

Text S1: Numerical procedures for parameters estimation

Several optimization algorithms implemented in Matlab [49] were preliminary tested for minimization of χ^2 and the function *lsqcurvefit* (with trust-region algorithm) was decided to be well-suited for most of the settings based on criteria of rapidity of convergence and ability to manage bounds constraints. For the identifiable models (in the sense of the practical identifiability reported below), no significant differences were obtained when comparing to other regression functions. For instance, the relative difference between *lsqcurvefit* and *nlinfit* (Levenberg-Marquardt algorithm) or *fminsearch* (Nelder-Mead algorithm) for parameters estimates of the full lung data set with the power law model was lower than 1.5×10^{-4} with p values of Student's t-test larger than 0.99. On the other hand, parameters estimations on non-identifiable models was significantly sensitive to the algorithm used. Values of the parameters used for initialization of the minimization algorithm were fixed from preliminary explorative analysis, sometimes with the help of the more global optimizer *fminsearch*. They are reported in the Table S1.

Two models required specific attention, namely the generalized logistic model (3) and the exponential-linear model (1). In the first setting, due to low identifiability, *lsqcurvefit* was found to converge to unrealistic local minima for the breast data set and we rather used the more global optimizer *fminsearch*. For the exponential-linear model, local minima issues are also likely to happen because, on a finite time-course and within some parameter ranges, the model could be insensitive to variation of one of the parameter and remain in a fully-linear or fully-exponential phase (if the resulting τ is larger than the maximum time or lower than the minimal one) that could be sub-optimal. A useful workaround was to impose upper bounds on the parameters (in particular a_1). To avoid numerical issues when solving the von Bertalanffy and power law models, we also imposed an upper bound on parameter γ . In the setting of *lsqcurvefit*, this required imposition of a bound also on parameters a and b , which were taken large enough not to be active.

Text S2: Practical identifiability of the models

Sensitivity of the fits obtained from our estimation procedure was assessed for each model by systematically varying initialization of the algorithm. Only the LLC data set was used for this study, in order to limit the computational cost and because the results should be similar with the LM2-4^{LUC+} data. For the generalized logistic model (3), due to computational limitations, only half of the data set was used. A compact subset of the parameter space of length 4 standard deviations above and below a baseline mean value (obtained by an *a priori* performed on all animals) in each parameter direction was meshed (11 discretization steps for each direction) and explored, with a total of 20×11^P individual fits performed (for the 20 animals growth curves), for each model, with P being the number of parameters in the model. We report in Table S3 results of sensitivity scores, defined as the fraction of fits that converged to the same parameter set as when performing minimization starting from the baseline value (within a 10% relative error). When global numerical identifiability was not observed, further study was performed and the resulting variation of the best-fit parameter sets computed (Table S3).

As could be expected from their substantially higher AICc (Tables 1 and 2), the three models with three parameters (von Bertalanffy (6), dynamic CC (5) and generalized logistic (3)) exhibited low identifiability scores (of respectively 49.9%, 46.4% and 1.2% out of 26620 fits). For the von Bertalanffy model, higher non-identifiability score was observed in the parameter b , probably due to the absence of identifiable range of convergence to an asymptotic volume in our data, which would be the growth range where parameter b is the most active under the von Bertalanffy model. The low identifiability of the dynamic CC model can be explained by its two-dimensional nature (volume and carrying capacity are variables) with only one observable used for the fits. This fact results in variability mostly in estimation of K_0 . The generalized logistic model had very low identifiability score (1.2%), mostly due to high volatility of parameter α (median deviation 390%).

All the other models exhibited good robustness in the parameter estimation, although the Gompertz model (4) had not a 100% identifiability score due to lack of identifiability of parameter K in a few situations, possibly due to the aforementioned absence of growth saturation in the data. This did not happen for the power law model.

Table S1: Initializations of the least squares minimization algorithm.

Model	Parameter	Initialization	Upper bound
Power law	a	1	100
	γ	2/3	1
Gompertz	a	0.1	-
	K	10000	-
Dynamic CC	a	3	-
	b	0.5	-
	K_0	10	-
Generalized logistic	a	10	-
	K	10000	-
	α	0.01	-
Von Bertalanffy	a	1	100
	γ	0.75	1
	b	0.1	100
Exponential V_0	a	0.1	-
	V_0	20	-
Exponential-linear	a_0	0.2	10
	a_1	100	200
Logistic	a	1	-
	K	10000	-
Exponential 1	a	0.1	-

Also reported are bounds used in *lsqcurvefit* for estimation of parameters of the power law, von Bertalanffy and exponential-linear models.

Tables S2: Comparison of individual fits between the individual and population approaches. Fits were performed using either an individual estimation of the growth curves based on weighted least-squares estimation or a population approach. In both settings, the error model was proportional to the volume to the power $\alpha=0.84$. The only difference was that Monolix estimation did not allow for a setting with a threshold volume V_m , which was thus taken to be 0. However, due to its low value ($V_m=83$ mm³), it was not very active in the individual approach. Reported are the total sums of weighted residuals (with $V_m = 0$, i.e. the Monolix setting) over all the animals growth curves, for both settings.

S2.A Lung data

Model	Indiv. (least squares)	Pop. (Monolix)
DynCC	42.2	92.1
Gomp	49.3	137
PL	48.1	176
VonBert	46.1	131
ExpV0	65.9	168
GLog	41.2	143
Log	63.5	185
Exp-L	59.1	122
Exp1	256	471

S2.B Breast data

Model	Indiv. (least squares)	Pop. (Monolix)
DynCC	24.3	56.8
Gomp	21.7	54.1
PL	22.5	49.1
VonBert	20.6	60.6
ExpV0	26.2	63.6
GLog	21.7	51.4
Log	33.8	41.1
Exp-L	20.5	25.1
Exp1	489	1.39e+03

Table S3: Practical identifiability. The identifiability score reported is the proportion of minimization run, among the $20 \times N^P$ performed, which converged to the same parameter set within a 10% relative error. When this scorer was lower than 100%, further analysis was performed and the same score was computed for each parameter of the model. We also report their median relative deviation to the base value, in percent. Par. = Parameter. Dev. = Deviation.

Model	Global score (%)	Param. score (%) (Median Dev.)
Power law	100.0	$\frac{a}{100.0 (0.00)} \quad \frac{\gamma}{100.0 (0.00)}$
Gompertz	85.7	$\frac{a}{99.5 (0.00)} \quad \frac{K}{86.2 (0.01)}$
Dynamic CC	46.4	$\frac{a}{87.5 (3.75)} \quad \frac{b}{85.4 (1.13)} \quad \frac{K_0}{58.9 (78.15)}$
Von Bertalanffy	70.7	$\frac{a}{89.4 (62.69)} \quad \frac{\gamma}{95.5 (1.66)} \quad \frac{b}{74.9 (88.41)}$
Generalized logistic	1.2	$\frac{a}{43.1 (87.17)} \quad \frac{K}{67.6 (72.45)} \quad \frac{\alpha}{25.5 (389.54)}$
Exponential V_0	100.0	$\frac{V_0}{100.0 (0.00)} \quad \frac{a}{100.0 (0.00)}$
Logistic	97.7	$\frac{a}{97.7 (0.00)} \quad \frac{K}{100.0 (0.01)}$
Exponential-linear	97.1	$\frac{a_0}{97.8 (0.00)} \quad \frac{a_1}{99.4 (0.00)}$
Exponential 1	100.0	$\frac{a}{100.0 (0.00)}$

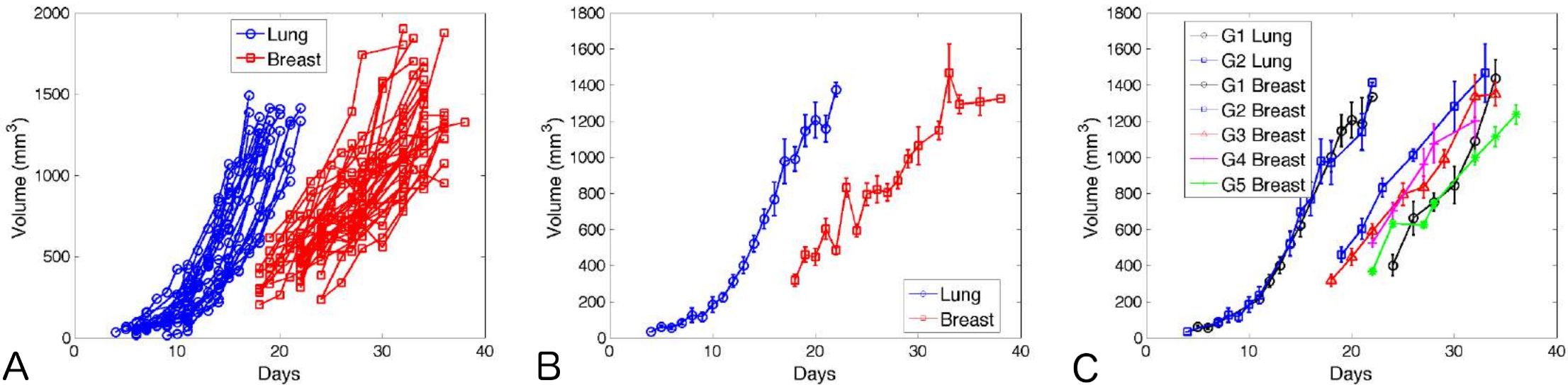
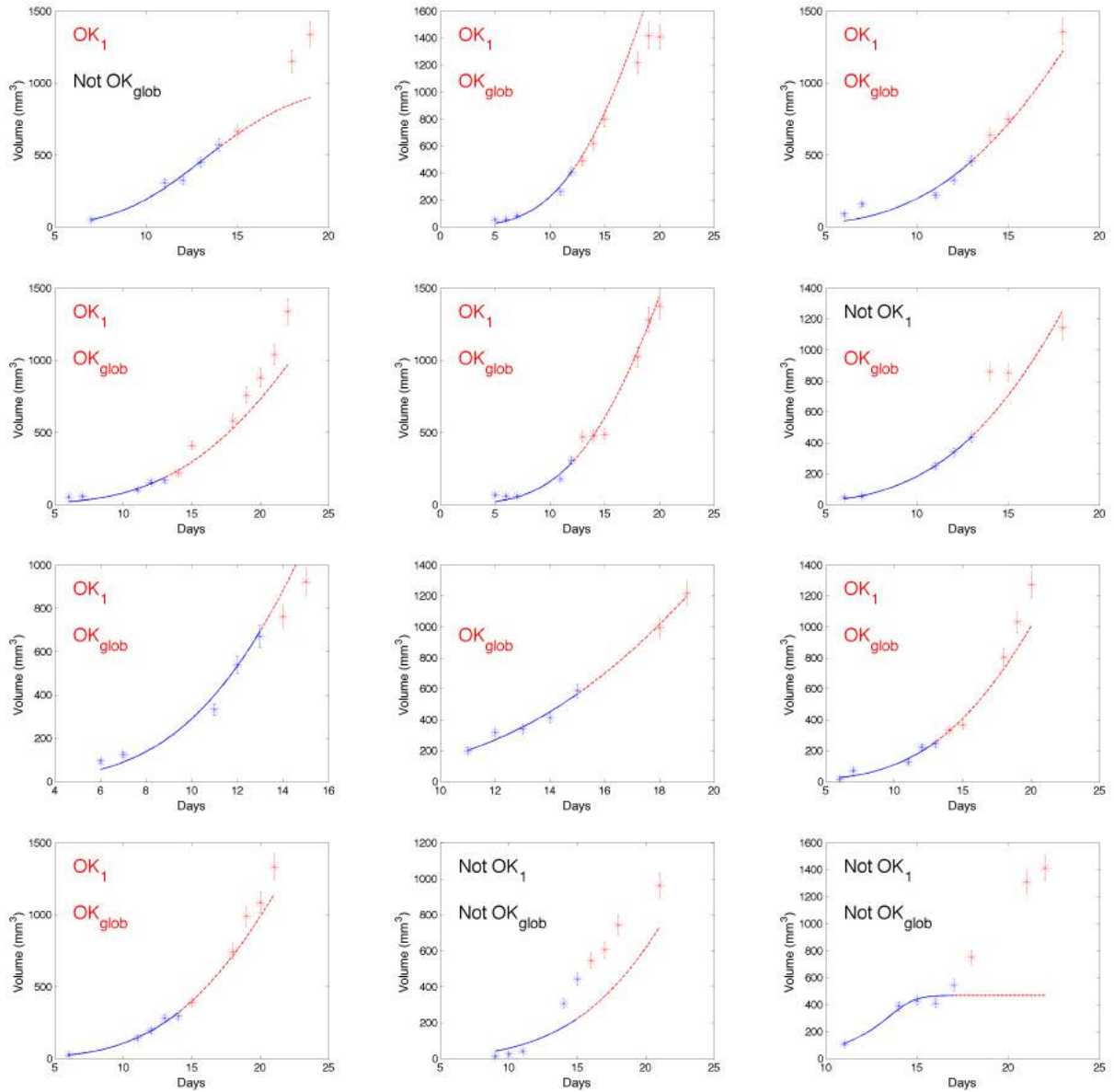


Figure S1: Data. Plots of the brute data sets from the lung and breast experiments. A. All animals growth curves. B. Average curves. C. Per group averages (lung and breast data resulted from combinations of respectively two and three separate experiments). G = group.

Figure S2: Examples of individual predictions. Lung data. Prediction success of the model are reported for the next day (OK_1) or global future curve (OK_{glob}), based on the criterion of a normalized error smaller than 3 (meaning that the median model prediction is within 3 standard deviations of the measurement error) for OK_1 and the median of this metric over the future curve for OK_{glob} . Future growth was predicted using 5 data points and the generalized logistic model.



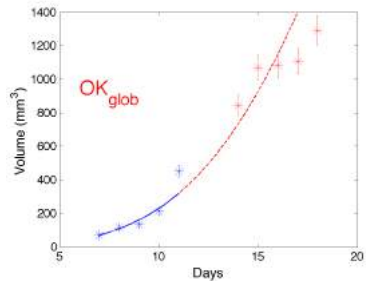
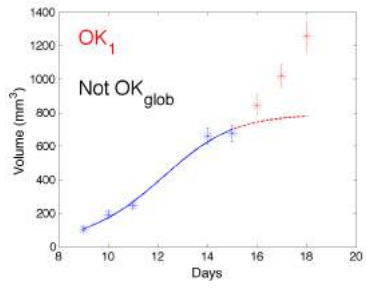
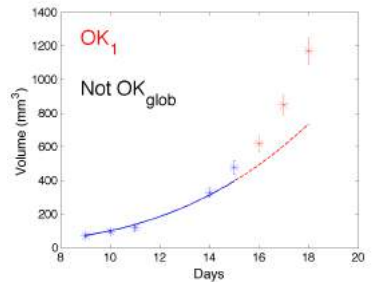
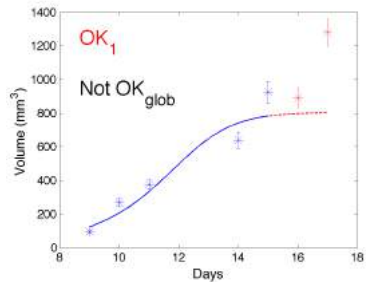
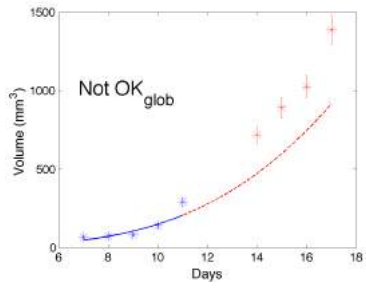
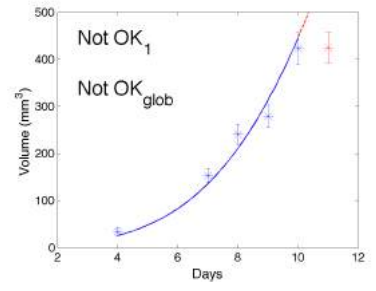
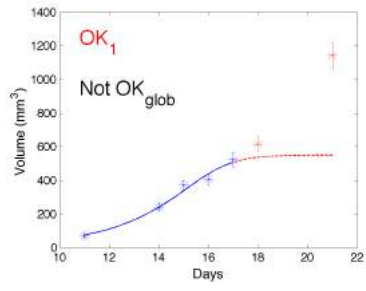
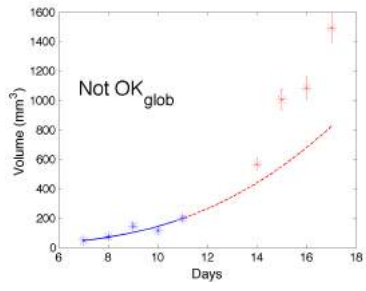
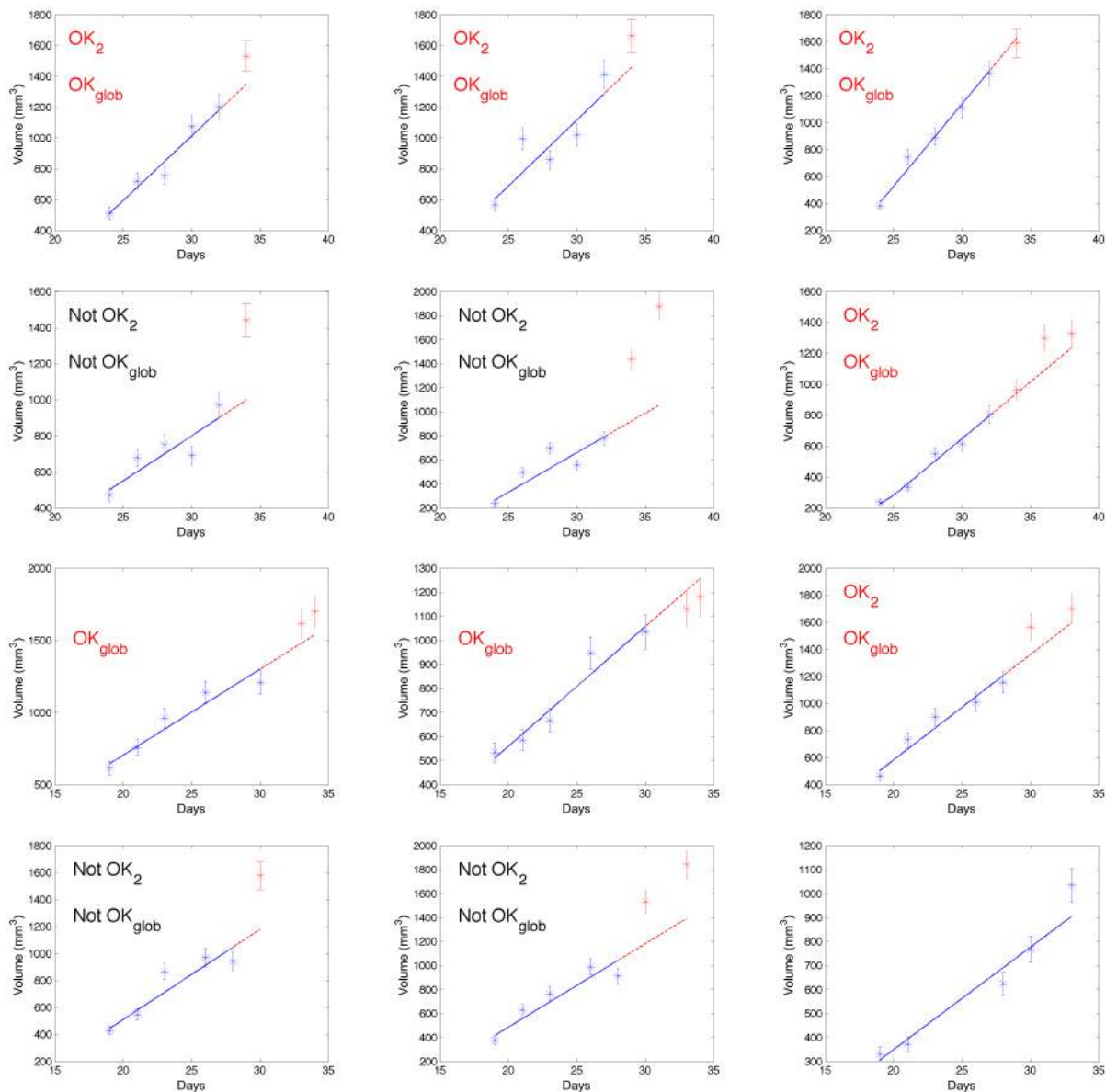
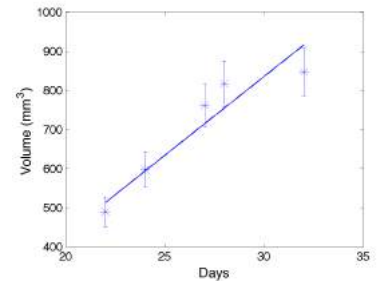
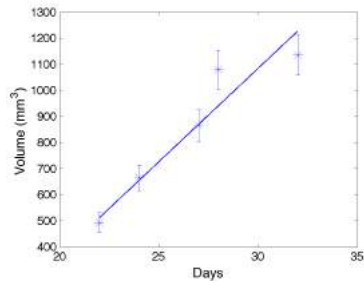
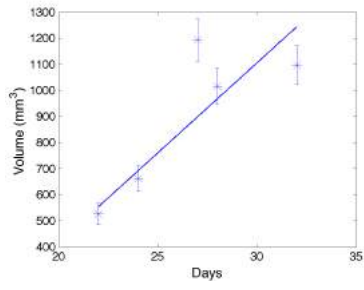
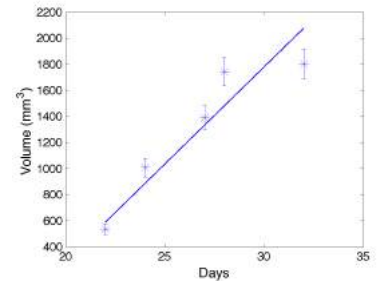
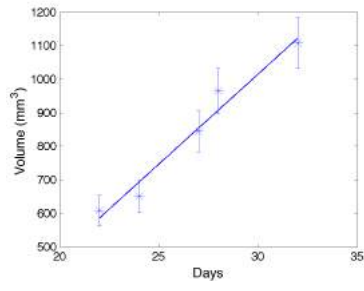
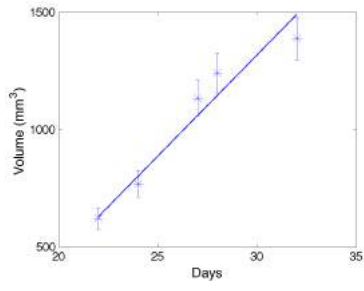
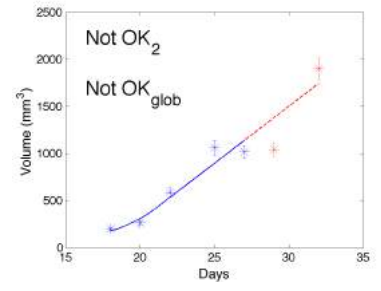
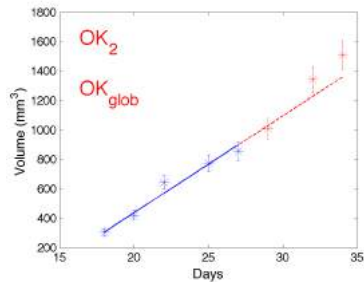
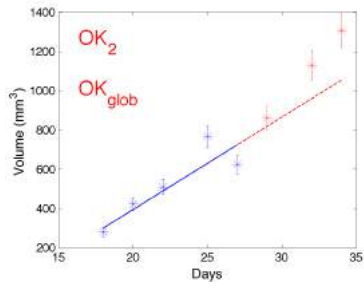
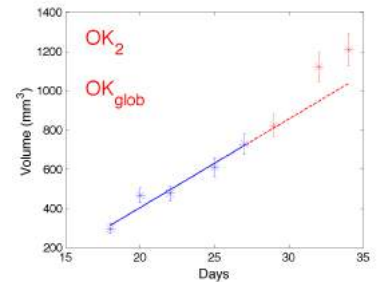
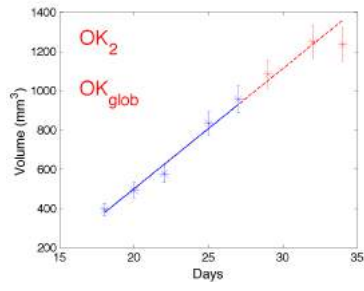
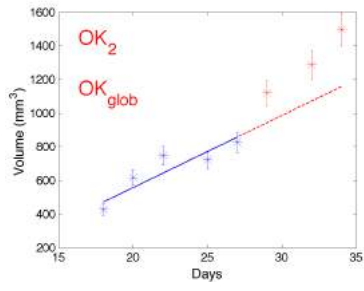
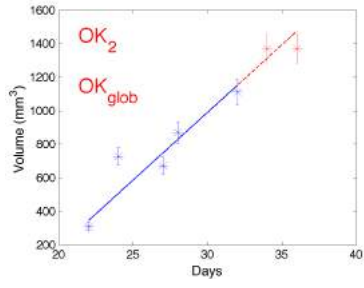
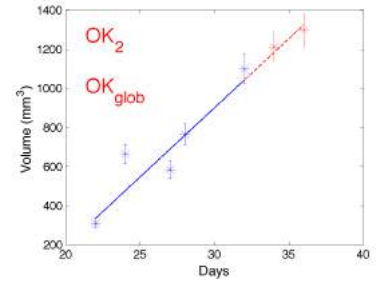
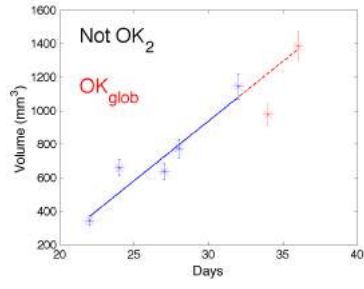
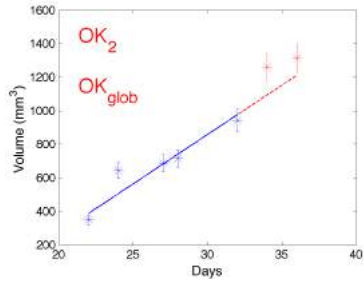
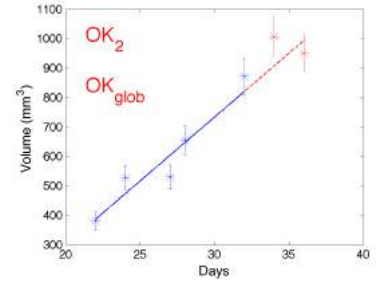
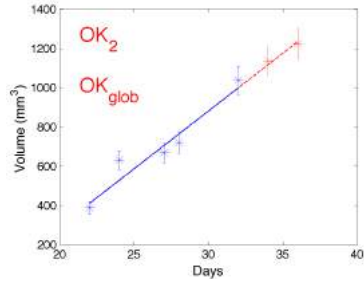
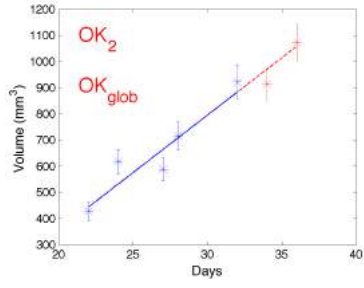
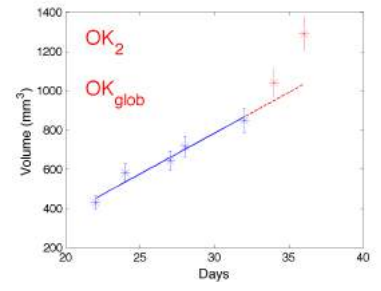
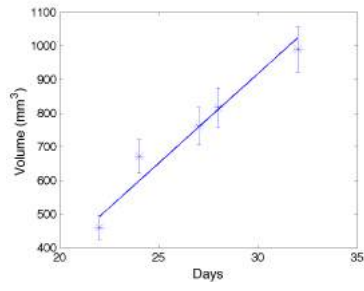
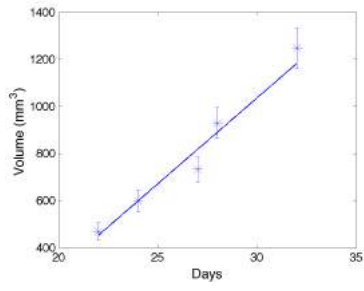


Figure S3: Examples of individual predictions. Breast data. Prediction success of the model are reported for the second next day data point (OK_2) or global future curve (OK_{glob}), based on the criterion of a normalized error smaller than 3 (meaning that the median model prediction is within 3 standard deviations of the measurement error) for OK_2 and the median of this metric over the future curve for OK_{glob} . Future growth was predicted using 5 data points and the exponential-linear model.



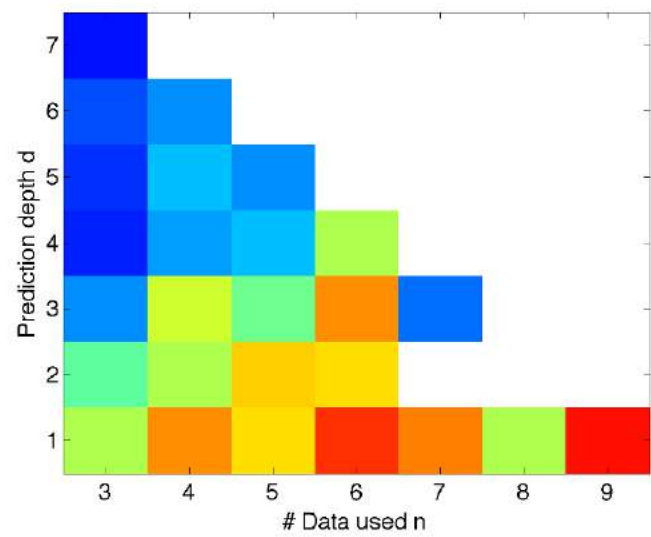




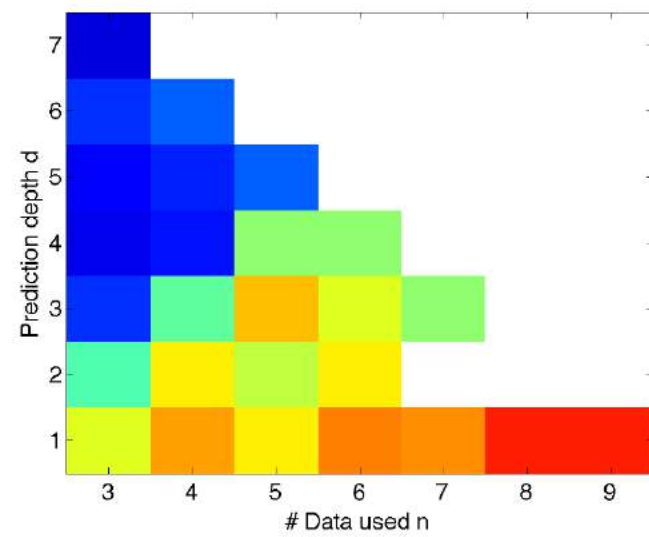
A. Lung

B. Breast

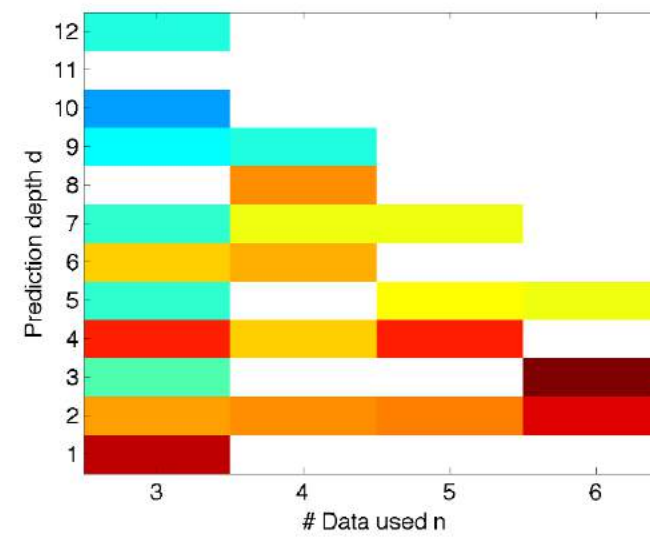
Dynamic CC



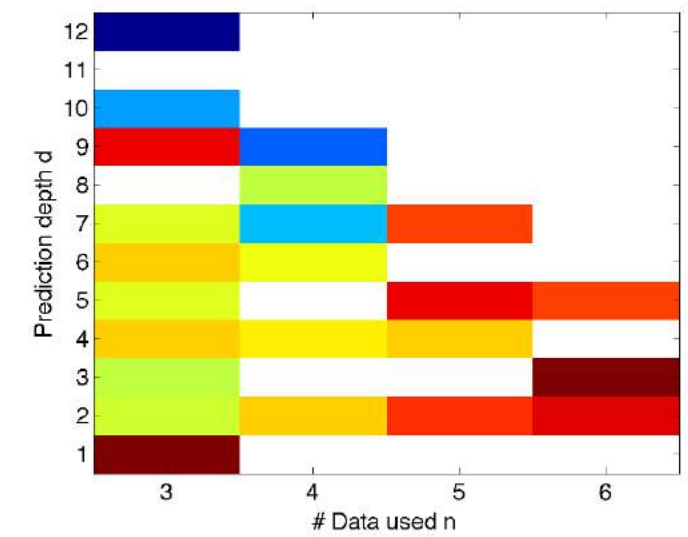
Von Bertalanffy



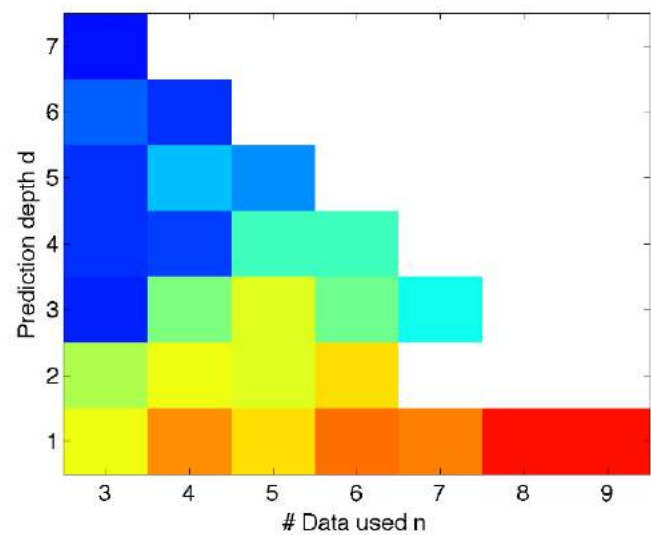
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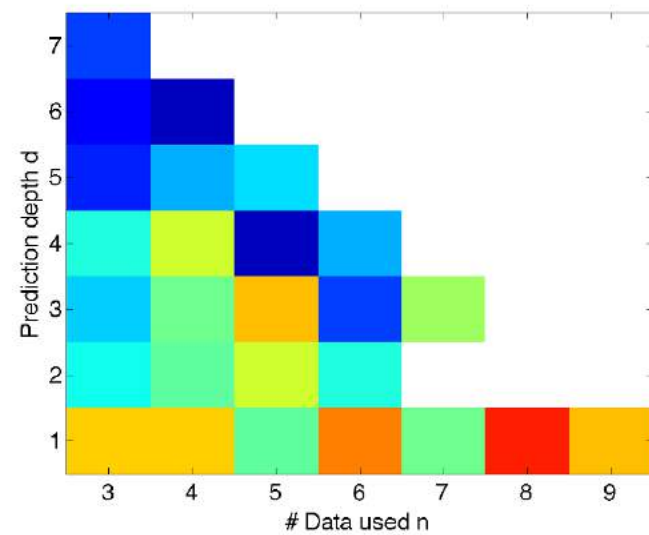
Dynamic CC



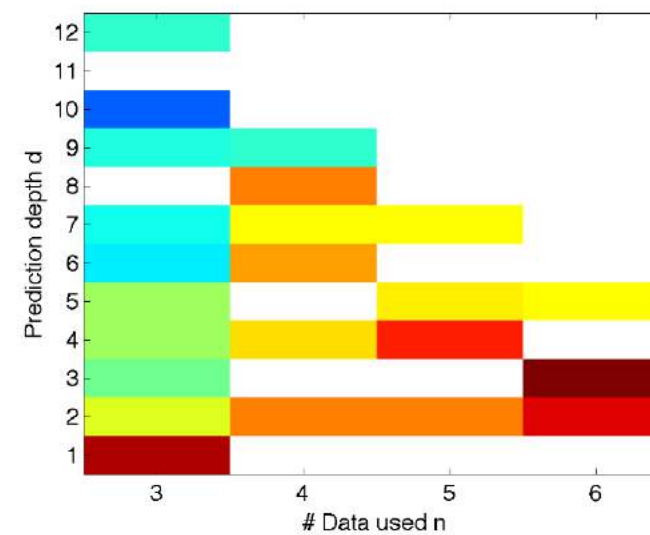
Power law



Exponential V0



Gompertz



Von Bertalanffy

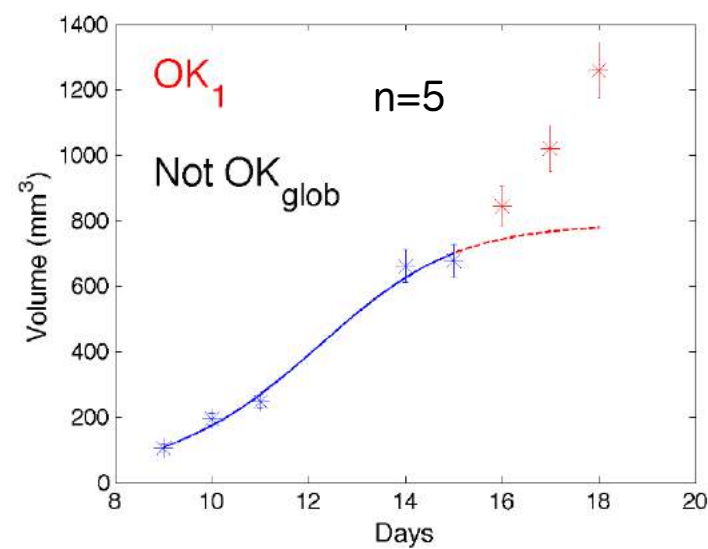
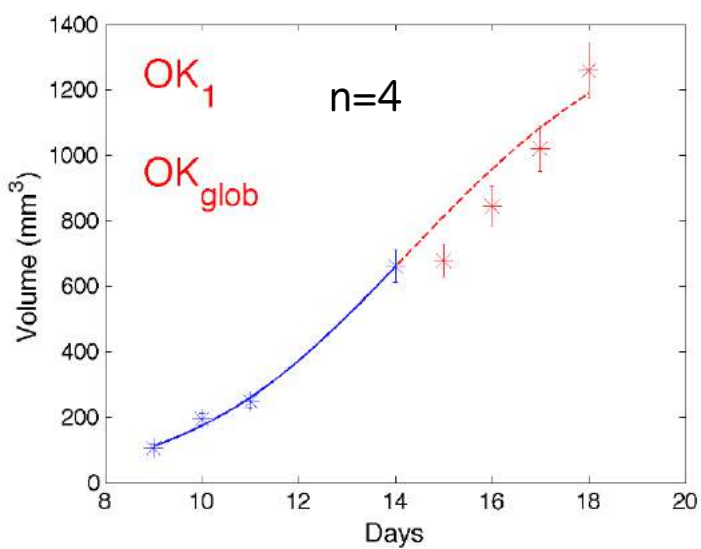
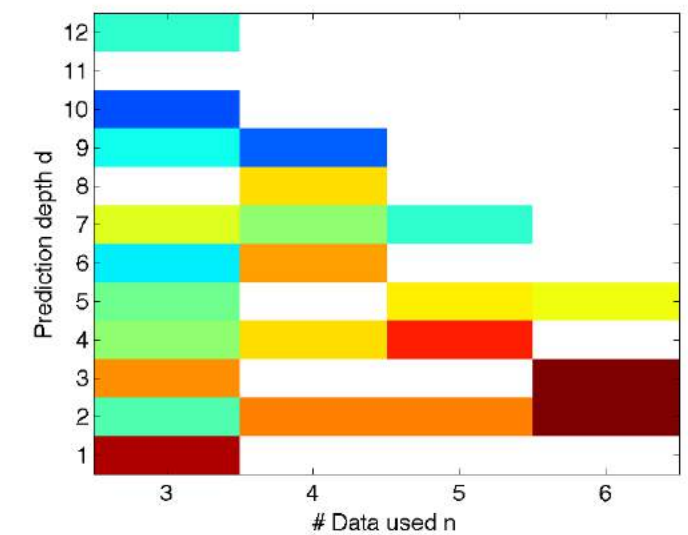


Figure S4: Prediction. Top: Prediction success for models that were not reported in Figure 4. Bottom: Example where prediction was less successful when using n=5 data points than when using n=4 data points, with the generalized logistic model.

No a priori

A priori

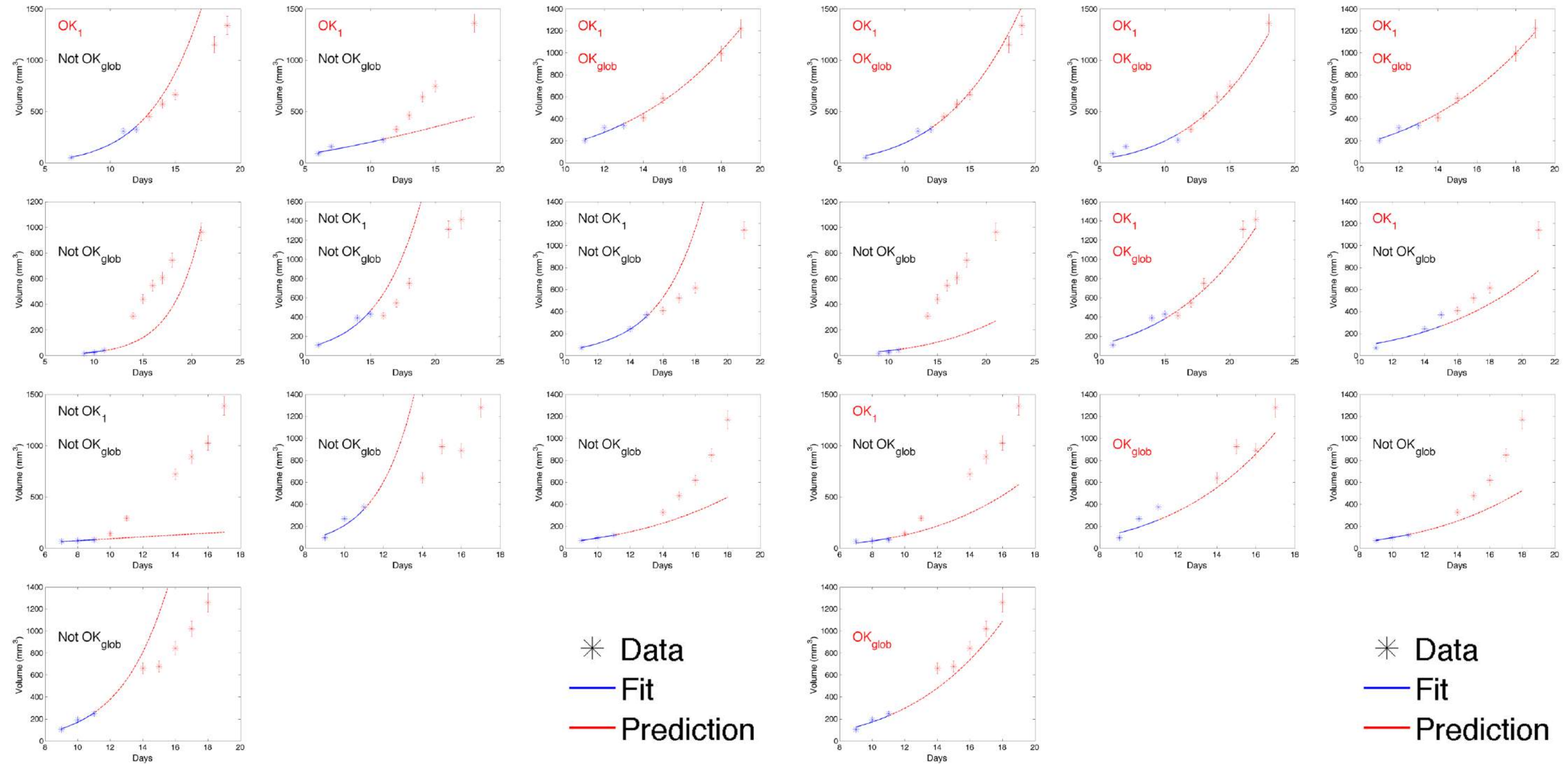


Figure S5: Forecast improvement of the power law model when using a priori information and the lung data set. Fits were performed using the first three data points, for each animal. A priori information (learned on a different data set) was added during the fit procedure for the predictions on the right. Shown is a particular replicate among the 100 subdivisions of the global group (20 mice) into one “learning” group and one “forecast” group.