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

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University of Tasmania
Outline

• Predictive Microbiology – an overview

• Case studies- industry/government/academic partnerships

• Sensors and databases (ComBase)
Global Food Drivers

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

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

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

PREDICTIVE

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)

Betweenness centrality

Global sources of food (and contamination)

**Chicken Kiev**

- **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)

Source: Wayne Anderson, IFSA and Martin Cole
Food Safety Modernization Act

Food Safety Objectives

\[ H_0 + \sum I + \sum R \leq FSO \]
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 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

Refrigeration Index Calculator

Temperature vs. time and F. coli growth prediction

- Temperature (°C)
- F. coli growth (CFU)
- Time (Hour)
Predictive models

Represent *condensed knowledge*, which

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

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

flexible
How can we be sure that we are producing the most effective models?
Technical Aspects of Applied Research

1. Research problem
2. Experimental design
3. Data generation
4. Data analysis
5. Publication
Social Aspects

Interacting with all end-users of the model 
(definition 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
  \[ \log x(t) = A + C \exp\left\{ - \exp\left[ - B(t - M) \right] \right\} \]

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

- Inactivation kinetics
  \[ N = N_0 e^{-kt} \]

- D-value
  \[ t = \log N_0 - \log N_1 \]

- 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

\[ y = a \cdot e^{-x/b} \]
Modeling the complexity of microbial interactions
SECONDARY MODELS
Change in parameter(s) as a function of environmental change

Effect of pH and Water Activity on Microbial Growth

- pH
- Water activity
- Log bacterial level

Graph showing the impact of pH and water activity on microbial growth.
Probabilistic models

**Growth/No-growth boundaries**
(e.g. product development)
Growth/No-Growth

Adapted from Ross

Temperature (°C)

Less risk
Growth/No-Growth

![Diagram](image)

More risk

Adapted from Ross
Measuring Model Performance (validation)

- **Bias factor**
  \[ B_f = 10 \left( \frac{\sum \log(GT_{predicted}/GT_{observed})}{n} \right) \]

- **Accuracy factor**
  \[ A_f = 10 \left( \frac{\sum \mid \log(GT_{predicted}/GT_{observed}) \mid}{n} \right) \]
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
Examples of common model interfaces
Case Studies
Case study #1: *Vibrio parahaemolyticus* and oyster supply chains

Problem: How can companies reduce uncertainties in supply chains?
V. cholerae

V. vulnificus

V. parahaemolyticus
V. cholerae
<1% salt

V. vulnificus
1-2% salt

V. parahaemolyticus
2->3% 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

\[ \log(Vp / g) = -1.03 + 0.12 \times TEMP \]
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

FAO/WHO Working Group 5 Risk Management Exercise 2006
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 (△); treatment resulting in ≥4.5-log reduction (○).

FDA *V. parahaemolyticus* Risk Assessment 2005
### Atlantic (subtidal harvest)

<table>
<thead>
<tr>
<th>month</th>
<th>water temperature (F)</th>
<th>air temperature (F)</th>
<th>maximum time unrefrigerated (hr)</th>
<th>expected cases per 100,000 servings</th>
<th>lower confidence limit on expected cases per 100,000</th>
<th>VPCP needed?</th>
<th>maximum time (hr) for lower confidence of 1 per 100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>38.3</td>
<td>33.3</td>
<td>36</td>
<td>0.0038</td>
<td>0.0003</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Feb</td>
<td>36.7</td>
<td>35.6</td>
<td>36</td>
<td>0.0018</td>
<td>0.00014</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Mar</td>
<td>42.6</td>
<td>41.0</td>
<td>36</td>
<td>0.0019</td>
<td>0.00015</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Apr</td>
<td>52.3</td>
<td>50.9</td>
<td>36</td>
<td>0.012</td>
<td>0.00095</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>64.0</td>
<td>59.9</td>
<td>36</td>
<td>0.56</td>
<td>0.044</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Jun</td>
<td>73.8</td>
<td>69.3</td>
<td>24</td>
<td>13</td>
<td>1</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>July</td>
<td>79.9</td>
<td>74.3</td>
<td>24</td>
<td>160</td>
<td>13</td>
<td>Y</td>
<td>12.3</td>
</tr>
<tr>
<td>Aug</td>
<td>81.1</td>
<td>73.0</td>
<td>24</td>
<td>120</td>
<td>9.5</td>
<td>Y</td>
<td>12.9</td>
</tr>
<tr>
<td>Sep</td>
<td>75.2</td>
<td>67.1</td>
<td>24</td>
<td>7.7</td>
<td>0.61</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Oct</td>
<td>64.6</td>
<td>56.3</td>
<td>36</td>
<td>0.2</td>
<td>0.016</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Nov</td>
<td>53.1</td>
<td>45.9</td>
<td>36</td>
<td>0.0074</td>
<td>0.00059</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Dec</td>
<td>43.0</td>
<td>36.0</td>
<td>36</td>
<td>0.0037</td>
<td>0.00029</td>
<td>N</td>
<td></td>
</tr>
</tbody>
</table>
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°C
- Growth (>15°C) and death rates (<15°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
### Models for *V. parahaemolyticus* growth and inactivation, and Total Viable Count

<table>
<thead>
<tr>
<th>Type</th>
<th>Formula</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vp growth</strong></td>
<td>$v_{\text{growth rate}} = 0.0303 \times (\text{temperature} - 13.37)$</td>
<td>0.92</td>
</tr>
<tr>
<td><strong>Vp inactivation</strong></td>
<td>$\ln \text{ inactivation rate} = \ln 1.81 \times 10^{-9} + 4131.2 \times \left(1/(T+273.15)\right)$</td>
<td>0.78</td>
</tr>
<tr>
<td><strong>TVC growth</strong></td>
<td>$v_{\text{growth rate}} = 0.0102 \times (\text{temperature} + 6.71)$</td>
<td>0.92</td>
</tr>
</tbody>
</table>

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

Sensitivity Analysis of Oyster Supply Chains

from Madigan 2008
Sensitivity Analysis of Oyster Supply Chains

![Graph showing temperature changes in supply chain stages]

- Harvest_loc
- Transport_domestic
- Load
- Transport_truck
- Storage_farm
- Storage_domestic
- Storage_retail
- Unload

From Madigan 2008
# Refrigeration vs Spoilage Cost Scenarios

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Possibilities of exceeding 7.9 log CFU/g</th>
<th>Cold storage cost</th>
<th>Cost of loss of product</th>
</tr>
</thead>
<tbody>
<tr>
<td>4°C</td>
<td>7.0%</td>
<td>$166,445.97</td>
<td>$1,234,975.35</td>
</tr>
<tr>
<td>6°C</td>
<td>9.4%</td>
<td>$158,687.03</td>
<td>$1,658,395.47</td>
</tr>
<tr>
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<td>12.3%</td>
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<td>$2,170,028.12</td>
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<tr>
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<td>$143,181.63</td>
<td>$2,893,370.82</td>
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<tr>
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<td>22.0%</td>
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<td>$3,881,351.10</td>
</tr>
</tbody>
</table>

~$23,000  ~$1.6 million
## Refrigeration vs Spoilage Cost Scenarios

By investing in refrigeration, the industry could save approximately $23,000 and $1.6 million in costs, as shown in the table below:

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</tr>
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</table>

- ~$23,000
- ~$1.6 million

By investing in refrigeration, the industry could save!
Integrating Sensors and Predictive Models
\[
\log V_p/g = -2.05 + 0.097 \cdot \text{temp}_{\text{water}} + 0.2 \cdot \text{sal} - 0.0055 \cdot \text{SAL}^2
\]

\[
growth\ rate = 0.0303 \times (\text{temp} - 13.37)
\]
Currently, predictive models are not commonly used in real-time (or even retrospectively), due to lack of data capture.

Sensors are a solution.
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?
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

Export Control (Meat and Meat Products) Orders 2005
total predicted E. coli growth during chilling; determines whether product is “acceptable” (< 1 log potential growth)
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**

### Temperature Profile (℃)

<table>
<thead>
<tr>
<th>Time (h)</th>
<th>Temp (℃)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00</td>
<td>70.0</td>
</tr>
<tr>
<td>0.50</td>
<td>60.0</td>
</tr>
<tr>
<td>1.00</td>
<td>50.0</td>
</tr>
<tr>
<td>1.50</td>
<td>40.0</td>
</tr>
<tr>
<td>2.00</td>
<td>30.0</td>
</tr>
<tr>
<td>2.50</td>
<td>25.0</td>
</tr>
<tr>
<td>3.00</td>
<td>20.0</td>
</tr>
<tr>
<td>3.50</td>
<td>15.0</td>
</tr>
<tr>
<td>4.00</td>
<td>10.0</td>
</tr>
<tr>
<td>4.50</td>
<td>5.0</td>
</tr>
</tbody>
</table>

### pH

- Uncured meat: 6.0
- Cured meat: 0.998

### Graph

- **Log count**
- **Temperature (℃)**
- **Time (h)**

**Total time**: 4.5 hours

**Net log increase in microbial count**: 0.22
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 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**

**Bacillus cereus in broth**

- **Matrix**
  - Temperature (°C)
  - Aw | NaCl
  - pH

- **Culturo medium**
  - 10
  - 0.997 (assumed)

- **Source**
  - Choma (et al.), 2000: Effect of temperature on growth characteristics of Bacillus cereus T2415

- **Conditions**

- **Properties**

- **Further specifications**
  - Strain(s): T2415

- **Details**
  - No details specified
  - Measurement: by colony counts.

**Chart**

- **Max. rate (log CFU/g)**
- **Fit data**

- **Prediction**
- **Fit**

- **Time (h)**

- **Log CFU/g**
### Bacillus cereus in broth

<table>
<thead>
<tr>
<th>Matrix</th>
<th>Culture medium</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.997 (assumed)</td>
</tr>
<tr>
<td></td>
<td>pH</td>
</tr>
<tr>
<td></td>
<td>7</td>
</tr>
</tbody>
</table>

**Source**

Choma (et al.), 2006: Effect of temperature on growth characteristics of Bacillus cereus T2415

**Conditions**

**Properties**

**Further specifications**

**Details**

No details specified.

Measurement by colony counts.

---

**Baranyi and Roberts Model (no lag) [FIT]**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.571</td>
</tr>
<tr>
<td>S.E. of Fit</td>
<td>0.287</td>
</tr>
<tr>
<td>Initial value</td>
<td>2.194 ± 0.232</td>
</tr>
<tr>
<td>Max. Rate</td>
<td>0.0378 ± 0.00402</td>
</tr>
<tr>
<td>Final Value</td>
<td>6.7 ± 0.302</td>
</tr>
</tbody>
</table>
ComBase Predictor
ComBase Predictor
Applications

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

- Predictive microbiology training
- Research collaborations
- ComBase workshops
- Scientist-Student exchange/degrees
Thank you for your generous hospitality!