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Multistate model for pharmacometric analyses of overall survival in anticancer treatments

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Background

- The primary endpoint in late-stage oncology trials: Overall survival (OS)
 - Defined as the time from randomization to death from any cause
 - Requires long follow-up (~3-5years)
 - The results might be confounded by second line treatments
- The primary endpoint in early clinical development: Progression free survival (PFS)
 - Defined as the time from randomization to disease progression/death
 - PFS improvements do not always result in corresponding improvements in OS



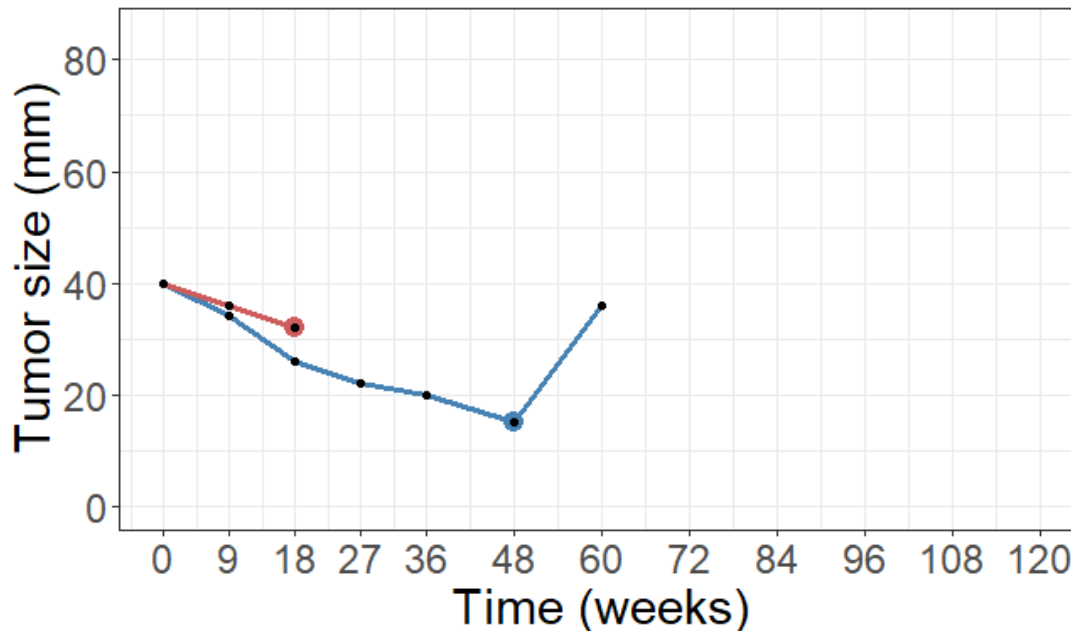
Survival analysis

Issues in handling time-dependent predictors

- Survival analysis

Time to event model using a survival function

- Hazard of death = $h_0(t) \cdot e^{(\beta_1 \cdot \text{predictor}_1)}$
- Ignoring immortal time bias can be a major issue
 - Example: “depth of tumor response” as a predictor of OS.



Patient 1 :

Depth of tumor response : **62%**

Patient 2 :

Depth of tumor response : **20%**



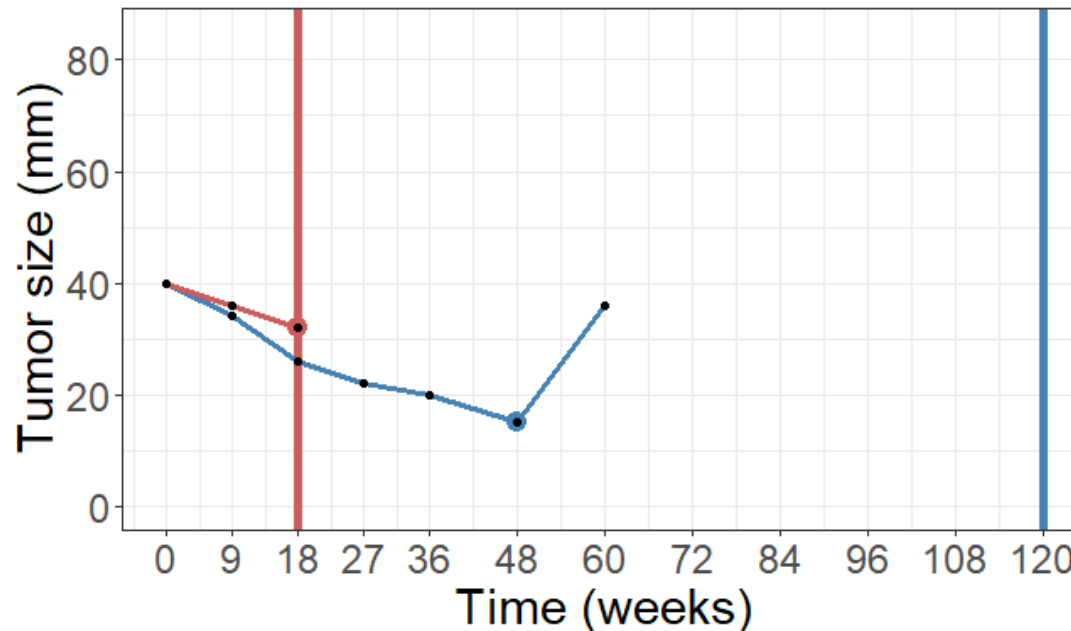
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Patient 1 :

Depth of tumor response : **62%**

Survival time : **120 weeks**

Patient 2 :

Depth of tumor response : **20%**

Survival time : **18 weeks**



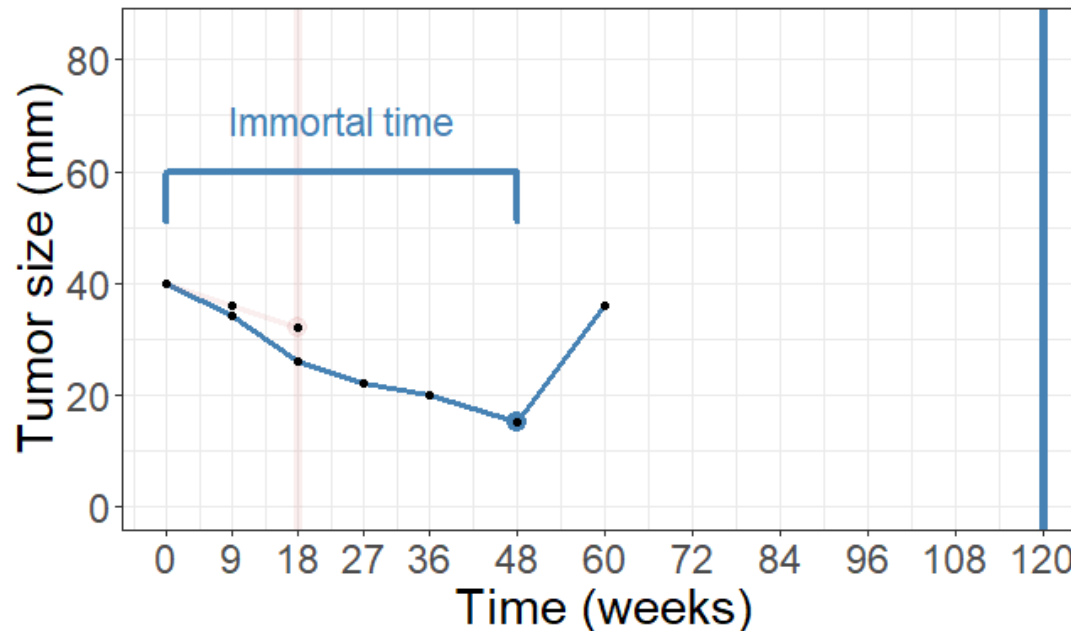
Survival analysis

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Time to event model using a survival function

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- Ignoring immortal time bias can be a major issue
 - Example: “depth of tumor response” as a predictor of OS.



Patient 1 :

Depth of tumor response : **62%**

Survival time : **120 weeks**

Time to depth of tumor response: **48 weeks**

Patient 2 :

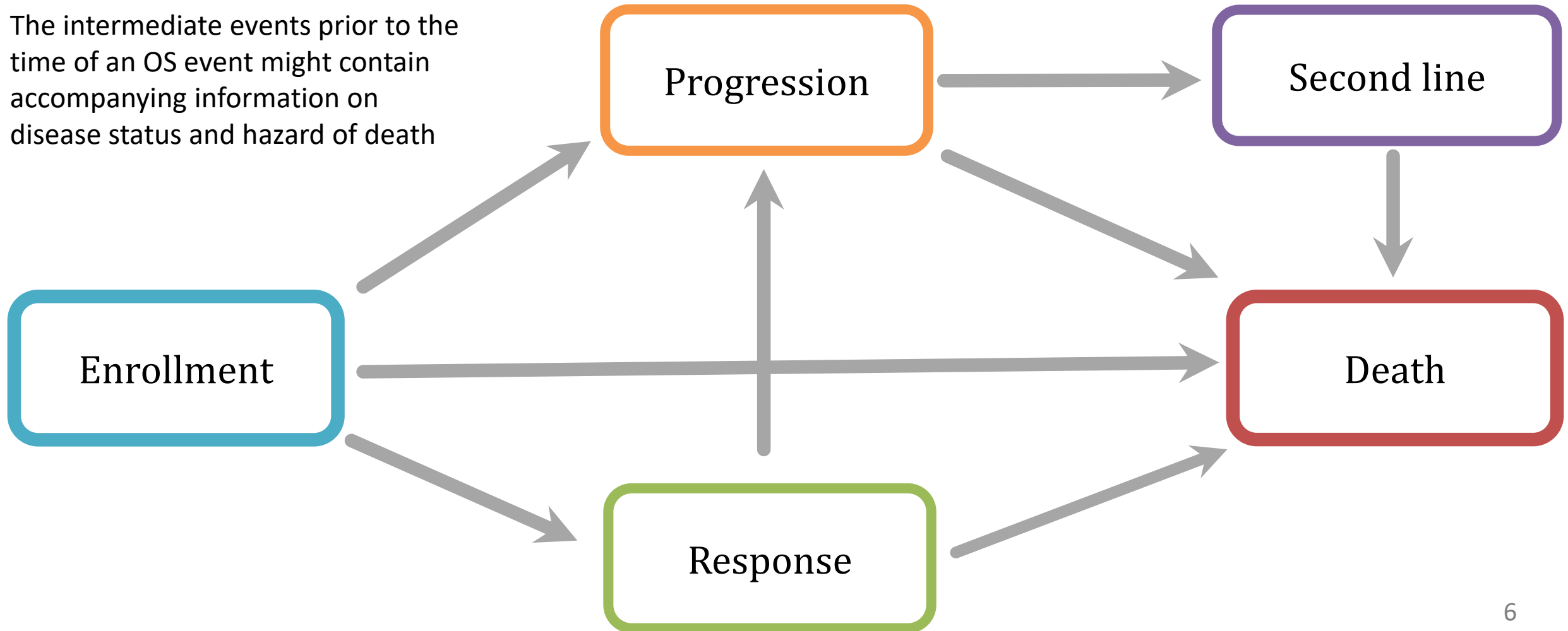
Depth of tumor response : **20%**

Survival time : **18 weeks**

Time to depth of tumor response: 18 weeks

Intermediate events

The intermediate events prior to the time of an OS event might contain accompanying information on disease status and hazard of death



Objectives

- Overall objective

To explore the potential of a multistate model, including its ability to predict OS using time-varying predictors while addressing the immortal time bias.

- Specific objectives

- To develop a multistate model to characterize the transition probabilities between states
- To investigate dynamic predictors on the transition hazards



Data

Simulation of data

- Longitudinal tumor size data (sum of longest diameters, SLD) and survival times for 1,000 subjects were simulated
 - Tumor size-OS joint model^{1,2} for docetaxel treatment in HER2-negative metastatic breast cancer patients³
 - Tumor sizes at zero, and every 9 weeks during the first 36 weeks and thereafter every 12 weeks until disease progression (20% increase in SLD from tumor nadir⁴)
 - Simulation duration: 3 years



Data

Definition of different states

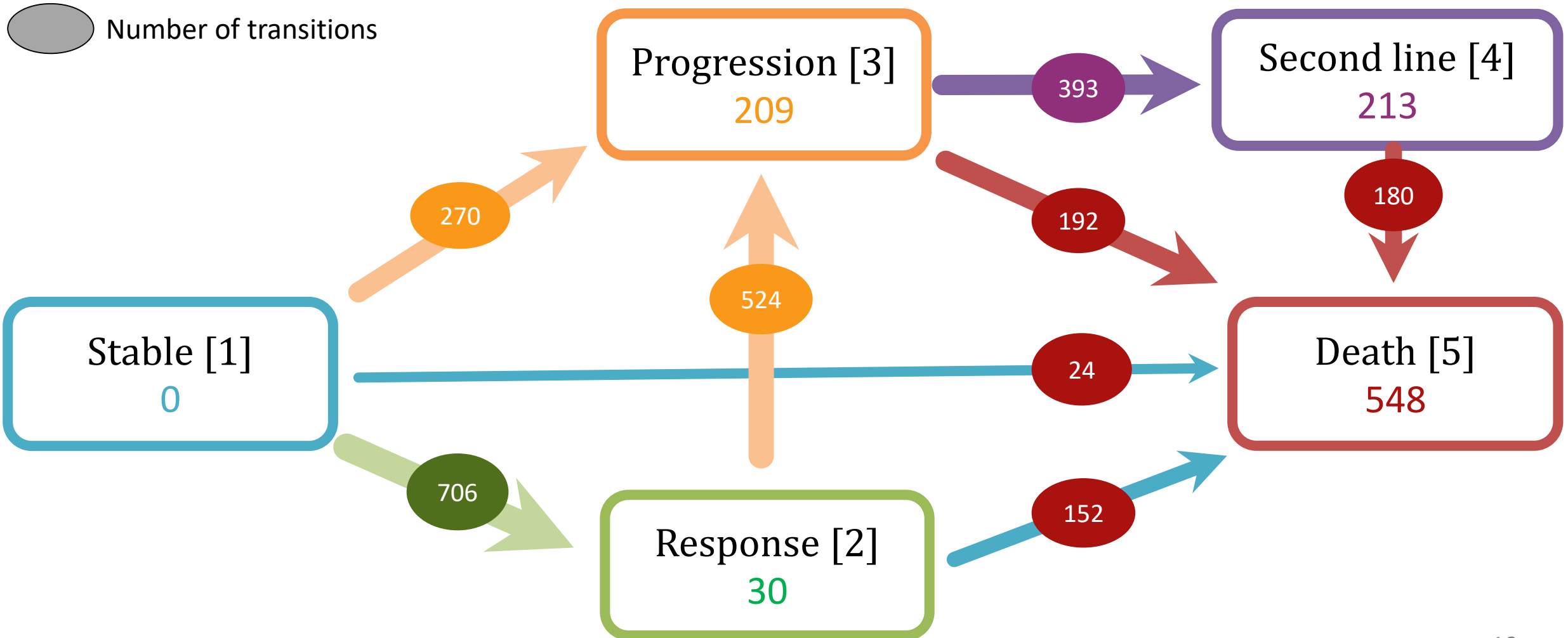
State	Name	Description
1	Stable disease	Initial state for all subjects
2	Response	$\geq 30\%$ decrease in SLD from baseline SLD*
3	Progression	$\geq 20\%$ increase in SLD from tumor nadir*
4	Second-line	50% of the patients who had disease progression were switched to second line treatment within 6 [0.5-12] weeks after progression
5	Death	Death event

*Response evaluation criteria in solid tumours (RECIST v1.1) Eisenhauer et al., *Eur J Cancer*. (2009)



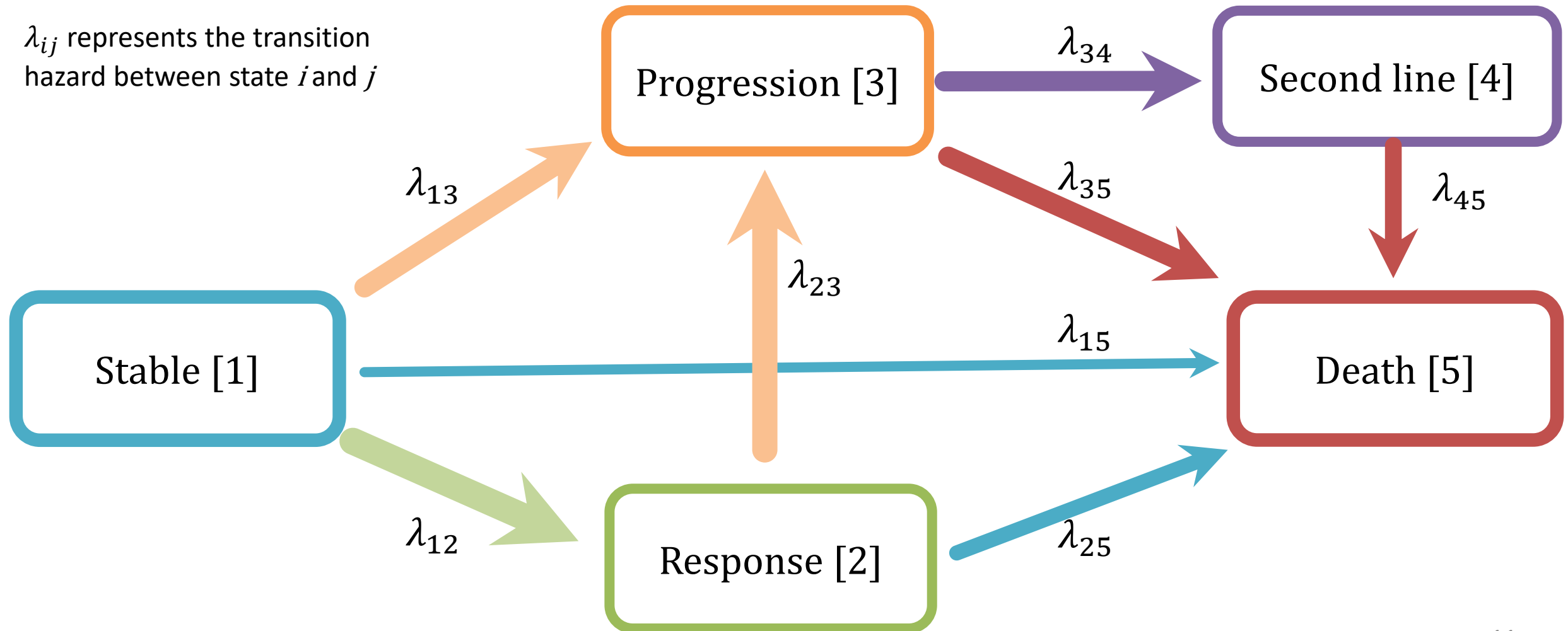
Multistate data

Number of transitions



Multistate model framework

λ_{ij} represents the transition hazard between state i and j



Predictors of transition hazards

Baseline covariates	Time-varying predictors*	Investigated on
Tumor burden (SLD ₀ , mm)	SLD change from baseline (%)	λ_{12}
Age (years)	SLD change between the two previous measurements (%)	λ_{13}
	SLD change from tumor nadir (%)	λ_{24}
		λ_{35}
		λ_{45}

* *The time-varying predictors were investigated in a way that the future tumor observations would not influence the present predictions of transition rates.
For example, SLD data until week 18 was used in the prediction of transition hazards at week 27.*



Results

Structural model – combination of hazard functions

Transition	Hazard function	Interpretation
Stable to response (λ_{12})	Weibull	Hazard diminished with time
Stable to progression (λ_{13})	Weibull	Hazard increased with time
Progression to death (λ_{35})	Weibull	Hazard decreased with time
Second line to death (λ_{45})		Not statistically different from λ_{35}



Results

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Progression to death (λ_{35})	Weibull	Hazard decreased with time
Second line to death (λ_{45})		Not statistically different from λ_{35}
Response to progression (λ_{23})	Exponential	Constant hazard
Progression to second line* (λ_{34})	Exponential	Constant hazard

*A mixture model with two sub-populations, where pop-1 received second-line treatment and pop-2 did not receive second-line treatment.



Results

Structural model – combination of hazard functions

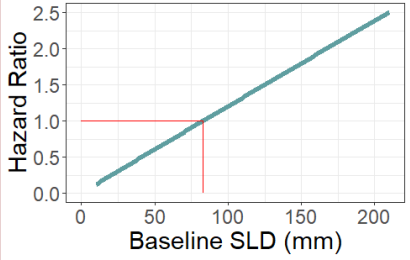
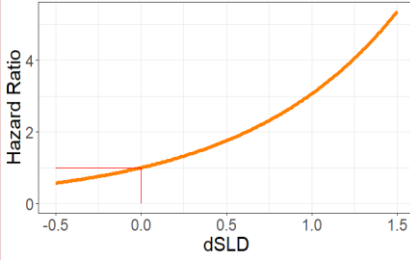
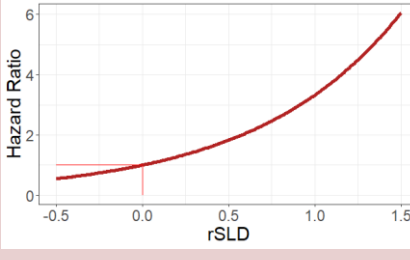
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Stable to death (λ_{15})	Gompertz-Makeham [#]	Age specific hazard
Response to death (λ_{25})		

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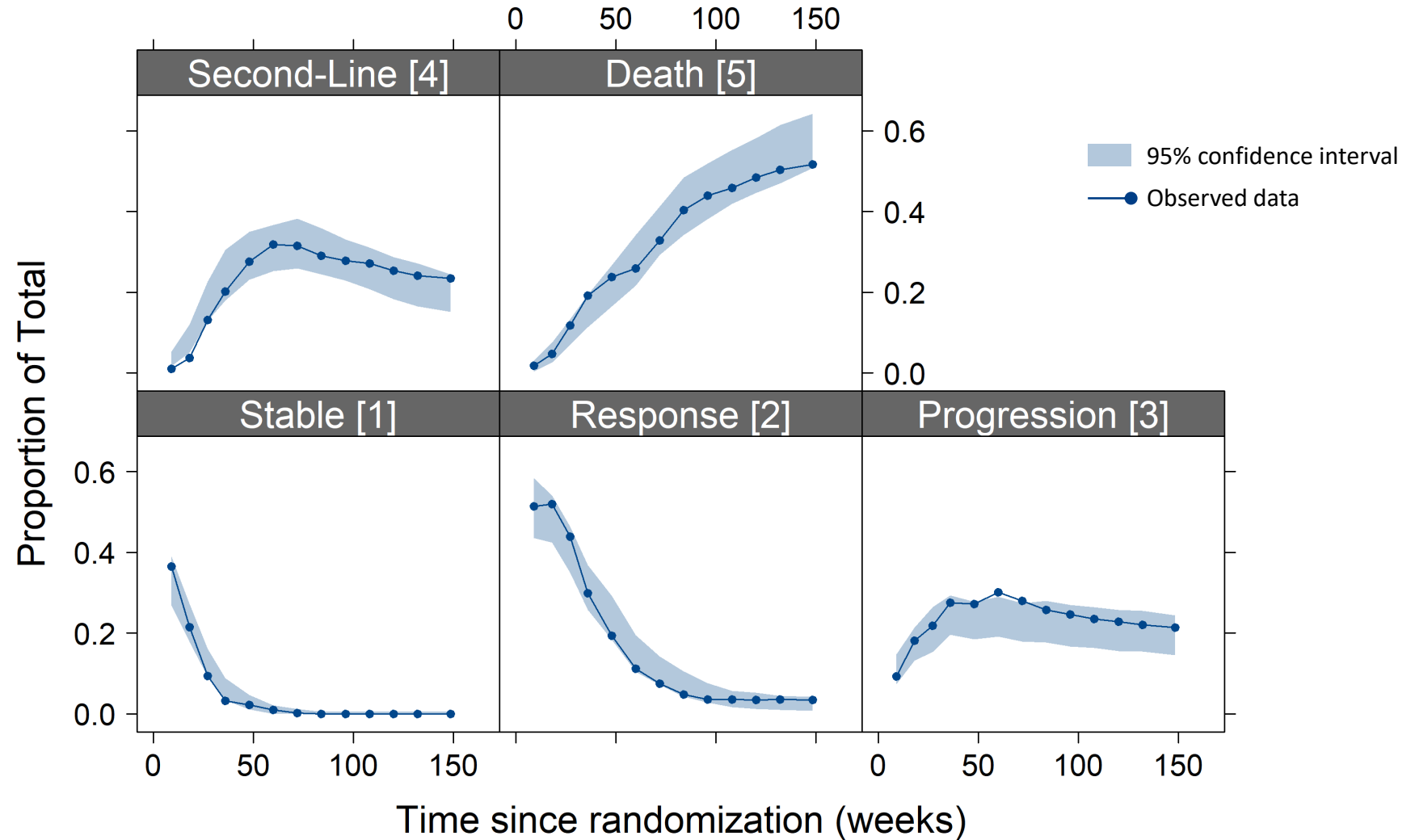
Results

Predictors of transition hazard

Transition	Predictor	Hazard ratio
Stable to response (λ_{12})	Baseline tumor size (SLD ₀)	Hazard ratio = 1.10/every 10 mm increase from median SLD ₀ 
Response to progression (λ_{23})	Change in SLD between two previous measurements (dSLD)	Hazard ratio = 1.12/10% increase in SLD 
Progression to death (λ_{35})	Baseline tumor size SLD change from baseline at progression (rSLD)	Hazard ratio = 1.08/every 10 mm increase from median SLD ₀ Hazard ratio = 1.12/10% increase in SLD from baseline 

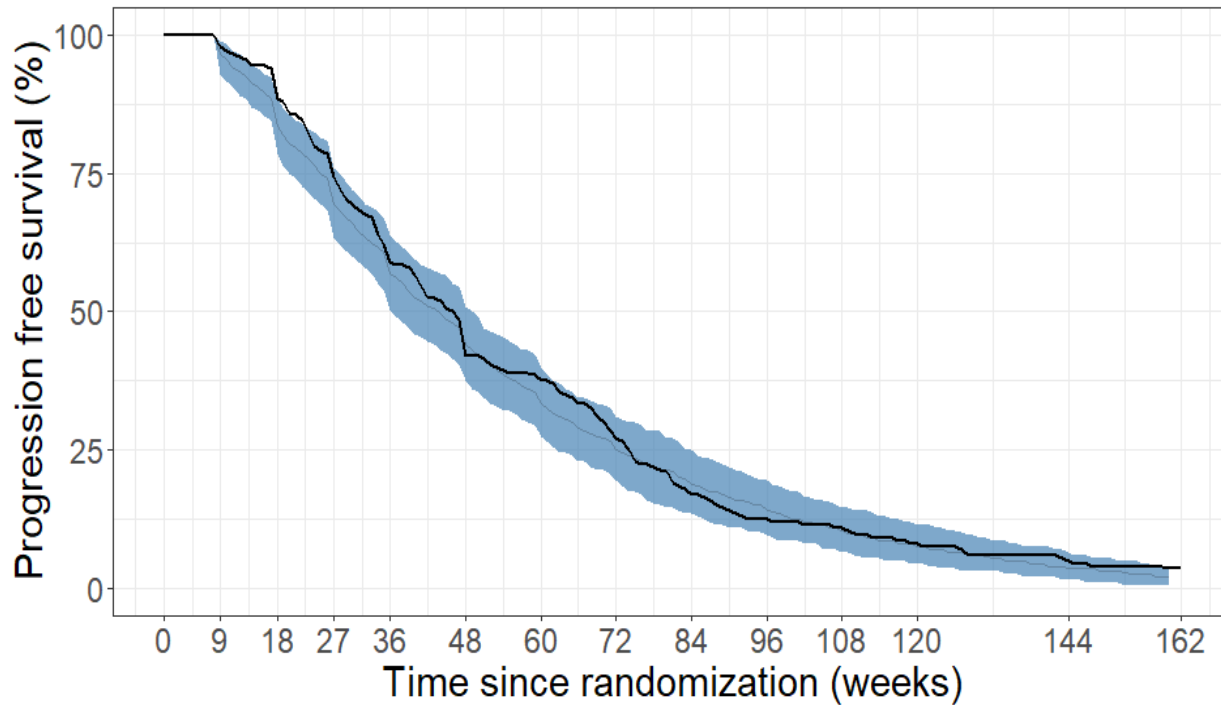


Visual predictive check

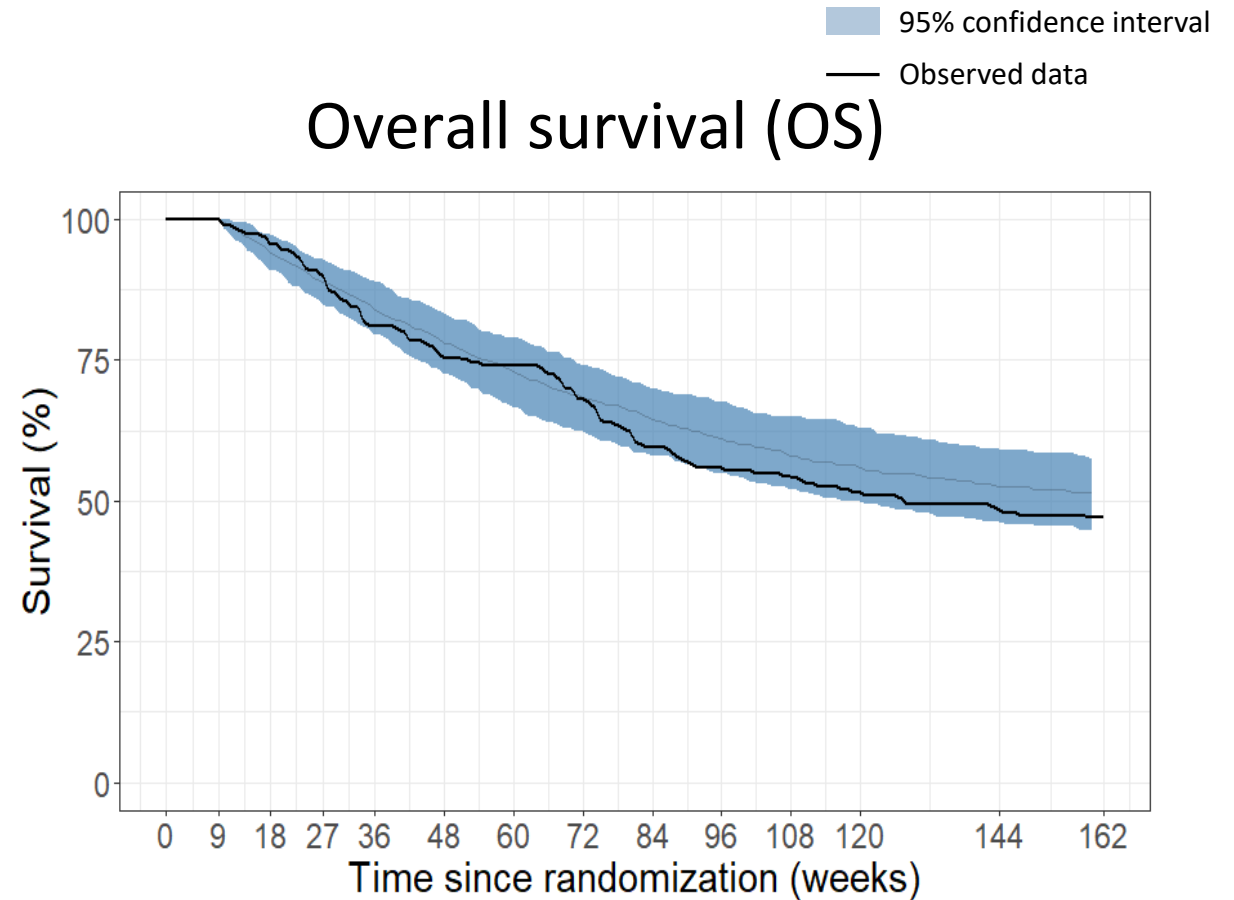


Clinical endpoints

Progression free survival (PFS)



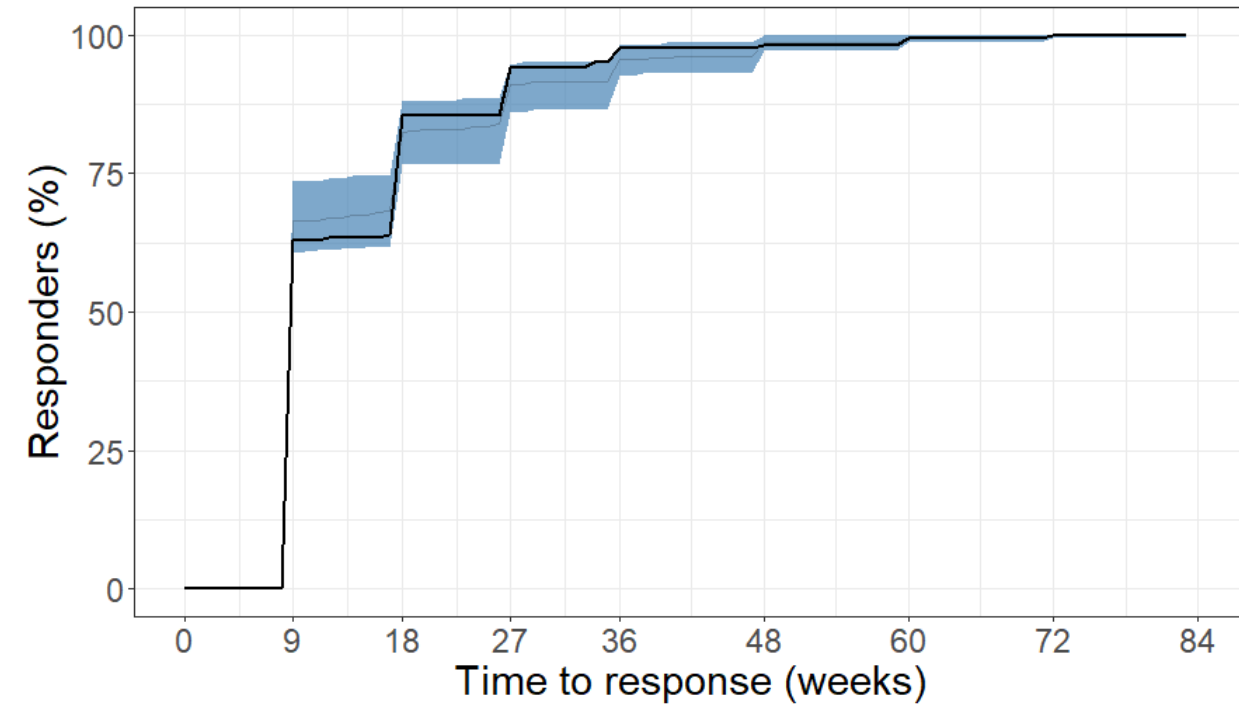
Overall survival (OS)



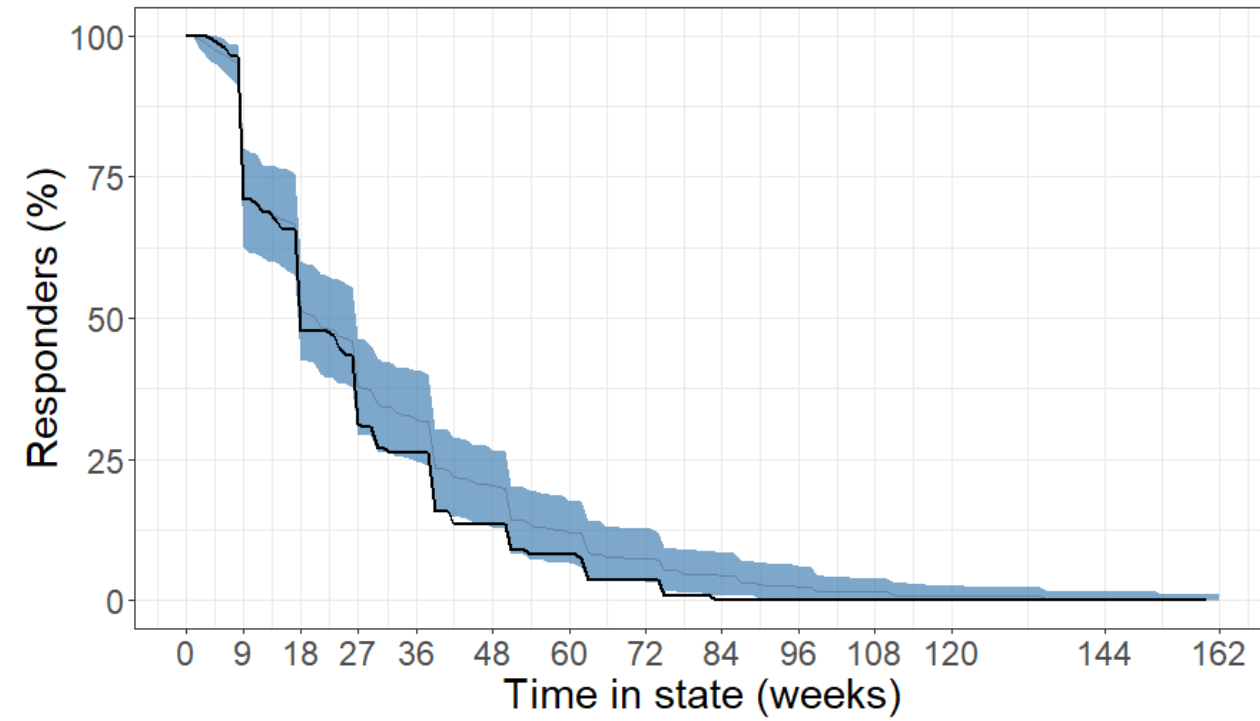
Docetaxel response

95% confidence interval
Observed data

Time to response



Duration of response





Conclusion

- This novel approach for analyzing oncology data successfully characterized the intermediate events prior to survival time and jointly described the OS event.
- The predictors were evaluated in a prospective manner so not to cause immortal time bias.
- This multistate model framework allows for
 - extension (pseudo-progression, dropout, etc.)
 - simplification (absence of second line treatment)
- The investigation of predictors and the characterization of time to develop response, duration of response, and the overall outcome events PFS and OS can be performed in a single multistate modeling exercise.



Further reading

- Sreenath M. Krishnan, Lena E. Friberg, René Bruno, Ulrich Beyer, Jin Y. Jin, and Mats O. Karlsson. 2021. “Multistate Model for Pharmacometric Analyses of Overall Survival in HER2-Negative Breast Cancer Patients Treated with Docetaxel.” *CPT: Pharmacometrics & Systems Pharmacology*. <https://doi.org/10.1002/PSP4.12693>.
- Ulrich Beyer, David Dejardin, Matthias Meller, Kaspar Rufibach, and Hans Ulrich Burger. 2020. “A Multistate Model for Early Decision-Making in Oncology.” *Biometrical Journal* 62 (3): 550–67. <https://doi.org/10.1002/bimj.201800250>



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Thank you for your attention