MINISTERIO DE CIENCIA E INNOVACIÓN

INIA Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria

Genetic selection as effective methane mitigation tool in livestock

Symposium on behalf of the PhD defence of Anouk van Breukelen

Genomic and metagenomic tools for climate change mitigation in Spanish dairy cattle

Óscar Gonzalez Recio

(INIA-CSIC, Madrid, Spain)

Solutions to achieve net zero carbon emissions

COP26

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COP26: 105 countries pledge to cut methane emissions by 30 per cent

ENVIRONMENT 2 November 2021

By Adam Vaughan

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COP26: US and EU announce global pledge to slash methane

2 November 2021

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/ Energy & Climate / Gas / The COP26 methane moment

GAS

The COP26 methane moment

This is the second installment of the Topic of the Month: Decarbonising Gas Markets

European Commission

English EN Search

Home > Press corner > Launch by US, EU and Partners of the Global Methane Pledge

Available languages: English

Statement | 2 November 2021 | Brussels

Launch by United States, the European Union, and Partners of the Global Methane Pledge to Keep 1.5C Within Reach

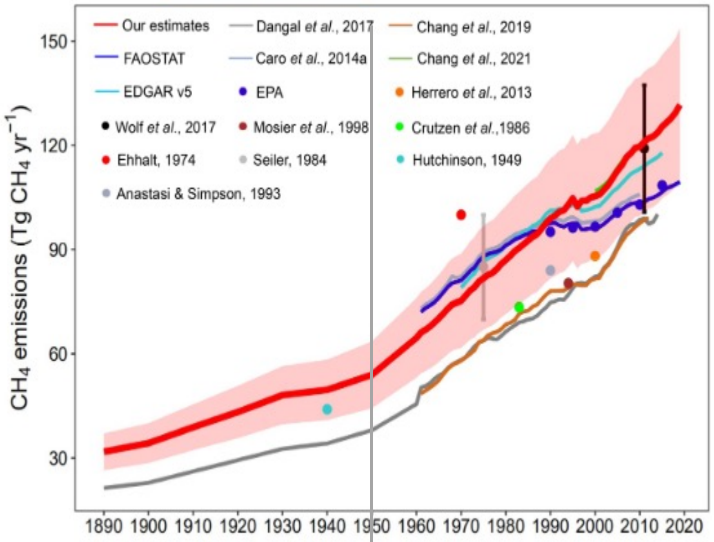
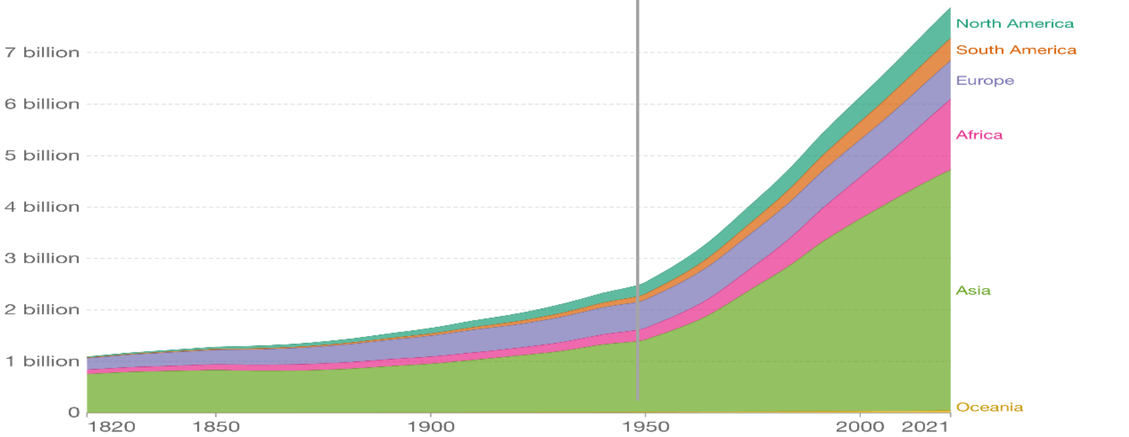


FIGURE 10 Estimates of CH_4 emissions from global livestock during 1890–2019 and comparisons with those reported in other inventories. The shaded area shows the 95% confidence interval of our estimates.

World populatio



Source: Gapminder (v6), HYDE (v3.2), UN (2019)

OurWorldInData.org/world-population-growth/ • CC BY

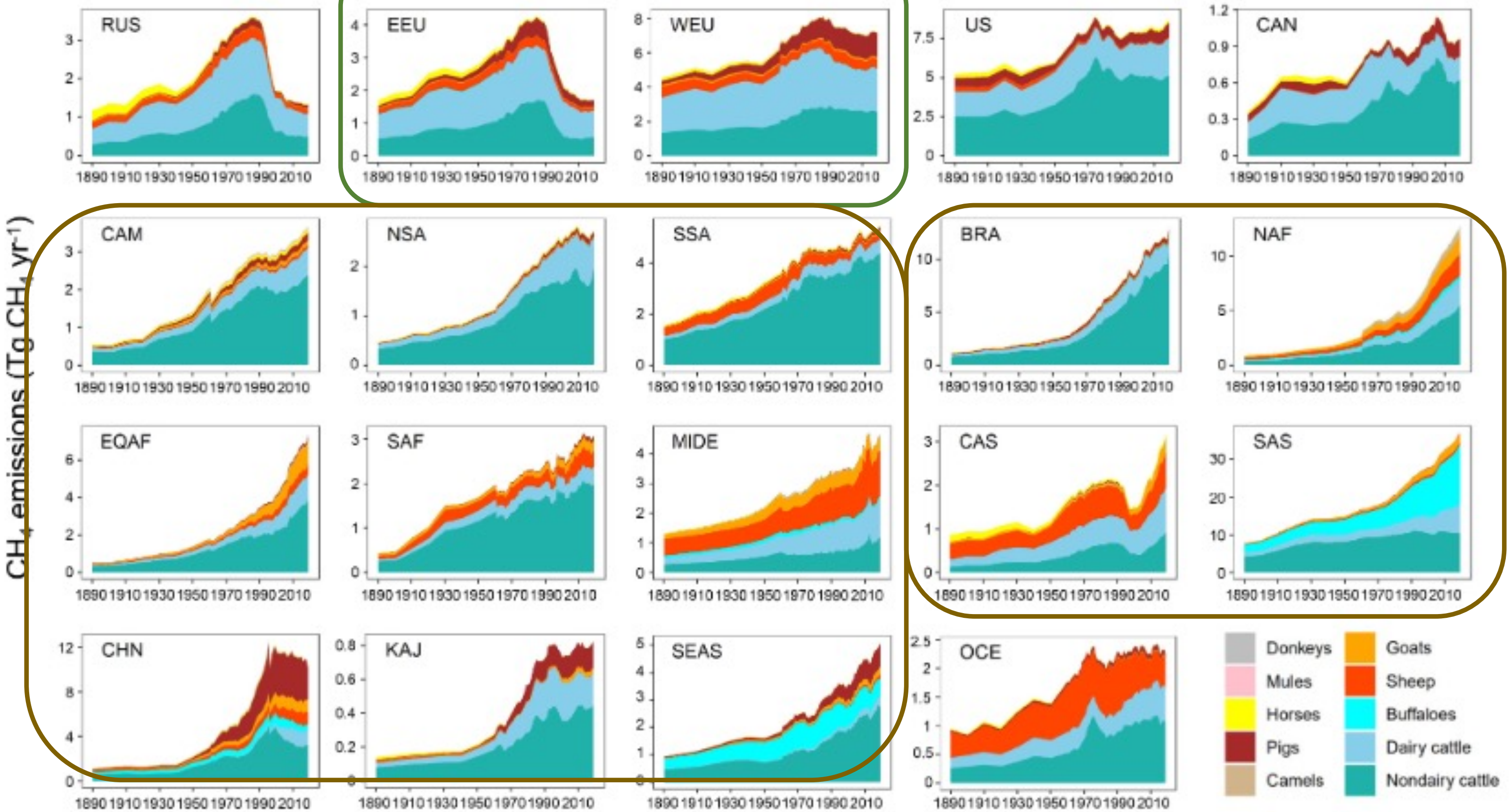
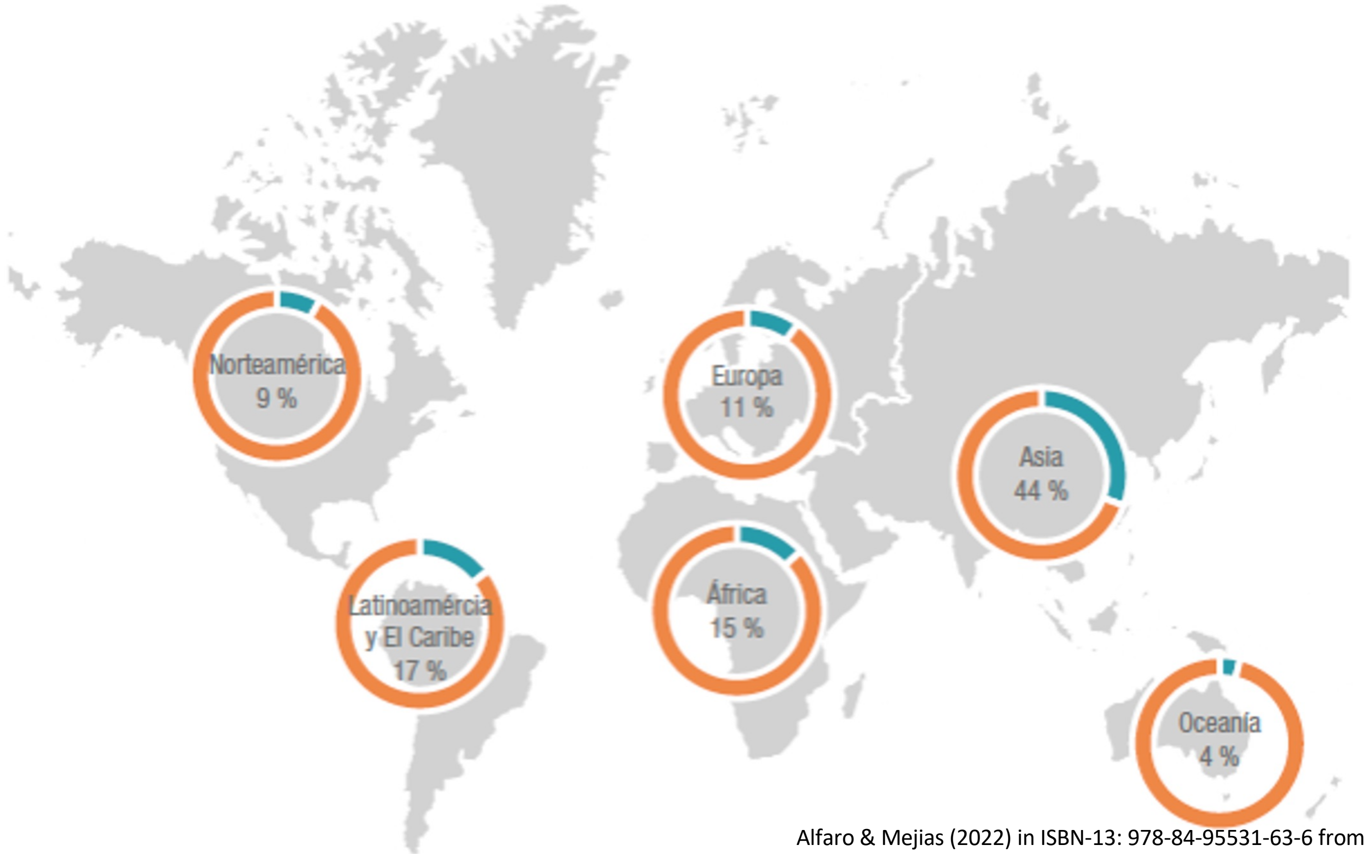


FIGURE 5 Temporal changes in regional CH_4 emissions from livestock during 1890–2019.

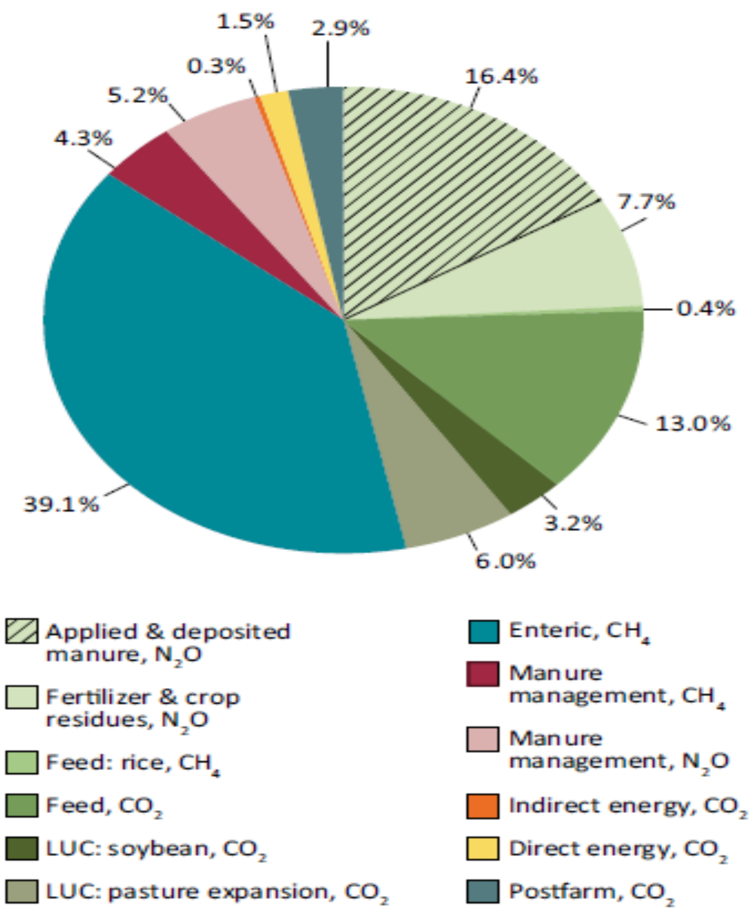
Zhang et al. (2022) in GCB



Alfaro & Mejias (2022) in ISBN-13: 978-84-95531-63-6 from FAO (2016)

Globally ~12% of total anthropogenic GHG emissions (direct and indirect) (FAO,2023)

FIGURE 4. Global emissions from livestock supply chains by category of emissions



- Reduce Methane from enteric fermentation
- Reduce Feed associated CO2 from improving Feed Efficiency

Solutions to achieve net zero carbon emissions

- Contribution of livestock to society
  - Healthy diet
  - Rural development and landscape maintanance
  - Negative consequences of eliminating livestock
  - Increase sustainability without compromising food security. New technologies and innovations are required.
- Evaluate each case scenario


WORLD ASSOCIATION for ANIMAL PRODUCTION

www.waap.it

Number 26 2021

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The World Animal Science News

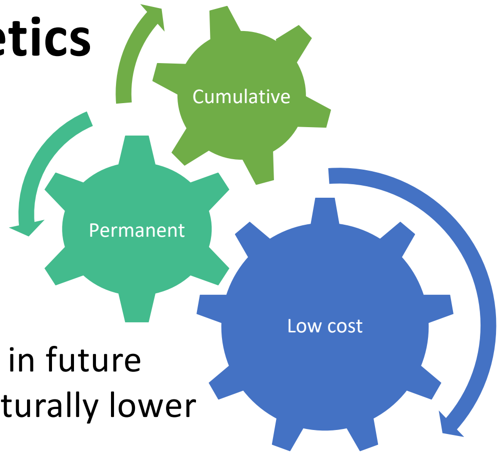
Main Topics

- From WAAP members
- News from Science
- News from Industry
- Job Offers
- Publications
- Meetings and Conferences

EDITORIAL

When methane returns to the forefront of the climate scene, ruminants are in great danger!

1. Implement proper calculation of GHG emissions*
2. Nutrition
3. Technology: in-farm use of methane
4. **Genetics**

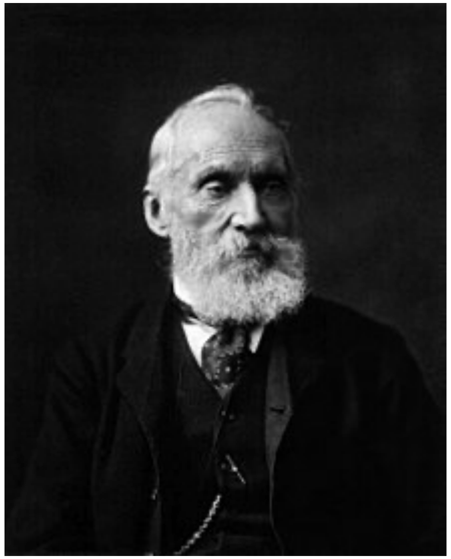


Targeted breeding can result in future generations of cattle with naturally lower emissions

MEASURING METHANE

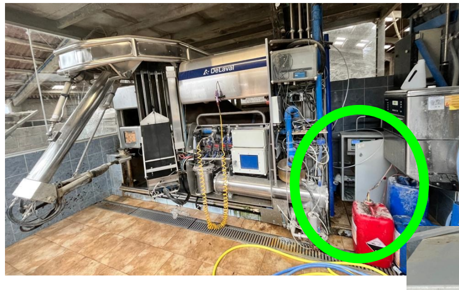
- If you **cannot measure** it, you **cannot improve** it.

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



Lord Kelvin (1824 – 1907)

METHANE PHENOTYPING



metalgen

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CONFEDERACIÓN DE ASOCIACIONES DE FRISONA ESPAÑOLA
CONAFE

- Precision farming
- Genotypes (50k SNPs)

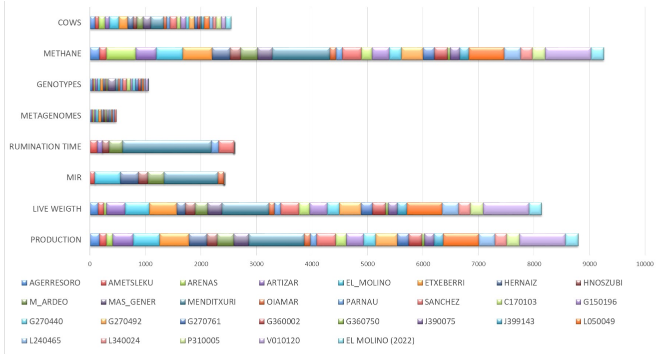
METHANE PHENOTYPING

1. Recording methane in commercial and experimental farms

Samples= 3281 dairy cows in 34 farms

METHANE PHENOTYPING

1. Recording methane and DMI in commercial and experimental farms



2. Genomic selection (genotyping, phenotyping). International collaborations

(AUS, CAN, DNK, ESP, GER, NDL, SWI, USA)

Re-Livestock
RESILIENT FARMING SYSTEMS

THE Resilient Dairy GENOME PROJECT

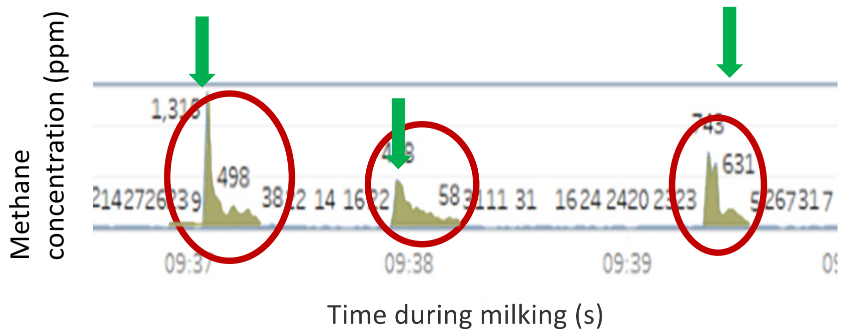
METHANE PHENOTYPING

- **Phenotype definition**

1. Mean CH_4 (by second and every 5 s)
2. Sum of peaks CH_4 (by second and every 5 s)
3. Sum of max peaks CH_4
4. Area under the curve (AUC CH_4)
5. Ratio of (mean) CH_4/CO_2
6. CH_4 grams per day (Madsen et al., 2010)

$$\text{Prod } CH_4\left(\frac{g}{d}\right) = 0.714 * \boldsymbol{ratio}(\boldsymbol{ppm}) * 180 * 24 * 0.001 * (5.6 * kg\ body\ mass^{0.75}) + 22 * \boldsymbol{ECM} + 1.6*10^{-5} * days\ in\ pregnancy$$

7. CH_4 grams per day (in-house*)



Weekly averages were used for all phenotypes

Heritabilities

Trait	h^2	h^2 (van Breukelen)	r^2
Mean CH4 (ppm)	0.08 (0.05-0.11)		0.54 (0.52;0.56)
Mean CH4 5 s(ppm)	0.08 (0.05-0.11)	0.21-0.27	0.54 (0.53;0.56)
Sum of peaks CH4 (ppm)	0.09 (0.06;0.12)		0.55 (0.53;0.57)
Sum of peaks CH4 5s (ppm)	0.10 (0.06;0.13)		0.55 (0.53;0.57)
Sum of max peaks (ppm)	0.08 (0.05;0.11)		0.52 (0.50;0.54)
AUC CH4 (ppm)	0.10 (0.07;0.13)		0.55 (0.53;0.57)
CO_2 (ppm)	0.02 (0.004;0.04)	0.23-0.44	0.58 (0.56;0.60)
CO_2 (L/d)*	0.02 (0.004;0.05)		0.61 (0.59;63
Ratio CH4/CO_2	0.10 (0.05;0.16)	0.02	0.42 (0.39;0.45)
MeP (g/d) (Madsen eq)	0.12 (0.06;0.17)	0.33 (GF)	0.51 (0.48;0.54)
MeP (g/d)*	0.10 (0.04;0.15)		0.55 (0.53;0.58)

Low to moderate heritabilities and large repeatability

Results: Genetic correlations between methane traits

Traits	Mean CH_4	Mean CH_4 5 s	MeP (g/d)*	Sum of peaks CH_4	Sum of peaks CH_4 5s	Sum of max peaks	AUC CH_4
Mean CH_4	0.08	0.99	0.99	0.82 (0.74;0.90)	0.82 (0.75;0.90)	0.77 (0.67;0.85)	0.83 (0.74;0.89)
Mean CH_4 5 s		0.08	-	0.82 (0.73;0.89)	0.84 (0.76;0.92)	0.72 (0.57;0.85)	0.84 (0.76;0.90)
MeP (g/d)*			0.10	0.52	-	0.63	0.52
Sum of peaks CH_4				0.09	0.99	0.99	0.99
Sum of peaks CH_4 5 s					0.10	0.99	0.99
Sum of max peaks						0.08	0.99
AUC CH_4							0.10

1

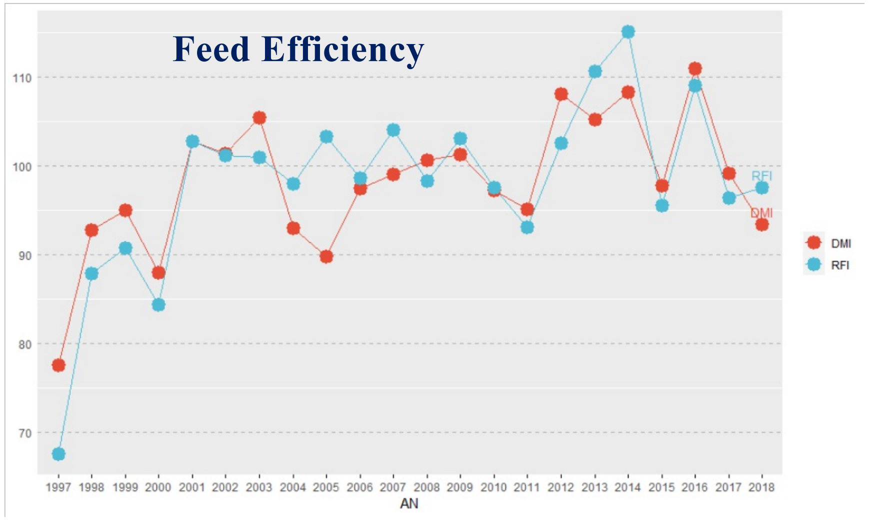
0

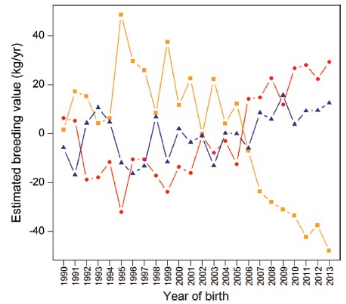
! High correlations between phenotypes

Genetic correlations

	DMI	RFI	CH4 (ppm)	CH4(g/d)	kg_milk	kg_prot	kg_fat
DMI	0.17	0.97	0.27	0.2	0.41	0.53	0.5
RFI		0.12	0.27	0.14	0.13	0.27	0.55
CH4 (ppm)			0.2	0.97	-0.05	0.07	0.3
CH4(g/d)				0.19	0.04	0.13	0.32
CO2 (ppm)					0.16	0.17	0.47

Genetic trendsx





J. Dairy Sci. 98:7340–7350
http://dx.doi.org/10.3168/jds.2015-9621

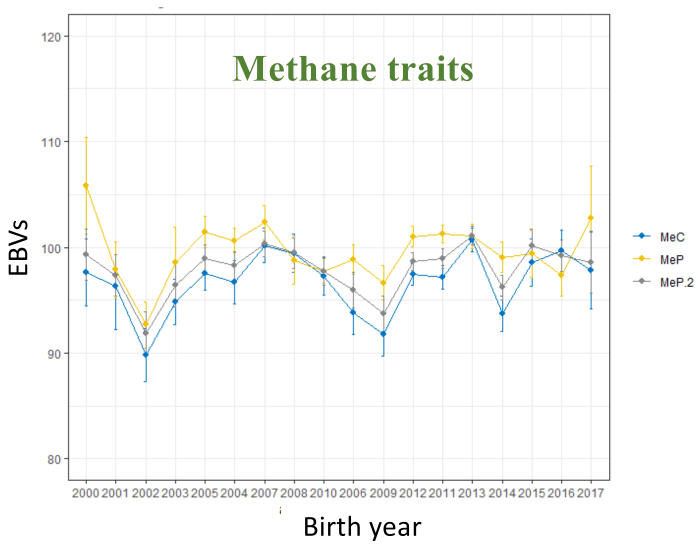
Hot topic: **Definition and implementation of a breeding value for feed efficiency in dairy cows**

J. E. Pryce,*† O. Gonzalez-Recio,* G. Nieuwhof,*‡ W. J. Wales,§ M. P. Coffey,# B. J. Hayes,*† and M. E. Goddard*||

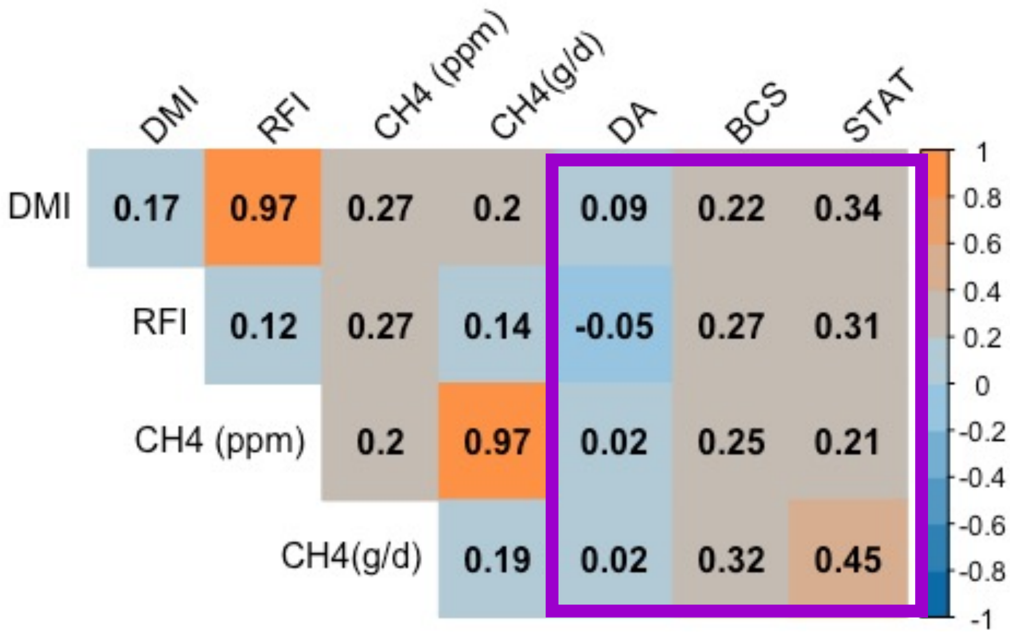
Genetic correlations

	DMI	RFI	CH4 (ppm)	CH4(g/d)	kg_milk	kg_prot	kg fat
DMI	0.17	0.97	0.27	0.2	0.41	0.53	0.5
RFI		0.12	0.27	0.14	0.13	0.27	0.55
CH4 (ppm)			0.2	0.97	-0.05	0.07	0.3
CH4(g/d)				0.19	0.04	0.13	0.32
CO2 (ppm)					0.16	0.17	0.47

Genetic trends



Genetic correlations

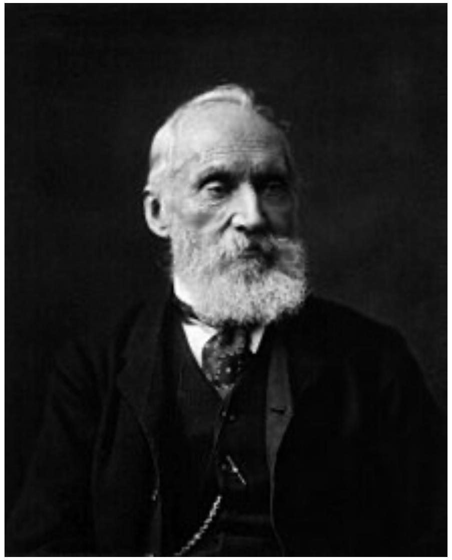


- Bigger cows tend to be less efficient and produce more methane

Challenges at methane phenotyping

- **Large scale phenotyping – sniffers, which can only be installed in AMS (yet)**
- **Rely on a reference population and genomic selection**

- **Other options to increase large scale phenotyping?**



"If you cannot measure it, you cannot improve it"

ROLE OF MICROBIOME IN
- *Feed digestion*
- *Feed efficiency (DMI)*
- *Production traits*

ROLE OF MICROBIOME IN
- *Methane emissions*

ROLE OF MICROBIOME IN
- *Overall health*
- *Dysbiosis*
- *Pathogenes*

ROLE OF HOST
- *Symbiosis*
- *Microbiome composition*
- *Heritability, and genetic correlation*

Previous findings (summary)

- **Rumen eukaryotes are the main phenotypic risk factors for larger methane emissions in dairy cattle (Saborío-Montero et al., 2022).**

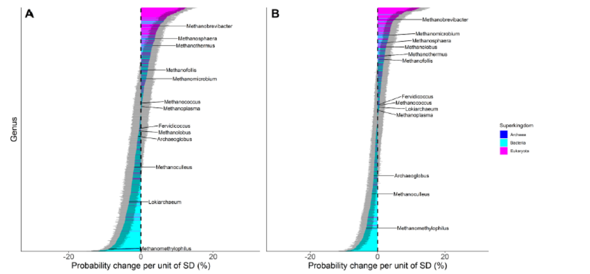
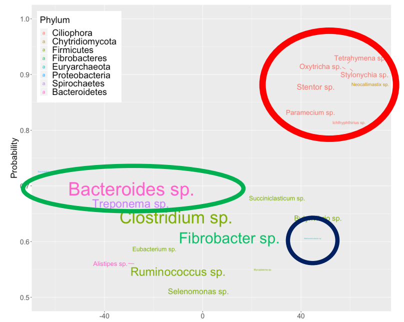


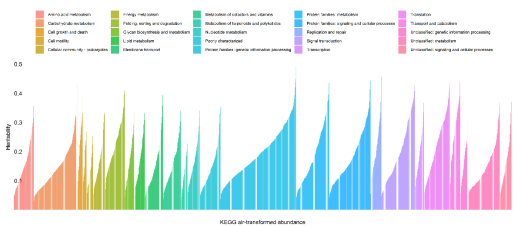
Fig. 3. Change in the probability of being classified in the upper quartile for (A) methane concentration (ppm CH_4) and (B) methane intensity (ppm CH_4/kg milk) per unit of standard deviation for relative abundance (%) of 1240 genera colored by superkingdom. Black dashed line indicates the baseline probability of being classified in the upper quartiles without any genus effect. All the archaea genera are explicitly indicated. Probability intervals based on posterior standard deviations are depicted in gray for all genera.

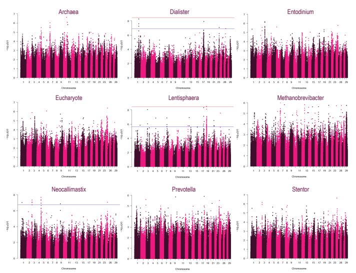
- **Certain microbial groups are likely causal effects of larger/lower methane production in the rumen (Saborío-Montero et al. 2019; López-Garcia et al. 2022).**



Causal effect

- **The cow genome partially controls the rumen microbiome composition (Saborío-Montero et al., 2019; González-Recio et al. 2023)**





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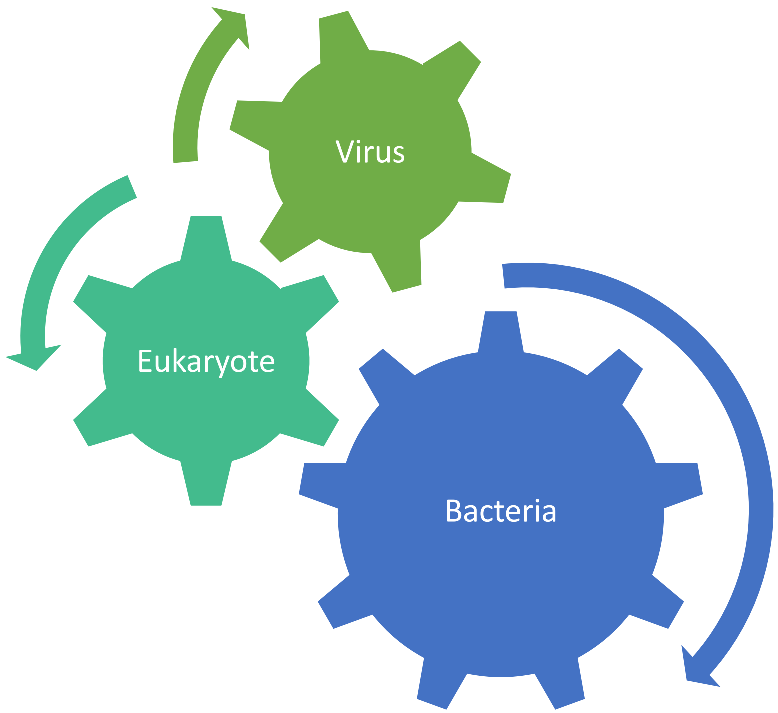
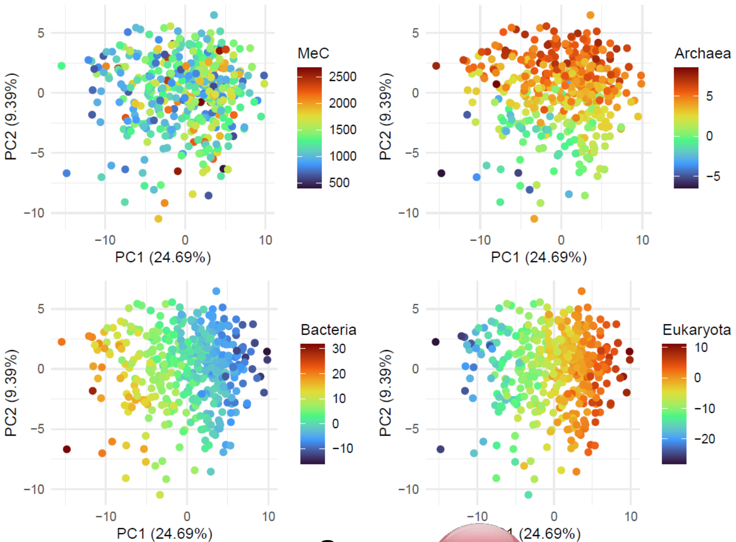
Rumen microbiome community

- **Large dimensionality, redundancy and interplay**
- **Should focus on one or few microbial taxa/genes as there will be changes in other groups**
- **Develop strategies to modulate the whole microbiome towards low emitting, efficient and healthy microbiomes.**



HOW TO ACCOUNT FOR MICROBIOME COMPLEXITY

- **Aggregated variables capture a relevant portion of microbial variability**



Spain

33% total microbiome variability

J. Dairy Sci. 104:8135–8151
https://doi.org/10.3168/jds.2020-20005

A dimensional reduction approach to modulate the core ruminal microbiome associated with methane emissions via selective breeding

Alejandro Saborío-Montero,[1,2] Adrian López-García,[1] Mónica Gutiérrez-Rivas,[1] Raquel Atxaerandio,[3] Idoia Goiri,[3] Aser García-Rodriguez,[3] José A. Jiménez-Montero,[4] Carmen González,[1] Javier Tamames,[5] Fernando Puente-Sánchez,[5] Luis Varona,[6] Magdalena Serrano,[1] Cristina Ovilo,[1] and Oscar González-Recio[1,7*]

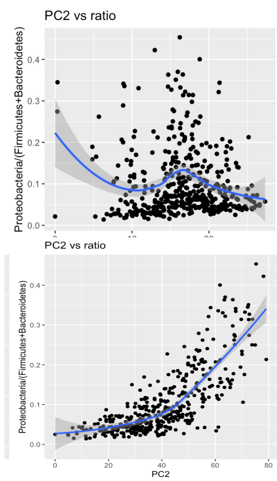
Paves the way to international collaborations to create multi country reference population for metagenome composition

Similar microbiome composition and relationship with methane under 2 different production systems (Australia and Spain)

Genetic correlations: Rumen microbiome community

Genetic correlation between PC and other traits

	PC1T	PC2T	PC1F	PC2F	MY	PY	FY	MeC	MeP	DMI	RFI
PC1T	1	-0.02	0.97	0.61	0.2	0.21	-0.35	-0.7	-0.67	-0.44	-0.54
PC2T		1	0.16	0.4	-0.03	-0.18	-0.3	-0.13	-0.34	-0.46	-0.38
PC1F			1	0.19	0.23	0.4	-0.23	-0.57	-0.53	-0.23	-0.36
PC2F				1	0.08	0.08	-0.33	-0.23	-0.36	-0.18	-0.29



- Aggregated microbial variables have heritabilites 0.20-0.30.
- Aggregated microbial variables are favorably genetically correlated with milk, protein, methane emissions and feed efficiency (unfavorable with fat)
- Breeding for lower methane or feed efficiency may impact microbiota composition (dysbiosis)
- What are the expected consequences?


Methane emissions in breeding goals and selection indices
CSIC
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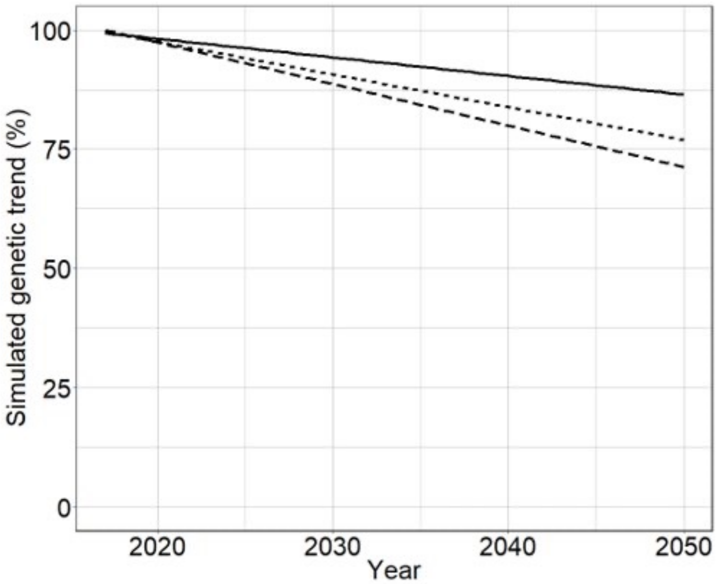
Animal breeding as a mitigation strategy

<u>Methane intensity (g/kg milk) & methane emissions (g/d)</u>

- Current trend
- Combined selection for CH4 and other traits
- Theoretical maximum (exclusively focusing on methane)



https://doi.org/10.1016/j.animal.2021.100294
(de Haas *et al.* 2021)

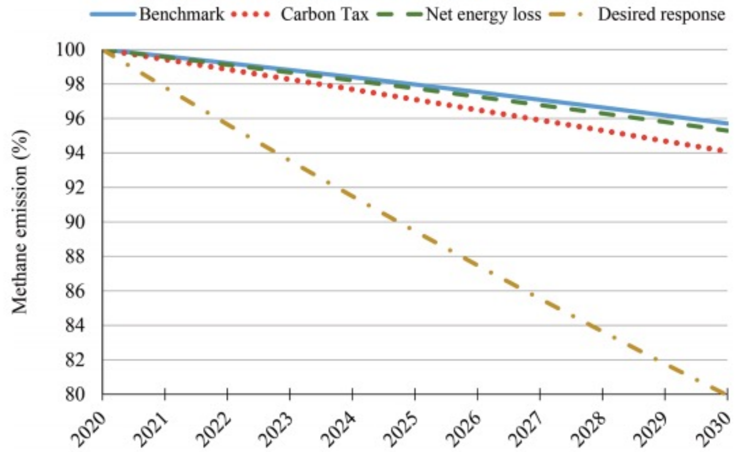


Figure 2. Expected reduction in percentage from current levels in methane emissions produced by Holstein cows in Spain based on genetic gain in methane emissions (MET; t/yr) under the 4 scenarios: benchmark, carbon tax, net energy loss, and desired response (i.e., number of cows × MET genetic gain × time/1,000). A decrease of 1.5% in the number of dairy cows was considered each year, following census data from the Spanish Holstein association: (http://www.conafe.com/VisorDocs.aspx?pdf=estadisticas_CENSO_DE_ANIMALES.pdf).

Genetic evaluations

Published as an individual trait in the catalog.

Evaluaciones Genéticas Nacionales | Pruebas Combinadas CONAFE-MACE | Buscador Toros | Listados | Info

200 Mejores Toros del Catálogo

Nº	Número	Nombre	Año nac.	Kg. Leche	% Grasa	Kg. Grasa	% Prot.	Kg. Prot.	Fiab. Prod.	IPP	ICU	IGT	RCS	Long.	Fiab Long.	DA	Fiab. DA	FPD	Fiab. FPD	ISP	VOR	MET	IM€T Leche	ICO	Perc.
1	CANM0012773216	SILVERRIDGE V TIMBERLAKE ET	2017	2034	-0,06	66	0,03	69	98	-0,81	1,62	0,98	112	122	65	102	76	115	82		103	110	328	1266	99
2	ESPM9204523525	NEMO G SANTI ET	2017	1444	0,18	72	0,08	55	95	1,86	1,12	1,57	126	113	59	95	68	118	73	111	97	100	287	1265	99
3	ESPM9204695956	K&L OH ROSSI GUAY	2018	752	0,42	70	0,18	43	98	0,88	2,19	1,9	119	123	59	109	68	112	94		79	66	274	1262	99
4	ESPM9204501760	LIEU THOMAIN BALTAZAR ET	2017	1132	0,26	68	0,12	49	84	1,3	1,14	1,08	119	121	55	107	65	109	55	113	92	115	286	1258	99
5	ESPM9204691049	SALUD ET	2017	1118	0,18	59	-0,02	34	93	2,88	1,35	1,64	125	120	57	100	66	114	82		89	96	263	1257	99
6	ESPM9204634816	SALVUS ET	2017	1520	-0,24	28	-0,08	40	97	1,01	1,87	1,36	132	124	57	108	66	108	88		74	100	251	1255	99
7	ESPM9204741024	PALMER ET	2018	925	-0,04	29	0,13	44	91	1,59	2,34	2,15	115	126	55	112	65	108	93		100	99	260	1253	99
8	ESPM9204828913	TIRSVAD HOTSPOT HONDO ET	2019	672	0,05	29	0,14	36	80	2	1,73	1,69	118	130	53	123	63	119	90		99	107	263	1253	99
9	ESPM9204628506	MANDY KODAK ET	2017	1736	0,12	76	0,01	57	93	0,42	0,98	1,22	118	116	55	99	65	101	55	110	109	83	282	1252	99
10	ESPM9204595970	HUNTER K&L SV ADRIAN SALVATIER	2017	993	0,13	49	0,12	45	93	1,13	1,4	0,9	125	123	57	107	66	116	82	116	88	90	275	1252	99
11	840M3130915944	COOKIECUTTER LGND HUSKY ET	2017	1488	-0,08	45	-0,07	40	98	-0,95	1,92	0,93	117	135	67	114	74	102	78		96	99	278	1251	99
12	ESPM2704487908	GRILO SANRECAM LUCKY ET	2017	1524	0,16	72	0,09	59	85	0,93	1,22	1,21	107	112	59	103	68	109	67	109	98	108	284	1250	99
13	840M3128557570	ABS MEDLEY ET	2015	1296	0,25	74	0,13	56	98	0,46	0,67	0,51	108	125	74	106	78	120	78		108	106	302	1249	99
14	ESPM9204631171	VEKIS RISK	2017	1104	0,05	45	0,05	41	90	0,92	1,02	1	120	131	61	116	68	115	65	113	83	98	267	1249	99
15	840M3138310311	REDROCK-VIEW KLUTCH ET	2016	783	0,13	41	0,16	42	99	-0,91	2,28	1,33	124	131	74	120	78	114	80		86	95	260	1249	99
16	ESPM9204630024	BANANA JOE ET	2017	1138	0,18	60	0,11	49	93	1,29	1,18	1,15	119	119	53	112	61	106	68	110	96	103	270	1247	99
17	ESPM9204631169	CLEVELAND SALARIO ET	2017	1113	0,11	52	0,08	45	98	1,4	1,53	1,54	124	116	57	109	65	120	88		100	96	264	1245	99
18	ESPM9204739617	MUGABE ET	2018	1455	-0,15	36	0,02	49	80	0,46	1,37	1,05	116	128	52	113	61	109	52		100	106	273	1245	99
19	ESPM9204595969	GYMNAST GENIAL ET	2017	1657	0,08	68	0,05	59	99	0,67	1,79	1,5	125	109	57	88	66	114	94	111	64	78	260	1244	99
20	ESPM9204631170	K&L POPPE GOAL	2017	995	0,14	50	0,05	38	99	1,52	2,07	1,83	118	121	55	105	65	95	93		115	103	255	1243	99
21	ESPM9204631173	SALVAT RED ET	2017	1579	-0,27	26	-0,04	46	85	1,18	1,16	0,86	131	118	55	107	65	115	55	115	88	91	252	1242	99
22	840M3132352752	ST GEN R-HAZE RAPID ET	2017	1055	0,37	77	0,16	51	95	1,46	1,4	1,69	96	120	69	104	76	109	79		117	104	289	1240	99

Economic Selection indices proposed in Spain (IM€T)

Economic value Feed intake:

- Cost of MFU per kg DM

Economic value methane:

- Carbon price voluntary market for traditional systems →-0.14 € (g/d/cow)
- Carbon price for organic systems →-0.72 € (g/d/cow)

Breeding goals

- Production
- Mastitis & Lameness
- Feed Efficiency
- Fertility
- Longevity
- Live Weight
- Calving Ease
- Methane production (g/d)

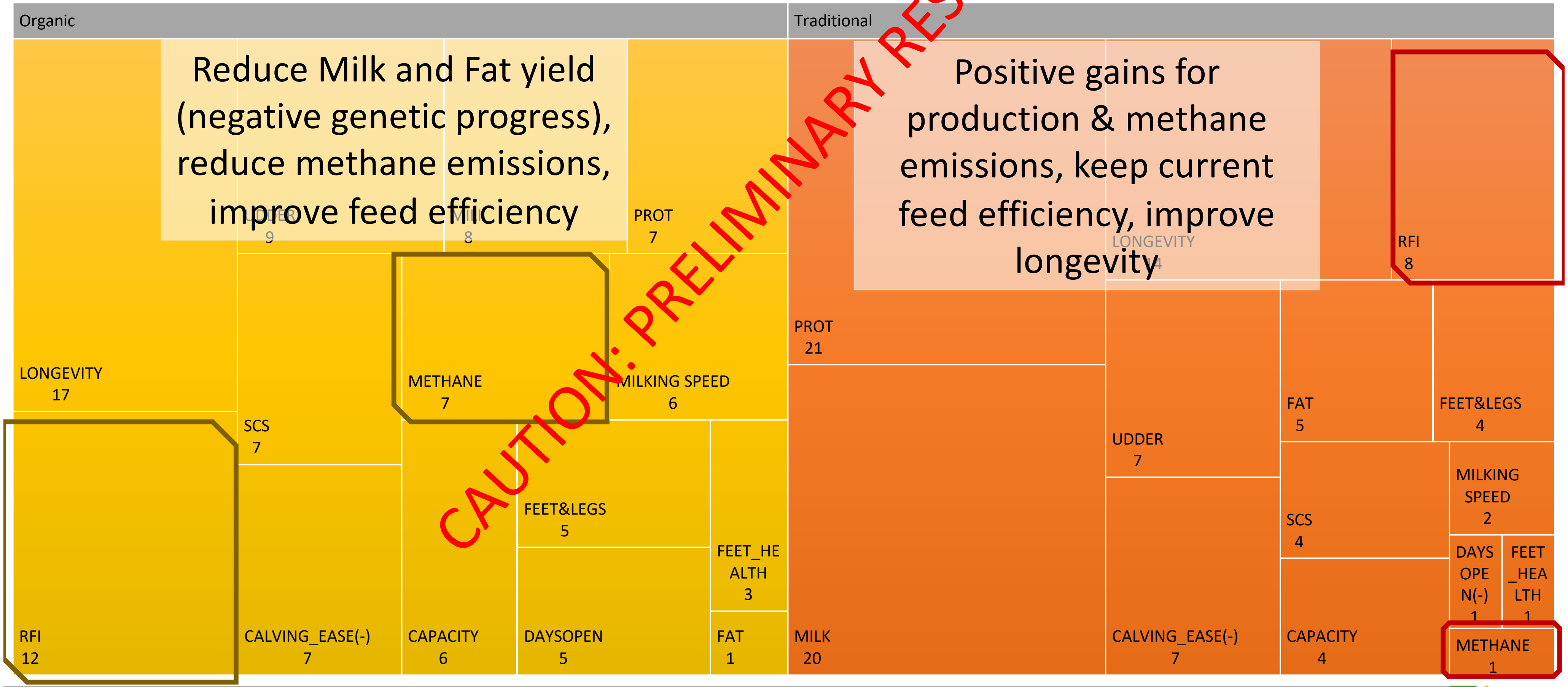
Selection index

Traditional, cheese focused, pasture, **organic**

- kg milk
- kg fat
- kg prot
- RCS
- Feet & Legs
- Days Open
- Longevity
- Milking speed
- Maternal calving ease
- Capacity
- Residual Feed Intake
- Methane (ppm)

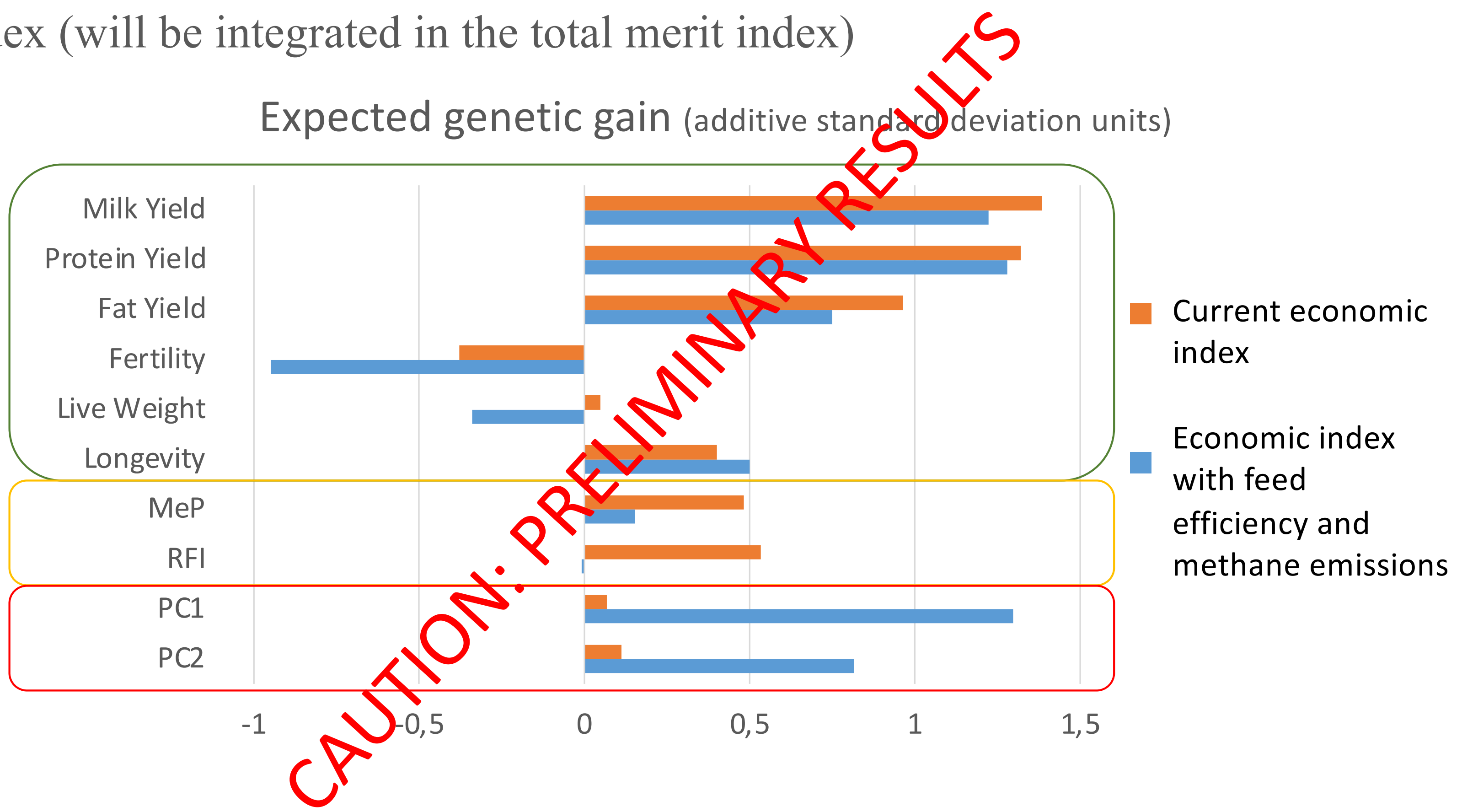
Example of implementation

- **Efficiency and sustainability index in Spanish Dairy cattle**



Example of implementation

- **Efficiency and sustainability index in Spanish Dairy cattle**
  - Subindex (will be integrated in the total merit index)



TAKE HOME MESSAGE

01

Measure, measure, measure

Also in beef and small ruminants

02

Reducing methane emission via selective breeding can have a great impact if, and only if, farmers are encouraged to breed for lower emissions

03

Rumen microbiome information is a suitable complementary phenotype for reducing methane emissions

Selecting for lower emissions and better feed efficiency may impact rumen microbiome health, and it should be controlled

Acknowledgments

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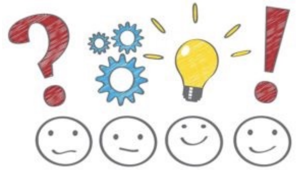

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