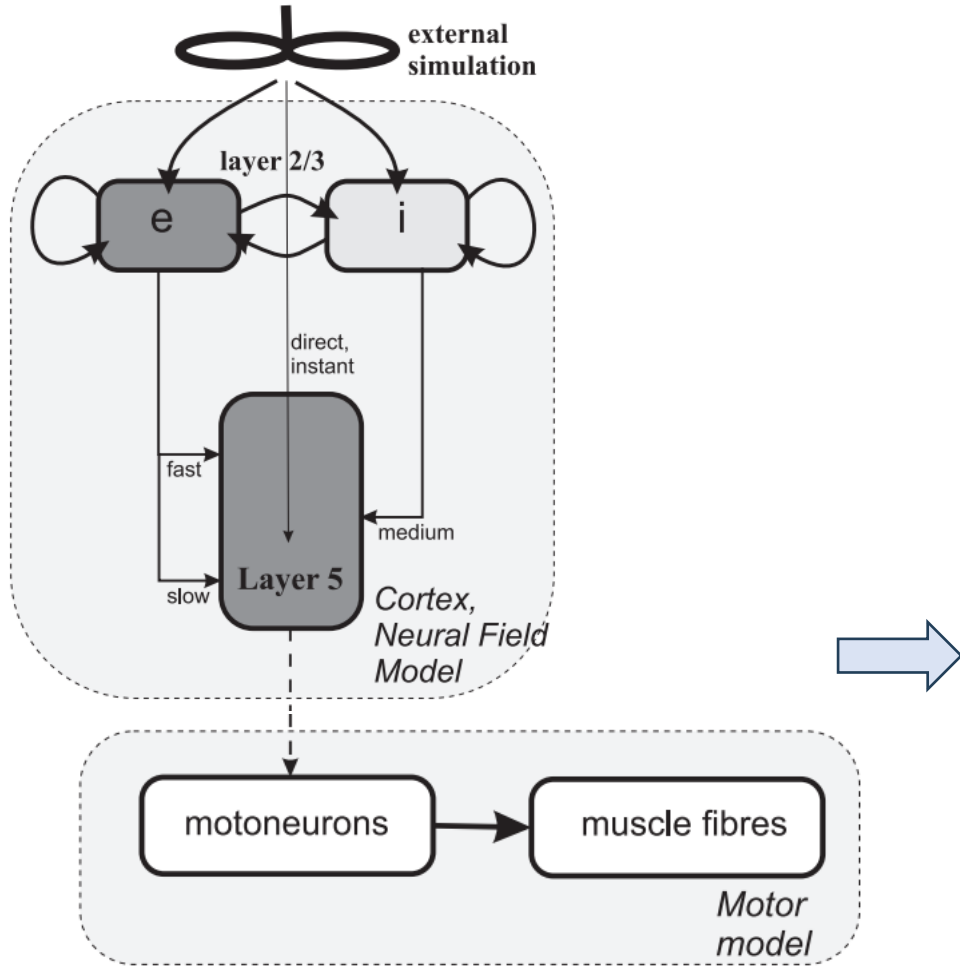
Where you start from

- Ultimate synaptic strength **varies with initial strength of synaptic weight**

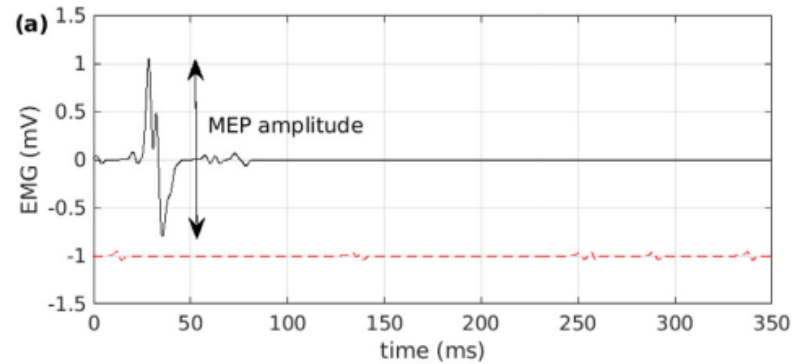
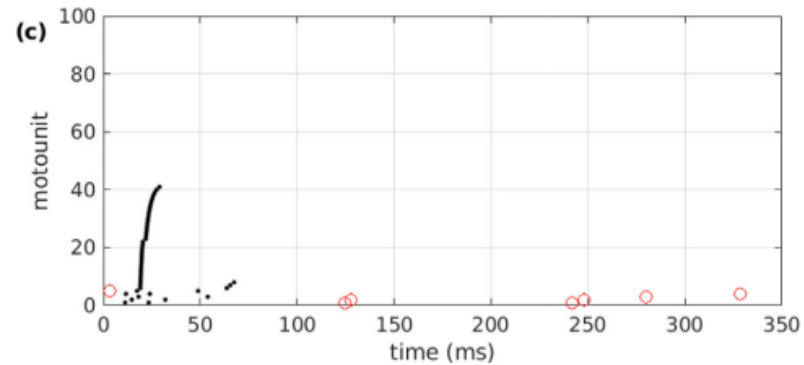


M.T. Wilson et al. *Clinical Neurophysiology* 129 (2018) 1230–1241, Figure 3

Modelling MEPs within neural field scheme

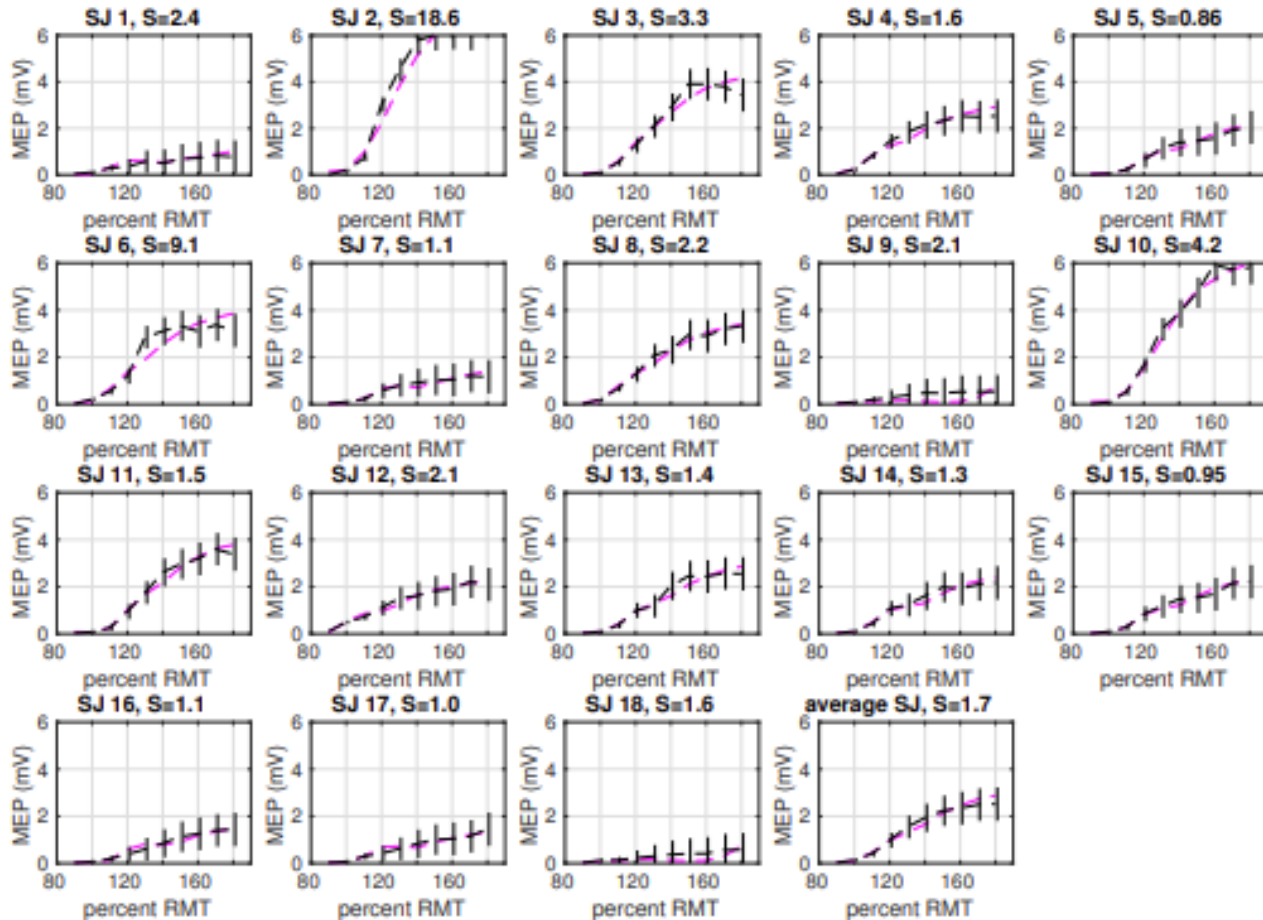


M.T. Wilson et al, *Clinical Neurophysiology* 132 (2021) 412–428. Figure 1



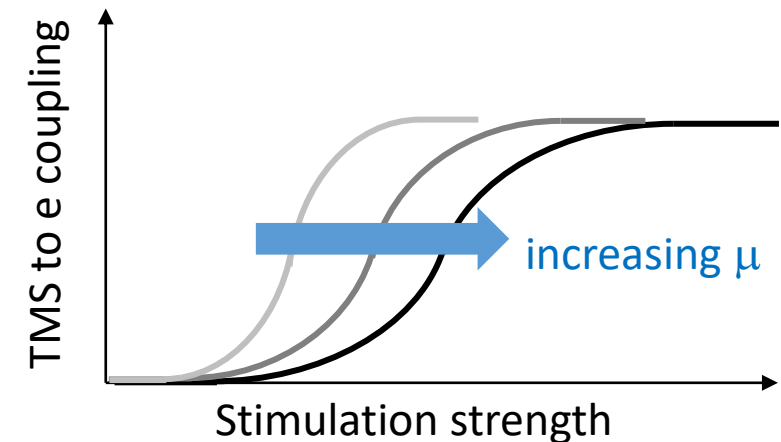
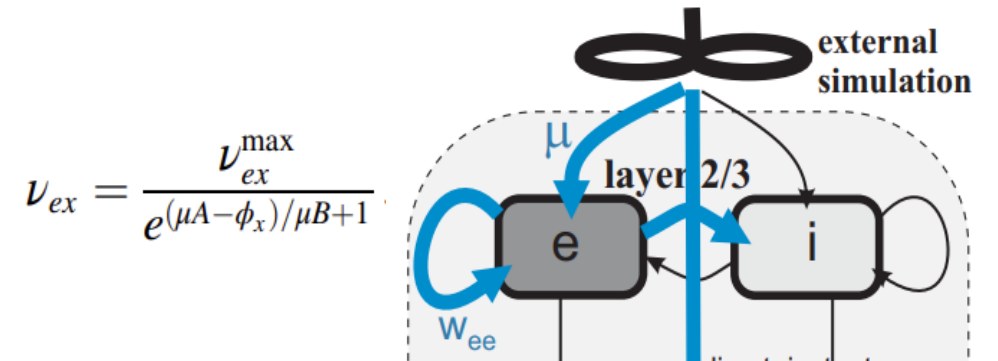
M.T. Wilson, B. Moezzi and N.C. Rogasch, *Clinical Neurophysiology* 132 (2021) 412–428, Figure 3

Fit model parameters to individual's input-output curves

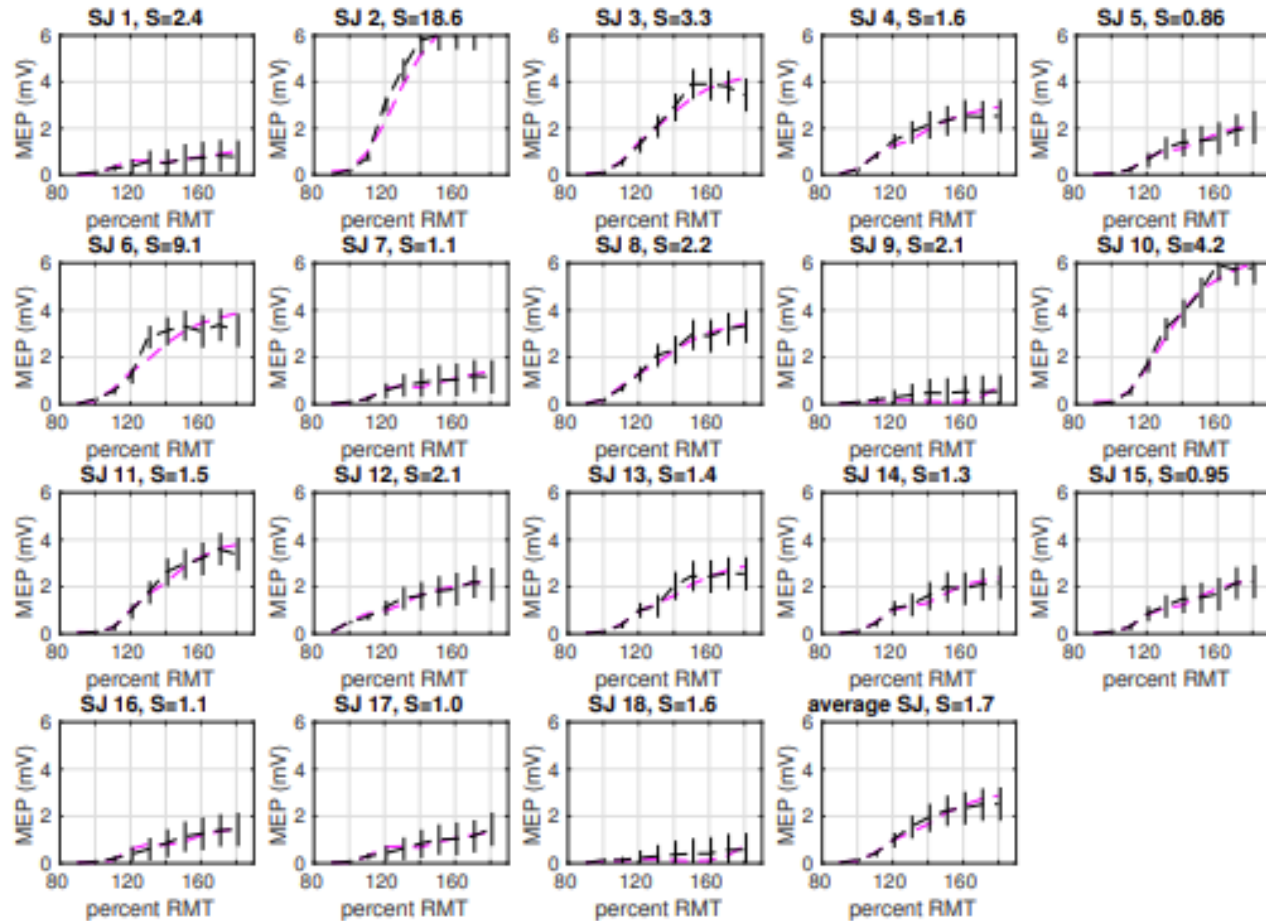


M.T. Wilson et al., Brain Research 1801 (2023) 148205, Figure 5

- Identify which parameters in model are most responsible for differences between individuals.

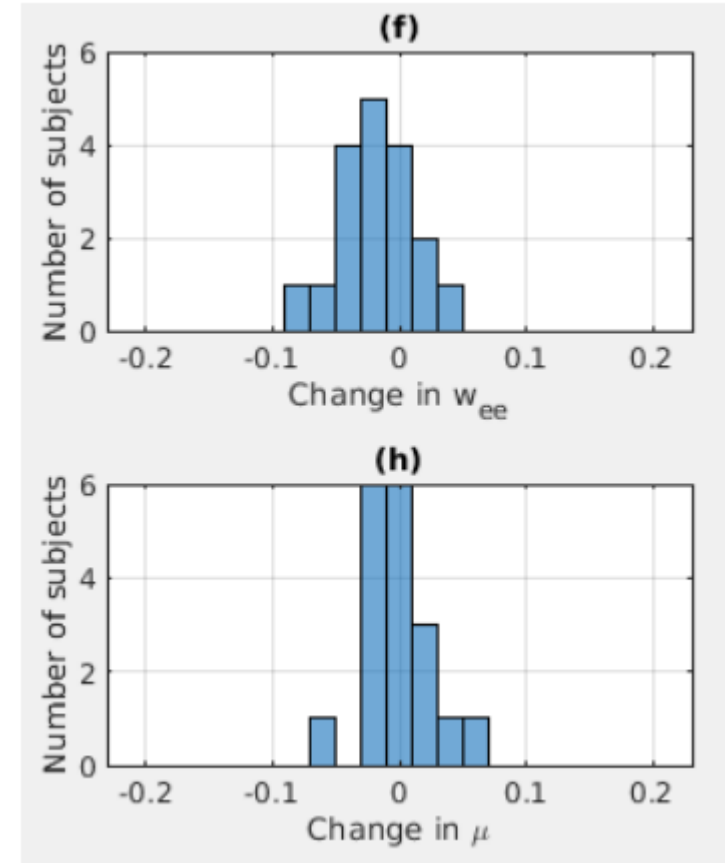


Fit model parameters to individual's input-output curves



M.T. Wilson et al., Brain Research 1801 (2023) 148205, Figure 5

How do w_{ee} and μ change post-cTBS?



M.T. Wilson et al., Brain Research 1801 (2023) 148205, Figure 8

Consequences for variability

- MEPs vary according to:

- TMS-to-e coupling strength (parameter μ)

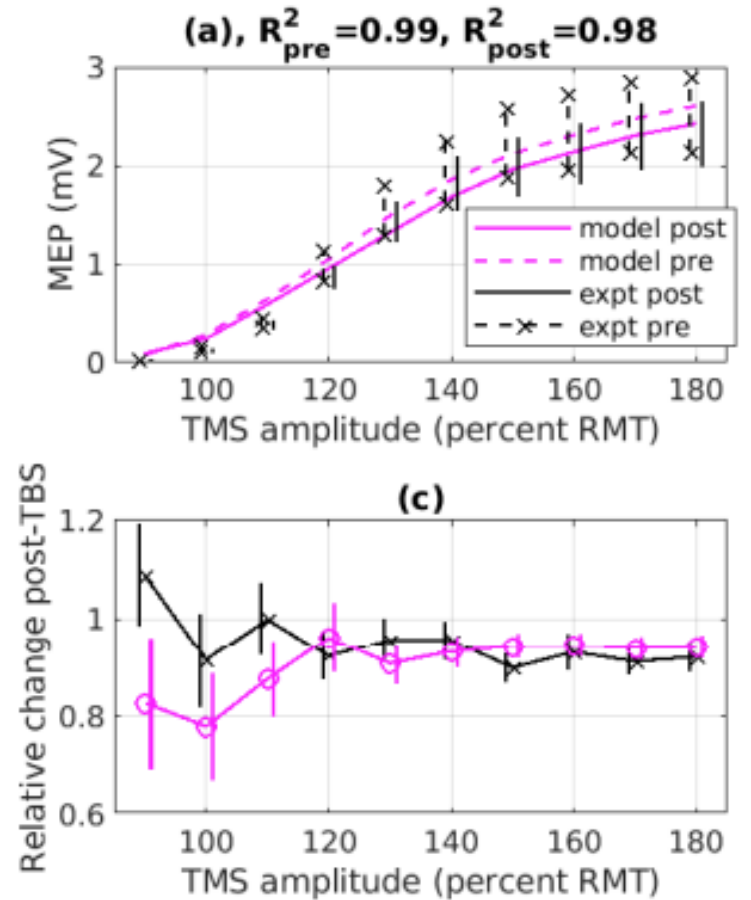
Depends on subject and placement/orientation of coil

- Excitatory-to-excitatory coupling strength w_{ee}

Depends on subject

Aside: Publish the raw data!

- MEPs often presented in terms of %RMT
- Modelling is more natural in terms of an actual amplitude
 - Electric field strength
 - %machine output (which machine?)
- Presenting input-output in terms of %RMT loses information unless the actual threshold is also quoted
- Makes comparison of model and literature-reported experimental data less direct



M.T. Wilson et al., Brain Research 1801 (2023) 148205, Figure 8

Conclusions

- We have modelled Calcium-dependent plasticity with a Neural Field scheme
- Developed the approach further to modelling MEPs
- Identify what parameters might be to produce an individual IO curve
- In terms of variability of MEPs, the following are important:
 - TMS-to-e coupling strength (parameter μ)
 - Excitatory-to-excitatory coupling strength w_{ee}
 - Number of pulses / time since stimulation
- Include reporting of actual thresholds when %RMT is used (and raw data in general)