

Microbial growth models and temperature monitoring technologies

Tom McMeekin, Nicholas Smale, Ian Jenson & David Tanner



Food Safety: the essential ingredient

PREDICTIVE MICROBIOLOGY: THE CONCEPT

A detailed knowledge of microbial responses to environmental conditions, synthesised in a mathematical model, enables objective evaluation of processing, distribution and storage operations on the microbiological safety and quality of foods, by monitoring the environment without recourse to further microbiological analysis The PROCESS of predictive microbiology: turning data into knowledge by *describing microbial population behaviour quantitatively*

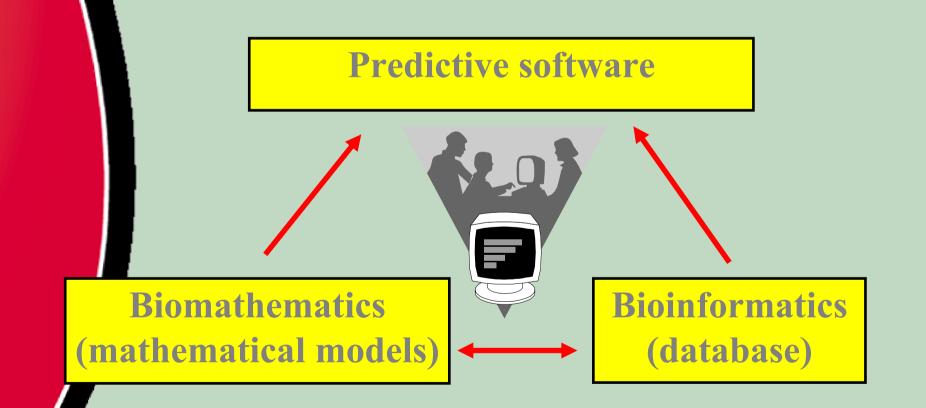
In vitro

Environment In vivo

- temperature, pH, water activity,
- atmosphere composition,
- additives, food structure
- competition among organisms

- <u>microbial response</u>
 - growth / no growth,
 - probability of growth,
 - lag time, doubling time,
 - time to reach a certain conc.
 - full growth / survival curves
 - (dynamic response)
 - metabolic production

The SCIENCE and TECHNOLOGY of predictive microbiology – monitor the environment without retrospective microbial counts



ComBase Consortium, 2003





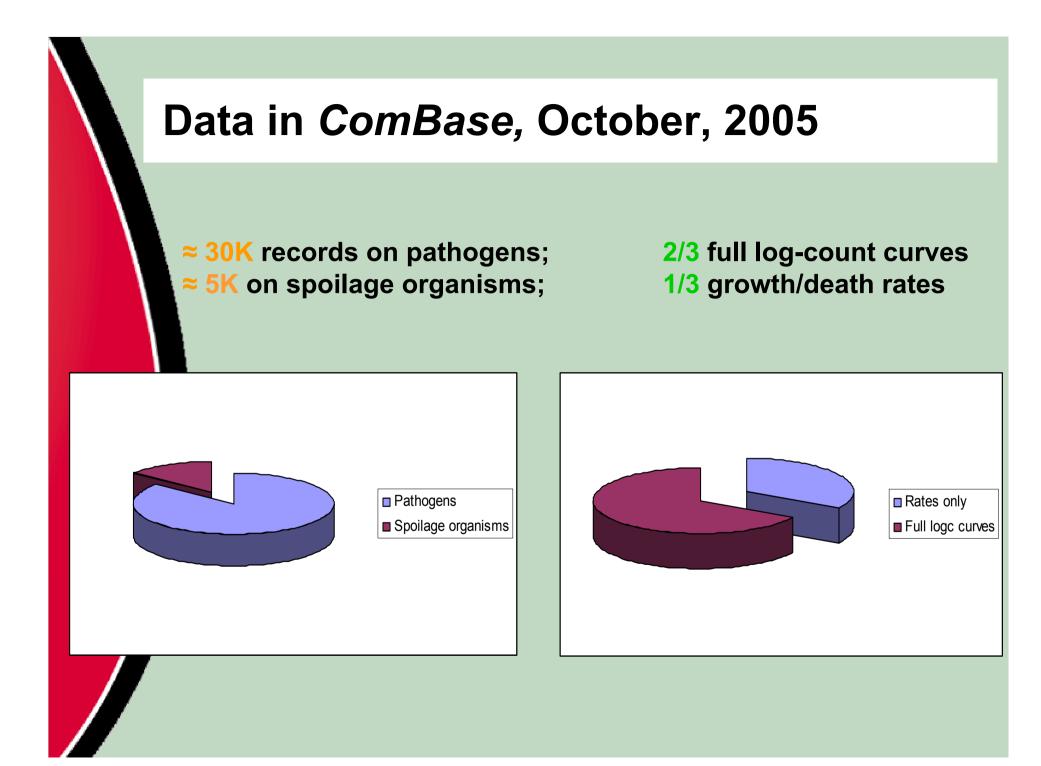
US Department of Agriculture, Agricultural Research Service

Eastern Regional Research Center Wyndmoor, PA, USA



e-ComBase: 2yrs Accompanying Measures project to populate ComBase by data from Supporting Partners

Quality of Life and Management of Living Resources (QoL) Action 1 - Food, Nutrition and Health



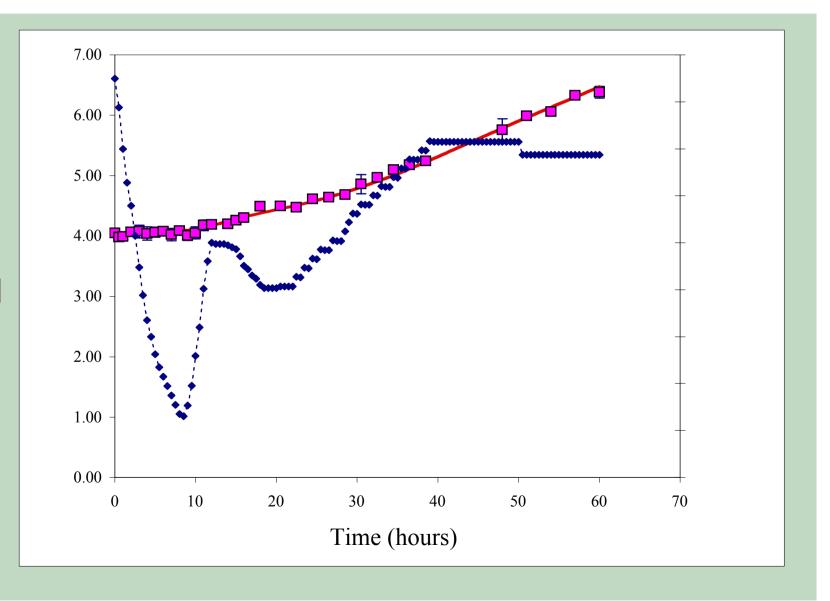
Australian data added to ComBase – Feb 2006

- Kinetic data : 5522 new records.
 Each record is a kinetic bacterial response to the environmental conditions (originally ComBase only incorporated this kind of data)
- Probability of growth data: 2466 new records

Every record is a set of replicated realizations of an experiment. Hence, data corresponds to **6143** independent experiments

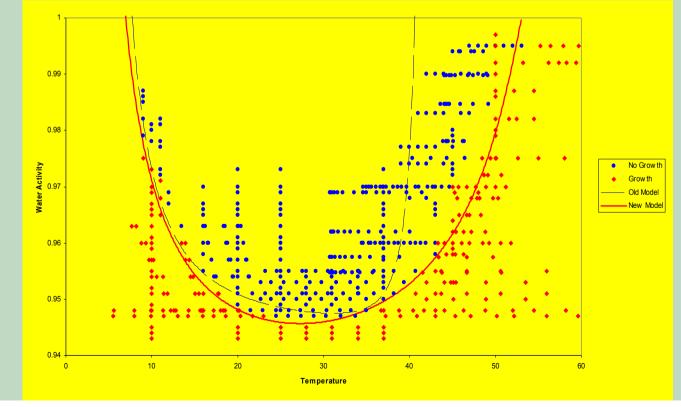
ComBase has been extended by adapting its fields to store this data

E.coli growth with fluctuating a_w (12°C)

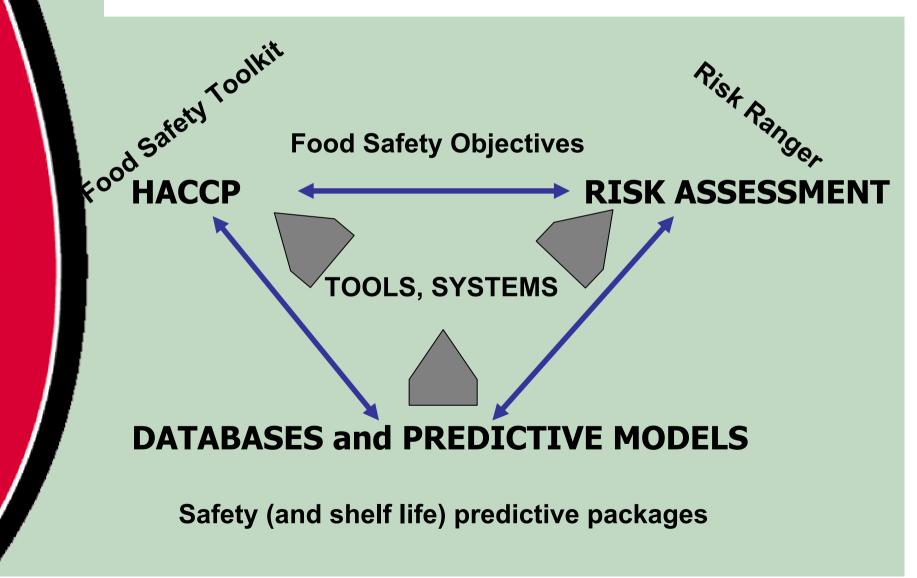


Formulation of safe foods using growth boundary models

- Quantifying the hurdle concept
 - *E. coli* boundary model for temperature and water availability



Systems and Technology to support Food Safety Management

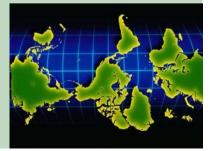


Regulatory and industry outcomes

- A detailed knowledge of the microbial ecology of any product / pathogen combination :
- Supports regulations that are defensible and challenges unwarranted regulations
- Indicates the need for outcome based regulations
- Underpins the paradigms of food safety management enabling:
 - real time process management
 - prospective formulation of safe products and design of safe processes
 - determination of the hygienic equivalence of products and efficacy of processes
 - flexibility in meeting regulatory requirements

Drivers to develop systems and technologies to assure safety and shelf life of food in international trade

- The food industry operates in a global market place
- Reliance on transport for delivery of high quality products to distant markets
- Distances and voyage times to market from Australia are long
- Temperature variability in supply chains



What technology options are available?

- Track and trace technologies
 - Barcoding
 - Radio frequency identification (RFID)
- Environment monitoring technologies
 - Data loggers
 - Time-temperature integrators (TTI's)







Temperature loggers

- Temperature measurement, data storage, retrieval
- Predictive models allow critical analysis of the consequences for shelf-life and safety
- Case studies in *in situ* process management
 - Frozen dairy product
 - Meat carcass chilling
 - Fermented meat processing

Frozen dairy product

• BACKGROUND:

- heat treated product, bulk packed, frozen
- testing indicated the product exceeded specifications
- inadequate cooling allowed growth of sporeformers
- cooling profiles and microbiological test results compared with model predictions

• COMPANY RESPONSE:

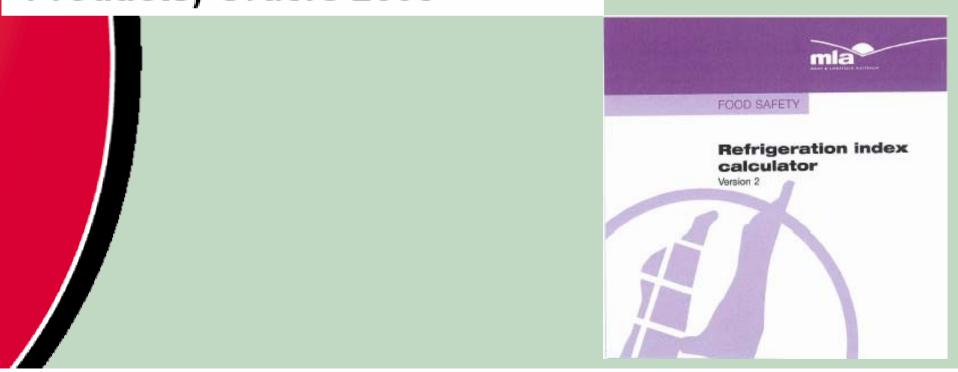
- numerous configurations trialed with temperature data logging and microbiology testing
- predictive model used throughout to give assurance of the effectiveness of cooling rates
- BENEFITS TO COMPANY:
 - used cooling profiles to monitor process performance
 - early identification of unsatisfactory performance
 - product shipped on basis of cooling profile without the expense and delay of testing

Meat carcass chilling

- Issues: safety of alternative processes (hot boning), weekend chilling, carcass rewarming, offal cooling
- *E. coli* "megamodel" for temperature, water activity, pH and lactate concentration
 - based on ~1000 observations, 1000 independent 'validation' data
 - more parameters, more applications
- Development: Ross *et al*. 2003 *Int. J. Food Microbiol.* 82: 33-44.
- Evaluation: Mellefont *et al*. 2003 *Int. J. Food Microbiol.* 82: 45-58.
- Application: Development, by AQIS, of a Refrigeration Index for carcass chilling in revised Export Meat Orders



Export Control (Meat and Meat Products) Orders 2005





Refrigeration Index Calculator

Welcome to the

Refrigeration Index Calculator

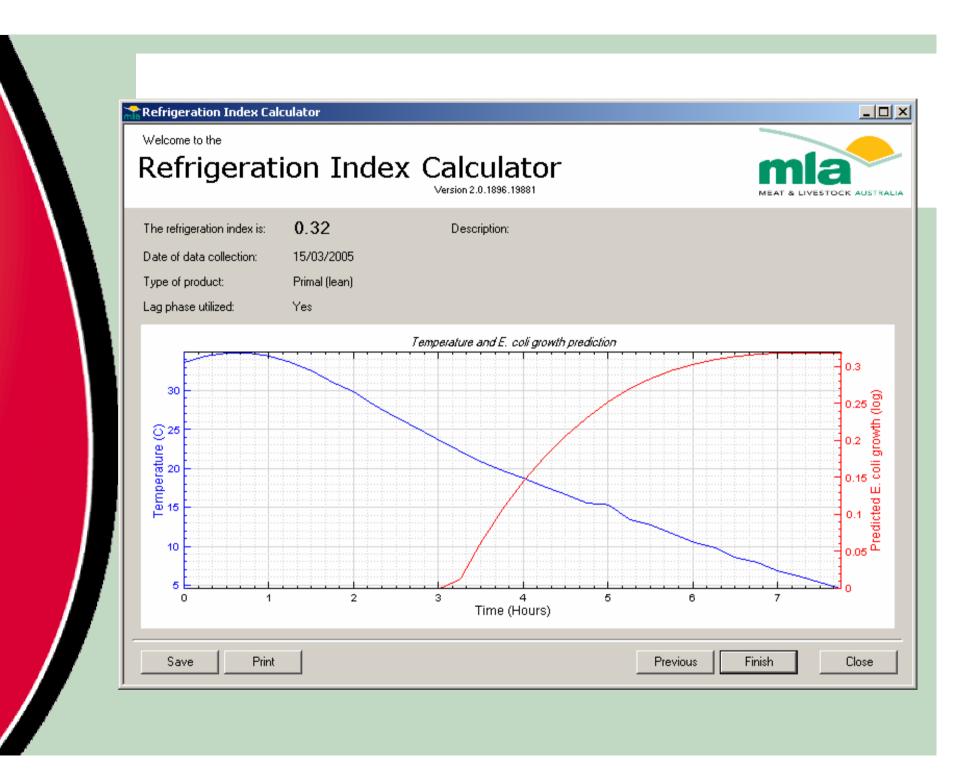


Version 2.0.1896.19881

Paste temperature data here:

	А	
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:			
C Carcase			
Soxed Trim			
Primal where the slowest cooling point is lean			
O Primal where the slowest cooling point is fat OR a mixture OR you're not sure			
C Offal			
C Recovered meat products			
The starting temperature is hot (as for initial cooling of a carcase):			
C 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			

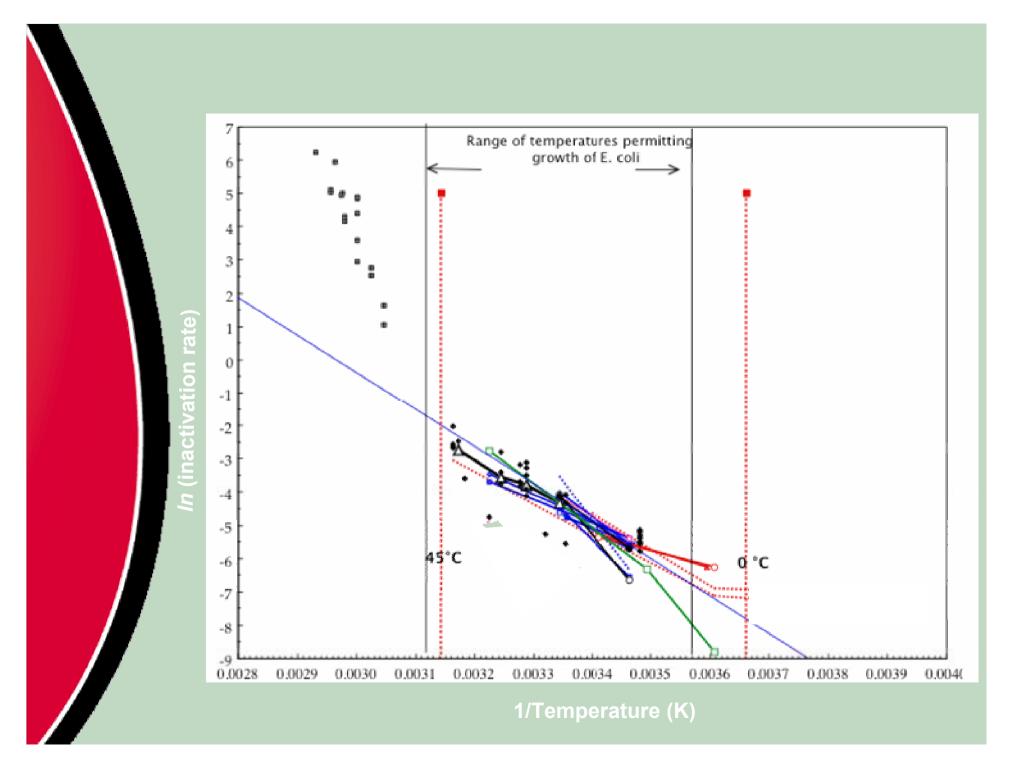


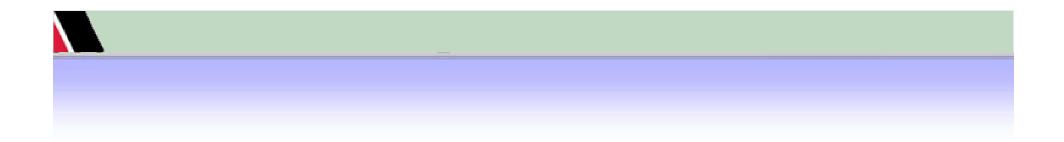
E. coli inactivation in uncooked fermented meat products

- severe EHEC outbreak in Oz in 1995
- national expert committee created to assess 'process safety', based on "3-log kill"
- impossible task due to lack of quantitative data
- industry funded a small project to look at data availability, build a model if possible
- data collated, synthesised, modelled

Outcomes

- literature review provides new insights
- model developed based on the published data
- model used to screen processes for approval (regulators), and to reassess processes (producers)
- dedicated project funded using broth modelling and evaluation in product
- original model confirmed, no improvement







E. coli Inactivation in Fermented Meats

Calculators to estimate the "log kill" of E. coli during production of fermented meats

Version 2.2 (1 August 2004). Developed for Meat and Livestock Australia by the Australian Food Safety Centre of





Supported by : Australian Government Department of Applications, Federals and Persety

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Click to Continue



Systematic analysis of the literature

- Ross (1999) Predictive Microbiology for the meat industry. Meat and Livestock Australia, Sydney, 196pp.
- Ross and Shadbolt (2001) Predicting *E. coli* inactivation in uncooked fermented meat products. Meat & Livestock Australia, 59pp. (<u>cis@mla.com.au</u>)
- Van Asselt and Zwietering (2006) A systematic approach to determine global thermal inactivation patterns for various food pathogens. Int. J. Food Microbiol. 107: 73-82.
- Adkin et al., (2006) Use of a systematic review to assist the development of Campylobacter control strategies in broilers. J. Appl. Microbiol. 100: 306-315.

Probabilistic modelling – an emerging trend

den Aantrekker et al. (2003). Estimating the probability of recontamination via the air using Monte Carlo simulations. Int. J. Food Microbiol. 87: 1-15.

Membre et al. (2006). A probabilistic modeling approach in thermal inactivation: estimation of postprocess *B. cereus* spore prevalence and concentration. J. Food Prot. 69: 118-129.

Tsutsui and Kasuga (2006). Assessment of the impact of cattle testing strategies on human exposure to BSE agents in Japan. Int. J. Food Microbiol. 107: 256-264.

Francois et al. (2006) Single cell variability of *L.monocytogenes* grown on liver pate and cooked ham: comparing challenge tests to predictive simulations. J.Appl.Microbiol. 100: 800-812.

Estimated economic benefits

Value of predictive microbiology to the Australian meat industry(source Meat and Livestock Australia)

Value (\$M) per annum
*15
*30
7.5
3*
*30
85.5

*Value calculated as a % of the market protected by predictive microbiology using 5% of the value of sales except for fermented meats where 20% is used based on the effect of past food~borne disease outbreaks on sales in this sector

Application of predictive models with temperature loggers

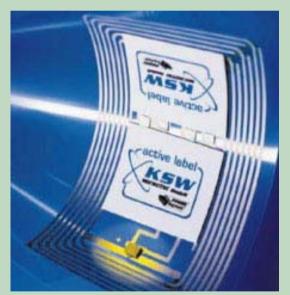
 The examples above normally use electronic temperature loggers which, for process control, present inherent problems in data recovery eg loss of information with non-return of loggers, retrospective analysis of information and manual examination for "progress reports"

Traceability

 Increasing interest in electronic chain traceability systems that communicate with finance software, business systems and work as an integrated part of production management

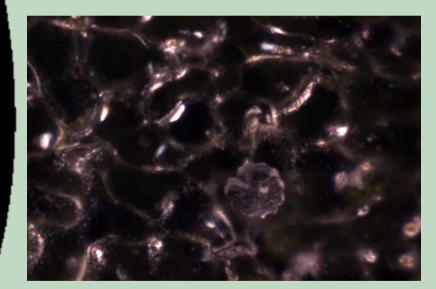
RFID ++

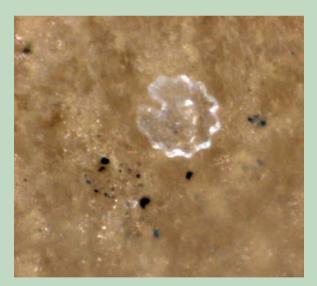
- Added functionality by incorporating sensors into tags to monitor:
 - Position
 - Temperature
 - Gases (incl. humidity)
 - Light



Microscopic, edible, information-dense, easily read, inexpensive, and, if necessary, t*hermosoluble* markers for foods, seeds, and drugs

www.burntsidepartners.com





Application of predictive models with real time reporting

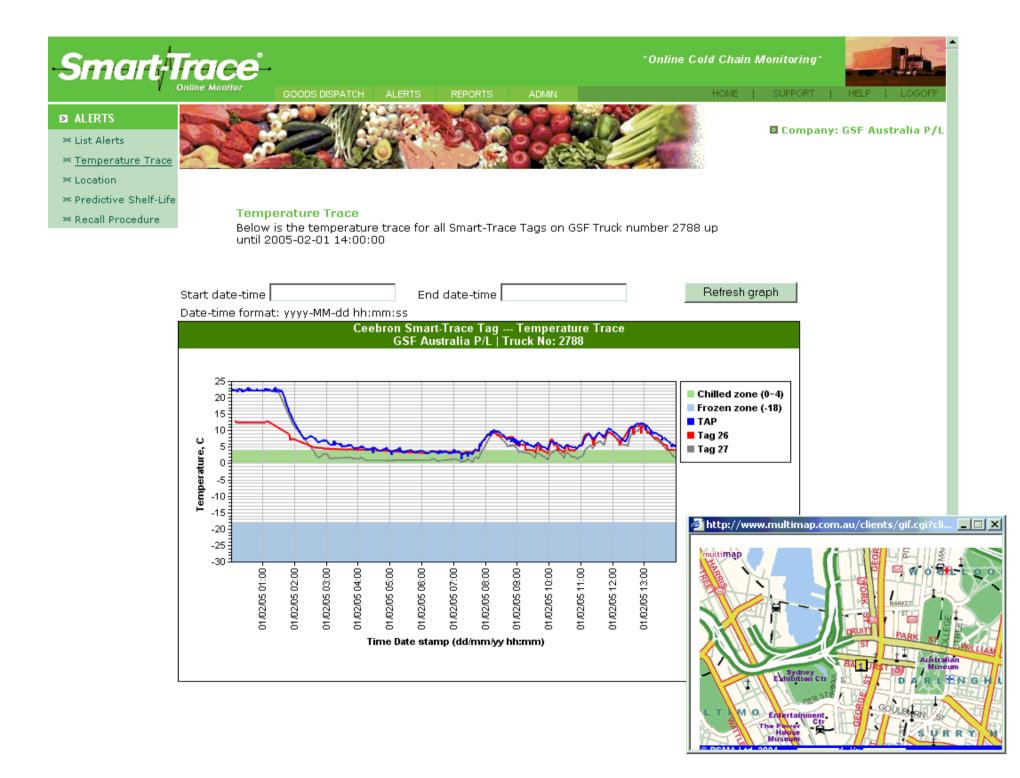
- Towards real time reporting by combining technological power with scientific precision
- Food safety management will achieve new levels of precision and flexibility when predictive models are integrated with radio frequency identification (RFID)/ad hoc wireless technology

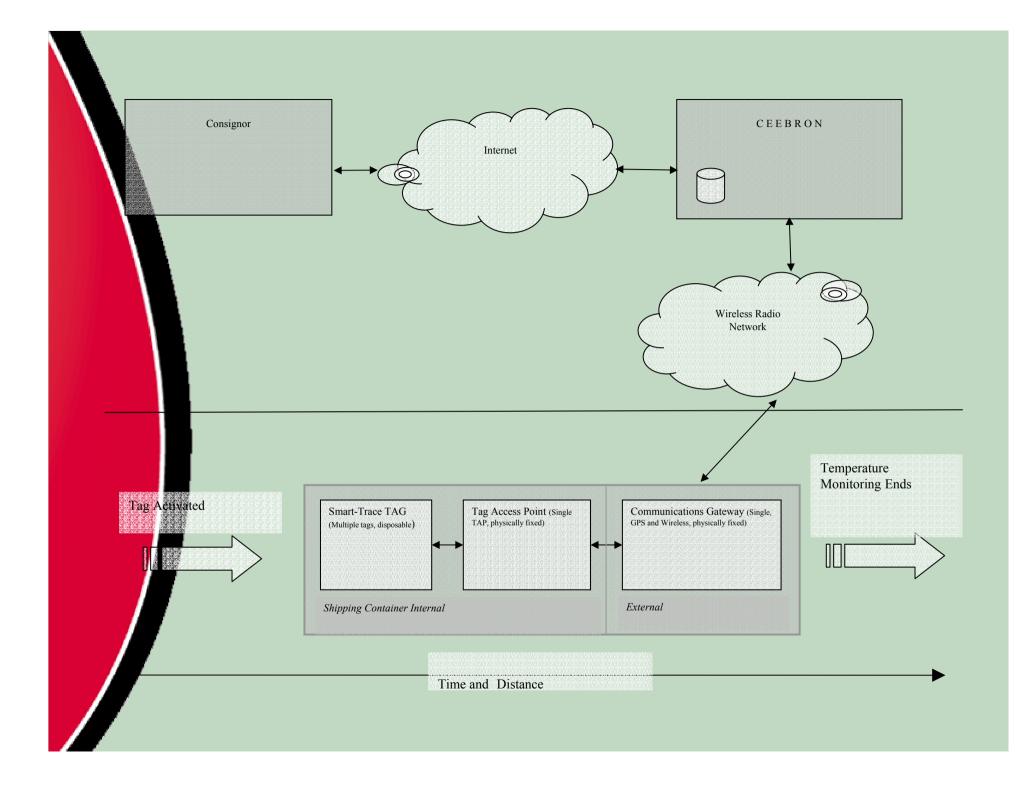
Case study: Smart-Trace

- A wireless monitoring technology for the cold chain
- **Real-time information availability** ullet
 - Product ID (EPC)
 - Product temperatures
 - Location (GPS)









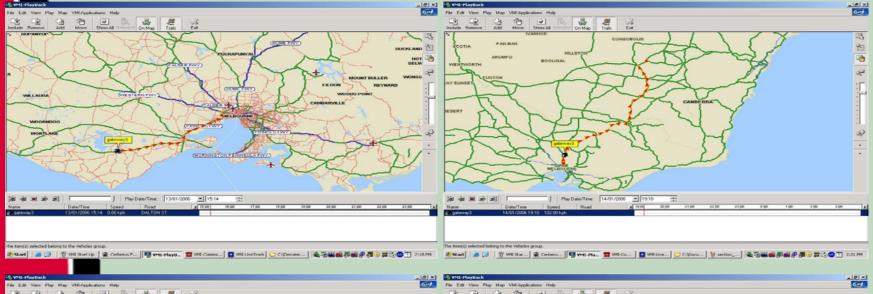
Case study: Smart-Trace

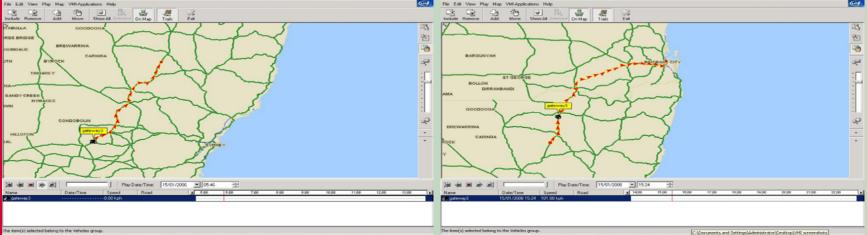
- Mesh network (ad hoc wireless network)
 - <u>P</u>latform <u>A</u>d-Hoc <u>W</u>ireless <u>N</u>etworking





Location Screenshots — Trial 1

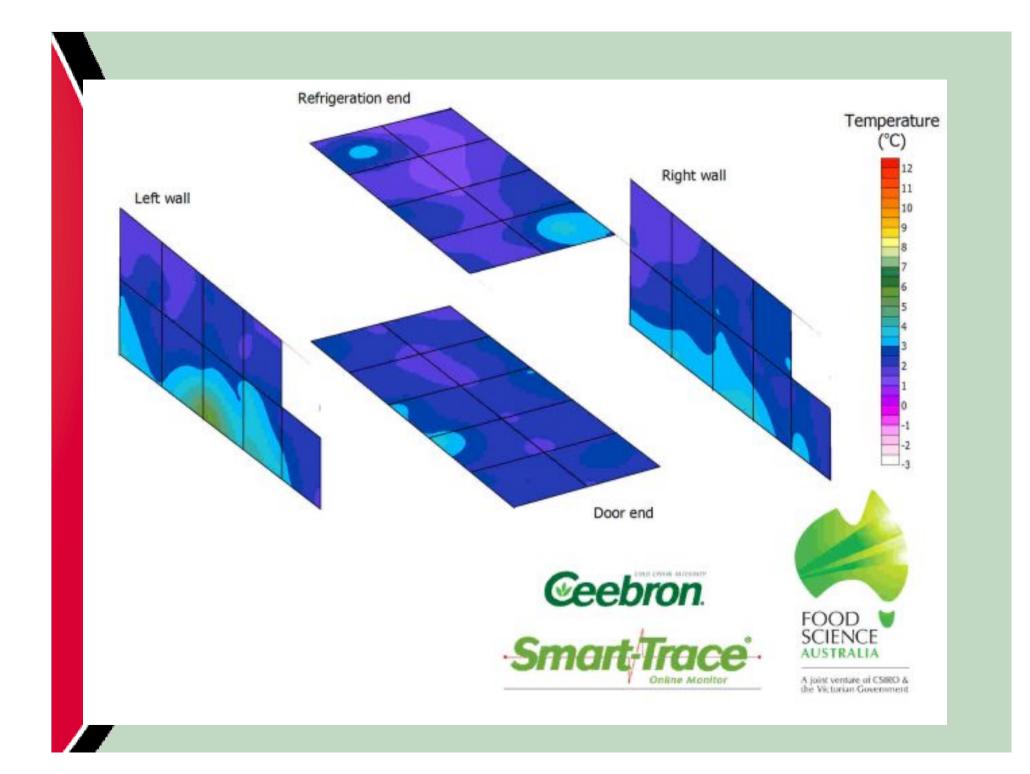




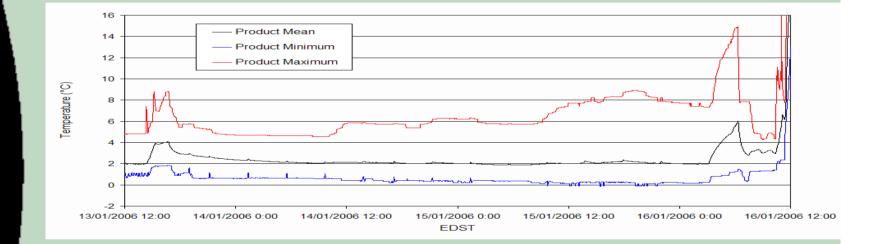
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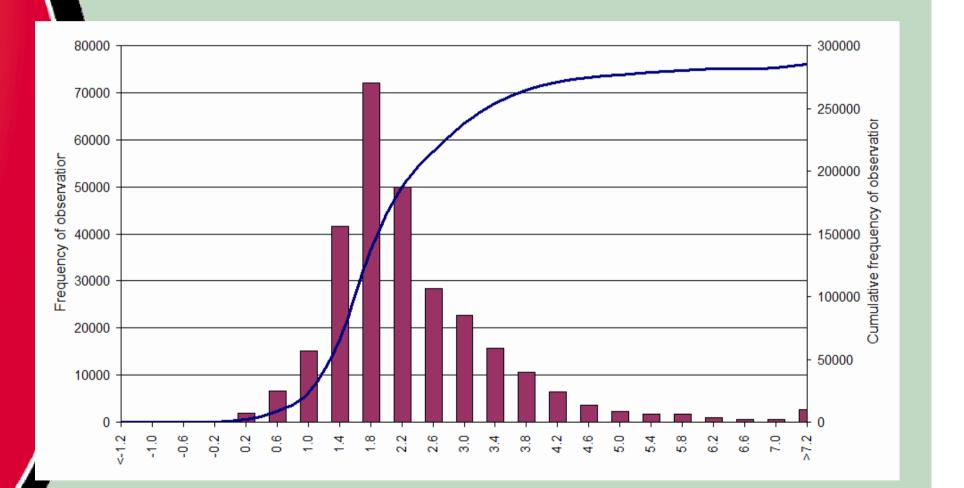


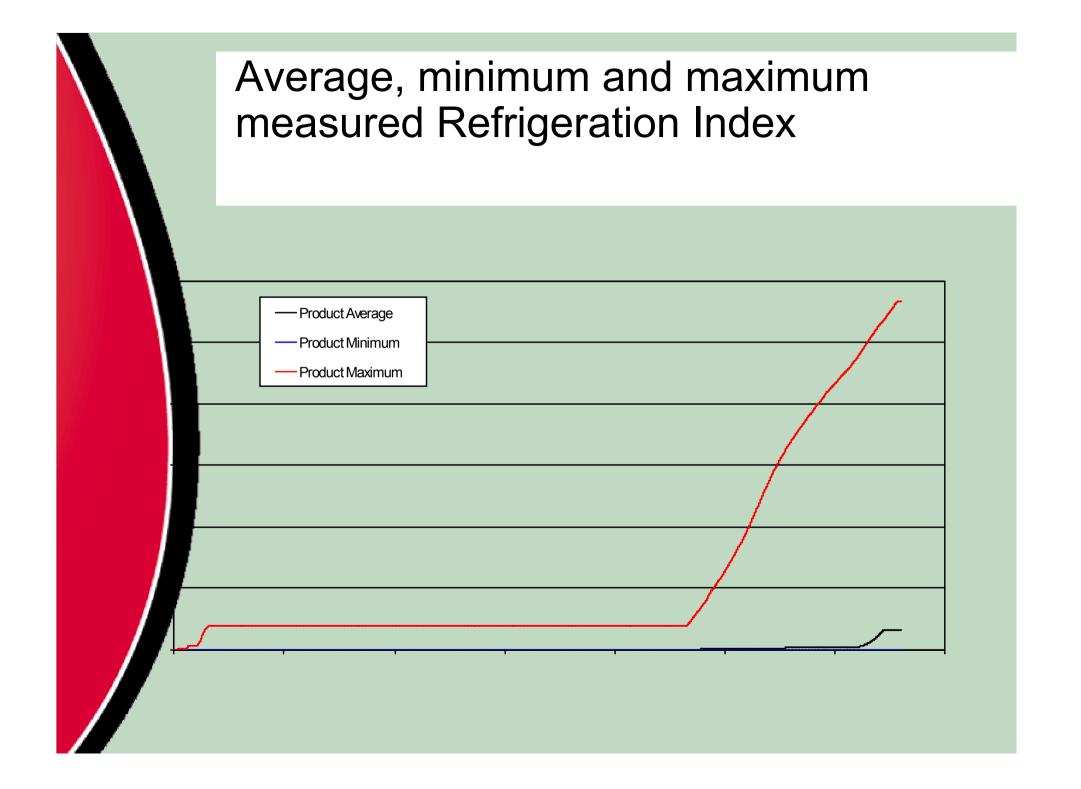


Average, minimum and maximum measured product temperatures

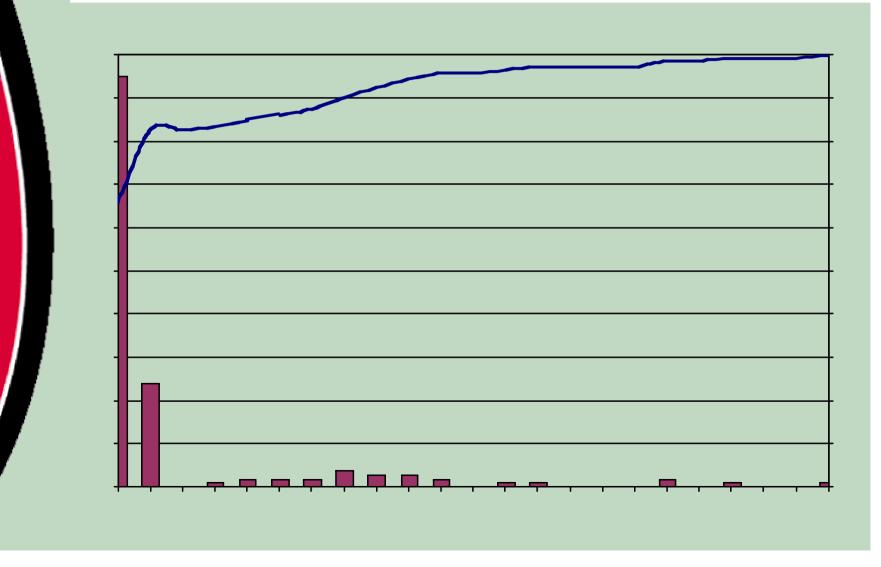


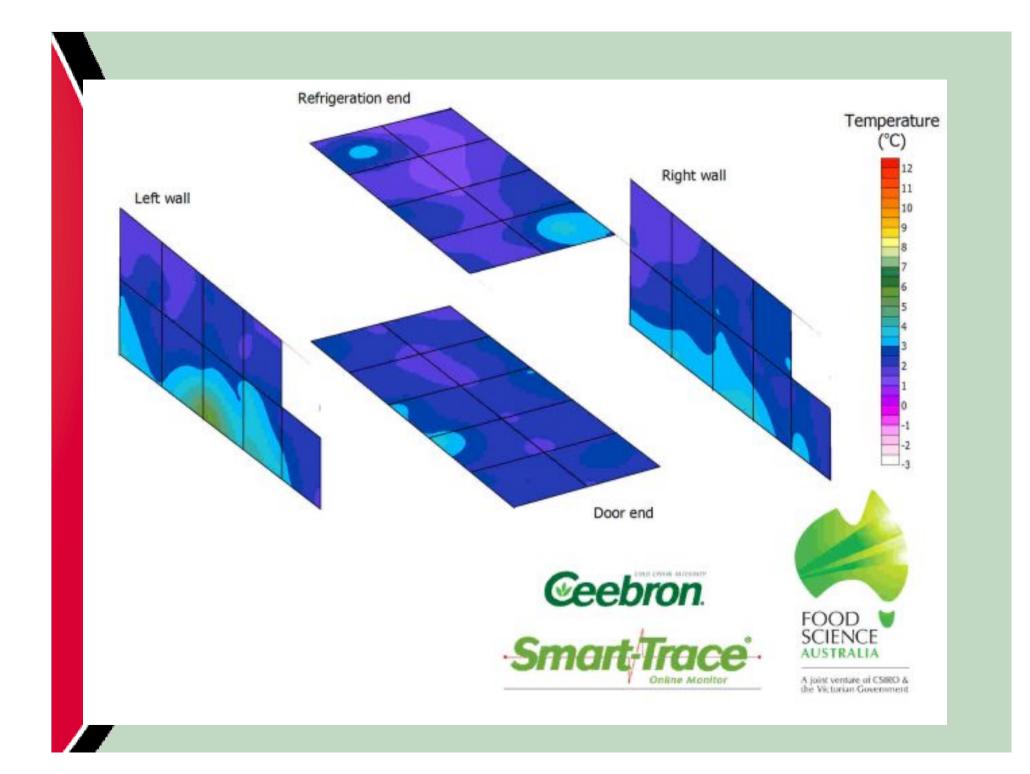
Frequency of observations of in-pallet temperatures



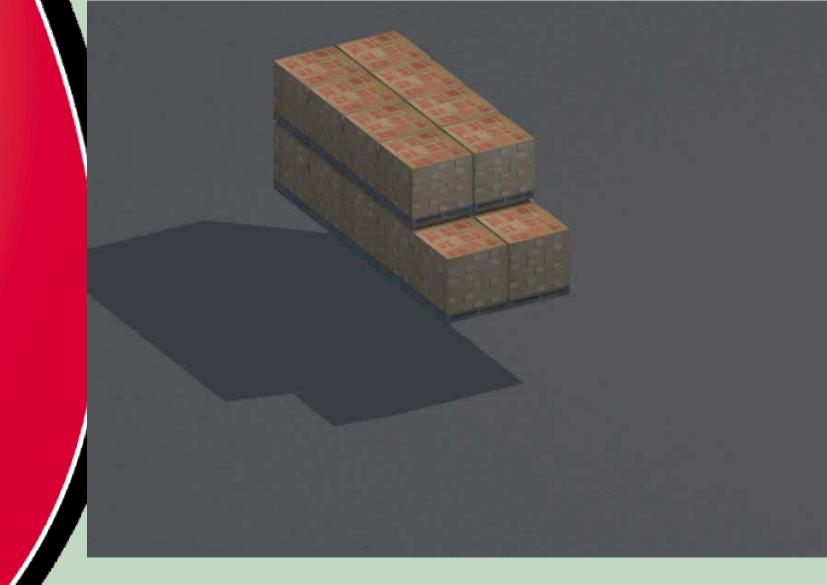


Frequency of observations of Refrigeration Index



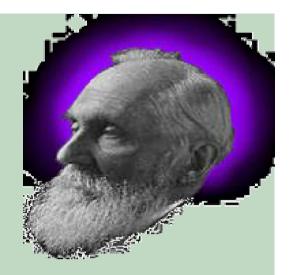


Smart-Trace Field Trials Thermographics 1





....when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot your knowledge is of a meagre and unsatisfactory kind;



"... it may be the beginning of knowledge, but you have scarcely in your thoughts advanced to the state of Science"

Lord Kelvin (William Thomson) 1824-1907





Claudio Bittencourt, PhD Candidate Olivia McQuestin, Research Assistant Dr John Bowman, Molecular Biologist Dr Lyndal Mellefont, Predictive Microbiologist Dr Janelle Brow, Postdoctoral Research Fellow Nazri Mohamed Naim, Honours Candidate Kim Chang, Honours Candidate Professor June Olley, Honorary Research Professor Jimmy Choo, Honours Candidate Lauri Parkinson, Laboratory Assistant Alison Dann, PhD Candidate Terry Pinfold, Honours Candidate Mark De'Pannone, PhD Candidate Sven Rasmussen.Research Assistant Dr Susan Dobson, Quantitative Microbial Risk Analyst Professor David Ratkowsky, Honorary Research Professor Esta Kokkoris, PhD Candidate Associate Professor Tom Ross, Predictive Food Microbiology Joseph Finn, Honours Candidate Dr Svetlana Shabala, Postdoctoral Research Fellow Mark Jackson, Honours Candidate Kathleen Shaw, PhD Candidate Sally Jones, Executive Assistant Julia Souprounov, PhD Candidate Mandeep Kaur, PhD Candidate Jimmy Twin, PhD Candidate Roger Latham, Research Assistant Wei Xiong, Masters Candidate Shih Hui Lee, Masters Candidate Donglai Zhang, Masters Candidate Sia Wee Lee, Honours Candidate Laura Maddock, Laboratory Assistant Sharee McCammon, Research Assistant Professor Tom McMeekin, Professor of Microbiology, Co-Director, AFSCoE



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