Integrated Predictive Models and Sensors in Food Supply Chains to Enhance Food Safety

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University of Tasmania

TASMANIAN INSTITUTE OF AGRICULTURE

UTAS

TIA is a joint venture of the University of Tasmania and the Tasmanian Government

Tasmania
Explore the possibilities

fssai

Food Safety and Standards Authority of India

CHIFSS

CII-HUL Initiative on Food Safety Sciences

Unilever

CII

Confederation of Indian Industry

Outline

- Predictive Microbiology – an overview
- Case studies- industry/government/academic partnerships
- Sensors and databases (ComBase)

Global Food Drivers

Globalization
- Global sourcing
- Global sourcing of R&D

Regulatory
- Increased scrutiny
- National vs International Standards
- New risk management approaches

Consumer
- Food safety
- Converging trends
  - health
  - convenience
  - premium
  - ethics
- Animal welfare

Environment
- Contaminants
- Climate Change
- Resource conservation

Safety
- Complex global supply chains
- Traceability
- Physical contaminants
- Microbial contamination
- Chemical contaminants
- Economic adulterants
- Allergens
- GMOs
- Emerging hazards
- Biosecurity
- Nano safety

Science & Technology
- Transformational in biology & nutrition
- Novel processing technologies
- Functional ingredients
- Nanotechnology

Demographics
- 2050, 9 billion population
- Urbanisation
- Aging population
- Increased ability to pay for value-added products

Retailers
- Larger than the biggest food processors
- Buying power
- Reduced margins affect systems downstream

Nutrition/Health
- Chronic illness
- Immunodeficiency
- Consumer behaviour difficult to change

Courtesy – Martin Cole

Microbiological Safety of foods:

Key areas of scientific capacity building

HEALTH SURVEILLANCE

Surveillance
- Ongoing collection
- Analysis
- Interpretation
- Dissemination

Public Health Action
- Priority Setting
- Planning, implementing, monitoring, and evaluating public health practice

Identification of critical health issues linked to foods – e.g. top 5 pathogens causing most illnesses (metrics - DALYs) for prioritization

FOODBORNE PATHOGENS

Global best practices for identification & characterization

Speed, precision and insights are actionable

DIGITAL / MODELING TOOLS

<u>PREDICTIVE</u>

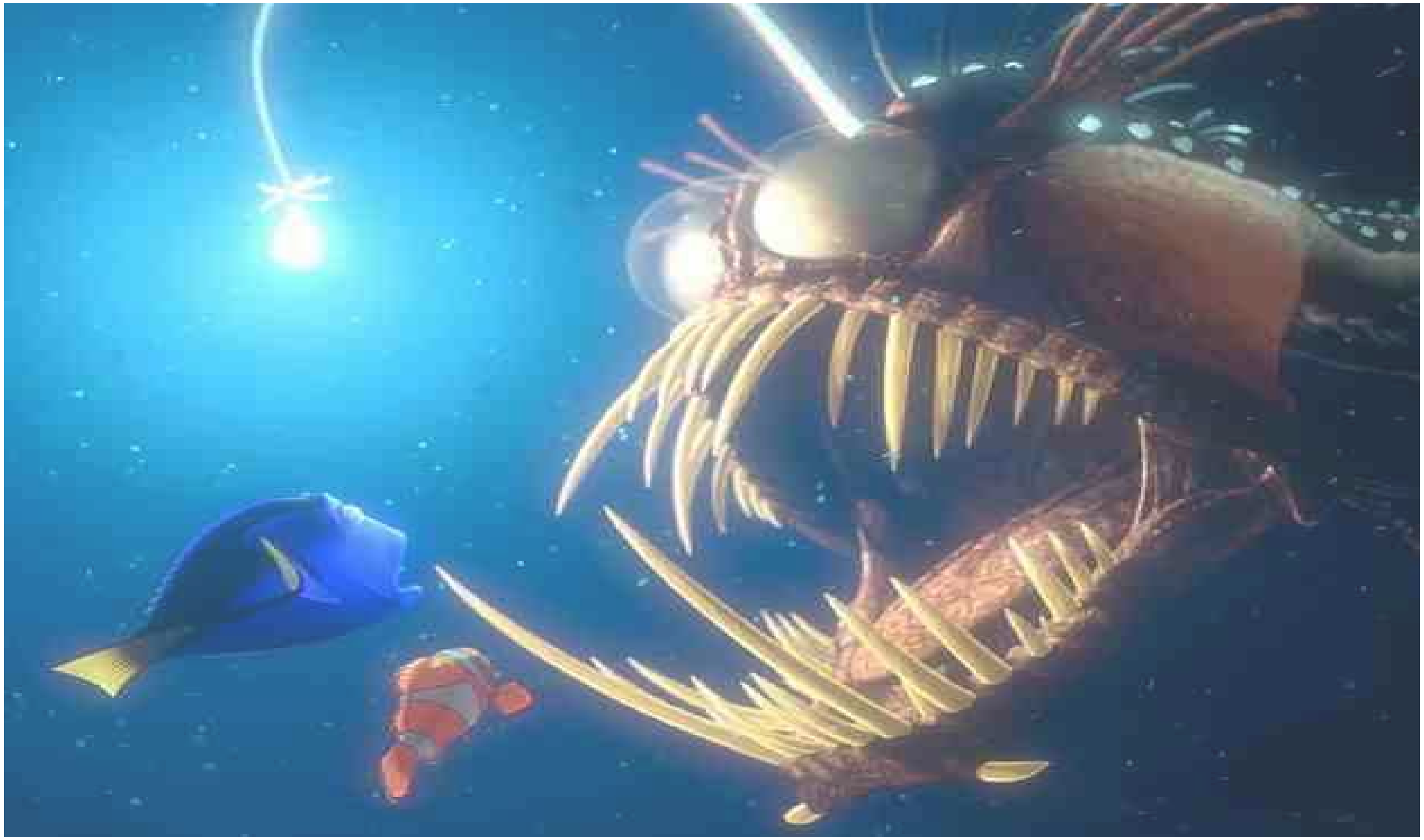
Risk based design of safe:
- **Formulations**
- **Processes**
- **Supply chain**

FOOD HYGIENE

- **Households**
- **Serviced foods**
- **Industry**

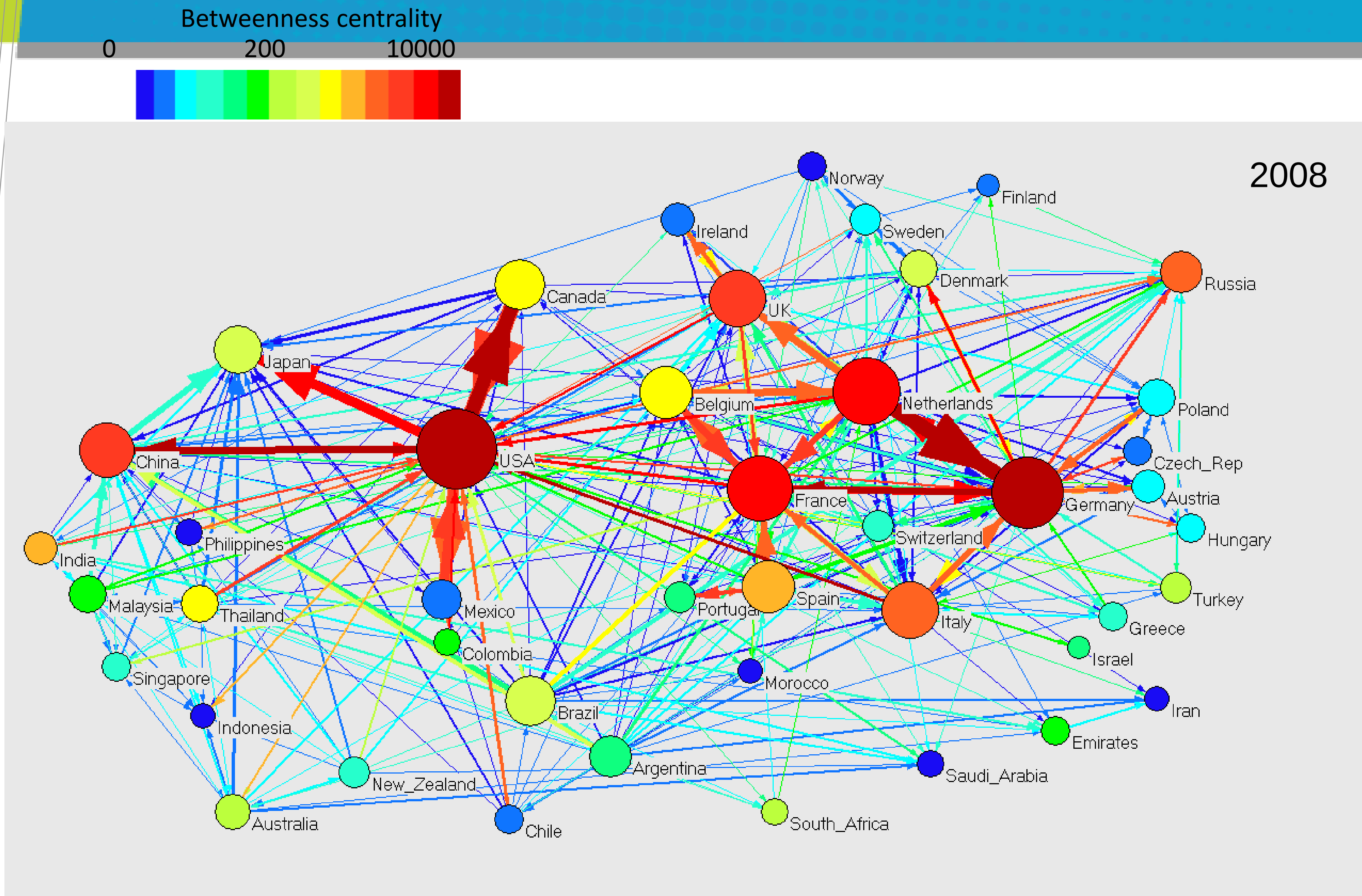
Climate Change

Emerging Hazards



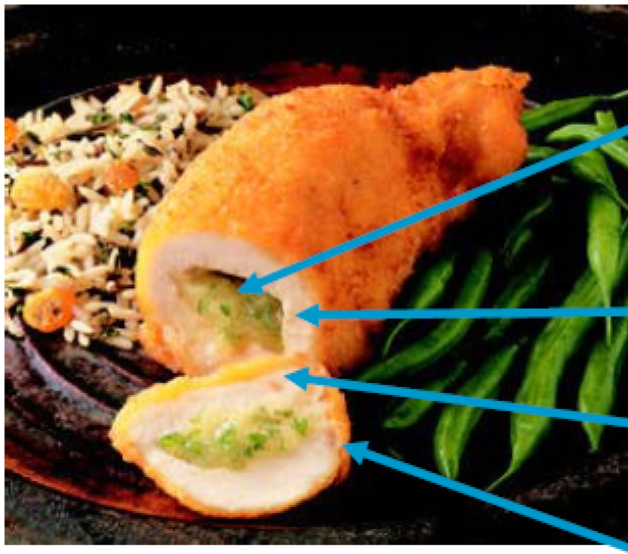
Food import-export ($-value) fluxes "The highway"

József Baranyi (personal Communication)



Ercsey-Ravasz, M., Toroczkai, Z., Lakner, Z., Baranyi, J., 2012. PloS One

Global sources of food (*and* contamination)



Chicken Kiev

Source: Wayne Anderson, IFSA and Martin Cole

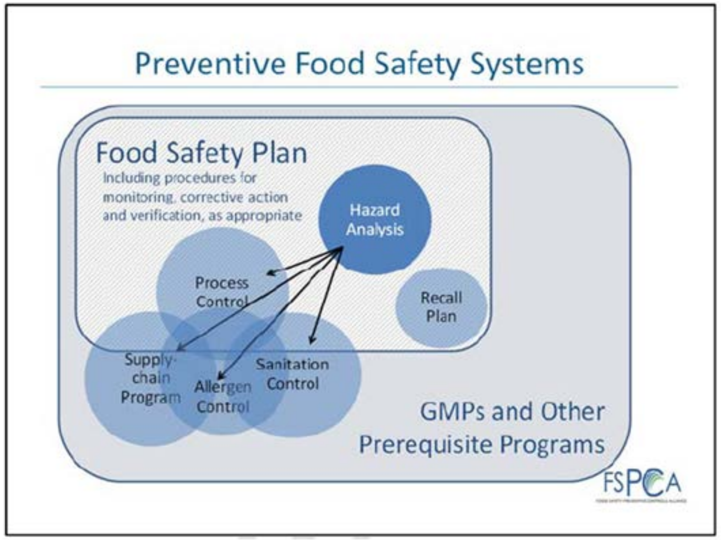
Herb Butter:
Salted butter (Ireland)
Garlic puree (China, USA, Spain)
Garlic salt (China, USA, Spain)
Lemon (USA)
Parsley (France, UK)
Pepper(India)
Water (Ireland)

Chicken Breast:
Chicken
(Ireland, Belgium,
UK, Thailand)

Batter:
Flour (Belgium, France)
Water (Ireland)

Bread Crumb:
Bread crumbs (Ireland, UK)
Rape-seed oil (EU, Australia,
Eastern Europe)

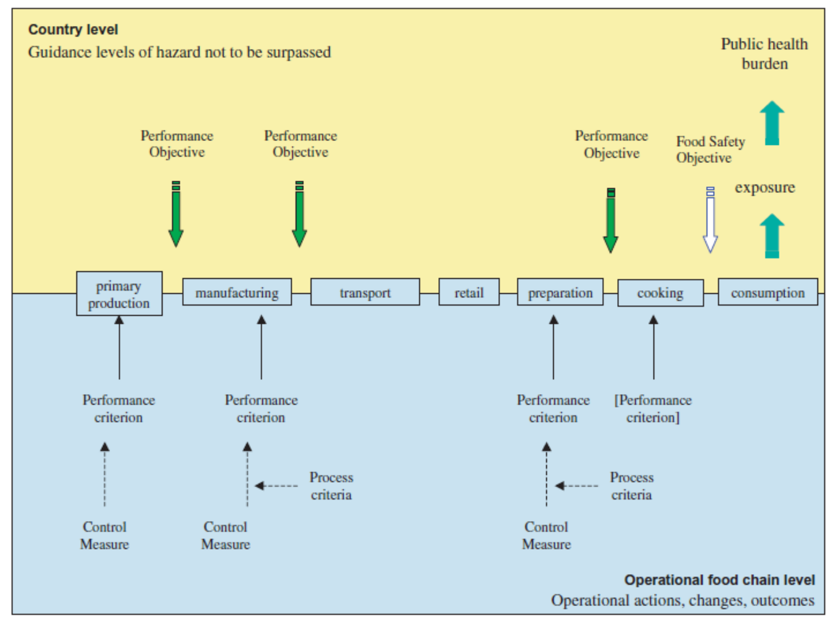
Food Safety Modernization Act



Food Safety Objectives

$$H_o + \Sigma I + \Sigma R \leq FSO$$

L.G.M. Gorris / Food Control 16 (2005) 801–809



Those at risk for serious foodborne illness:

- persons with chronic disease
- very young and elderly
- immuno-compromised

A basic tenet of food safety

Successful risk management systems rely on knowing how hazards respond to environmental conditions.

……such information reduces uncertainty

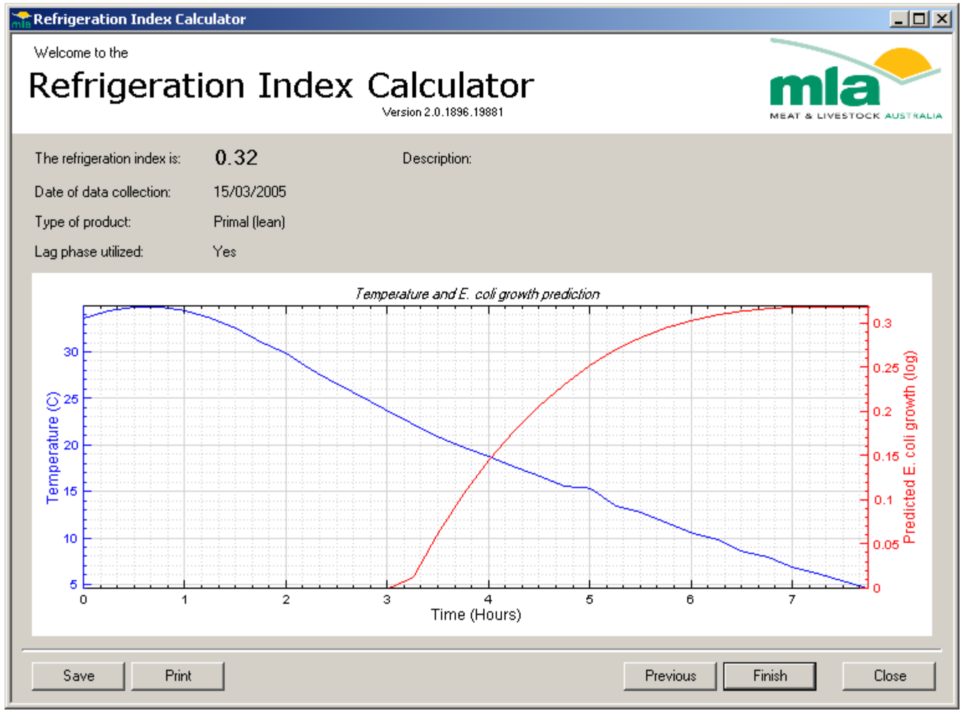
A basic tenet of food safety

A successful risk management system relies on knowing how hazards respond to environmental conditions.

……such information reduces uncertainty

But are we using all of the available tools to manage risk?

Predictive Microbiology



Predictive models

Represent ***condensed knowledge***, which

- describe microbial behavior in different environments
- help us better understand and manage the ecology of foodborne microorganisms

$$\frac{dx}{dt} = \frac{q(t)}{q(t)+1} \cdot \mu_{\max} \cdot \left(1 - \left(\frac{x(t)}{x_{\max}}\right)^{m}\right) x(t)$$

Predictive microbiology

Assumes microbial behavior is:

- reproducible
- quantifiable by characterizing environmental factors

Benefits of predictive models

- **Identify factors** that control microbial viability (e.g. temp, a_w, pH, organic acids)
- Assist in **defining preventive controls** (e.g. critical limits)
- Help regulatory authorities **develop** standards, and help companies **meet standards**
- **Minimize microbiological testing**
- **Inform exposure assessment**

…and just as important

Predictive models advance food safety risk management systems

prescriptive → *outcome-based*

flexible

How can we be sure that we are producing the most effective models?

Technical Aspects of Applied Research

Research problem

↓

Experimental design

↓

Data generation

↓

Data analysis

↓

Publication

Social Aspects

Interacting with all end-users of the model
(defining the intended outcomes)

↓

Determining the necessary resources

↓

Research

↓

Communicating with end-users

Other associated benefits

- Predictive microbiology brings together persons with diverse but complimentary skills, including microbiologists, mathematicians, engineers, and other disciplines.
- Excellent approach for capacity-building

PRIMARY MODEL PRODUCTION

Experimental design

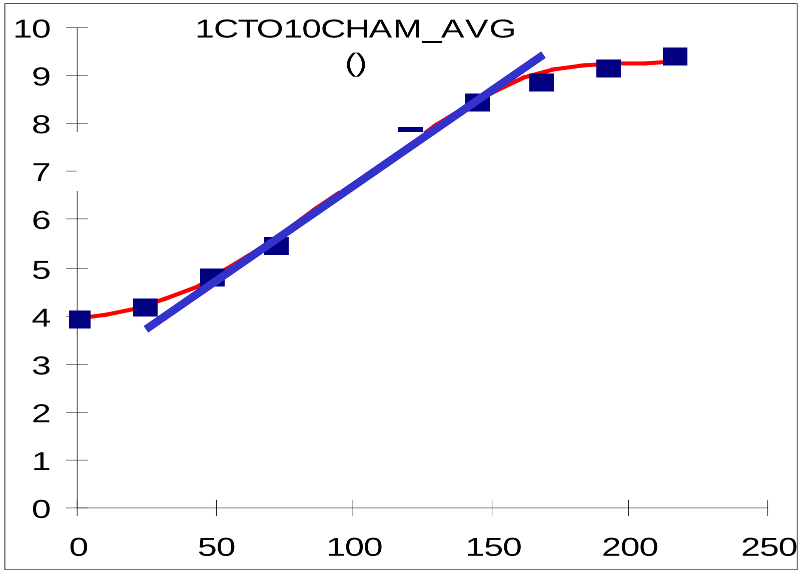
Extrinsic factors

- temperature
- atmosphere (e.g. packaging gas, humidity)

Intrinsic factors

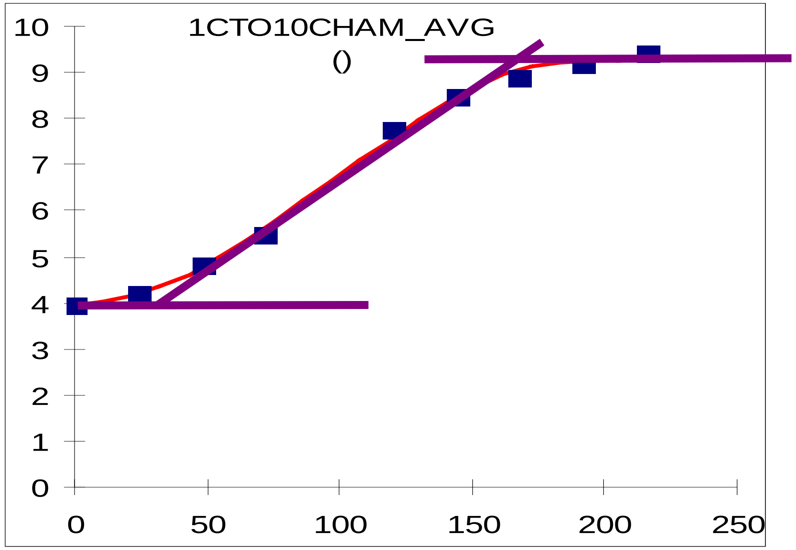
- food matrix
- pH
- water activity
- additives (e.g. NaCl, acidulants)

Growth



Kinetic parameters

- **Lag phase** — ***lag phase duration***
- **Growth** — ***growth rate***
- **Stationary phase** — ***maximum population density***



Growth Models

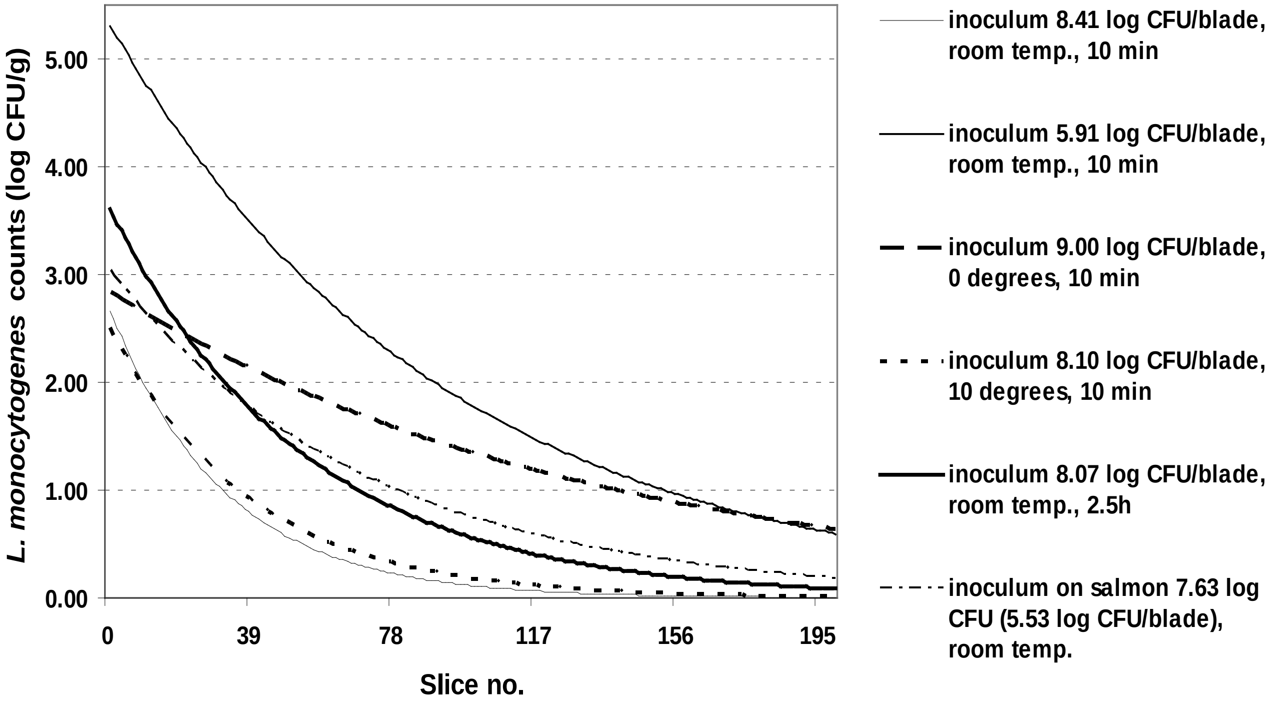
- Gompertz $$\log x(t) = A + C\exp\{-\exp[-B(t-M)]\}$$

- Baranyi $$\frac{dx}{dt} = \frac{q(t)}{q(t)+1}\cdot\mu_{\max}\cdot\left(1-\left(\frac{x(t)}{x_{\max}}\right)^{m}\right)x(t)$$

Inactivation Models

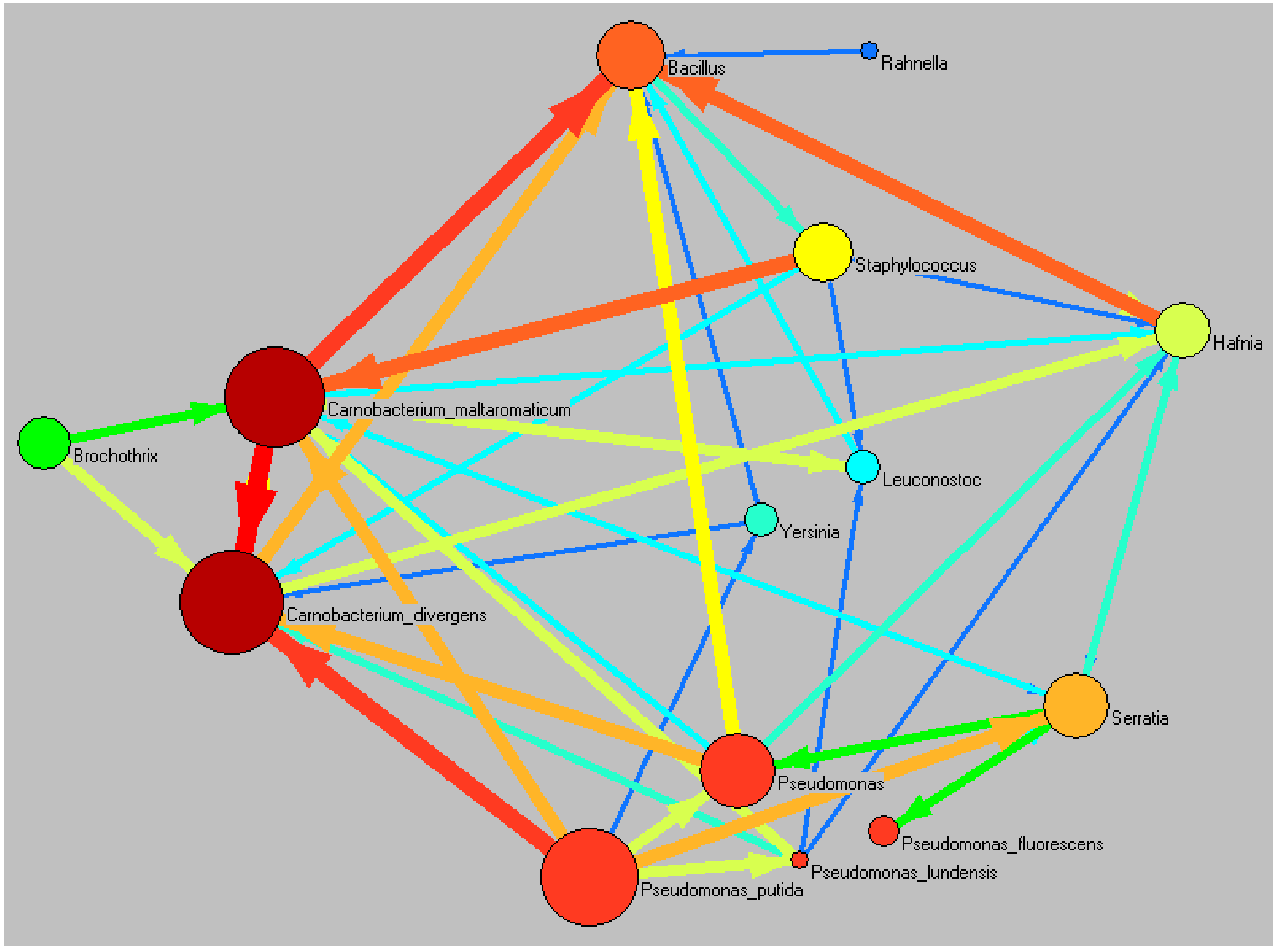
- Inactivation kinetics $$N = N_0 e^{-kt}$$
- D-value $$\frac{t}{\log N_0 - \log N_1}$$
- Z-value $$\frac{(T_2 - T_1)}{\log(D_1 / D_2)}$$
- Process lethality $$F = \int_0^t 10^{(T(t) - T(ref))/z} dt$$

Transfer Models



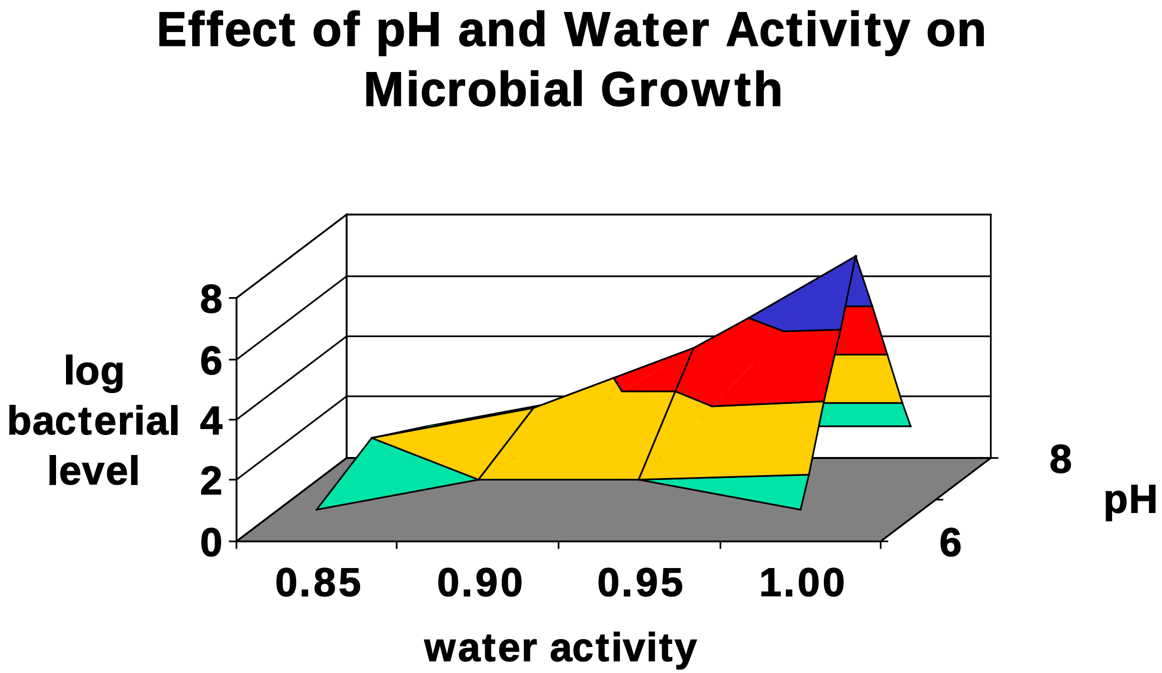
$$y=a*e^{(-x/b)}$$

Modeling the complexity of microbial interactions



SECONDARY MODELS

Change in parameter(s) as a function of environmental change

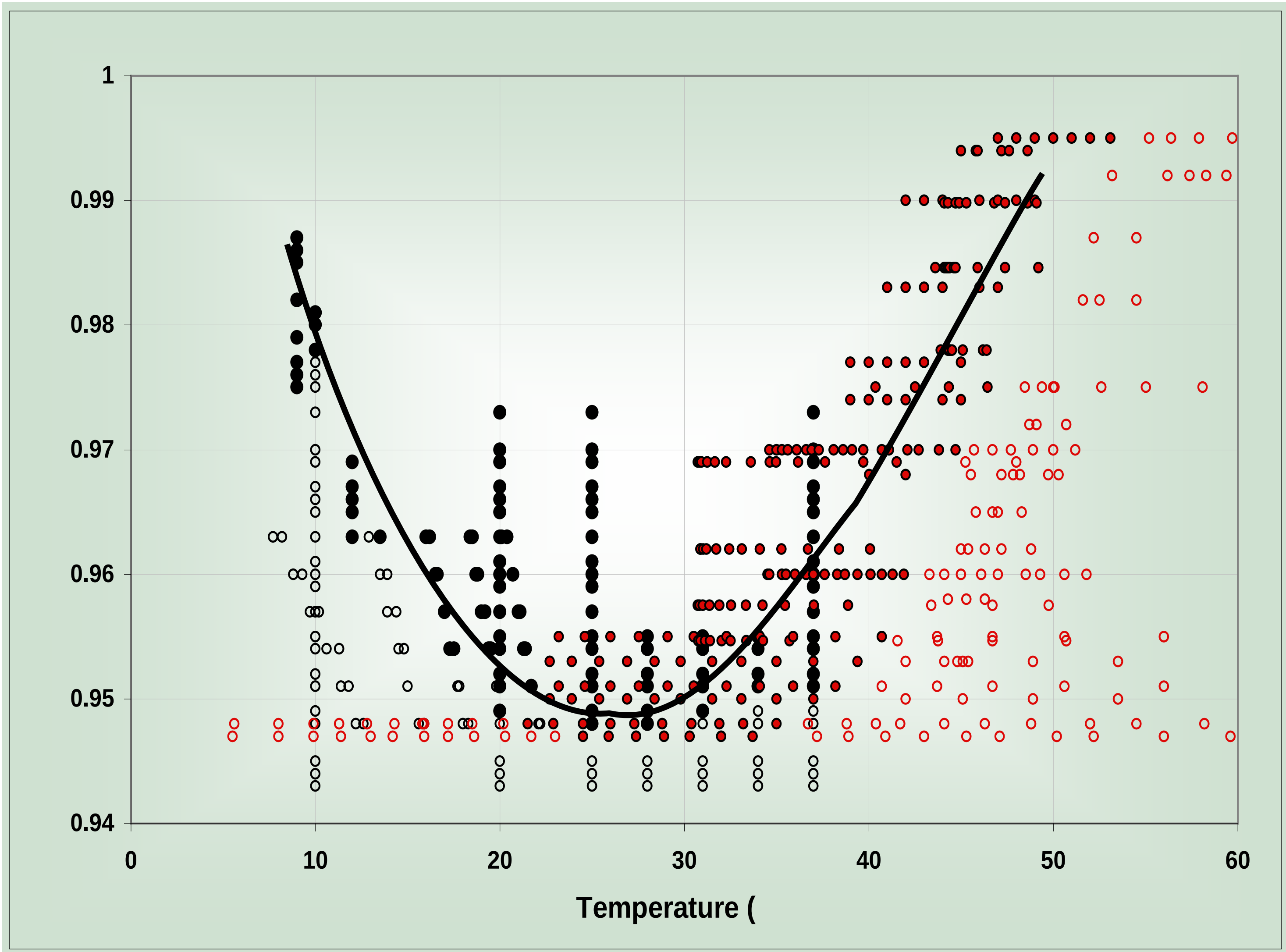


Probabilistic models

Growth/No-growth boundaries

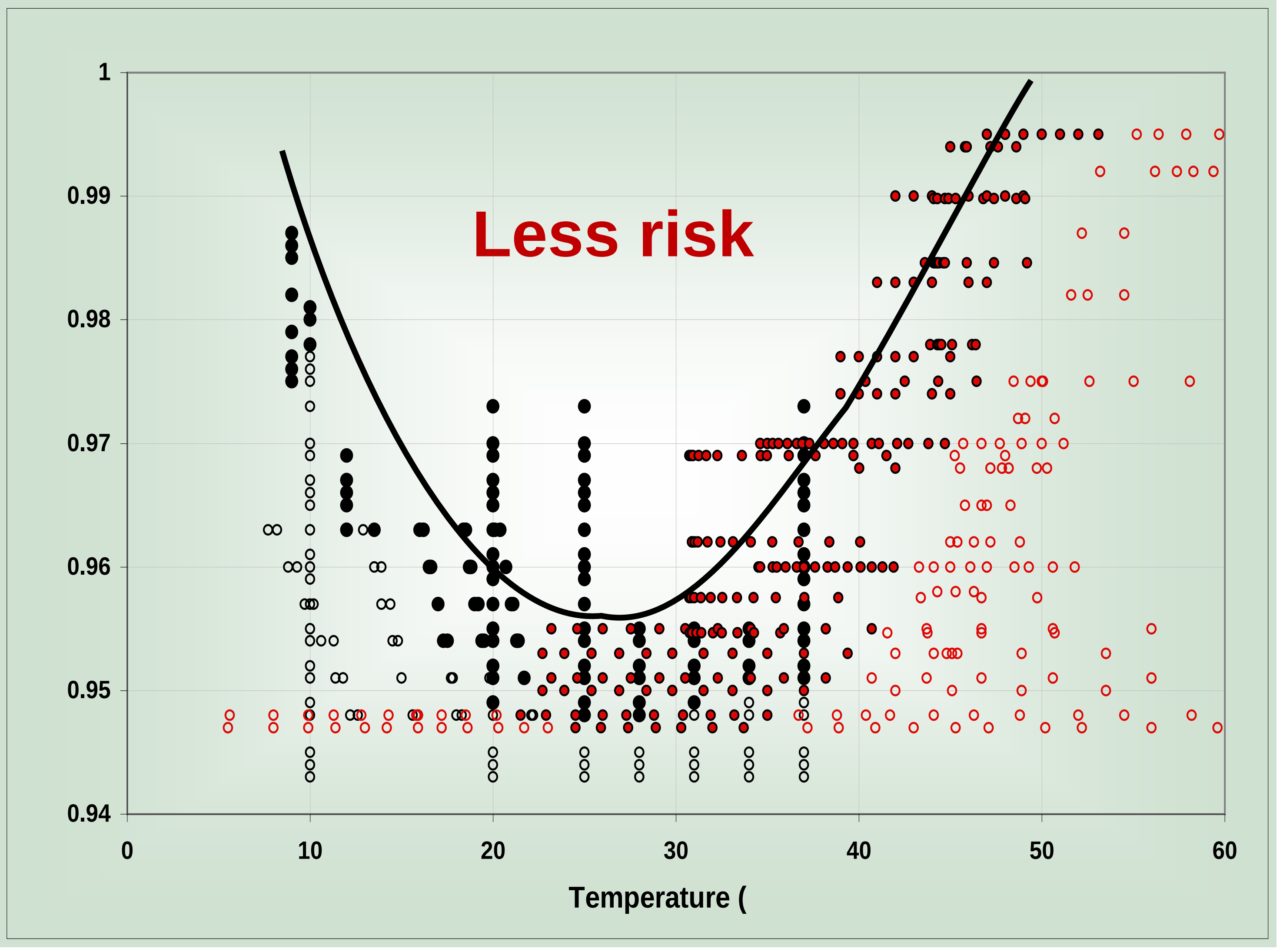
(e.g. product development)

Growth/No-Growth



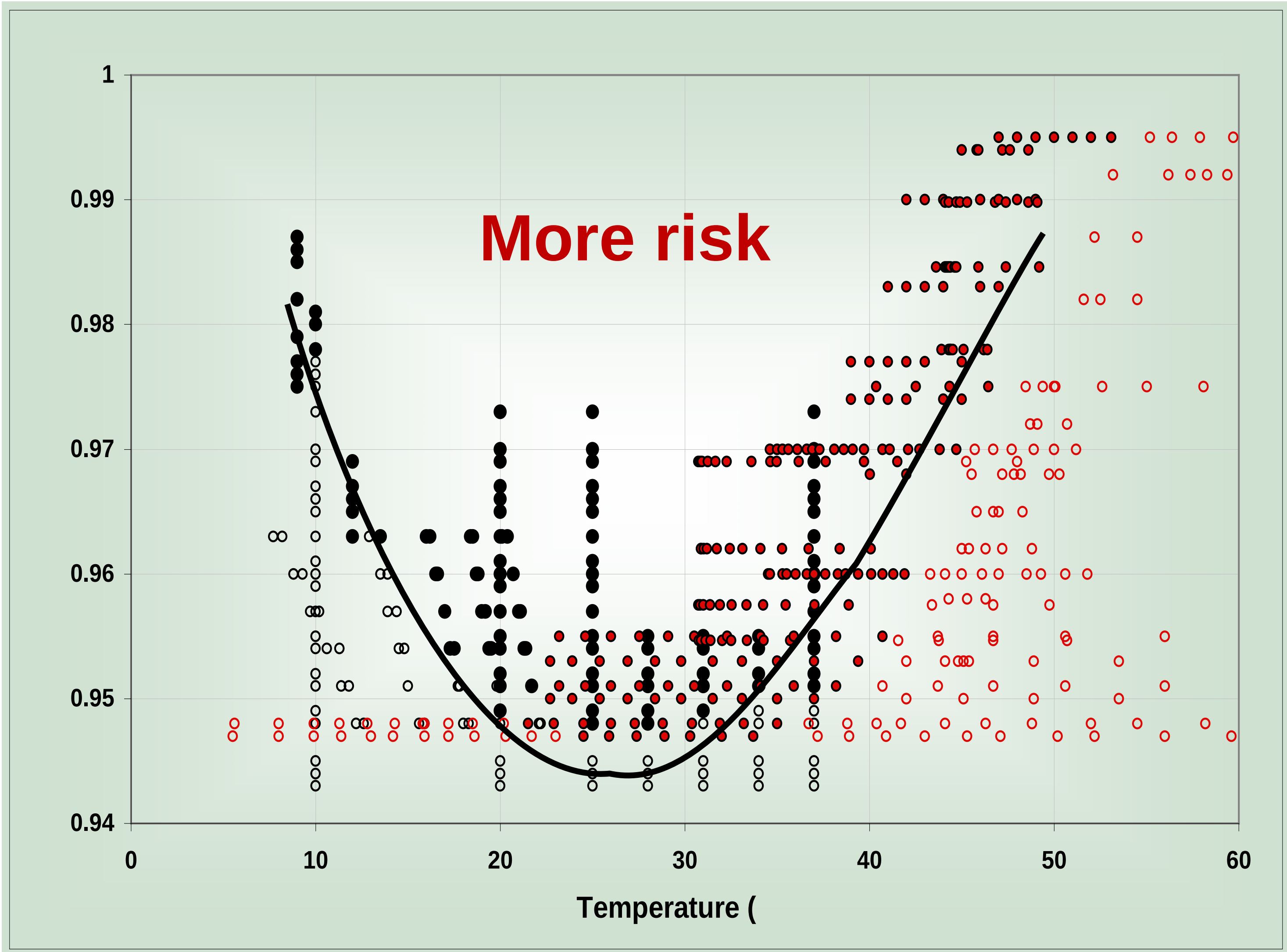
Adapted from Ross

Growth/No-Growth



Adapted from Ross

Growth/No-Growth



Adapted from Ross

Measuring Model Performance
(validation)

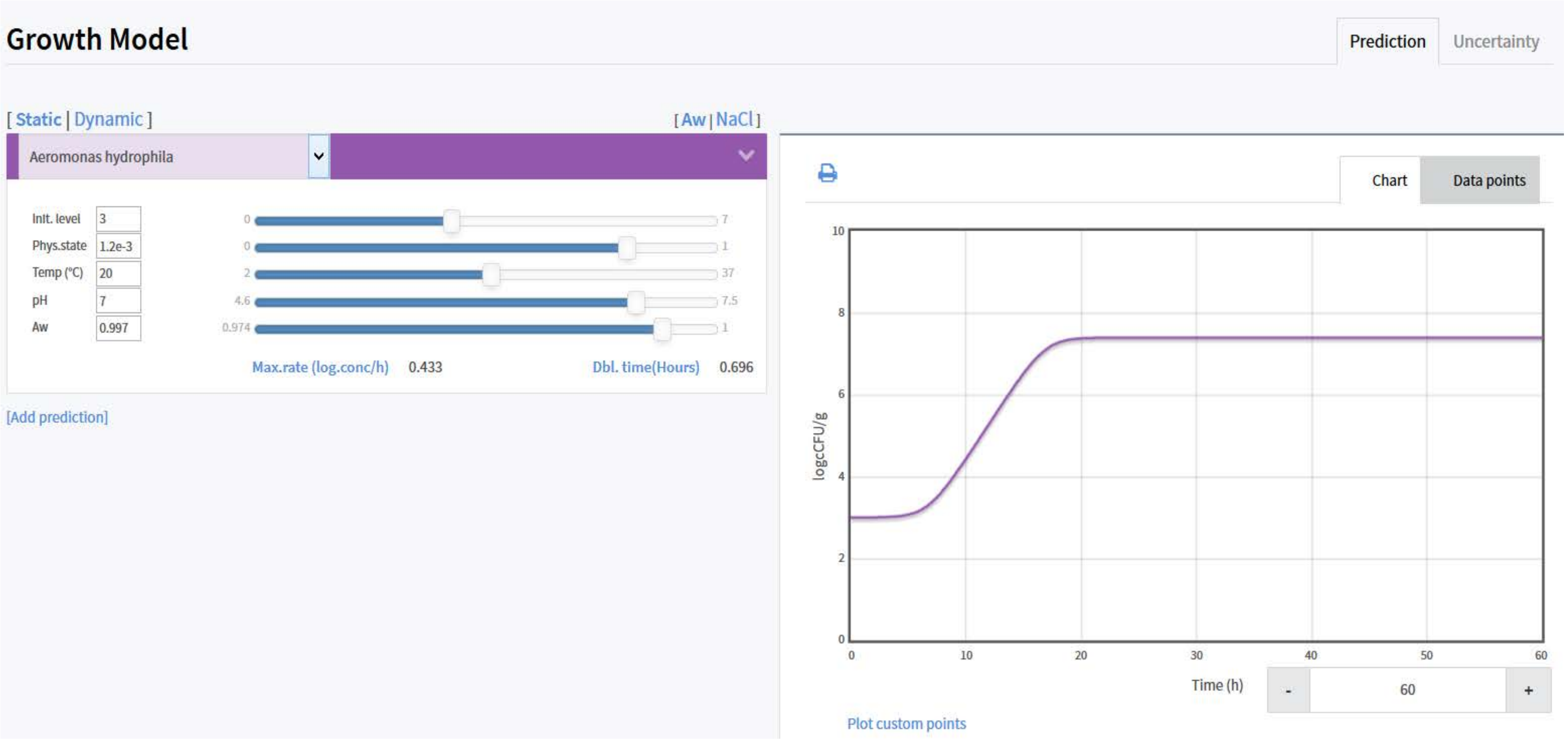
- **Bias factor**

$$B_f = 10^{(\sum \log(GT_{predicted} / GT_{observed}) / n)}$$

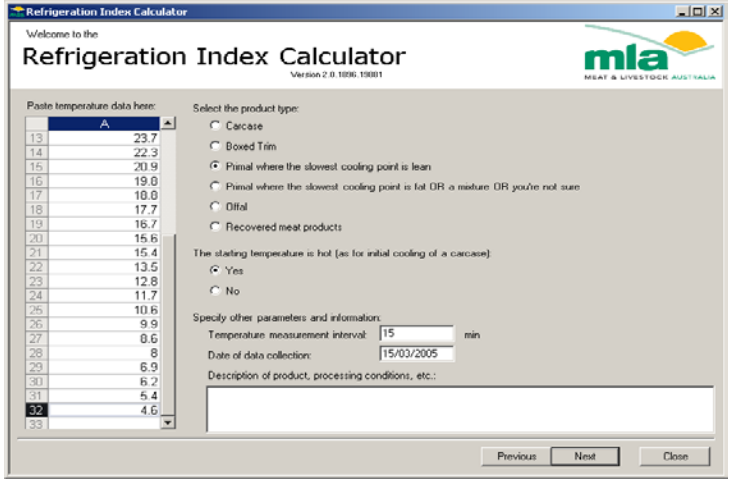
- **Accuracy factor**

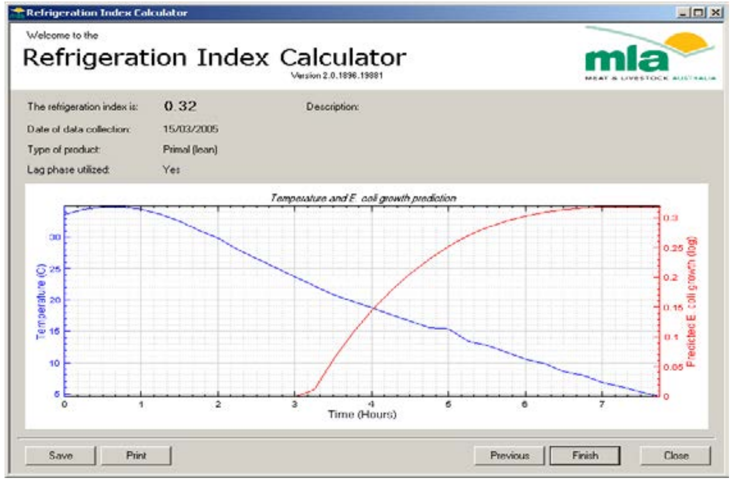
$$A_f = 10^{(\sum \left| \log(GT_{predicted} / GT_{observed}) \right| / n)}$$

TERTIARY MODELS

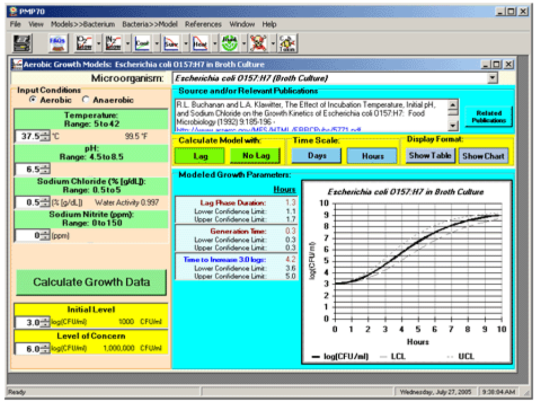


$$GR\ (\log\ cfu/h) = -0.0146 + 0.0098T - 0.0206L - 0.2220D - 0.0013TL - 0.0392TD + 0.0143LD + 0.0001T^2 + 0.0053L^2 + 2.9529D^2$$


Refrigeration Index Calculator
Welcome to the
Refrigeration Index Calculator
Paste temperature data here:
Select the product type:
Carcase
Boxed Trim
Primal where the slowest cooling point is lean
Primal where the slowest cooling point is fat OR a mixture OR you're not sure
Offal
Recovered meat products
The starting temperature is hot (as for initial cooling of a carcase):
Yes
No
Specify other parameters and information:
Temperature measurement interval:
15
min
Date of data collection:
15/03/2005
Description of product, processing conditions, etc.:
Previous
Next
Close


Refrigeration Index Calculator
Welcome to the
Refrigeration Index Calculator
The refrigeration index is:
0.32
Description:
Date of data collection:
15/03/2005
Type of product:
Primal (lean)
Lag phase utilized:
Yes
Temperature and E. coli growth prediction
Temperature (C)
Predicted E. coli growth (log)
Time (Hours)
Save
Print
Previous
Finish
Close

Examples of common model interfaces



Lanzamiento de la nueva versión de MicroHibro!!!

microHibro 2.0

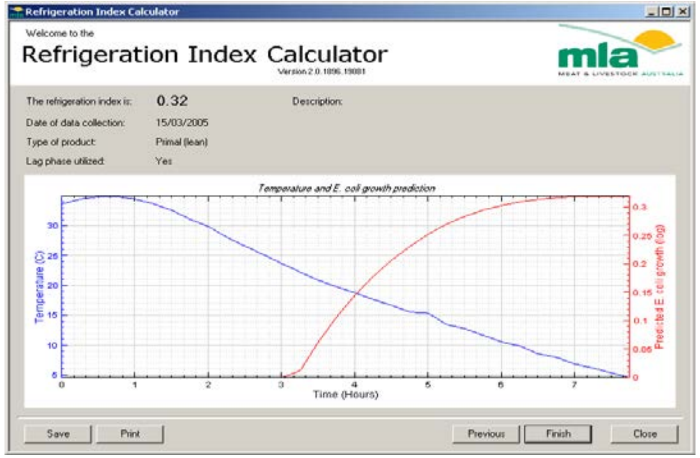
Γεωπονικό Πανεπιστήμιο Αθηνών
Agricultural University of Athens

GroPIN Modelling DataBase

Laboratory of Food Quality Control & Hygiene
Department of Food Science and Technology
Agricultural University of Athens

FSSP

Food Spoilage and Safety Predictor (FSSP)



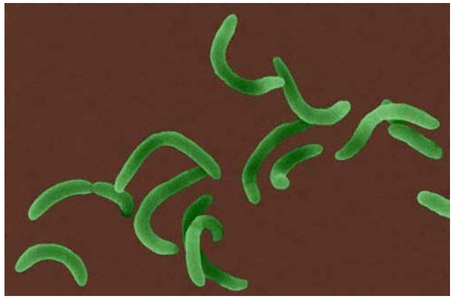
ComBase

FDA-iRISK® 2.0

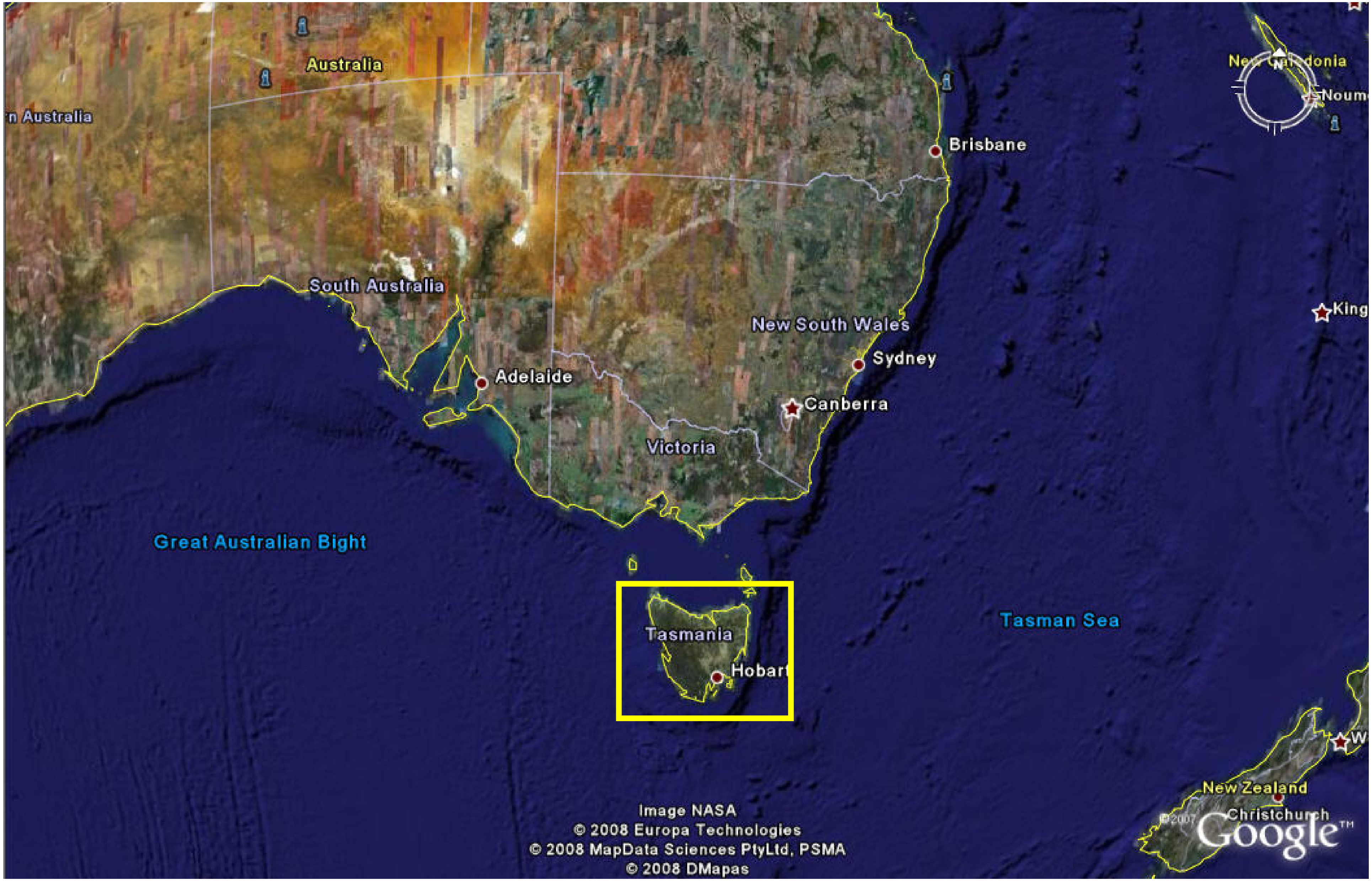
MRV
Microbial Responses Viewer

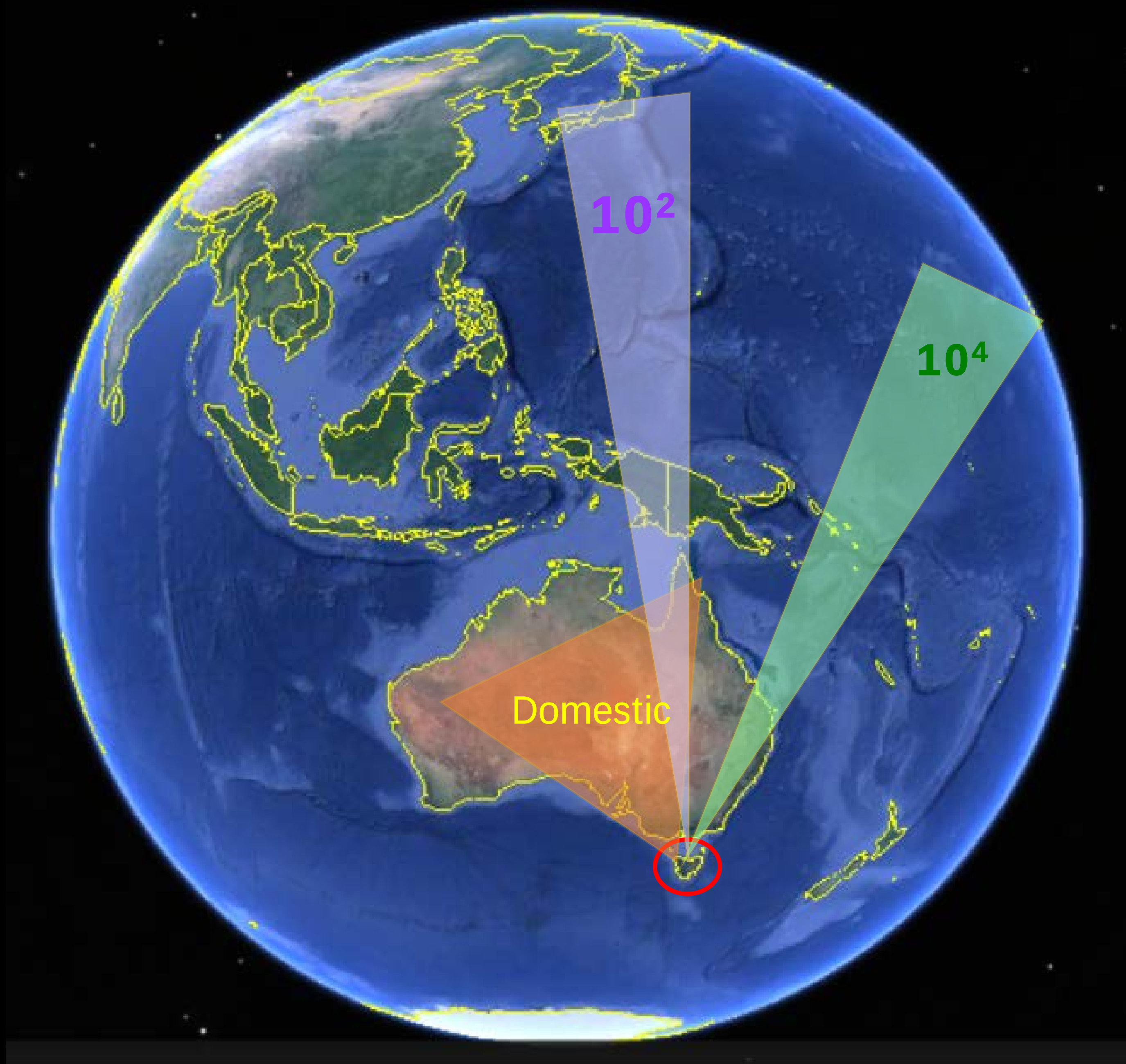
Case Studies

Case study #1: *Vibrio parahaemolyticus* and oyster supply chains

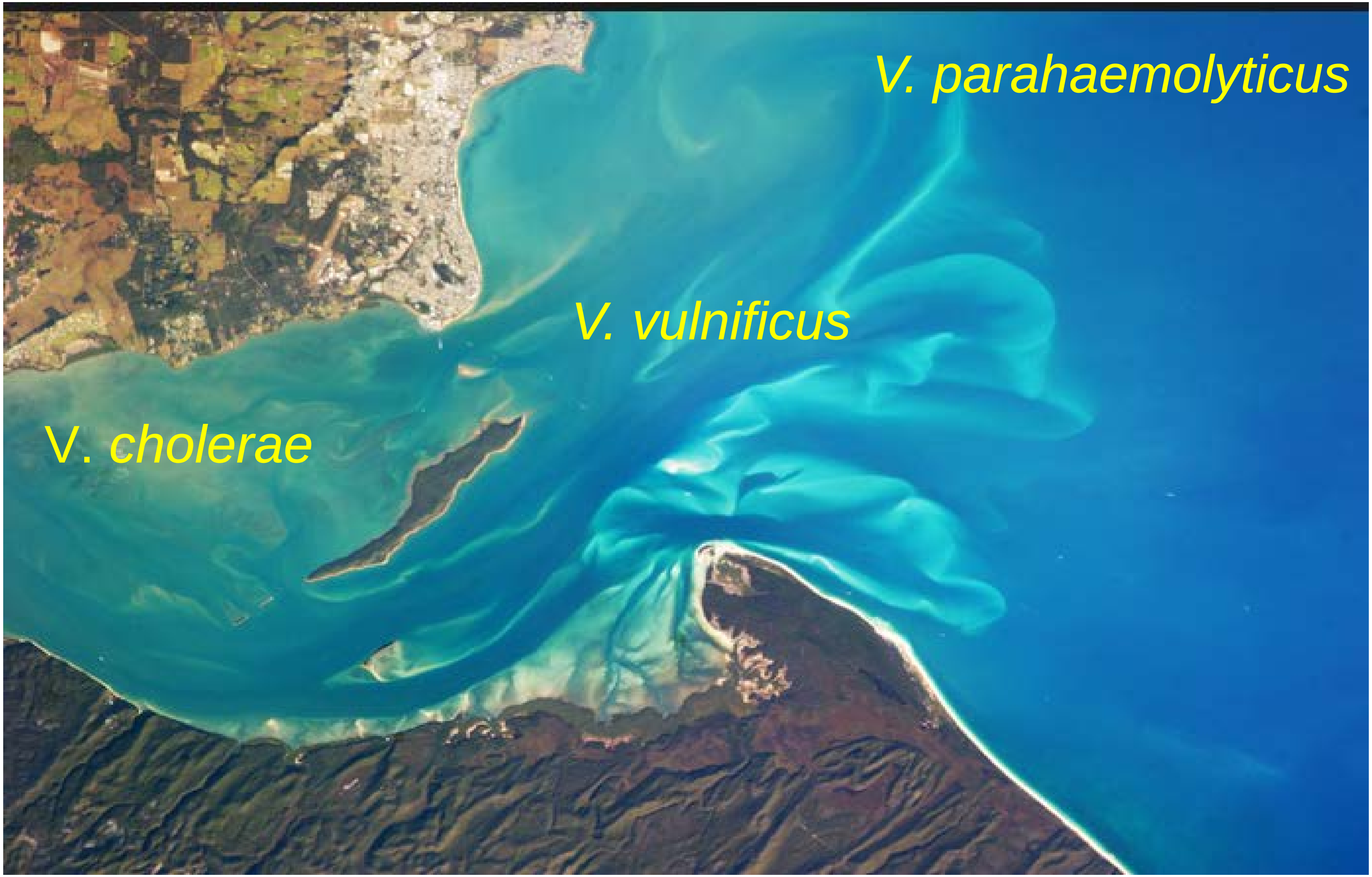


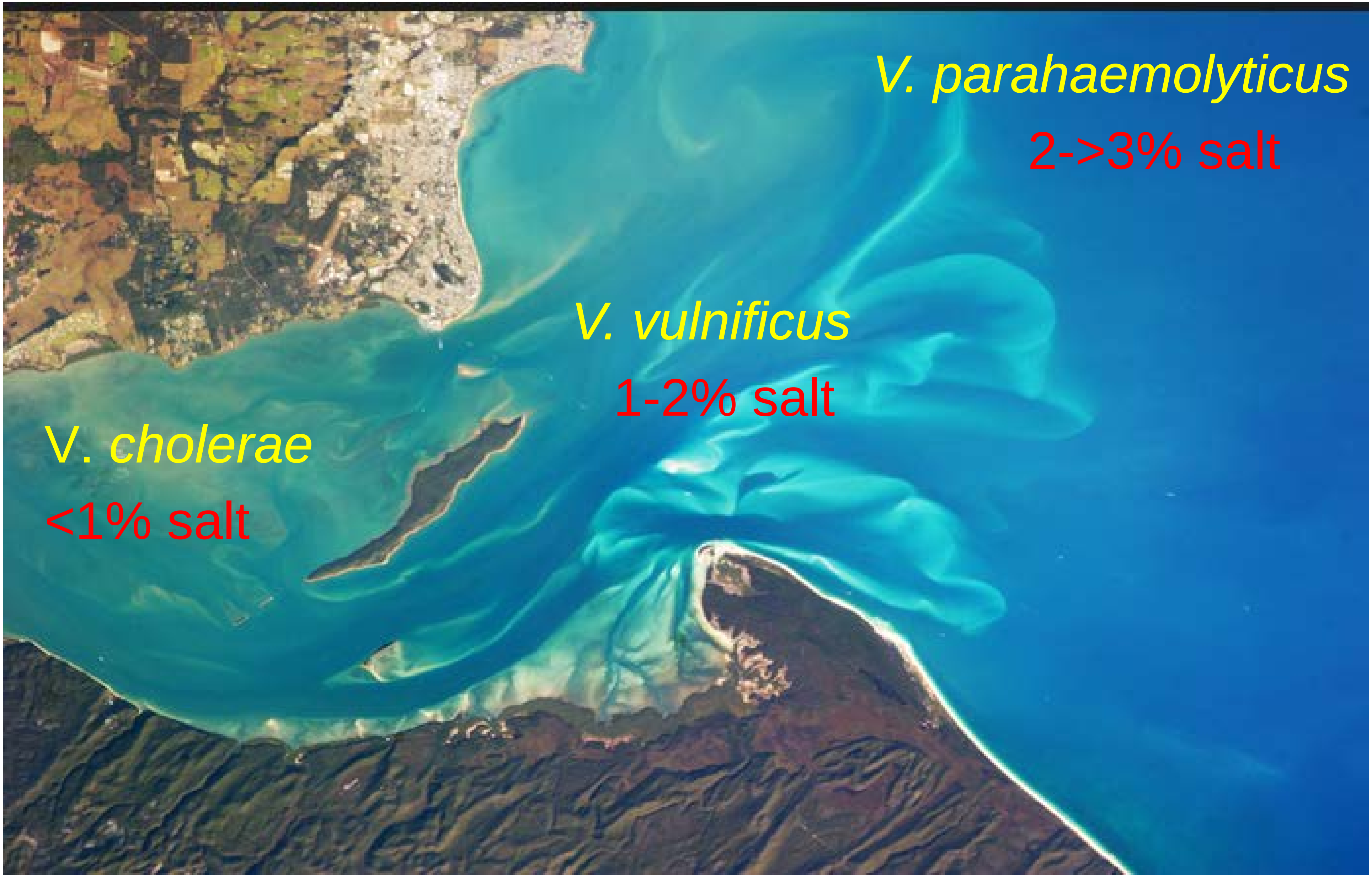
Problem: How can companies reduce uncertainties in supply chains?


Australia
South Australia
New South Wales
Brisbane
Sydney
Canberra
Adelaide
Victoria
Great Australian Bight
Tasmania
Hobart
Tasman Sea
New Zealand
Christchurch
Image NASA
© 2008 Europa Technologies
© 2008 MapData Sciences PtyLtd, PSMA
© 2008 DMapas
Google

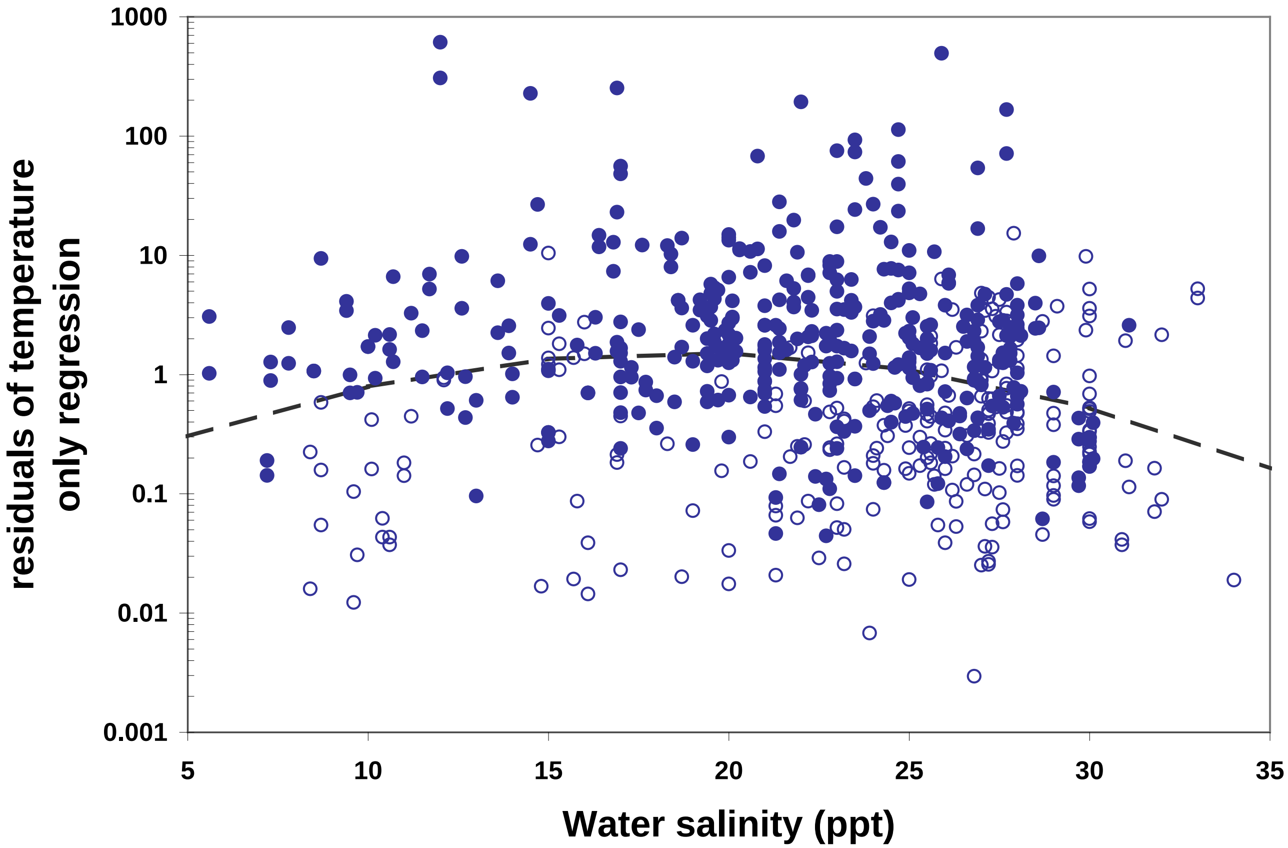


10^2
10^4
Domestic

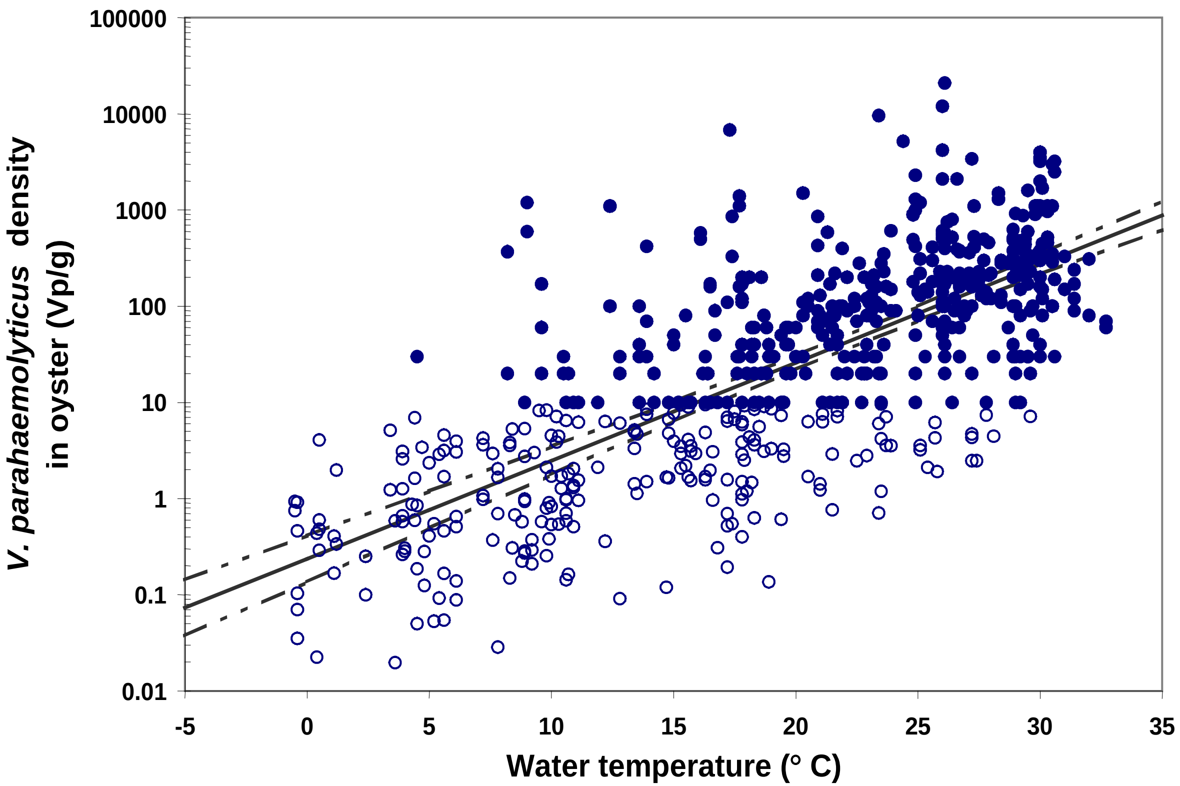

V. parahaemolyticus
V. vulnificus
V. cholerae


V. parahaemolyticus
2->3% salt
V. vulnificus
1-2% salt
V. cholerae
<1% salt


V. parahaemolyticus
2->3% salt



Residuals of predicted versus observed log10 *V. parahaemolyticus* (Vp) densities in oysters versus salinity based on linear regression of log10 *V. parahaemolyticus* (Vp) densities against water temperature.



Regression fit of $\log_{10}$ *V. parahaemolyticus* (Vp) densities in oysters versus water temperature (DePaola *et al*., 1990). Mean $\log_{10}$ Vp/g or median Vp/g (solid line) and 95% confidence limits (dashed lines).

Relationship Between Seawater Surface Temperature and *V. parahaemolyticus* Densities in Oysters

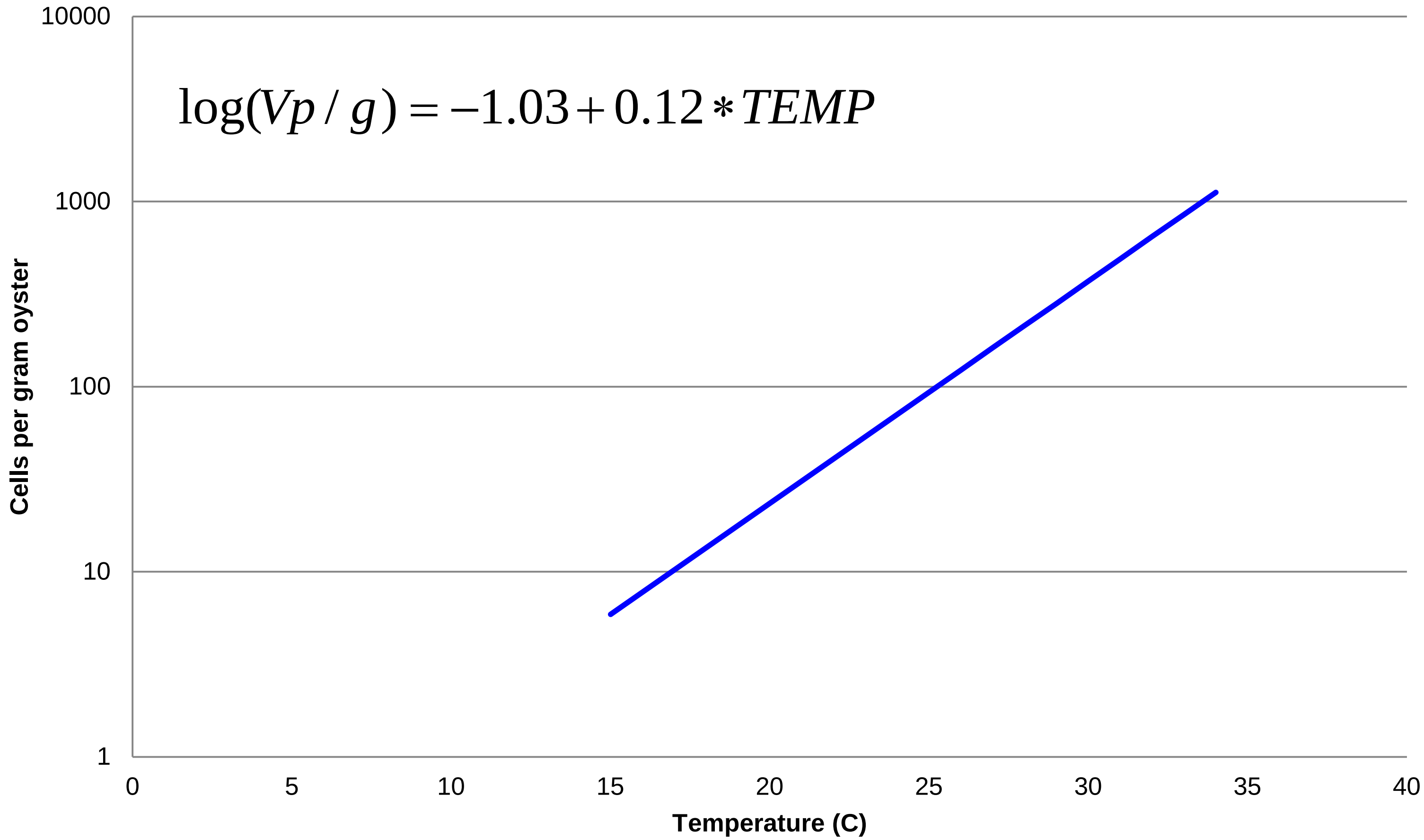


Figure 5: Water temperature

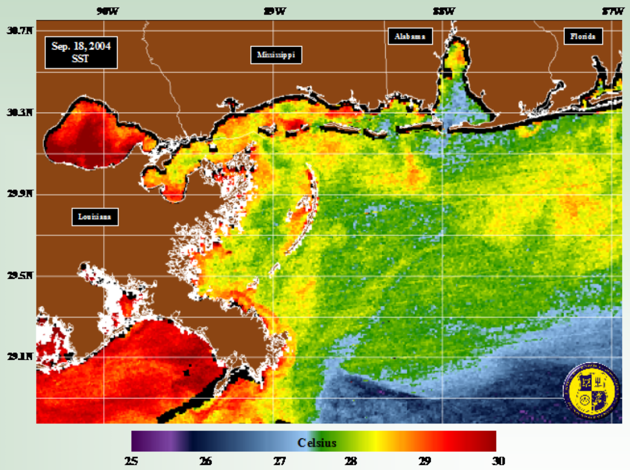
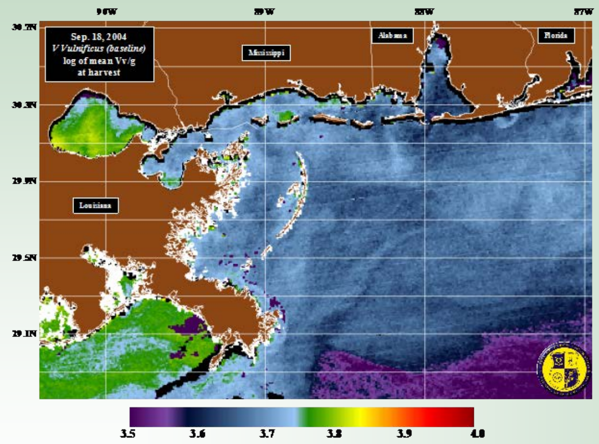


Figure 6: *V. vulnificus* baseline levels



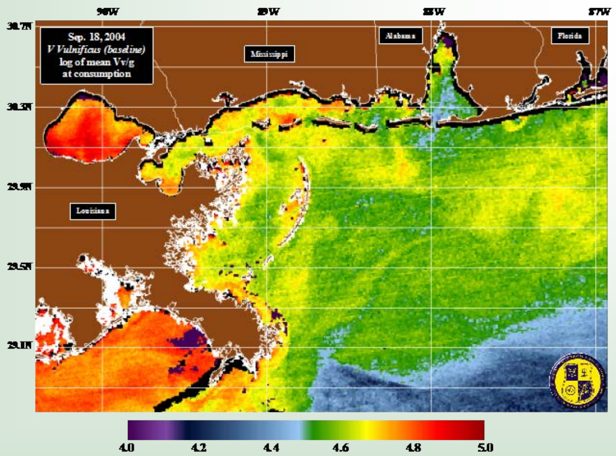


Figure 7: *V. vulnificus* levels at time of consumption

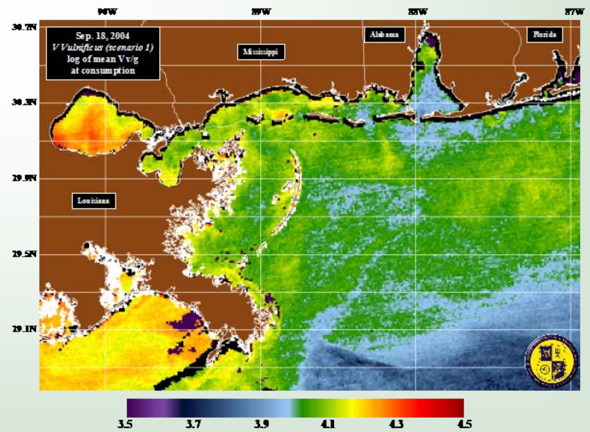
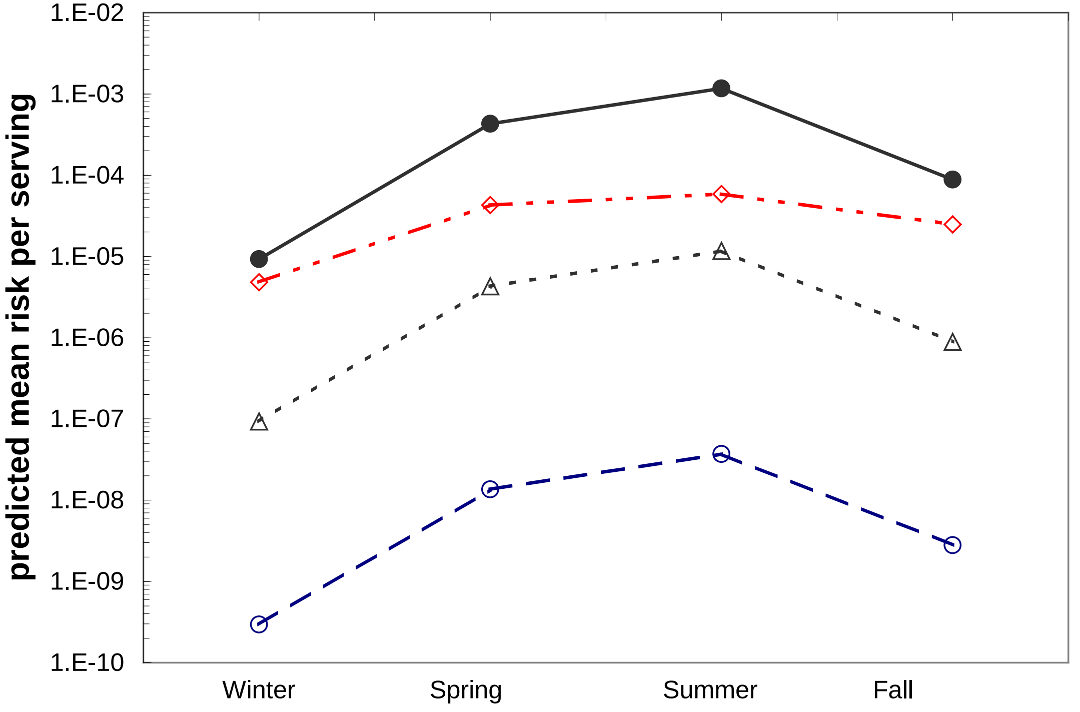


Figure 8: Log mean risk at consumption

Risk Management



Effect of potential mitigations on the distribution mean risk of *V. parahaemolyticus* illnesses per serving associated with Gulf Coast harvest. No mitigation (●);rapid cooling (◊);treatment resulting in 2-log reduction (Δ); treatment resulting in ≥4.5-log reduction (○).

FDA *V. parahaemolyticus* Risk Assessment 2005

V. parahaemolyticus harvest control plan

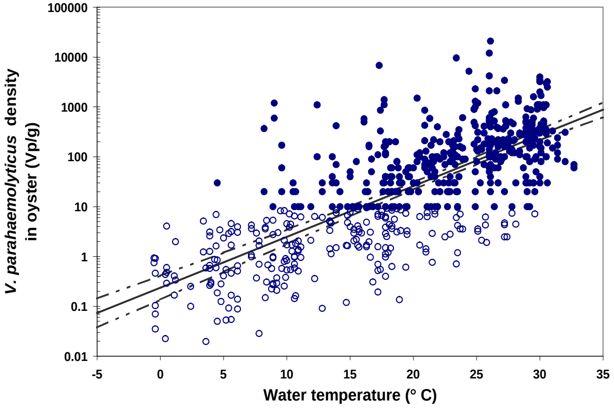
Atlantic (subtidal harvest)

month	water temperature (F)	air temperature (F)	maximum time unrefrigerated (hr)	expected cases per 100,000 (servings)	lower confidence limit on expected cases per 100,000	VPCP needed?	maximum time (hr) for lower confidence of 1 per 100,000
Jan	38.3	33.3	36	0.0038	0.0003	N	
Feb	36.7	35.6	36	0.0018	0.00014	N	
Mar	42.6	41.0	36	0.0019	0.00015	N	
Apr	52.3	50.9	36	0.012	0.00095	N	
May	64.0	59.9	36	0.56	0.044	N	
Jun	73.8	69.3	24	13	1	N	
July	79.9	74.3	24	160	13	Y	12.3
Aug	81.1	73.0	24	120	9.5	Y	12.9
Sep	75.2	67.1	24	7.7	0.61	N	
Oct	64.6	56.3	36	0.2	0.016	N	
Nov	53.1	45.9	36	0.0074	0.00059	N	
Dec	43.0	36.0	36	0.0037	0.00029	N	

Climate Change

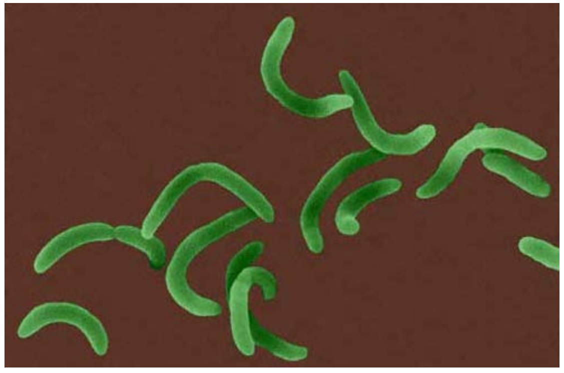
Vibrio species

- *Vibrio* diseases are increasing
- Outbreaks of *V. parahaemolyticus*
  - Example: 2004-2007- outbreak in Puerto Montt, Chile
  - >7,000 cases
  - O3:K6 serotype
  - El Nino Southern Oscillation (ENSO)



A Predictive Model to Manage the Risk of *Vibrio parahaemolyticus* in Australian Pacific Oysters (*Crassostrea gigas*)

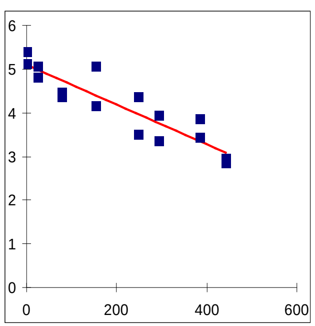
Dr. Judith Fernandez-Piquer

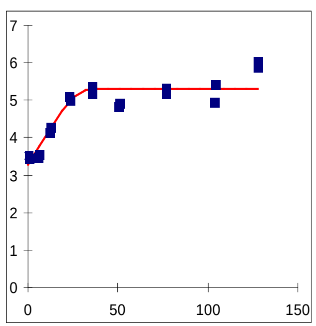


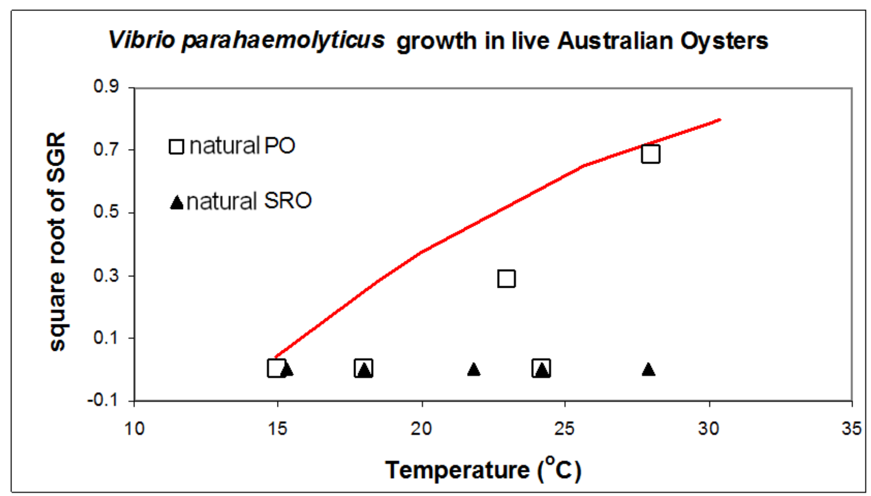
Fernandez-Piquer et al., Appl. Environ. Microbiol. 2011

Model development

- *V. parahaemolyticus* growth kinetics measured from 4 - 30^{o}C
- Growth (>15^{o}C) and death rates (<15^{o}C) determined
- Models tested (validated) against naturally-occurring Vp

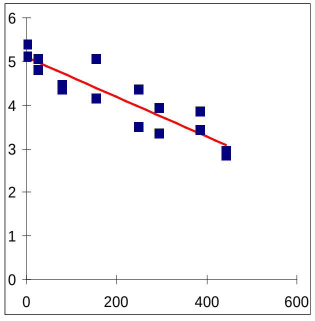


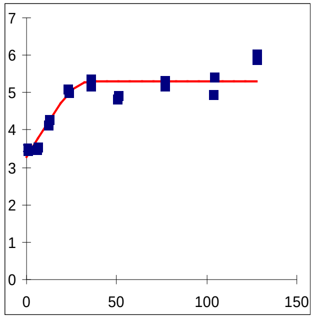




Model validation

- *V. parahaemolyticus* growth was measured from 4 - 30°C
- Growth (>15°C) and death rates (<15°C) determined
- Models tested (validated) against naturally-occurring Vp





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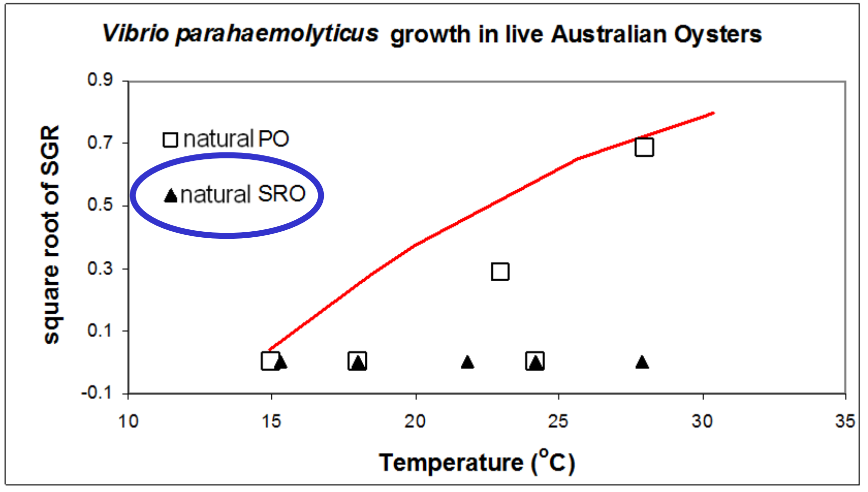

Models for *V. parahaemolyticus* growth and inactivation, and Total Viable Count

Vp growth	√growth rate = 0.0303 x (temperature - 13.37) R^2= 0.92
Vp inactivation	ln inactivation rate = ln $1.81 \times 10^{-9} + 4131.2 \times (1/(T+273.15))$ R^2= 0.78
TVC growth	√growth rate = 0.0102 x (temperature + 6.71) R^2= 0.92

Fernandez-Piquer et al., Appl. Environ. Microbiol. 2011

AUSTRALIAN SEAFOOD COOPERATIVE RESEARCH CENTRE

Oyster Refrigeration Index

food safety centre

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Oyster Refrigeration Index

The Australian Seafood CRC Oyster Refrigeration Index is a predictive model that estimates the growth and survival of *V. parahaemolyticus* and total viable count (TVC) bacteria in Pacific oysters (*Crassostrea gigas*).

Temperature is a key factor for controlling *V. parahaemolyticus* growth and this tool helps oyster companies design and monitor supply chains to maximise both oyster safety and quality. The Oyster Refrigeration Index can be especially useful for companies that have long supply chains and those exporting to countries that have maximum *V. parahaemolyticus* and TVC limits.

The model predictions were field-tested with Pacific oysters which contained natural populations of *V. parahaemolyticus*. The tests demonstrated that the model provided "fail-safe" predictions for *V. parahaemolyticus* growth in Pacific oysters over a temperature range of 4 to 30°C.

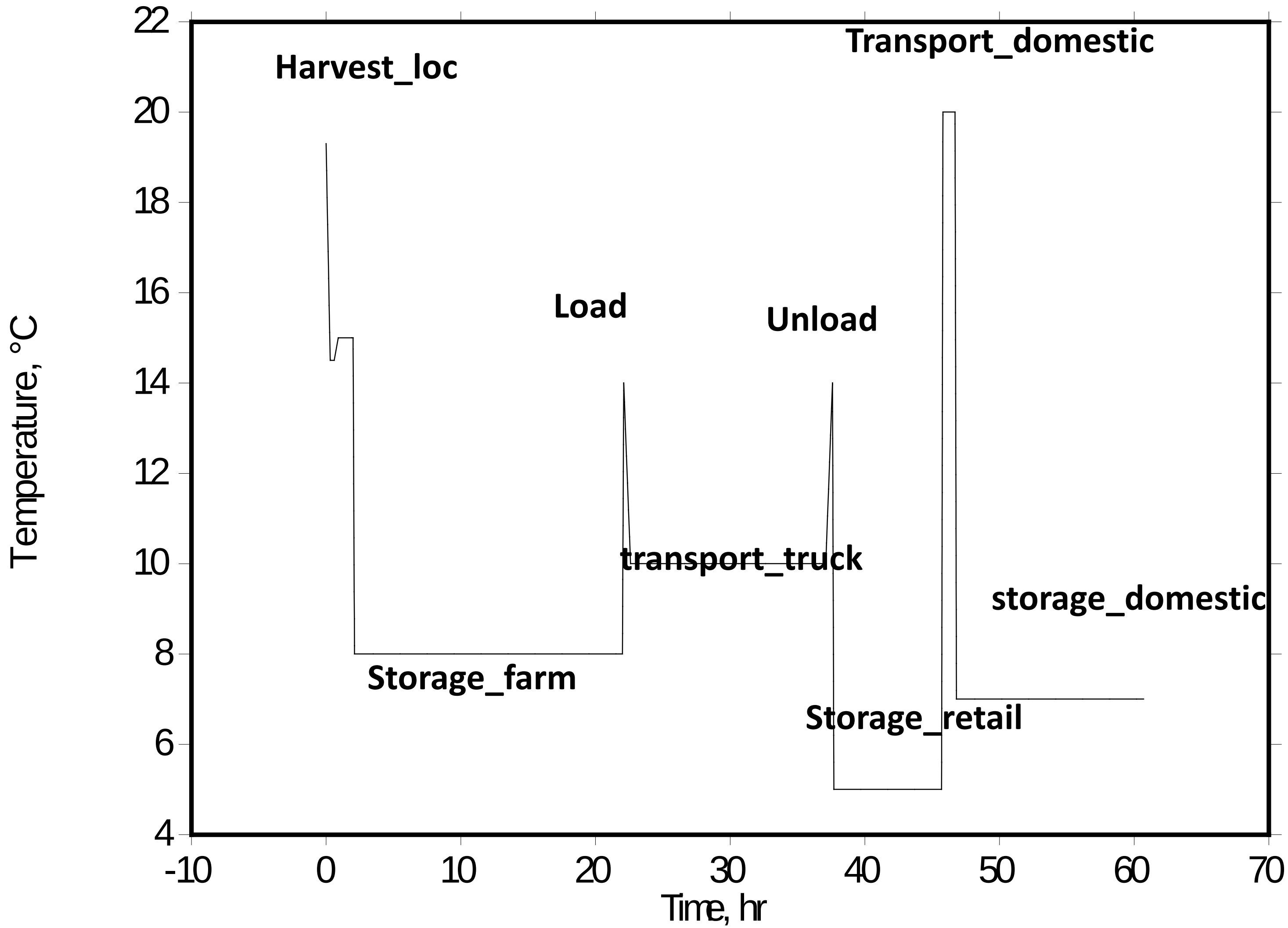
After registering, you can access both a web-based and Excel® downloadable version of the *V. parahaemolyticus* and TVC models.

We hope you find this tool useful. If you have technical questions or wish to provide us with feedback, please see the "Contact us" link below.

- Login
- New user? Register to use the predictor
- Documents and Downloads (User Guide and Excel® versions)
- Contact Us
- Acknowledgments
- Funding sponsors
- Disclaimer

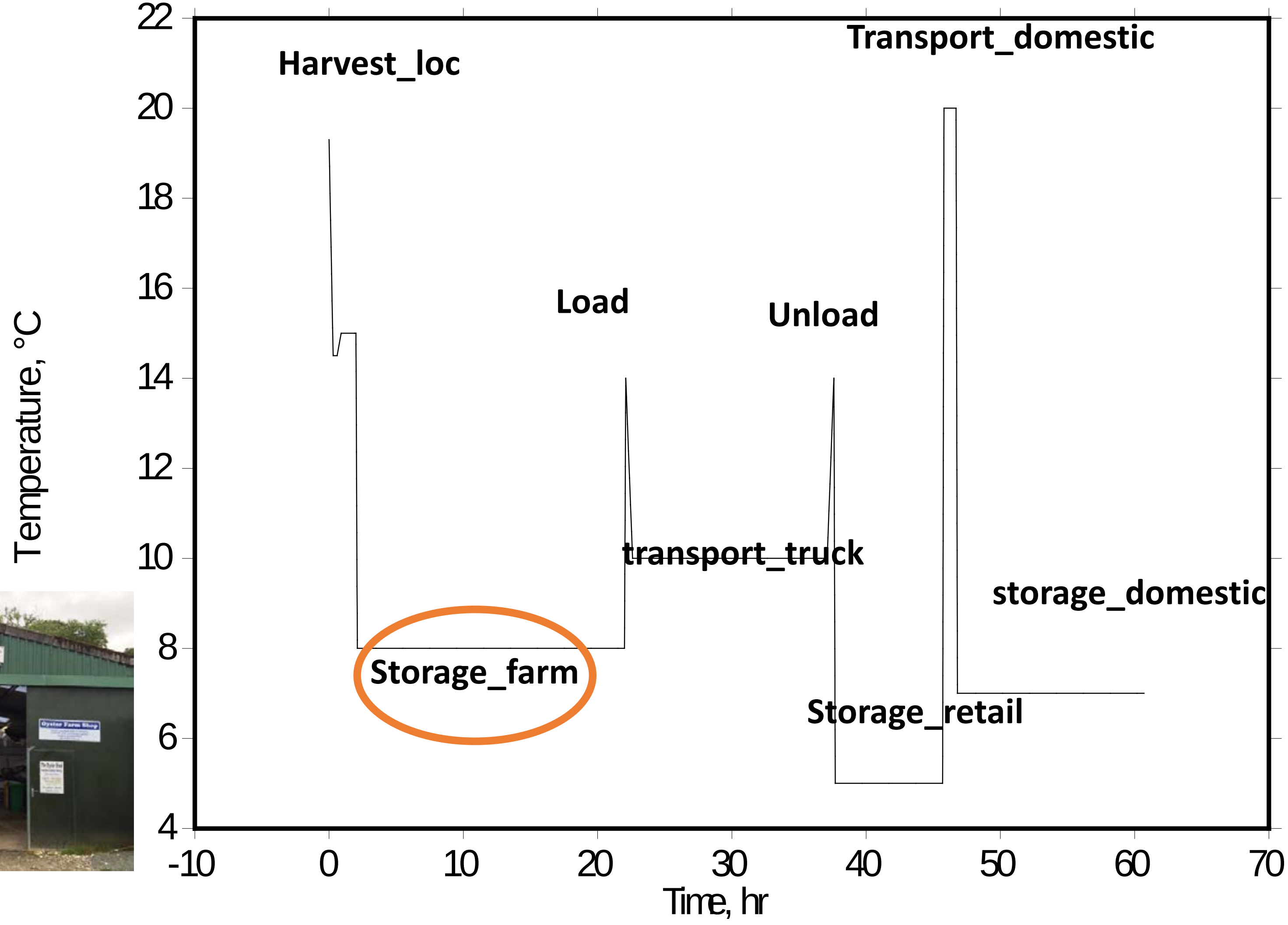
http://vibrio.foodsafetycentre.com.au/

Sensitivity Analysis of Oyster Supply Chains



from Madigan 2008

Sensitivity Analysis of Oyster Supply Chains

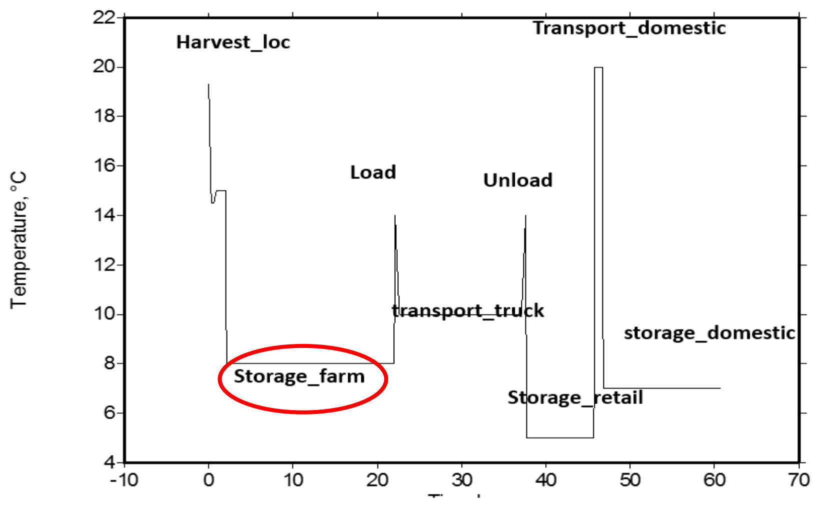


from Madigan 2008

Refrigeration vs Spoilage Cost Scenarios

Temperature	Possibilities of exceeding 7.9 log CFU/g	Cold storage cost	Cost of loss of product
4 C	7.0%	$ 166,445.97	$ 1,234,975.35
6 C	9.4%	$ 158,687.03	$ 1,658,395.47
8 C	12.3%	$ 150,931.67	$ 2,170,028.12
10 C	16.4%	$ 143,181.63	$ 2,893,370.82
12 C	22.0%	$ 135,445.05	$ 3,881,351.10

~$23,000 **~$1.6 million**



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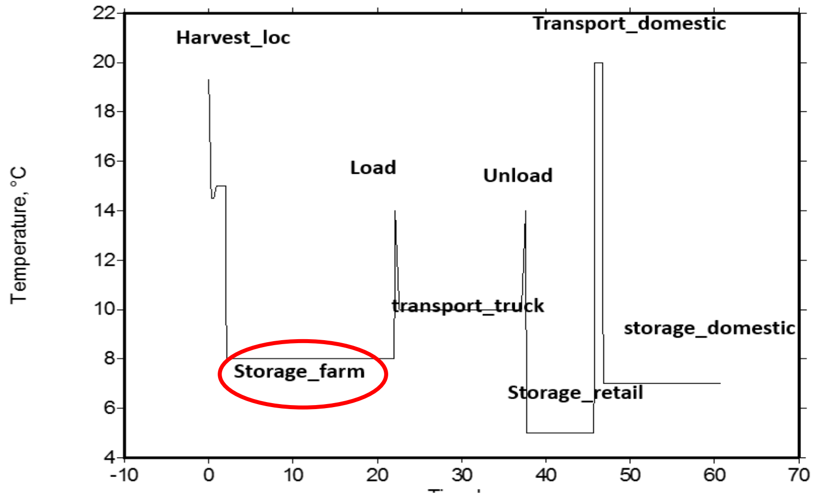
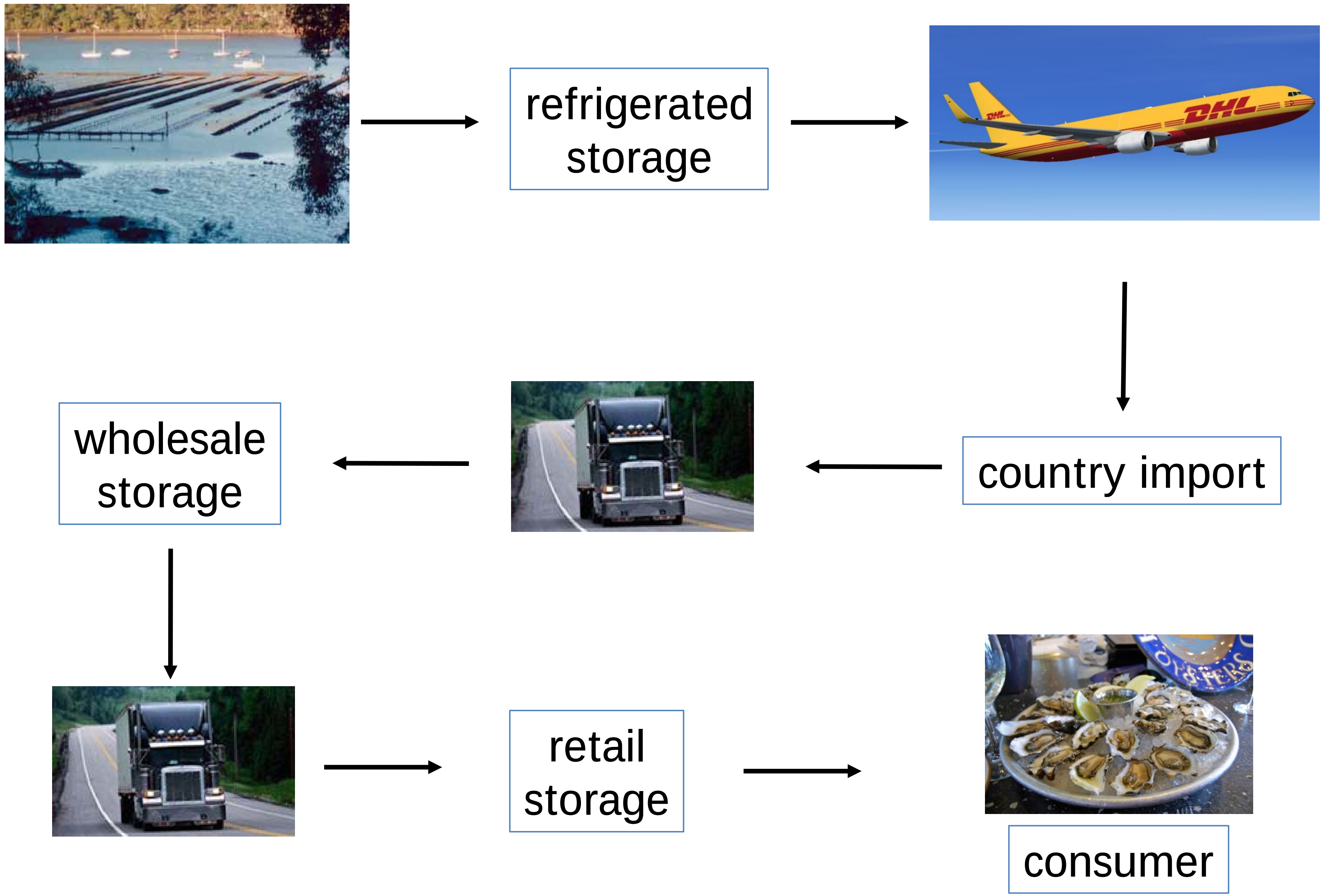


~$23,000 **~$1.6 million**

By investing

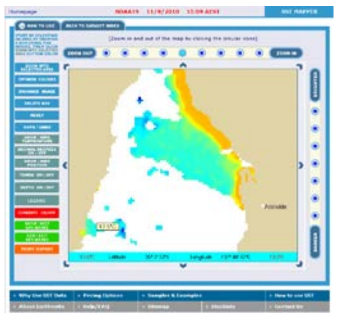
The industry could save!

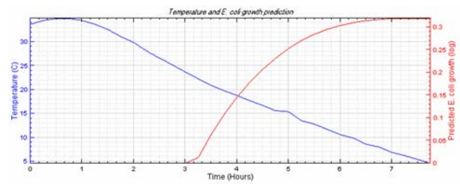
Integrating Sensors and Predictive Models

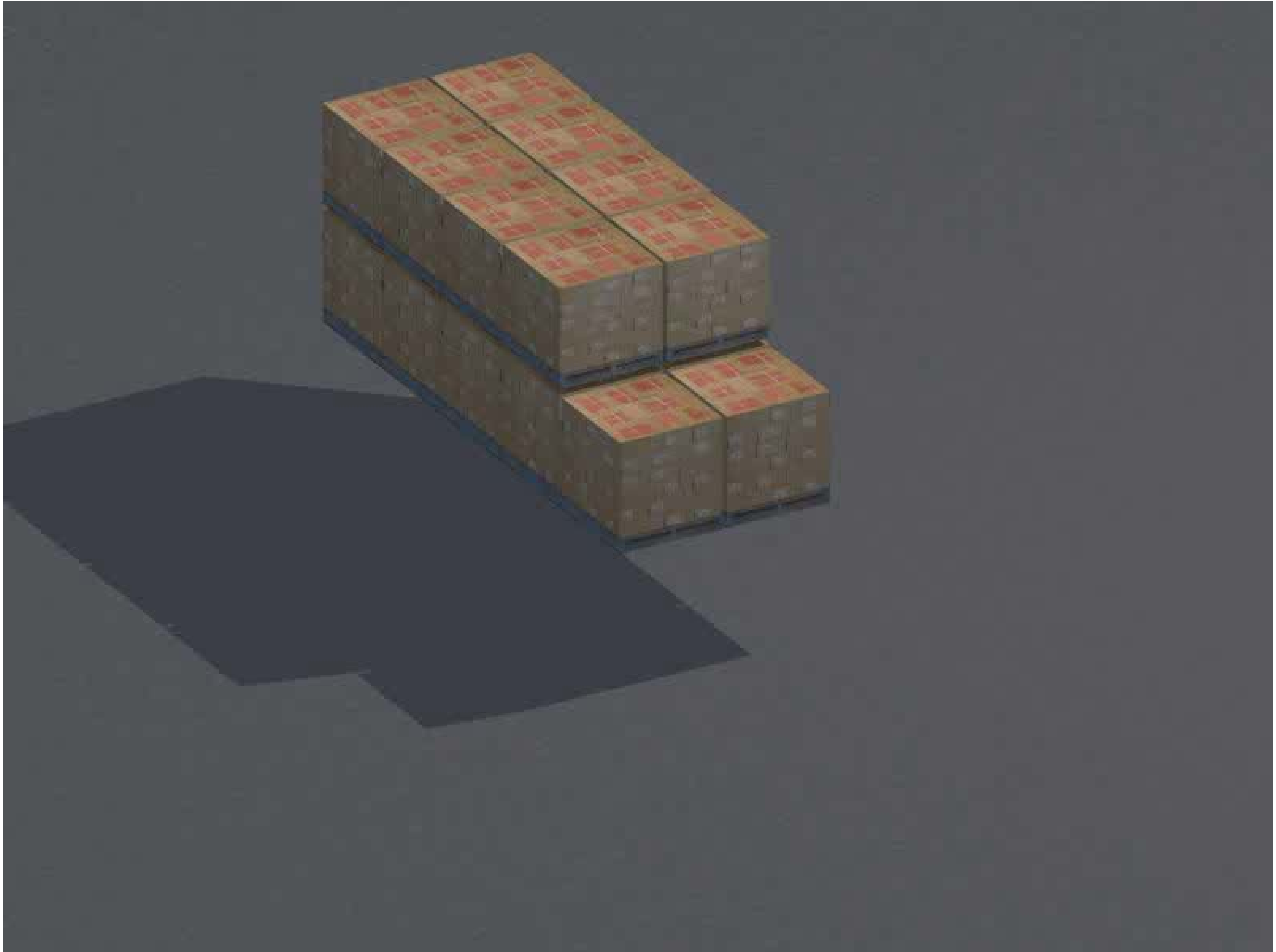

refrigerated storage
DHL
country import
wholesale storage
retail storage
consumer

$$\text{Log Vp/g}=-2.05+0.097*\text{temp}_{water}+0.2*\text{sal}-0.0055*\text{SAL}^2$$

$$\sqrt{\text{growth rate}} = 0.0303 \times (\text{temp}-13.37)$$

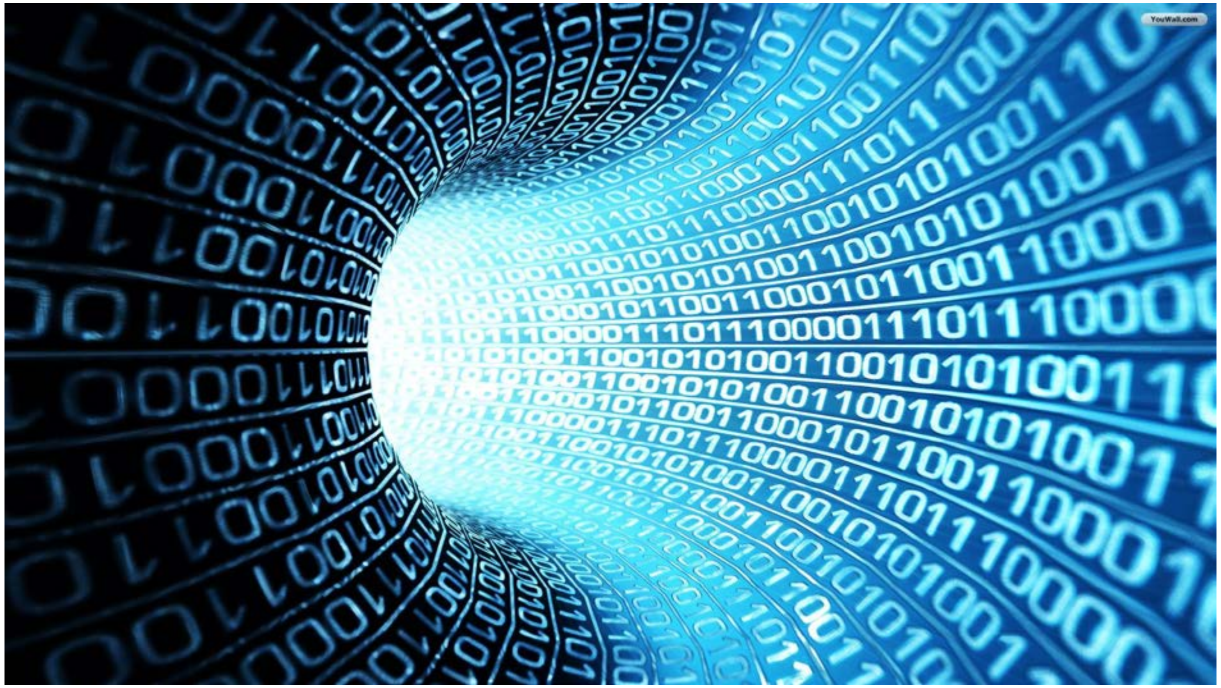


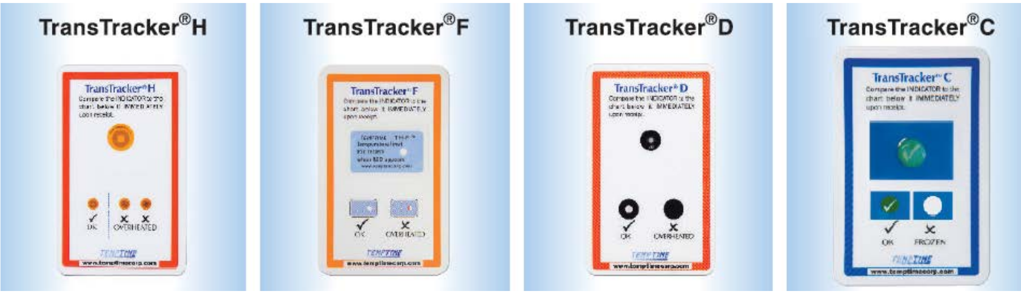


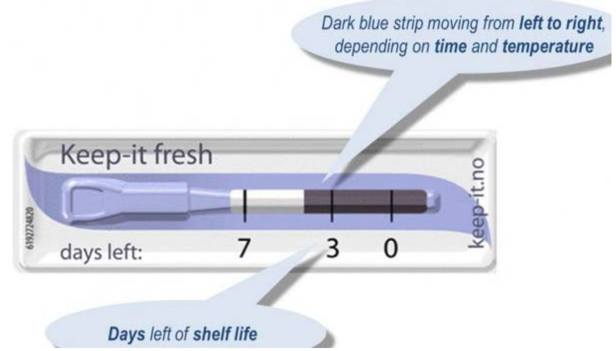


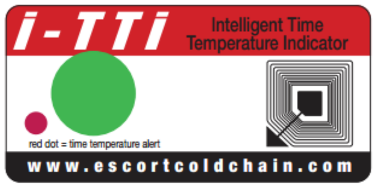
Currently, predictive models are not commonly used in real-time (or even retrospectively), due to lack of data capture.

Sensors are a solution.



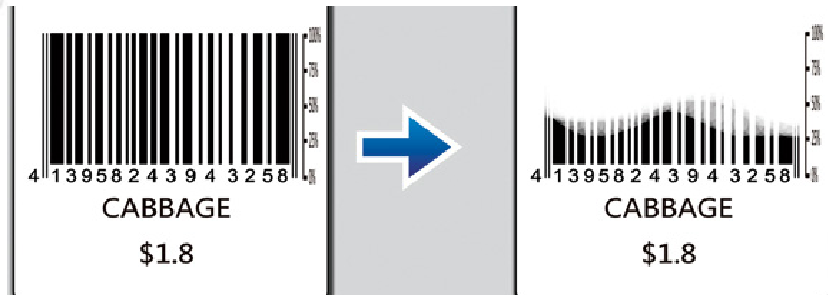

TransTracker®H
TransTracker®F
TransTracker®D
TransTracker®C

3M MonitorMark™
TTI
9860D
10°C (50°F), 1 week
INDEX/INDICE/
1 2 3 4

Dark blue strip moving from left to right, depending on time and temperature
Keep-it fresh
days left: 7 3 0
keep-it.no
Days left of shelf life

i-TTi
red dot = time temperature alert
www.escortcoldchain.com

i-TTi
Intelligent Time Temperature Indicator
red dot = time temperature alert
www.escortcoldchain.com

ONVU ice
ONVU
THAW INDICATOR

Check Point
LS-8
Do NOT use when dot is ORANGE/RED
0% NOT ACTIVATED

THINFILM
RF Sensor Tag

4 139582 4394 3258
CABBAGE
$1.8
4 139582 4394 3258
CABBAGE
$1.8

012345
PAKSENSE
32°F - 39°F
TW06F-PAK03
6 day
ULTRAcontact
Over
OK
Under
Press & Hold

LogTag


Integration of Time Temperature Indicator (TTI) sensors with predictive models for consumer-direct delivery of food products

Case study #2: Pathogenic *E. coli* in beef

Boxed trim destined for export

Problem: What innovations can help export companies more quickly reach their markets?

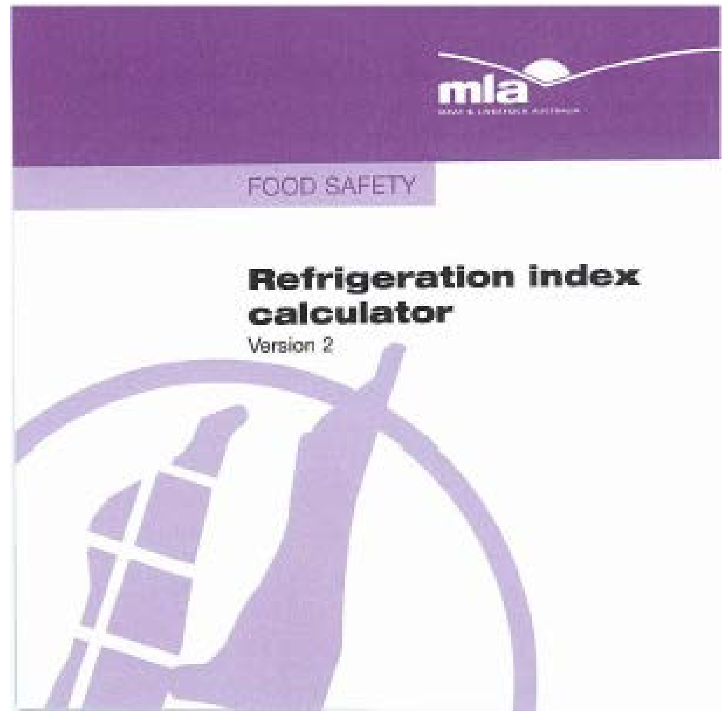
Refrigeration Index (RI)

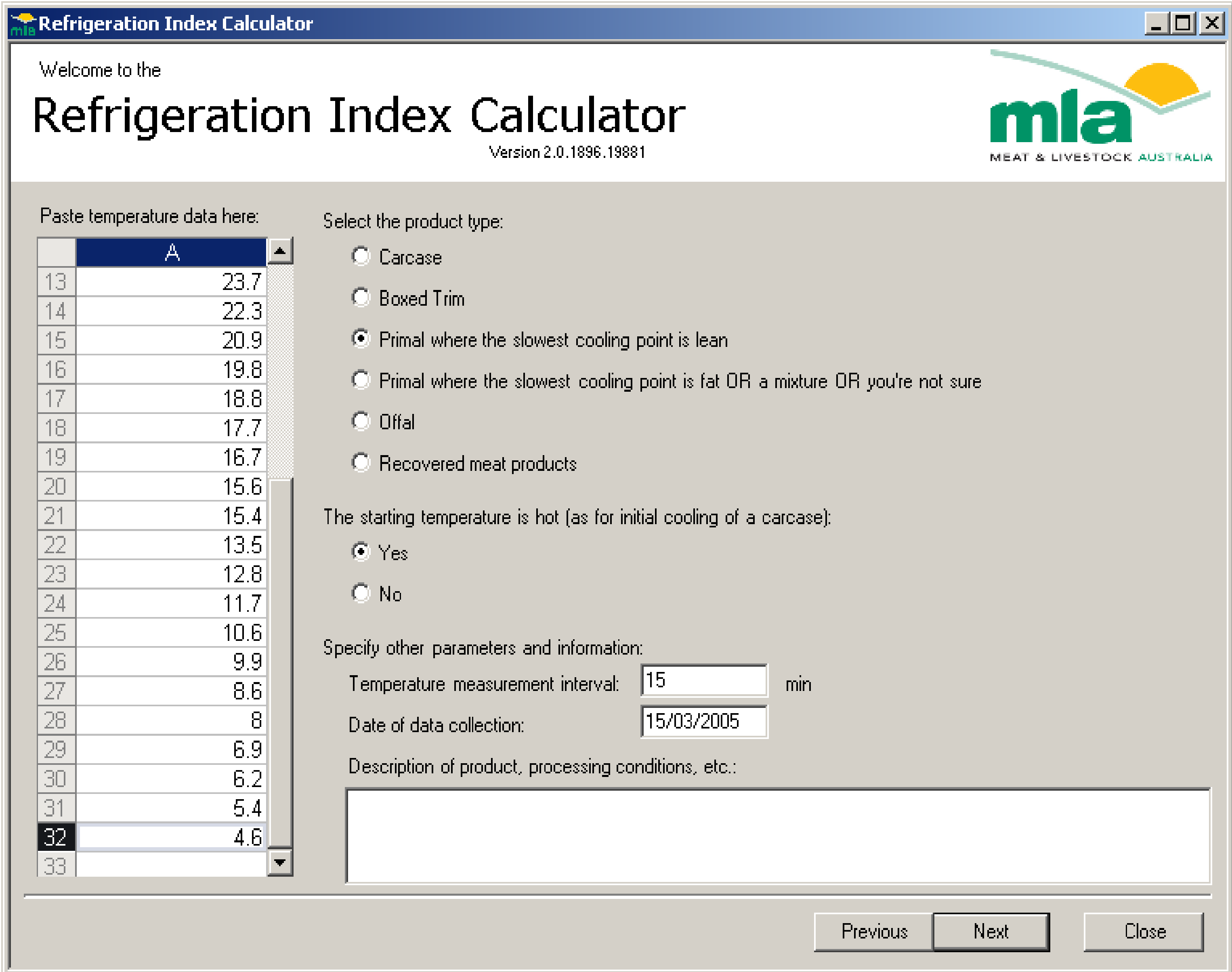
- Previous regulation required carcases to be cooled to 7°C in < 24 hours
  - *this could be done in many ways with quite different food safety outcomes*
- The industry wanted to package hot-boned beef trim
- A predictive model was developed through a government-industry-university partnership
- The Refrigeration Index predicts potential growth of *E. coli* based on a growth model

RI now part of Australian food safety law for meat

AUSTRALIA

Export Control (Meat and Meat Products) Orders 2005




Refrigeration Index Calculator
Welcome to the
Refrigeration Index Calculator
Version 2.0.1896.19881
mla
MEAT & LIVESTOCK AUSTRALIA
Paste temperature data here:
A
13 23.7
14 22.3
15 20.9
16 19.8
17 18.8
18 17.7
19 16.7
20 15.6
21 15.4
22 13.5
23 12.8
24 11.7
25 10.6
26 9.9
27 8.6
28 8
29 6.9
30 6.2
31 5.4
32 4.6
33
Select the product type:
Carcase
Boxed Trim
Primal where the slowest cooling point is lean
Primal where the slowest cooling point is fat OR a mixture OR you're not sure
Offal
Recovered meat products
The starting temperature is hot (as for initial cooling of a carcase):
Yes
No
Specify other parameters and information:
Temperature measurement interval: 15 min
Date of data collection: 15/03/2005
Description of product, processing conditions, etc.:
Previous
Next
Close

Refrigeration Index Calculator

Welcome to the

Refrigeration Index Calculator

Version 2.0.1896.19881

MEAT & LIVESTOCK AUSTRALIA

The refrigeration index is: **0.32**

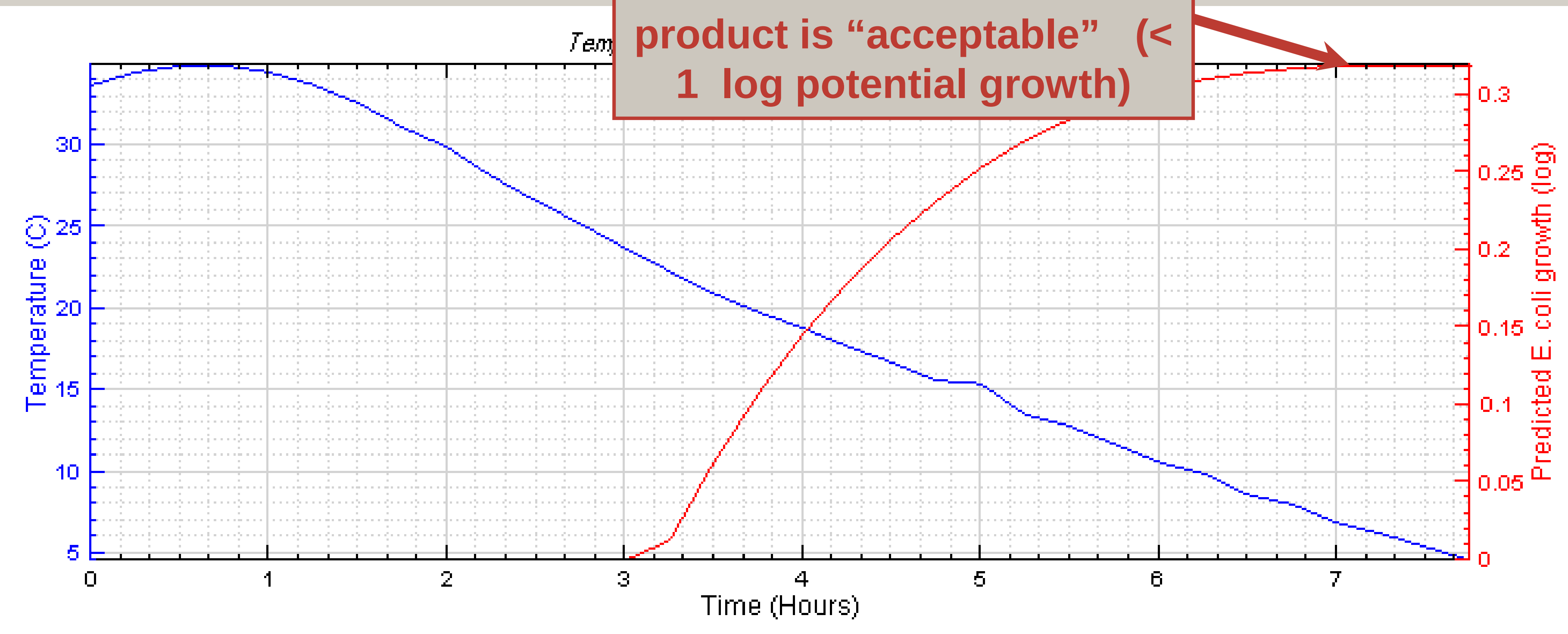
Description:

Date of data collection: 15/03/2005

Type of product: Primal (lean)

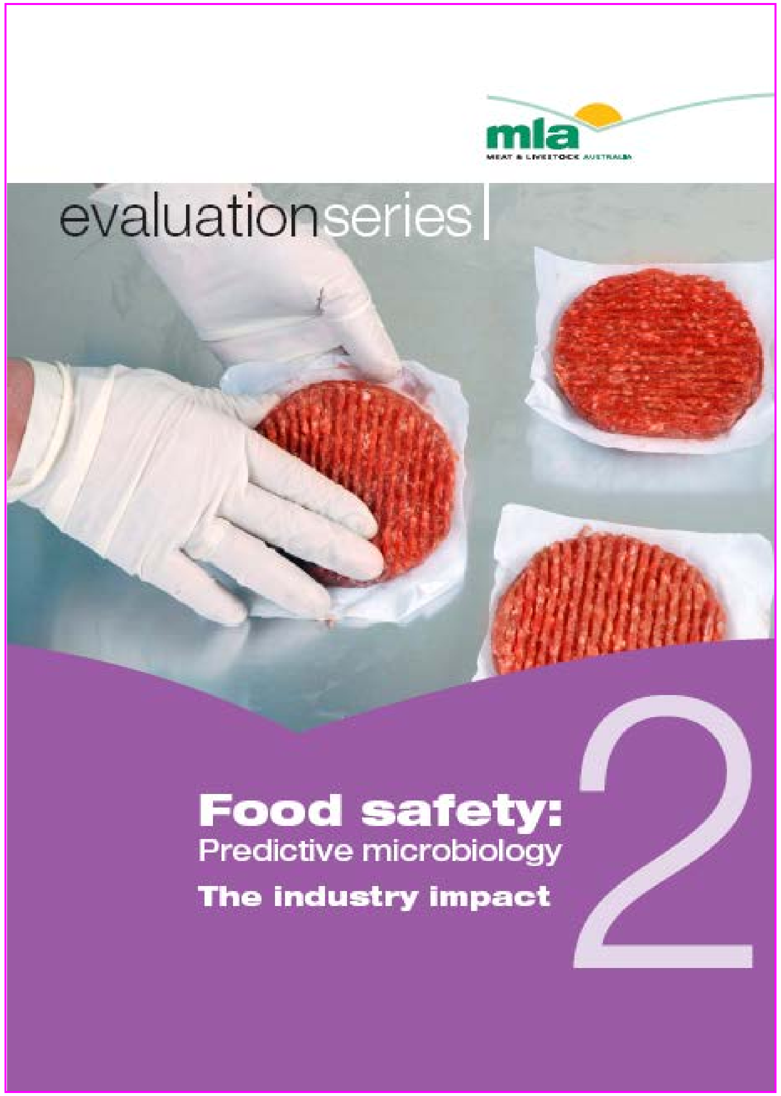
Lag phase utilized: Yes

total predicted *E. coli* growth during chilling; determines whether product is “acceptable” (< 1 log potential growth)



Save | Print | Previous | Finish | Close

Benefits



Analysis by Australian Centre for International Economics

- **$160 million increase in Australia’s GDP**

- **$280 million in social benefits**

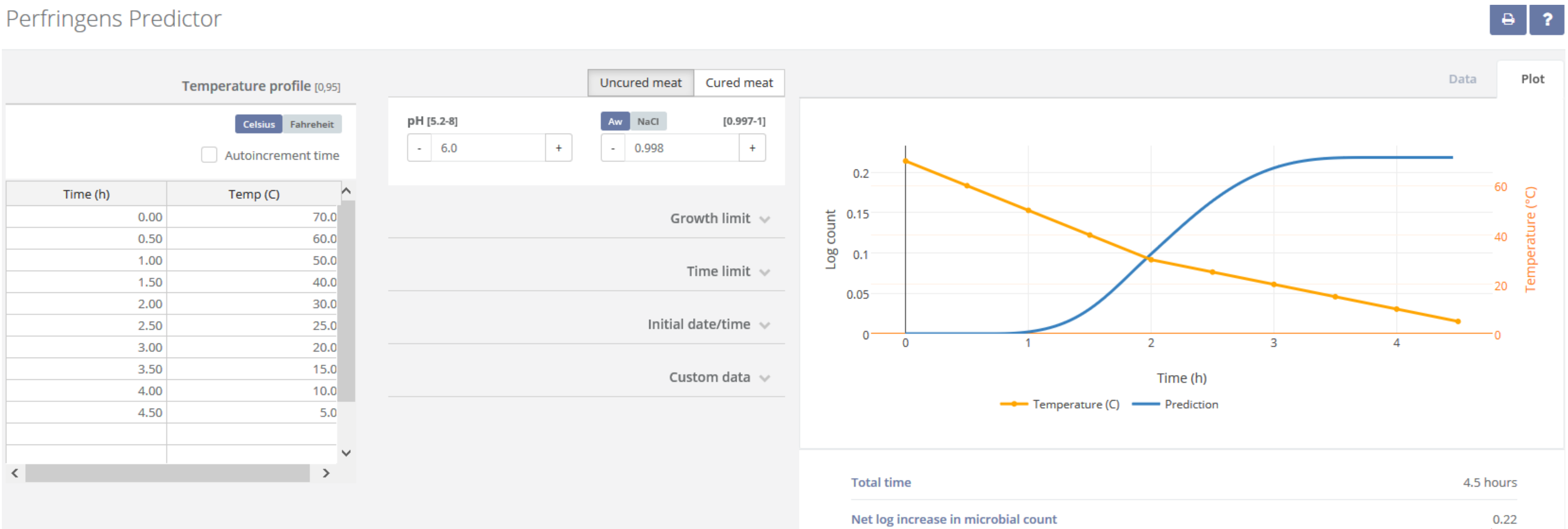
Case study #3: *Clostridium perfringens* in cooked primals

Problem: How can companies better manage temperature deviations when cooling primals?

Perfringens Predictor

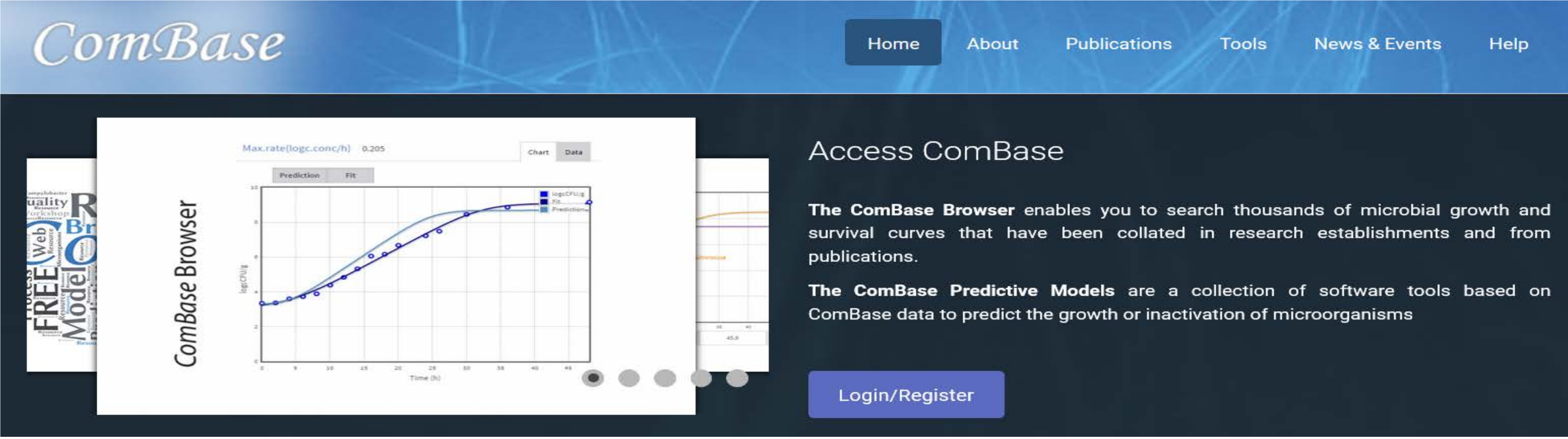
- Previous regulation about cooling cooked primals was highly prescriptive
- Occasionally, cooling profiles deviated
- Sampling plans and testing were not cost-effective
- An outcome-based model was developed through a government-industry partnership
- Accepted criteria was <1 log growth of *C. perfringens*

Perfringens Predictor



ComBase

(www.combase.cc)



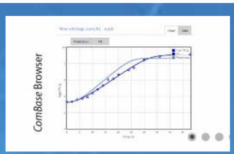
A database of microbial behaviour in food environments

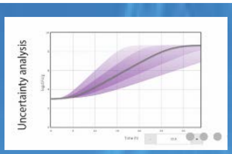
http://www.combase.cc

Vision: ComBase data and models will be used to support global food safety and quality programs.

Goal: To engage with the international food microbiology community, and provide it with robust data and models that describe how food safety and spoilage organisms respond to food environments.

ComBase





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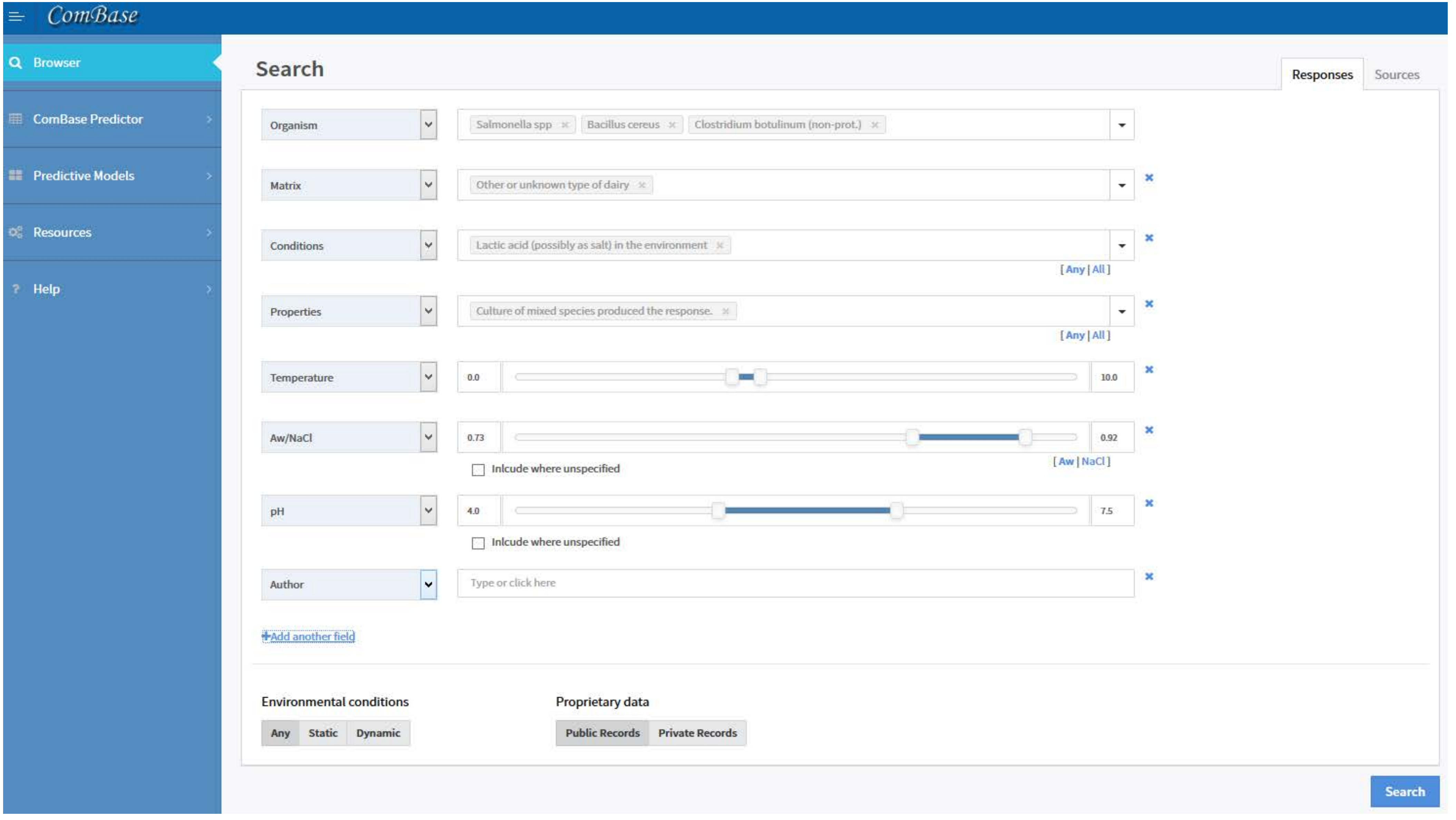
ComBase Advisory Group

- Unilever
- Nestlé
- IZLER
- USFDA
- USDA
- Rutgers University

The ComBase Scientific Group is being formed, and we are looking for more interested partners.

ComBase Browser



ComBase Browser

⟵ Back to search

Search results [1924 records]

Export ?

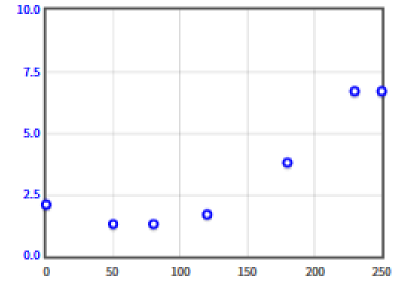
Organism (Ascending)

1/193

☐ 1. ***Bacillus cereus* in broth**

Matrix	Culture medium
Temp (°C)	7
Aw	0.997(assumed)
pH	7
Conditions	Not specified
Source	*Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus TZ415*

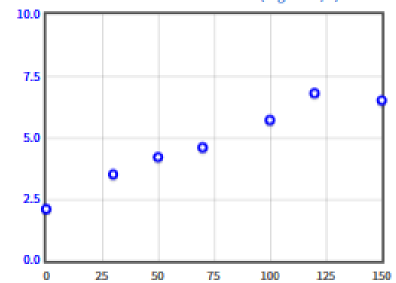
Max.rate(log.conc/h) Fit data



☐ 2. ***Bacillus cereus* in broth**

Matrix	Culture medium
Temp (°C)	10
Aw	0.997(assumed)
pH	7
Conditions	Not specified
Source	*Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus TZ415*

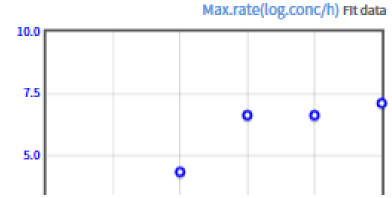
Max.rate(log.conc/h) Fit data



☐ 3. ***Bacillus cereus* in broth**

Matrix	Culture medium
Temp (°C)	15
Aw	0.997(assumed)
pH	7
Conditions	Not specified
Source	*Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus TZ415*

Max.rate(log.conc/h) Fit data



ComBase Browser

⟵ Back to results

Previous **Next** | **Export to csv**

Bacillus cereus in broth | ID: *GMW_1055*

Matrix	Culture medium
Temperature (°C)	10
Aw | NaCl	0.997 (assumed)
pH	7

Source
Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus TZ415

Conditions

Properties

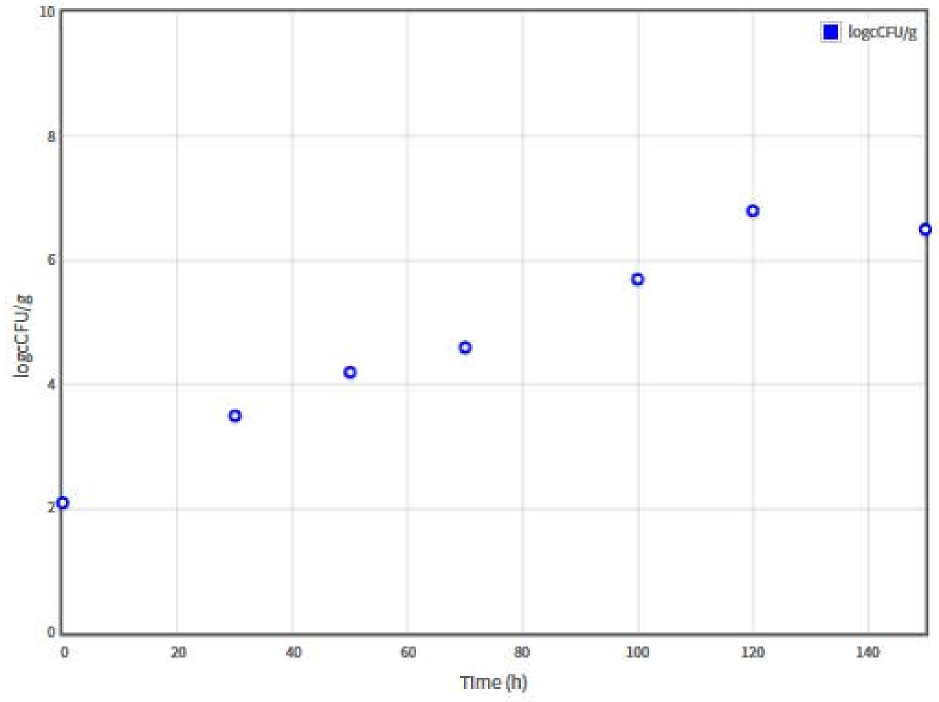
Further specifications
Strain(s): T2415

Details
No details specified

Measurement by colony counts.

Max.rate(logc.conc/h) | Fit data | Chart | Data

Prediction | Fit



ComBase Browser

⟵ Back to results

Previous Next

Export to csv

Bacillus cereus in broth

ID: *GMW_1055*

Matrix	Culture medium
Temperature (°C)	10
Aw | NaCl	0.997 (assumed)
pH	7

Source

Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus TZ415

Conditions

Properties

Further specifications

Strain(s): T2415

Details

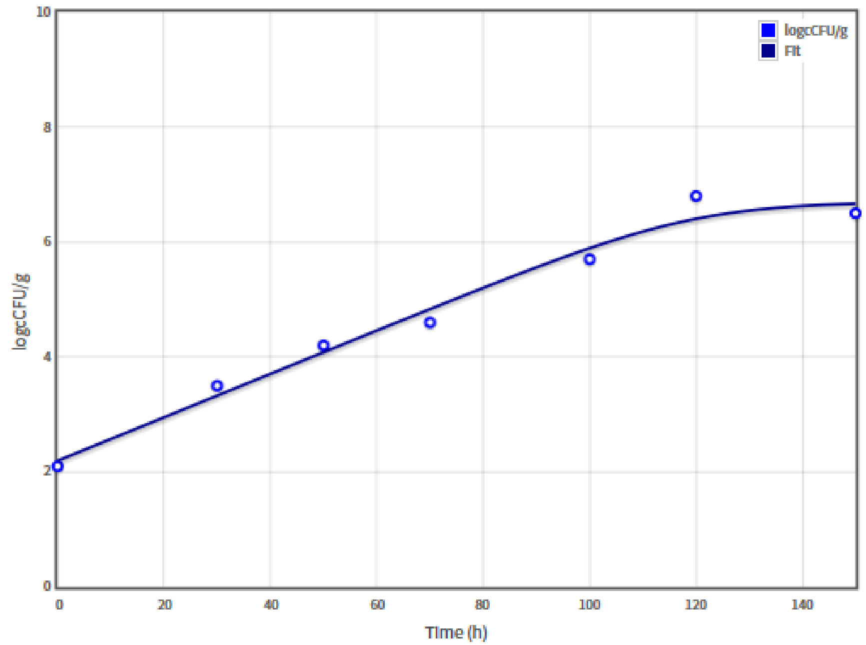
No details specified

Measurement by colony counts.

Max.rate(logc.conc/h) Fit data

Chart Data

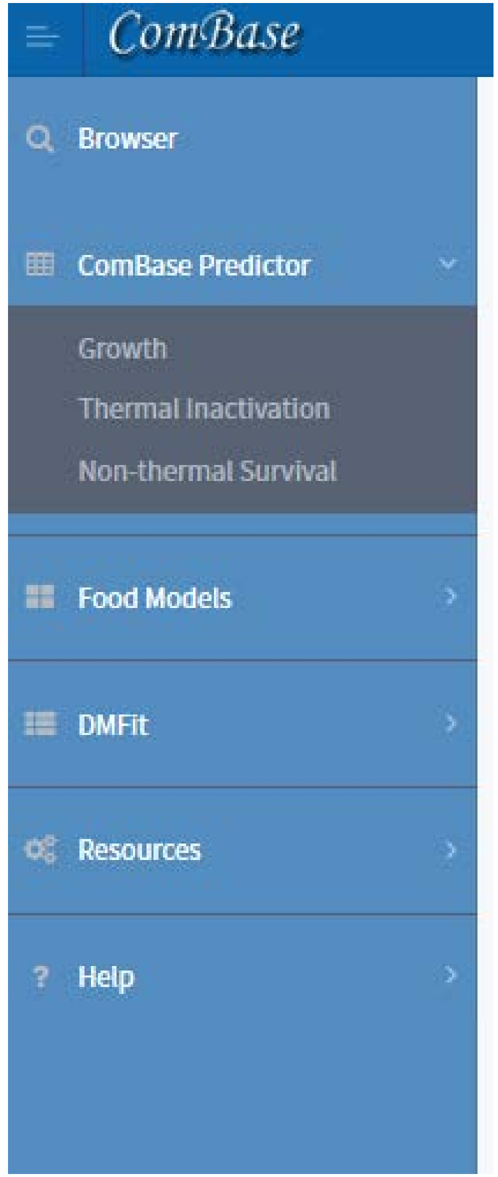
Prediction Fit



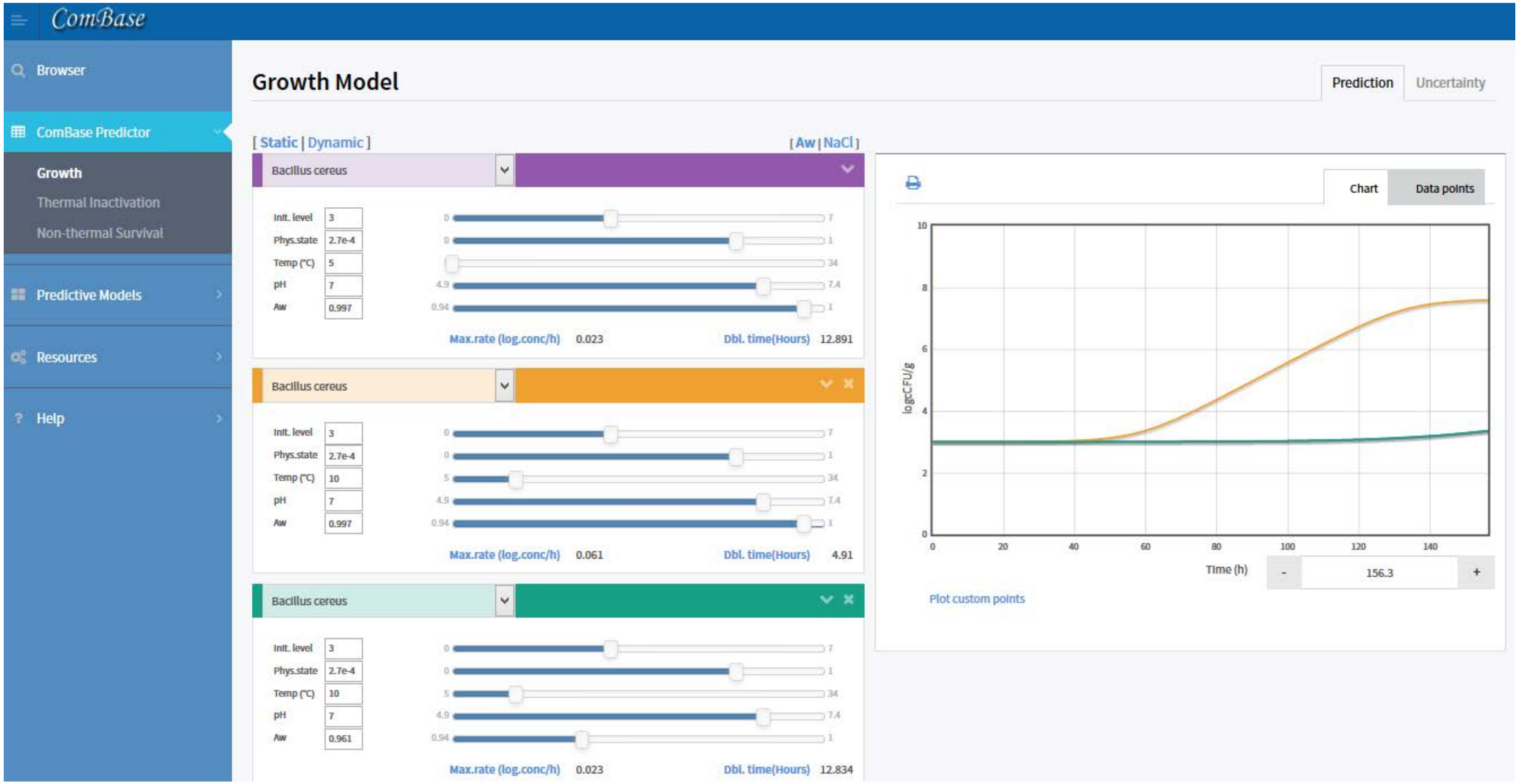
Baranyi and Roberts Model (no lag) [fit]

R-square:	0.971
SE of Fit:	0.287
Initial value	2.194 ± 0.232
Max. Rate	0.0378 ± 0.00402
Final Value	6.7 ± 0.302

ComBase Predictor

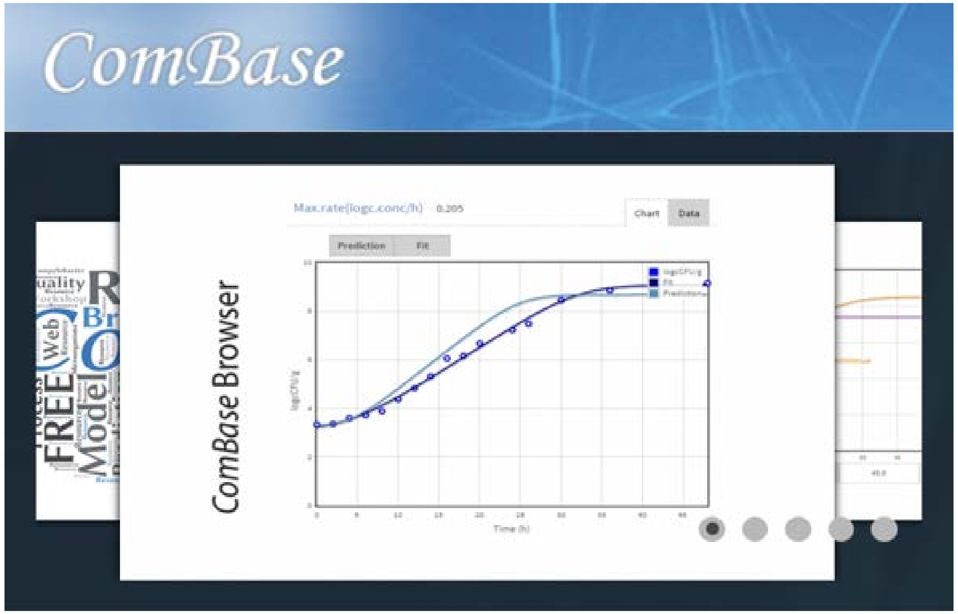


ComBase Predictor



Applications

- Growth/thermal and non-thermal inactivation
- Shelf-life
- Hazard identification
- Product development
- Process deviations



Database

Application Program Interface (API)

Sensors

Collaborative opportunities

- Predictive microbiology training
- Research collaborations
- ComBase workshops
- Scientist-Student exchange/degrees

fssai

Food Safety and Standards Authority of India

CHIFSS

CII-HUL Initiative on Food Safety Sciences

Thank you for your generous hospitality!

Unilever

CII

Confederation of Indian Industry