International Association for FOOD Protection_® WEBINAR

PRACTICAL APPLICATIONS OF MICROBIAL MODELING -WEBINAR SERIES

November 29, 2017

10:00 a.m. EST

Practical Applications of Microbial Modeling Webinar Series

Webinar Series:

Part I of

 This IAFP webinar is sponsored by the following Professional Development Groups:

Microbial Modelling and Risk AnalysisMeat and Poultry Safety and Quality



Practical Applications of Microbial Modeling

Webinar Series: Part I of III



Dr. Betsy Booren



Senior Policy Advisor Olsson, Frank, Weeda, Terman, and Matz PC Washington, DC



WEBINAR HOUSEKEEPING

For best viewing of the presentation material, please click on 'maximize' in the upper right corner of the 'Slide' window, then 'restore' to return to normal view.

Audio is being transmitted over the computer so please have your speakers 'on' and volume turned up in order to hear. A telephone connection is not available.

Questions should be submitted to the presenters during the presentation via the **Q & A section** at the right of the screen



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

This webinar is being recorded and will be available for access by IAFP members at <u>www.foodprotection.org</u> within one week.



- Introduction
 - Dr. Betsy Booren
- Overview of Predictive Microbial Modeling
 Dr. Tom Ross
- Tertiary Models for Estimation of Microbial Behavior in Real Situations – Meat Products
 Dr. Peter Taormina
- Questions and Answers

Dr. Tom Ross

Director ARC Industrial Transformations Training Centre for Innovative Horticultural Products University of Tasmania Tasmania, Australia



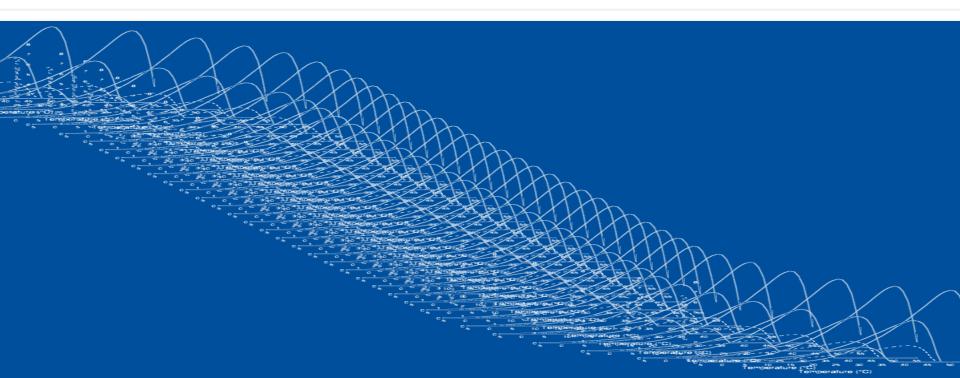
Dr. Peter Taormina



President Etna Consulting Group Cincinnati, OH

Overview of Predictive Microbial Modeling

Assoc Prof Tom Ross



Predictive Microbiology

□ The *quantitative* microbial ecology of foods

Overview

- Basic concept of predictive microbiology
- Basic mathematical ideas
- □ Kinds of microbial responses that can be predicted
- Current status of predictive microbiology
- Building models
- How can predictive microbiology models help the food industry
- Critically assessing model applicability and reliability

Predictive Microbiology – basic ideas

- microorganisms react reproducibly to environ conditions
 - the fundamental premise is that *microorganis think*, so that they behave reproducibly (or "predictably") in ways dictated by their environment. thus
 - if we can measure their environment, we can predict what they will do, and how quickly they will do it.

do you all believe this?

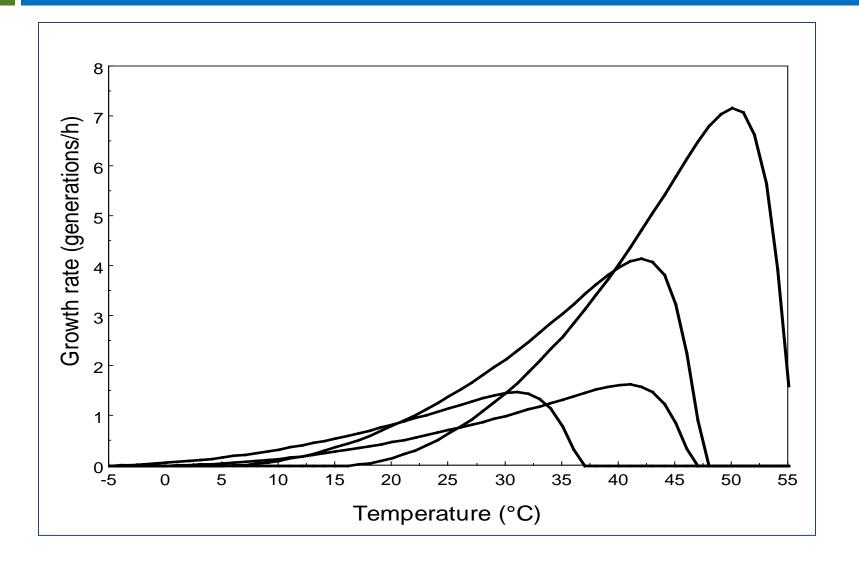
Modern Predictive Microbiology

"the growth responses of the microbes of concern would be modelled with respect to the main controlling factors such as temperature, pH and a_w ...

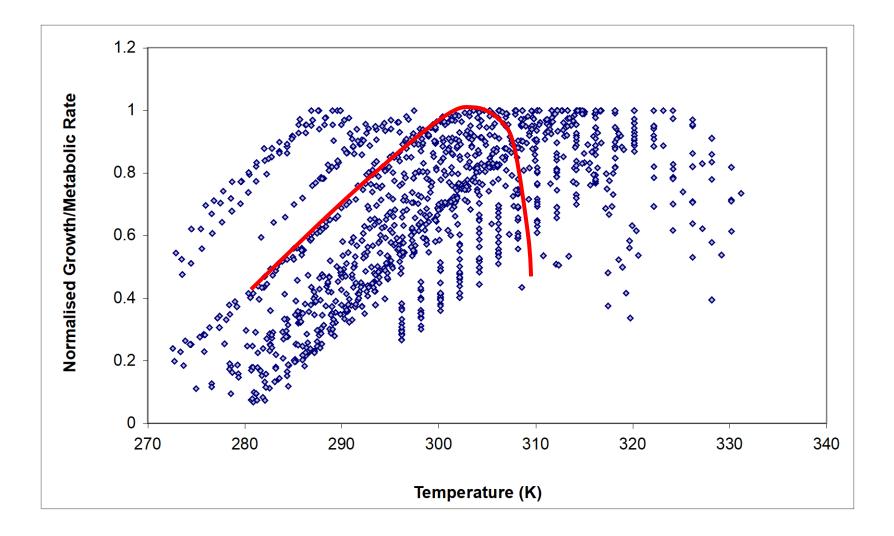
... Models relevant to broad categories of foods would greatly reduce the need for ad hoc microbiological examination and enable predictions of quality and safety to be made speedily with considerable financial benefit."

Roberts and Jarvis (1983; Food Microbiology: Advances and Prospects, Academic Press, New York, NY)

Consistent patterns of response: the temperature-growth rate relationship



Universality of the temperature-growth rate relationship



Predictive Microbiology - concepts

- there is a small number of environmental factors of main importance, namely:
 - temperature
 - □ pH
 - water activity
- for some foods this works, for processed foods its probably an oversimplification, so

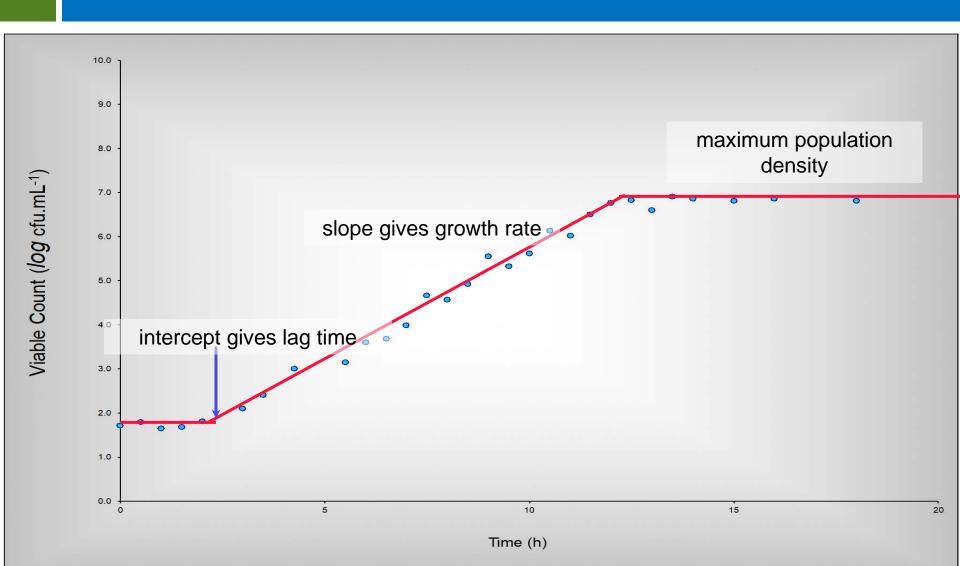
increasingly, as we adopt 'hurdle technology', other factors need to be considered explicitly: e.g., organic acid type and level, nitrite, gaseous atmosphere, smoke compounds, other microbes in the food, etc.

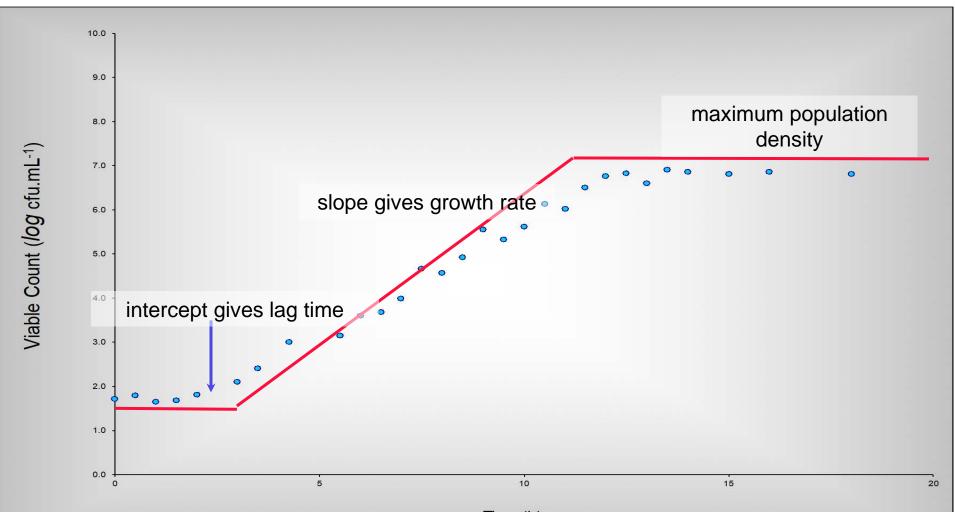
Predictive Microbiology - concepts

main controlling factors - *microbial death*

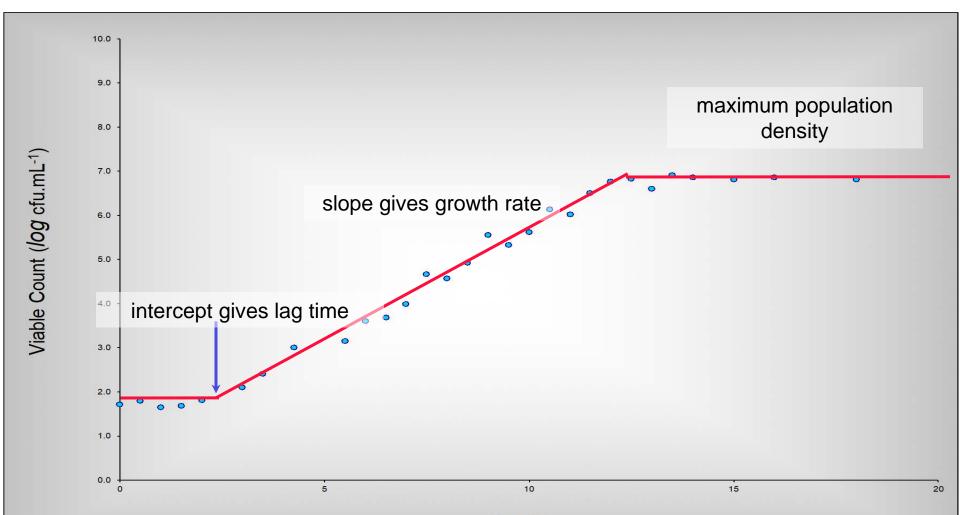
- its also assumed that *death rate* is affected by physicochemical conditions in the food, but normally death rate is most strongly governed by the treatment, *e.g.:*
- temperature
- pressure
- □ *irradiation (UV, gamma etc.)*
- electric field strength

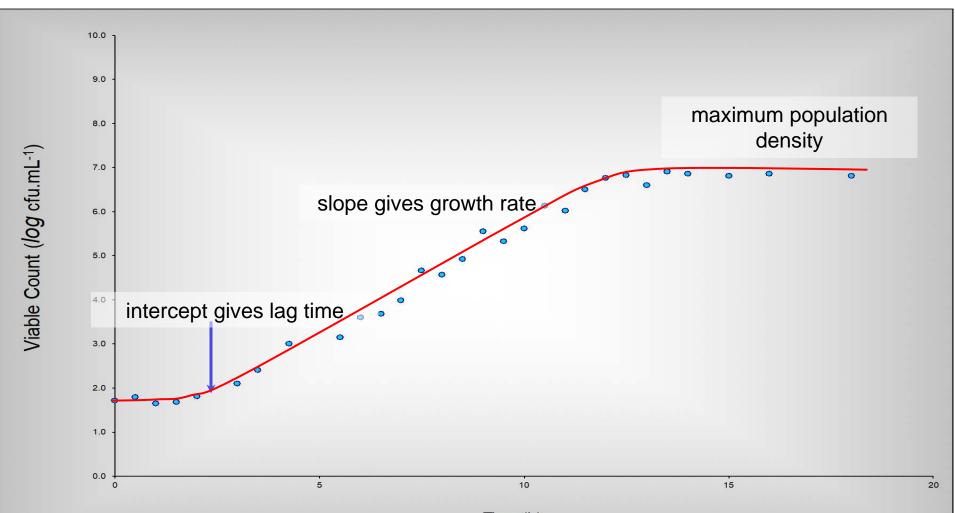
Basic mathematical ideas





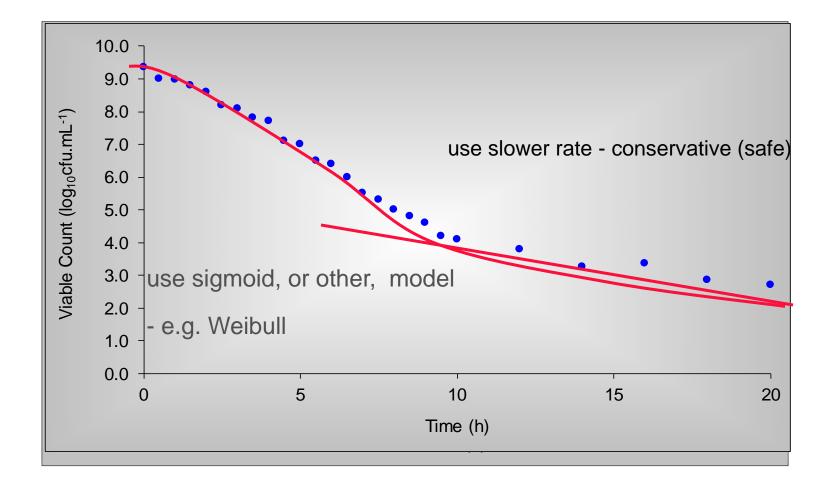
Time (h)





Time (h)

Inactivation modelling



Thermal inactivation kinetics: summary

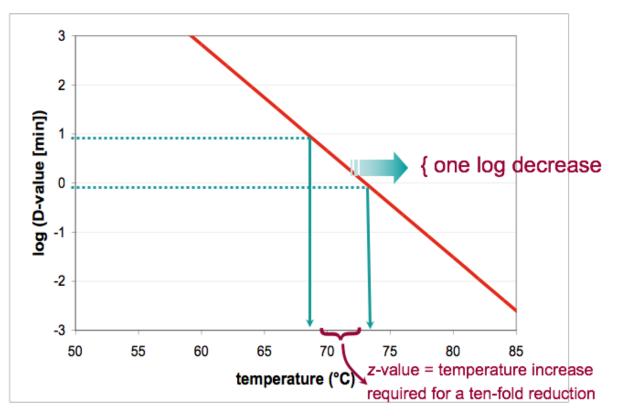
D-value

time required at given temperature to reduce microbial load by a facto of of 10

z-value

temperature increase required to reduce Dvalue by a factor of 10

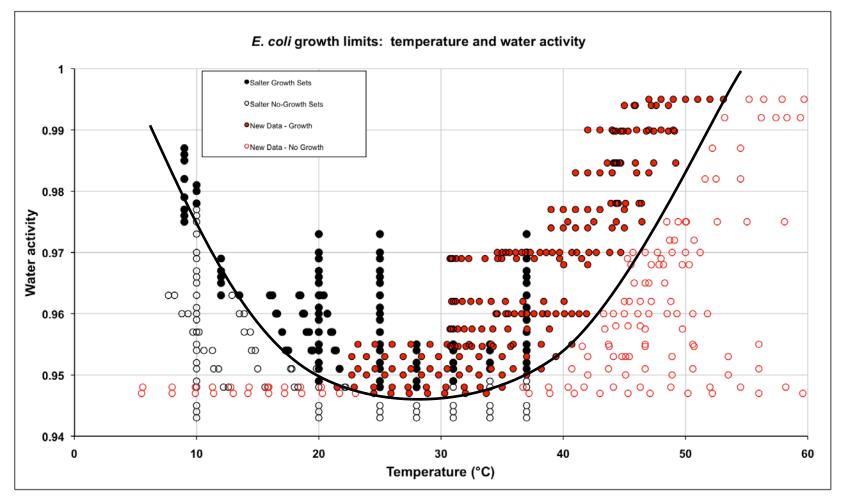
Analogous terms (Dp, Zp, ZpH) proposed for other lethal factors



What else can (or would) we 'predict'

- amount of microbial *growth* after time, (from temperature and product formulation; includes lag time, growth rate, germination and outgrowth of spores)
- reduction in microbial numbers over time, from knowledge of treatment conditions and product formulations (includes delay, death rate)
- probability of growth/toxin production
 - stability of foods (absolute or within defined time)
- □ sporulation
- recontamination/cross-contamination processes

Interaction of a_w and temperature on *growth limits* of *E. coli*



Data of Salter et al. (2000) for E. coli (augmented 2002)

What is modelled?

□ growth rates

- bacteria
- yeasts and molds
- □ inactivation (death) rates
 - bacteria
 - yeasts and molds
 - viruses
 - protozoa
 - microbial toxins?
- probability of growth/toxin formation
 - bacteria
 - yeasts and molds
 - micro-algae*

Current status of Predictive Microbiology ...

PM approach is now firmly established:

- in the scientific literature
- in industry for HACCP planning, product/process design
- supports food safety risk assessment and "Sciencebased" risk management decisions
- is used in setting government regulations/laws
 - e.g., Codex (and (EFSA) regulations for Listeria monocytogenes in RTE foods
 - *e.g., C. perfringens* model for meat cooling (USDA)
 - *e.g., E. coli* growth in raw meats (NZ and Australia)

How models are 'built'

- based on measurements of changes in microbial numbers over time and environmental conditions
- can be from
 - deliberately designed de novo studies
 - "data mining"
 - studies in broths, or in foods
 - n.b., assumed that the actual food is less important than the physico-chemical properties of the environment (*i.e.*, the food and its storage conditions), so long as basic nutritional needs are met, *i.e.*, nutrients are non-limiting
 - Sometimes a model is developed for just one food

How models are 'built'

- data are analysed and patterns of response are identified
- these patterns are expressed in the form of mathematical relationships
- the relationships are turned into equations by finding the best values of the parameters to describe individual sets of data, *i.e.*, specific to a particular organism - this is the process of 'model fitting'
- performance of the model is then evaluated and, if necessary, the model revised or new models constructed

Predictive Microbiology modelling

systematically make/collate lots of observations
 summarise the data as mathematical equations

Mathematical descriptions of temperature-growth rate relationship

• 'mechanistic model'

$$I = \frac{CT \exp(\Delta H^{\ddagger} / RT)}{1 + \exp(-n(\Delta H^{\ast} - T\Delta S^{\ast} + \Delta C_{p}[(T - T^{\ast}_{H}) - T\ln(T / T^{\ast}_{S})]) / RT)}$$

□ square root model ("empirical")

$$\sqrt{rate} = b \times (T - T_{min}) \times (1 - e(c \times (T - T_{max})))$$

Predictive Microbiology models

- systematically make/collate lots of observations
- summarise the data as mathematical equations
- convert into computer software, spreadsheets
- users enter data/numbers in, get answers out

'Nomenclature' of models

Primary model

describes the response of microbial numbers over time (e.g., inactivation curve, growth curve, etc.)

Secondary model

describes how outputs of the primary model (death rate, growth rate, combined limits to growth) are affected by environmental conditions (*i.e.*, quantifies microbial ecology)

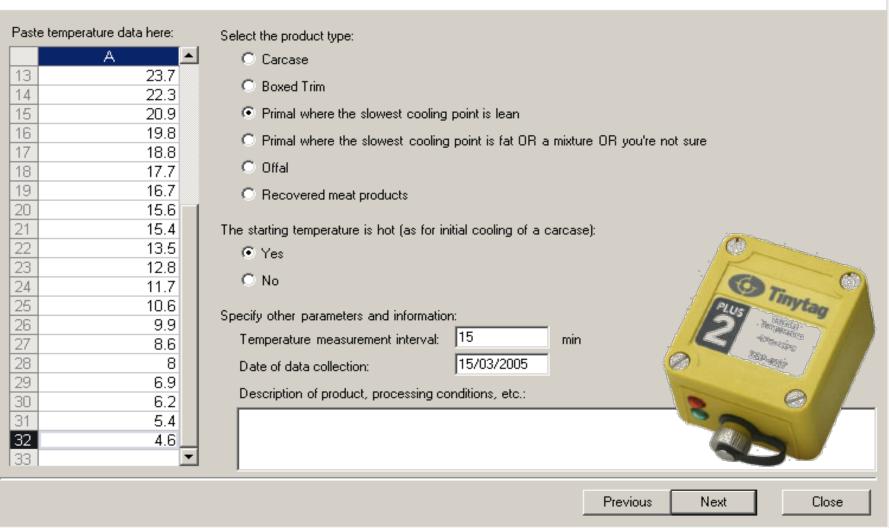
Tertiary model

makes the knowledge and data contained in the primary and secondary models available for prediction via an accessible software interface (software program, web-site, 'app')

🔓 Refrigeration Index Calculator

Welcome to the

Refrigeration Index Calculator



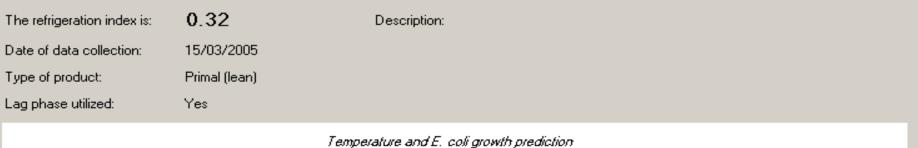
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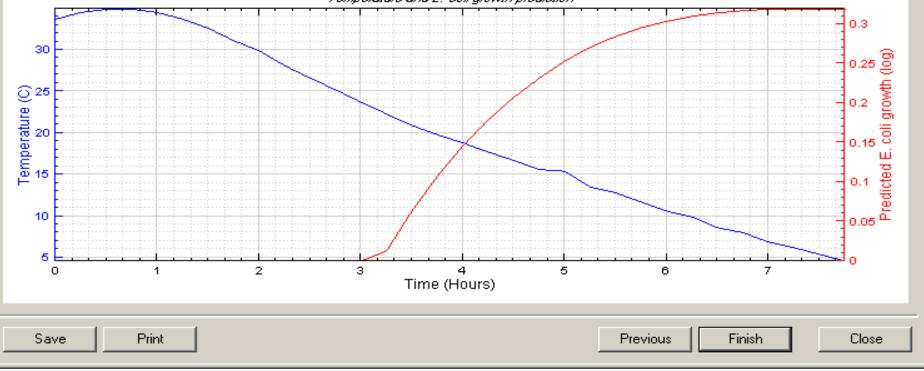
Refrigeration Index Calculator

Welcome to the

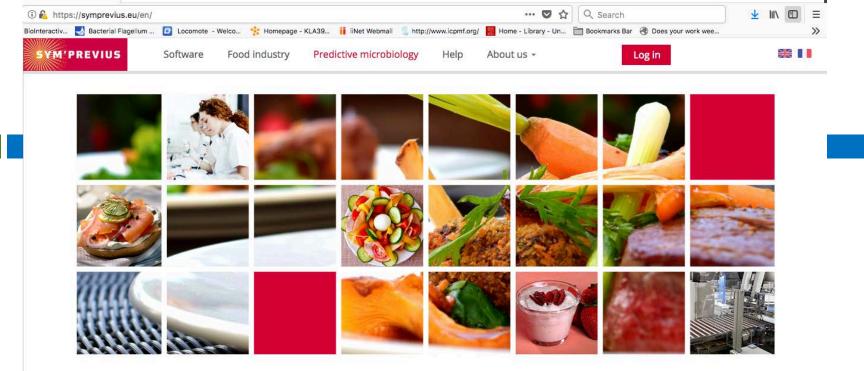
Refrigeration Index Calculator







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Sym'Previus is a complete tool for microbiological data prediction. It helps food manufacturers, from international groups to SMB, in their product development. Recognized by the scientific community and regulations, it provides a guarantee in quality and food safety. Thanks to the expertise provided by its partners and to its ease of use, Sym'Previus supplies its users with personalized results, adapted to their industrial issues.

n

Sym'Previus in brief



- Recommended and recognised by regulation (ISO WG19, EC 2017/2005))
- Its use allows increased result relevancy and so reduces costs

Over 40 microorganisms available and the possibility of adding customised strains

The Sym'Previus network of experts can provide made-to-measure solutions

Applications of Predictive Microbiology

- proactive
 - product or process design
- □ reactive
 - recognising, averting or minimising a problem
 managing consequences of loss of control

Pro-active Predictive Microbiology

using knowledge of microbial ecology in models we can

- design products to extend their shelf life
- find minimal conditions (better product quality) to achieve required shelf life
- design shelf-stable products
 - *e.g.,* processed cheese spread

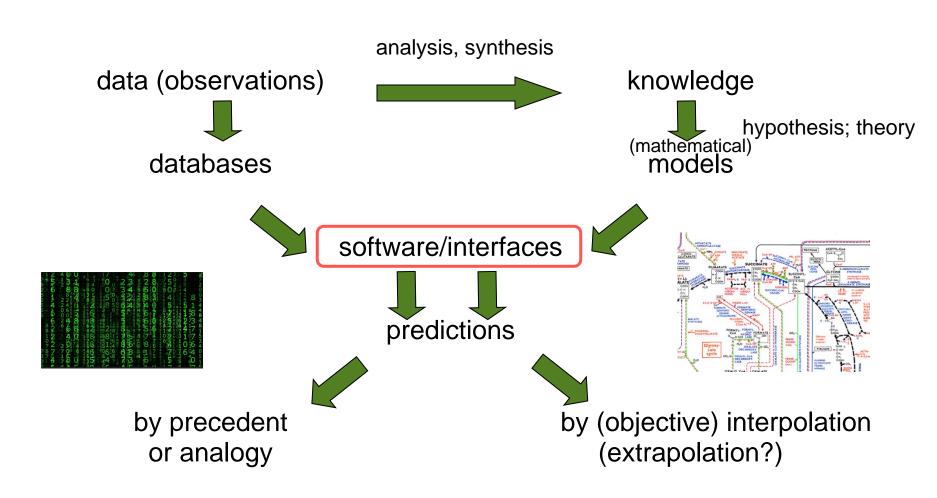
Re-active Predictive Microbiology

using knowledge of microbial ecology and models
how much growth has already occurred?
how much loss of shelf life has occurred?

or

- how long will it take for the initial levels of SSOs to grow to the spoilage level, if we know:
 - product characteristics (pH, a_w, etc)
 - storage conditions (temperature, atmosphere)
 - characteristics (growth rate, limits) of the SSO

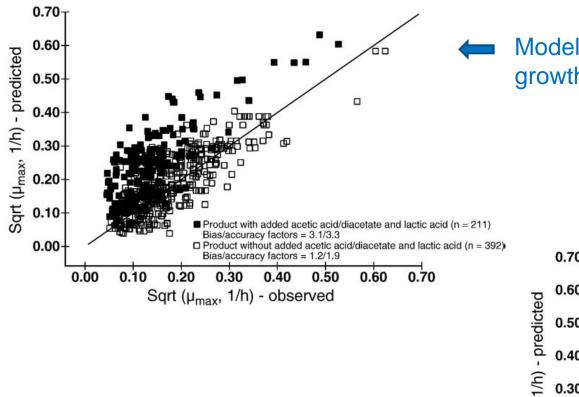
Data and Models



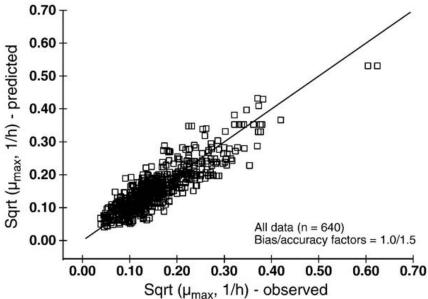
Choosing a Model/Assessing its Reliability

Model applicability

- Does the model describe the right organism? Are there strain differences?
- Is the model relevant to the food does it include all influential factors?
- Model reliability
 - Does the model accurately describe the biological phenomena?
- Various measures of reliability
 - Two aspects goodness of fit, systematic lack of fit
 - e.g., Bias and accuracy factors; bias and precision factors; t-test and F-test; etc.



 Model without terms for effect on growth rate of common organic acids



Model with terms for effect on growth rate of common organic acids

Variability

Variability

- between strains
- experimental (*e.g.*, variations within food matrix, sampling error)
- models should detail 'confidence intervals' on predictions, or 'error term'

Growth Model

[Static Dynamic] Listeria monocytogenes/innocua			[Aw NaCl]			
Init. level 3 Phys.state 2.1e-2 Temp (°C) 20 pH 7 4 NaCl (%) 0.5	Max.rate (log.conc/h) 0.221	0	7 1 40 7.5 10.2 Dbl. time(Hours) 1,364		Pred	liction Uncertainty
				Rate uncertainty	Phys. state uncertainty	Combined uncertainty
		10				
		8				
		logcCFU/g				
		<u>0</u> 4				
		•	10	20 30	40	50 60

Time (h)



\square and over to Peter \bigcirc

Tertiary Microbial Models

Utilization of Tertiary Models for Estimation of Microbial Behavior in Meat-Containing Products

Dr. Peter Taormina

Reasons for Using Predictive Models

- Hazard Analysis
 - Assessing microbiological risks
- Process Preventive Control Limits
 - Times, Temperatures
- Product Development
 - Formulation (e.g., pH, a_w, preservatives)
 - Shelf Life
- Preliminary Assessment of Process Deviation
 Cooking, cooling deviations

Types of Tertiary Models

- Bacterial Transfer
 - Surface/Product/Human
- Survival
 - Shelf Life
- Growth
 - Boundary
 - Rate
- Inactivation

Available Predictive Tools

- Baseline Software Tool
- Bioinactivation SE
- ComBase Predictor
- Dairy products safety predictor
- DMRI predictive models for meat
- E. coli Inactivation in Fermented Meats Model
- □ <u>EcSF E. coli SafeFerment</u>
- □ <u>FDA-iRISK®</u>
- □ Food Spoilage and Safety Predictor □ (FSSP) □
- □ <u>FISHMAP</u>
- □ <u>GroPIN</u>
- Listeria Control Model 2012
- Listeria Meat Model

- <u>Microbial Responses Viewer (MRV)</u>
- <u>MicroHibro: Predictive Models</u>
- MLA Refrigeration Index Calculator
- PMM-Lab
- Process lethality determination spreadsheet
- Perfringens Predictor
- Praedicere
- Salmonella predictions
- Shelf Stability Predictor
- SWEETSHELF
- Sym'Previus
- □ <u>Therm 2.0</u>

Some Examples of Tertiary Models



https://pmp.errc.ars.usda.gov



https://www.combase.cc

DANISH MEAT RESEARCH INSTITUTE PREDICTIVE MODELS FOR MEAT

http://dmripredict.dk

Pathogen Modeling Program 7.0

PMP70 le View Models>>Bacterium Bacteria>>Mod	del References Window Help				
📓 😰 🖾 · 💹 · 🔤 · 🖬	🗽 • <u> •</u> • 😻 • 💥 • 👬				
💒 Aerobic Growth Models: Bacillus cereus (vegetative) in Broth Culture					
3	Bacillus cereus (vegetative) (Broth	-			
InputConditions • Aerobic	R.C. Benedict, T. Partridge, D. Wells and	I R.L. Buchanan, Bacillus cereu	us: Aerobic Growth		
Temperature: Range: 5 to 42	Kinetics: Journal of Food Protection (199 http://www.arserrc.gov/MFS/HTML/ER		Related Publications		
19.0 ♥ ℃ 66.2 °F	Calculate Model with: Tir	ne Scale:	Display Format		
Range: 4.7 to 7.5	Lag No Lag	Days Hours	Show Table Show Chart		
6.5 Sodium Chloride (% [g/dL]): Range: 0.5 to 5	Modeled Growth Parameters: <u>Hours</u>	Bacillus cereus (veg	etative) in Broth Culture		
2.5 (% [g/dL]) Water Activity 0.986 Sodium Nitrite (ppm): Range: 0 to 150	Lag Phase Duration: 13.9 Lower Confidence Limit: 10.3 Upper Confidence Limit: 18.7	9 8 7			
150 (ppm)	Generation Time: 1.1 Lower Confidence Limit: 0.8 Upper Confidence Limit: 1.5				
Calculate Growth Data	Time to Increase 3.0 logs: 25.2 Lower Confidence Limit: 18.5 Upper Confidence Limit: 34.2	4 4 2			
Initial Level 3.0 log(CFU/ml) 1000 CFU/ml Level of Concern		1 0 0 5 10 15 2	0 25 30 35 40 45 50		
6.0 - log(CFU/ml) 1,000,000 CFU/ml		— log(CFU/ml) — LC	Hours :L UCL		

Corbion[®] Listeria Control Model



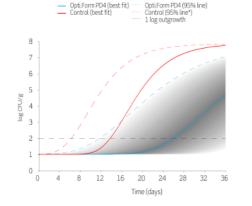
Corbion[®] Listeria Control Model

Food characteristics

Enter the characteristics of your finished cured meat product as specifically as possible. If you are unsure of a food parameter, please use the default value. You may also select a Corbion ingredient and enter an addition level.

Moisture	70 %
pН	6.2
NaCl	1.7 %
Sodium nitrite 📀	0 ppm (on total formulation)
Storage conditions	
Temperature	40 OF \$
Corbion Solution	
Opti.Form PD4 \$	2.5 %
Microorganism data	
Initial level	1 log CFU/g
Maximum allowed level	2 log CFU/g

Listeria growth in chicken



About this graph

Time to 1 log outgrowth in days

	Control	With Opti.Form PD4
Best fit	14	26
95% line*	6	12

* The lines are based on specifically designed and validated Listeria challenge studies. According to these studies, 95% of growth is expected to be slower than the 95% line.

Spoilage Model

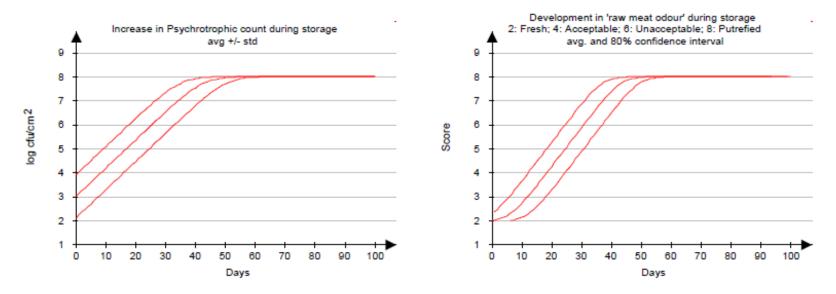
PREDICTIVE MODELS FOR MEAT



Shelf life of Bacon (cured pork)

Vacuum packed, 2-5,5 % salt in aqueous (% Sodium Chloride in the water phase, w/w), With/without Ascorbate, 60-120 ppm nitrite/nitrate added, No smoke. Version 1.0

Average	3.00	log cfu/cm	2	
Standard deviation (std)	0.90	log cfu/cm	2	
% salt in aqueous	2.00	%		
1. Temperature	7.00	°C in	100	days
2. Temperature	5.00	°C in	0	days
3. Temperature	5.00	°C in	0	days
4. Temperature	5.00	°C in	0	days



Australia's Food Safety Information Portal



University of Wi	CCP Sconsin - Madison Center for M	f Wisconsin - Madison Ieat Process Validation
Home Validation Pathogen Modeling Additional Info Deviations	Model HACCP Plans Documentation/Support Prerequisite Programs Research Results	
avigation : <u>Home</u> > Pathogen Modeling Pathogen	n Modeling	Search Search Questions? Dr. Barbara Ingham
THERM 2.0 Shelf Stability Predictor	Pathogen Modeling Pathogen modeling programs can be helpful in setting critical limits, determining hazard severity, and justifying corrective actions.	Food Safety Specialist Phone: 608-263-7383 Email: bhingham@wisc.edu
USDA Pathogen Modeling 7.0	_	
USDA Predictive Microbial Information Portal		



Cooked Chicken Cooling

Marinated Chicken Breast

Cooked Chicken Cooling – Marinated, Cooked Chicken Breast

- Chicken breasts are vacuum tumbled in a marinade containing phosphates, sea salt, seasonings, and potassium lactate.
- Marinated chicken breasts are cooked through continuous impingement oven, then cooled on racks.
- □ pH 6.8, a_w 0.987, 1.7% salt
- □ Temperature probes:
 - **5** hours from 130 to 60°F (54.4 to 15.6°C)

Which Model?

Pathogen Modeling Program (PMP) Online



United States Department of Agriculture Agricultural Research Service

Pathogen Modeling Program (PMP) Online

PMP Home	You are here: <u>PMP Home</u> / PMP Online						
PMP Online	SELECT A PATHOGEN MODEL						
About PMP							
Tutorial	The models are based on extensive experimental data of microbial behavior in liquid microbiological						
Frequently Asked Questions	media and food.						
Reference Material	There can be no guarantee that predicted values will match those that would occur in any specific food system. Before the models could be used in such a manner, the user would have to validate						
Project Scientists	models for each specific food of interest.						
	ок						

ARS.USDA.gov

Pathogen Modeling Program (PMP) Online

Model >> Bacterium

COOLING	٠
Clostridium botulinum (broth culture)	
Clostridium perfringens in cooked cured pork	
Clostridium perfringens in cooked beef	
Clostridium perfringens in cooked uncured beef	
Clostridium perfringens in cooked uncured chicken	<
Clostridium perfringens in cooked uncured pork	
GROWTH	ı
HEAT INACTIVATION	I
SURVIVAL	I
TRANSFER	ı

Bacteria >> Model

AEROMONAS HYDROPHILA	٠
BACILLUS CEREUS	•
CLOSTRIDIUM BOTULINUM	•
CLOSTRIDIUM PERFRINGENS	•
ESCHERICHIA COLI [0157:H7]	•
LISTERIA MONOCYTOGENES	•
SALMONELLA DUBLIN	•
SALMONELLA ENTERITIDIS	•
SALMONELLA HADAR	•
SALMONELLA KENTUCKY	•
SALMONELLA TYPHIMURIUM	•
SALMONELLA SPP.	•
SHIGELLA FLEXNERI	•
STAPHYLOCOCCUS AUREUS	•
YERSINIA PSEUDOTUBERCULOSIS	•

Time and Temperature Data

18.85	133.0	114.2	114.1	101.8	149.5	122.6	137.0	106.4	89.8	105.9	115.0	
18.87	132.2	113.4	113.4	100.9	148.9	121.8	136.3	105.6	89.4	105.2	114.2	114.5
18.88	131.5	112.7	112.7	100.1	148.2	121.0	135.6	104.8	89.0	104.5	113.3	
18.90	130.7	111.9	112.0	99.3	147.6	120.3	134.8	104.0	88.6	103.8	112.6	$63 \circ 3/15 = 0.14 2.30 = 0.14 0.000$
18.92	129.9	111.1	111.3	98.5	146.9	119.5	134.1	103.2	88.1	103.1	111.8	470 $3/15/2$ 14320 0 100
18.93	129.2	110.4	110.6	97.8	146.3	118.8	133.4	102.4	87.8	102.5	111.0	42 4 3/15/2 100 0
18.95	128.4	109.6	109.9	97.0	145.6	118.0	132.7	101.7	87.2	101.8	110.2	41 0 3/15 2014 7:20 3:00 1.00
18.97	127.7	108.9	109.3	96.2	145.0	117.3	132.0	100.9	85.9	101.1	109.4	410 0/15/0 19/20 0/00 100
18.98	127.0	108.1	108.6	95.5	144.3	116.6	131.4	100.2	84.7	100.4	108.7	474 V/16/2 / 111:00 / 100 5.00
19.00	126.2	107.4	108.0	94.7	143.7	115.9	130.7	99.4	83.5	99.7	107.9	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
19.02	125.5	106.7	107.4	94.0	143.0	115.1	130.0	98.7	82.4	99.1	107.2	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
19.03	124.8	105.9	106.7	93.3	142.4	114.4	129.4	98.0	81.3	98.4	106.5	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
19.05	124.1	105.2	106.1	92.6	141.7	113.7	128.7	97.3	80.3	97.8	105.7	
19.07	123.3	104.5	105.5	91.9	141.1	113.0	128.0	96.6	79.5	97.1	105.0	
19.08	122.6	103.8	104.9	91.2	140.4	112.3	127.4	95.9	78.7	96.5	104.3	
19.10	121.9	103.1	104.2	90.5	139.8	111.6	126.8	95.2	77.8	95.8	103.6	+0.4 $0.15/204$ 0.30 13.00 12.00
19.12	121.2	102.4	103.6	89.8	139.1	110				1		5/2014 13:00 13:00
19.13	120.5	101.8	103.0	89.2	138.5	110			000	7/1/	THE	5/2014 17:30 14:00 13.00 7/2014 18:30 15:00 14.00
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19.18	118.5	99.8	101.2	87.3	136.6	108	4/			and a		2014 20:02 $17:00 $ $16.53 $ $16.00 $ 16.53
19.20	117.8	99.2	100.7	86.6	135.9	107	144			S total		
19.22	117.2	98.6	100.1	86.0	135.3	107			1			
19.23	116.5	97.9	99.5	85.4	134.6	106	THE STATE					18:20 18:20
19.25	115.8	97.3	98.9	84.8	134.0	105	THE	HH		Million	P	⁴ 21:30 18:32 18.00 14 22:02 19:00 18:53 4 22:02 19:00 18:53
19.27	115.2	96.7	98.4	84.2	133.4	105	ITT	111	XX	XAT T		4 22:02 19:00 18.53 4 22:02 19:00 18.53
19.28	114.5	96.1	97.8	83.7	132.7	104	1H		XaH	14444	- port	4 22:30 19:32 19.00
19.30	113.9	95.6	97.3	83.1	132.1	104	71		MAH		++ ont	23:02 20:00 19.53
19.32	113.2	95.0	96.7	82.5	131.4	103			ATH	1111	teo	<3:30 <0:32 <0.00
19.33	112.6	94.4	96.1	82.0	130.8	102	2	(and	HI	+++1	HH	0:02 < 1:00 < 20.52
19.35	112.0	93.8	95.6	81.5	130.2	102		201	HI		HH	0:30 < 7:32 < 21.00
19.37	111.3	93.3	95.1	80.9	129.5	101		94		TH	HT	<2:00 21.53
									4	81	Contraction of the local division of the	22.00
												-0

Pathogen Modeling Program (PMP) Online

Time-Temperature Data Format

This page loads with sample data in the textbox. This format should be followed when entering or pasting data into the textbox. Specifically, please enter cooling profile data as follows:

- · Start with header row (e.g. time(hour), temperature)
- · Enter each data point on a separate line, separated by a comma (e.g. 1.0, 44)
- Specify time first, in cummulative hours (e.g. 15 minutes = 0.25 hours)
- · Specify temperature second, in the units selected using the radio buttons (°C or °F)
- · A minimum of five (5) data time-temperature points must be provided
- At least three of the data points must be above 70°F (21°C)
- · The time point in row 1 must always be 0 hours
- · Data not following this format will be ignored

If using the Browse button to load the data from a text file, the file must:

- · Follow the same format as above
- Be in text format (e.g. .txt, .csv)

Clicking on the **Calculate Growth Data** button will use data provided in the file, if specified, or the data in the textbox if no file is specified. The data from the file will be loaded into the textbox. Please confirm the temperature profile is charted correctly.

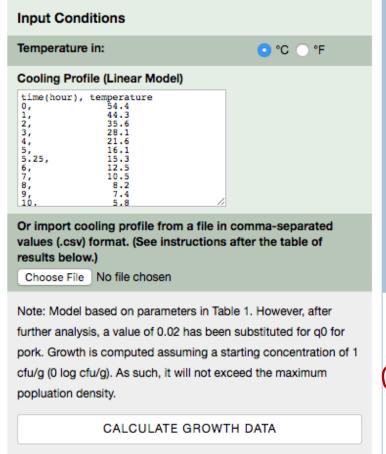
Prepare Time/Temp Data

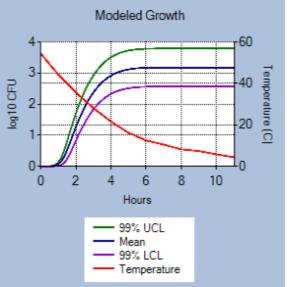
- Download or Manual Entry
- Select data range or points
 - Convert units
- Save as .CSV file (optional)
- Adjust for temperatures outside of model range

11/14/17 0:34	54.4				
11/14/17 0:44	52.0				
11/14/17 0:54	50.0				
11/14/17 1:04	48.0				
11/14/17 1:14	47.5				
11/14/17 1:24	45.2				
11/14/17 1:34	44.3				
11/14/17 1:44	42.1				
11/14/17 1:54	40.5				
11/14/17 2:04	38.8				
11/14/17 2:14	37.2				
11/14/17 2:24	35.6				
11/14/17 2:34	33.9				
11/14/17 2:44	32.2				
11/14/17 2:54	30.5				
11/14/17 3:04	30.0		time (hour)	temperature (°C)	
11/14/17 3:14	29.6		0,	54.4	
11/14/17 3:24	29.1		1,	44.3	
11/14/17 3:34	28.1		2,	35.6	
11/14/17 3:44	27.7		3,	28.1	
11/14/17 3:54	27.2		4,	21.6	
11/14/17 4:04	26.6		5,	16.1	
11/14/17 4:14	26.0		5.25,	15.3	
11/14/17 4:24	25.4		6,	12.5	
11/14/17 4:34	21.6		7,	10.5	
11/14/17 4:44	21.7		8,	8.2	
11/14/17 4:54	20.4		9,	7.4	
11/14/17 5:04	19.2		10,	5.8	
11/14/17 5:14	18.0		11,	4.4	
11/14/17 5:24	16.8				
11/14/17 5:34	16.1				
11/14/17 5:44	15.8				
11/14/17 5:54	15.3				
11/14/17 6:04	14.6				
11/14/17 6:14	14.3				
11/14/17 6:24	14.1				
11/14/17 6:34	13.9				

PMP Online – Marinated, Cooked Chicken Breast Example

Growth of Clostridium perfringens during cooling of cooked uncured Chicken





Modeled Growth Parameters

Total Cooling Time: 11.00 (hours)

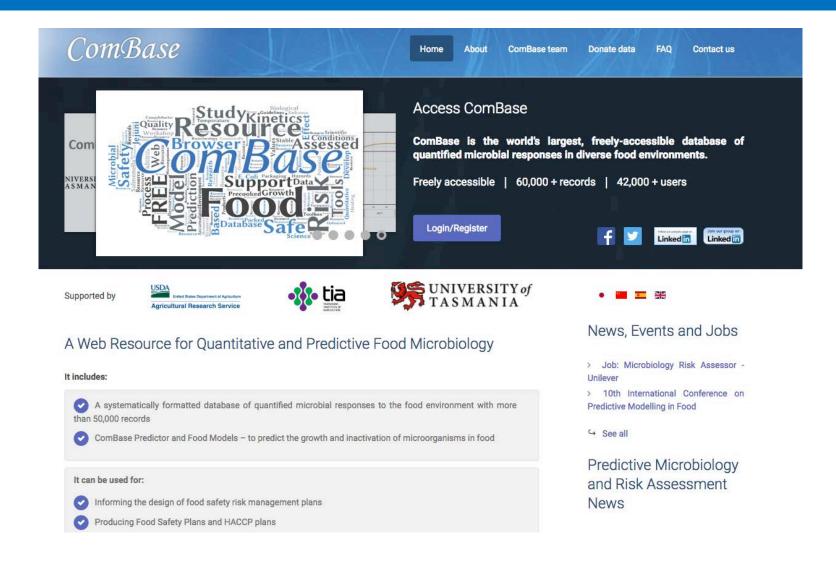
Predicted Mean Growth: 3.18 (log10 CFU)

- 99% UCL: 3.80 (log10 CFU)
- 99% LCL: 2.57 (log10 CFU)
- Maximum Population Density: 8.00 (log10 CFU/g)

PMP Online – Marinated, Cooked Chicken Breast Example

- □ 3.18-Log Increase (2.57 to 3.80 99% CL)
- Source: Juneja V.K., Marks H., Huang L., and Thippareddi H. Predictive model for growth of *Clostridium perfringens* during cooling of cooked uncured meat and poultry. Food Microbiology 28 (2011). P. 791-795.

■ What about pH, a_w, % salt?

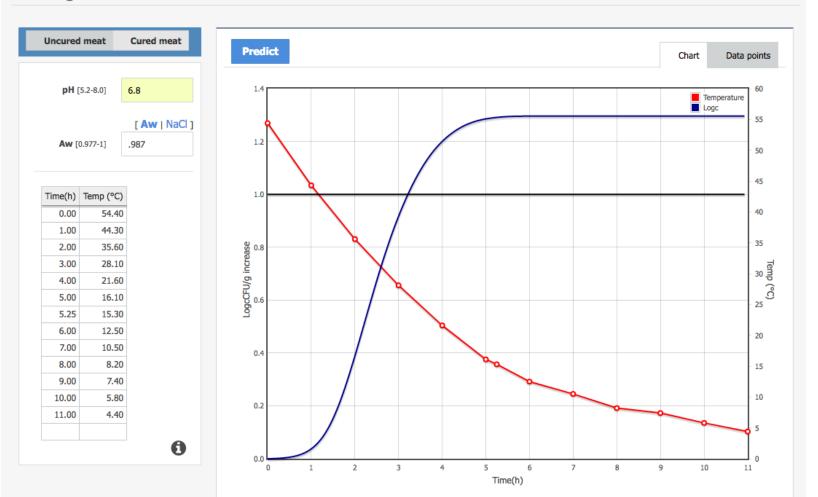


Combase – Perfringens Predictor

	ComBase	
Q	Browser	Search
m	ComBase Predictor >	Organism
==	Food Models ~	+Add another field
\langle	Perfringens Predictor	
	Salmonella in egg	Environmental conditions
	DMFit >	Any Static Dynamic
¢ŝ	Resources >	
	Help >	

1.3-Log Increase

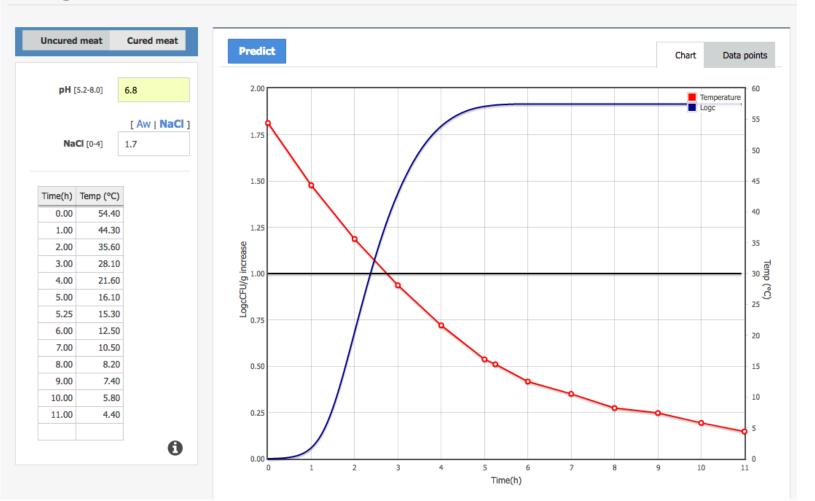
Perfringens Predictor



₽?

1.92-Log Increase

Perfringens Predictor



₽.

?

Cooked Chicken Cooling – Marinated, Cooked Chicken Breast

- Chicken breasts are vacuum tumbled in a marinade containing phosphates, sea salt, seasonings, and potassium lactate.
- Marinated chicken breasts are cooked through continuous impingement oven, then cooled on racks.
- □ pH 6.8, a_w 0.987, 1.7% salt
- Temperature probes:

5.5 hours from 130 to 60°F (54.4 to 15.6°C)

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Research Note

Inhibition of *Clostridium perfringens* Growth by Potassium Lactate during an Extended Cooling of Cooked Uncured Ground Turkey Breasts

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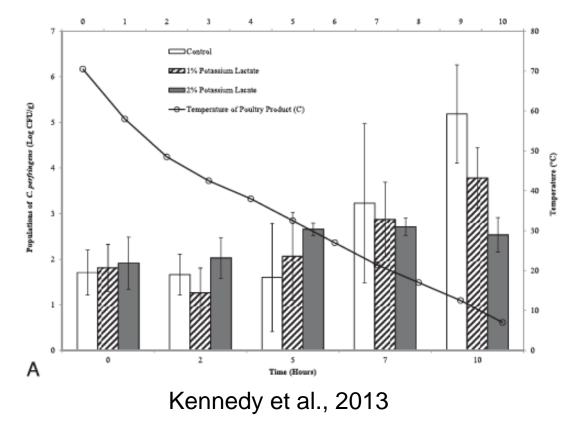
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MS 13-106: Received 17 March 2013/Accepted 26 June 2013

ABSTRACT

The U.S. Department of Agriculture's Food Safety and Inspection Service compliance guideline known as Appendix B specifies chilling time and temperature limits for cured and uncured meat products to inhibit growth of spore-forming bacteria, particularly *Clostridium perfringens*. Sodium lactate and potassium lactate inhibit toxigenic growth of *Clostridium botulinum*, and inhibition of *C. perfringens* has been reported. In this study, a cocktail of spores of three *C. perfringens* strains (ATCC 13124, ATCC 12915, and ATCC 12916) were inoculated into 100-g samples of ground skinless, boneless turkey breast formulated to represent deli-style turkey breast. Three treatment groups were supplemented with 0 (control), 1, or 2% potassium lactate (pure basis), cooked to 71°C, and assayed for *C. perfringens* growth during 10 or 12 h of linear cooling to 4°C. In control samples, populations of *C. perfringens* increased 3.8 to 4.7 log CFU/g during the two chilling protocols. The 1% potassium lactate treatment supported only a 2.5- to 2.7-log increase, and the 2% potassium lactate treatment limited growth to a 0.56- to 0.70-log increase. When compared with the control, 2% potassium lactate retarded growth by 2.65 and 4.21 log CFU/g for the 10- and 12-h cooling protocols, respectively. These results confirm that the addition of 2% potassium lactate inhibits growth of *C. perfringens* and that potassium lactate can be used as an alternative to sodium nitrite for safe extended cooling of uncured meats.

Compare pH, a_w, percent lactate in published study with your product.





Prepared Meal Cooling Example

Gumbo with Rice

Prepared Meal Cooling - Gumbo

- Gumbo ingredients: Cooked rice, Andouille sausage, vegetables, shrimp, seasonings
- Rice is cooked in a commercial rice cooker. Meat, shrimp, and vegetables are cooked separately in a kettle.
- Rice is dispensed into plastic trays, and Gumbo mixture is ladled onto rice. Trays are sealed, placed on racks and wheeled into walk-in freezer.
- □ Reaches 41°F (5°C) in 6 h.

Prepared Meal Cooling - Gumbo

Oops! Temperature Deviation

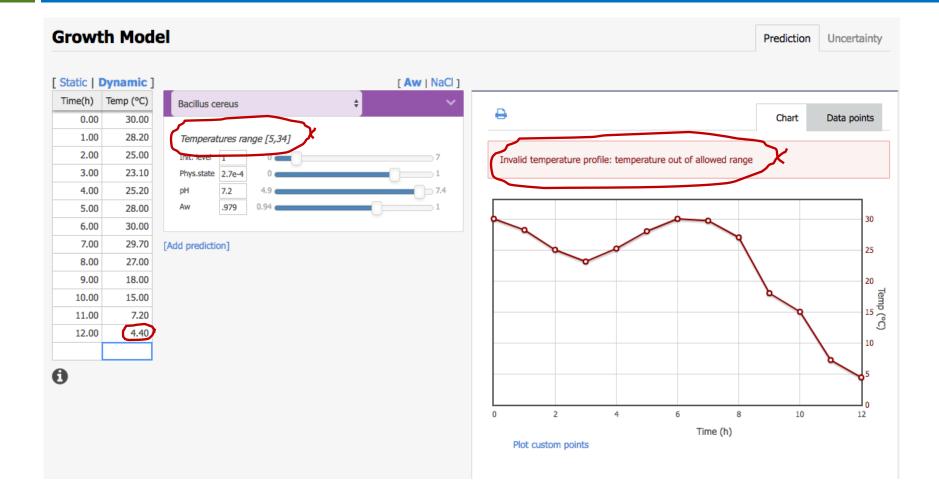


Image source: Bing search – "free to share and use" https://hongkongphooey.wordpress.com/2009/02/

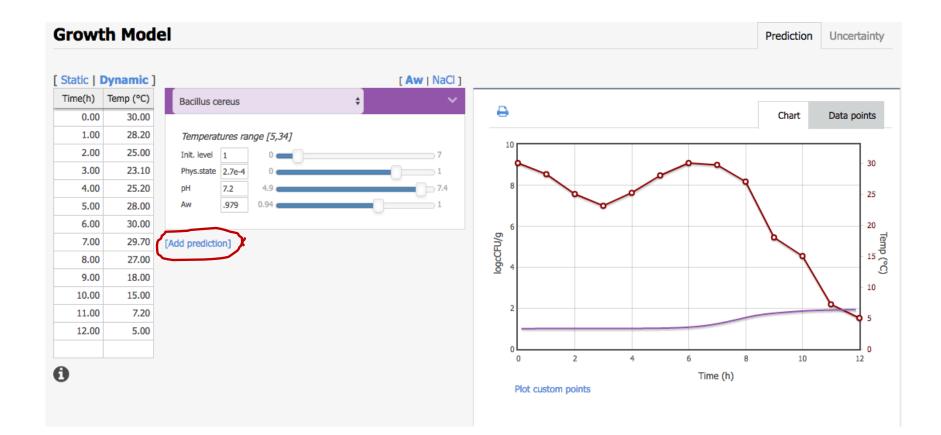
Combase Predictor – Growth Model



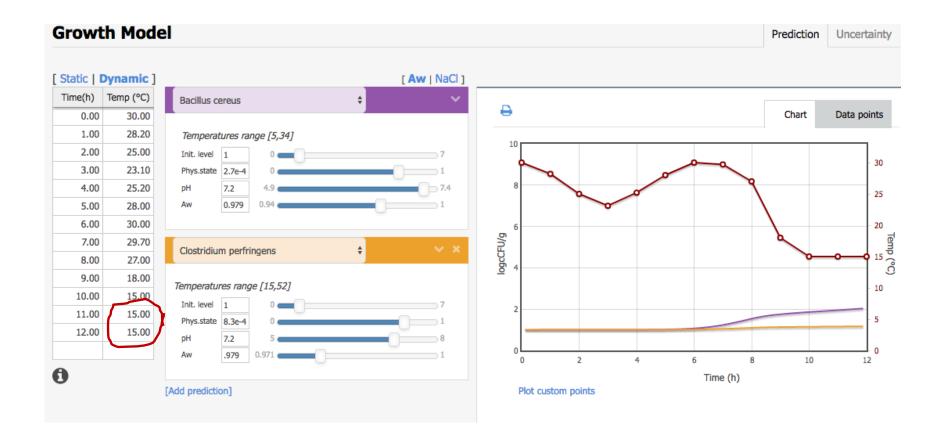
Gumbo Example - Combase



Gumbo Example – Combase 0.92-Log Increase *Bacillus cereus*



Gumbo Example – Combase

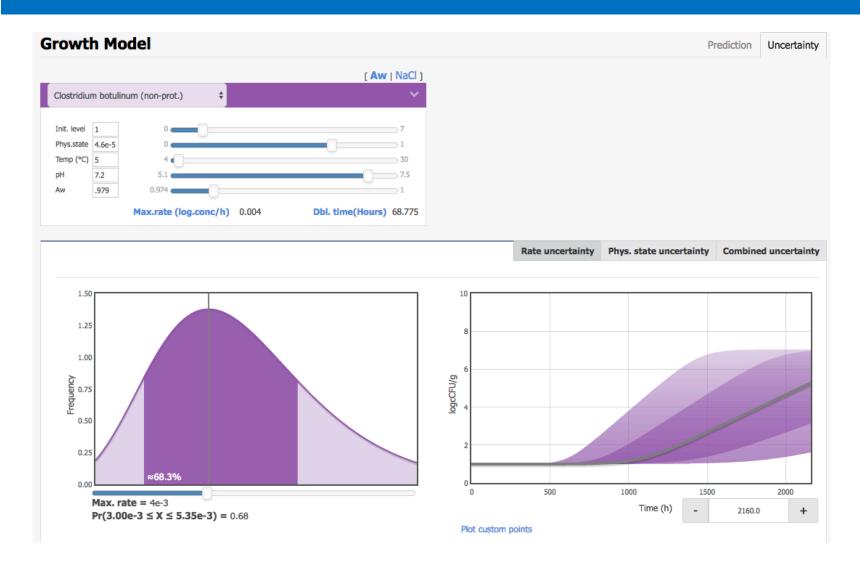


Growth of non-proteolytic *C. botulinum* at 5°C within about 40

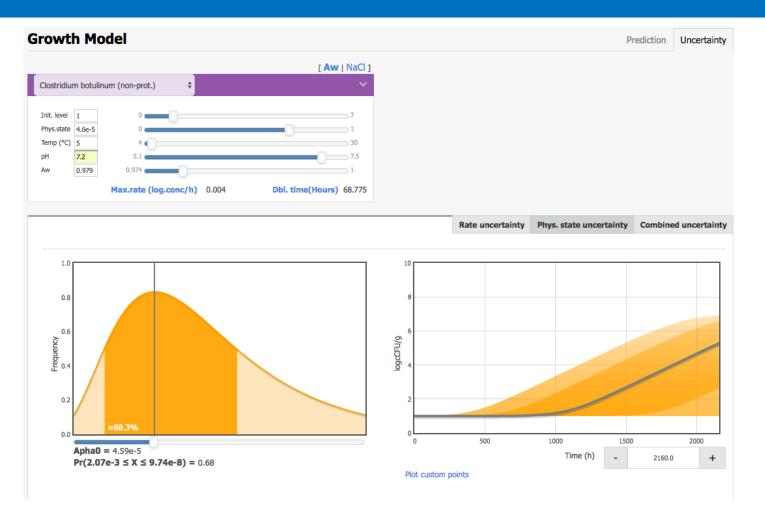
avs

Int. level Phys.state 4,6e-5 pH 7,2 0.979 0.974 0.979 0.974 0.974 Dbl. time(Hours) 68.775	Growth Model					Prediction	Unce	rtain
Int. level Image: Constrained and the second and t	Static Dynamic]	[Aw NaCl]						
Phys.state 4.6e-5 0 1 Image: Phys.state 4.6e-5 0 0 pH 7.2 0.974 0 0 Max.rate (log.conc/h) 0.004 Dbl. time(Hours) 68.775 Add prediction] 0 0 0 0 Time(h): 932.8, Prediction: 1.19 0 0 0	Clostridium botulinum (non-prot.)	~	Ð			Chart	Data p	points
2 0 Time(h): 932.8, Prediction: 1.19	Phys.state 4.6e-5 0 Temp (°C) 5 4 pH 7.2 5.1 Aw 0.979 0.974	7.5	8					
	tdd prediction]		2	Time(h): 9	32.8, Prediction: 1.19			
				500	1000	1500	20	000

Gumbo Example – Combase Shelf Life?

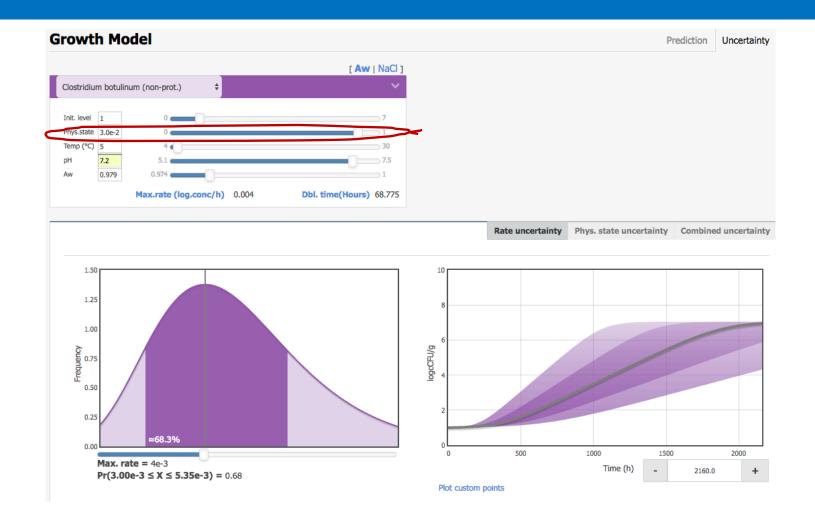


Gumbo Example – Combase Shelf Life?



Growth of non-proteolytic C. botulinum within about 14 days

Growth Model		Prediction	Uncertainty
[Static Dynamic] [Aw NaCl]			
Clostridium botulinum (non-prot.)	Ð	Chart	Data points
Init. level 1 0 7 Phys.state 3.3e-2 1 Temp (°C) 5 4 pH 7.2 0.974 0.979 0.974 1 Max.rate (log.conc/h) 0.004 Dbl. time(Hours) 68.775 1 Kdd prediction] 1	10 8 6 6 7 7 7 7 7 7 7 7 7 7 7 7 7	1500	2000
	Time (b)		
	Plot custom points	- 2160	.0 +



Summary

- Various Tertiary Models Exist
 - Some of which were demonstrated in this webinar
- Select Model Based Upon Your Unique Situation and Parameters
- Be Careful with Assumptions and Interpretation
 - Read and follow guidelines and disclaimers
- Validate and Verify





Dr. Tom Ross



Dr. Peter Taormina

QUESTIONS & ANSWERS

Dr. Betsy Booren

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Practical Applications of Microbial Modeling Webinar Series

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 Part III – Risk Modeling
 Spring 2018