1	Shelf-life predictive models for Australian beef and lamb products in
2	overwrap trays and modified atmosphere packs: development and
3	evaluation
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21 Abstract

22 The Australian red meat industry has a reputation for producing meat with excellent shelf-23 life, which services both domestic and export markets in the retail and further processing 24 sectors. However, this reputation is constantly challenged throughout supply chains due to 25 unexpected temperature fluctuations and transit delays. Such incidences can result in 26 unnecessary product wastage or markdowns, or otherwise require timely and costly 27 evaluation of its sensory and microbiological condition to decide its disposition. To address 28 this challenge within export markets, shelf-life predictive models for vacuum-packed (VP) 29 beef and lamb primals were previously developed and are being adopted as a rapid, reliable 30 and cost-effective decision-support tool to predict the remaining shelf-life, providing 31 enormous economic benefits to the industry. This tool has the potential to provide further 32 benefits to the Australian meat industry by expanding its applicability to retail-ready 33 products within domestic markets. To this end, we used the data generated previously 34 (Rood et al., publication in preparation) to develop predictive models for the shelf-life 35 remaining for Australian beef and lamb products (*i.e.*, mince and steak) in overwrap (OW) 36 trays and modified atmosphere packs (MAP, 20% CO₂ and 80% O₂). The remaining shelf-life 37 is predicted based on the products initial total bacterial count or Pseudomonas numbers, 38 and time:temperature parameters. The models were then validated using independent data 39 and have bias and accuracy factors ranging from 0.93 to 1.03, and 1.10 to 1.11, respectively, 40 when used for predicting the shelf-life of OW and MAP products. This indicates a good 41 agreement between the observed and predicted shelf lives and generally underpredict the 42 shelf-life of products with approximately \leq 10% deviation, providing 'fail-safe' predictions. 43 These new models together with the existing models for shelf-life prediction of VP red meat 44 were incorporated into a 'ready to use' decision-making tool (known as 'Shelf-life Calculator 45 for Red Meat') for the Australian red meat industry to effectively and reliably manage 46 diverse supply chains to ensure high quality meat products with excellent shelf-life.

47 **1.** Introduction

The Australian red meat industry has a reputation for producing meat with excellent shelflife, which services both domestic and export markets in the retail and further processing sectors (contributing \$18.5 billion to Gross Domestic Product in 2017/2018) (Small et al., 2012). This reputation is constantly challenged by the need to minimise the loss of product shelf-life along different supply chains through unexpected temperature fluctuations and transit delays, and to meet a wide range of shelf life-related specifications imposed by intended international markets.

55 It is well established that the shelf-life of meat depends upon the degree of bacterial 56 contamination obtained during processing and a range of intrinsic (meat biochemistry) and 57 extrinsic (storage conditions) factors, of which temperature is considered the most 58 important factor (Nychas et al., 2008). Chill storage temperature (-1.5 to 0°C) is the most 59 common approach to maximise the shelf-life of fresh meat products by slowing bacterial 60 growth rates (Borch et al., 1996; Doulgeraki et al., 2012). However, even small increases in 61 storage temperature have been shown to significantly reduce the shelf-life, for instance, at 62 temperatures of 0°, 2° or 5°C, the storage life was reduced by about 30, 50 or 70%, 63 respectively, compared with storage at -1.5°C (Gill et al., 1988). 64 Temperature abuse, defined by Mills et al., (2014) as higher than 5°C during any stage of the

65 cold chain, is onerous for the supplier. It can result in unnecessary product wastage and 66 markdowns or, otherwise requires evaluation of its sensory and microbiological condition to 67 decide its disposition. In many instances, the time taken to conduct an evaluation (*i.e.*, 68 locate consignment, select and sample representative units, and await test results) increases 69 the likelihood that the contents might be deemed sensorially unacceptable or do not comply 70 with market specifications (Huynh et al., 2016). It is, therefore, critical for the success of the 71 Australian red meat industry to be able to assure quality shelf-life remaining for products in 72 diverse supply chains, and to improve the accuracy and timeliness with which a disposition 73 decision can be made.

To address this challenge, shelf-life predictive models for vacuum-packed (VP) beef and lamb primals were successfully developed to predict the remaining shelf-life rapidly and accurately. These models were developed based on the growth rate of microorganism's present (total viable count, TVC) and processes of spoilage (based on odour) as a function of temperature (Huynh et al., 2016; Kaur et al. 2021). The models have been validated by independent data from commercially available products in both simulated and commercial 80 cold chains, both within Australia and internationally, and are being adopted as a reliable 81 and cost-effective decision-support tool, providing enormous economic benefits to the 82 industry. However, the focus of this tool to date has been on the shelf-life prediction of 83 Australian VP beef and lamb in supply chains, especially for distant markets. To provide 84 additional benefits to the Australian meat industry, this tool has potential to be further 85 developed for red meat in common retail packaging formats within domestic markets, such 86 as modified atmosphere packs (MAP, 20% CO_2 and 80% O_2) and overwrap (OW) trays 87 (aerobic conditions).

88 Previously, we assessed the microbiological and sensorial qualities of beef and lamb 89 products in MAP (i.e., mince) and OW trays (i.e., mince and steak) sourced from several 90 Australian processors at different storage temperatures (ranging from 0°C to 12°C) (Rood et 91 al., publication in preparation). These trials involved products with and without prior wet 92 aging in VP at low temperatures (between 0°C and 4°C) for different durations (up to 35 days 93 for beef and 14 days for lamb). In contrast to VP formats, it was found that colour quality 94 was the most appropriate indicator for determining the shelf-life of all MAP and OW 95 products, and the rate of colour quality loss was not affected by the wet aging durations 96 tested, or product type (i.e., mince or steak for OW). Furthermore, the end of shelf-life of 97 OW products corresponded to the time taken for *Pseudomonas* spp. to reach a certain 98 population level of. This agrees well that this organism is a specific spoilage organism (SSO) 99 for chilled foods under aerobic conditions (Gill et al., 1977). The findings of those trials 100 indicated the feasibility of developing models for separately predicting the shelf-life of MAP 101 and OW products based on the rate of colour quality loss and time taken to reach 102 Pseudomonas numbers that correspond to spoilage, respectively, as functions of 103 temperature. To this end, we used the data from Rood et al. (publication in preparation) to 104 develop predictive models for the shelf-life of beef and lamb products in MAP (*i.e.*, mince) 105 and OW trays (*i.e.*, mince and steak) with prior wet aging durations up to 35 days for beef 106 and 14 days for lamb. This paper describes the development of these models and the 107 evaluation of their performance in simulated supply chains, with the overall aim to 108 incorporate these new models together with the existing models for shelf-life prediction of 109 VP red meat into a 'ready-to-use' decision-making tool for the Australian red meat industry. 110

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114 **2.** Materials and methods

115 2.1 Model development

116 2.1.1 Model development for OW products based on pseudomonas levels

Data for specific growth rates of *Pseudomonas* on OW beef and lamb steak and mince at
different storage temperatures (ranging from -0.5°C to 12°C) were obtained from Rood et al.
(publication in preparation). To describe the effects of storage temperature on the rates of *Pseudomonas* growth, linear regression analysis was performed for each meat type
(Ratkowsky et al., 1982) and the following model derived:

122
$$\sqrt{\mu_{Pseudomonas}} = (a \times T) + b$$
 (Eq. 1)

where $\mu_{Pseudomonas}$ is the specific growth rate of *Pseudomonas* (in days); *a* is the slope of the regression line; *T* is the temperature at which meat is stored (°C); and *b* is the regression coefficient.

Given the observed lag phase of *Pseudomonas* growth and the consistent relative lag time (RLT) observed across all product types and storage temperature (Rood et al., manuscript in preparation), the increase in *Pseudomonas* numbers over a given period of time could be estimated based on the growth rate from Equation 1 and the average relative lag time (RLT) as follows:

131 for:
$$t \ge (RLT/GT)$$
: $Log_{10} N_t = Log_{10} N_o + 0.301 \times \left[\frac{\left(t - \left(\frac{RLT}{GT}\right)\right)}{GT}\right]$

132 else $Log_{10} N_t = Log_{10} N_o$ (Eq. 2)

where N_t is the number of *Pseudomonas* spp. after a period of time (t); N_o is the starting number (CFU/cm² or g); RLT is the observed relative lag time; GT (day) is generation time estimated based on the predicted growth rate from Equation 1 (*i.e.*, GT = 0.301/ $\mu_{Pseudomonas}$); and t is time in day.

Based on the growth data for *Pseudomonas* spp. (parameters obtained from Equation 1) and
its levels at which the spoilage of beef and lamb products occurred (based on colour), the
remaining shelf-life of a given OW product could be predicted using the following equation:

140
$$SL_{remaining} = \left[\frac{Log_{10} N_{spoilage} - Log_{10} N_t}{0.301}\right] \times GT_T$$
(Eq. 3)

141

142 where *SL*_{remaining} is the remaining shelf-life of a given OW product at a given temperature (T);

143 $N_{spoilage}$ is the *Pseudomonas* numbers at the time of spoilage for OW products; N_t is the

144 observed Pseudomonas numbers (log₁₀ CFU/cm² or g) of that product after lag time is

145 considered; GT_{T} (day) is estimated based on the predicted growth rate from Equation 1 (*i.e.*,

- 146 GT = 0.301/GR) at a given temperature (T); and T is the expected future storage temperature (°C).
- 147

2.1.2 Model development of MAP products based on rate of quality loss 148

149 The shelf-life of MAP products could be predicted based on the rate of colour quality loss as 150 a function of temperature (Rood et al., manuscript in preparation). Accordingly, Equation (4) 151 can then be expressed as:

152

153
$$SL = \left[\frac{1}{a \times (T - T_{\min})}\right]^2$$
 (Eq. 4)

154

155 where SL is the shelf-life of MAP products in (days); a is the slope of the regression line; T is 156 the temperature at which meat is stored (°C); and T_{min} is the minimum temperature where 157 the rate of colour loss is zero.

158 Equation (4) was further modified to predict remaining shelf-life by accounting for the 159 observed initial TVC (at the time of packaging). This was achieved by calculating a correction 160 factor that considers the initial TVC numbers and the calculated TVC numbers of a given 161 product at the time of spoilage at a given temperature. This correction factor was then 162 incorporated to Equation (4) to predict the remaining shelf-life (*SL*_{remaining}; day).:

163

$$SL_{\text{remaining}} = \left[\frac{N_0 - (N_{\text{obs}}) + N_s}{N_s}\right] \times \left[\frac{1}{a \times (T - T_{\text{min}})}\right]^2$$
(Eq. 5)

165

166 where N_0 is the initial TVC that was typically observed on MAP products based on the 167 previous data of Rood et al. (publication in preparation) (log CFU/g); Nobs is the observed 168 initial TVC (log CFU/g); and N_s is the nominal population level on MAP beef and lamb at the 169 time of spoilage (log CFU/g). The N_s value was estimated by extrapolation of the regression 170 line of TVC data to the time at which spoilage occurs at -0.5°C.

- 171 172
- 2.1.3 Production of a model interface

173 Based on the developed Equations (2) and (3) for OW, and (4) and (5) for MAP products a

174 model interface was produced in MS 365 [®]Excel to predict the remaining shelf-life of beef

and lamb products in OW (*i.e.*, mince and steak) and MAP (*i.e.*, mince) with or without prior

176 wet aging for up to 35 days for beef and 14 days for lamb.

177

178 2.2 Validation of the developed models in simulated supply chains

179 2.2.1 Validation shelf-life trials

180 Microbiological and sensorial assessments for MAP mince and OW mince and steak were

181 conducted in accordance with Rood et al. (manuscript in preparation). Shelf-life trials were

182 conducted at either constant (ranging from -0.5 to 12°C) or dynamic temperature profiles.

183 The dynamic temperatures tested were representative of time:temperature profiles for

domestic supply chains, which were obtained from industry partners (Table 1). This is with

185 the exception of the final retail holding temperature, which was modified to represent

- 186 different scenarios, including 'worse case'.
- 187

188 **Table 1:** Dynamic temperature profiles used for shelf-life validation trials simulating

189 domestic supply chains.

	Scenario 1		Scenario 2		Scenario 3	
Supply chain phase	Temperature (°C)	Duration (h)	Temperature (°C)	Duration (h)	Temperature (°C)	Duration (h)
Chiller storage	2.4	10	2.4	10	2	17.5
Truck	0.3	1	0.3	1	1.5	1
Warehouse storage	1.7	20	1.7	20	1.7	21.25
Retail	8	Indefinitely	6	Indefinitely	4	Indefinitely

190

191

2.2.2 Determination of the shelf-life

192 The shelf-life of each product type was determined from colour assessments as described

193 previously (Rood et al., manuscript in preparation). Specifically, products that were rated as

194 'marginal – colour off' were considered as commercially unacceptable and the time taken to

reach that endpoint was recorded as the shelf-life of the product. Due to the variability of

196 product characteristics even within the same trial, the shelf-life was determined when at

197 least one of the replicates were rated as unacceptable at any given time point and

198 subsequent time points.

200 2.2.3 Comparison between observed and predicted shelf-life

The shelf-life of each product type was estimated using the developed predictive models based on initial TVC or *Pseudomonas* numbers, and time:temperature history. The performance of the developed models to predict the shelf-lives of different products was evaluated using the methods described by Ross (1996). Bias and accuracy factors for the models were calculated from observed and predicted shelf lives (days) of each packaging type.

207 **3.** Results and Discussion

208 Shelf-life predictive models for VP beef and lamb primals were previously developed based 209 on the growth rate of TVC and processes of spoilage (based on odour) as a function of 210 temperature (Huynh et al., 2016; Kaur et al. 2021). The models have been validated by 211 independent data from commercially available products in both simulated and commercial 212 cold chains and are being adopted as a reliable and cost-effective decision-support tool to 213 predict the remaining shelf-life rapidly and accurately. To provide additional benefits to the 214 Australian meat industry, this study developed shelf-life predictive models for red meat in 215 common retail packaging formats, such as OW trays and MAP, to be incorporated into the 216 decision-support tool.

217 To develop shelf-life predictive models for OW and MAP beef and lamb products, a 218 comprehensive study was conducted to determine the microbiological and sensory qualities 219 of meat as they relate to spoilage (Rood et al., manuscript in preparation). That study, 220 consistent with previous studies, indicated that the rate of quality loss could be predicted as 221 a function of temperature (Gill et al., 1988; Kaur et al., 2021). It was also evident that the 222 spoilage process was different between MAP and OW trays. These results were expected 223 given the unique selection pressures created by the different gaseous atmospheres between 224 MAP and OW packaging formats (Kameník et al., 2014; Kiermeier et al., 2013; Taylor et al., 225 1990). Specifically, *Pseudomonas* spp. is a specific spoilage organism (SSO) for chilled foods 226 under aerobic conditions, such as OW meat. However, its growth is suppressed by CO_2 under 227 MAP conditions (Gill et al., 1977). Accordingly, separate shelf-life predictive models were 228 developed for each packaging format.

229

230 3.1. Development of shelf-life predictive models for OW beef and lamb products

- 231 Given that the growth rates of *Pseudomonas* were similar at a given temperature regardless
- of their source, type of product (mince or steak) and meat type (beef or lamb) (Rood et al.,
- 233 manuscript in preparation), the growth rate data generated was combined and was fitted
- with the square root model of Ratkowsky et al., (1982) to describe the effects of storage
- 235 temperature on the growth rate of *Pseudomonas* on OW products. This was in accordance
- with Equation (1). However, the RLT and the *Pseudomonas* numbers at the time of spoilage
- 237 were found to be different between meat type. Beef had a larger RLT and higher
- 238 *Pseudomonas* spoilage threshold compared to lamb (Rood et al., manuscript in preparation).
- 239 This indicated the need to develop two different models. Table 2 shows the model
- 240 parameters for different meat types in accordance with Equations (1) and (2).
- 241

242 **Table 2.**

243 Estimated values of the parameters of Equation (1) and (2) for OW beef and lamb products

244 (mince and steak), based growth rate of *Pseudomonas*.

245

Product type	а	b	T _{min} (°C)ª	RLT
OW beef	0.0145	0.1566	-10.8000	5.3406
OW lamb	0.0145	0.1566	-10.8000	4.2066
· · · · ·				

246 $a \tau_{min}$ is the theoretical minimum temperature and was estimated by extrapolation of the regression line to247 $\sqrt{\mu_{quality loss}/\mu_{Pseudomonas}} = 0.$ 248249With the parameters obtained above, models specifically to predict the remaining shelf-life250of OW beef and lamb products were developed and can be defined by their respective

251 Equations (6) and (7).

7)

252

253
$$SL_{remaining (beef)} = \left[\frac{6.933 - Log_{10} N_t}{0.301}\right] \times GT_T$$
(Eq. 254 6)

255 256

257

258

$$SL_{remaining (lamb)} = \left[\frac{6.291 - Log_{10} N_t}{0.301}\right] \times GT_T$$
(Eq

259

- where *SL*_{remaining} is the remaining shelf-life of a given OW product at a given temperature (T);
- 261 N_{spoilage} is the Pseudomonas numbers at the time of spoilage for OW beef (6.933 log₁₀
- 262 CFU/cm² or g) or lamb (6.291 \log_{10} CFU/cm² or g) (Rood et al., manuscript in preparation); N_t
- 263 is the observed *Pseudomonas* numbers (log₁₀ CFU/cm² or g) after lag time is considered; GT_T
- 264 (h) is estimated based on the predicted growth rate from Equation 1 (*i.e.*, GT =
- 265 0.301/ $\mu_{Pseudomonas}$) at a given temperature (T); and T is the expected future storage
- 266 temperature (°C).
- 267
- 268 3.2 Development of shelf-life predictive models for MAP beef and lamb products
- 269 Similar to Section 3.1, we applied the square root model of Ratkowsky et al., (1982) to the 270 relevant data of Rood et al. (manuscript in preparation) to describe the effects of storage 271 temperature on the rates of quality loss for MAP (based on colour scores) as described in 272 Equation (4). Table 3 shows the model parameters (a and T_{min}) for MAP products for 273 different meat types. It was found that different meat types (beef and lamb) have different 274 model parameters. This was likely due to differences in their biochemistry, particularly 275 glycogen and lactic acid contents, as well as pH, where beef (pH 5.5-5.8) tends to be lower 276 compared to lamb (pH 5.6-6.8) (Carse & Locker, 1974). Such differences can affect the 277 growth of bacteria with consequential effects on shelf-life. Accordingly, two separate models 278 were developed to predict the shelf-life of beef and lamb in MAP. A similar observation was 279 also made for the development of shelf-life predictive models for VP beef and lamb primals 280 (Huynh et al., 2016; and Kaur et al., 2021)

281

- 282 **Table 3.**
- 283 Estimated values of the parameters of Equation (4) for MAP beef and lamb mince based on
- rate of quality loss.
- 285

Product type	а	T _{min} (°C) ^a
MAP beef	0.0059	-8.4641
MAP lamb	0.0064	-7.6875

286

- 288 $\sqrt{\mu_{\text{quality loss}}/\mu_{Pseudomonas}} = 0.$
- 289

²⁸⁷ *a T_{min}* is the theoretical minimum temperature and was estimated by extrapolation of the regression line to

290 With the parameters (a and T_{min}) obtained above, predictive models for the shelf-life of MAP 291 products were developed in accordance with Equation (4). However, such models could not 292 be used to specifically predict the remaining shelf-life. This requires a number of factors (*i.e.*, 293 N_0 , and N_s to be determined based on previous data from Rood et al. (publication in 294 preparation) for the shelf-life of MAP products (*i.e.*, as defined in Equation (5)). Specifically, 295 N_0 is the initial TVC for MAP beef and lamb based on the experimental data for a given 296 product stored at -0.5° C (4.1 and 4.6 log CFU/g, respectively); N_{obs} is the observed initial 297 TVC (log CFU/g) of the product in question; and N_s is the nominal population level of MAP 298 beef and lamb at the time of spoilage (log CFU/g). The N_s value was estimated by 299 extrapolation of the regression line of observed TVC data to the time at which spoilage 300 occurs at -0.5 °C. The extrapolated $N_{\rm s}$ value was estimated to be 8.77 log CFU/g for beef and 301 8.46 log CFU/g for lamb. These, taken together, were used to develop models to predict the 302 remaining shelf-life of MAP beef (Equation (8)) and lamb (Equation (9)) as follows:

303

$$SL_{\text{remaining}} = \left[\frac{4.10 - (N_{obs}) + 8.77}{8.77}\right] \times \left[\frac{1}{0.059 \times (T - 8.464)}\right]^2$$
 (Eq. 8)

305

304

306

$$SL_{\text{remaining}} = \left[\frac{4.64 - (N_{obs}) + 8.43}{8.43}\right] \times \left[\frac{1}{0.0064 \times (T - 7.688)}\right]^2$$
 (Eq. 9)

307

308 The developed models were incorporated into a software tool (implemented in MS 365 309 [®]Excel) that allows prediction of remaining shelf-life of beef and lamb MAP (mince) and OW 310 (steak and mince) reprocessed from VP primals aged up to 35 days for beef and 14 days for 311 lamb. To use this tool, the user selects the meat type (beef or lamb), packaging format (OW 312 or MAP), and product type (mince or steak), enters the starting bacterial numbers 313 (Pseudomonas for OW or TVC for MAP), and a time:temperature profile, typically collected 314 by a temperature logger. The tool then predicts the remaining shelf-life of the product based 315 on assessment of predicted growth and colour kinetic responses.

316

317 3.3 Shelf-life data for model validation

The shelf-life validation data obtained for various OW (n=11) and MAP (n = 16) products at constant and simulated supply chains (*i.e.*, at fluctuating temperatures) are summarise in Table 4 and 5, respectively. These include bacterial numbers at the start of the trial (*Pseudomonas* for OW and TVC for MAP), average storage temperatures, and observed shelf lives. The data was then used to evaluate the performance of the developed models.

- 323 Table 4: Summary of the observed and predicted shelf-lives (based on colour score) of
- 324 overwrapped beef and lamb products reprocessed from wet aged VP primals and stored at
- 325 different temperatures.

Packaging format and meat type	Retail cut	Wet aging duration (days)ª	Initial count (log ₁₀ CFU/cm ² or g) ^b	Average temperature ^c	Observed Shelf-life (days) ^d	Predicted Shelf-life (days) ^e	Model bias factor ^f	Model accuracy factor ^f
				5.76 ^g	4	3		1.11
		19	3.85	3.89	4	4		
OW Boof	Steak			-0.34	8	9	0.94	
OW Been		25	4.12	6.28	3	3	0.94	
		55		2.29	5	5		
	Mince	Fresh	3.15	4.03 ^h	5	4		
		Fresh	2.39	1.94	7	6		1.08
	Steak			-0.71	10	10		
OW Lamb	Steak	1/	3 03	5.23 ^g	3	3	0.93	
		14 5.55	5.55	3.78	3	3		
	Mince	Fresh	3.26	4.62 ^h	5	4		
326 327 328	a. Prima b. Initia	Ils were aged in \ I Pseudomonas	/P at 0-3°C for dif	ferent durations be ne commencemen	efore reprocess t of the trials,	ing into OW pr	oducts. 0 mins after	

- b. Initial Pseudomonas counts (upon the commencement of the trials, i.e., within 30 mins after
- 329 reprocessing and packaging).
- 330 c. Observed average temperature during trial. 331
 - d. The time taken for OW products to reach end of shelf-life based on colour score (*i.e.*, score of \leq 4).
- 332 e. The predicted shelf-life generated by the developed Shelf-life Calculator.
- 333 f. Bias and accuracy factor indices of Ross (1996) to assess the performance of the model.
- 334 g. Dynamic temperature profile (based on scenario 2 in Table 1).
- 335 h. Dynamic temperature profile (based on scenario 3 in Table 1).
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- 339 **Table 5:** Summary of the observed and predicted shelf-lives (based on colour score) of
- 340 modified atmosphere packed beef and lamb mince reprocessed from wet aged VP primals
- 341 and stored at different temperatures.

N	leat type	Wet aging duration (days)ª	Initial count (log ₁₀ CFU/g) ^b	Average temperature ^c	Observed Shelf-life (days) ^d	Predicted Shelf-life (days) ^e	Model bias factor ^f	Model accuracy factor ^f
				8.24	4	4		1.07
		Fresh	4.93	2.3	10	9		
	Beef			-0.27	19	16		
		12	F F 4	3.62 ^g	7	7	0.93	
			5.54	-0.20	14	15		
		21	E OE	6.19	5	4		
		21	5.95	2.01	9	9		
		Fresh	4.42	4.20 ^g	7	8		1.03
				8.22	4	4		
		Fresh	4.72	5.62	6	6	1.03	
				1.92	11	11		
	Lamb			0.11	16	17		
		12	3.96	8.36	4	4		
				1.93	11	12		
				0.1	18	18		
		12	4.60	11.98	2	3		
 342 343 344 345 346 347 348 349 350 351 352 		 a. Primals were aged in VP at 0-3°C for different durations before reprocessing into MAP products. b. Initial counts (upon the commencement of the trials, <i>i.e.</i>, within 3.5 hours after reprocessing and packaging). c. Observed average temperature during trial. d. The time taken for MAP products to reach end of shelf-life based on colour score (<i>i.e.</i>, score of ≤4). e. The predicted shelf-life generated by the developed Shelf-life Calculator. f. Bias and accuracy factor indices of Ross (1996) to assess the performance of the model. g. Dynamic temperature profile (based on scenario 2 in Table 1). 						
353	3.3 Pe	3 3 Performance of predictive models						
354	The sh	The shelf-life predictive models for OW and MAP heef and lamb products were evaluated for						
355	their p	their performance by comparison with independent data not used to generate the models						
356	The M	The MS 365 [®] Excel tool as described above (Section 2.1.3) was then used to predict the						
357	shelf-life of different meat products based on their time:temperature history and initial							

microbial counts. The observed *vs.* predicted shelf lives (days) of each product are shown inTables 4 and 5.

360 The bias and accuracy factor analyses of Ross (1996) were used to assess the performance of 361 the predicted shelf-life generated by the model compared with the observed data. Ross 362 (1996) reported that the bias factor serves as a measurement index for the average variation 363 between the predicted and observed values, whereas the accuracy factor is used to estimate 364 the accuracy of an established model. Bias and accuracy factor values of 1 indicate a perfect 365 agreement between observed and predicted values. In this study, the models were found to 366 have a bias factor of 0.94 and 0.93, and an accuracy factor of 1.11 and 1.08 when used for 367 predicting the shelf-life of beef and lamb steak and mince in OW trays, respectively. Similar 368 results were found for models used for predicting the shelf-life of beef and lamb mince in 369 MAP which were found to have bias factor of 0.93 and 1.03, and an accuracy factor of 1.07 370 and 1.03, respectively. These indices showed a good agreement between the observed and 371 predicted shelf lives of OW and MAP beef and lamb products. The models generally 372 underpredict the shelf-life of products with approximately $\leq 10\%$ deviation, providing 'fail-373 safe' predictions. These results are also in accordance with previous models developed for 374 shelf-life prediction of beef and lamb in VP in which the bias factor of 1.02 and 0.90, and an 375 accuracy factor of 1.10 and 1.11, respectively, indicating a 'fail-safe' predictions with 376 approximately 10% deviation (Huynh et al., 2016). It should also be noted that an over-377 prediction of time to spoilage was also observed by Albrecht et al., (2019), Bruckner et al., 378 (2013) and Tang et al., (2013) for their shelf-life predictive models for poultry and pork meat. 379 From the above, the developed models were successfully validated to provide an accurate 380 and reliable prediction of the shelf-life of beef and lamb products stored under common 381 retail ready packaging formats, such as OW and MAP. Such models, along with existing 382 models for shelf-life prediction of VP red meat can be readily adopted as a reliable decision-383 making tool in commercial supply chains. This tool will offer a cost-effective approach for 384 meat processors to optimise and better understand their supply chains. Disposition of 385 product affected by adverse events, such as unexpected temperature fluctuations or 386 extended delivery times can be resolved speedily by using this tool.

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391 4. Conclusion

This study describes the development of 'ready-to-use' shelf-life predictive models for OW and MAP beef and lamb products. The models were validated by independent data from commercially available products in simulated supply chains and were found to generally underpredict the shelf-life with approximately ≤ 10% deviation, providing 'fail-safe' predictions. The new models together with the existing models for shelf-life prediction of VP red meat can be incorporated into a 'ready-to-use' decision-making tool for the Australian red meat industry to optimise and monitor meat quality in diverse supply chains.

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