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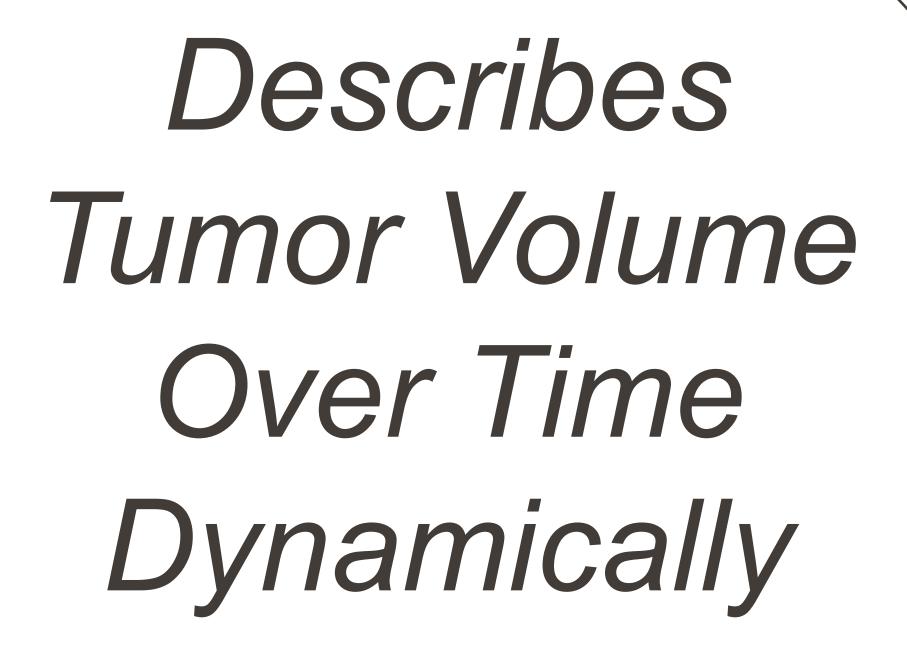
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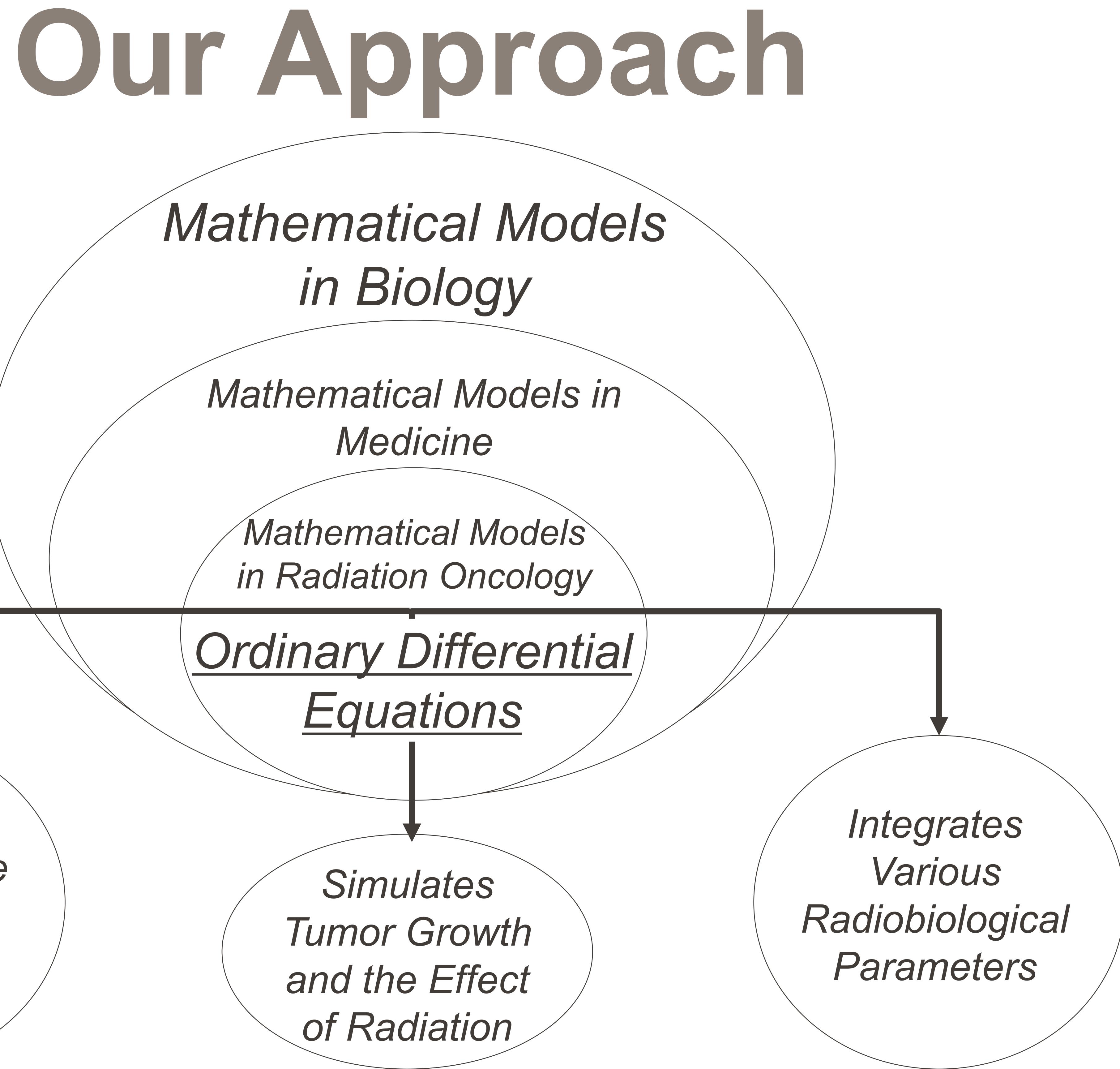


Background Head and neck squamous cell carcinomas (HNSCCs) arise from the mucosal lining of the upper aerodigestive tract and are also the most common cancer type in this region [1]. Within this subtype of cancer, radiation therapy has become a crucial cornerstone in developing standard of care for these patients [2]. Radiation as a therapeutic intervention possesses unique dynamics that may lead to disparities in outcomes and in the biological response on both the tumor and normal tissues [3, 4].

Despite the advancements in radiation therapy for HNSCCs, a significant challenge remains in predicting individual patient responses during the course of treatment. The variability in how patients respond to radiation poses difficulties in optimizing therapy, often leading to under/over-treatment and possibly adverse effects [2]. Because there is no biomarker, this underscores the need for reliable predictive measures that can guide clinical decisions in real-time [3, 4].

The Problem



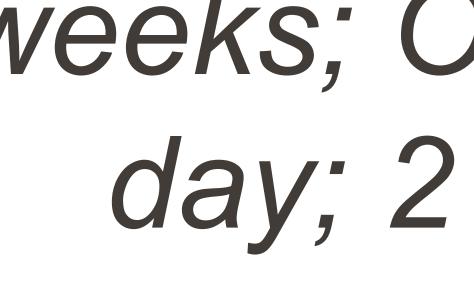




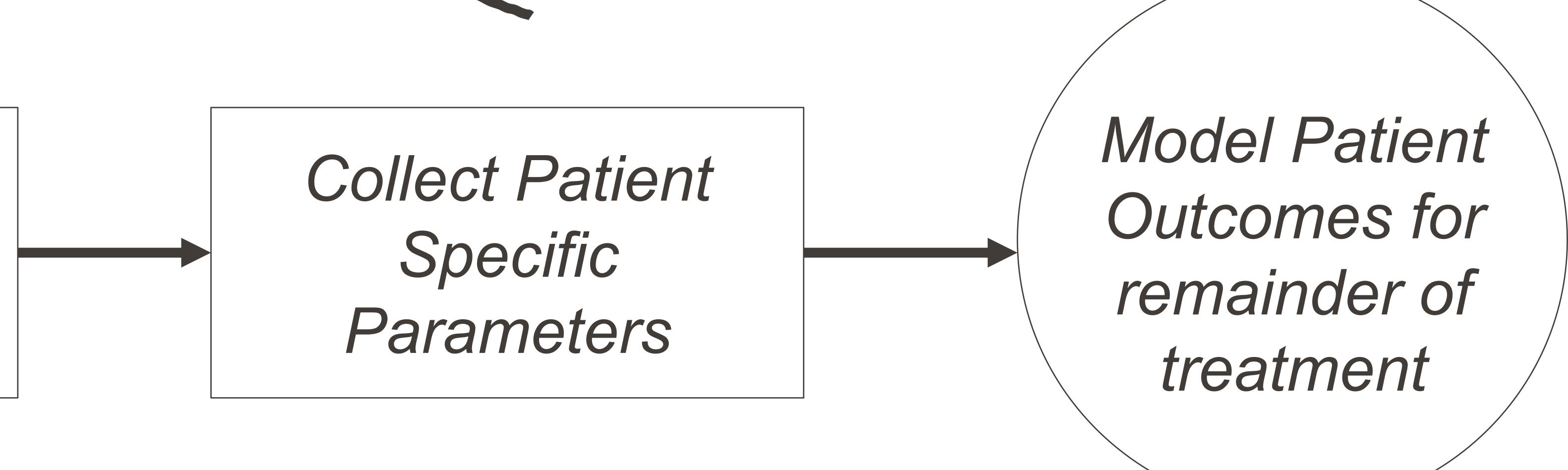
30 HNSCC Patients treated with MRLinac

Input GTVP-RD data into ODE model

Methods: Dataset Implementation GTVP-RD Treated for 7 recorded at weeks; Once a beginning of day; 2 Gy each week







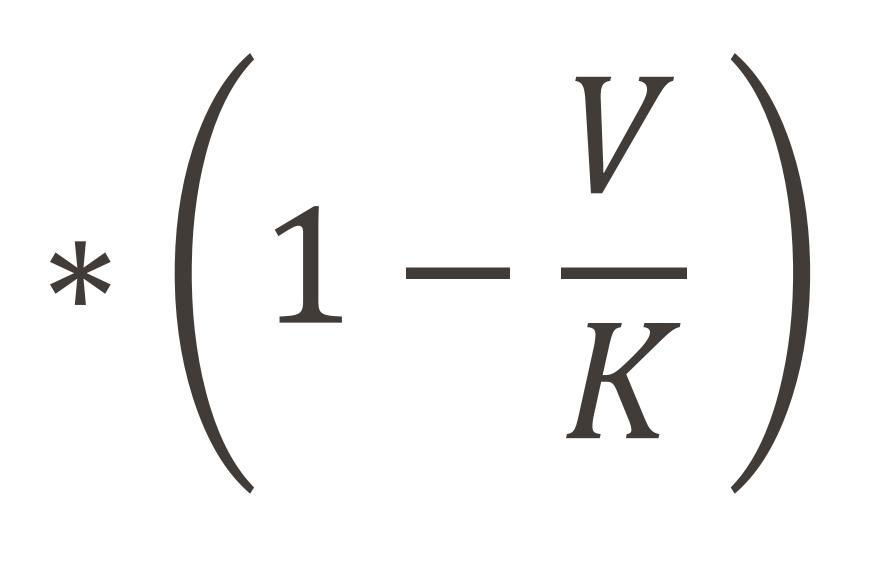
Implement ODE

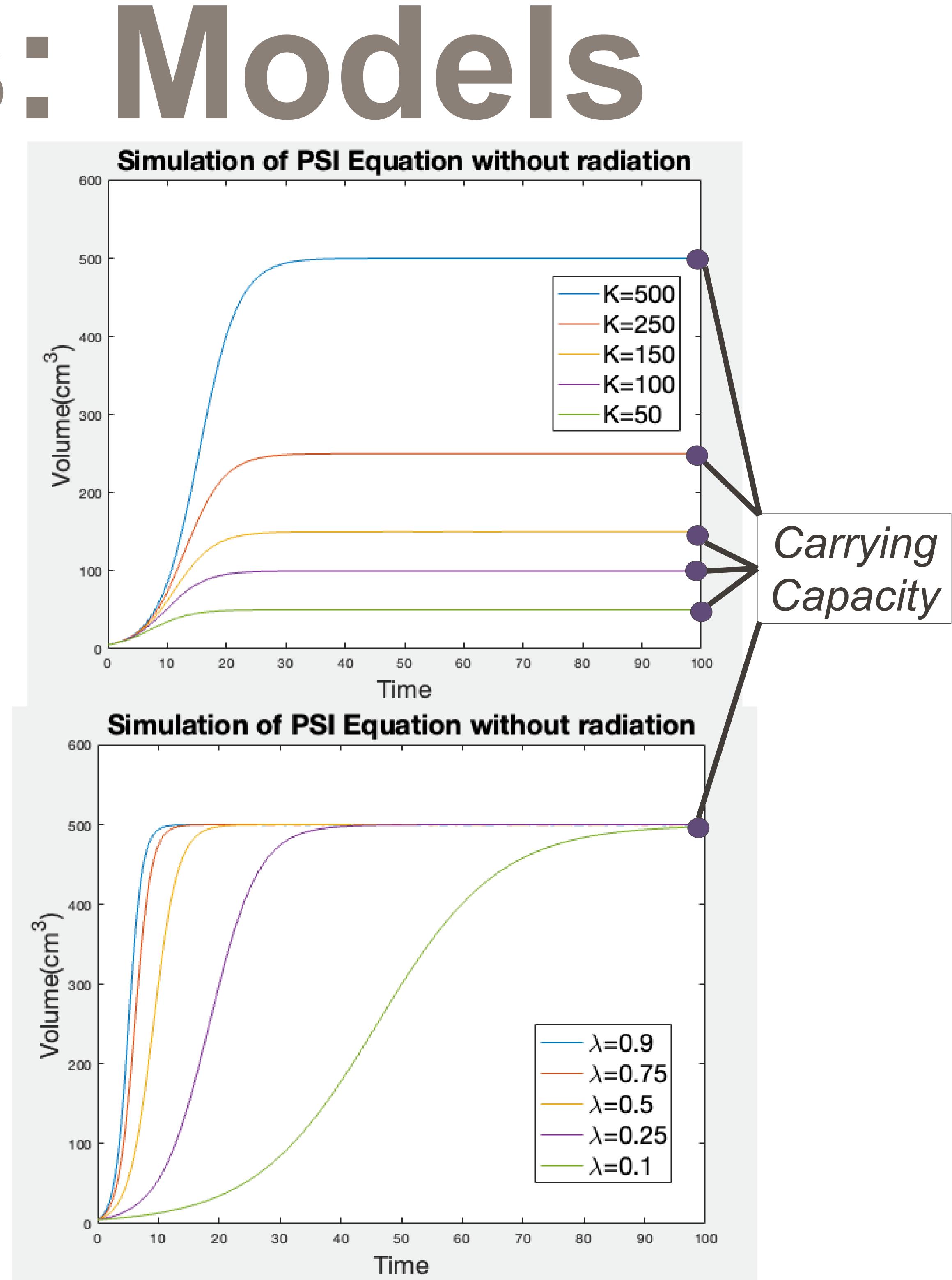


Methods: Models We introduce a model that determine tumor volume(V(t)) at a certain time(t):

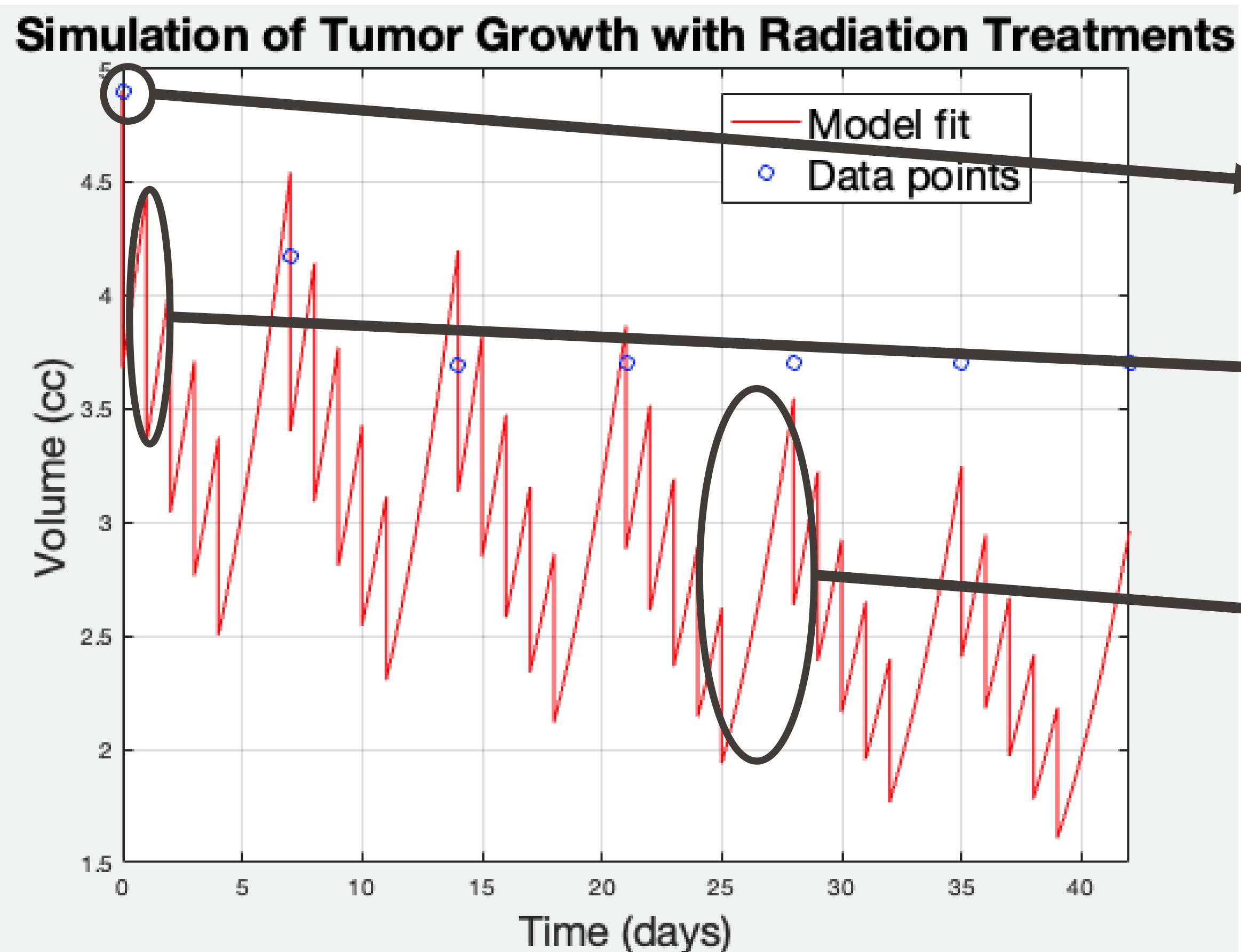
*

 λ represents the intrinsic growth rate of the tumor(day ⁻¹) K represents the carrying capacity(cm³)

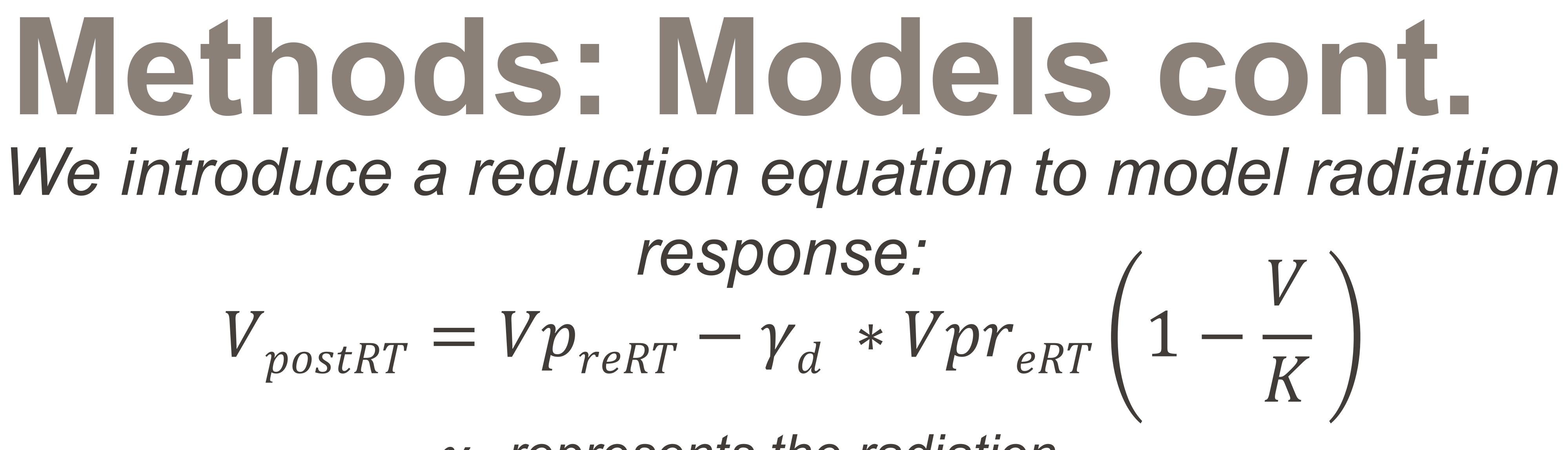




Methods: Models cont.



γ_d represents the radiation induced death

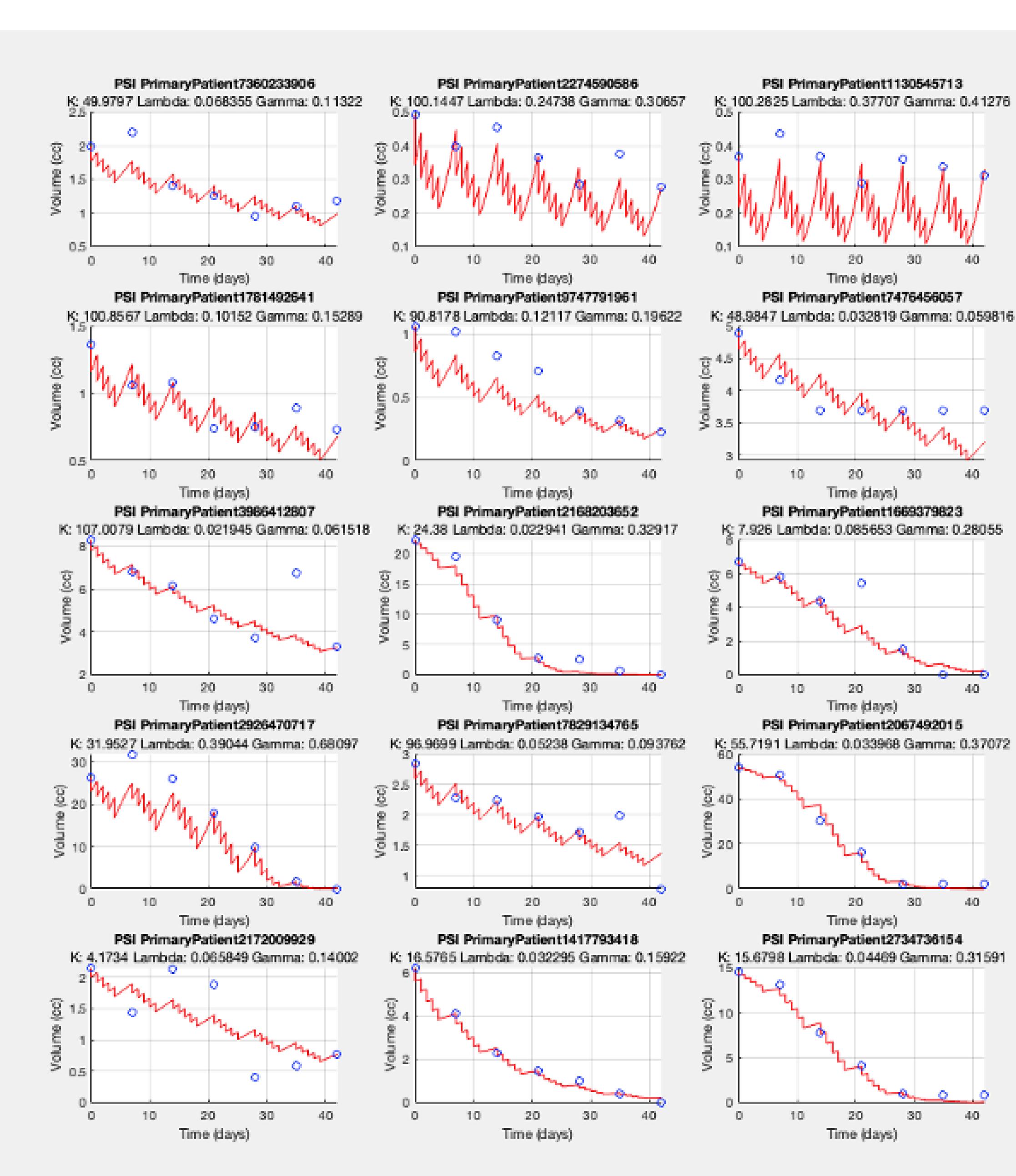


Proliferation Saturation Index: $PSI = \frac{V_0}{V}$

Represents one day of radiation

Represents the weekend



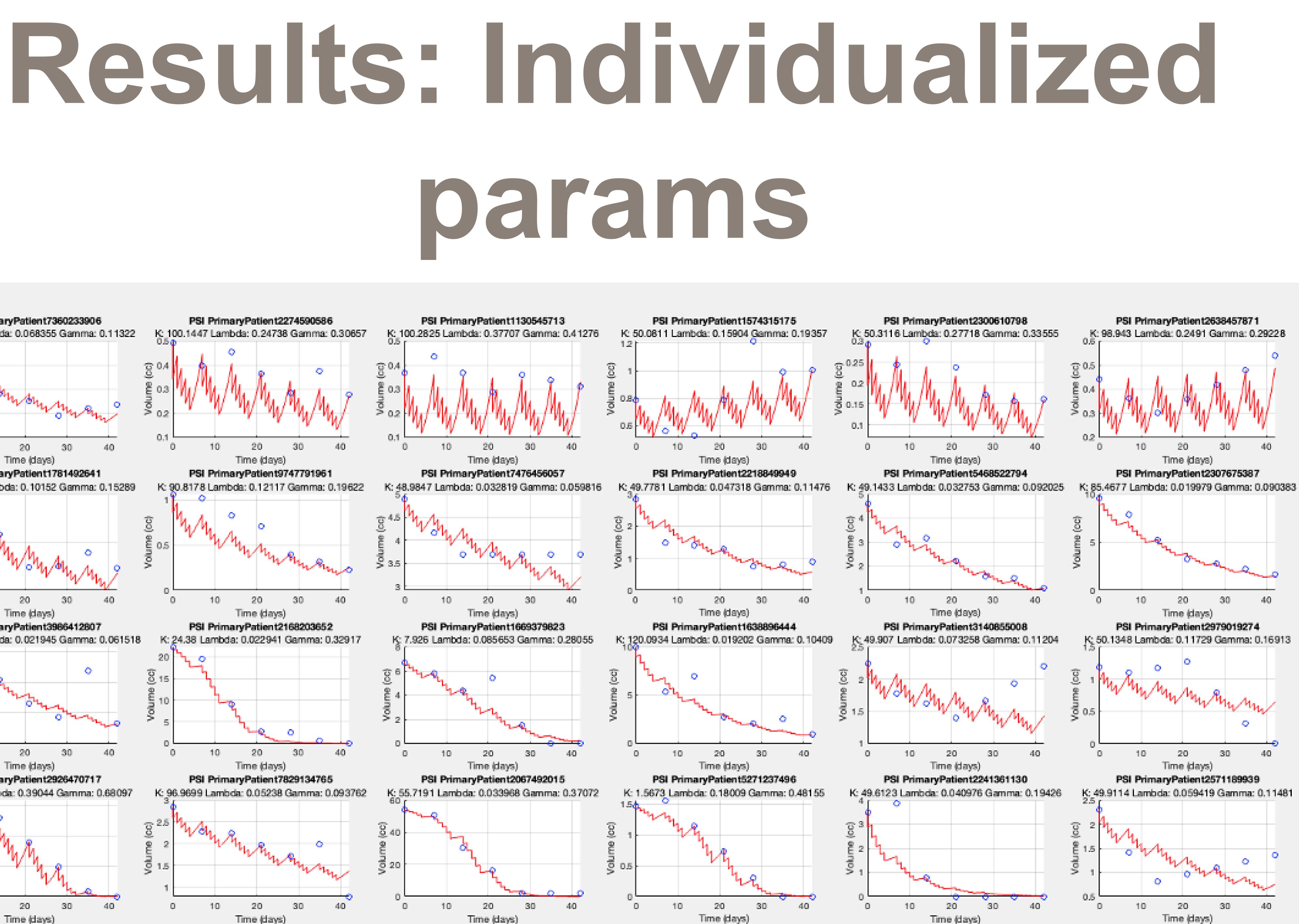


Darams

121

 \overline{a}

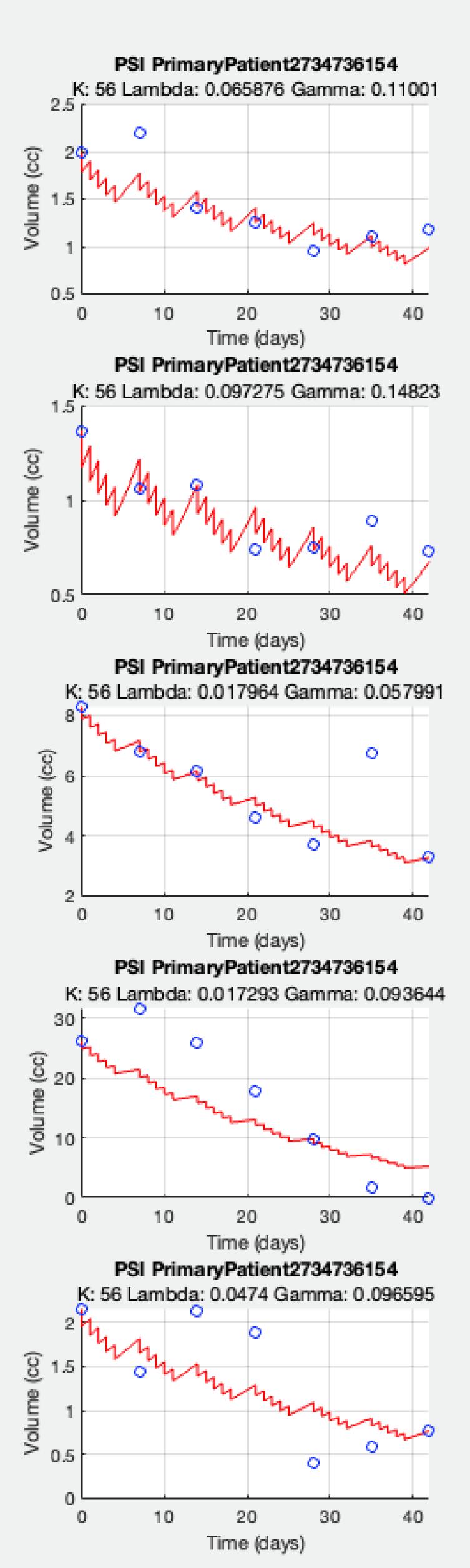
2 0.5

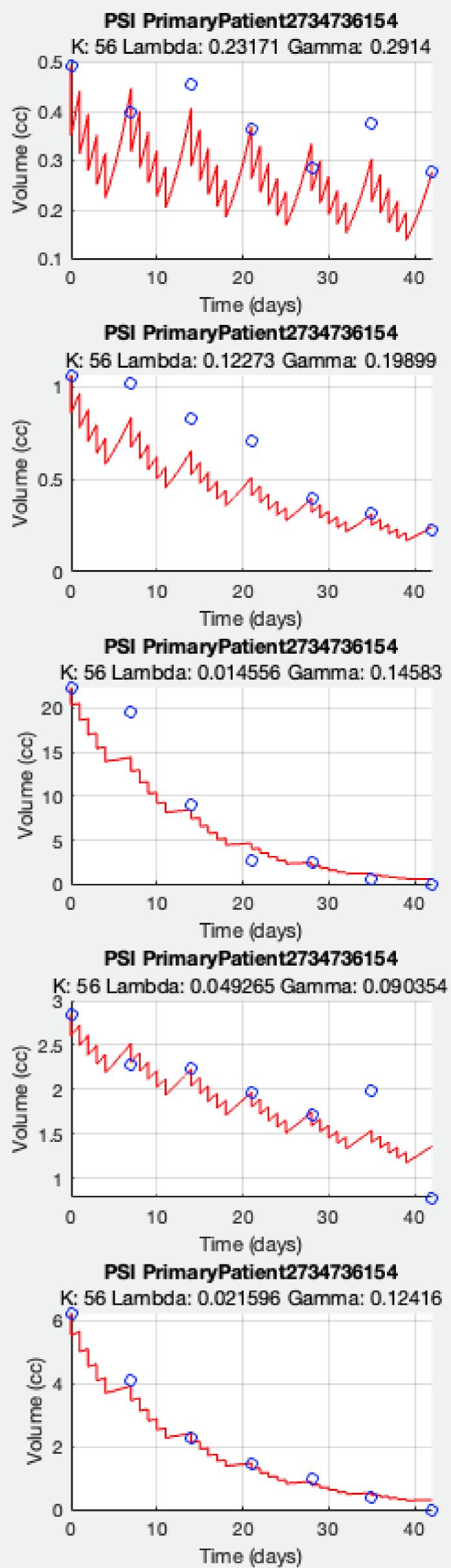


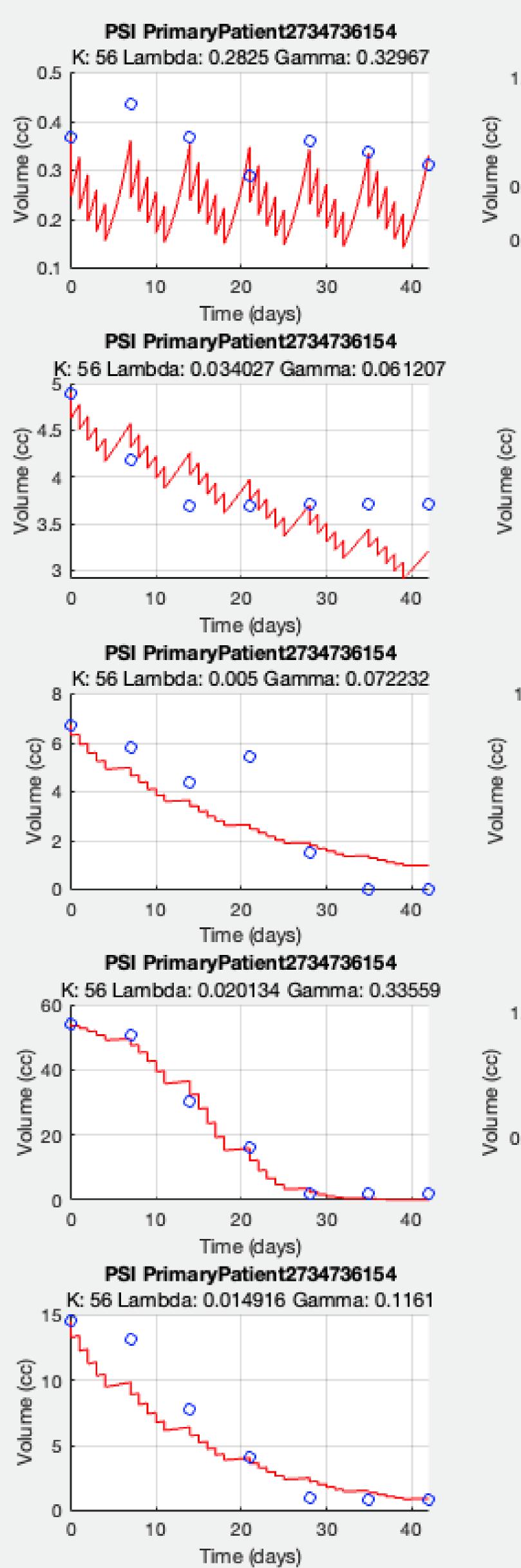
Time (days)

Time (days)

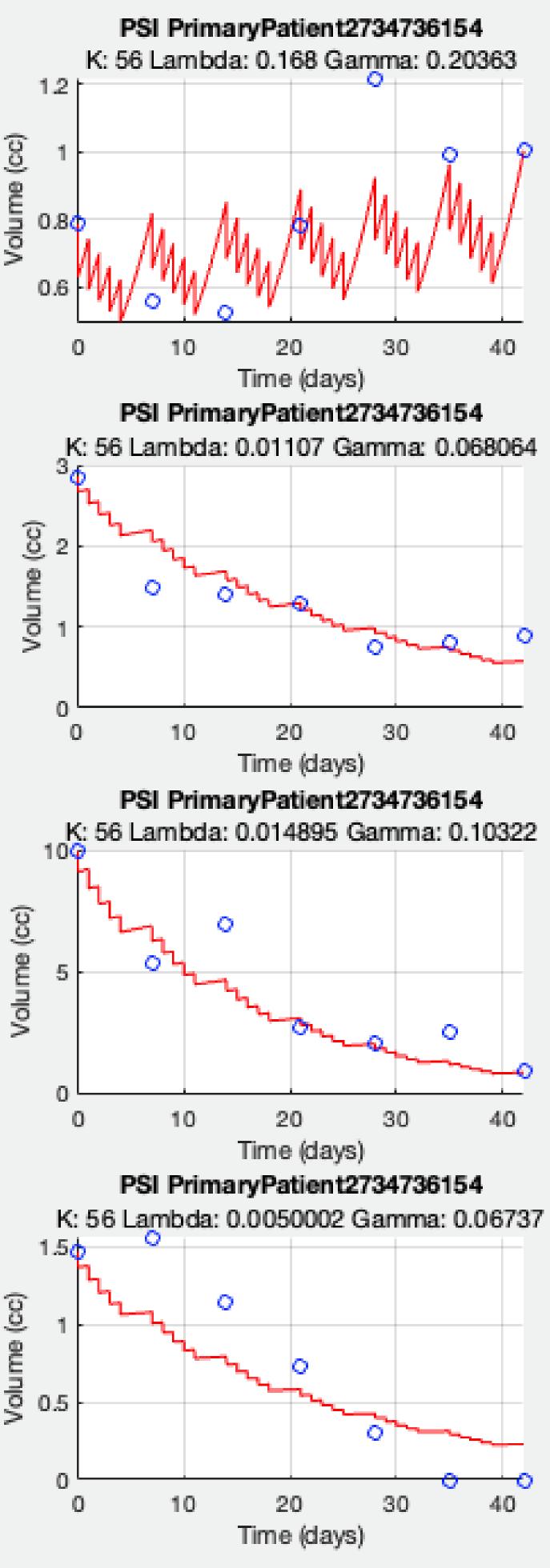


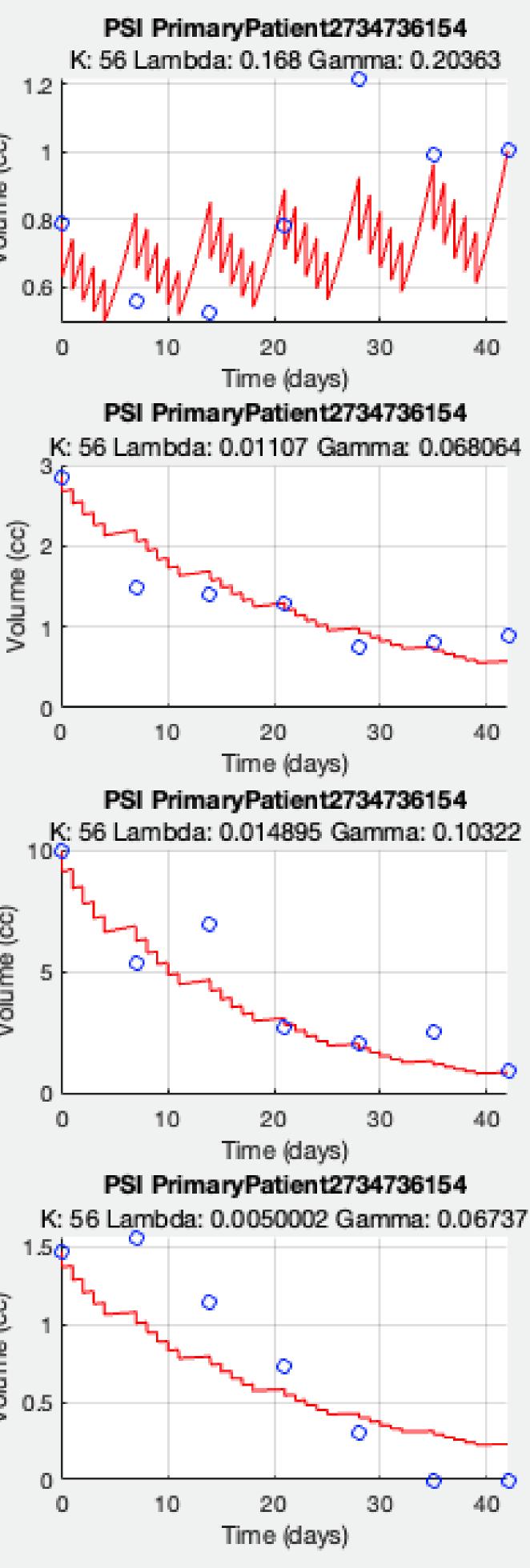


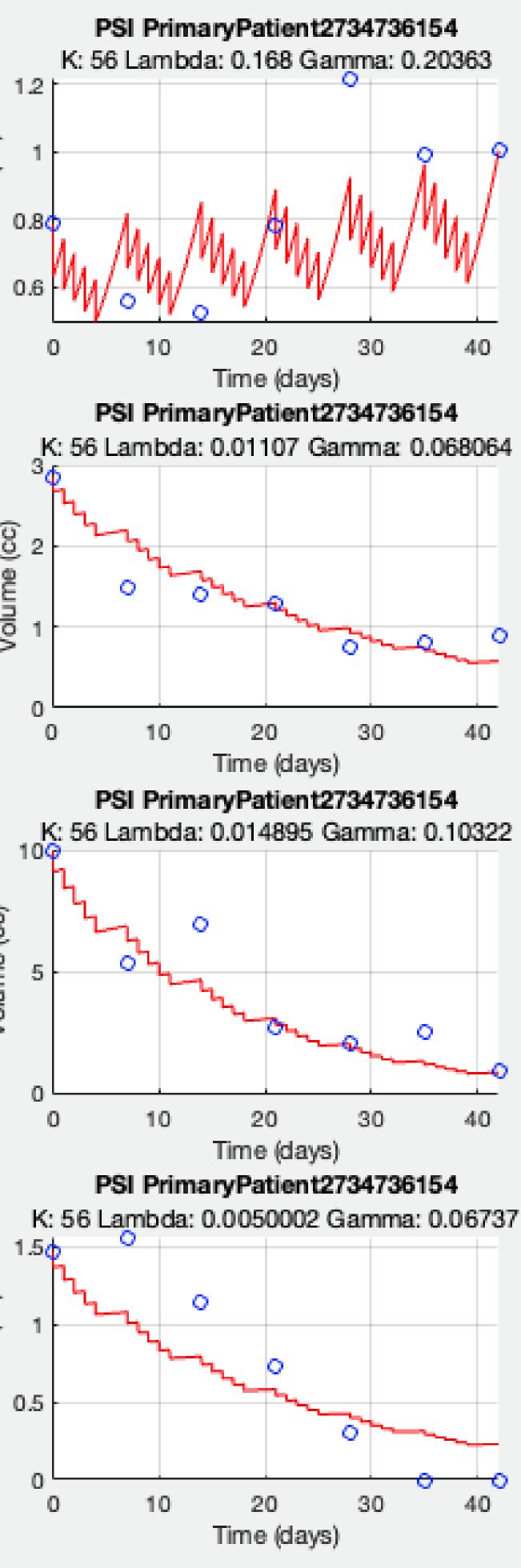




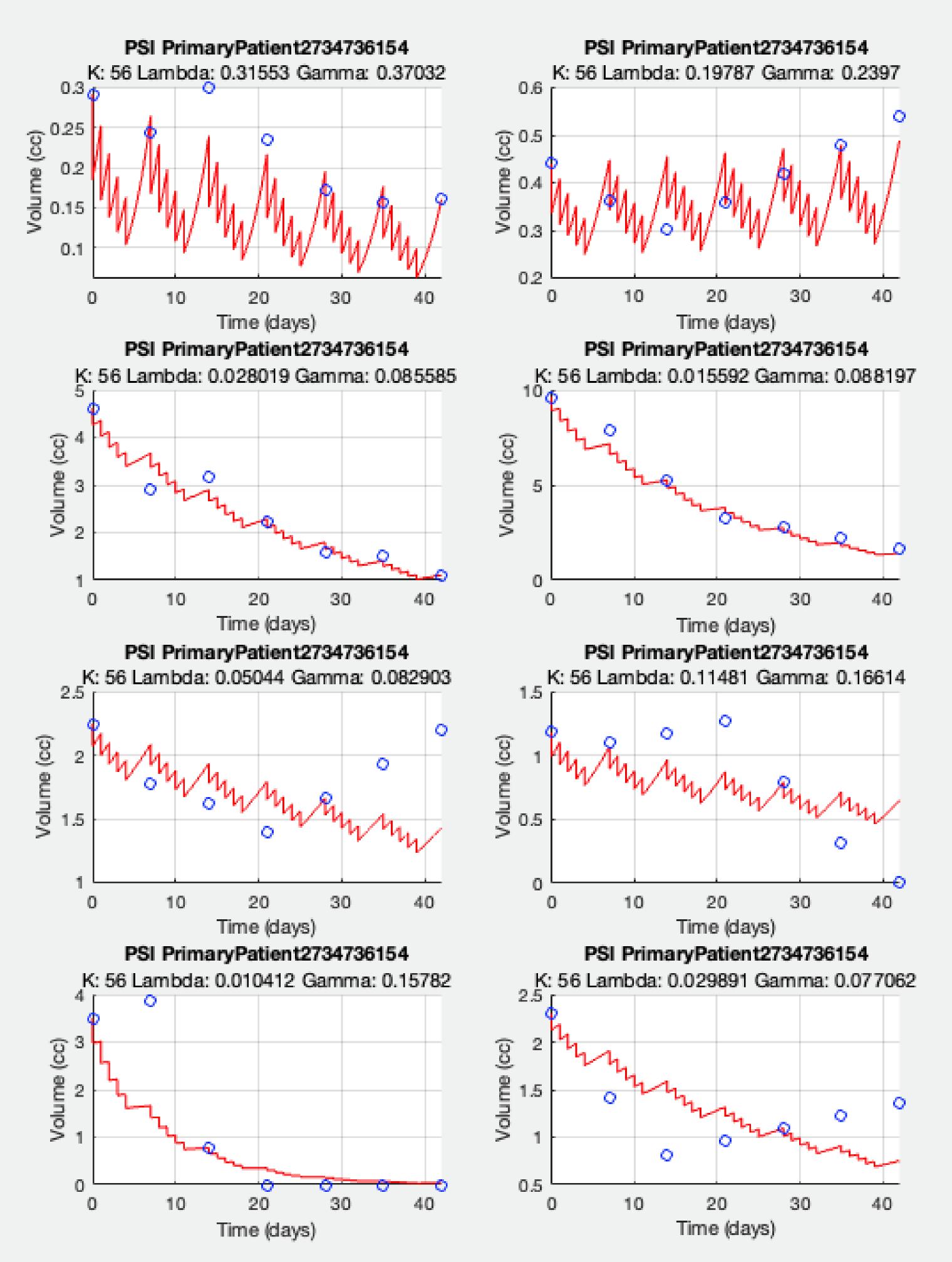
0.8

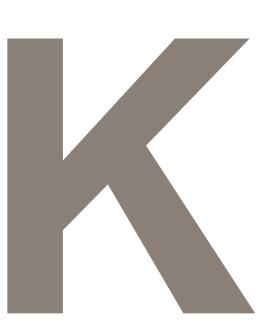




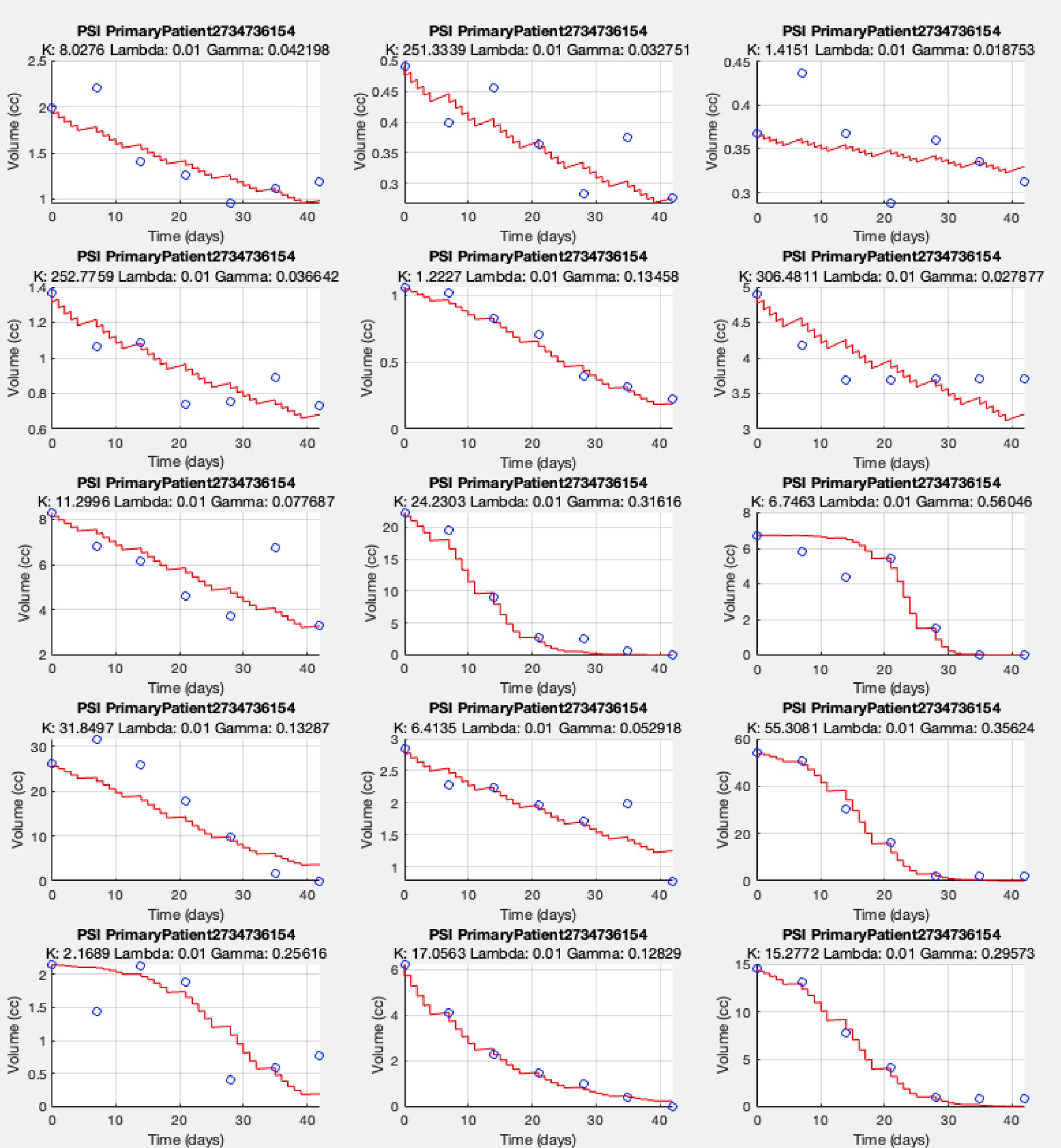


Results: Global K



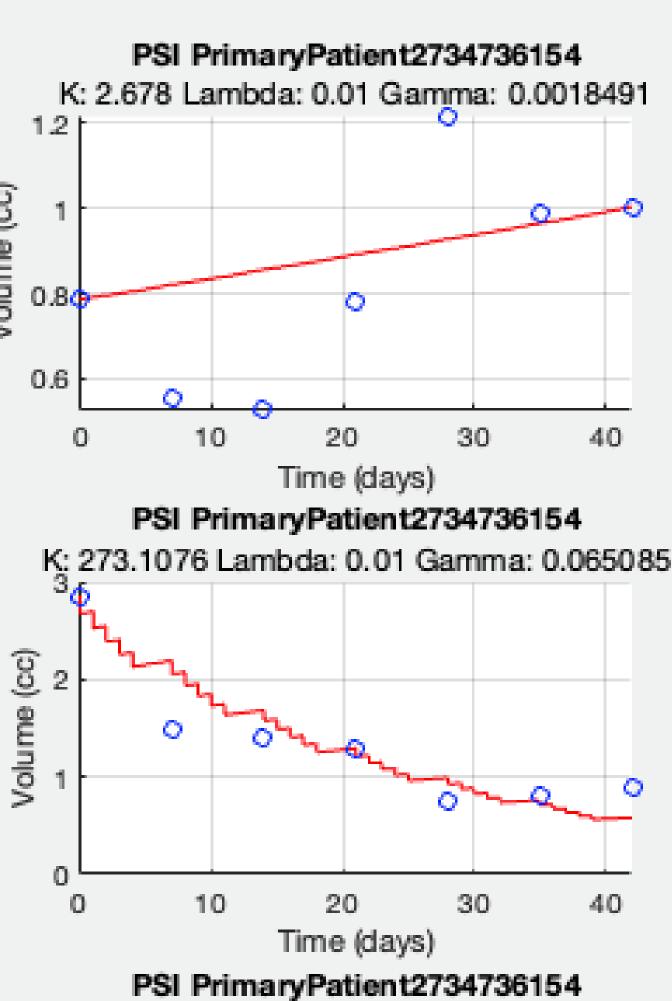


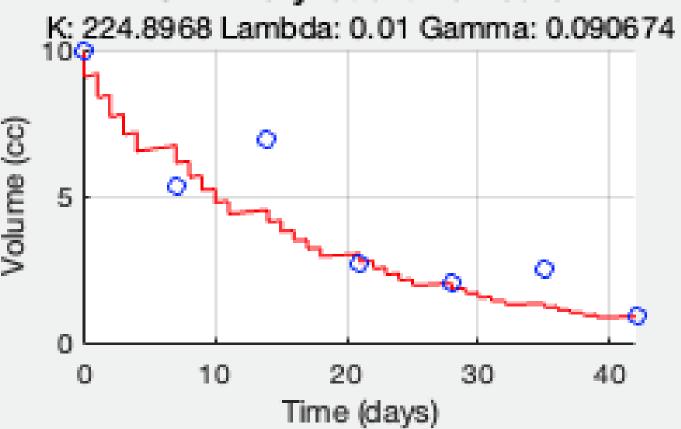


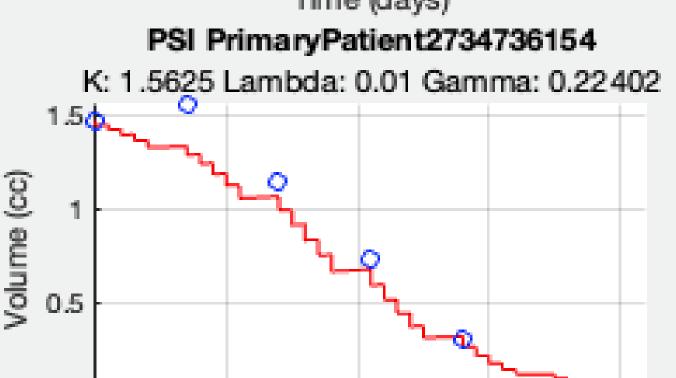


Results: Global

6 0.8 -0.6







20

Time (days)

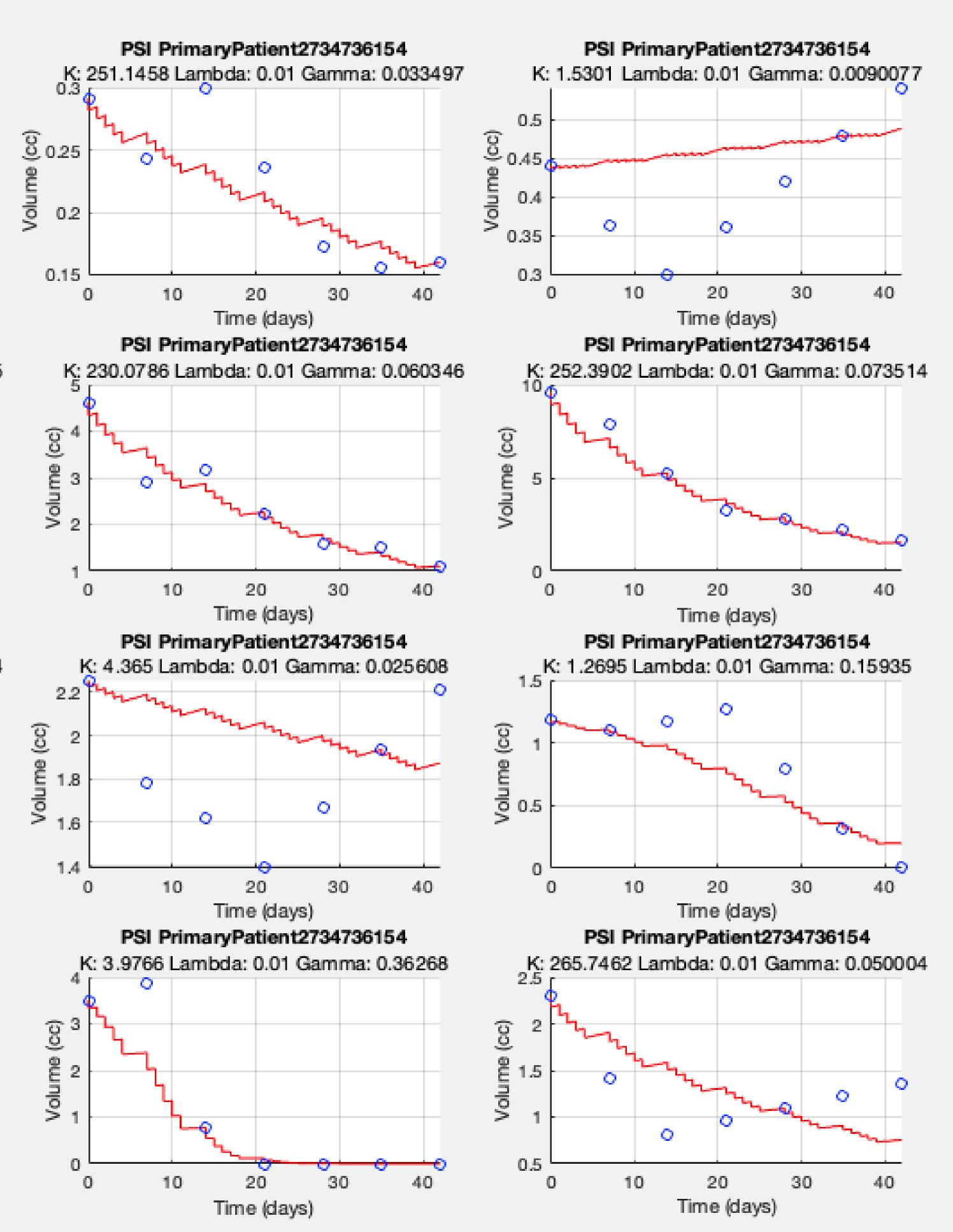
10

- 0

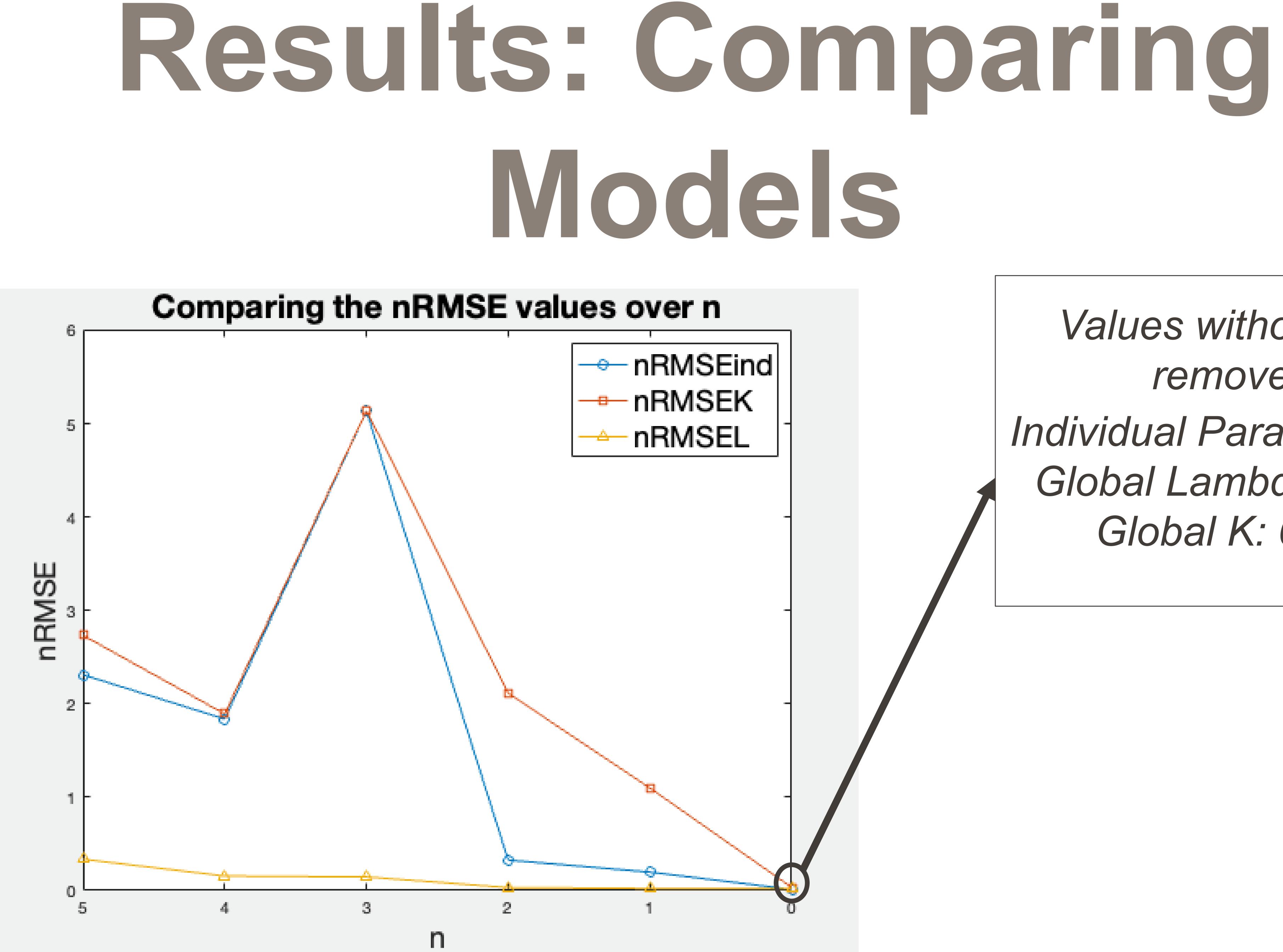
30

40

Lambda







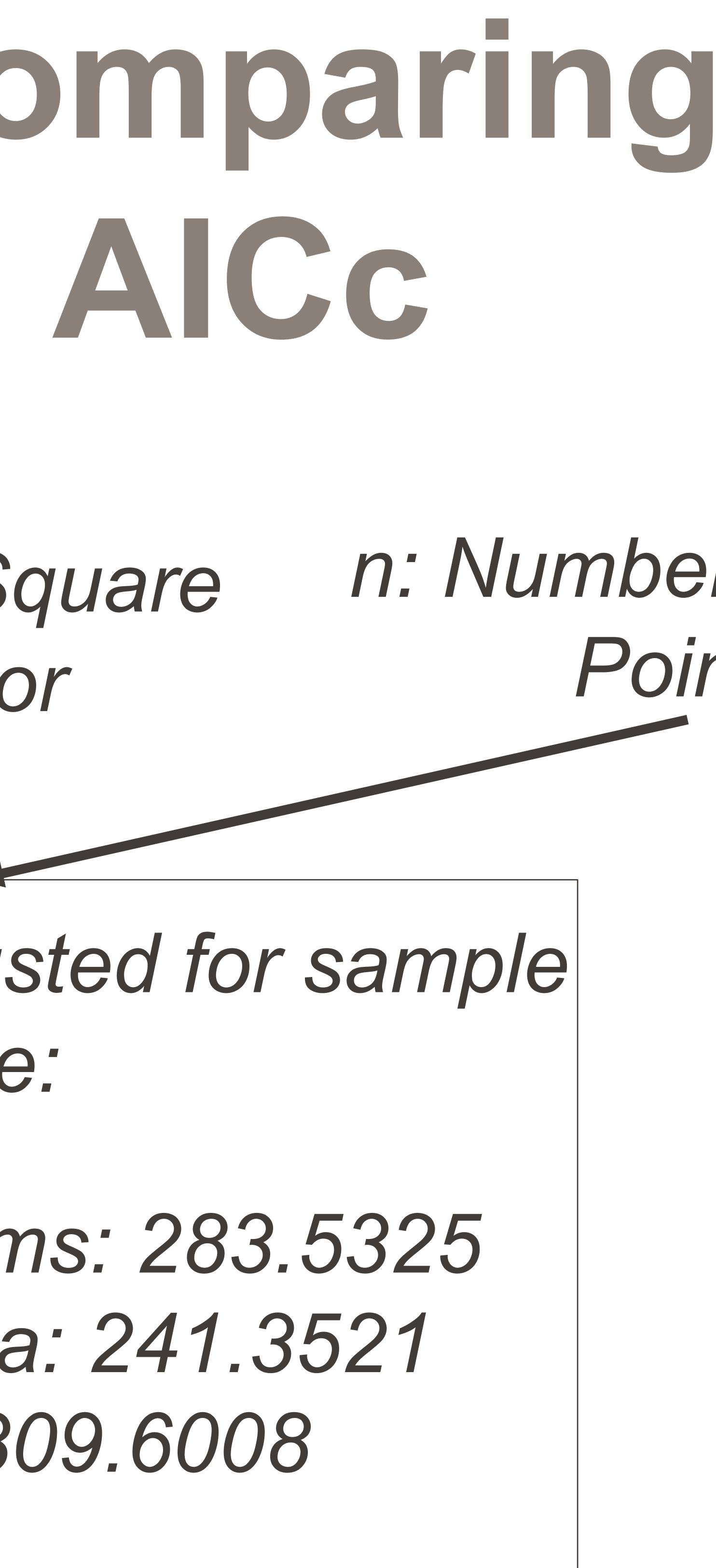
Values without data removed: Individual Params: 0.014 Global Lambda: 0.024 Global K: 0.034



Results: Comparing Nodels AlCc P: number of Mean Square parameters Error AICc values adjusted for sample SIZe.



Individual Params: 283.5325 Global Lambda: 241.3521 Global K: 309.6008

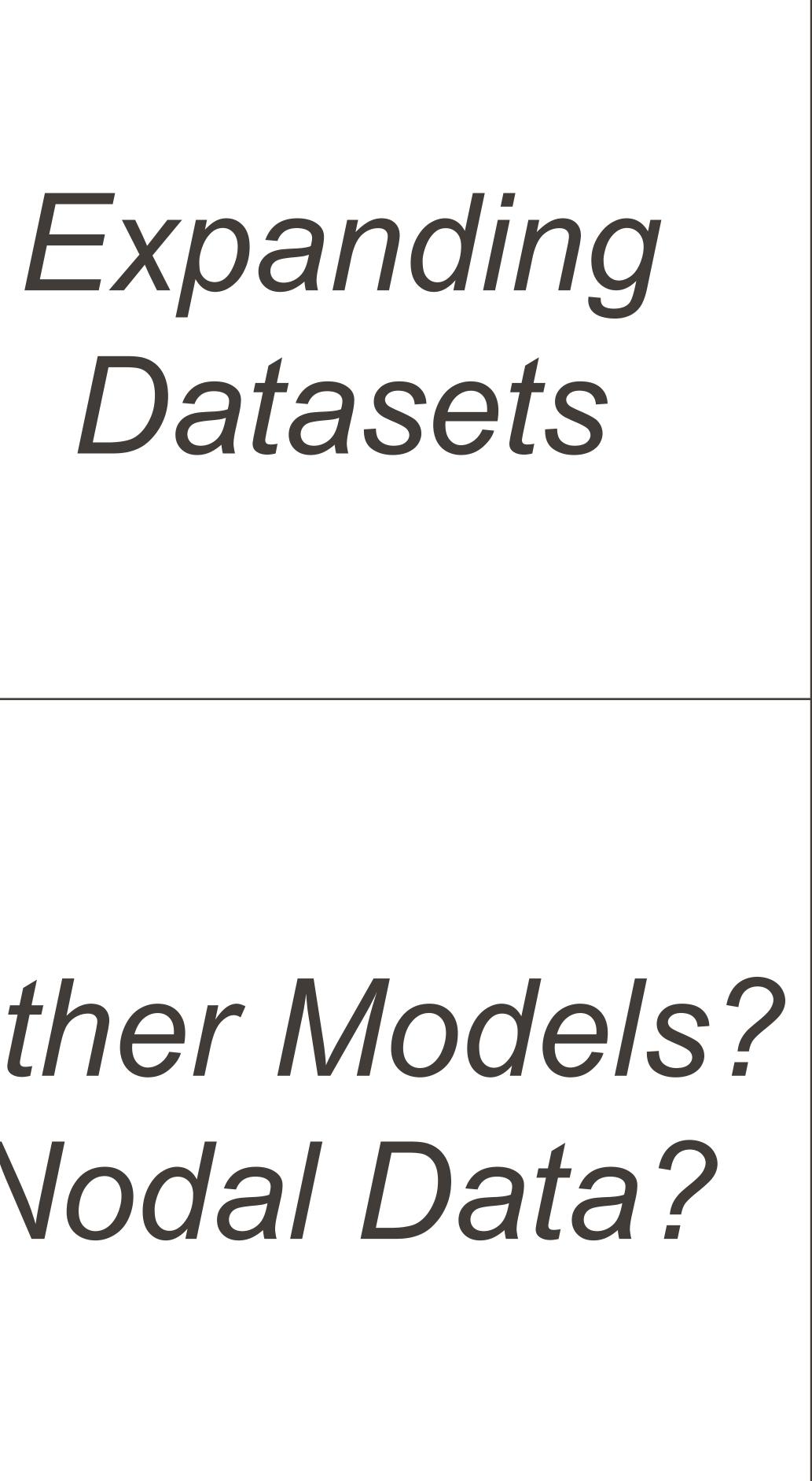


n: Number of Data Points





Further Validation of *Models* **Optimizing Other Models?** Algorithms Nodal Data?



Conclusions

The integration of mathematical models in radiation therapy for HNSCC patients holds great potential for enhancing patient outcomes. The model incorporating a global lambda demonstrates the capability of these models to accurately predict treatment responses beyond just a few weeks. By offering a framework to predict individual treatment responses, these models address the challenge of variability in patient reactions, which can lead to improved survival rates and quality of life. Ongoing research and validation using additional datasets and the refinement of global parameters are essential before these models can be adopted in clinical practice.



Acknowledgements

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