



Predicting the Troublemakers: Guidance and a Computer Tool for Microbial Growth

IAFP Webinar: May 15, 2025, 10:30-11:30 AM CST

Moderated by Dr. Abdullatif Tay, PepsiCo

Organized by Modelling and Risk Analysis PDG

WEBINAR HOUSEKEEPING

- It is important to note that all opinions and statements are those of the individual making the presentation and not necessarily the opinion or view of IAFP.
- All attendees are muted. Questions should be submitted to the presenters during the presentation via the Q&A or Chat section on your screen. Questions will be answered at the end of the presentations.
- This webinar is being recorded and will be available for access by IAFP members within one week.

Meet Our Expert Speakers



Dr. Heidy den Besten

Wageningen University

"How to predict growth of microorganisms?" Fundamental principles of microbial growth prediction, key factors affecting growth kinetics, and mathematical models



Dr. Mariem Ellouze

Ferrero

"Development of an international standard on the determination and use of cardinal values for growth" Insights on ISO's standardization efforts for microbial growth prediction



Dr. Panagiotis Skandamis

Agricultural University of of Athens

"User-friendly, freely available computer tool to predict microbial growth" Demonstration of accessible tools for food safety professionals with practical applications

How to predict growth microorganisms?

Professor Heidy den Besten, heidy.denbesten@wur.nl

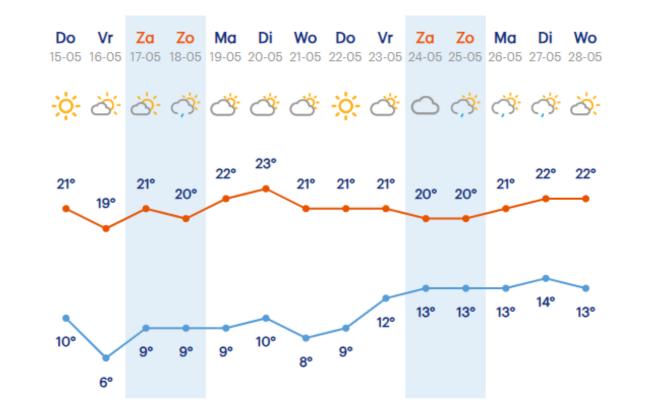
15 May 2025







Decision **support** system



Buienrader.nl

- All models are wrong some are useful (Box)
- All models are correct but they are not perfect (Zwietering)



Growth of microorganisms

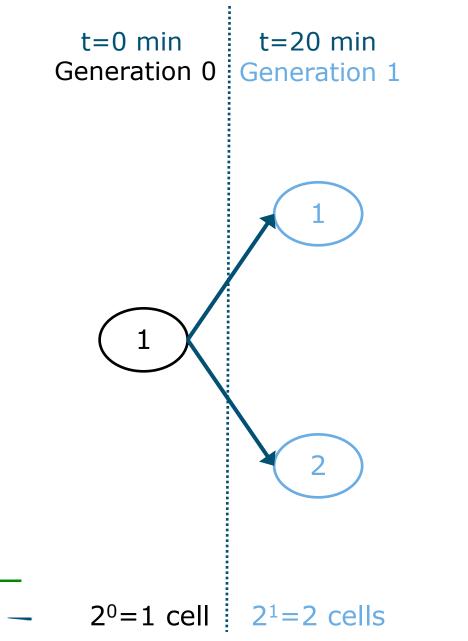
- Bacterial growth: 1 2 4 8 16 32 (=2ⁿ)
- Generation time: time to generate a new generation

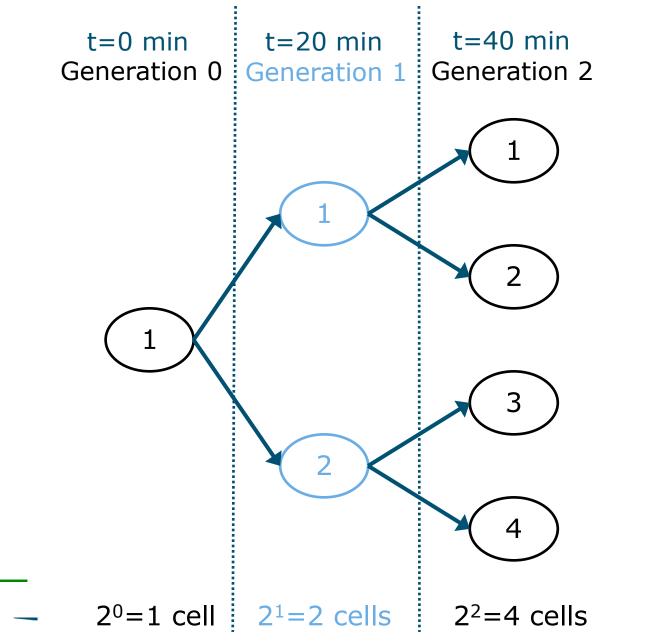


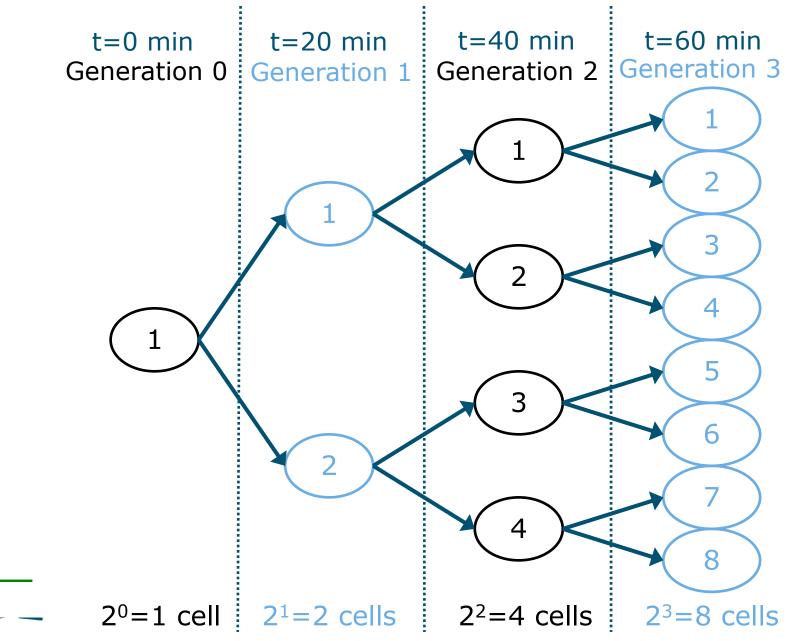


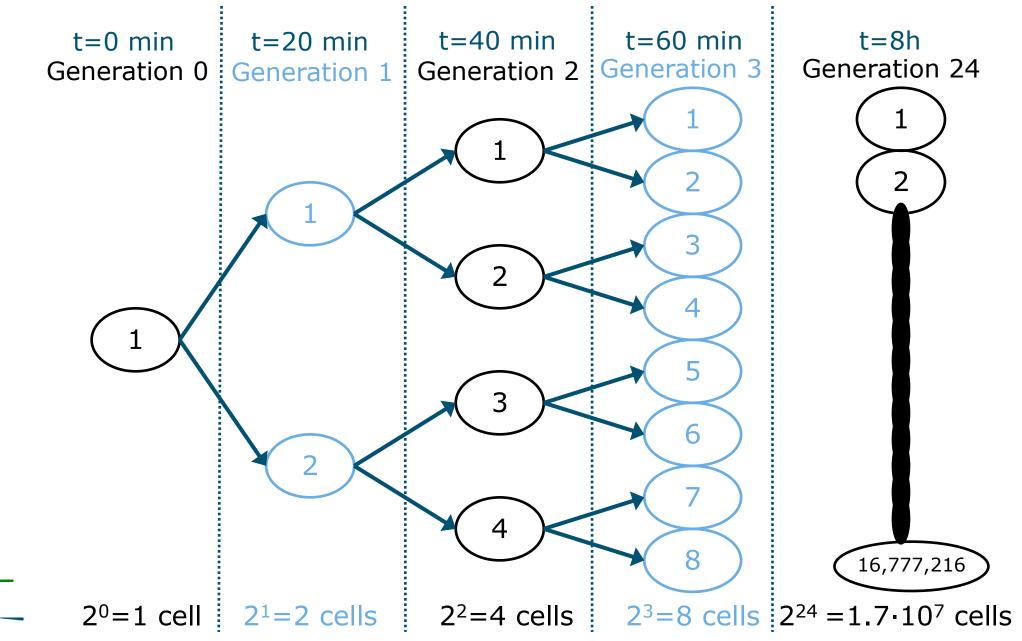
t=0 min Generation 0

 $\left(1\right)$



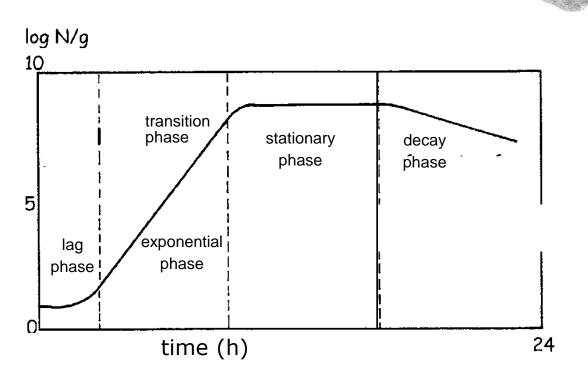






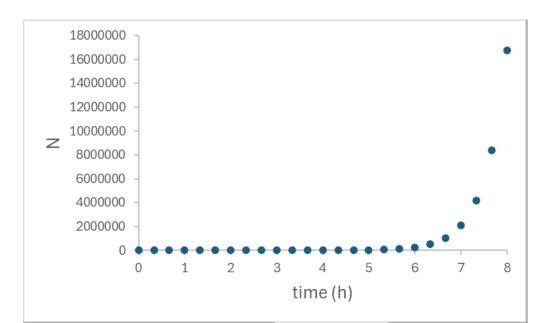
Growth of bacteria

- Exponential growth: 1 2 4 8 16 32 (=2ⁿ)
- Growth curve: log N / g
- N = number of cells



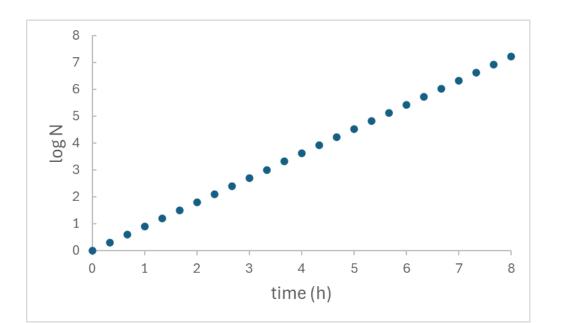


$$N_t = N_0 \cdot 2^n \to N_t = N_0 \cdot 2^{\frac{t}{GT}}$$



- n = number of generationst = time (hour)
- GT = generation time (hour)

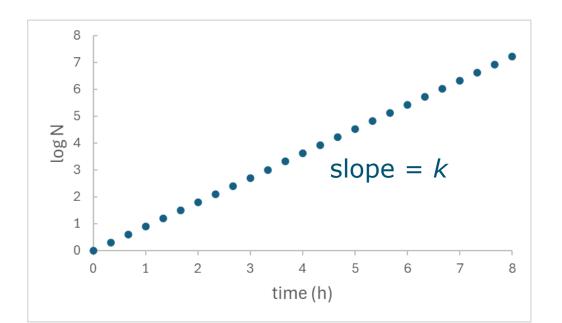
$$N_t = N_0 \cdot 2^n \rightarrow N_t = N_0 \cdot 2^{\frac{t}{GT}} \qquad \log N_t = \log(N_0 \cdot 2^{\frac{t}{GT}})$$



- *n* = number of generations
- *t* = time (hour)
- GT = generation time (hour)

$$N_t = N_0 \cdot 2^n \to N_t = N_0 \cdot 2^{\frac{t}{GT}} \qquad \log N_t = \log(N_0 \cdot 2^{\frac{t}{GT}})$$
$$\log N_t = \log N_0 + \log(2^{\frac{t}{GT}}) \to \log N_0 + \frac{t}{GT} \cdot \log(2) \to \log N_0 + \frac{\log(2)}{GT} \cdot t \to$$

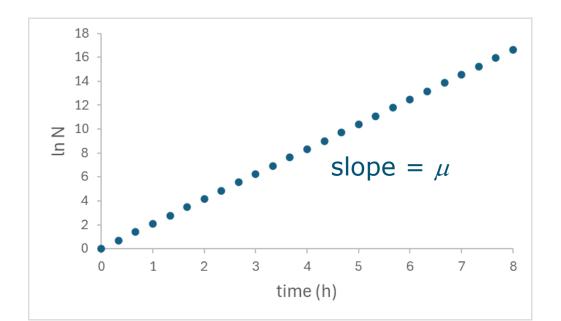
 $\log N_t = \log N_0 + k \cdot t$



- *n* = number of generations
- *t* = time (hour)
- GT = generation time (hour)
- $k = \text{growth rate on log-scale (log_{10}/h)}$

$$N_t = N_0 \cdot 2^n \to N_t = N_0 \cdot 2^{\frac{t}{GT}} \qquad \ln N_t = \ln(N_0 \cdot 2^{\frac{t}{GT}})$$
$$\ln N_t = \ln N_0 + \ln(2^{\frac{t}{GT}}) \to \ln N_0 + \frac{t}{GT} \cdot \ln(2) \to \ln N_0 + \frac{\ln(2)}{GT} \cdot t \to$$

 $\ln N_t = \ln N_0 + \mu \cdot t$



- *n* = number of generations
- *t* = time (hour)
- GT = generation time (hour)
- μ = growth rate on ln-scale (/h)
- $\mu = \ln(10) \cdot k$

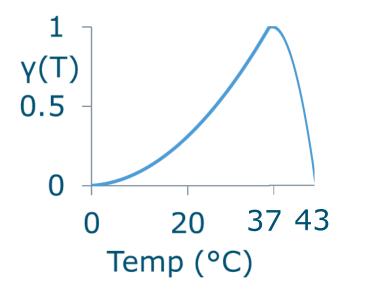
Prediction of μ using gamma model

Growth rate is affected by multiple factors (e.g., Temp, pH, HA, a_w) that act independently

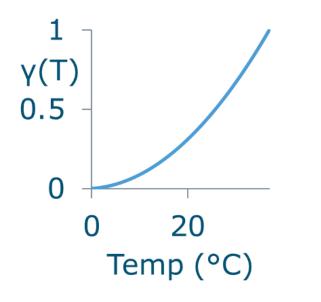
 $\mu = \mu_{opt} \cdot \gamma(T) \cdot \gamma(pH) \cdot \gamma(HA) \cdot \gamma(a_w)$

$$\gamma$$
(condition) = $\frac{\text{growth rate at actual condition}}{\text{growth rate at optimal condition}}$ γ [0-1]

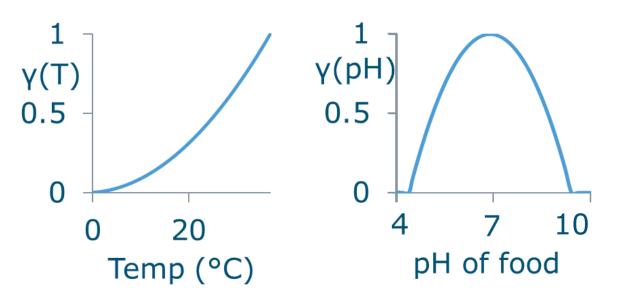




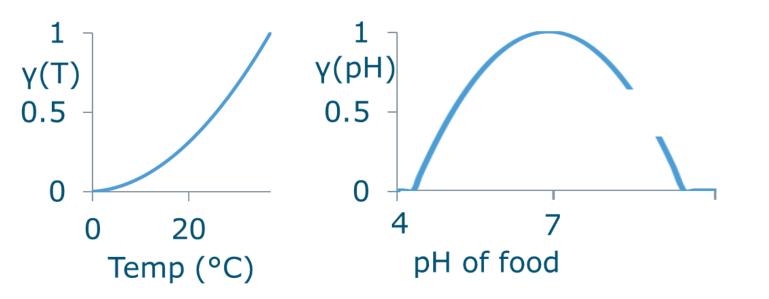




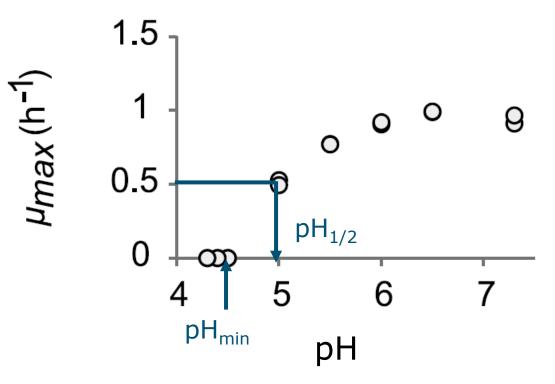








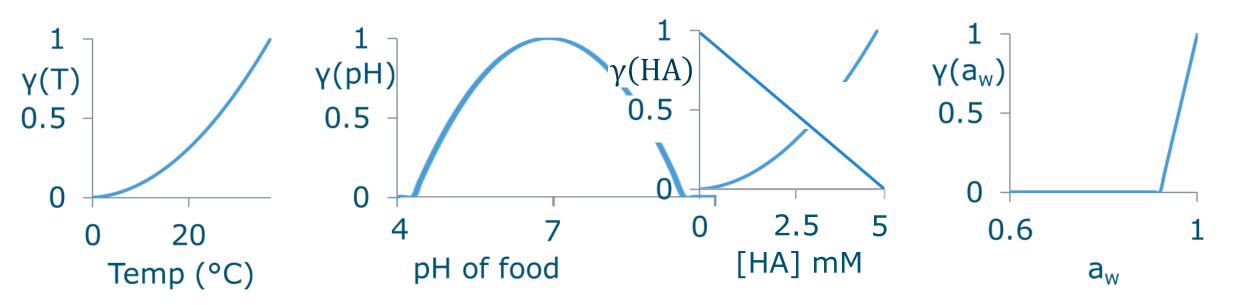




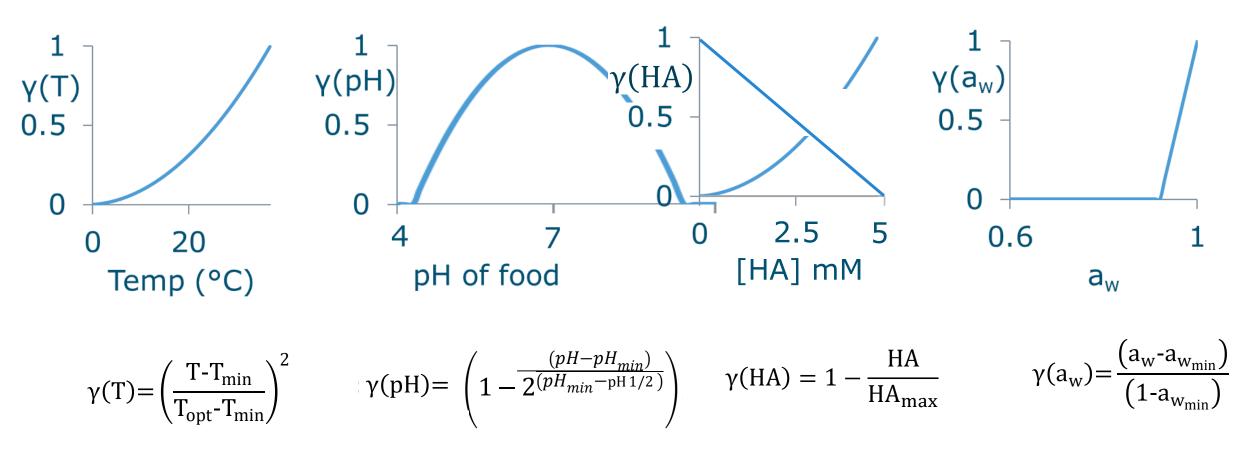
$$\mu_{\max} = \mu_{opt} \left(1 - 2^{\frac{(pH - pH_{\min})}{(pH_{\min} - pH_{1/2})}} \right)$$



Aryani et al., 2015

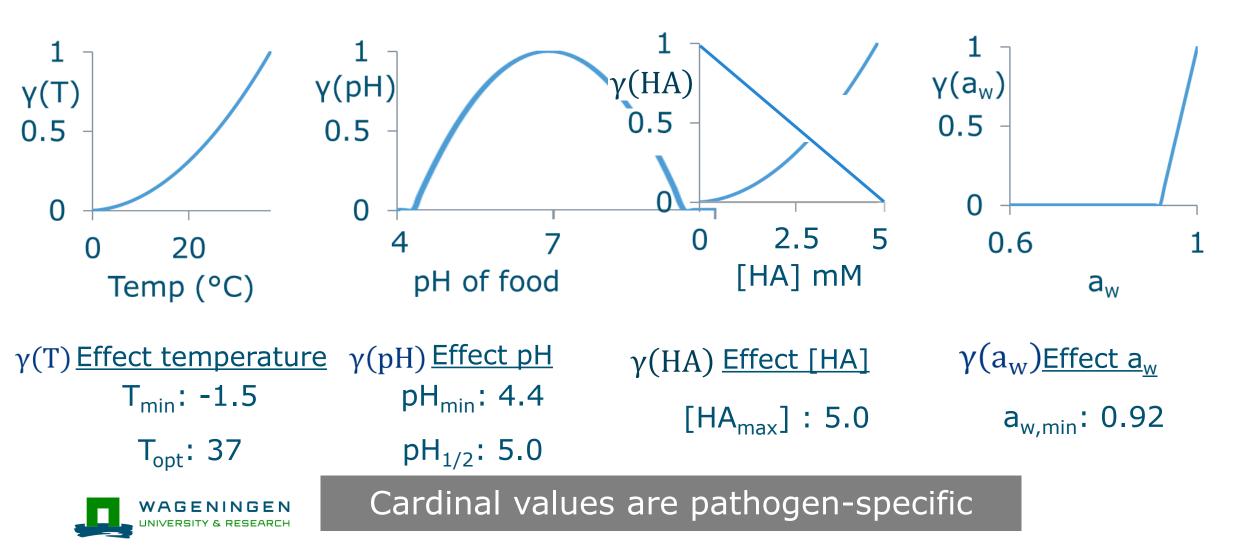






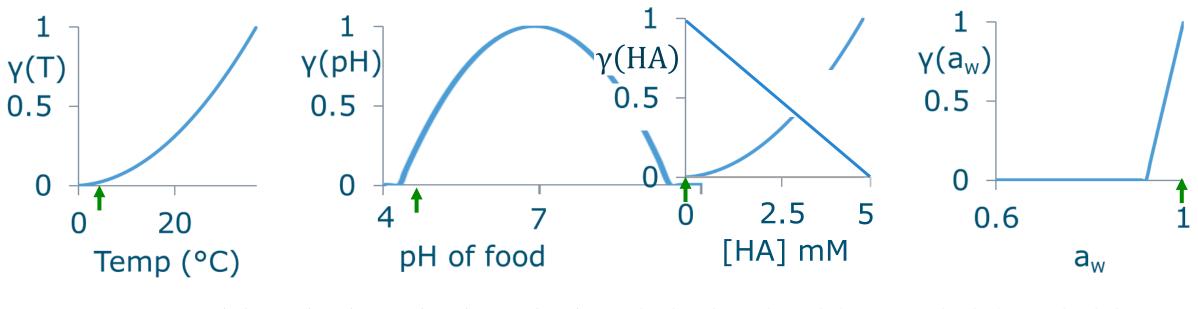


Cardinal parameters Listeria monocytogenes



Estimation of μ

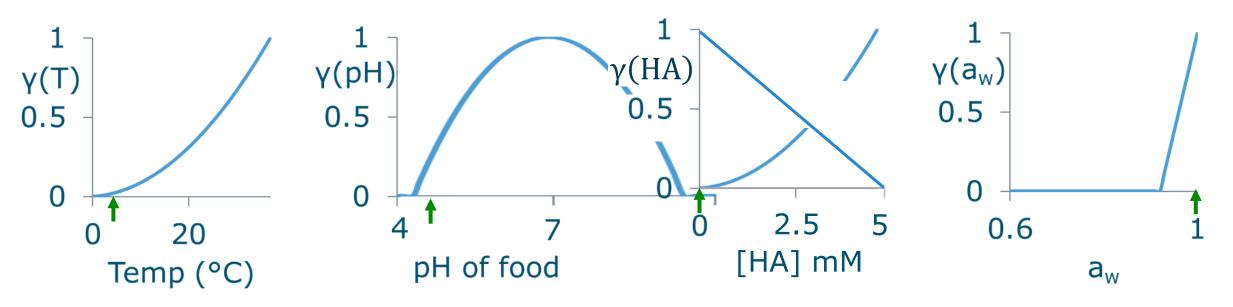
Vegetable product: T=7°C, pH=4.5, HA = 0 mM, a_w =0.997



$$\begin{split} \gamma_{tot} &= \gamma(T) \cdot \gamma(pH) \cdot \gamma (HA) \cdot \gamma(a_w) = 0.049 \cdot 0.109 \cdot 1 \cdot 0.96 = 0.005 \\ \mu &= \gamma_{tot} \cdot \mu_{opt} = 0.005 \cdot 1 = 0.005 \ h^{-1} \end{split}$$

Estimation of μ and ranking of effects

Vegetable product: T=7°C, pH=4.5, HA = 0 mM, a_w =0.997

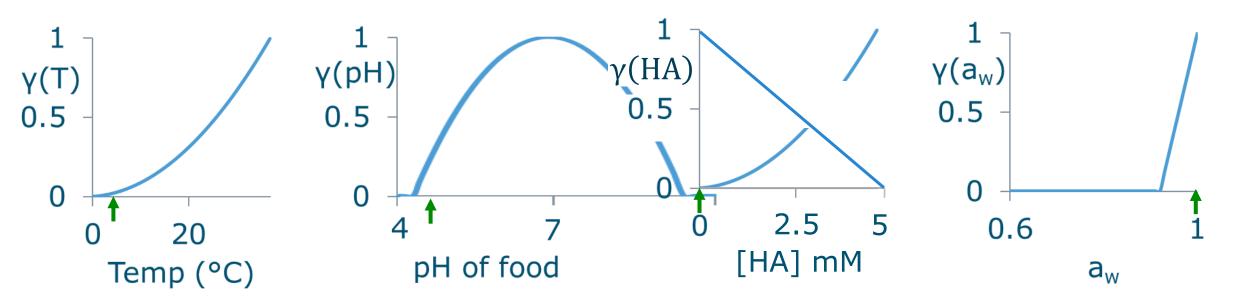


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reduction factors Temp: 20.5, pH: 9.2, HA: 1, a_w: 1.04

Estimation of μ and ranking of effects

Vegetable product: T=7°C, pH=4.5, HA = 0 mM, a_w =0.997



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reduction factors Temp: 20.5, pH: 9.2, HA: 1, a_w: 1.04 generation time = $\frac{\ln(2)}{\mu}$ = 135 h ≈ 5.6 days

Pro of gamma model

- Structured/transparent/simple
- Insight (gamma's: ranking, how to influence)
- Quantitative



Pro of gamma model

- Structured/transparent/simple
- Insight (gamma's: ranking, how to influence)
- Quantitative

But

All models are correct but they are not perfect









Development of an international standard on the determination and use of cardinal values for growth

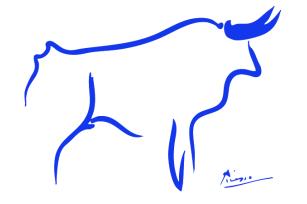
15/05/2025

Mariem Ellouze,

Group Food Microbiology Senior Manager

Why do we need standardization?





From data to mathematical models

From descriptive to predictive science

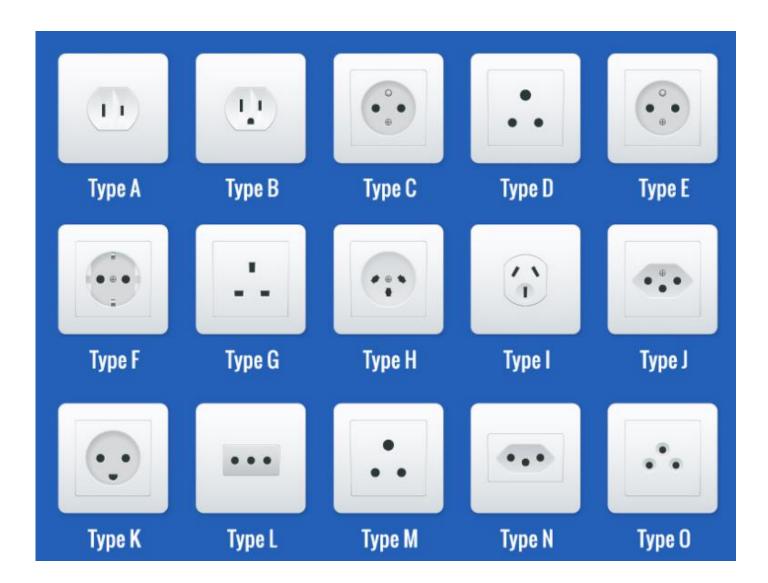
Model: Simplification from a certain point of view

What to omit is like an art.

- How you standardize the «wet» part is relatively easy
- How you standardize the «dry» part is less straightforward

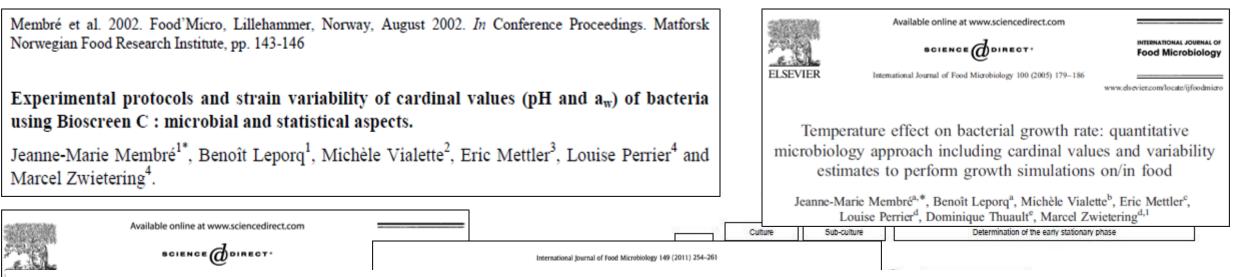
Why do we need standardization?





Why do we need standardization?





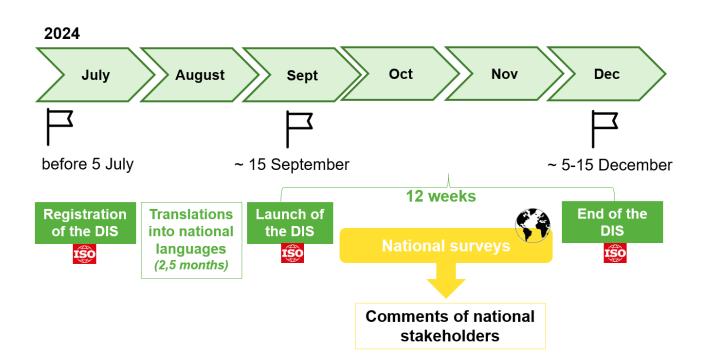
Abundant literature on the topic... but great differences!

- Possible methods for measurements : indirect (OD) vs direct (CFU) and others (conductivity)
- Conditions of experiments: static (fixed) conditions vs dynamic (fluctuating) conditions
- Models used: cardinal models vs square root model
- Raw data used: growth rates vs transformations of the growth rates (sqrt, ln)
- Experimental design: a single or several factors tested at a time

 \rightarrow All this has an influence on the result !! And on the use of predictive microbiology models for industrial applications. Need for harmonization.

A journey that strated in 2017

- Secretariat: Marine Huart, AFNOR, Convenior: Nicolas Nguyen Van Long, ADRIA, Project Lead: Mariem Ellouze, Ferrero
- Working Group:
- 1. Heidy M.W. den Besten, Wageningen University
- 2. Jeanne-Marie Membre, INRAE / ONIRIS
- 3. Yvan Le Marc, ADRIA
- 4. Panagiotis Skandamis, Agricultural Univerity of Athens
- 5. Rachel Binet, FDA
- 6. Valérie Stahl, AERIAL
- 7. Thiemo Albert, University of Leipzig
- 8. Vasilis Valdramidis, National and Kapodistrian University of Athens
- 9. Jurgen Chardon, RIVM
- 10. Aldo Evers, Normec Foodcare
- 11. Paul in't Veld, Netherlands Food and Consumer Product Safety Authority
- 12. Jiska Oostveen, FoodConsult
- 13. Ursula Gonzales Barron, CIMO, LA SusTEC, Instituto Politécnico de Bragança
- 14. Vasco Cadavez, CIMO, LA SusTEC, Instituto Politécnico de Bragança
- 15. Alberto Garre, Universidad Politécnica de Cartagena
- 16. Fabio Zuccon, Istituto Zooprofilattico Sperimentale del Piemonte
- 17. Ruben Barcia Cruz, ANSES
- 18. Nathalia Buss Da Silva, Nestlé Research





The standard



ISO/DIS 23691:2024(E)

ISO/TC 34/SC 9/WG 19

Secretariat: AFNOR

Date: 2025-xx-xx

Microbiology of the food chain — Determination and use of cardinal values

DIS stage

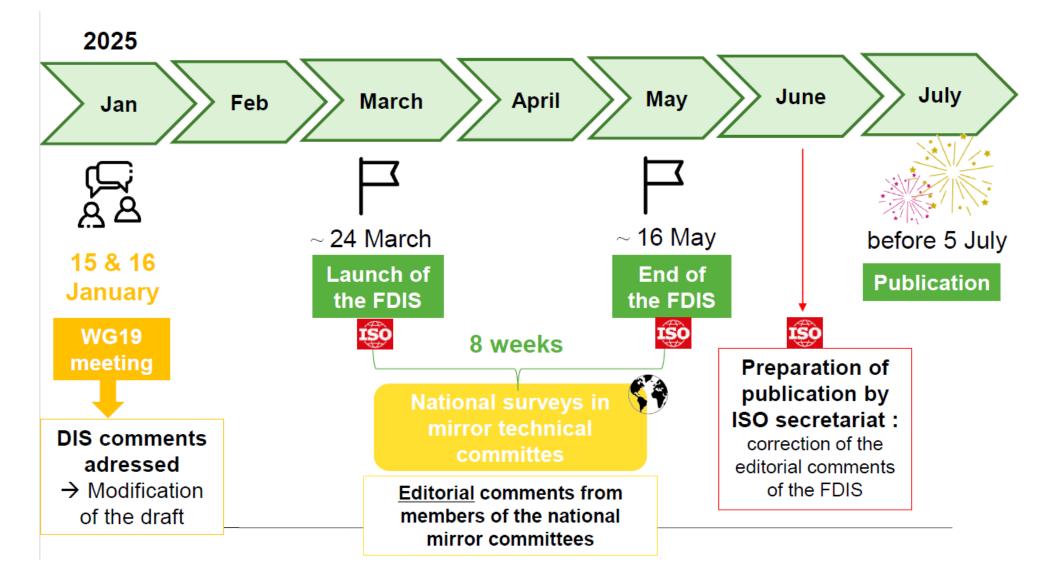
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The finishing line





User-friendly, freely available computer tool to predict microbial growth

Professor Panos N. Skandamis

Agricultural University of Athens, Greece

pskan@aua.gr



Predicting the troublemakers: Guidance and a computer tool to predict microbial growth, IAFP Webinar, 15 May 2025



Welcome to Growth Predictor

A predictive modelling and QMRA software based o gamma concept models

Developer: Prof. Panos N. Skandamis

Agricultural University of Athens,pskan@aua.gr

The tool is comprised of three modules: primary and secondary model fitting, growth simulations and QMRA.

Primary model fitting is carried out with the Baranyi model, acc. to the templates provided. Secondary model fitting involves the fitting of garman models with 1 to 6 explanatory variables, acc. to the templates provided. Growth simulations under static or dynamic conditions (relevant templates are provided. Lorowth simulations and expressions for each variables can be selected both for fitting and growth simulations one of the novel features is the use of normal distributions to describe the variability in T, pH, a., the levels of a single inhibitor and the interstrain variability in growth limits ($\mu_{gar} = \frac{1}{m_{gar}} \frac{1}{m_{gar}}$

The QMRA is comprised of 4 consecutive modules from primary production until consumption. In addition to prevalence, the modules may also consider partition, mixing and cross-contamination (i.e., changes in prevalence and levels). Variability can be introduced through a variety of probability distributions, for initial contamination, or re-contamination, storage time and temperature, product characteristics, serving size and maximum population density. Fixed or variable log reductions during cooking, may be introduced as user-defined values or probability distributions, respectively, or estimated by a Bigelow thermal inactivation model.

Variability in the cardinal values can be addressed in this module, too. Log change upwards (growth) or downwards (reduction) is described as a fixed value, or a normal distribution, or estimated with growth models. The *tilinear primary growth models* is used for estimating (got changes, based on μ_{mo} obtained by got gramma models. The QMRA outputs include graphical distribution of ingested by an another of the QMRA outputs include graphical distributions of the grade distributions of the second P_{ma} mode and the 5 and 95 percentiles of the corresponding distributions.

The user may select built-in **dose-response models**, e.g., for *Salmonella*, EHEC and *Listeria monocytogenes*, or use own models by defining the parameters values of exponential, beta-Poisson, beta-binomial and binomial dose-response models. Outputs can be downloaded in XL files.



Food Research International Available online 4 April 2025, 116329

In Press, Journal Pre-proof ⑦ What's this?



"Growth Predictor": A new predictive modelling and quantitative microbial risk assessment tool

Panagiotis N. Skandamis 🖾

GROWTH PREDICTOR

https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/

Growth Predictor

User-defined conditions

Imported 'e-Platon' file

🕑 Modular process Risk model

Estimation of cardinal values

Primary model fitting

Gamma models for the following terms:

T, pH, aw and up to 6 inhibitors

Available modules

- Fitting (primary/secondary)
- Stochastic growth simulations under
 - static/dynamic conditions
- Variability in:
 - Factors controlling microbial growth
 - Growth limits
 - Lag time (expressed as "ho"='the work to be done')
- QMRA with 4 consecutive modules

Fitting module Primary & Secondary models

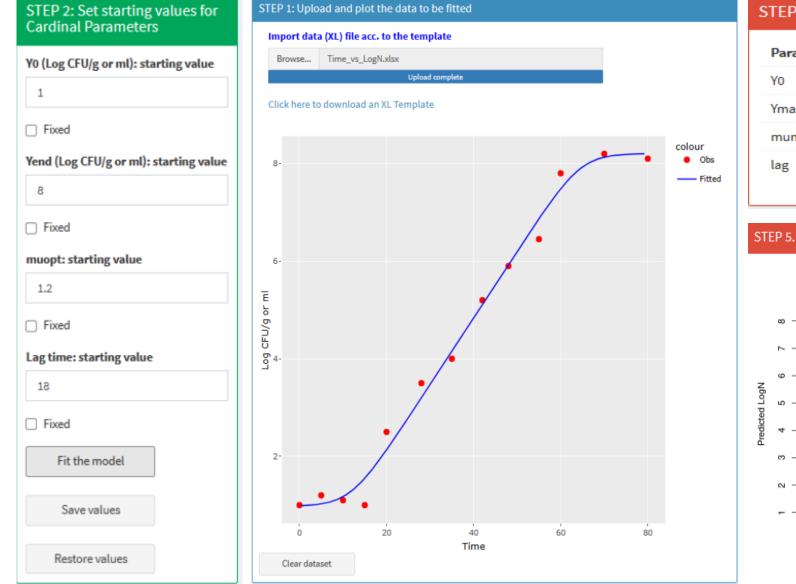
https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/

Predicting the troublemakers: Guidance and a computer tool to predict microbial growth, IAFP Webinar, 15 May 2025

Primary model fitting

$$\frac{dN}{dt} = \frac{q_t}{q_t + 1} \mu_{\max} \left(1 - \left(\frac{N_t}{N_{max}}\right)^m \right) N_t, \quad \text{where} \quad q_t = \frac{P_t}{K_p}$$

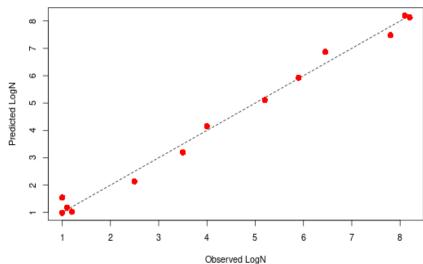
$$h_0 = ln\left(1 + \frac{1}{q_0}\right) = -ln(a_0) = \mu_{\max}$$



STEP 3. Assess the Parameter Estimates

Parameter	Estimate	Std_Error	Percent_Rel_Std_Error
Yo	2.276	0.4934	21.68
Ymax	18.893	0.5606	2.97
mumax	0.315	0.0197	6.26
lag	11.863	2.7659	23.32

STEP 5. View the Predicted vs Observed plot



Growth Predictor



User-defined conditions

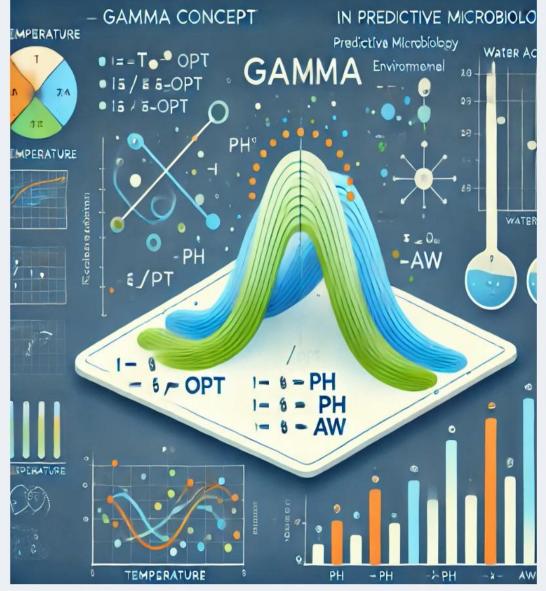
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Modular process Risk model

BESTIMATION OF CARDINAL VALUES

Primary model fitting

Click here for user guide files



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The tool is comprised of three modules: primary and secondary model fitting, growth simulations and QMRA.

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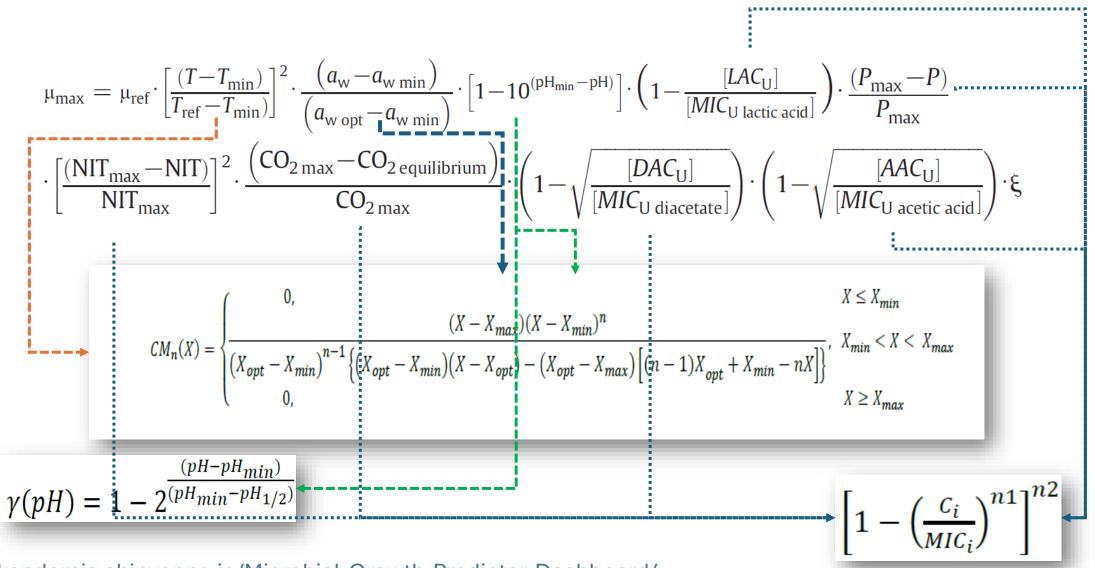
The QMRA is comprised of **4 consecutive modules** from primary production until <u>consumption</u>. In addition to prevalence, the modules may also consider partition, mixing and cross-contamination (i.e., changes in prevalence and levels). **Variability** can be introduced through *a variety of probability distributions*, for initial contamination, or re-contamination, storage time and temperature, product characteristics, serving size and maximum population density. Fixed or variable log reductions during cooking, may be introduced as user-defined values or probability distributions, respectively, or estimated by a Bigelow thermal inactivation model.

Variability in the cardinal values can be addressed in this module, too. **Log change upwards (growth)** or **downwards (reduction)** is described as a fixed value, or a normal distribution, or estimated with growth models. The *trilinear primary growth model* is used for estimating log changes, based on μ_{max} obtained by gamma models. The QMRA outputs include graphical distribution of ingested dose and probability of illness (P_{ill}), as well as tabular estimates of the average dose and P_{ill} mode and the 5 and 95 percentiles of the corresponding distributions.

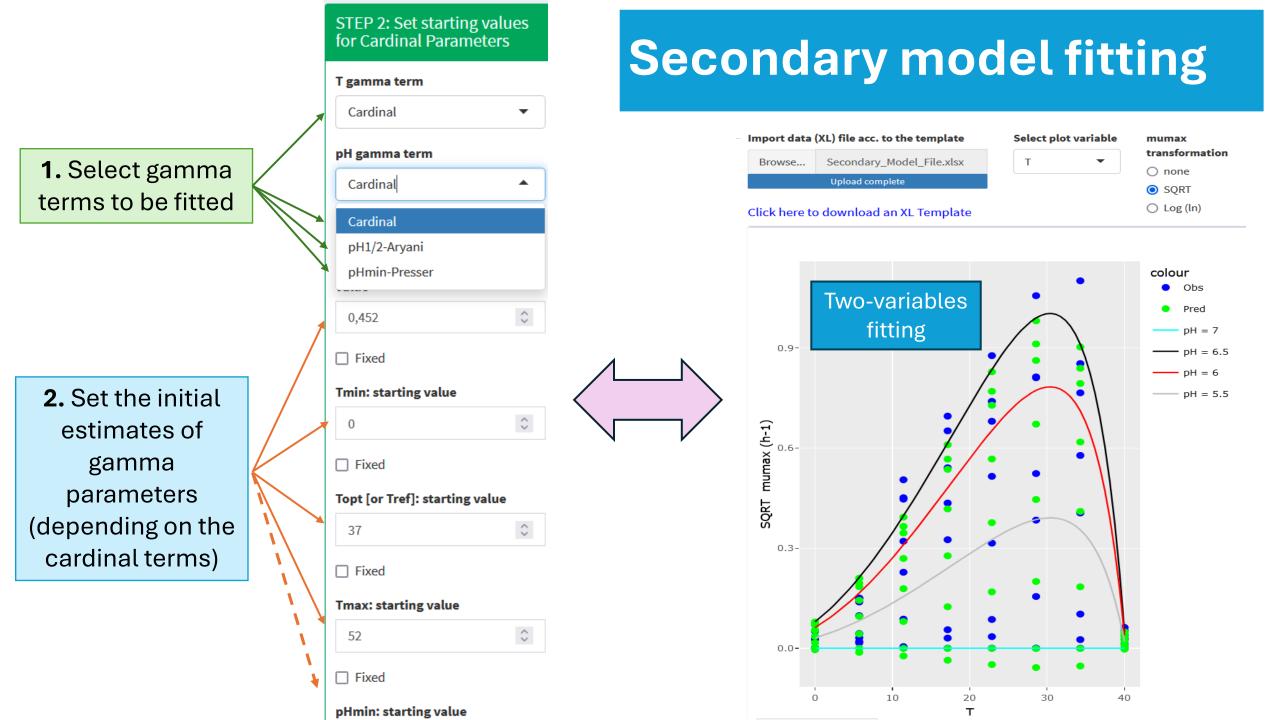
The user may select built-in **dose-response models**, e.g., for *Salmonella*, EHEC and *Listeria monocytogenes*, or use own models by defining the parameters values of exponential, beta-Poisson, beta-binomial and binomial dose-response models. Outputs can be downloaded in XL files.

Fitting Secondary (cardinal) models

Gamma terms



https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/



Fitting outputs

STEP 3. Assess the Parameter Estimates

Parameter	Estimate	Std_Error	Percent_Rel_Std_Error
SQRT mumax (h-1) or muref	1.00	0.02606	2.5966
Tmin	-8.64	1.91517	-22.1783
Topt	30.38	0.58475	1.9246
Tmax	40.16	0.12899	0.3212
pHmin	5.06	0.03118	0.6158
pHopt	6.51	0.03275	0.5029
pHmax	7.00	0.00477	0.0682

STEP 4. Assess the Goodness-of-Fit criteria

RMSE	R2	AIC	BIC
0.0649	0.956	-152.45	-135.17

Growth Predictor

About



https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/we082f2fef80945f28565e76616afa252/#shiny-tab-Intro

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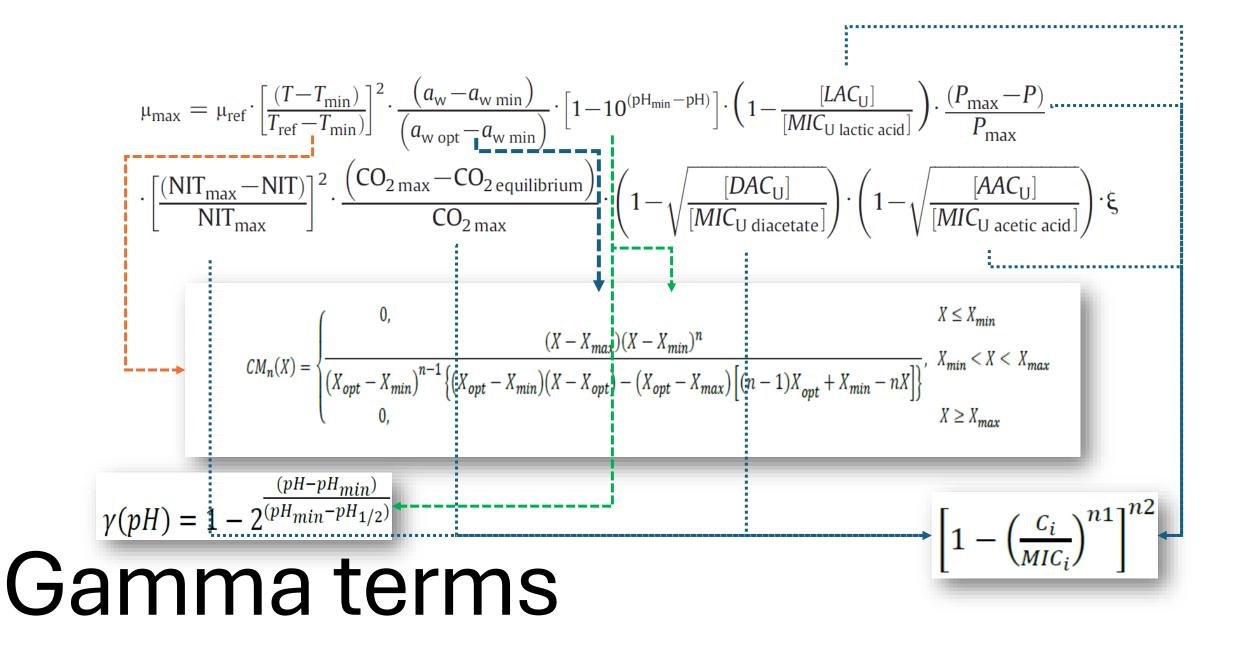
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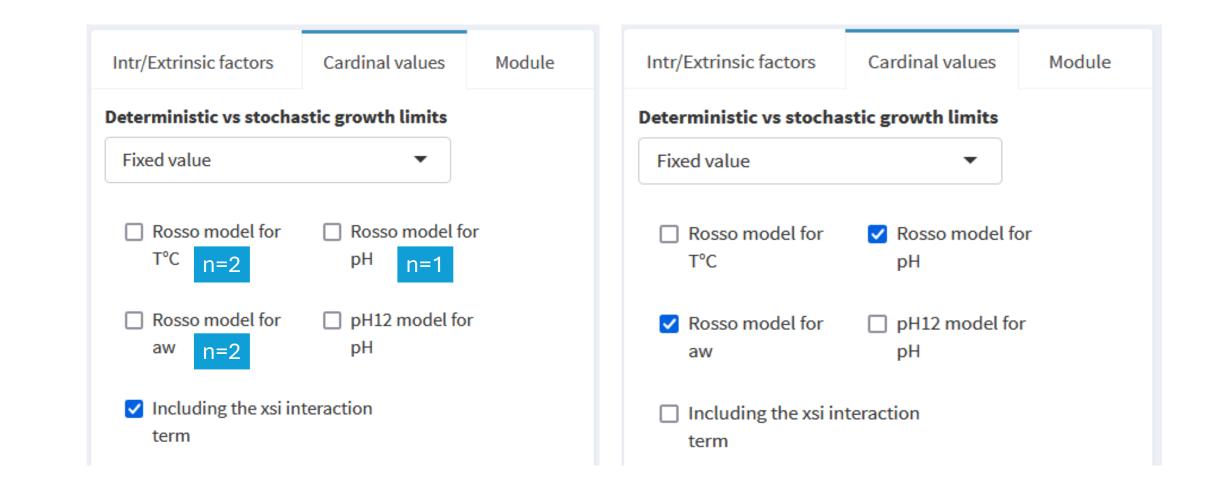
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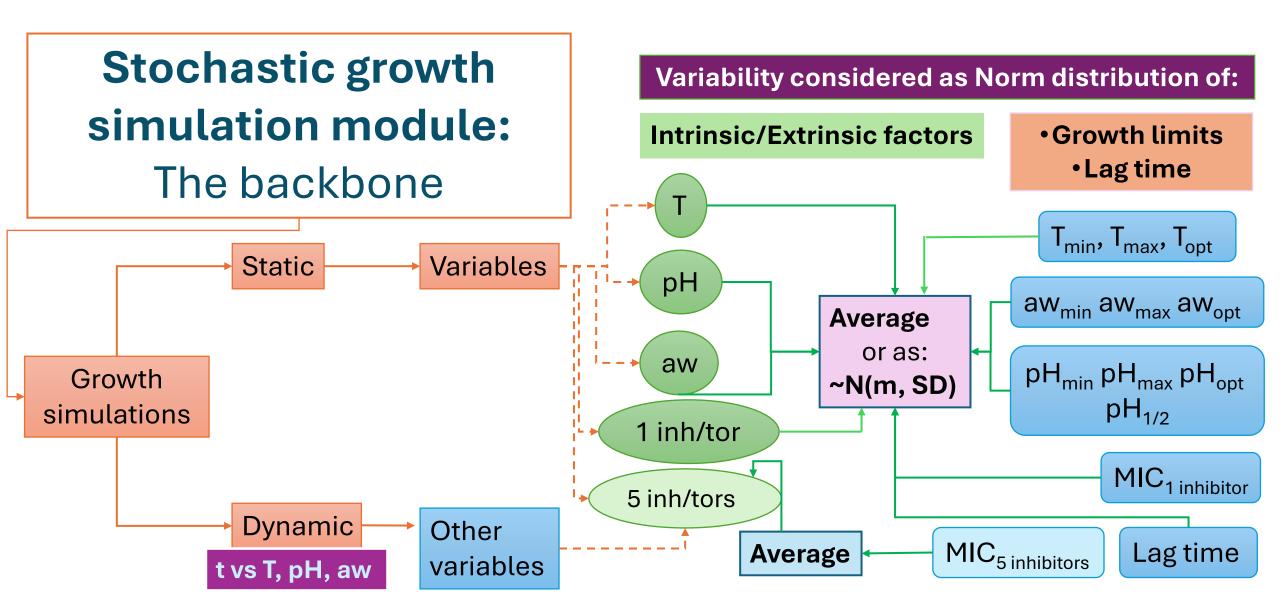
Growth simulation module





Selecting gamma terms

Applicable both for fitting & growth simulations



https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/

Defining cardinal values

You may calibrate the model to different foods or strains via this parameter

≥
σ
р Н

muref (or muopt) 1/h	
0,413	$\hat{\mathbf{v}}$
ſmin	
-0,92	$\hat{\mathbf{v}}$
Tref (or Topt)	
25	$\hat{}$

Tmax (when Rosso model is enabled)

48	\$
pHmin	
4,4	\Diamond
pHopt (when Rosso model is	enabled)
7	\$
pHmax (when Rosso model	is enabled)
8	\$
pH12 (when pH12 model is e	enabled)
5,1	\$
awmin	
0,915	$\hat{}$

nhibitors

0

 $\hat{}$

Intr/Extrinsic factors	Cardinal values	Module	Intr/Extrinsic factors	Cardinal values	Module
ppm or % of CO2, or C)2 in the product		MIC CO2, or O2		
0			Exp. 1 of CO2 or O2 term	Exp. 2 of CO2	or O2 term
			0.5	1	
Phenolics (ppm, mM,	%, or else)		MIC Phenolics		
0			20		
U			Exp. 1 of phenolics term	Exp. 2 of pher	iolics term
Lactate or citrate (pp	m, mM, %, or else)		MIC Lactate or Citrate		
			50000		
0			Exp. 1 of Lact/Citr. term	Exp. 2 of Lact	/Citr. term
Acatata au cituata (ana	m mH (k orolco)		1	1	
Acetate or citrate (pp	m, mm, %, or else)		MIC Acetate or Citrate		
0			Exp. 1 of Acet/Citr. term	Exp. 2 of Acet	/Citr. term
			0.5	1	,
Sorbate, benzoate, or	r diacetate (ppm, ml	M, %, or	MIC Sorbate, benzoate of	r diacetate	
else)			2500	\$;
			Exp. 1 of Sorb/benz/DA	Exp. 2 of Sorb	/benz/DA

awillax	

1

1

awopt or awref

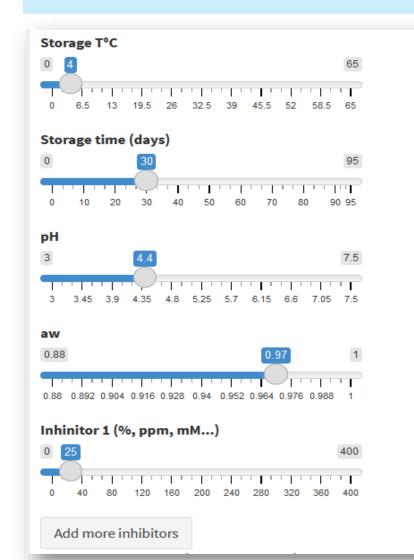
0.5
0.0

term

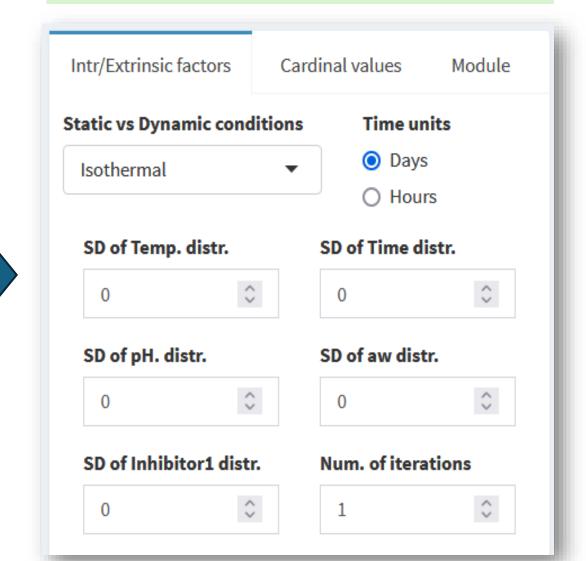
term

1

Use this panel to define the **mean value** (as point estimate) or as the mean value of the distribution



Use this panel to define the **SD** of each factor for use in the **normal distributions**



Use this panel to if you want to use ONLY the mean value of cardinal parameters

Intr/Extrinsic factors	Cardinal values	Module	
Deterministic vs stocha	stic growth limits		
Fixed value	-		
)	
Rosso model for T°C (n=2)	Rosso model for pH (n=1)	or	
 Rosso model for aw (n=2) 	pH12 model fo pH	r	
Including the xsi in	teraction term		
muref (or muopt) 1/h			
0.419			
Tmin			
-2.83			
Tref (or Topt)			
25			
Tmax (when Rosso mod	el is enabled)		
48			
pHmin			
4.97			
pHopt (when Rosso mod	del is enabled)		

pHmax (when Rosso model is enabled)

Use this panel to define the **SD** cardinal parameters following normal distributions

Intr/Extrinsic factors	Cardinal values	Module
Deterministic vs stocha	stic growth limits	
Normal dist.	•]
□ Rosso model for T°C (n=2)	Rosso model pH (n=1)	for
 Rosso model for aw (n=2) 	pH12 model f pH	or
Including the xsi in	teraction term	
Average muref(muop	ot) SD muref(n	nuopt)
0.419	0	
Average Tmin	SD Tmin	
-2.83	0.5	
Average Topt	SD Topt	
25	0	
Average Tmax (when Ro	osso model is enable	d)
48		
SD Tmax (when Rosso n	nodel is enabled)	

Average pHmin

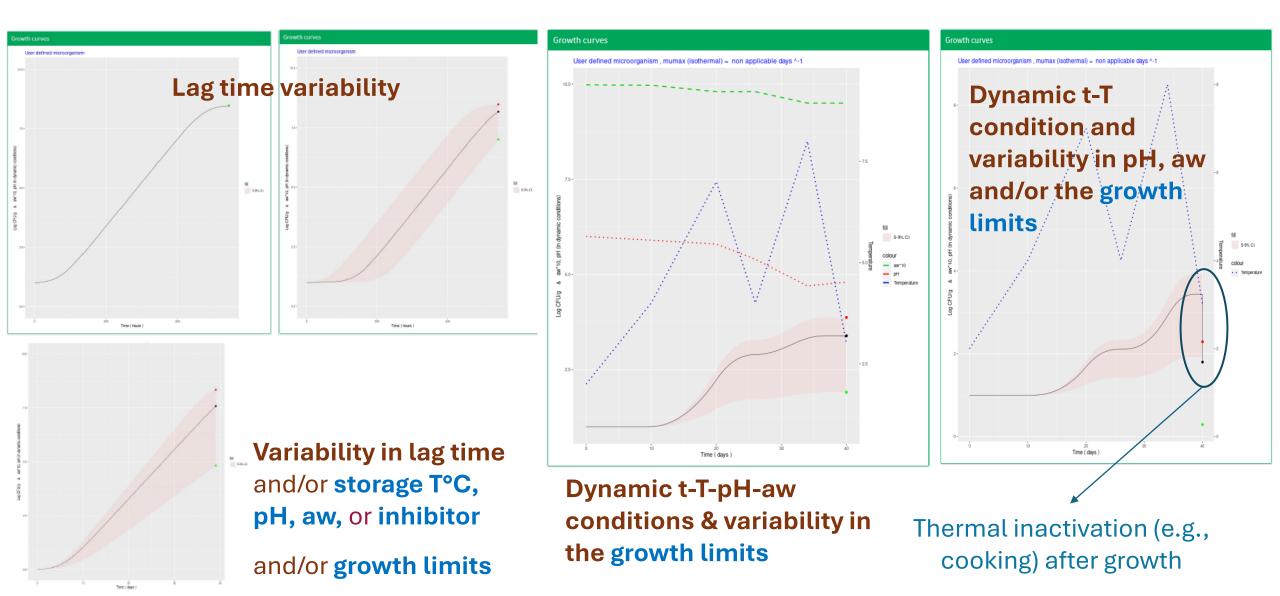
4.97

SD pHmin

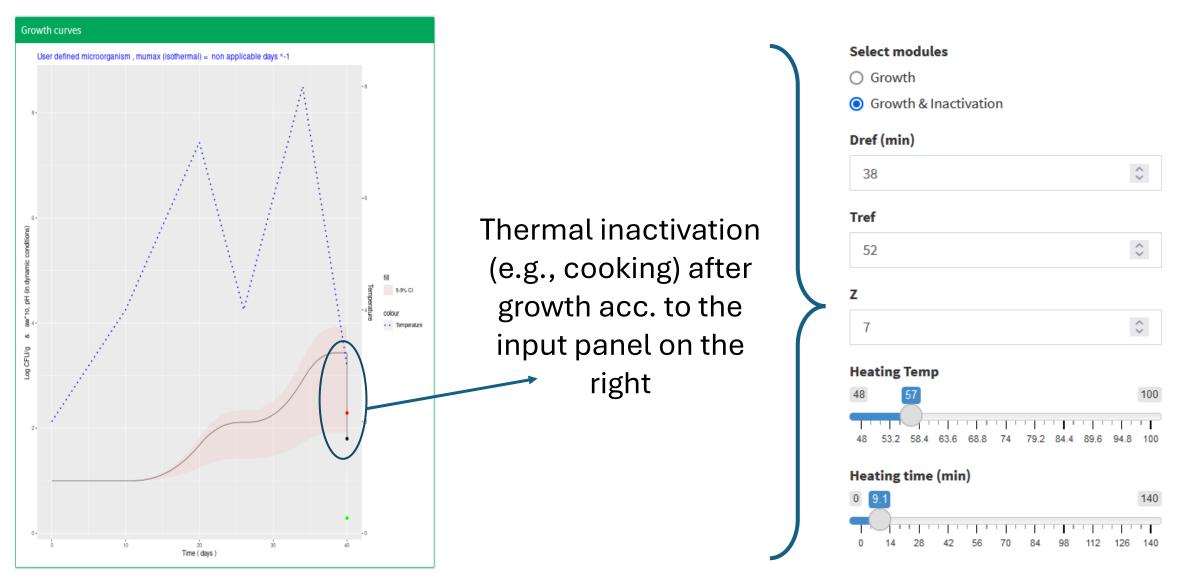
0

variability inter-strain Introducing

Representative graphical outputs (also capturing strain-to-strain variability



Digging further to thermal inactivation module



1. Simulations under **static** conditions, *deterministically* or *stochastically*

Predicting the troublemakers: Guidance and a computer tool to predict microbial growth, IAFP Webinar, 15 May 2025

Growth Predictor Prof. P.N. Skandamis, Agricultural University of Athens, Greece (pskan@aua.gr)



Welcome to Growth Predictor

A predictive modelling and QMRA software based on gamma concept models

Developer: Prof. Panos N. Skandamis

Agricultural University of Athens, pskan@aua.gr

WATER

AW

The tool is comprised of three modules: primary and secondary model fitting, growth simulations and QMRA.

Primary model fitting is carried out with the Baranyi model, acc. to the templates provided. Secondary model fitting involves the fitting of gamma models with 1 to 6 explanatory variables, acc. to the templates provided. Growth simulations under static or dynamic conditions (relevant templates are provided too) are based on gamma models with or without interactions. Alternative gamma expressions for each variables can be selected both for fitting and growth simulations. One of the novel features is the use of normal distributions to describe the variability in T, pH, aw the levels of a single inhibitor and the interstrain variability in growth limits (μ_{out} , T_{min} , pH_{min} , aw_{min} , MIC, etc.).

The QMRA is comprised of 4 consecutive modules from primary production until consumption. In addition to prevalence, the modules may also consider partition, mixing and cross-contamination (i.e., changes in prevalence and levels). Variability can be introduced through a variety of probability distributions, for initial contamination, or re-contamination, storage time and temperature, product characteristics, serving size and maximum population density. Fixed or variable log reductions during cooking, may be introduced as user-defined values or probability distributions, respectively, or estimated by a Bigelow thermal inactivation model.

Variability in the cardinal values can be addressed in this module, too. Log change upwards (growth) or downwards (reduction) is described as a fixed value, or a normal distribution, or estimated with growth models. The trilinear *primary growth model* is used for estimating log changes, based on μ_{max} obtained by gamma models. The QMRA outputs include graphical distribution of ingested dose and probability of illness (P_{ii}) , as well as tabular estimates of the average dose and P_{ijk} mode and the 5 and 95 percentiles of the corresponding distributions.

The user may select built-in dose-response models, e.g., for Salmonella, EHEC and Listeria monocytogenes, or use own models by defining the parameters values of exponential, beta-Poisson, beta-binomial and binomial dose-response models. Outputs can be downloaded in XL files.

2a.

Simulations under **dynamic** conditions, *deterministically* or *stochastically (STARTING FROM A TABLE)*

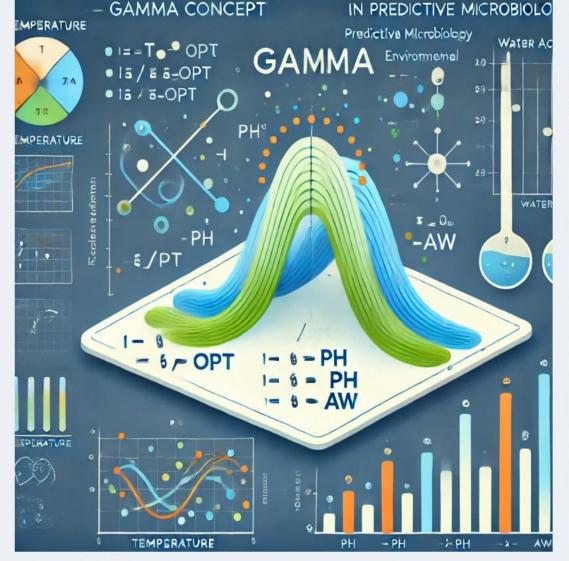
Growth Predictor = Prof. P.N. Skandamis, Agricultural University of Athens, Greece (pskan@aua.gr)



User-defined conditions
 Imported 'e-Platon' file
 Modular process Risk model
 Estimation of cardinal values

Primary model fitting

Click here for user guide files



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The QMRA is comprised of **4 consecutive modules** from primary production until <u>consumption</u>. In addition to prevalence, the modules may also consider partition, mixing and cross-contamination (i.e., changes in prevalence and levels). **Variability** can be introduced through *a variety of probability distributions*, for initial contamination, or re-contamination, storage time and temperature, product characteristics, serving size and maximum population density. Fixed or variable log reductions during cooking, may be introduced as user-defined values or probability distributions, respectively, or estimated by a Bigelow thermal inactivation model.

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The user may select built-in **dose-response models**, e.g., for *Salmonella*, EHEC and *Listeria monocytogenes*, or use own models by defining the parameters values of exponential, beta-Poisson, beta-binomial and binomial dose-response models. Outputs can be downloaded in XL files.

2b.

Simulations under dynamic conditions, deterministically or stochastically (STARTING FROM A FILE)

Growth Predictor Prof. P.N. Skandamis, Agricultural University of Athens, Greece (pskan@aua.gr)

About



Welcome to Growth Predictor

A predictive modelling and QMRA software based on gamma concept models

Developer: Prof. Panos N. Skandamis

Agricultural University of Athens, pskan@aua.gr

The tool is comprised of three modules: primary and secondary model fitting, growth simulations and QMRA.

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Growth/No Growth interface based on gamma concept

Growth Predictor

E Prof. P.N. Skandamis, Agricultural University of Athens, Greece (pskan@aua.gr)

🚯 About

User-defined conditions

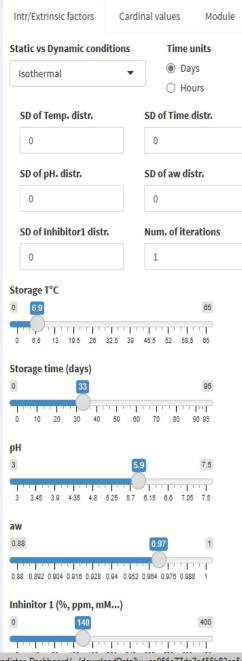
Imported 'e-Platon' file

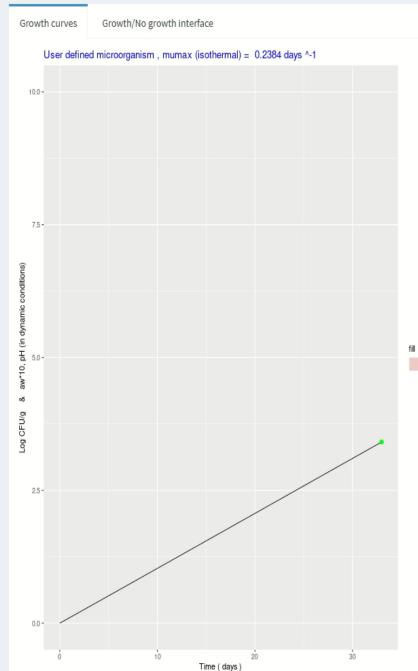
🚯 Modular process Risk model

Estimation of cardinal values

Primary model fitting

Click here for user guide files





Import/Export data Independent data Choose one of the following Download Model Outputs

Built-in dbase models

Microorganism	pHmin	pH12	Tmin	Tmax	awmin	awopt	awı
Salmonella	4.50	5.10	7.20	48.00	0.93	1.00	
STEC	4.50	5.50	9.20	48.00	0.94	1.00	
Bacillus cereus	4.30	5.90	10.30	55.00	0.95	1.00	

5-9% CI

timating time for certain log increase

Logincrease	From	То	Average
3	29.2 days	29.2 days	29.2 days

skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/.../downloadData?w=ea956e77de7e455b82ea54d22...

QMRA Module

Need

3

R

Agricultural University of Athens

Technology

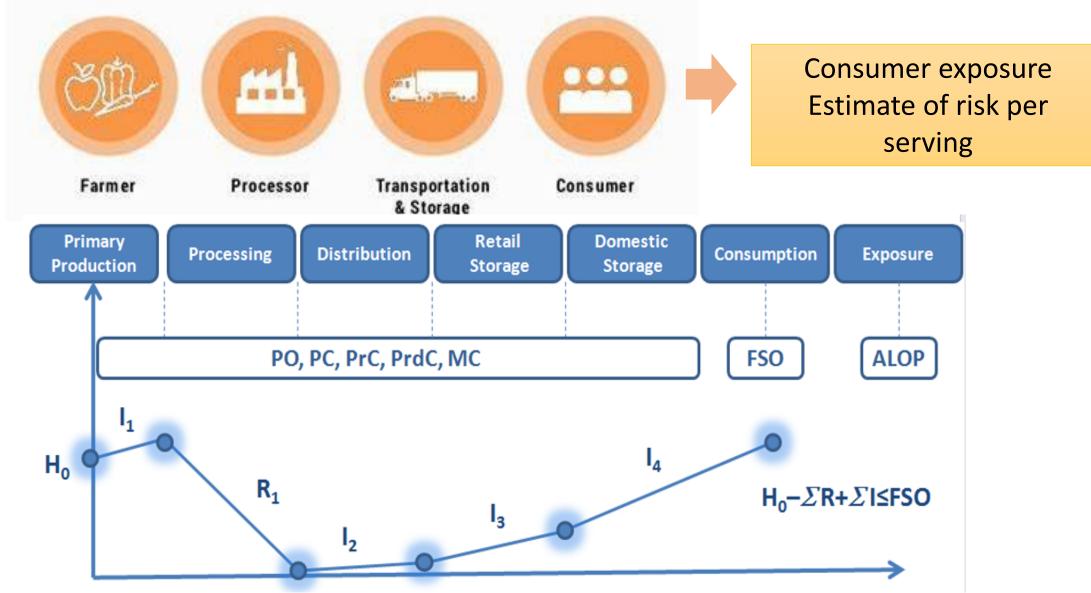
Department of Food Science

Concept-Design

Interactive tool

On-line demo

Modular process Quantitative Microbial Risk Assessment



Specific features



Partitioning (0-1)

Mixing (Initial + Added mass) Cross-contamination (P, levels)

Variability (Probability dist/tions)

- Initial contamination
- Time, T, ho, Cardinal values, Growth/reduction
- Serving size + uncertainty in prevalence (Beta distr.)

Partitioning

No partition

O Partition

Mixing

Initial mass (g: 0-infinity)

Added mass (g: 0-infinity)

L

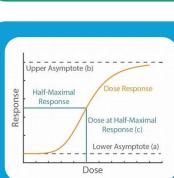
P cross-contamination (0-1)

0			

Cross- (re-)contamination levels

|--|





Dose response

- Built-in (literature) DR models
- User-defined models
- Beta-Poisson, (Beta-)Binomial, Exponential

Need

Agricultural University of Athens

Technology

of Food Science

Department

Concept-Design

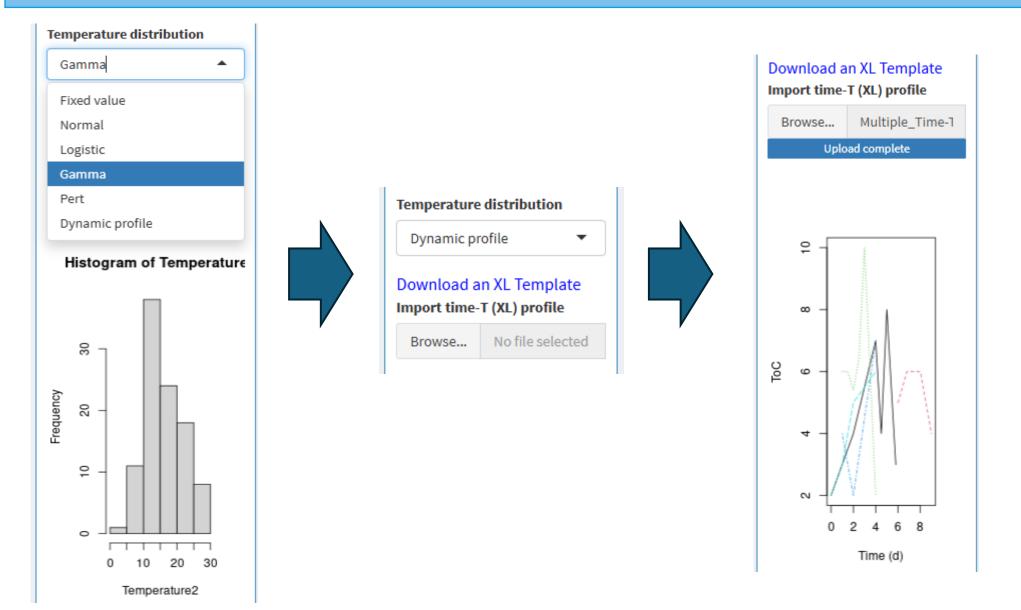
Interactive tool

On-line demo

Modular process Quantitative Microbial Risk Assessment



Integrating time-T profiles in QMRA for 3 modules



Exposure & Illness metrics

Annual number of services

1

Risk

outputs

Risk Table

÷

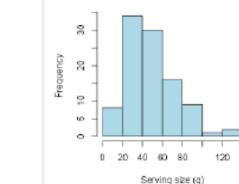
Exposure_Metrics	LogCFU_per_g_OR_ml	Ilness_Metrics	Estimate
Average Dose per serving	5.7	Average Pill per serving	6.036e-07
-	-	Cases per annum	6.036e-07
Mode	5.5	Mode	3.162e-07
р5	4.6	p5	4.972e-08
p50	5.62	p50	5.233e-07
p95	6.89	p95	9.611e-06
	Select Mode	Iteration	s

Select Mode

Serving size (g) Serving Size Distr/tion



Histogram of Serving

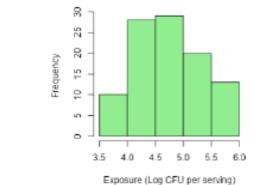




100

alpha of gamma dist.

beta of gamma dist.



Select plot Iterations Probability of illness 1000 . Serving size (g) Serving Size Distr/tion alpha of gamma dist. beta of gamma dist. 61 12 Gamma -4 Initial Prevalence (0-1) Dose response L. monocytogenes susceptible 0 * FDA, 2014 Click to render Plot or resample Histogram of P_of_illness P lness 8 Frequency 8 8 -12 -10 -7 -11 -0 -8 -6 Log10 Probability of illness **A** Download FULL MODEL

Growth Predictor

E Prof. P.N. Skandamis, Agricultural University of Athens, Greece (pskan@aua.gr)

About

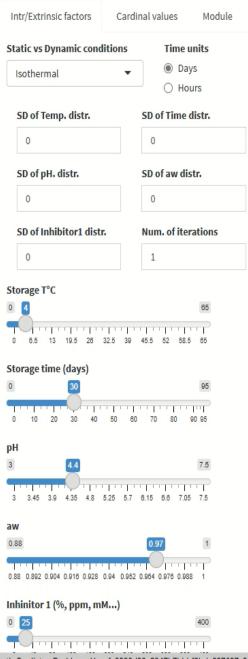
⑦ User-deftund conditions
 Ⅲ Imported 'e-Platon' file

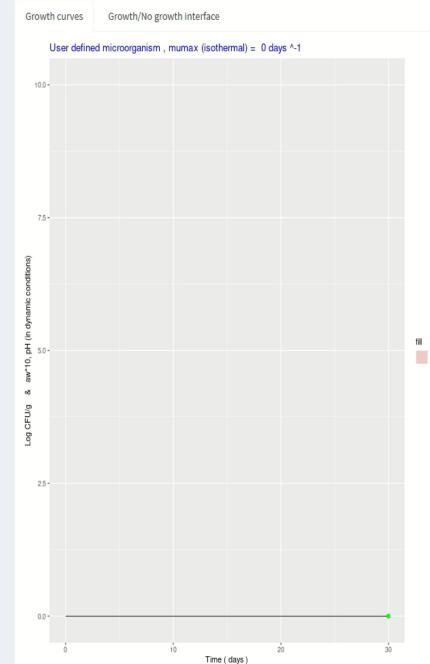
🚯 Modular process Risk model

Estimation of cardinal values

Primary model fitting

Click here for user guide files





Import/Export data	
Independent data	
Choose one of the following	•
🛓 Download Model Outputs	

Built-in dbase models

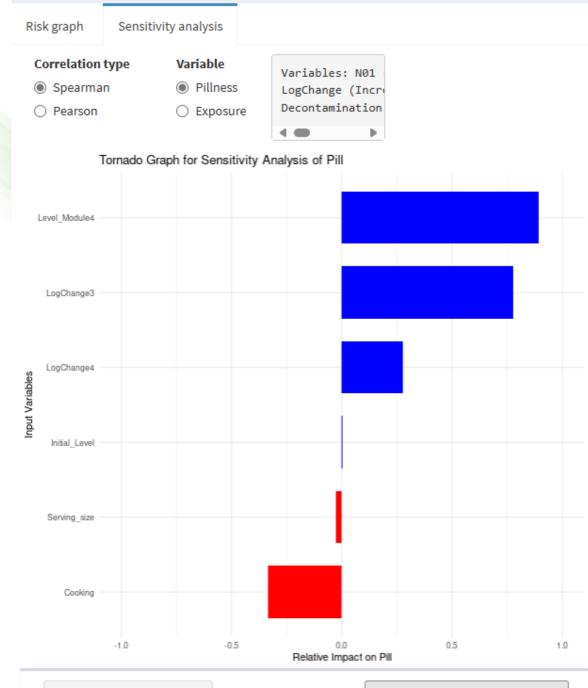
Microorganism	pHmin	pH12	Tmin	Tmax	awmin	awopt	aw
Salmonella	4.50	5.10	7.20	48.00	0.93	1.00	
STEC	4.50	5.50	9.20	48.00	0.94	1.00	
Bacillus cereus	4.30	5.90	10.30	55.00	0.95	1.00	

5-9% Cl

timating time for certain log increase

Log increase	From	То	Average
0	> 30 days	> 30 days	> 30 days

https://skandamis.shinyapps.io/Microbial-Growth-Predictor-Dashboard/_w_fe2528d33a9347b7bbbf0bda897697a5/#...



Sensitivity analysis

🛓 Download FULL MODEL

Click to render Plots or resample

Thank you!

Professor Panos N. Skandamis

Agricultural University of Athens, Greece

pskan@aua.g



1. Load	Training	Dataset	
---------	----------	---------	--

No file selected

Download an XL Template

Specify the number of variables

19

Browse ...

Independent variable type

Continuous (ANN,SVM,PLSR)

Categorical (PLS-DA)

Actions for fitting (pre-processing)

Log10 transformation of dependent variable

Savitzky-Golay smoothing

SNV transf/tion to independent (predictor) variables

(Auto)-scaling of independent variables for fitting

Actions for PCA

Apply autoscaling for PCA

Apply rangescaling for PCA

Machine learning algorithm

Artificial Neural Networks (1 hidden layer)

O Random Forest Regression

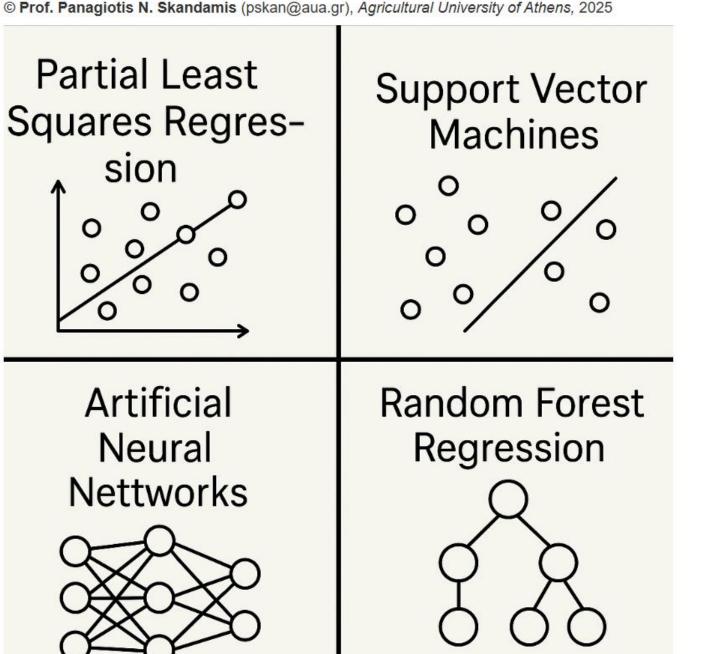
Supporting Vector Machines (Linear)

Supporting Vector Machines (Non Linear)

Partial Least Square Regression

Bootstrapping for CI estimation of PLSR coefficients

0



Training Graphs

PCA

About

Need

Concept-Design

Interactive tool



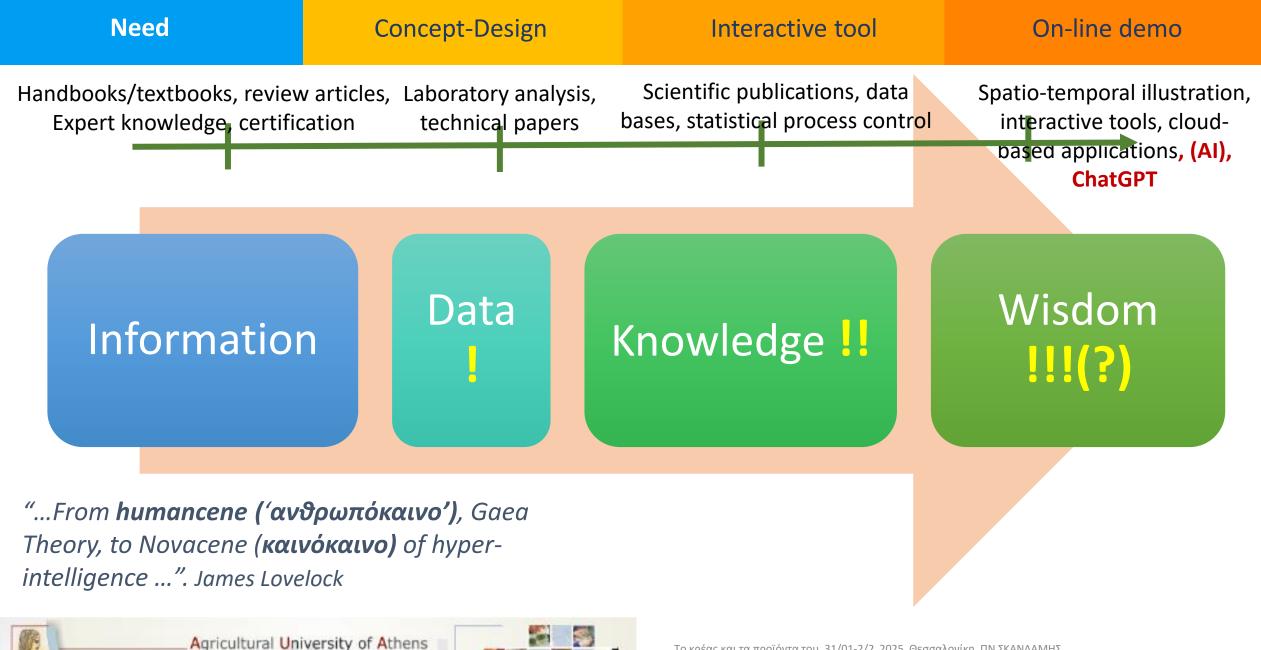
International Journal of Food Microbiology 141 (2010) 137-150



Predicting growth rates and growth boundary of *Listeria monocytogenes* – An international validation study with focus on processed and ready-to-eat meat and seafood

Ole Mejlholm^a, Annemarie Gunvig^b, Claus Borggaard^b, Jesper Blom-Hanssen^b, Lyndal Mellefont^c, Tom Ross^c, Francoise Leroi^d, Tony Else^e, Diana Visser^e, Paw Dalgaard^{a,*}

$$\mu_{\max} = \mu_{ref} \cdot \left[\frac{(T - T_{\min})}{T_{ref} - T_{\min}} \right]^{2} \cdot \frac{\left(a_{w} - a_{w\min} \right)}{\left(a_{wopt} - a_{w\min} \right)} \cdot \left[1 - 10^{(pH_{\min} - pH)} \right] \cdot \left(1 - \frac{[LAC_{U}]}{[MIC_{U \ lactic \ acid}]} \right) \cdot \frac{(P_{\max} - P)}{P_{\max}}$$
$$\cdot \left[\frac{(NIT_{\max} - NIT)}{NIT_{\max}} \right]^{2} \cdot \frac{\left(CO_{2 \ max} - CO_{2 \ equilibrium} \right)}{CO_{2 \ max}} \cdot \left(1 - \sqrt{\frac{[DAC_{U}]}{[MIC_{U \ diacetate}]}} \right) \cdot \left(1 - \sqrt{\frac{[AAC_{U}]}{[MIC_{U \ acetic \ acid}]}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U}]}{[MIC_{U \ acetic \ acid}]}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid}]}{[MIC_{U \ acetic \ acid}]}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid}]}{[MIC_{U \ acetic \ acid}]}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid}]}{[MIC_{U \ acetic \ acid}]}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid}]}{[MIC_{U \ acetic \ acid}]}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid}]}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}} \right) \cdot \left(1 - \sqrt{\frac{[MIC_{U \ acetic \ acid]}}{[MIC_{U \ acetic \ acid]}}} \right)$$



Department of Food Science _____ Technology

Το κρέας και τα προϊόντα του, 31/01-2/2. 2025, Θεσσαλονίκη, ΠΝ ΣΚΑΝΔΑΜΗΣ

Roadmap of quantitative microbiology

Botulinum cook Software Fair sessions: HACCP **Predictive CPMF** (Paris, Rio de Janeiro, Braganca): 2011, 2015, 2019 Risk analysis Variability and FoodMicro (Berlin): uncertainty 2018 Single cell level IAFP (Tampa, Louisville): 2017, 2019 **Omics**-**Bioinformatics**

Software apps



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June 3, 2025 Sanitation Break: Legal Interpretation and Industry Practice

June 3, 2025 Risk-Based Approaches to Sanitation in Dry Processing Environments

June 5, 2025 Hygienic Design & Monitoring Strategies to Prevent In-Process Contamination in Food and Beverage Applications

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