

Scotland's Rural College

## Modeling European ruminant production systems: facing the challenges of climate change

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1 Modeling European ruminant production systems: facing the challenges of climate change

2

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25

26 **Abstract**

27 Ruminant production systems are important producers of food, support rural communities and  
28 culture, and help to maintain a range of ecosystem services including the sequestering of carbon in  
29 grassland soils. However, these systems also contribute significantly to climate change through  
30 greenhouse gas (GHG) emissions, while intensification of production has driven biodiversity and  
31 nutrient loss, and soil degradation. Modeling can offer insights into the complexity underlying the  
32 relationships between climate change, management and policy choices, food production, and the  
33 maintenance of ecosystem services. This paper 1) provides an overview of how ruminant systems  
34 modeling supports the efforts of stakeholders and policymakers to predict, mitigate and adapt to  
35 climate change and 2) provides ideas for enhancing modeling to fulfil this role. Many grassland  
36 models can predict plant growth, yield and GHG emissions from mono-specific swards, but  
37 modeling multi-species swards, grassland quality and the impact of management changes requires  
38 further development. Current livestock models provide a good basis for predicting animal  
39 production; linking these with models of animal health and disease is a priority. Farm-scale  
40 modeling provides tools for policymakers to predict the emissions of GHG and other pollutants  
41 from livestock farms, and to support the management decisions of farmers from environmental and  
42 economic standpoints. Other models focus on how policy and associated management changes  
43 affect a range of economic and environmental variables at regional, national and European scales.  
44 Models at larger scales generally utilise more empirical approaches than those applied at animal,  
45 field and farm-scales and include assumptions which may not be valid under climate change  
46 conditions. It is therefore important to continue to develop more realistic representations of  
47 processes in regional and global models, using the understanding gained from finer-scale modeling.  
48 An iterative process of model development, in which lessons learnt from mechanistic models are

49 applied to develop ‘smart’ empirical modeling, may overcome the trade-off between complexity  
50 and usability. Developing the modeling capacity to tackle the complex challenges related to climate  
51 change, is reliant on closer links between modelers and experimental researchers, and also requires  
52 knowledge-sharing and increasing technical compatibility across modeling disciplines. Stakeholder  
53 engagement throughout the process of model development and application is vital for the creation  
54 of relevant models, and important in reducing problems related to the interpretation of modeling  
55 outcomes. Enabling modeling to meet the demands of policymakers and other stakeholders under  
56 climate change will require collaboration within adequately-resourced, long-term inter-disciplinary  
57 research networks.

58

## 59 **Keywords**

60 Food security, livestock systems, modeling, pastoral systems, policy support, ruminants

61

## 62 **1. Introduction**

63 The world’s livestock production systems are facing unprecedented challenges – the need to reduce  
64 greenhouse gas (GHG) emissions, currently estimated to represent 15% of global anthropogenic  
65 emissions (Ripple et al., 2014), to adapt to global climatic and socio-economic changes (Soussana,  
66 2014; Thornton, 2010), to provide ecosystem services, and to meet the expected rapid increase in  
67 demand for meat and dairy products resulting from changes in human diets in the developing world  
68 (Tilman and Clark, 2014). In order to avoid significant environmental costs, these goals must be  
69 reached through increased production efficiency to avoid further encroachment of agriculture into  
70 pristine natural ecosystems (Popp et al., 2014).

71

72 Several major global and European reports have mapped the strategic research areas in which  
73 progress is required to overcome the challenges to livestock production systems (ATF, 2013, 2014;  
74 FACCE-JPI, 2012; Soussana, 2014). All highlight the need for research that takes account of  
75 interactions between agricultural systems, between these systems and natural ecosystems, and  
76 between strategic policy choices and on-farm management decisions.

77

78 Assessments of how climate change, policy, management, and socio-economic factors impact  
79 livestock production, require an understanding of complex systems beyond that possible through  
80 direct analysis of empirical data. In this respect, mathematical modeling has an essential role in the  
81 process of developing production systems capable of overcoming the multi-faceted problems  
82 described (Graux et al., 2013; Kipling et al., 2014). The aforementioned strategic research agendas  
83 represent challenges that the livestock and grassland modeling community must address if it is to  
84 play the role required of it by society (Scholten, 2015).

85

86 For modelers of ruminant production systems, the complexity of farm-scale interactions creates a  
87 major challenge for the scaling up of 'animal' and 'field' scale modeling to the national, regional and  
88 global levels most relevant for policy makers. A range of modeling approaches has been applied to  
89 European ruminant livestock systems and their various components (Box 1) with a number of  
90 technical reviews providing comprehensive comparisons of a range of models, for example  
91 (Holzworth et al., 2015; Snow et al., 2014; Tedeschi et al., 2014).

92

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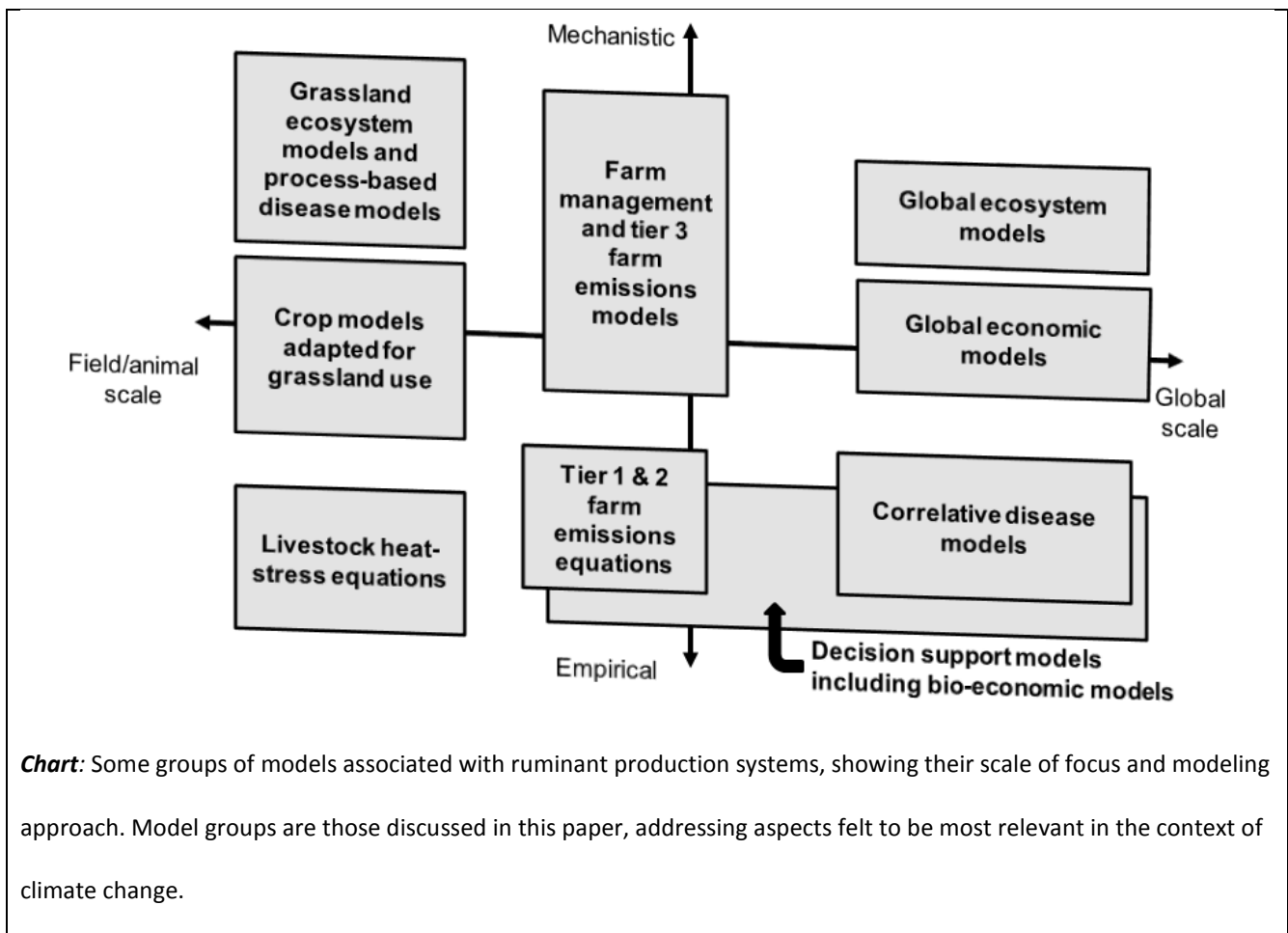
94

95 | **Box 1:** Description of technical aspects of agricultural models) including the characteristics of the modeling areas  
96 | described in this paper  
97

*Empirical and mechanistic modeling:* Empirical models derive from fitting statistical functions to experimental response data. Their accuracy is dependent on the characteristics of the datasets used to define the modeled relationship. They can be used to predict new conditions as determined by changes in the variables considered. However, they cannot respond to changes which might affect the nature of the statistical relationships they are based on. Empirical models may therefore provide inaccurate predictions when the values of the modeled variables are beyond the range for which the relationship was tested. Mechanistic approaches model the underlying mechanisms that drive observed empirical relationships, and can therefore reveal and explain unexpected systemic responses to future change. However, they cannot predict changes arising from the effects of un-modeled processes, which may become relevant under altered systemic conditions. In some cases, the variables used to derive empirical models can incorporate mechanistic understanding, blurring the distinction between the two approaches. Models often use a mixture of empirical and mechanistic approaches to characterise different relationships, so that there is a continuum between relatively mechanistic and relatively empirical modeling.

*Time and variation:* Models can be dynamic, to investigate how systems change over time, or static (not considering time as a variable). They can be deterministic (giving unique predictions) or stochastic (including random variation and reporting the dispersion as well as the predicted value of output variables).

*Scale and complexity:* As scale increases so does systemic complexity, as the number of variables and interactions between them rises at an increasing rate. Using mechanistic models at increasing scales (from plot or animal upwards) therefore requires increasing effort (in terms of systemic understanding and computing power) and involves increasing uncertainty. At the same time, some processes average out at larger scales, and can be represented by simpler functions. These factors mean that more empirical approaches are used as the scale of the modeled system increases.

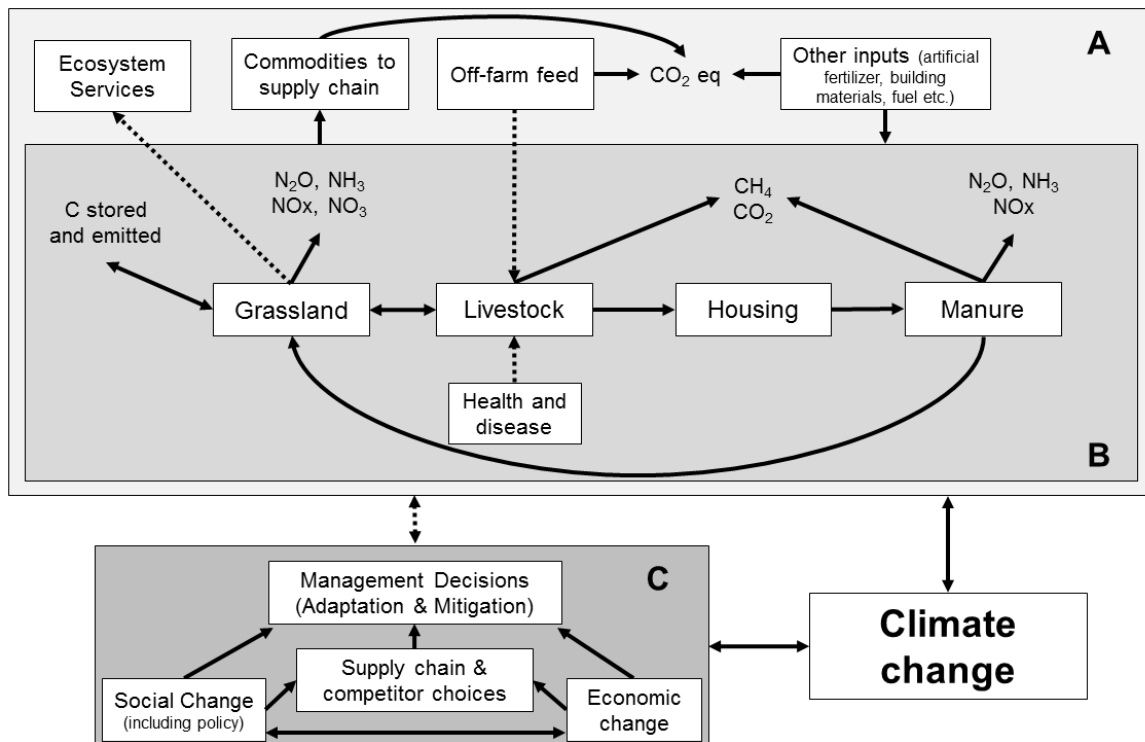


98

99

100 A recent review of modeling of grazed agricultural systems (Snow et al., 2014) highlighted the need  
 101 for better modeling of extreme events, animal-mediated nutrient transfers, pests, weeds and gene-  
 102 environment interactions. The present paper provides a strategic overview of ruminant production  
 103 systems modeling in Europe in the context of climate change. The focus on Europe reflects the  
 104 continent’s large agricultural sector and its importation of agricultural products, which make it a  
 105 major contributor to agricultural GHG emissions (Davis and Caldeira, 2010), while its recognition of  
 106 the serious impacts of climate change make it a key location for research and innovation related to  
 107 food security (Soussana et al., 2012a). The overview of ruminant production systems modeling  
 108 presented here (Fig. 1) includes consideration of stakeholder engagement in the modeling process,  
 109 and the role of economic modeling (at farm, regional and global scale). The purpose is: 1) to

110 provide an overview of how current ruminant systems modeling supports the efforts of  
 111 stakeholders and policymakers to predict, mitigate, and adapt to climate change and 2) to provide  
 112 ideas about how modeling resources can be enhanced to best meet these challenges.  
 113



114  
 115 **Fig. 1:** An overview of a ruminant production system in the context of modeling of how climate change is affected by  
 116 and affects such systems. For clarity, this system does not include on-farm arable production. Key: A = physical system  
 117 including off-farm inputs and outputs (emissions included in LCA); B = on-farm system (emissions included in farm-scale  
 118 modeling); C = Impacts of changes in management and its drivers; Dashed lines = relationships requiring further  
 119 development in models

120  
 121  
 122 In relation to climate change, models of ruminant systems can be divided into those that focus on  
 123 the impacts of climate change on such systems (Section 2), and those that focus on emissions of  
 124 GHGs from them (Section 3). At the regional and global levels, economic modeling seeks to gain an  
 125 overview of both of these processes and the interactions between them, in order to inform policy



126 choices (Section 4), while engagement with stakeholders is essential to ensuring that modeling has  
127 a positive real-world impact (Section 5). Section 6 considers how best to overcome the challenges  
128 to the integration of these different aspects of modeling, and recommends some priorities for  
129 action.

130

## 131 **2. Modeling the impacts of climate change on ruminant livestock systems**

132

133 Climate change is expected to have a range of impacts on ruminant production systems, including  
134 the direct effects of changing conditions on grass and feed crop production (such as changing yields  
135 and quality) and livestock health (such as increased heat stress) and indirectly, for example through  
136 impacts on livestock pathogens, and pests affecting grasses and other crops. Section 2 explores  
137 some of the main climate change impacts and the state of modeling in relation to each.

138

### 139 **2.1. Modeling livestock pathogens and disease**

140

141 Climate change has already affected patterns of livestock disease (Kenyon et al., 2009; Purse et al.,  
142 2005; Wilson and Mellor, 2008), and further changes are predicted (Fox et al., 2015; 2011; van Dijk  
143 et al., 2008). A variety of climatic factors influence pathogen survival and development, including  
144 moisture, temperature and UV levels (Chaparro et al., 2011; O'Connor et al., 2006; Stromberg,  
145 1997; van Dijk et al., 2009). These variables affect spatial distribution, parasite and disease  
146 intensity, and seasonal patterns of infection (Fox et al., 2011). Climate change will not influence all  
147 pathogens equally. Vector-borne parasites are especially sensitive to climate, as vector lifecycles  
148 and vectorial capacity are strongly influenced by abiotic conditions (Purse et al., 2005; Wilson and  
149 Mellor, 2008). Climate change is also having profound impacts on macro-parasites (Broughan and

150 Wall, 2007; Fox et al., 2011), as survival and development of their free-living stages are governed by  
151 temperature and moisture availability. Despite potential for pathogen outbreaks to compromise  
152 food security and animal welfare, there are few predictions of future disease risk in livestock (Fox et  
153 al., 2012). In this context, modeling is a vital tool for understanding how climate change will affect  
154 pathogen risk, supporting the development of effective prevention and control measures.

155

156 Predictive species distribution models are often based on correlative ecological niche models in  
157 which species' environmental requirements are inferred from current geographic distributions  
158 (Elith and Leathwick, 2009; Heikkinen et al., 2006; Pagel and Schurr, 2012). Insights into the biology  
159 of parasite dynamics should be used to improve and parameterize these models, and to choose the  
160 most proximal environmental predictors (Guisan and Thuiller, 2005). Correlative modeling has  
161 already provided projections of future risk for livestock pathogens including vector borne Blue  
162 Tongue Virus (Tatem et al., 2003) and liver fluke, which spends large parts of its lifecycle outside its  
163 definitive host (Fox et al., 2011). A bottleneck for developing models for a broader range of species  
164 is the limited availability of pathogen distribution data. Additionally, correlative models do not  
165 contain underlying dynamical processes, rapidly accruing uncertainty when projected climate  
166 change forces extrapolation (Fox et al., 2012). To overcome this limitation, and to identify potential  
167 for qualitative shifts in system behaviour, a process-based mechanistic approach is needed.

168 Mechanistic models are based on detailed knowledge of host and pathogen physiology and attempt  
169 to replicate underlying mechanisms that drive species' responses to environmental variables  
170 (Robertson et al., 2003). As such models do not rely on empirical relationships between climate  
171 variables that may alter with climate change, they are comparatively robust under spatio-temporal  
172 extrapolation (Dormann, 2007; Hijmans and Graham, 2006) and can predict consequences of subtle  
173 interactions between system components under climate influence. Fox et al., (2015) used a

174 process-based model to demonstrate that small temperature changes around critical thresholds  
175 can drive sudden changes in nematode risk in grazing livestock. There is now a need to  
176 parameterise such models for particular pathogens, and apply them to specific farming systems  
177 under climate change projections.

178

179 At the farm level, husbandry has a dominant influence on disease transmission (Fox et al., 2013;  
180 Smith et al., 2009); long term predictive models therefore need to incorporate the effects of  
181 management responses to climate change. An optimal modeling approach is likely to combine  
182 mechanistic processes and physiological thresholds with correlative bioclimatic modeling,  
183 incorporating changes in livestock husbandry and disease control. Despite recent advances in  
184 statistical methodologies, model-fitting and climate projections, progress remains limited by the  
185 paucity of active surveillance data, and empirical data on physiological responses to climate  
186 variables. By combining improved empirical data and refined models with a broad view of livestock  
187 systems, robust projections of livestock disease risk can be developed.

188

## 189 **2.2. Modeling heat stress in cattle**

190

191 High and extreme temperatures, in combination with other factors such as humidity and solar  
192 radiation, are known to cause heat stress in a range of domestic animals, with effects on  
193 productivity, growth, development (Collier and Gebremedhin, 2015) and reproduction (de Rensis et  
194 al., 2015). The Temperature Humidity Index (THI) has been widely used to explore these  
195 relationships in livestock, and to model expected responses to climatic change (Gaughan and Hahn,  
196 2010). THI has some recognized limitations, including the assumption that all animals respond to  
197 thermal stressors in the same way, and a lack of consideration of other important variables

198 (including solar radiation, wind speed, duration of exposure) (Gaughan et al., 2012). Improved  
199 indices have been proposed, including THI adjusted for wind speed and solar radiation, a number of  
200 respiration rate indices and the heat load index (Gaughan et al., 2012). Whatever the index used,  
201 climate change is expected to raise average temperatures and increase the frequency of  
202 temperature extremes. Heatwaves are predicted to become more frequent, particularly in  
203 Southern Europe and the Mediterranean, with expected decreases in relative humidity away from  
204 the coasts unlikely to offset the impacts of increased temperature (Fischer and Schar, 2010). As a  
205 result, increases are expected in the number of days when THI in Europe exceeds calculated  
206 thresholds for heat stress in dairy cattle (Dunn et al., 2014; Segnalini et al., 2013).

207

208 Mechanistic models have been developed to characterise heat flows and changes in body  
209 temperature in cattle (Thompson et al., 2014) and thermal balance in pigs and poultry (Mitchell,  
210 2006), while empirical equations are used to model the negative relationship between increases in  
211 THI above calculated thresholds, dairy cow milk yield and milk composition (Bertocchi et al., 2014;  
212 Bohmanova et al., 2007; Gorniak et al., 2014; Hammami et al., 2013; Hill and Wall, 2015) and dairy  
213 and beef cattle mortality (Morignat et al., 2015; Vitali et al., 2009). Models are also used to test the  
214 design of livestock housing in relation to airflow and temperature (Herbut and Angrecka, 2015) and  
215 to model the temperature effects on animals of other physical variables such as bedding type  
216 (Radoń et al., 2014).

217

218 Although the empirical modeling of thermal comfort zones and THI thresholds is valuable for  
219 livestock management, empirical approaches cannot incorporate the whole range of factors that  
220 modify livestock susceptibility to increasing THI, such as geographic location, production system,  
221 breed, genotype, age, physiological and productive phase, acclimation state, presence and type of

222 cooling systems, and management (Bernabucci et al., 2010; Nardone et al., 2010) or interactions  
223 between these variables. For ruminants, mechanistic modeling of thermal balances and heat stress  
224 needs to be linked to models of productivity and growth, and scaled up to herd level, taking  
225 account of variation in individual growth and performance. The impacts of rising temperatures on  
226 livestock need to be characterised in regional and global modeling, to better understand the  
227 economic consequences of climate change related heat stress at a broader scale (see Section 4). In  
228 addition, more modeling is needed to explore the impact of heat stress on livestock water  
229 requirements(Howden and Turnpenny, 1998) , given that demand for water for crops is also likely  
230 to rise under climate change (Leclère et al., 2013), putting pressure on European water resources.  
231 There is a need to develop mechanistic models capable of identifying the most effective adaptation  
232 options in relation to heat stress (Lacetera et al., 2013) at farm- and policy-levels, from the  
233 exploration of genetic approaches (Collier and Gebremedhin, 2015) to systemic switches away from  
234 dairy cows towards more heat-tolerant livestock such as goats in southern Europe (Silanikove and  
235 Koluman, 2015).

236

### 237 **2.3. Modeling grassland productivity and nutritional value**

238

239 Climate change impacts on grasslands are expected to vary across Europe, with warmer  
240 temperatures and higher rainfall extending growing seasons in the north (Höglind et al., 2013) while  
241 the risk of drought is likely to increase in Mediterranean regions (van Oijen et al., 2014). Grassland  
242 productivity is known to be sensitive to temperature and water stress (Knapp et al., 2001) with  
243 impacts varying between different plant communities (Kreyling et al., 2008; Peterson et al., 1992).

244

245 Several types of model have been applied to grassland systems (Bellocchi et al., 2013); grassland-  
246 specific models (Kochy, 2008; Ma et al., 2015; Wu et al., 2007) models originally developed for  
247 crops and adapted to grasslands (Coucheney and Buis, 2015; Perego et al., 2013; Williams et al.,  
248 2008), and plant functional type-based models (Chang et al., 2013; Dury and A Hambuckers, 2011;  
249 Hidy et al., 2012; Waha et al., 2012). Previous modeling focussed on grassland productivity (Li et al.,  
250 2011; Woodward, 2001), mainly characterising monospecific swards or simple mixtures (Blackburn  
251 and Kothmann, 1989; Lazzarotto et al., 2009). Such models do not address the need for modeling of  
252 more diverse plant communities (Duru et al., 2009). Although functional classifications can simplify  
253 the characterisation of plant species (Cruz et al., 2002; Jouven et al., 2006) process-based  
254 biogeochemical models such as PaSim (Ma et al., 2015) usually use an average vegetation when  
255 simulating mixed swards, due to the challenges of modeling changes in botanical composition.

256

257 Although modeling of the impacts of climate change on yields from mono-specific grassland swards  
258 is well developed (Graux et al., 2013; Vital et al., 2013), fewer models assess the impacts of climate  
259 on nutritive value, which is vital with respect to animal production. Some models can simulate the  
260 development of nutritive value in timothy on cut swards (Bonesmo and Belanger, 2002; Jégo et al.,  
261 2013) and on pastures (Duru et al., 2010), and PaSim includes parameters relating to sward quality,  
262 including variation in digestibility with plant age and between plant components (Ben Touhami et  
263 al., 2013). However, in general the simulation of nutritive value is limited to species-specific  
264 responses, with little modeling of how interactions between species affect sward quality responses  
265 in multi-species grasslands. The characterisation of physiological and genetic adaptation of  
266 grassland species to changing conditions also requires more attention from modelers.

267

268 In addition to simulating the impacts of climate change in southern Europe, grassland models need  
269 to characterise changes in yield and nutritive value related to the expected prolongation of the  
270 growing season in northern and high altitude grasslands. Adding 'winter' modules to process-based  
271 models of grass growth offers one solution to this challenge. Such modules need to include the  
272 effects of changing winter conditions on sward growth (Höglind et al., 2013; Jégo et al., 2014; Jing  
273 et al., 2013) and to model the presence or absence of snow and the process of hardening and de-  
274 hardening, which is particularly important for Scandinavian grasslands (Höglind et al., 2010;  
275 Thorsen and Höglind, 2010a, b). Run-off of phosphorous from grasslands is also an issue of concern  
276 in the context of higher predicted rainfall in northern Europe. A number of models characterise  
277 phosphorous run-off (Benskin et al., 2014) but modeling of how this is affected by interactions  
278 between changing weather conditions and management choices needs to be improved.

279

280 To support grassland-based agriculture under climate change, grassland models require improved  
281 soil-water components, and need to be applicable to a wider range of species mixtures and  
282 management types. The capacity of models to predict the impacts of climate change on both yields  
283 and the nutritive value of forages needs to improve, in order to support policy choices and  
284 management decisions aimed at optimizing these parameters (Höglind and Bonesmo, 2002; Jégo et  
285 al., 2013; Jing et al., 2013). Lessons may be learnt from modeling developed for non-European  
286 semi-arid grazing lands, for example relating to the impact of grazing on erosion (Bénié et al., 2005).  
287 Integrated approaches including environmental and socio-economic aspects of grassland systems,  
288 such as the Sustainability and Organic Livestock Model (SOL) (FAO, 2012) demonstrate potential  
289 pathways for improving grassland modeling in the context of climate change.

290

#### 291 **2.4. Modeling grassland biodiversity and interactions with productivity**

292

293 European grasslands are often hot-spots of biodiversity (Marriott et al., 2004) despite severe  
294 declines in species-rich grassland habitats driven by agricultural intensification and land  
295 abandonment (Henle et al., 2008). The development of the EU Biodiversity Strategy to 2020  
296 exemplifies concern about the loss of biodiversity and related ecosystem services (Maes et al.,  
297 2012) highlighting the importance of models that characterise the effects of agricultural practices  
298 and climate change on grassland biodiversity (above and below ground and including plants,  
299 invertebrates, birds and mammals).

300

301 Decision Support System (DSS) models seek to predict the impacts of policies (and related changes  
302 in management practices) that target biodiversity conservation as an objective in itself. Recently,  
303 these have included approaches which bridge the gap between detailed models of specific sites and  
304 regional models that may overlook many important aspects of biodiversity (Johst et al., 2015;  
305 Mouysset et al., 2014). In such models, management information and knowledge of the ecological  
306 niches of different species or species groups are combined to predict the biodiversity impacts of  
307 different strategies, and the economic costs associated with achieving more favourable  
308 environmental outcomes (Johst et al., 2015; Mewes et al., 2015). Designed to characterize different  
309 management strategies and conditions, they could potentially be adapted to include the impacts of  
310 climate change on biodiversity (Johst et al., 2015; Mewes et al., 2015). Lee et al., (2010) addressed  
311 climate change related issues directly, combining empirical models with projections of future CO<sub>2</sub>  
312 and nitrogen deposition to identify areas where grassland productivity may increase and  
313 biodiversity decrease.

314



315 Bio-economic optimisation models have also been applied to investigate how policy changes and  
316 subsequent management decisions could affect biodiversity (Mouysset et al., 2014; Schönhart et  
317 al., 2011). This can be achieved by including biodiversity as a target in multi-objective models, by  
318 assessing the impacts on biodiversity of choices made to meet other objectives, by including limits  
319 to biodiversity damage as constraints, or by including agrobiodiversity (such as mixed cropping) in  
320 management options (Allen et al., 2014). Nelson et al., (2009) used a spatially explicit model of land  
321 use change in Oregon (USA) to demonstrate a positive relationship between biodiversity and  
322 ecosystem services, and to show how a trade-off between these characteristics and commodity  
323 production could be alleviated using payments for carbon sequestration. This type of model can be  
324 applied to increase understanding of how management choices relating to climate change  
325 mitigation and adaptation impact biodiversity as well as productivity.

326

327 While the aforementioned models consider trade-offs between production and biodiversity treated  
328 as a goal in itself, biodiversity can also be viewed in terms of its contribution to productivity. This is  
329 the context in which (plant) biodiversity is considered in the grassland models described in Section  
330 2.3. The positive relationship between biodiversity and a range of ecosystem services (Isbell et al.,  
331 2011; Oliver et al., 2015) provides a framework for a more 'holistic' quantification of the value of  
332 biodiversity, beyond its direct relationship with productivity. Modeling grassland biodiversity under  
333 different managements and environmental conditions requires a formalization of the role of  
334 mechanisms of plant species coexistence (Chesson, 2000), and their impacts on community  
335 structure (HilleRisLambers et al., 2012). Some mechanistic models of plant community dynamics  
336 include the explicit simulation of plant growth, development, and competition among species  
337 (Soussana et al., 2012b) including developmental plasticity in plant morphology arising from  
338 interaction with neighbours (Maire et al., 2013). Studies of biodiversity in permanent grasslands

339 have often focused on this sub-plot scale, but do not consider how the landscape context affects  
340 biodiversity (Zobel, 2015). This would require comparative studies of local communities along  
341 broad-scale environmental gradients and in different biogeographic regions (Lessard et al., 2012).  
342 At this larger scale, detailed plant competition models are not feasible, being complex and difficult  
343 to initialize and parameterize. This explains the simplified treatment of these processes in larger  
344 scale models (see Section 2.3) achieved, for example, by identifying a main plant species and  
345 representing the others implicitly as a single competing species (Soussana et al., 2012b).

346

347 Principles have been developed for bridging the gap from small-scale mechanistic modeling to  
348 whole community approaches (Confalonieri, 2014), and there are opportunities to learn from  
349 modeling of crop systems (Balbi et al., 2015) and from techniques applied in other modeling  
350 disciplines. Tixier et al., (2013) consider the use of ecological network modeling approaches to  
351 enable multi-scale explorations of the impacts of environmental and management change on  
352 biodiversity and productivity. Examples include the use of linked crop and food web models to  
353 quantify feedbacks between crop management and pest-predator interactions, thus addressing  
354 trophic relationships which are often overlooked (Tixier et al., 2013).

355

356 The modeling of grassland biodiversity can help to capture important non-commodified benefits of  
357 livestock systems. Ignoring such benefits can lead to sub-optimal policy and management decisions  
358 (Meier et al., 2015). Given the pressure to increase agricultural production and efficiency under  
359 climate change, ensuring that biodiversity impacts are incorporated into models used to advise  
360 decision-makers is vital. To achieve this with an increasing level of sophistication will require new  
361 research and empirical data, particularly in poorly understood but highly important aspects of  
362 biodiversity, such as its role in soil dynamics (Lemaire et al., 2005). Modeling complex multi-scale

363 agri-ecosystems can reveal hidden relationships and improve policy and management choices  
364 (Allen et al., 2014; Tixier et al., 2013). In the context of climate change, and its potential impacts on  
365 ecosystem services, this capability is essential.

366

### 367 **3. Modeling GHG emissions from ruminant systems**

368

#### 369 **3.1. Farm-scale GHG emissions**

370

371 On-farm GHG emissions are most often modeled using the IPCC (2006) methodology, in which  
372 emissions factors are defined according to ascending levels of detail (Tiers 1, 2 and 3). Tiers 1 and 2  
373 use empirical emission factors, standardised across countries (Tier 1) or using country-specific  
374 variables which better represent aspects of farming technology (Tier 2). Tier 3 models usually  
375 represent a change in approach from empirical to mechanistic modeling. For the construction of  
376 emission inventories, Tier 2 approaches are adequate, while for on-farm purposes the data  
377 demands of complex Tier 3 type models make simpler approaches more useable. However, the  
378 applicability of empirical Tier 1 and 2 approaches is limited by the data from which they were  
379 derived. For the estimation of emissions factors and how changes in management affect them,  
380 more detailed Tier 3 type modelling is required. The main on-farm sources of GHGs from ruminant  
381 production systems are emissions of CH<sub>4</sub> from enteric fermentation and from manure, losses of  
382 NO<sub>3</sub>, NH<sub>3</sub> and N<sub>2</sub>O from manure management and application, and from housing, and N<sub>2</sub>O  
383 emissions from grasslands and other soils (Gerber et al., 2013).

384

385

386 While Tier 2 approaches to predicting enteric CH<sub>4</sub> emissions ignore digestive and fermentative  
387 processes, some models allow the assumption of a fixed CH<sub>4</sub> emission per unit of gross energy  
388 intake to be replaced with predictions that vary with dietary characteristics such as digestibility  
389 (Graux et al., 2011) or diet composition (Schils et al., 2007). More mechanistic approaches including  
390 an integrated assessment of digestive and fermentative aspects of enteric CH<sub>4</sub> emissions provide a  
391 more detailed analysis for a wider range of conditions (Bannink et al., 2011). Predictions may  
392 include effects on nitrogen utilisation and excreted nitrogen compounds as a source of GHG  
393 emissions (Dijkstra et al., 2011).

394

395 Since emissions from one link in the manure management chain (e.g. housing) reduce the source  
396 strength in subsequent links (e.g. storage), predicting responses to changes such as the  
397 implementation of mitigation strategies requires the use of models based on mass-conservation  
398 principles (Sommer et al., 2009). Current Tier 3 type modelling of CH<sub>4</sub> emissions from manure  
399 incorporates the non-linear effects of management variables (type and quantity of organic matter  
400 inputs to the manure, manure storage type, duration and temperature) (Li et al., 2012; Sommer et  
401 al., 2009). However, although there are complex models of anaerobic slurry digestion (Batstone et  
402 al., 2002) – an important mitigation option (Weiske et al., 2006) –, it is not generally incorporated  
403 in farm-scale models.. Modelling of this process at farm-scale should include the leakage of CH<sub>4</sub>  
404 which can significantly reduce the offset of GHG emissions (Miranda et al., 2015). The main sources  
405 of NH<sub>3</sub> emissions from manure management are animal housing, manure storage and applications  
406 to land. In addition to factors affecting CH<sub>4</sub> emissions, NH<sub>3</sub> emissions are dependent on the air  
407 temperature and ventilation of housing and the weather conditions during manure application.  
408 These factors can be mediated by management changes (e.g. acidification of slurry, anaerobic  
409 digestion, covering manure storage, and the use of injection equipment to apply slurry to land). The

410 modelling method recommended in the Air Pollutant Emission Inventory Guidebook (EEA, 2013)  
411 improves on IPCC Tier 1 and 2 approaches by separately recognising housing as an NH<sub>3</sub> emissions  
412 source. This makes it easier to assess the efficacy of mitigation options and to synthesize empirical  
413 data, as both often focus on individual emissions sources. Tier 3 approaches, such as that of Rotz et  
414 al. (2014) (based on the Integrated Farm System Model) enable a more nuanced investigation of  
415 the effect of manure management on NH<sub>3</sub> emissions, which is particularly useful when assessing  
416 relative sensitivity to climatic variables and interactions with other pollutant emissions. Nutrients in  
417 manure originate primarily from animal excreta, so are affected by the quantity and quality of the  
418 feed ration. Estimating feed intake and quality for grazing animals remains a challenge for modeling  
419 NH<sub>3</sub> emissions.

420

421 Mechanistic (Tier 3 type) models of N<sub>2</sub>O emissions from manure and soil (Li et al., 2012) are  
422 available, however, some aspects (such as parameterizing and predicting oxygen deficit in soil when  
423 require further improvement. N<sub>2</sub>O emissions also arise from leaching of NO<sub>3</sub> from pastures, and  
424 this process has been modeled from the microcosm to the catchment-area scale (Cannavo et al.,  
425 2008). The approach of Cichota et al., (2013) tackles the complex spatial element of NO<sub>3</sub> leaching  
426 from urine patches, but further efforts are needed to represent the effect of different management  
427 options on nitrogen dynamics, including interactions with soil variables and weather conditions.

428

429 Across all areas of GHG emissions modeling, better model characterisation of interactions between  
430 different components of ruminant systems are required, in order to meet the need for more  
431 robust, flexible farm-scale modeling of strategies to mitigate GHG emissions and adapt to climate  
432 change. One example is the need to better incorporate the impacts of heat stress and animal  
433 disease (Sections 2.1 and 2.2) into farm-scale models of GHG emissions. More focus is required on

434 the simultaneous modelling of the effect of management on carbon, nitrogen and phosphorus  
435 losses as exemplified by Ryals et al. (2015). This would allow the multiple pollutant cost  
436 effectiveness of mitigation measures to be assessed (Eory et al., 2013) (taking into account the  
437 impacts of mitigation measures targeting one GHG source on the emissions of other pollutants).

438

### 439 **3.2. Modeling carbon sequestration in grassland soils**

440

441 Grasslands managed for ruminant production store and sequester large amounts of carbon; in  
442 Europe, modeling studies have estimated that there are currently 5.5 Gt of soil carbon stored in the  
443 top 30cm of grassland soils (Lugato et al., 2014) giving grassland carbon sequestration a potentially  
444 major role in climate change mitigation (Glaesner et al., 2014). The importance of soil carbon to soil  
445 quality is also being recognised (Lugato et al., 2014) leading to increased interest in modeling the  
446 effect of agricultural management on soil carbon stocks. Modeling of this positive impact of  
447 grassland-based ruminant production is therefore vital to understanding the interactions between  
448 mitigation and adaptation strategies, to improving production efficiency, and to viewing farms in  
449 the context of 'Climate Smart Landscapes' (Scherr et al., 2012).

450

451 The IPCC (2006) have identified Tier 3 modeling as having the greatest potential for understanding  
452 the effect of agricultural management and climatic and soil conditions on soil carbon. These models  
453 could be applied to improve the current Marginal Abatement Cost Curve analyses used to identify  
454 cost-effective measures for reducing GHG emissions, which often make a range of assumptions in  
455 relation to soil carbon (Leip et al., 2010; Nayak et al., 2015). They may also provide uncertainties  
456 associated with mitigation strategies and their interaction with climatic factors, nitrogen cycles and  
457 management practices. Tier 3 models used range from those requiring the user to define the

458 monthly input of plant residues, such as RothC (Coleman and Jenkinson, 1996) to those describing  
459 agricultural production in as much detail as soil processes, such as SPACSYS (Wu et al., 2007) and  
460 PaSim (Ma et al., 2015). There are also dynamic deterministic models of soil processes, such as  
461 DNDC (Li et al., 1992) and DailyDayCent (Parton et al., 1998), which represent crop growth using  
462 empirical functions. Many of the models can be applied to a range of plant species (Yagasaki and  
463 Shirato, 2013) and are typically verified at a small number of sites, where detailed data can be  
464 readily obtained (El-Maayar and Sonnentag, 2009; Yagasaki and Shirato, 2014).

465

466 One of the main objectives of soil carbon modeling is to assess the effects of management and  
467 climate change across management systems and pedo-climatic zones. For this purpose, Tier 3  
468 models are currently being run at regional, national, continental and global scales (Gottschalk et al.,  
469 2012; Lugato et al., 2014). The DNDC model has also been coupled to CAPRI to provide predictions  
470 on soil carbon at the European scale (Britz and Leip, 2009). However, the analysis was limited by  
471 the emissions factor for carbon sequestration embedded in CAPRI, which assumes continual carbon  
472 sequestration by grasslands (Soussana et al., 2007; 2010).

473

474 The assumptions used in CAPRI highlight how differences in model design, and in the level of detail  
475 at which processes are characterised, will have an impact on the predictions produced. In order to  
476 understand the range of possible results predicted by models, ensemble modeling may be used  
477 (Robertson et al., 2015; Smith et al., 1997; van Oijen et al., 2014). However, to reduce differences in  
478 the outcomes of current modeling of carbon and nitrogen cycles, model algorithms and structure  
479 also need to be improved in order to better characterise physical and biophysical processes (Lu and  
480 Tian, 2013; Tian et al., 2011). Particular challenges surround the initialization of such models,  
481 including a lack of information about the initial state of carbon and nitrogen pools for particular

482 sites (limited by measuring techniques and the detailed data and parameterisation required) (Hill,  
483 2003) and the need to improve methods such as ‘spin-up’ simulations to overcome these practical  
484 limitations (Lardy et al., 2011). The sensitivity of soil carbon and nitrogen stocks and GHG emissions  
485 to climatic changes demands model based integrated assessment approaches (Li et al., 1994).  
486 Properly validated process-based biogeochemical models incorporating coupled carbon-nitrogen  
487 cycling can be effective tools for examining the magnitude and spatial-temporal patterns of carbon  
488 and nitrogen fluxes. However, the development and testing of such models will require more  
489 effective collection, collation and sharing of high quality experimental data (del Prado et al., 2013;  
490 Smith et al., 2002).

491

### 492 3.3. Environmental impacts beyond the farm

493

494 The impacts of livestock production extends far beyond the farm, including local impacts on  
495 surrounding ecosystems and wider impacts related to the production and transport of purchased  
496 inputs. The modeling of on-farm emissions supports the identification of mitigation strategies that  
497 are efficient at farm level. However, approaches (such as IPCC methodologies) which do not take  
498 into account off-farm environmental impacts, can risk favouring systems and strategies that  
499 transfer emissions to other locations, rather than reducing them (O'Brien et al., 2012). The Global  
500 livestock environmental assessment model (GLEAM) applies a static process-based modelling  
501 approach to assess GHG emissions associated with meat and dairy products, incorporating both on-  
502 and off-farm emission sources (Opio et al., 2013). GLEAM uses Tier 2 equations and regional scale  
503 data to capture the impacts of varying local conditions not revealed by global or national average  
504 data (FAO, 2016). Models such as GLEAM that integrate simulation modeling and Life Cycle analysis  
505 (LCA) approaches, offer modeling solutions that make environmental sense at the global as well as



506 the local scale (de Boer et al., 2011). The development of more holistic LCA methodologies  
507 (Bruckner et al., 2015; Huysveld et al., 2015) and the exploration of new LCA applications, for  
508 example as a farm decision support (DSS) tool (Meul et al., 2014) may present further opportunities  
509 to combine farm-scale modeling and LCA approaches. Farm-scale modelers share many of the  
510 challenges recognised in LCA, such as the need to increase standards and consistency of data and  
511 assumptions (Eshel et al., 2015) and to ensure that users correctly interpret the outcomes of  
512 studies (Cederberg et al., 2013; Meul et al., 2014).

513

#### 514 **4. Regional and global economic modeling of livestock systems**

515

516 The development of economic models of livestock systems, including modules that balance and  
517 optimise animal diets in terms of cost, has been driven by the high share of livestock products in EU  
518 agricultural outputs, with animal production accounting for 42% of EU-28 agricultural output  
519 (Marquer et al., 2014), as well as by the high cost of feed. At global and regional level, models of  
520 agriculture and trade are used to explore how livestock production may alter in response to the  
521 impacts of climate change on the economics of production (Audsley et al., 2015; Havlík et al., 2014)  
522 This may include the effects of technological change, population growth (Schneider et al., 2011),  
523 the consequences of various assumptions about land availability (Schmitz et al., 2014), and the  
524 impact of changes in human diet (Bajzelj et al., 2014). Modeling is also used to explore the regional  
525 and global consequences of different approaches to climate change mitigation, in order to identify  
526 optimal solutions (Havlík et al., 2014).

527

528 Results from recent modeling of European agriculture suggest that socio-economic factors will have  
529 a greater impact than climate change on land use, production systems and their outputs (Audsley et

530 al., 2006; Leclère et al., 2013). However, with respect to ruminant production systems, most  
531 regional and global models only take into account indirect climate change impacts, arising from  
532 changes in crop yields and prices. Aspects not currently addressed include, the effects of increased  
533 and extreme temperatures on livestock health and production, changes in pathogen spread and  
534 abundance, changes in grassland yield, changes in crop and grassland nutritional quality,  
535 competition for water resources and the impact of adaptation strategies (from animal genetics to  
536 changing management choices). Work in these areas is developing; Chang et al., (2015) modeled  
537 changes in European grassland productivity between 1961 and 2010, while Schönhart and Nadeem  
538 (2015) used empirical relationships between THI and animal health to estimate the costs of climate  
539 change impacts on dairy cow productivity in Austria. Other aspects, such as the non-commodified  
540 benefits of ruminant systems (Section 2.4) are often overlooked. Policies affect individual farmers  
541 and their choices, making exploration of the impacts of farm-level decisions valuable for the  
542 assessment of policy and mitigation strategies (Eory et al., 2014). Leclère et al., (2013)  
543 demonstrated how autonomous farm-scale decision making could be incorporated into regional  
544 modeling. However, their characterisation of livestock systems focussed only on impacts of climate  
545 change stemming from changes in crop prices and yield. Achieving a fuller representation of  
546 livestock systems in regional and global economic modeling, by increasing the number of variables  
547 considered, and by strengthening the basis of assumptions, should therefore be a priority.

548

549 In the context of the previous discussion, modeling of climate change impacts on livestock  
550 production still remains highly uncertain. Developing a range of consistent future scenarios would  
551 improve model comparability, and might allow more factors to be incorporated into modeling. The  
552 development of such scenarios has begun (Antle et al., 2015) however, comparisons of global  
553 economic models within the Agricultural Model Intercomparison and Improvement Project (AgMIP)

554 (<http://www.agmip.org>) (von Lampe et al., 2014) revealed wide inter-model variation in predictions  
555 even when models used identical future scenarios (Nelson et al., 2014; Valin et al., 2014). Although  
556 the uncertainty in such predictions is normal in the field of economics, it is great compared to that  
557 usually encountered in the natural sciences. The problem of modeling uncertainty has been tackled  
558 in climate and crop modeling using model ensembles (Martre et al., 2015) but for economic  
559 modeling, other improvements are needed before this approach can be considered. Models  
560 developed to make predictions about relatively stable economic environments need to be  
561 evaluated to understand if they are adequate for characterising the periods of high socio-economic  
562 uncertainty expected to accompany climate change, including developing a better understanding of  
563 the parameters driving empirically modeled relationships. Improved transparency and sharing of  
564 methods is required for such model evaluation and improvement to be effective. In addition to  
565 improving existing regional scale economic models, new models are needed to adequately analyse  
566 complex dynamic processes and uncertainty; dynamic stochastic general equilibrium models, which  
567 could be useful in this context, are so far only applied to financial market analyses.

568

569

## 570 **5. Stakeholders and modeling**

571

572 Engagement between agricultural stakeholders and modelers has long been recognised as vital to  
573 developing models that can support effective farm- and policy-level decision making (Voinov and  
574 Bousquet, 2010), with engagement processes involving the development of modeling tools  
575 (participatory modeling) or the application of existing models to solve a problem. Different  
576 approaches to stakeholder engagement in the context of agricultural systems have been defined  
577 (Colvin et al., 2014; Neef and Neubert, 2011). Martin et al (2013) identified two types of approach

578 to farm system design initiatives that make use of modeling: 1) optimisation approaches and 2)  
579 participation and simulation-based approaches. These types of stakeholder engagement are  
580 consistent with descriptions of 'hard' and 'soft' system approaches (Matthews et al., 2011; van  
581 Paassen et al., 2007). Optimisation or hard system approaches are positivist; the problem to be  
582 addressed is quickly identified and is not contested, system boundaries are identified, and scientific  
583 data are used to generate a range of solutions, using modeling tools to explore these options  
584 (Martin et al., 2013). Stakeholders are engaged most in the process of understanding system  
585 parameters, processes and inputs and outputs, but rarely in defining the problem or evaluating  
586 solutions. In contrast, participatory or 'soft' system approaches emphasise the need to explore  
587 stakeholder perceptions in order to identify problems and potential solutions, in a process of  
588 collaborative or collegiate engagement. This goes beyond the contractual and consultative levels of  
589 participation (Barreteau et al., 2010) more common in optimisation approaches. Processes are  
590 based on mutual learning, from which solutions can emerge through iterative and reflective  
591 relationships between stakeholders and researchers (Colvin et al., 2014; Martin et al., 2013). This  
592 reflects the fact that, in addition to being learning tools, models can play an important role in  
593 creating a community from disparate groups of stakeholders, and in putting issues onto the political  
594 agenda (Sterk et al., 2011). In a wider context, these categories relate to the knowledge production  
595 practices identified by Rodela et al., (2012) which range from 'positivist truth-seeking' (in which the  
596 scientist has the role of a neutral outsider) to 'post-normal searches for negotiated agreement' (in  
597 which the scientist is an advocate and participant in the process).

598

599 Challenges for participatory approaches include the time and effort required by stakeholders and  
600 researchers to engage fully in mutual learning, which can lead to 'participation fatigue' (Neef and  
601 Neubert, 2011) and the difficulty of generalising from tailor-made solutions to inform policy level

602 decision making at a larger scale (Colvin et al., 2014). Van Latesteijn (1999) illustrated the challenge  
603 of relating small-scale, deep scientific findings to the large scale, wide and shallow outlook of  
604 policymakers, with scientists required to present more simple and convincing ‘facts’ about the  
605 future. Another challenges is that processes including stakeholders often arrive at ‘exploitative  
606 innovation’ solutions, which use existing knowledge to adjust current systems, rather than  
607 ‘explorative innovation’ solutions that facilitate novel changes (Martin et al., 2013). The bottom-up  
608 way in which explorative innovations emerge can challenge existing frameworks, and as a result  
609 may face institutional barriers to implementation (Colvin et al., 2014). However, these types of  
610 innovation are important in adapting agricultural production systems to climate change conditions  
611 (Martin et al., 2013).

612

613 In order to develop and best utilise modeling tools to support farm- and policy-level decision-  
614 making in the context of climate change, it will be essential for modelers to work with social  
615 scientists to identify and apply effective approaches to stakeholder engagement, integrating many  
616 knowledge forms and perspective (Rodela et al., 2012). If existing models are to be available for  
617 application to real-world problems, they need to be open to modification, ‘tested, wrapped,  
618 documented and archived’ (Voinov and Bousquet, 2010). A range of recent work contributes to  
619 building the modeling capacity required to support effective decision making in relation to climate  
620 change adaptation and mitigation in livestock production systems. This includes, successful trans-  
621 disciplinary approaches to supporting agricultural systems vulnerable to climate change (van  
622 Paassen et al., 2007) and deliberative approaches to model evaluation (Bellocchi et al., 2015).

623

## 624 **6. Synthesis**

625

626 The preceding sections demonstrate the richness and complexity of modeling relating to European  
 627 ruminant production systems, with models applied at all scales to support stakeholders facing the  
 628 challenges of climate change (Table 1). Ruminant systems are multi-faceted, with each component  
 629 interacting with others, and (singly and as part of the wider systemic whole) interacting with other  
 630 biophysical, economic and social systems and processes. A number of broad challenges to the  
 631 modeling of ruminant systems in the context of climate change have been identified here (Table 1).

632

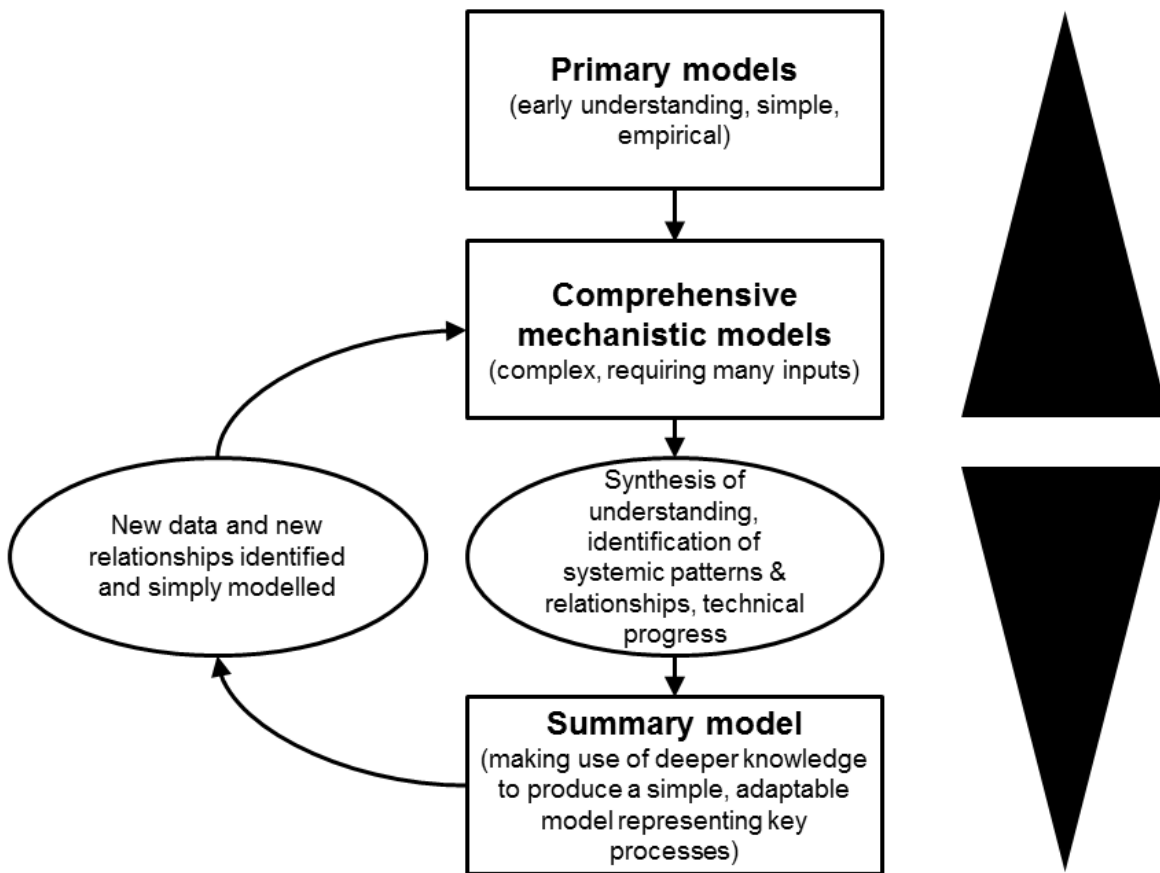
633 **Table 1:** Areas of ruminant systems modeling covered in this paper, their current applications and broad challenges for  
 634 improvement in relation to climate change

<b>Modeling topic</b>	<b>Current applications</b>	<b>Some broad Challenges</b>
Farm-scale emissions	DSS at farm level, contributions to national emissions inventories, assessing impacts of policy	Need for more Tier 3 type modeling to improve understanding of systemic interactions, to validate empirical (Tier 1 & 2 type) relationships and to incorporate adaptation and mitigation strategies and impacts of impaired animal health
carbon sequestration	Contributions to inventories of carbon stocks, policy level predictions of variation with climate & changes in land use	Improved data collation and sharing, facilitating more mechanistic (Tier 3 type) modeling of the impacts of climate change, land use change and adaptation and mitigation options
LCA	Providing evidence to guide policy level and on-farm choices	Linking to farm-scale modeling to incorporate wider environmental impacts into farm-scale environmental and economic assessments; standardising assumptions and data
Heat Stress	DSS at farm level to support avoidance/control of heat stress, estimates of impacts of increased THI on	Need for more mechanistic modeling of heat stress and its impacts under climate change, incorporation of the variables affecting stress,

	production & reproduction	and of adaptation and mitigation strategies
Pathogens	DSS at farm level, estimates of impacts on productivity, policy support (risks of spread for specific pathogens and vectors), assessing impacts of policy	Improved data on pathogen ecology and spread to facilitate more mechanistic modeling of future impacts under climate change, outbreak intensity and management responses
Grasslands	DSS at farm level, projections of yield change under future climates at the regional scale	Modeling of climate change impact on grass quality, modeling multi-species swards, modeling impact of adaptation and mitigation strategies
Biodiversity & ecosystems	DSS at farm level, bio-economic optimisation models including biodiversity constraints/goals, links to ecosystem services and regional impacts of policy	Developing linkages to agricultural models to facilitate multi-species modeling and to include the non-commodified value of ruminant systems in environmental/economic evaluations
Regional economics	Policy level assessments of economic impacts of climate change on livestock agriculture, based on changes in crop yield and price, including changes in livestock systems land use	Incorporating impacts of climate change on ruminant systems beyond changes in feed prices/yield (e.g. impact of heat stress, increased water use, increased disease risk, potential changes in soil carbon storage). Including non-commodified benefits from these systems
Stakeholder engagement	Defining modeling scenarios and priorities (including climate change impacts and relevance of modeled adaptation and mitigation strategies), use of models for learning, community building and highlighting issues at policy level (Sterk et al. 2011)	Finding approaches that overcome issues relating to the time taken for engagement (researchers and stakeholders), scaling up lessons learnt in specific case studies to policy level, finding ways to incorporate qualitative values communicated by stakeholders (including the public) into modeling, such as the social value of biodiverse landscapes.

636 One major challenge for ruminant systems modeling is that regional and global scale models often  
637 overlook the direct impacts of climate change on such systems. This is of concern given the role of  
638 ruminant systems in the provision of ecosystem services and other social benefits (Section 2.4), and  
639 due to the interactions between livestock agriculture and other systems. The development of socio-  
640 economic scenarios representing consistent, realistic suites of management and policy choices  
641 ‘packaged’ at regional level (Valdivia et al., 2013) offers a path for better incorporating  
642 understanding of farm- and policy-level decision making into models, and for giving weight to the  
643 ‘non-commodified’ value of ruminant systems. At the same time, empirical representations of  
644 biophysical processes and interactions in regional and global models can be evaluated and  
645 improved using knowledge gained from mechanistic modeling at field, animal and farm-scales. In  
646 this respect, complex and simple modeling approaches can be seen not in opposition, but as part of  
647 an iterative process of model development (Fig. 2) applicable to all levels of modeling, not just the  
648 regional level. This can allow the development of ‘smart’ empirical modules which reduce model  
649 complexity in a robust manner, rather than through the use of assumptions to fill gaps in  
650 knowledge.





651

652 **Fig. 2:** How the simple-complex model problem can be re-framed as an iterative development process. Black triangles  
 653 represent the level of model complexity.

654

655 The purpose of modeling is not to fully represent every aspect of real world systems (Cederberg et  
 656 al., 2013); models will always incorporate simplification and uncertainty. Rather, their value is in  
 657 providing an understanding of complex systems, predicting change in such systems, and revealing  
 658 systemic relationships that would otherwise be hidden (van Paassen et al., 2007). Modelers need to  
 659 clearly present and explain model outputs, their meaning and limitations. In turn, decision-makers  
 660 (particularly at policy level) need to develop a sufficiently good understanding of the real world  
 661 systems with which they are dealing for them to use model outputs and other evidential sources

662 appropriately. In this context, the interpretation of modeling results becomes a joint concern of  
663 modelers and the users of model outputs.

664

665 Engaging with stakeholders at all stages of research, including in the definition of problems, is likely  
666 to increase the chances that model outputs and their strengths and weaknesses will be understood  
667 at a deep rather than superficial level (Voinov and Bousquet, 2010). Through such engagement, the  
668 required level of model complexity, accuracy and scope can emerge from deliberative processes  
669 (Bellocchi et al., 2015; Colvin et al., 2014). In this respect, individuals with knowledge of both the  
670 research and stakeholder communities can act as 'bridges' between different groups (Sterk et al.,  
671 2011). Social scientists are often well placed to fulfil this role, promoting and guiding mutual  
672 learning and facilitating the achievement of positive outcomes (Colvin et al., 2014). The challenge  
673 for modelers is to use the process described to create models that are both 'user friendly' and  
674 robust at appropriate levels of complexity.

675

676 The disparate nature of modeling relating to ruminant systems, demonstrated in this paper, means  
677 that there are many barriers to achieving the types of collaborative interaction between modelers  
678 required to meet the challenge of climate change. Technical issues related to linking models are  
679 one major obstacle to more joined-up modeling of ruminant systems. The development of  
680 modeling platforms supporting modular approaches and utilising compatible software and coding,  
681 can help build capacity within a highly adaptive framework (Holzworth et al., 2015). Such systems  
682 can also facilitate the exchange of methods and information between modeling fields and between  
683 groups within a field, stimulate the spread of best practice, prevent duplication, and increase model  
684 comparability. Strategic modeling platforms can also play a valuable role in providing policy level  
685 advice. Livestock modelers can look towards initiatives set up in relation to crop systems, such as

686 MARS (Monitoring Agricultural ResourceS) (<https://ec.europa.eu/jrc/en/mars>), for examples of  
687 what is required to communicate model predictions at the European level.  
688

689 Developing models of ruminant farming systems can take years, while major decisions relating to  
690 GHG mitigation and the adaptation of livestock systems to climate change are required urgently.  
691 Therefore, in addition to developing new modeling, it is important that best use is made of existing  
692 data and models, ensuring that knowledge gained and tools developed are made available to  
693 decision-makers at a range of scales. In this context, researchers and funders need to support the  
694 development of data sharing resources such as those within the Global Research Alliance (GRA)  
695 (<http://globalresearchalliance.org>) (Yeluripati et al., 2015) and in projects such as the EU knowledge  
696 hub Modeling European Agriculture for Food Security under Climate Change (MACSUR)  
697 (<http://macsur.eu>). As technological capacity for data sharing and data processing grows, it also  
698 needs to be matched by the development of better communication between modelers and  
699 experimental and theoretical researchers. Such connections support modelers by facilitating model  
700 development, but also benefit data providers, by providing a path to demonstrate and explore the  
701 implications of their findings and to indicate areas for future research. The development of  
702 networks that bring together the disparate collection of disciplines relevant to livestock systems  
703 modeling is therefore essential, both for the sharing of current data and modeling resources, and  
704 for the development of new modeling platforms. Barriers to inter-disciplinary working (Siedlok and  
705 Hibbert, 2014) mean that creating structures to build modeling capacity and share knowledge  
706 across disciplinary boundaries requires carefully considered, coherent and long-term support from  
707 funders and policymakers.  
708

709 This paper has attempted 1) to provide an overview of how current ruminant production systems  
710 modeling supports the efforts of stakeholders and policymakers to predict, mitigate, and adapt to  
711 climate change and 2) to provide ideas about how modeling resources can be enhanced to best  
712 meet these challenges. More focussed assessments of specific modeling fields and the priorities for  
713 their development, would be useful in shaping priorities for future research in the context of  
714 climate change.

715

## 716 **7. Future Perspectives**

717

718 The overview of European ruminant system modeling presented provides pointers towards the  
719 future development required across modeling disciplines, in order to meet the challenges of  
720 climate change. Unfolding challenges for modelers in a climate change world include 1) Better  
721 characterisation of adaptation strategies and complex biophysical processes, 2) More modeling of  
722 interactions between the diverse components of agro-ecosystems (including management  
723 strategies addressing different policy targets) and 3) Better linkage between animal health and  
724 disease, animal growth and nutrition, crop and grassland and farm- and regional-scale modelers.  
725 Four key areas need to be addressed if the potential for agricultural modeling to help tackle the  
726 challenges of climate change is to be properly exploited:

727

- 728 • Making modeling more relevant to real-world problems by increasing the accessibility,  
729 visibility and comparability of models for different uses, and by engaging with stakeholders  
730 at all stages in modeling research and development
- 731 • Developing modeling capacity through mutual learning and increased technical  
732 compatibility across modeling disciplines, and between modelers working at different scales

- 733 • Fostering better links between modelers and empirical researchers to ensure that high  
734 quality data and research findings can be easily accessed by modelers, and that modeling  
735 outputs can more effectively inform the focus of new experimental and theoretical research
- 736 • Ensuring that modeling outputs, their strengths, limitations and purpose are understood by  
737 those that use them, recognising that achieving this will require the commitment of time  
738 and resources by both modelers and stakeholders, including policymakers

739

740 Within Europe and beyond, achieving progression in these areas is an undertaking that will require  
741 coherent long-term support from funders, policymakers, and academics across the plethora of  
742 organisations involved in the creation of inter-disciplinary research structures. Modeling can offer  
743 vital insights into the complex interacting relationships between climate change, management and  
744 policy choices, food production and the maintenance of vital ecosystem services. Modelers,  
745 empirical researchers and social scientists need to work together across disciplines, in collaboration  
746 with stakeholders, to develop and make effective use of this potential.

747

## 748 **8. Conclusion**

749 A continuing stream of papers has been published on agricultural modeling over recent years, with  
750 research supported by a range of global initiatives. However, the inherent complexity associated  
751 with ruminant system modeling has meant that it has been less developed than other areas such as  
752 crop modeling. In this context, the aim here has been to provide an overview of ruminant systems  
753 modeling in Europe. Modeling of ruminant production is currently supporting on-farm decisions to  
754 minimise GHG emissions and maximise efficiency, helping to assess and evaluate policy choices in  
755 the context of climate change, and developing our understanding of the likely impacts of global  
756 warming on European food production. It is hoped that the synthesis of modeling presented here

757 will help strengthen the basis for constructive and strategic engagement between the European  
758 modelling community, non-European modelers and experimental researchers, through initiatives  
759 such as MACSUR, AgMIP and GRA.

760

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768

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