

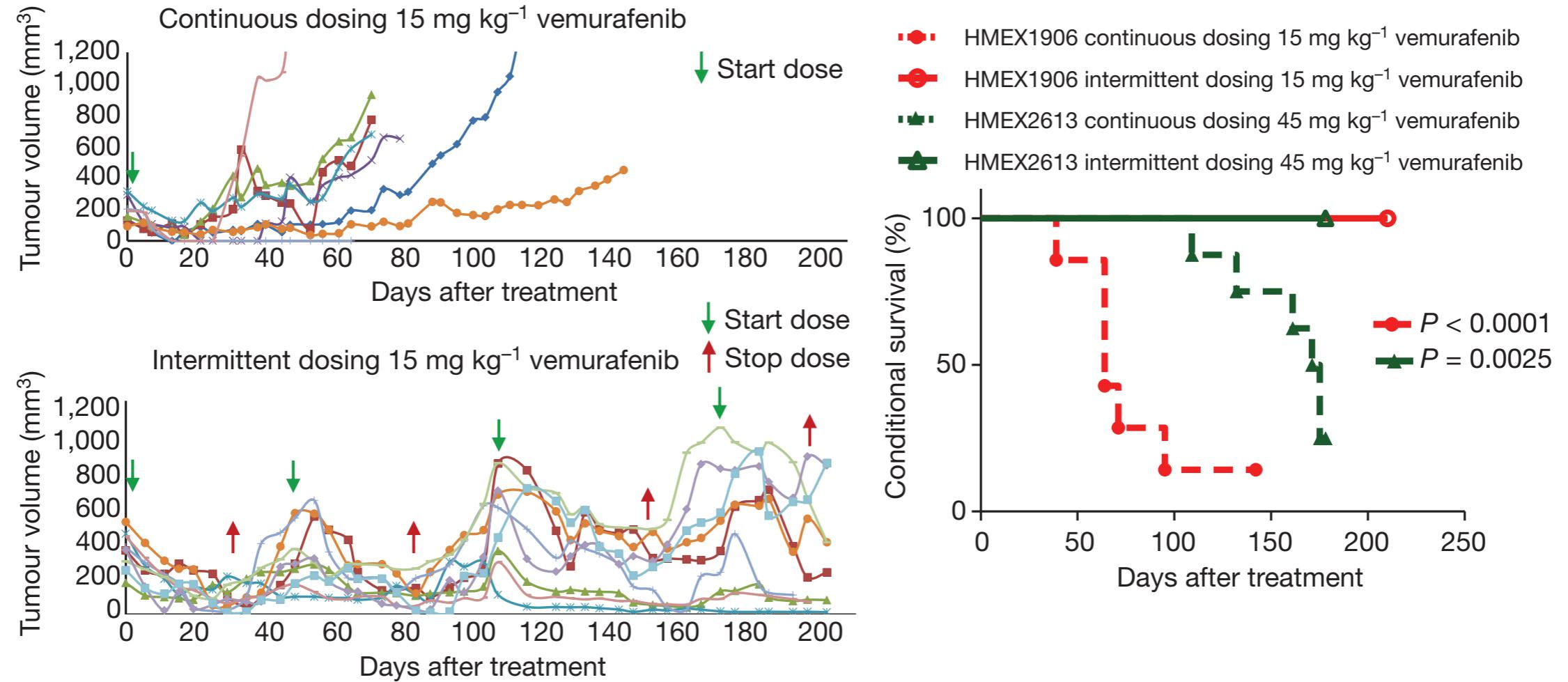
# Understanding potential benefits of adaptive therapy

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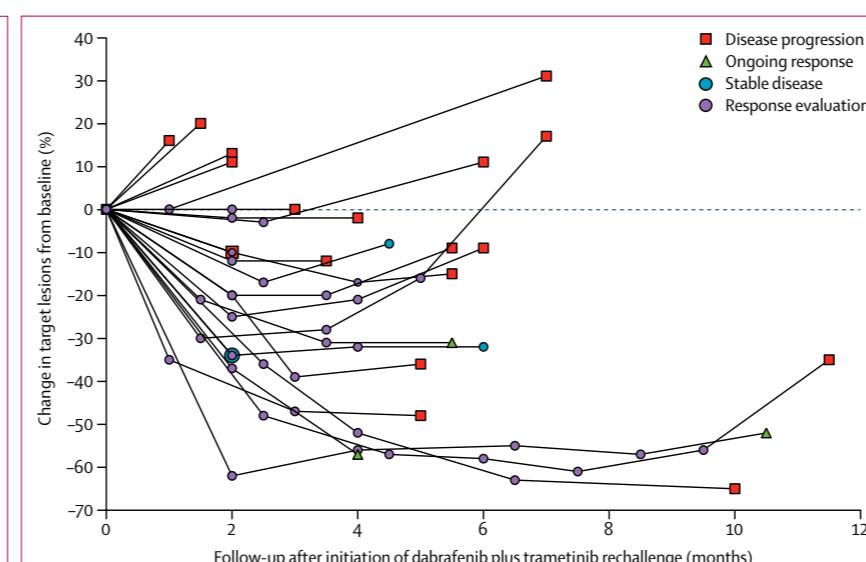
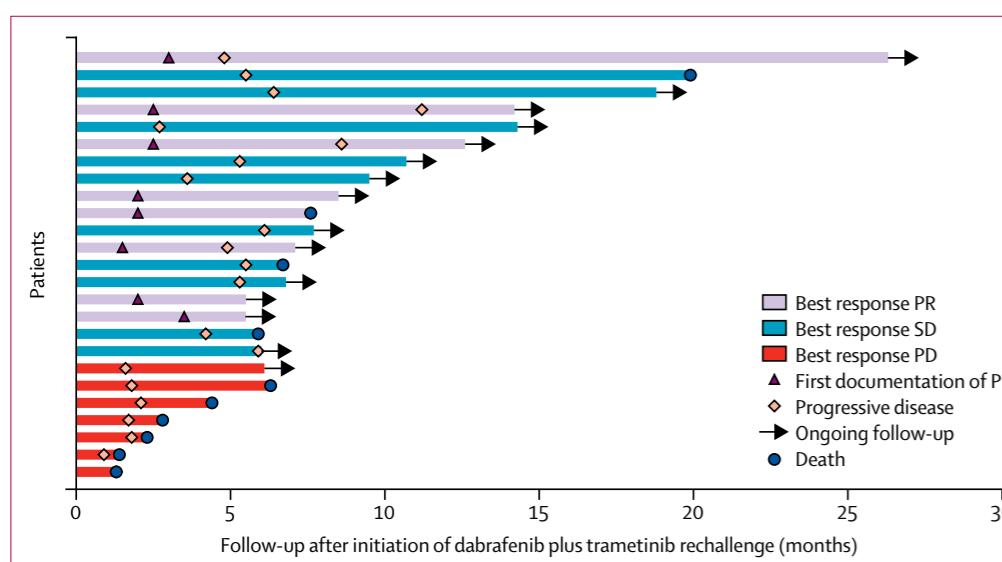
# Melanoma intermittent therapy (in vivo)



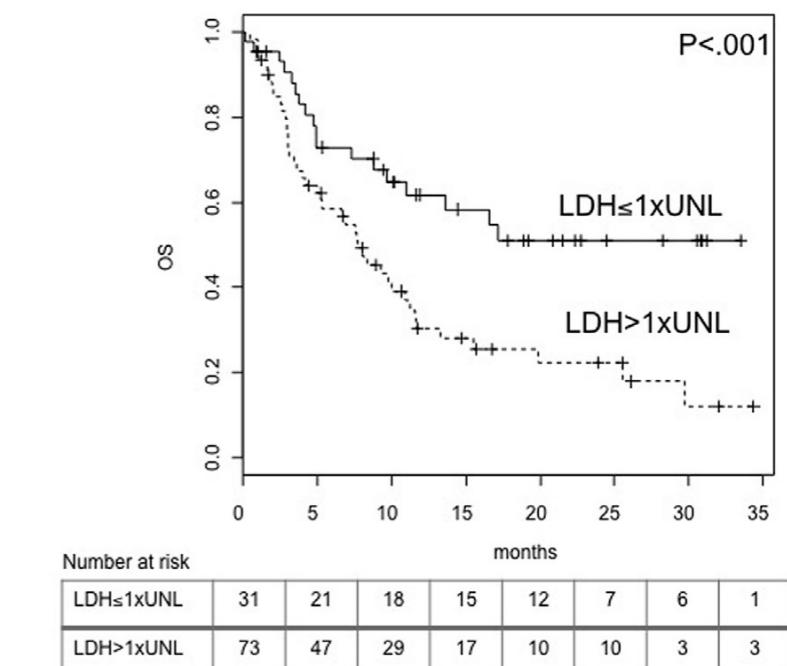
Das Thakur et al. Nature, 2013, 494:251-5

- Intermittent therapy (4 week on/2 week off) improves response in vivo
- Various responses: some regression vs. gradual increase
- Resistant cells become drug dependent for continued proliferation
- Cessation of drug leads to regression of drug-resistant cells

# Intermittent therapy clinical trials



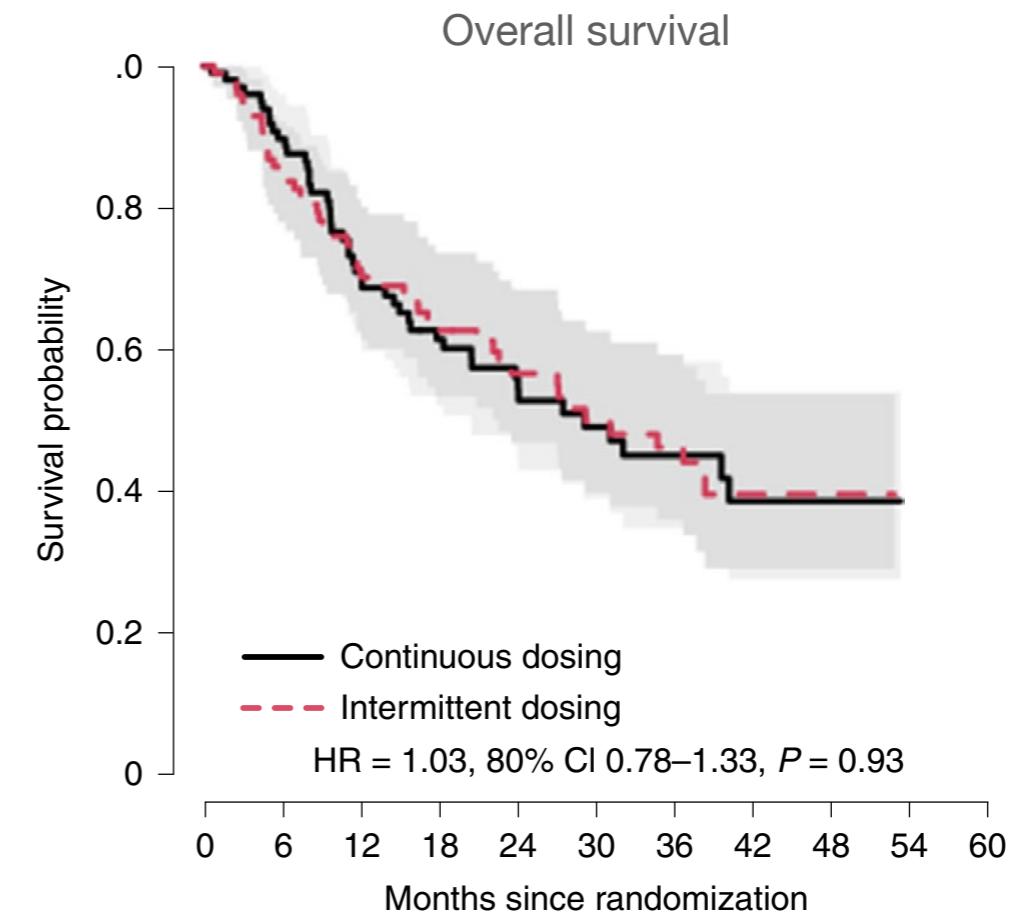
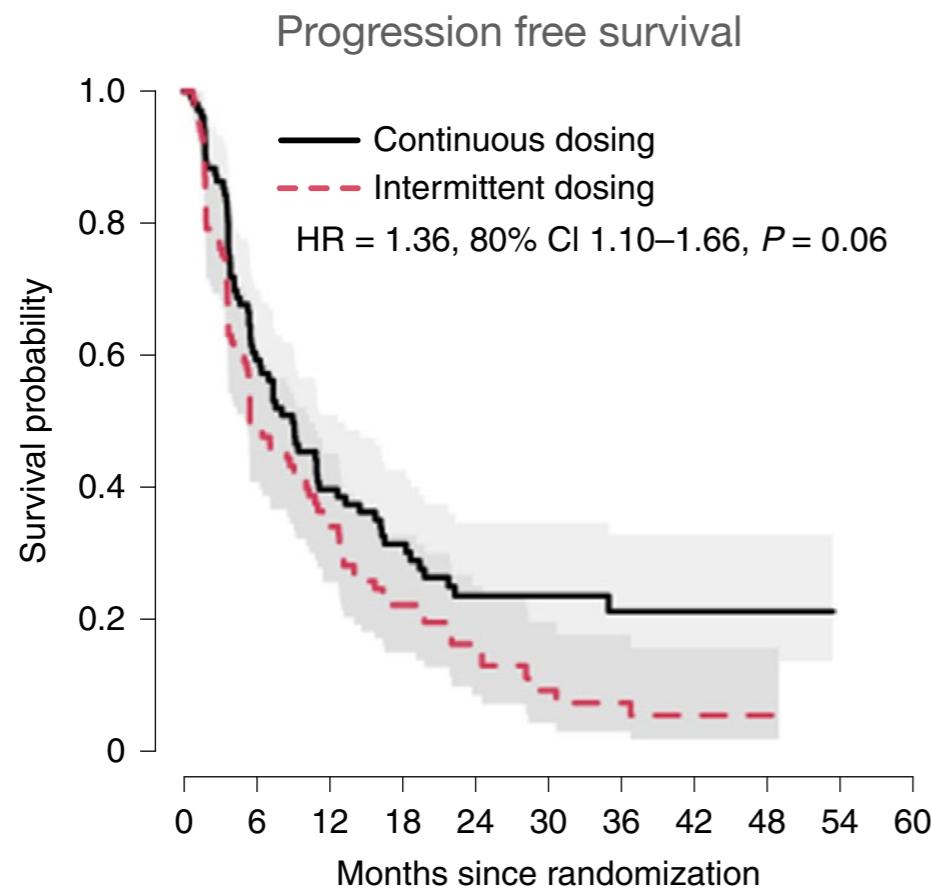
Schreur et al. Lancet Oncol, 2017



Valpione et al. Eur J Cancer, 2018

- Re-challenge after treatment break or other therapy due to progression or other causes
- Drug holidays: 4-12 weeks
- Re-challenge clinically meaningful
- Diverse response and duration

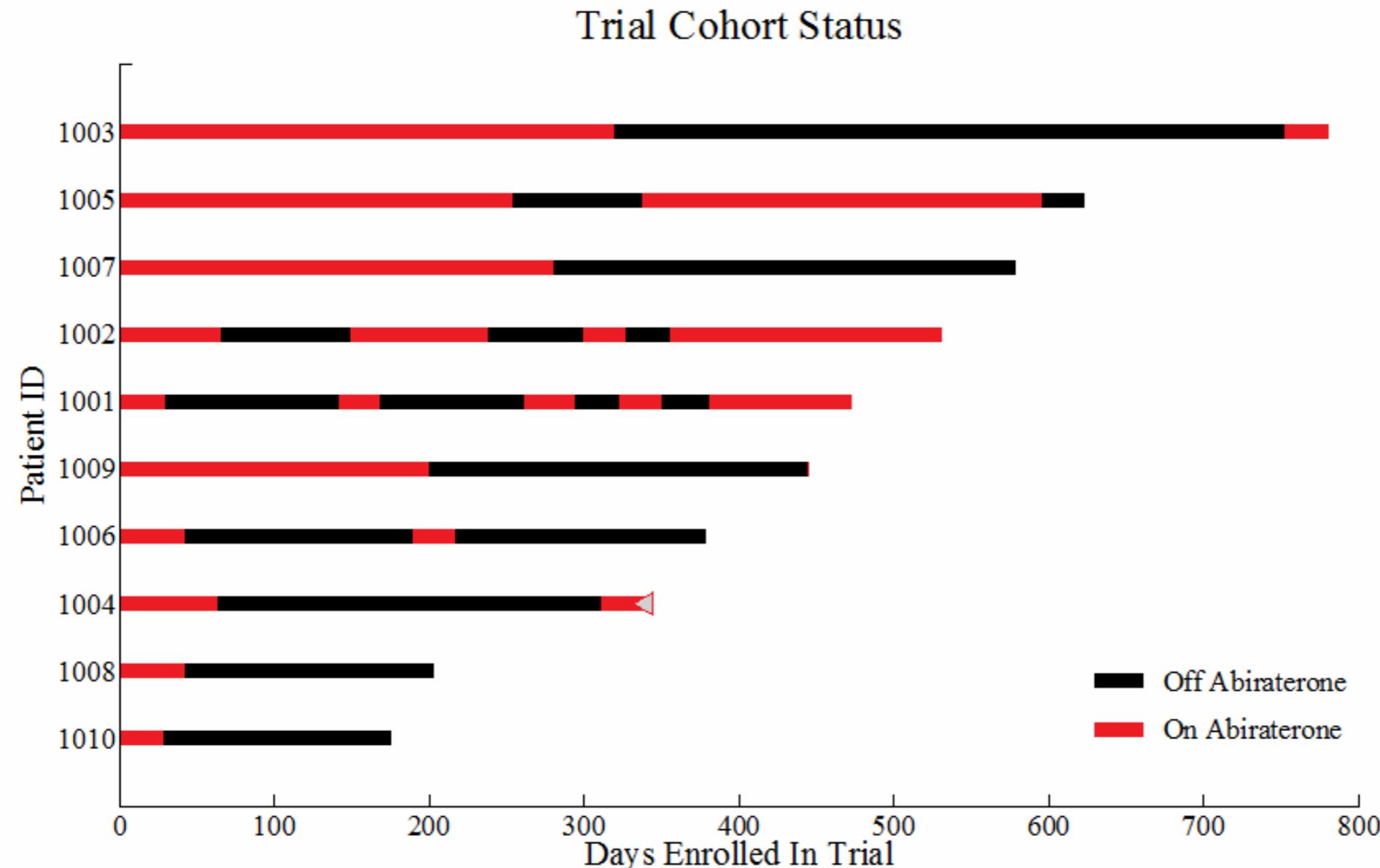
# Intermittent therapy clinical trials



Algazi et al. Nature Medicine, 2020, 26:1564-1568

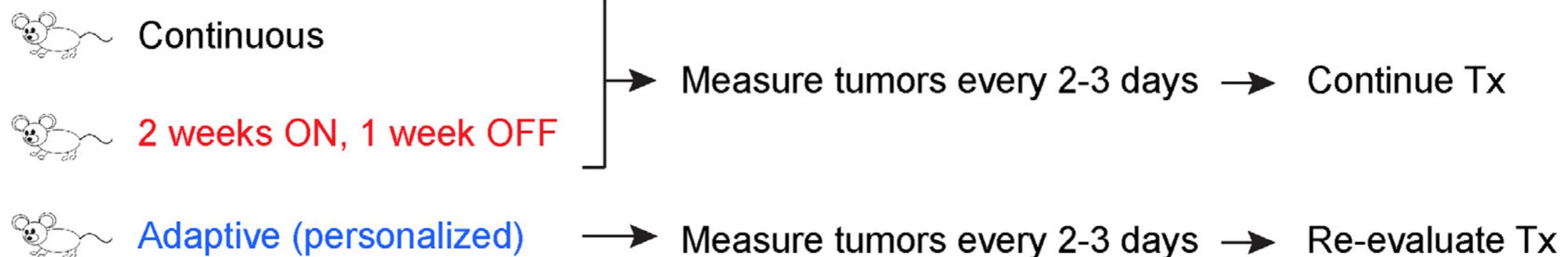
- Phase 2 trial of intermittent therapy
  - 8 week continuous therapy lead in, 3 week off and 5 week on or continuous therapy
  - Intermittent dosing did not improve progression free survival
  - No difference in the overall survival and the overall toxicity
  - This one-size-fits-all approach unlikely to be optimal clinically

# Inter-patient variability

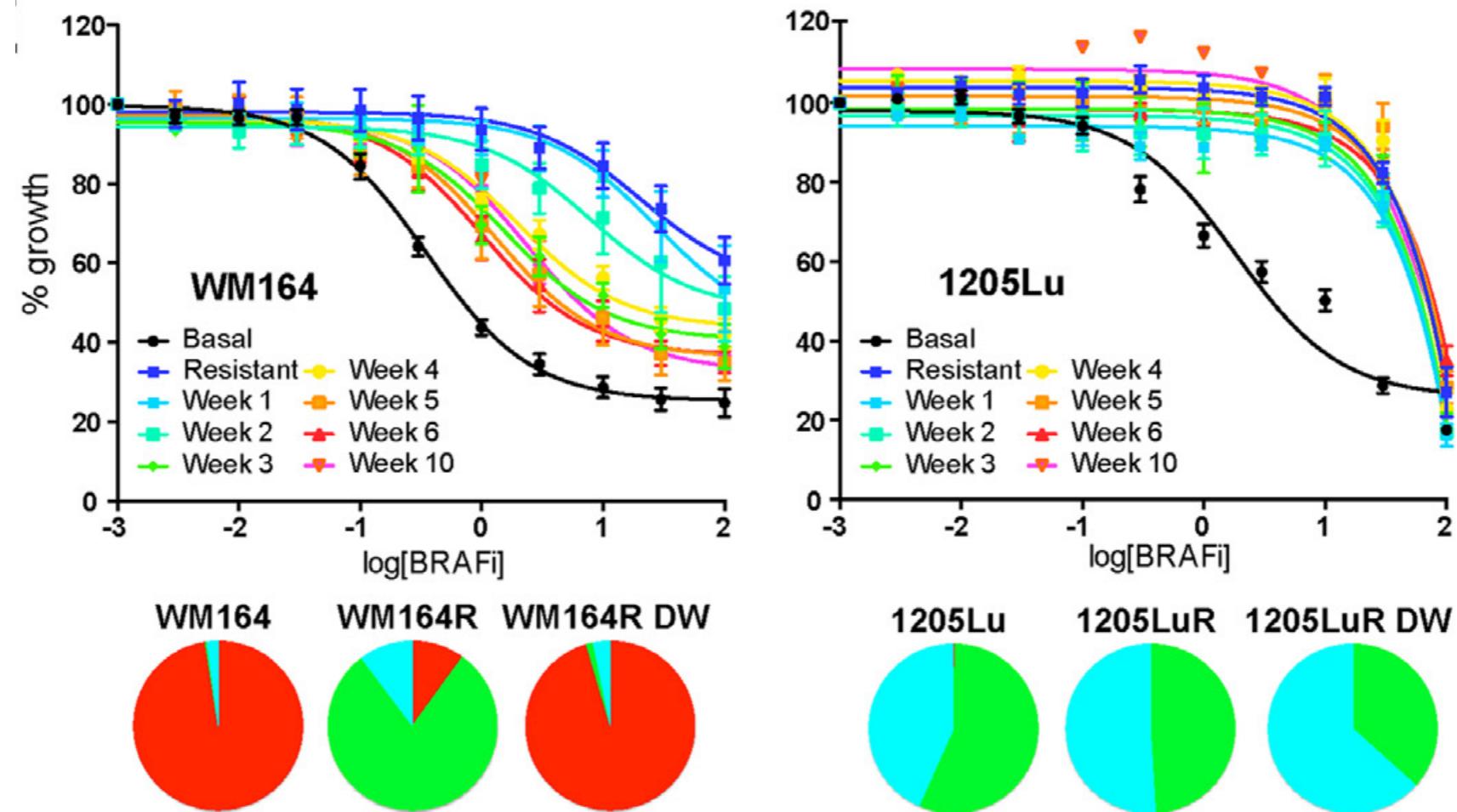


Zhang et al. Nature Comm, 2017

# Melanoma adaptive therapy in vivo



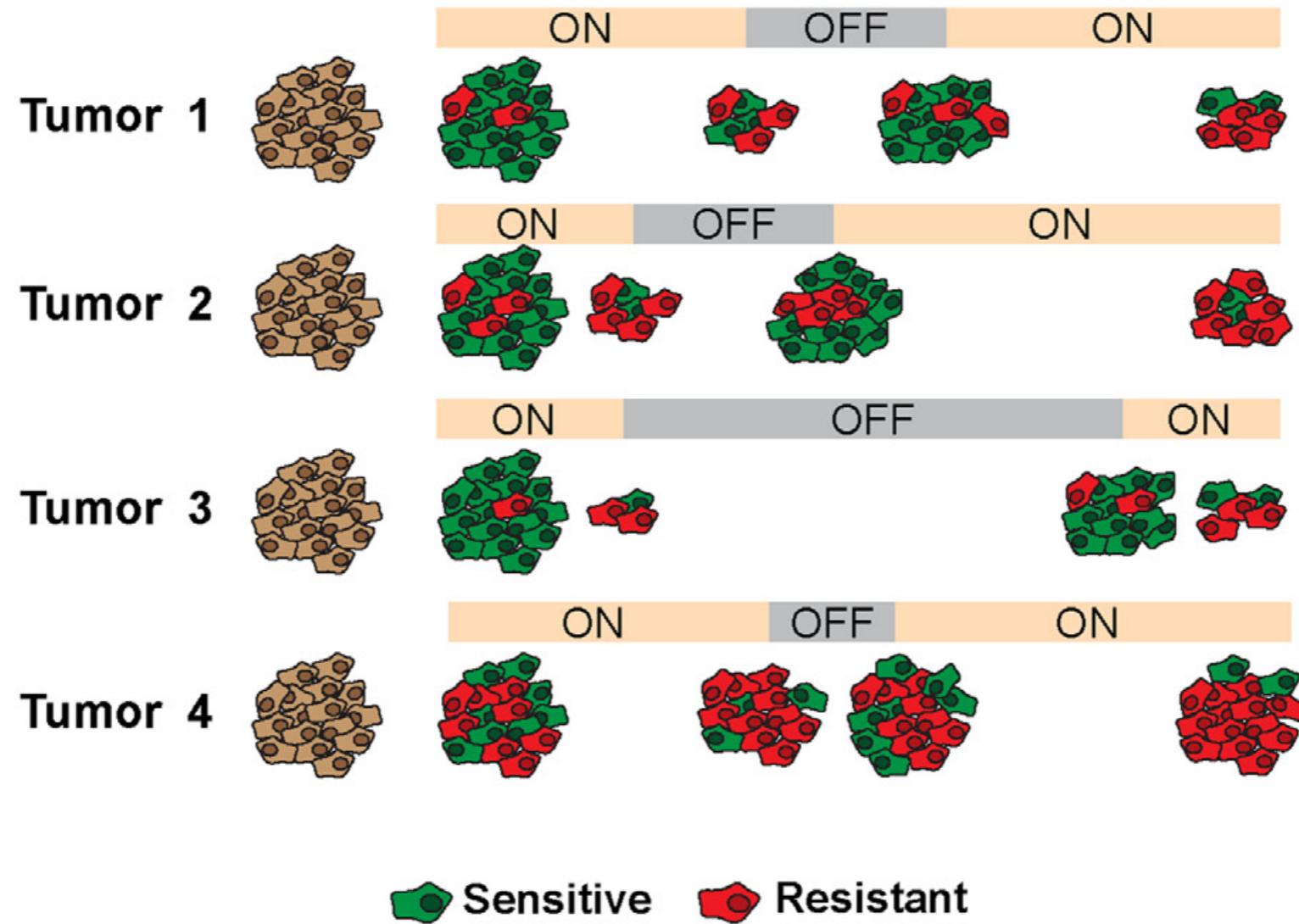
# Melanoma adaptive therapy in vivo



Smalley et al. *Ebiomedicine*, 2019

- Transcriptional heterogeneity in melanoma cell lines
- Drug induced distribution changes
- WM164 cell lines seems to be recovering drug sensitivity
- Inhibition of growth in 4-10 week off WM164 vs. drug sensitivity of basal cell line
- Decided to use WM164 cell line xenograft model

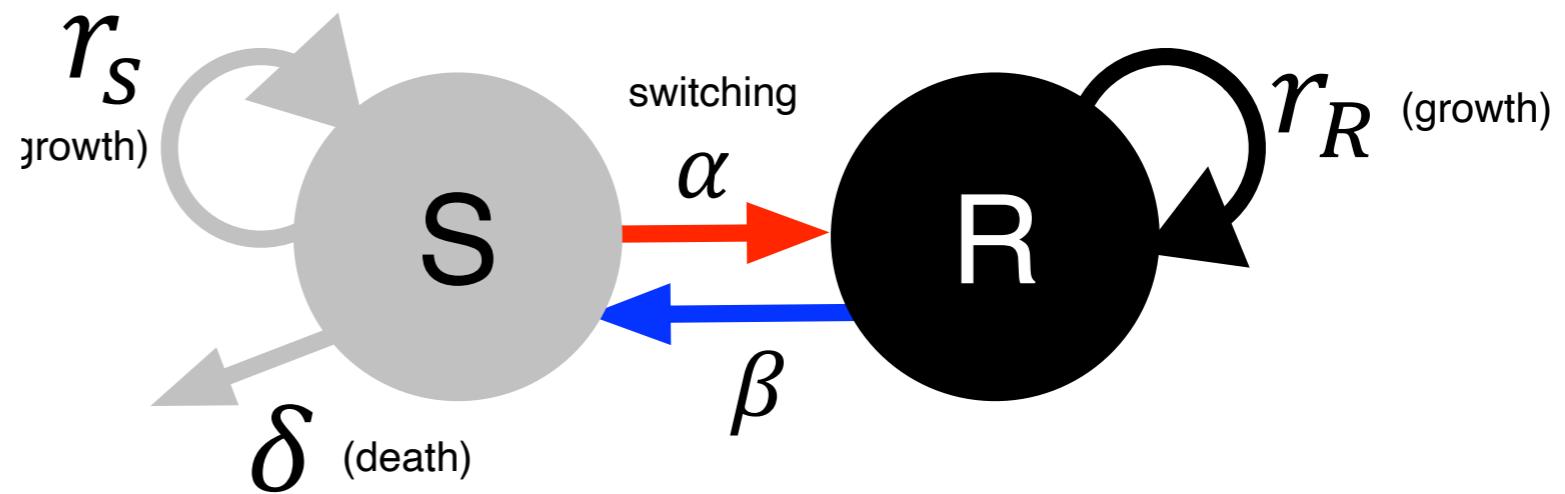
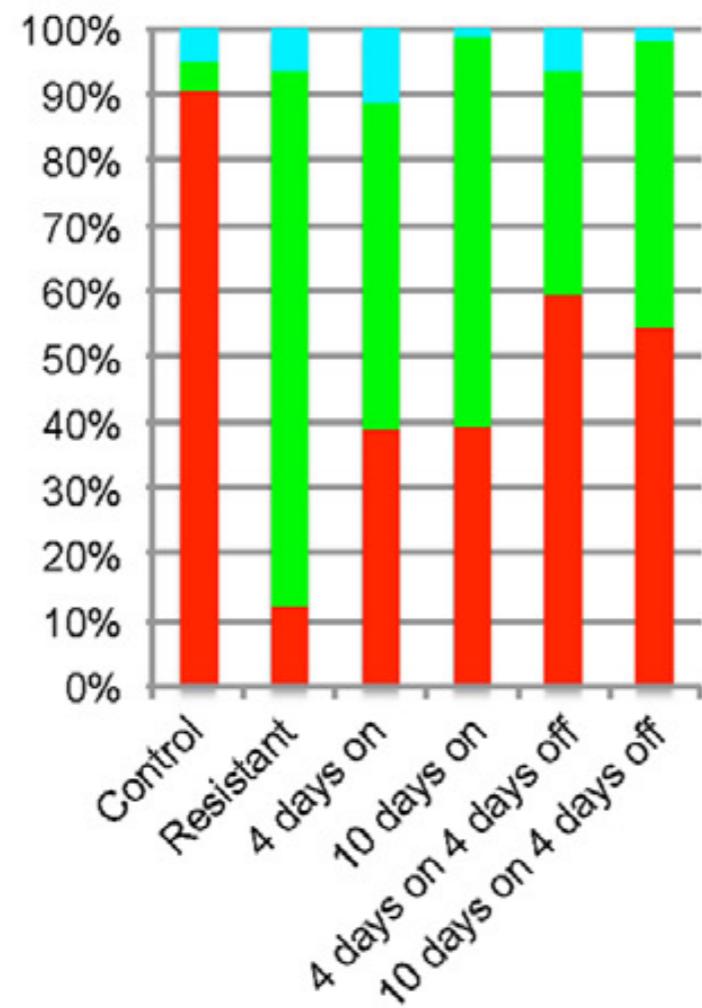
# Melanoma adaptive therapy in vivo



- Goal: maintain drug-sensitive transcriptional states through adaptive dosing
- Mathematical model guided scheduling
- Drug holiday associated with drug sensitivity

# Mathematical model

■ State 1 ■ State 2 ■ State 3

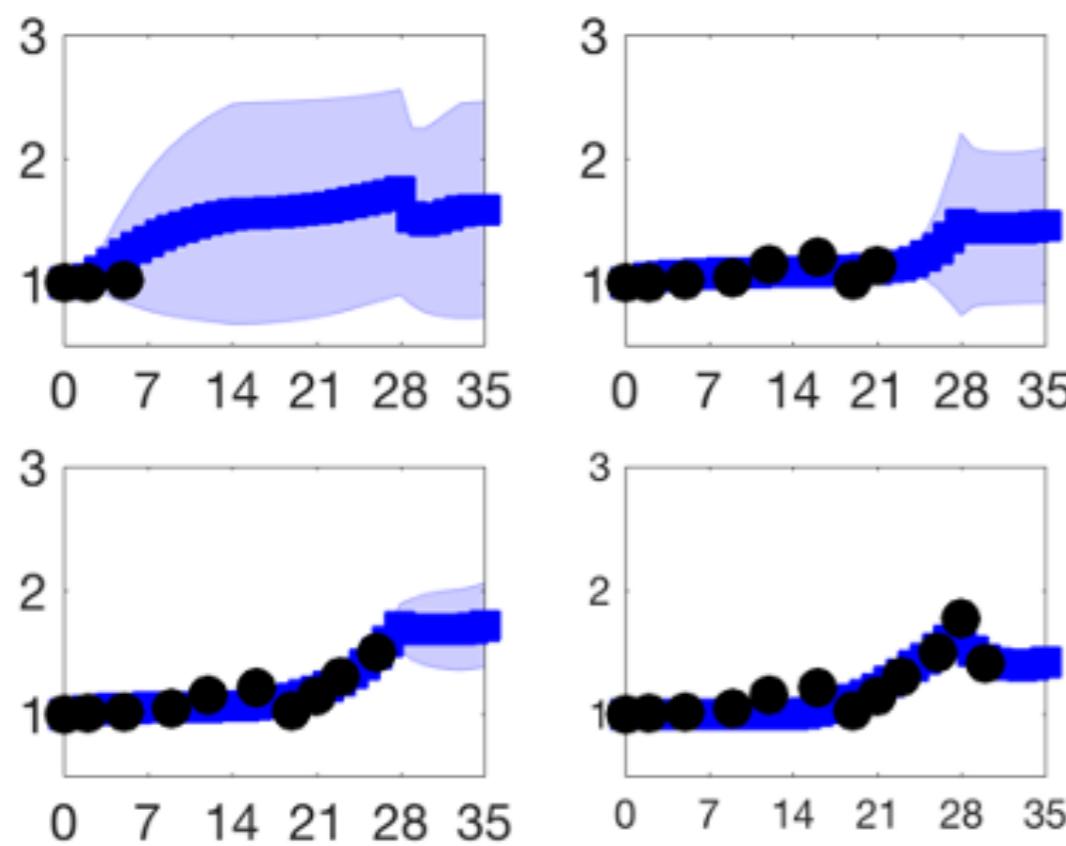


Smalley et al. Ebiomedicine, 2019

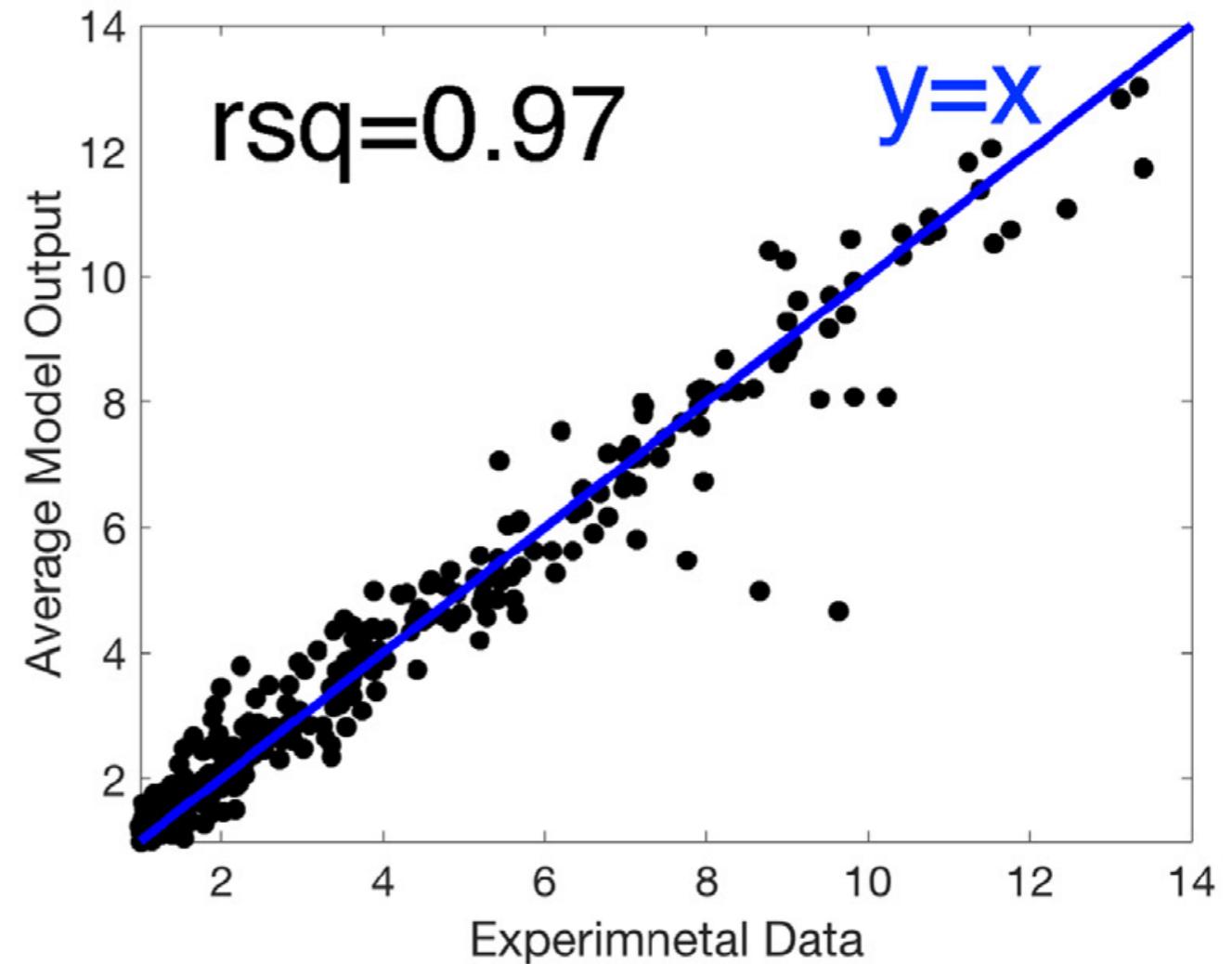
$$\frac{dS}{dt} = r_S \left(1 - \frac{S + R}{K}\right)S - \delta S - \alpha S + \beta R,$$

$$\frac{dR}{dt} = r_R \left(1 - \frac{S + R}{K}\right)R + \alpha S - \beta R.$$

# Model calibration & prediction



$$\min f(H) = \min \sqrt{\sum_i (V(t; H) - D(t)/D(0))^2}$$



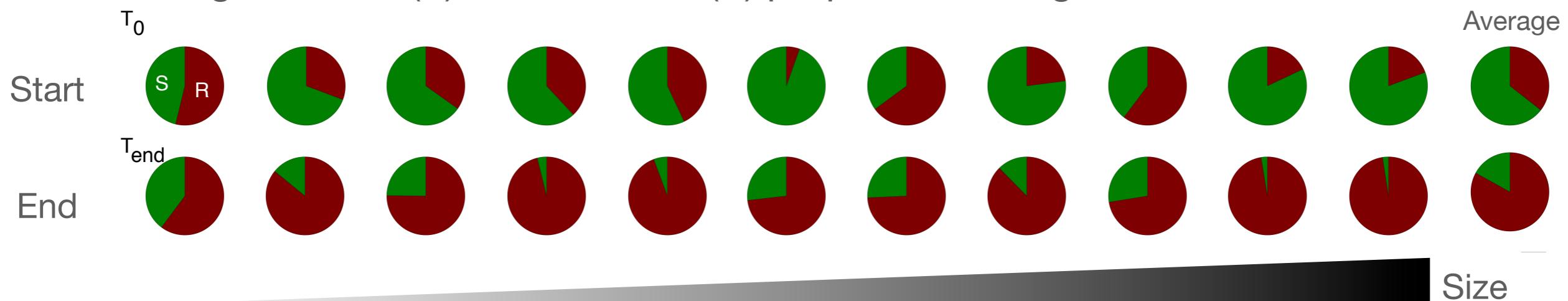
- 11 one-side xenograft models
- Measure individual mouse tumor volume changes every 2~3 days
- Estimate model parameters ( $H$ ) that minimize the difference between model predicted tumor volume and mouse tumor volume every 2~3 days

# Model calibration & prediction

| Mouse # | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37      | Tumor Growth |
|---------|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|---------|--------------|
| 1       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 297.88% |              |
| 2       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 168.68% |              |
| 3       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 363.69% |              |
| 4       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 125.76% |              |
| 5       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 222.10% |              |
| 6       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 228.48% |              |
| 7       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 812.75% |              |
| 8       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 114.86% |              |
| 9       |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 319.33% |              |
| 10      |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 920.55% |              |
| 11      |   |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    | 535.32% |              |

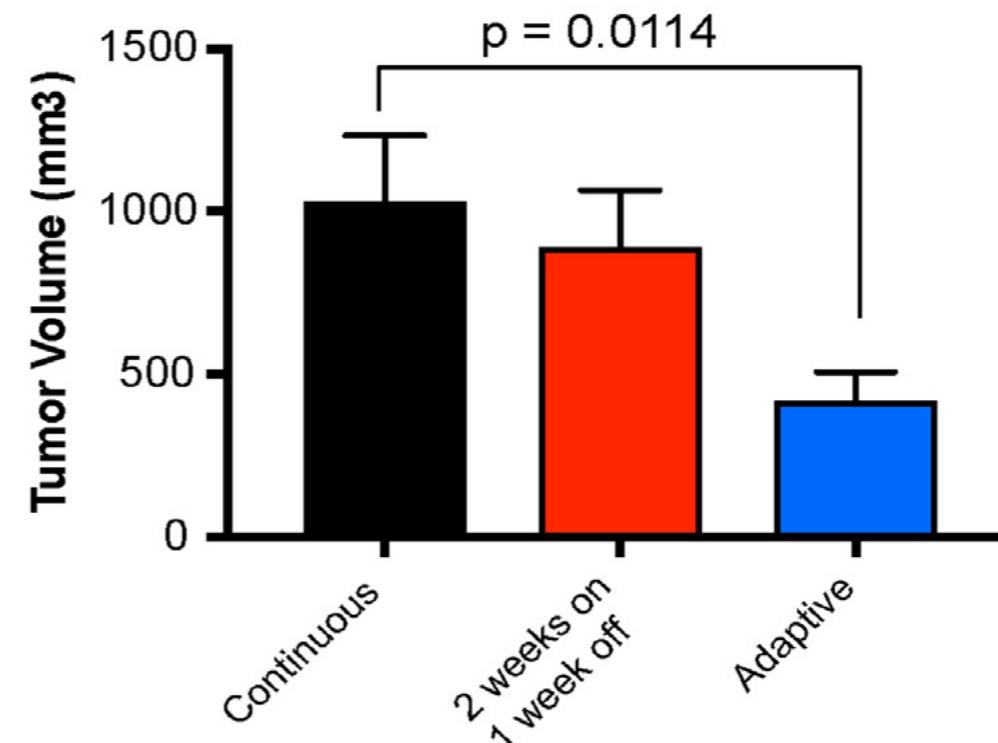
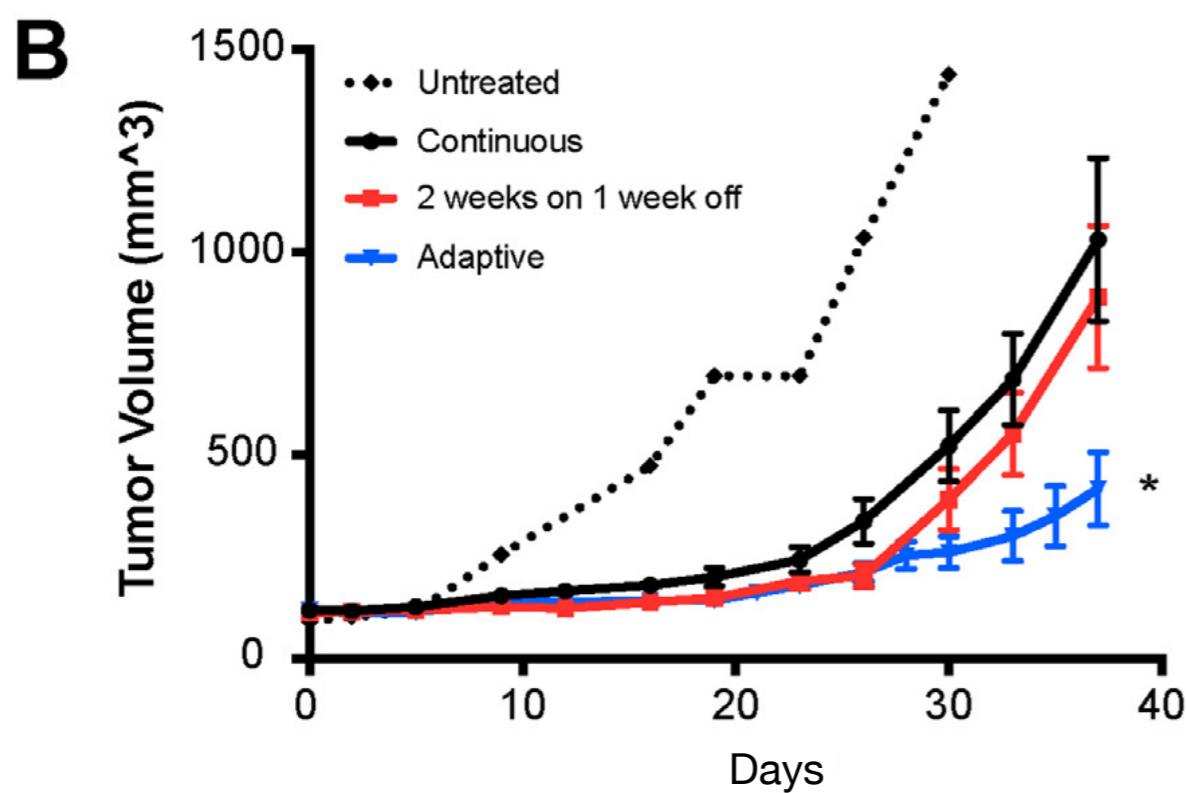
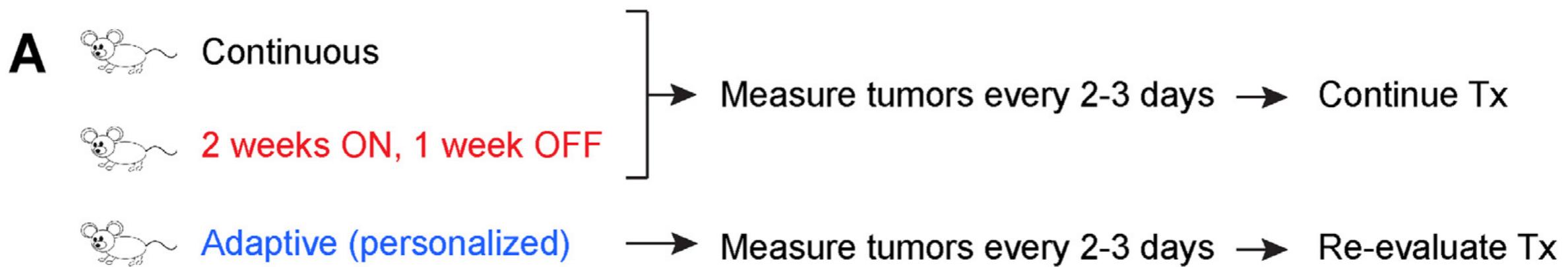
Smalley et al. *Ebiomedicine*, 2019

Predicted drug sensitive (S) and resistant (R) proportion change



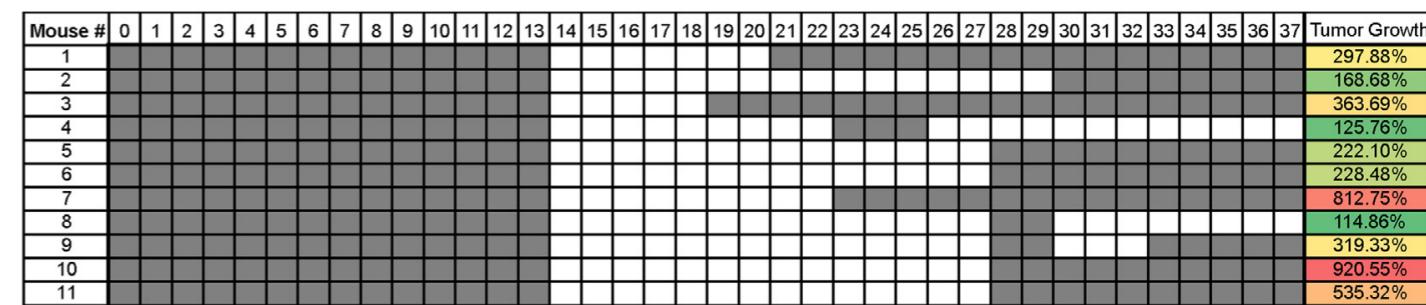
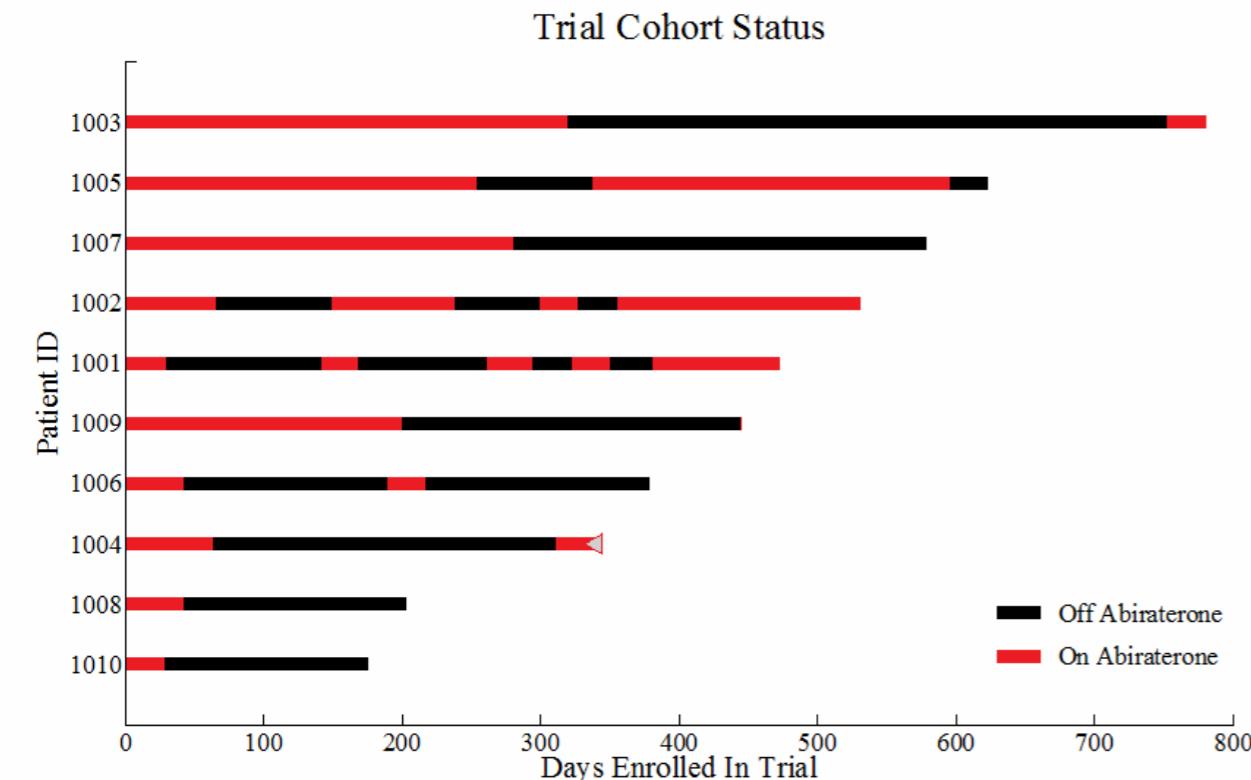
- Make predictions of tumor volume changes in 2 treatment scenarios: on and off
- Follow model predicted treatment decision (on or off) for subsequent 2~3 days
- Diverse treatment on and off schedule
- ~ 50% less tumor volume & ~64% dose rate compared to continuous MTD
- Not all xenograft model benefits from adaptive therapy

# In vivo study summary



Smalley et al. Ebiomedicine, 2019

# Benefits of adaptive therapy diverse



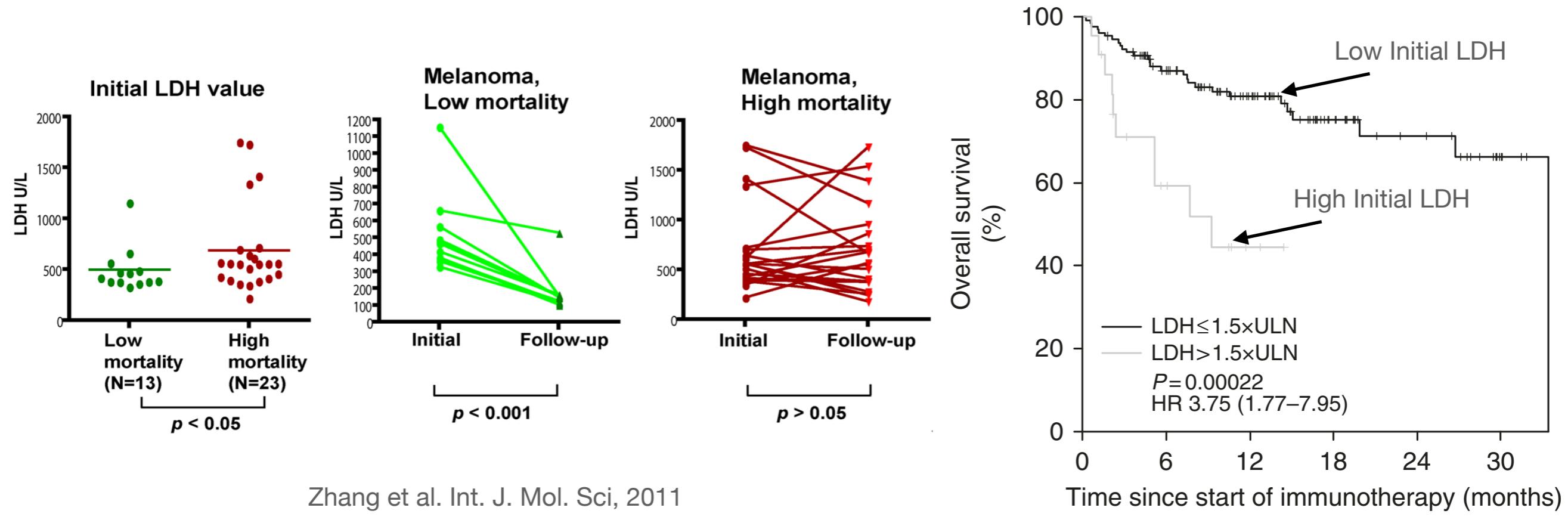
Smalley et al. *Ebiomedicine*, 2019

Zhang et al. *Nature Comm*, 2017

- Effectiveness of adaptive therapy will vary among patients
- Who will likely benefit most from adaptive therapy?
- Predictive factors

- Who will likely benefit most from adaptive therapy?
- What are predictive factors?

# Melanoma tumor burden marker

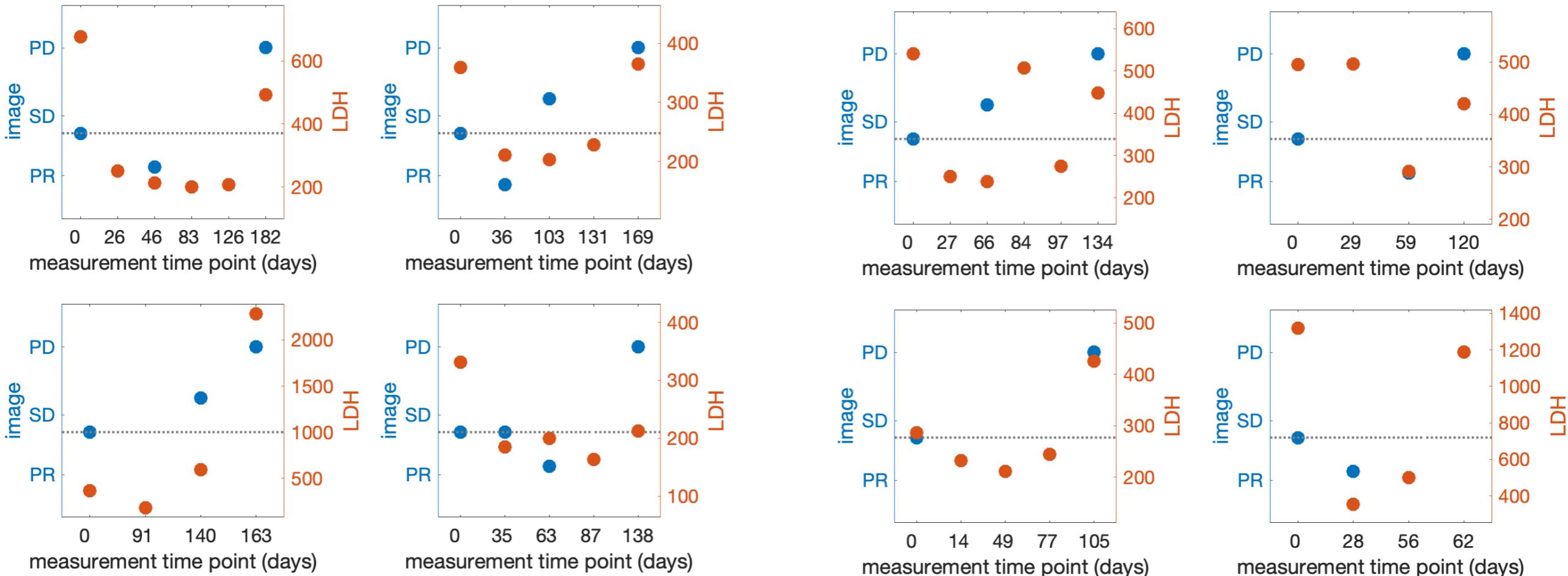


Zhang et al. Int. J. Mol. Sci, 2011

Wagner et al. Br. J. Cancer, 2018

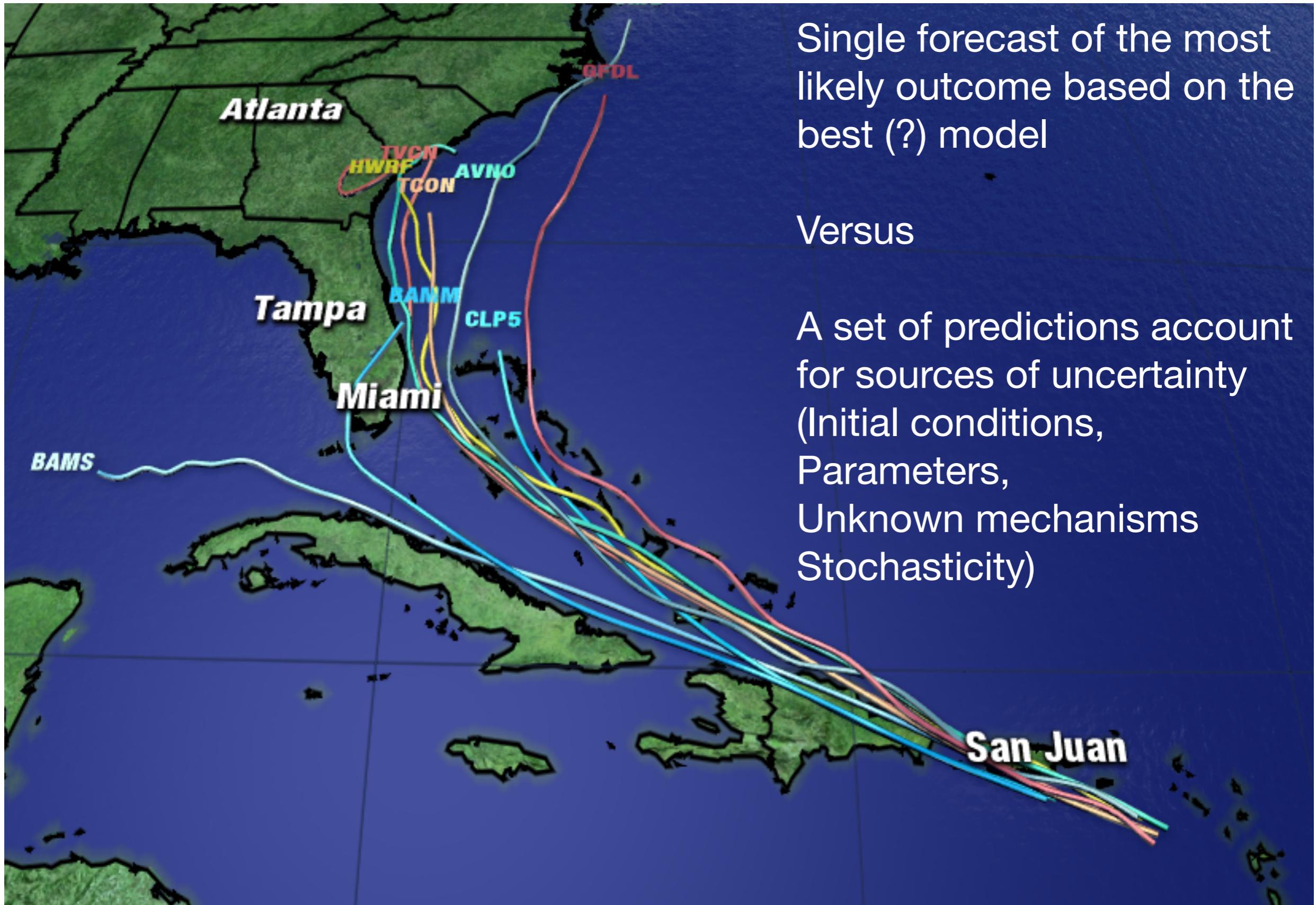
- Critical to obtain tumor burden as frequent as possible
- Serological marker that can be measured frequently
- Melanoma tumor burden marker: LDH, lactate dehydrogenase
- LDH is only serologic marker used for monitoring advanced melanoma in US
- Elevated serum LDH is associated with worse outcomes in patients treated with BRAF/MEK inhibitors

# Applying the model to patient data

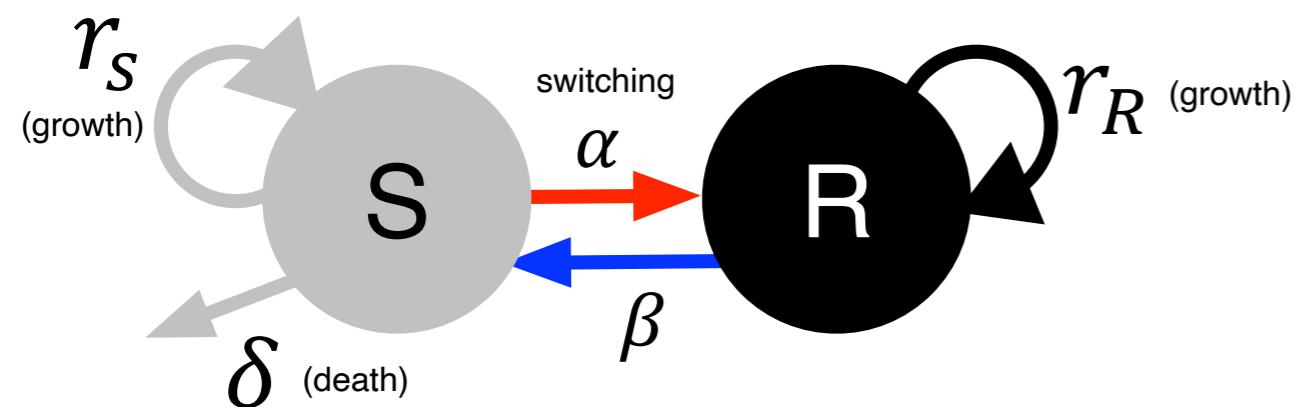


- 8 patients with metastatic melanoma, treated with continuous MTD BRAF/MEK
- LDH: every 2~4 weeks
- PD: progression disease ( $> +20\%$ ), SD: stable disease ( $\leq +20\%$ ), PR: partial response ( $< -25\%$ )

# Ensemble prediction

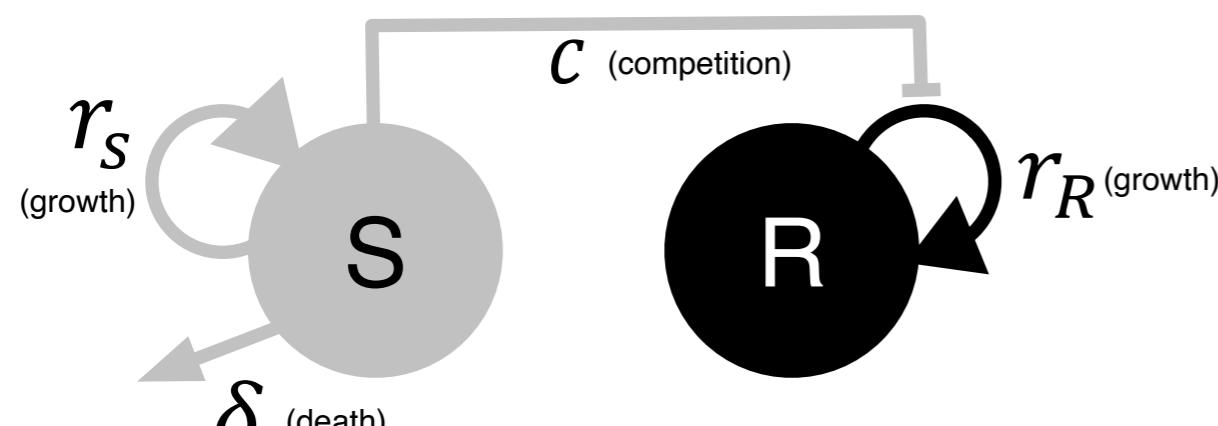


# Two different mathematical models



$$\frac{dS}{dt} = r_S \left(1 - \frac{S + R}{K}\right) S - \delta S - \alpha S + \beta R,$$

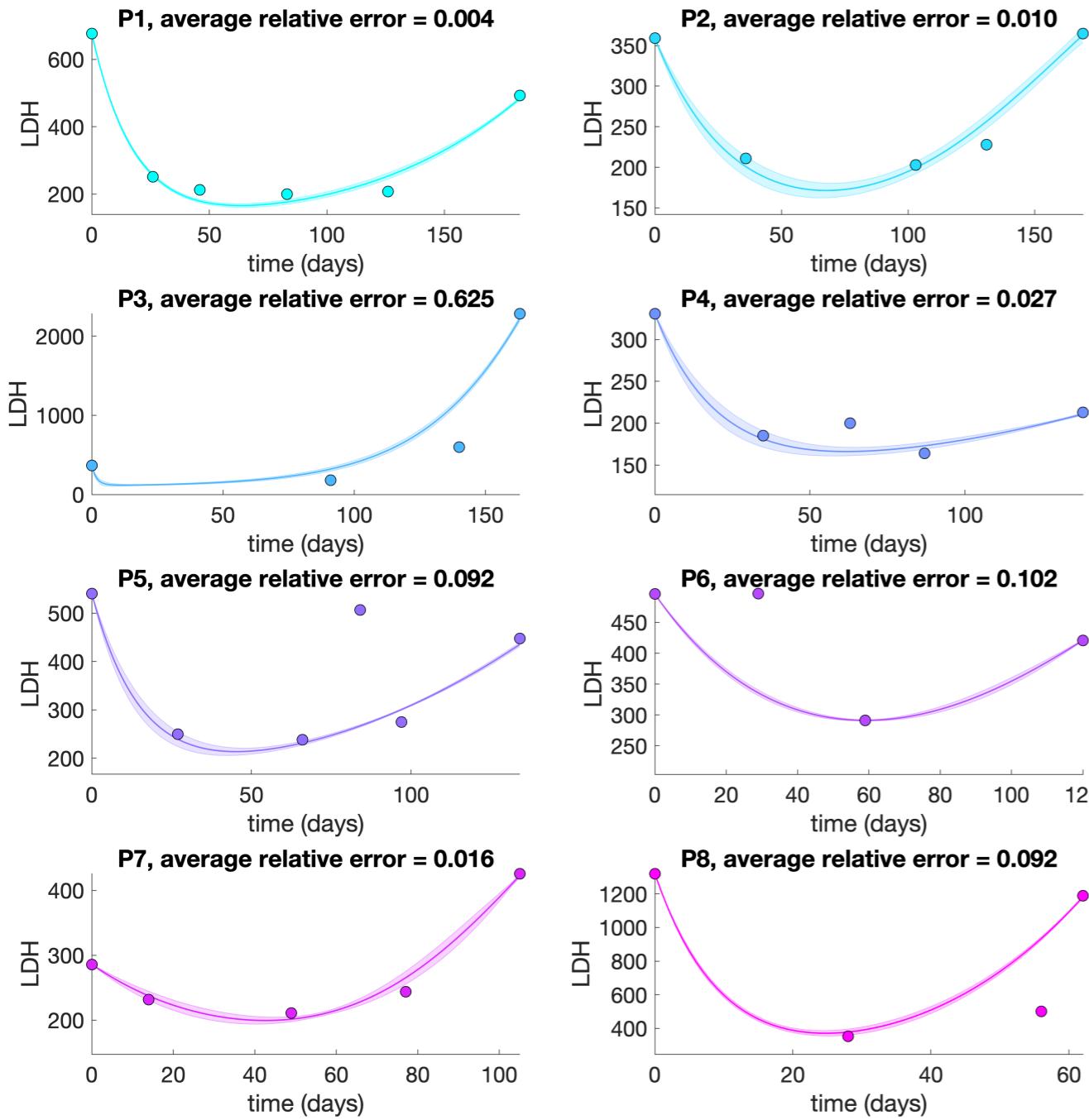
$$\frac{dR}{dt} = r_R \left(1 - \frac{S + R}{K}\right) R + \alpha S - \beta R.$$



$$\frac{dS}{dt} = r_S \left(1 - \frac{S + R}{K}\right) S - \delta S,$$

$$\frac{dR}{dt} = r_R \left(1 - \frac{C * S + R}{K}\right) R.$$

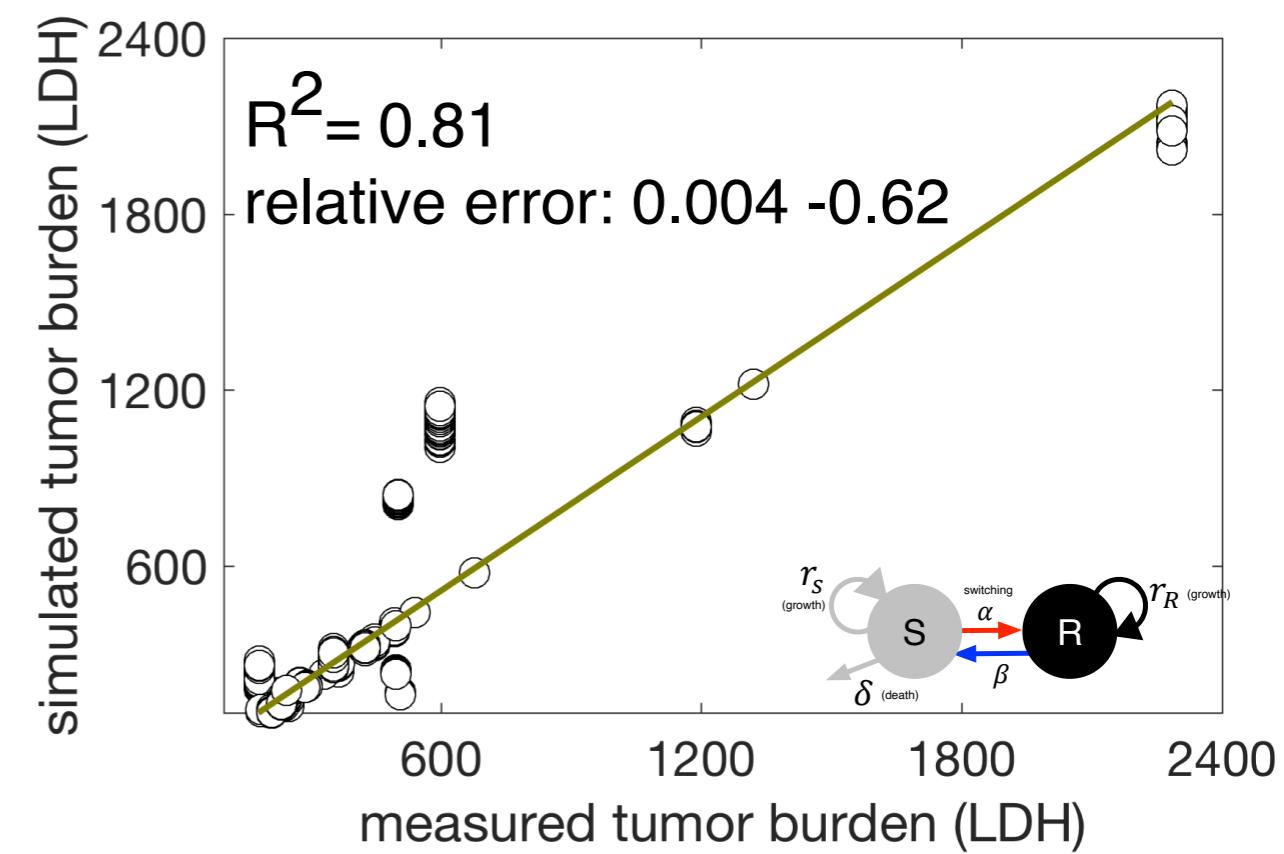
# Model calibration



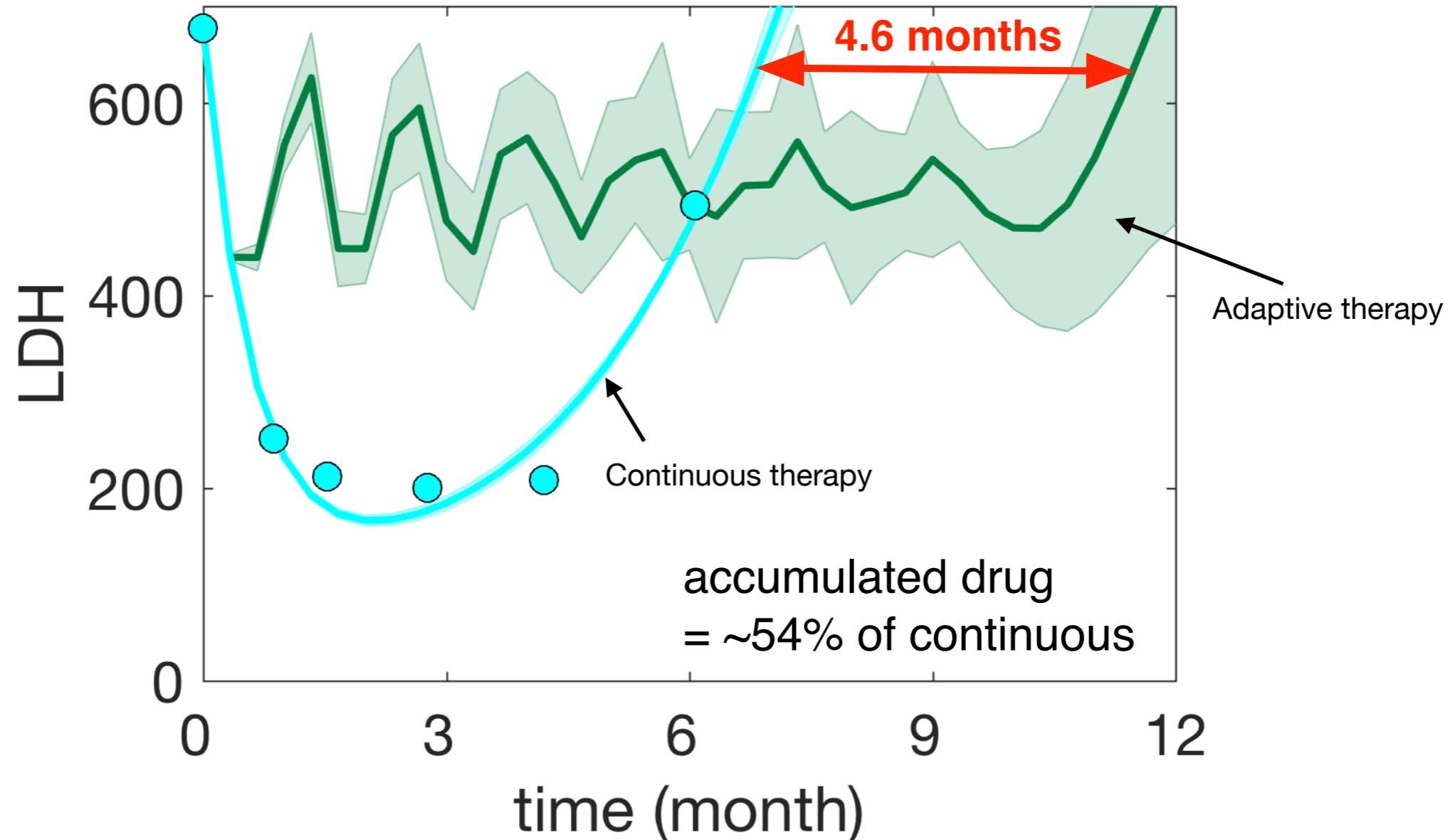
$$\min_{\vec{\theta}} \left\| V(t; \vec{\theta}) - L(t) \right\|_2^2,$$

$$\theta = \{S_0, K, \delta, r_R, \alpha\}$$

$r_S = 0$ , when therapy is on

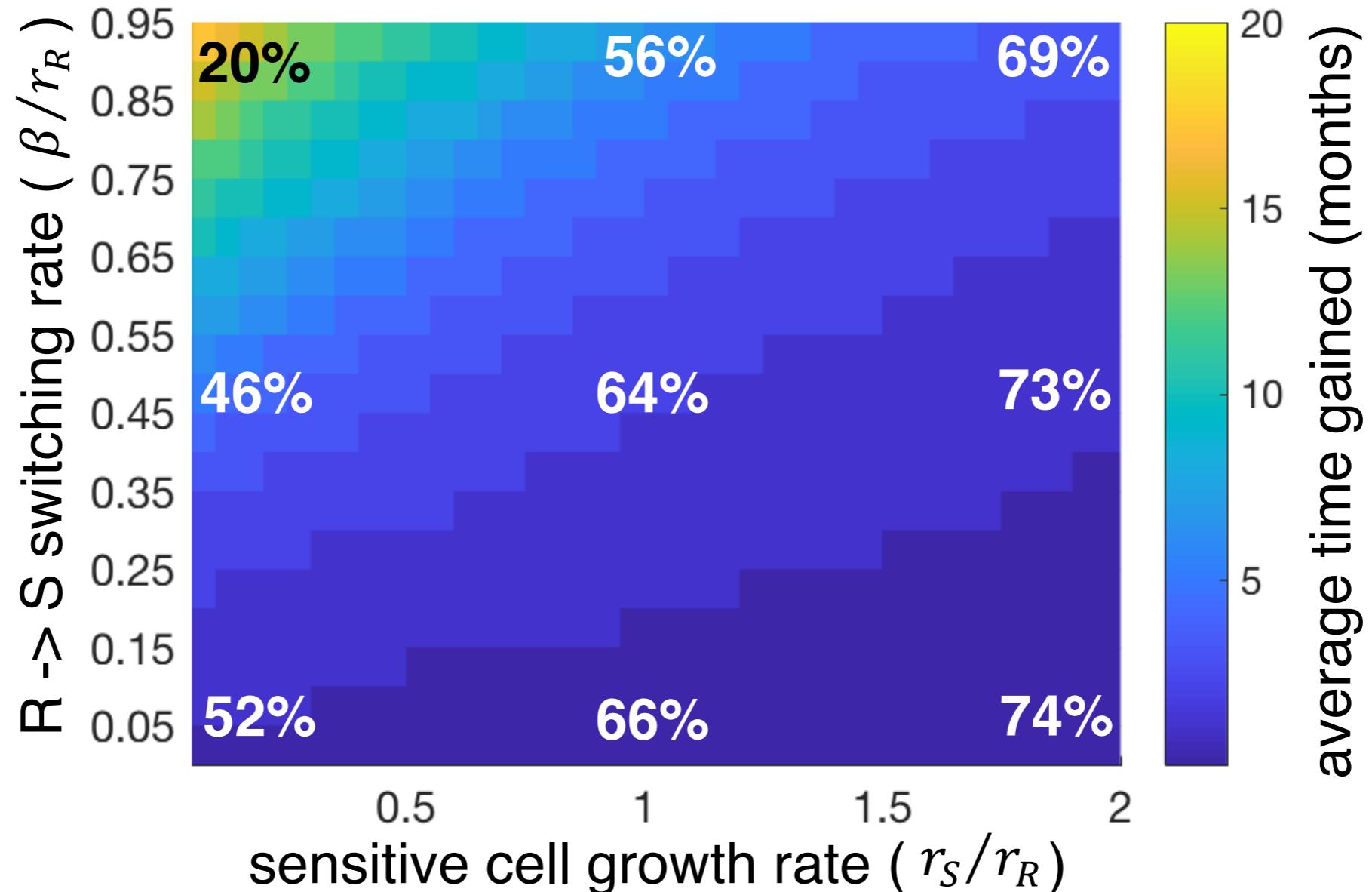


# Model predicted adaptive therapy



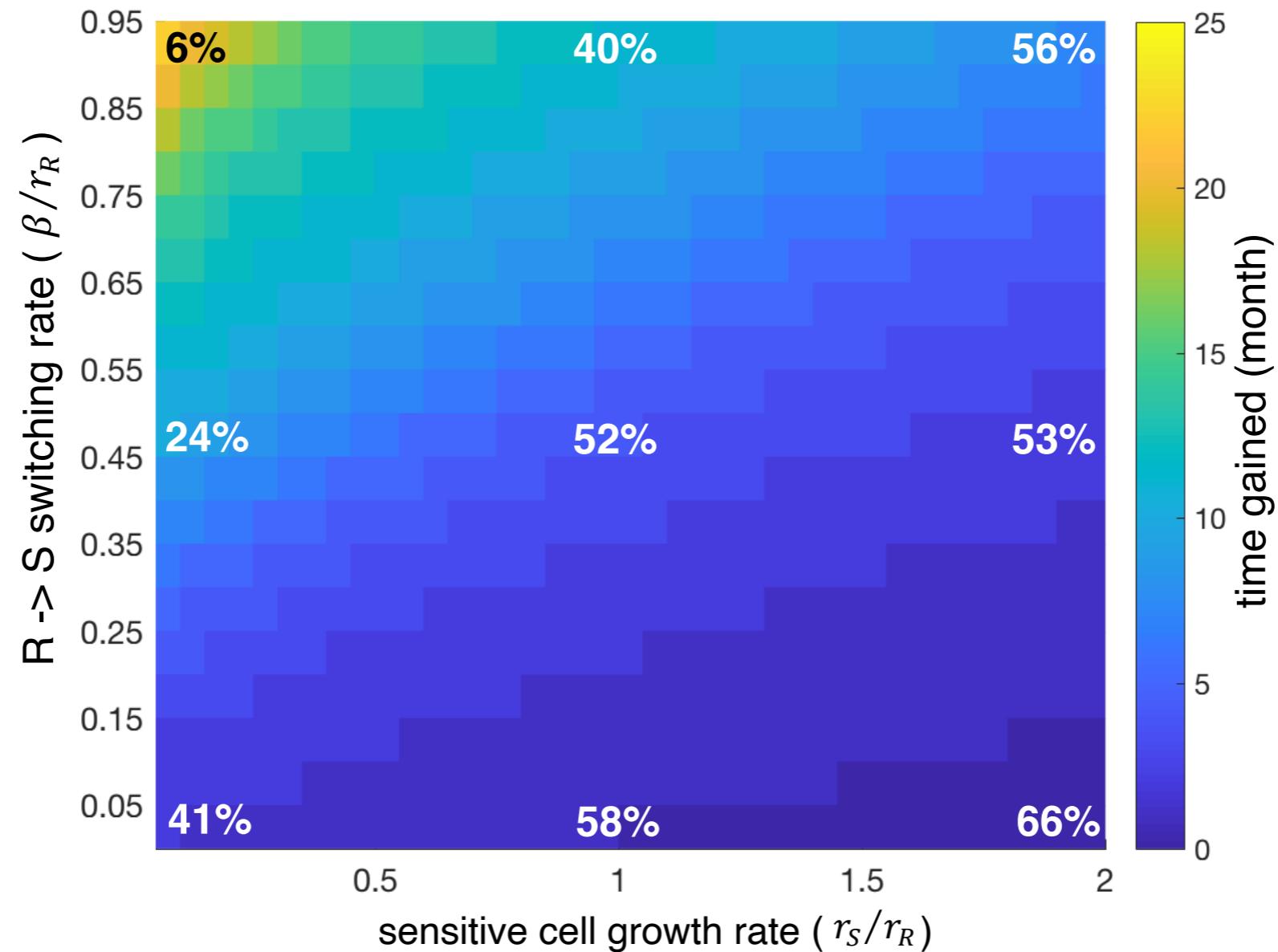
- Treatment stop when  $\text{LDH} \leq -50\%$  of initial, re-start:  $\text{LDH} = \text{initial}$
- Adaptive therapy delayed time to progression:  $\sim 4.6$  months with  $\sim 54\%$  dose rate compared to continuous MTD

# Predicted benefit



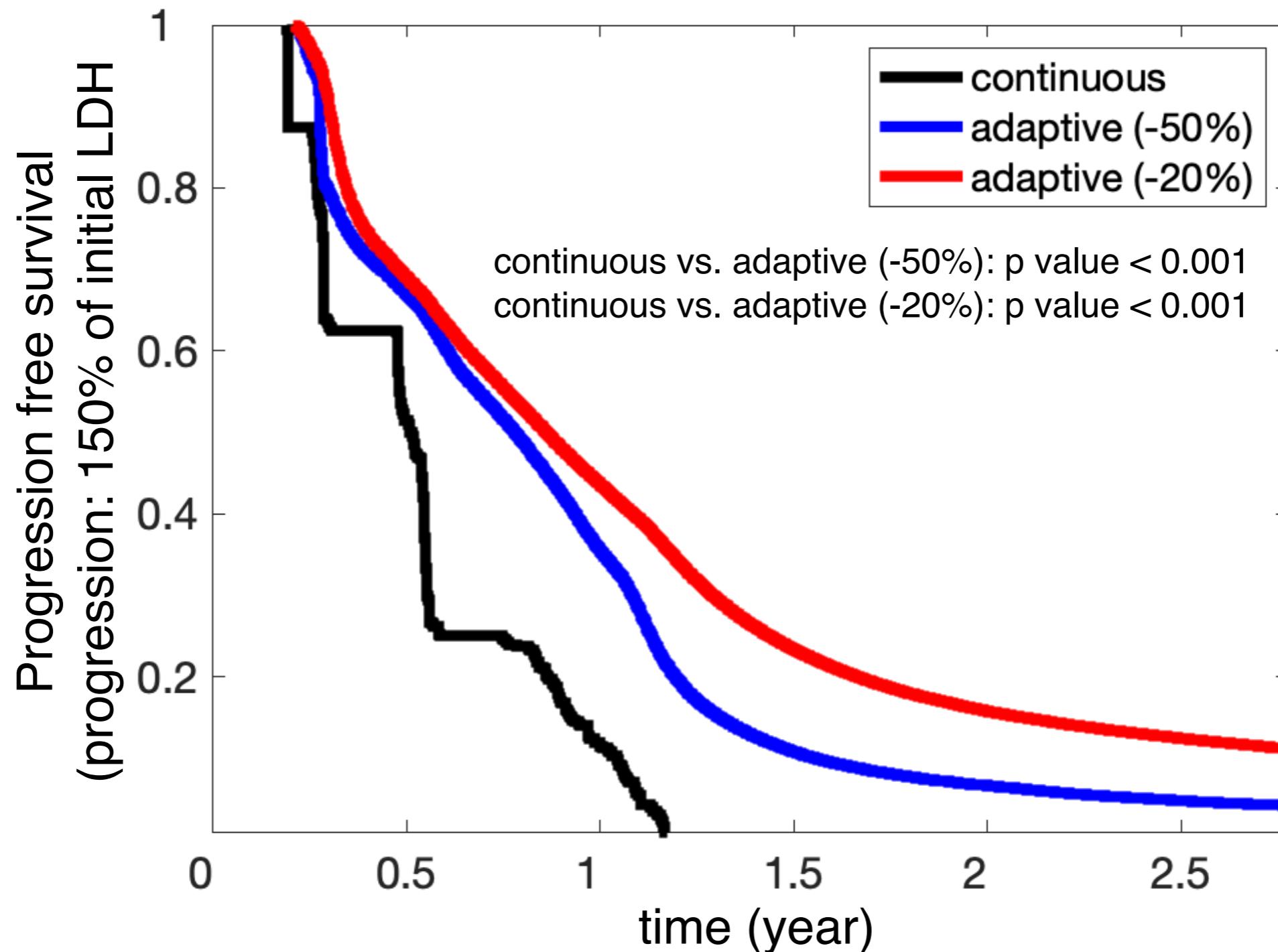
- Various parameters (not estimated) considered
- Time gained from continuous therapy:  $\sim 20$  months
- Dose rate: 20~74% of continuous MTD
- Most beneficial:  $R \rightarrow S$  switching rate is high & sensitive cell growth rate is low

# Different threshold:-20%



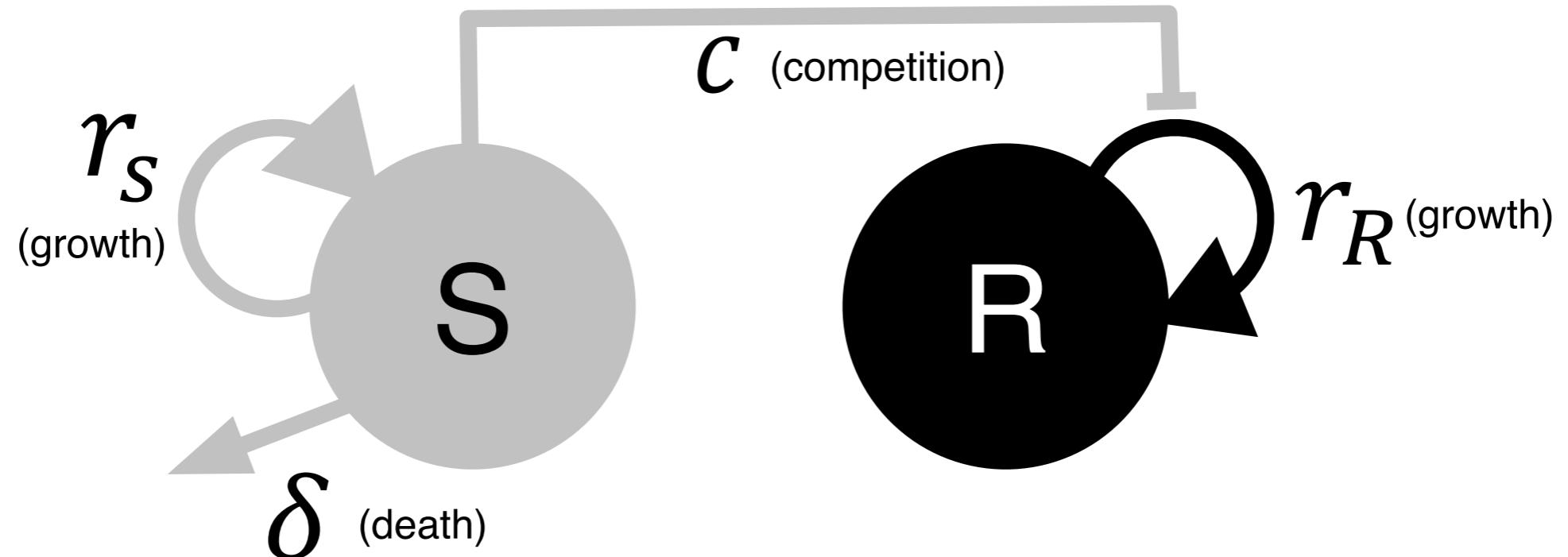
- Treatment stop when LDH  $\leq -20\%$  of initial, re-start: LDH = initial
- Time gained from continuous therapy: up to 25 months
- Dose rate: 6~66% of continuous MTD

# Progression free survival



- PFS of adaptive therapy is significantly higher than MTD
- -20% is better than -50% stopping criteria

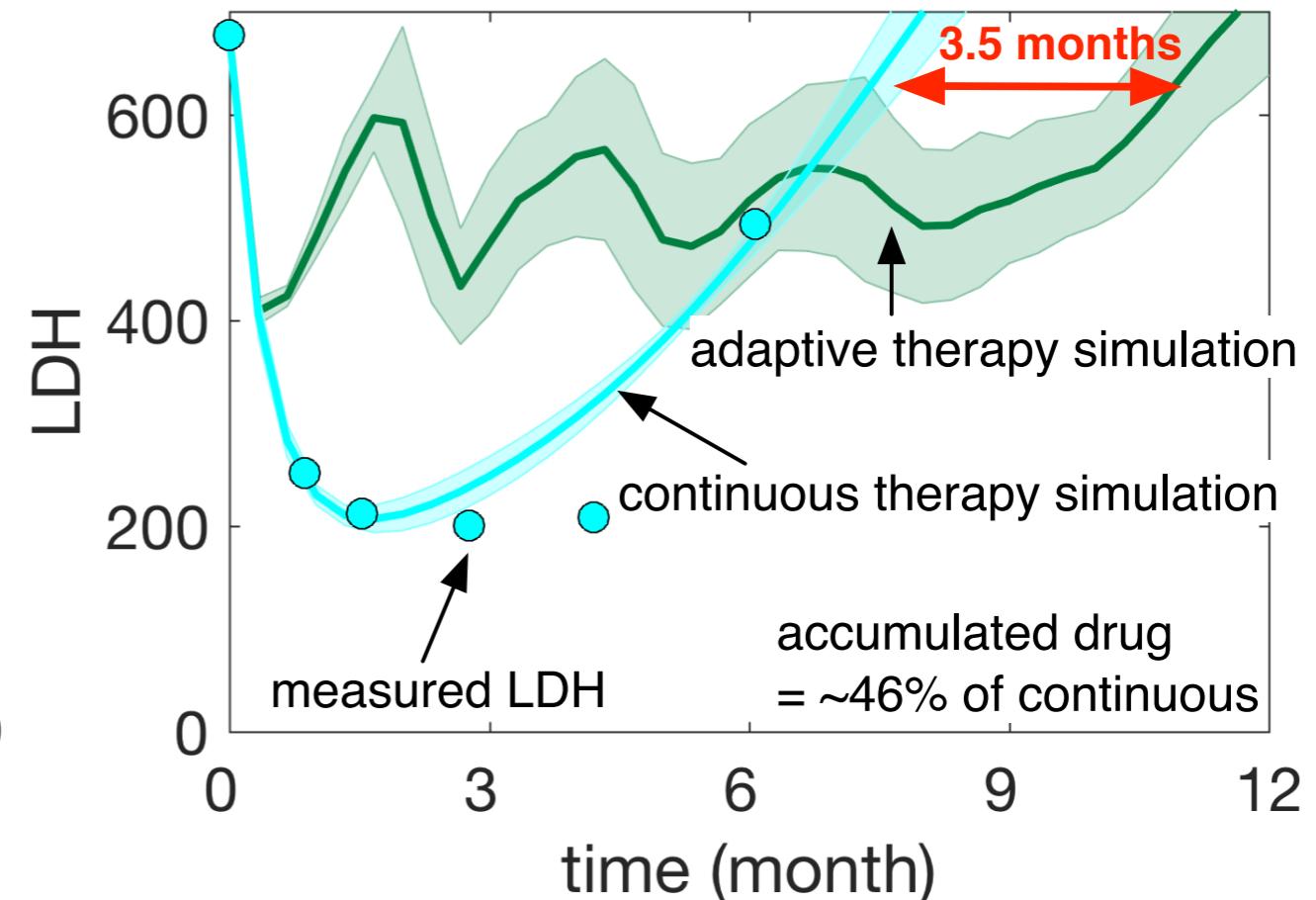
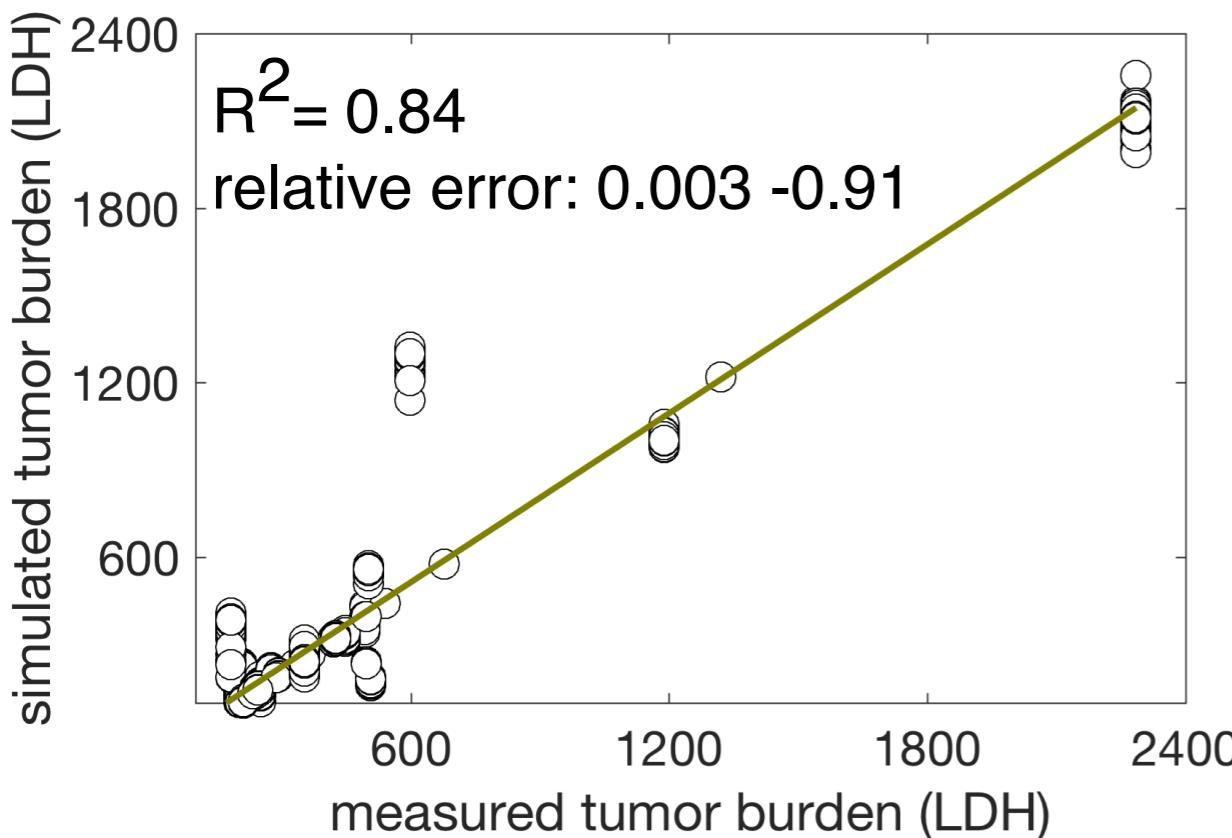
# Mathematical model: competition



$$\frac{dS}{dt} = r_S \left( 1 - \frac{S + R}{K} \right) S - \delta S,$$

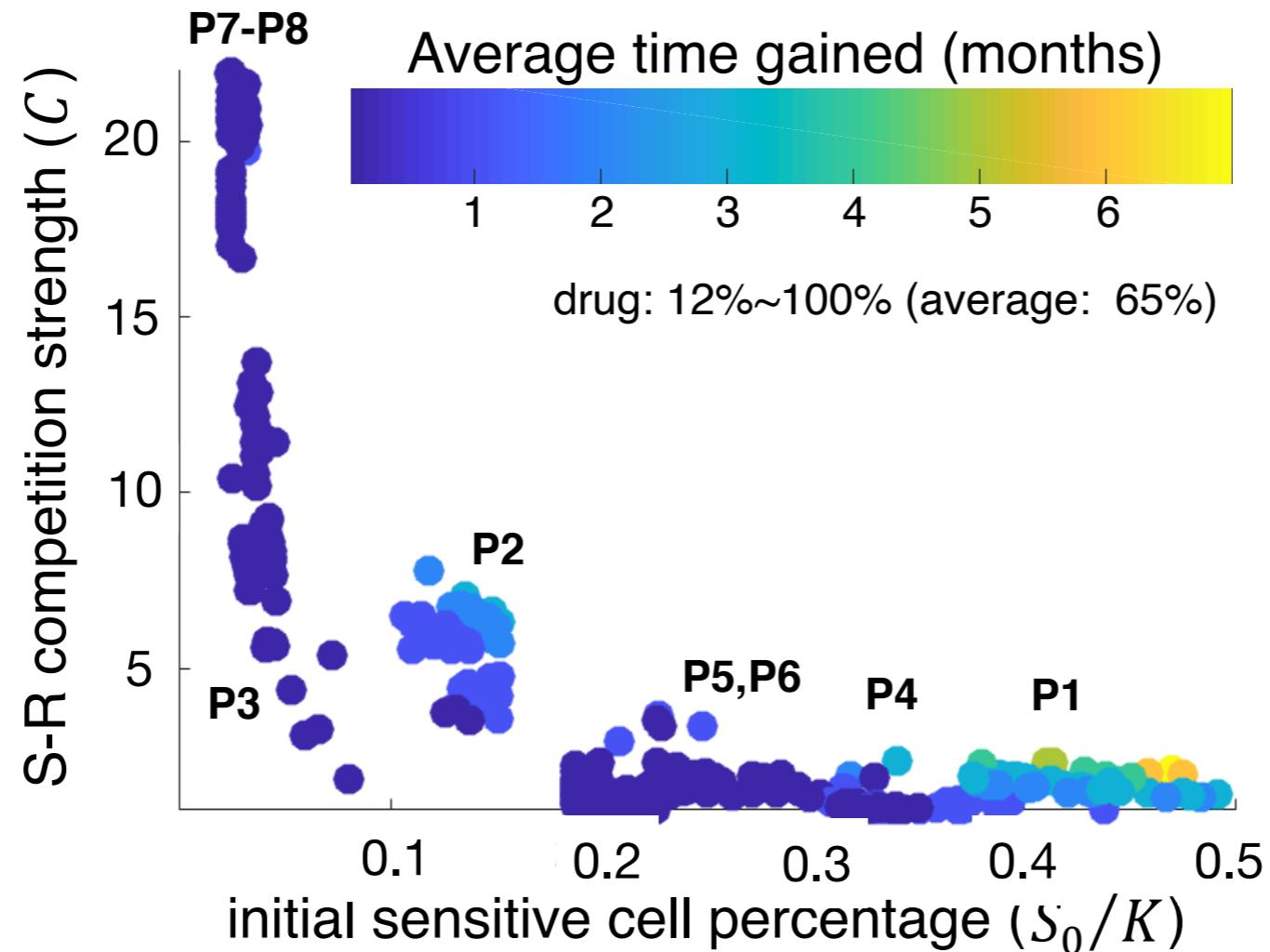
$$\frac{dR}{dt} = r_R \left( 1 - \frac{C * S + R}{K} \right) R,$$

# Model calibration & prediction



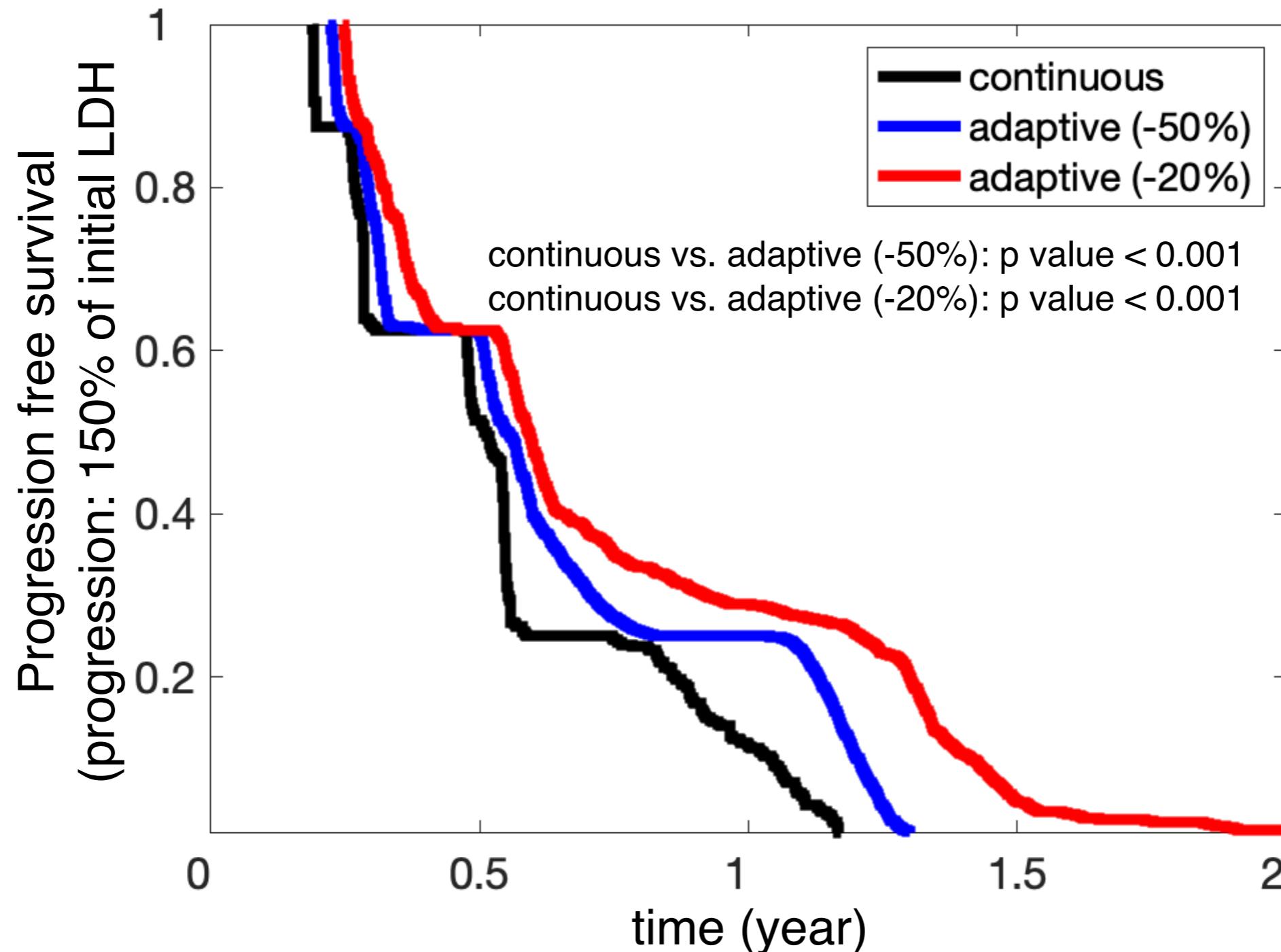
- Predicted time gained: ~3.5 months (vs. 4.3 months from the previous model)
- Dose rate: ~46% of continuous MTD

# Predicted benefit



- Various growth rates of sensitive cell population considered:  $r_s$ : 0~95% of  $r_R$
- Dot: average time gained for each patient
- Time gained: ~6 months (vs. 20 months from the drug induced resistance model)
- Dose rate: 12~100% of continuous MTD
- Most beneficial: large number of initial sensitive cells

# Progression free survival



- PFS of adaptive therapy is significantly higher than MTD
- -20% is better than -50% stopping criteria

# Conclusion

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- Effectiveness of adaptive therapy varies among patients
- Understanding the underlying mechanism for the variability for patient selection
- Multiple mathematical and computational models may be required
- Two different mathematical models: competition and plasticity
- Adaptive therapy improves progression free survival compared to MTD continuous therapy
- Key predictive factors: initial number of sensitive cell population, switching rate from R to S, and growth rate of drug sensitive cell population

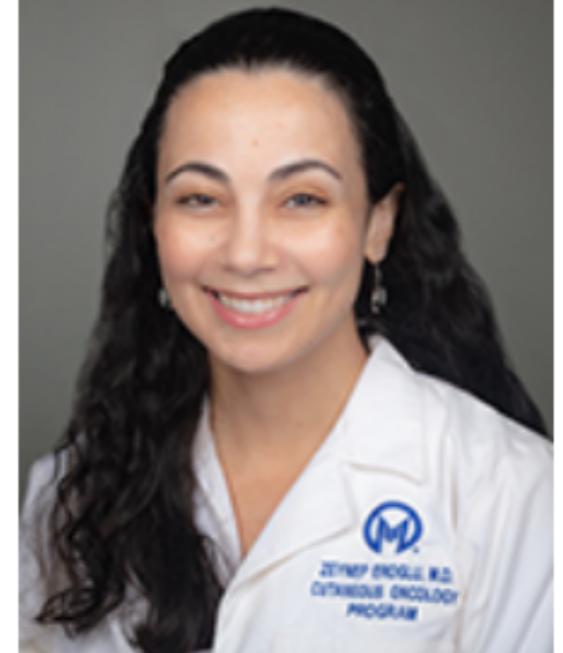
# Thanks



Sandy Anderson



Joel S. Brown



Zeynep Eroglu



Keiran Smalley



Inna Smalley

