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- 1 Microbiota in milk from healthy and mastitis cows varies greatly in diversity, species
- 2 richness and composition, as revealed by PacBio sequencing
- 3
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16 Abstract

17 Mastitis is the most economically important disease of dairy cows. This study used PacBio 18 single-molecule real-time sequencing technology to sequence the full-length of the I6S rRNA from the 19 microbiota in 27 milk samples (18 from mastitis and 9 from healthy cows; the cows were at different 20 stages of lactation). We observed that healthy or late stage milk microbiota had significantly higher 21 microbial diversity and richness. The community composition of the microbiota from different groups 22 also varied greatly. In milk from healthy cows the microbiota was predominantly comprised of 23 Lactococcus lactis, Acinetobacter johnsonii and Bacteroides dorei, while from mastitis cows it was 24 predominantly comprised of Bacillus cereus, Clostridium cadaveris and Streptococcus suis. The 25 prevalence of La. lactis and B. cereus in milk from healthy and mastitis cows was confirmed by digital 26 droplets PCR. Differences in milk microbiota composition could suggest an important role for these 27 microbes in protecting the host from mastitis. Based on the milk microbiota profiles, the Udder Health 28 Index was constructed to predict the risk of bovine mastitis. Application of this predictive model could 29 aid early identification and prevention of mastitis in dairy cows, though the model requires further 30 optimisation using a larger dataset.

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32 KEYWORDS

bovine mastitis, PacBio single-molecule real-time sequencing, I6S rRNA, digital droplets PCR, milk
 microbiota

36 1 INTRODUCTION

37	Bovine mastitis is an inflammatory reaction that occurs in the cow's mammary glands; it is caused either
38	by invasion of pathogenic microbes or by physical/chemical stimulants (Rasmussen, Fogsgaard,
39	Rontved, Klaas, & Herskin, 2011). In general, depending on the degree of inflammation, mastitis can be
40	divided into subclinical and clinical mastitis. Clinical mastitis was diagnosed when the milk from the
41	udder had visible abnormalities (e.g. the presence of floc and/or granules in milk or watery/reduced
42	milk/no milk) or cows showing clinical symptoms, such as elevated body temperature, loss of
43	appetite/refusal to eat, swelling/oedema of the affected quarter (Carolina Espeche et al., 2012; Metzger et
44	al., 2018). In subclinical cases, animals are outwardly healthy, but when the somatic cell count (SCC) of
45	milk samples is greater than 200,000 cells/mL and there is no evidence of clinical infection, they are
46	classified as having subclinical mastitis (Pantoja, Hulland, & Ruegg, 2009). Bovine mastitis is one of the
47	most common and serious diseases in the dairy farming industry; not only does it lead to a decline in
48	milk production and milk quality, but it also increases the elimination and mortality rate of cows.
49	Approximately 33% of the 231 million cows in the world have mastitis, and annual losses due to mastitis
50	are as high as \$3.5 billion (Halasa, Huijps, Osteras, & Hogeveen, 2007). Owing to the huge economic
51	significance of bovine mastitis, it is of major global concern.

The etiology of bovine mastitis is complicated and varies amongst countries and farms; it is influenced by environmental/geographical factors, feeding management methods, sanitary conditions, microbial infections, and attributes of individual cows (e.g. age, lactation stage, parity, body type, heredity). In general, the main cause of mastitis is bacterial infection (Haltia, Honkanen-Buzalski, Spiridonova, Olkonen, & Myllys, 2006), as supported by numerous reports of the isolation and

57	identification of mastitis-causing microbes using traditional microbiological methods. However,
58	traditional bacterial culture is relatively slow and laborious and no pathogenic bacteria are detected, using
59	conventional methods, in approximately 25% of milk samples collected from mastitis cows (Taponen,
60	Salmikivi, Simojoki, Koskinen, & Pyorala, 2009). Second-generation sequencing technology only
61	produces short sequence reads with low taxonomic resolution and has failed to identify mastitis-causing
62	microbes (Dohoo et al., 2011; Liao, Lin, & Lin, 2015). Third-generation sequencing technology, such as
63	the PacBio single-molecule real-time (SMRT) sequencing platform, is increasingly being used to
64	characterize the microbiota of environmental samples (e.g. dairy products (Hui et al., 2017), milk (Hou et
65	al., 2015) and food (Nakano et al., 2016) etc. In contrast to the older sequencing technologies, PacBio
66	SMRT sequencing is high throughput and produces long reads capable of microbial identification to
67	species level when used in conjunction with polymerase chain reaction (PCR) of full-length 16S rRNA
68	genes (Mosher et al., 2014).
69	This study aimed to identify differences in the microbiota of milk from healthy and mastitis cows at
70	different stages of lactation. Milk samples were collected from healthy and mastitis cows from the same
71	dairy. Microbiota profiles in these samples were characterized at the species level by PacBio SMRT
72	sequencing. Abundances of specific microbes were determined using ddPCR. With these data, an Udder
73	Health Index was constructed using the Random Forest Algorithm. Our results serve as a useful reference
74	for designing strategies to prevent and treat mastitis.
75	

76 2 MATERIALS AND METHODS

77 2.1 Experimental design and selection of cows

78	This present study was conducted at Aoya Modern Ranch in Tai'an City (Shandong Province, China)
79	using 2- to 6-year-old Holstein cows. The average age of calving is 23-76 months, and the milk
80	production is about 3800 kg. From 26 dairy cows with severe clinical mastitis identified by professional
81	veterinarians, 18 were randomly selected as mastitis group. For comparison, 9 milk samples obtained
82	from healthy cows was used, and these cows had no history of mastitis and found to have a SCC lower
83	than 15,000 cells/mL. Milk from the mastitis cows contained obvious floc or granules which prevented
84	measurement of SCC. According to Vijayakumar et al (Vijayakumar et al., 2017). lactation in cows can
85	be divided into early (1 \leq d \leq 100), middle (101 \leq d \leq 200), and late lactation (201 \leq d \leq dry milk
86	period). Dairy cows are managed in accordance with the practices of the herd in the pasture, providing
87	them with green fodder and calculating the amount of concentrated mixture. Furthermore, none of the
88	cows had received antibiotics or any other medication known to influence the microbiota of their milk, in
89	the three months before the study.

91 **2.2 Collection of milk samples**

Milk samples were collected from 27 cows in total (18 mastitis and 9 healthy cows; 8 early, 5 middle and 14 late lactation stage cows); detailed information was shown in Table S1. Quarter milk samples were collected during the morning milking from all cows in the following way: Udders were thoroughly wiped using a clean dry cloth to remove bedding and visible contaminants; teats were sanitized; two or three streams of foremilk per teat were discarded; a 0.5% iodine solution was applied to the udder; after 60s the iodine was wiped off using another clean dry cloth towel; the collector then put on clean gloves; a further two to three streams of milk per teat were discarded; all teats were scrubbed with 70%

99	isopropanol; a further two streams of milk per teat were discarded after the isopropanol had dried;
100	finally, approximately 10ml were collected into a sterile vial. All raw milk was stored and transported
101	back to the laboratory on ice.
102	
103	2.3 Extraction of metagenomic DNA
104	DNA was extracted from 3 ml of each raw milk sample using the PowerFood TM Microbial DNA
105	Isolation Kit (MoBio Laboratories, Qiagen, USA) following the manufacturer's instructions. The quality
106	of the extracted genomic DNA was examined by agarose gel electrophoresis and spectrophotometer
107	analysis (ratio of optical density at 260 nm/280 nm). High quality DNA samples were temporarily stored
108	in the refrigerator at -20°C prior use and for no longer than 6 hours.

110 **2.4 Droplet digital PCR**

111 To verify the sequencing results, ddPCR was used to quantify La. lactis and B. cereus, as they were the 112 most abundant species in milk from healthy and mastitis cows, respectively. Nine samples from each 113 group were included in this analysis. The ddPCR was done using the QX200 system (Bio-Rad, Hercules, 114 CA, USA). Primer 5.0 software was used to design the primers targeting La. lactis (lactisF, 115 5'-AGCAGTAGGGAATCTTCGGCA-3'; lactisR, 5'-GGGTAGTTACCGTCACTTGATGAG-3') and B. 116 5'-GGATTCATGGAGCGGCAGTA-3'; (PCERF, PCERR3, cereus 117 5'-GCTTACCTGTCATGGTGTAACTTCA-3') based on the species-specific genomic region (Francisco 118 Martinez-Blanch, Sanchez, Garay, & Aznar, 2011; Ma et al., 2018). The ddPCR reaction solution was 119 prepared by mixing 2 µl DNA, 0.2 µl each of the upstream and downstream primers, 10 µl 2-fold

120	EvaGreen ddPCRSuperMix and 7.6 μ l of sterilized ultra-pure water. The prepared ddPCR reaction
121	solution and the droplet generation oil were added to the droplet generation card and partitioned into
122	20,000 droplets per sample by the QX200 droplet generator (Cremonesi et al., 2016). The droplets
123	produced by each sample were transferred to a 96-well plate and PCR amplification carried out using the
124	EvaGreen program: 95°C for 10 min, 40-cycles of 94°C for 30 sec, 60°C for <i>La. lactis</i> and 62°C for <i>B.</i>
125	cereus for 1 min, and 4°C for 5 min, followed by 90°C for 5 min and a hold at 4°C. After thermal
126	cycling, the 96-well plate was loaded into the QX200 droplet reader. Data were collected using
127	QuantaSoft software, and the number of target DNA molecules calculated based on Poisson statistics.
128	
129	2.5 Amplification of full-length 16S rRNA genes and SMRT sequencing
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130 131 132 133	The 16S rRNA genes were amplified by PCR using the purified extracted genomic DNA as templates, with the universal primer pair 27F (5'-AGAGTTTGATCCTGGCTCAG-3') and 1495R (5'-CTACGGCTACCTTGTTACGA-3') (Mosher, Bernberg, Shevchenko, Kan, & Kaplan, 2013). At the same time, to identify different samples in the same library, a 16-base identification barcode was added
 130 131 132 133 134 	The 16S rRNA genes were amplified by PCR using the purified extracted genomic DNA as templates, with the universal primer pair 27F (5'-AGAGTTTGATCCTGGCTCAG-3') and 1495R (5'-CTACGGCTACCTTGTTACGA-3') (Mosher, Bernberg, Shevchenko, Kan, & Kaplan, 2013). At the same time, to identify different samples in the same library, a 16-base identification barcode was added to both ends of all primers. The specific amplification conditions were as follows: 95°C for 3 min, 98°C

- 138 constructed library, sequencing primers and DNA polymerase, were added to the SMRT cells for
- 139 sequencing using the PacBio RS II instrument.
- 140

2.6 Bioinformatics processing of high-quality sequences

143 Portal version 2.3. Specific quality control conditions were based on the follow	wing criteria: minimum
144 cycle sequencing number, minimum prediction accuracy, minimum insertion	n sequence length and
145 maximum insertion sequence length, which were set to 5, 90, 1,400 and 1,800 re	respectively (Hou et al.,
146 2015). Then all sequences were divided into different samples according to	to the barcodes on the
147 amplicons. After removal of barcodes and primer sequences, bioinformatics ar	analysis of high-quality
148 sequences was done using the QIIME package (version 1.7), briefly, PyNAST ((Caporaso et al., 2010)
149 was used to align the sequences, and UCLUST (Edgar, 2010) was done under	der 100% clustering of
150 sequence identity to obtain representative sequences. Afterwards, sequences	es were classified into
151 operational taxonomic units (OTU) according to 97% similarity. Chimeric OTU se	sequences were detected
152 and removed using ChimeraSlayer (Haas et al., 2011). The Ribosomal Database	e Project (RDP, Release
153 11.5) (Cole et al., 2007), Greengenes (version 13.8) (DeSantis et al., 2006	06) and Silva (version
154 128) (Quast et al., 2013) databases were used to assign the taxonomy of eac	ach OTU representative
155 sequence with an 80% confidence threshold (Hou et al., 2015). A <i>de novo</i>	vo taxonomic tree was
156 constructed for representative OTU sets using FastTree for downstream analysis ((Price, Dehal, & Arkin,
157 2009). The alpha diversity of each sample was assessed based on the sample with	th the lowest sequencing
158 depth. All sequencing data generated have been uploaded to the MG-RAST data	tabase under the project
159 number mgp88495 (http://www.mg-rast.org).	

2.7 Random Forest algorithm for predicting cow udder health

162	Here a mastitis prediction model was built to predict the udder health status of dairy cows based on the
163	default settings of the Random Forest machine learning algorithm available in R package (3.1.1) (Cutler,
164	Edwards, Beard, Cutler, & Hess, 2007). Briefly, the prediction was based on regression of the milk
165	microbiota profiles of all 27 cows against their mastitis health status. The Random Forest algorithm
166	ranked all species into 'character importance' and used the 'rfcv' function to generate more than 100
167	predictions to determine the number of top discriminant species required for calculating the Udder Health
168	Index. Then the Udder Health Index was calculated based on the relative abundance of the predicted top
169	discriminatory milk microbes.
170	
171	2.8 Statistical analyses
172	The R software package was used for statistical analysis (http://www.rproject.org/). Wilcoxon and
173	Kruskal-Wallis tests were used to evaluate differences in microbial between groups with a cut-off
174	confidence level of 95%. Principal coordinate analysis (PCoA) was used to observe the distribution of
174 175	confidence level of 95%. Principal coordinate analysis (PCoA) was used to observe the distribution of samples. Permutational multivariate analysis of variance (PERMANOVA) (Anderson & Walsh, 2013)
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175 176	samples. Permutational multivariate analysis of variance (PERMANOVA) (Anderson & Walsh, 2013) was done on the different groups of samples in the R language 'vegan' (Nilsson et al., 2010) package to
175 176 177	samples. Permutational multivariate analysis of variance (PERMANOVA) (Anderson & Walsh, 2013) was done on the different groups of samples in the R language 'vegan' (Nilsson et al., 2010) package to reveal the effect of different groups on the target microbiota of healthy and mastitis cows. The 'ggplot2'
175 176 177 178	samples. Permutational multivariate analysis of variance (PERMANOVA) (Anderson & Walsh, 2013) was done on the different groups of samples in the R language 'vegan' (Nilsson et al., 2010) package to reveal the effect of different groups on the target microbiota of healthy and mastitis cows. The 'ggplot2' package (Ginestet, 2011) was used to analyze and visualize the raw results obtained by QIIME.

182 **3.1** Sequence coverage and alpha diversity of microbiota from milk

183	A total of 169,308 high-quality 16S rRNA sequences were produced from the 27 samples included in this
184	study (average = 6,270; range = 1,010-15,174; SD = 3,905). After PyNAST alignment and UCLUST
185	classification at 100% similarity, 82,592 representative sequences remained. Upon removal of chimeric
186	sequences, they were classed into 6,850 OTUs for downstream analysis.
187	All Shannon diversity curves leveled off, suggesting that the sequencing depth was sufficient to
188	capture representative microbial populations present in the samples (Figure S1), although new
189	phylotypes may still be found with further sequencing. The microbial abundance and species richness in
190	each sample were assessed by the number of observed OTUs and the Shannon diversity index,
191	respectively. Both the number of observed OTUs and Shannon diversity index were significantly higher
192	in healthy compared with mastitis cows (Figure 1a, b; $P < 0.001$). We also found that both indices were
193	significantly higher during late compared with early lactation, while no significant difference was
194	observed amongst other lactation stages (Figure 1c, d; $P < 0.05$).
105	

196 **3.2 Identity of microbiota in milk**

197 Firmicutes (73.0%) and Bacteroidetes (10.9%) were the two main bacterial phyla. At the genus level,

there were 12 genera with an average relative abundance of more than 1% (Figure 2a), including Bacillus

- 199 (28.5%), Clostridium (10.6%), Lactobacillus (10.4%), Lactococcus (7.9%) and Bacteroides (6.1%). At
- 200 the species level, 15 of which had an average relative abundance of over 1% (Figure 2c), including B.
- 201 cereus (27.6%), La. lactis (7.8%), Lactobacillus helveticus (6.3%), Clostridium limosum (4.4%),
- 202 *Helcococcus ovis* (3.4%), and *Clostridium cadaveris* (3.2%) et al.

203	The mean microbiota composition varied largely between groups. Whereas the horizontal lines in the
204	box-plots indicate the median, we found that more Lactobacillus, Lactococcus, Bacteroides and
205	Acinetobacter were detected in healthy cows, while more Bacillus, Clostridium and Streptococcus were
206	observed in mastitis cows (Figure 2b). Significantly more La. lactis was found in the milk of healthy
207	cows, while <i>B. cereus</i> was found in the mastitis cows ($P < 0.05$, Figure 2d). The relative abundance of
208	Bacillus and Clostridium were not significantly different in milk collected during the early and middle
209	compared with late lactation. In addition, significantly more La. lactis, S. suis, A. johnsonii, and B. dorei
210	were detected in milk from late compared with early and middle lactation cows ($P < 0.05$). The relative
211	abundance of <i>H. ovis</i> and <i>P. heparinolytica</i> gradually decreased as lactation day increased (Figure S2).
212	
213	3.3 Comparative analysis of community structure in milk from cows
214	A PCoA was done based on the Bray Curtis distance to visualize differences in the milk microbiota

between the healthy and mastitis groups. Two distinct clusters formed on the PCoA score plot, representing milk samples collected from healthy and mastitis cows, respectively (Figure 3a). This suggests large difference in the microbiota community structure and compositon between the two groups. Results of the PERMANOVA test revealed that mastitis was a significant factor contributing to differences in microbiota between the two groups (P = 0.001).

When samples were grouped based on the three lactation stages, the distinction between groups were less clear. Clusters associated with early and middle lactation milk overlapped each other and were separate from the cluster representing late lactation milk. This indicates that the former two groups were more similar to each other than they were to the latter group (Figure 3b). The PERMANOVA test

224	revealed significant difference in the milk microbiota composition of the three lactation stages ($P =$
225	0.016). However, the effect size of lactation stage on milk microbiota was smaller than that of mastitis
226	status. It is worth noting that most late lactation dairy cows were healthy.
227	Wilcoxon and Kruskal-Wallis tests were done to identify differentially abundant taxa in the different
228	groups. Species that were significantly differentially abundant (average relative abundance $> 0.5\%$) are
229	listed in Table S2 and S3. Significantly more La. lactis, A. johnsonii and B. dorei were found in the milk
230	of healthy ($P < 0.01$) compared with mastitis cows, while significantly more <i>B. cereus</i> and <i>S. suis</i> were
231	found in the milk of mastitis compared with healthy cows ($P < 0.05$). Meanwhile, significantly more La.
232	lactis, A. johnsonii, B. dorei, S. stercoricanis and S. suis were present in the milk of late lactation cows
233	compared with other lactation stages ($P < 0.05$); the two latter species were found only during late
234	lactation.
235	

236 **3.4 Correlation analysis of microbiota community structure in milk from cows**

Spearman correlation analyses were done to identify co-occurrence relationships amongst the major bacterial genera (an average relative abundance > 0.5%) in milk from healthy and mastitis cows. The results are expressed as correlation network diagrams. The milk microbiota of the healthy group seemed to be closely interrelated, contrasting with the overall weak networking apparent amongst bacterial genera in milk from mastitis cows. In milk from healthy cows, *Lactococcus* was significantly and negatively correlated with *Acinetobacter* (r = -0.78; p = 0.01) and *Massilia* (r = -0.70; p = 0.04, Figure 3c), respectively. It is interesting to note that the *Faecalibacterium* formed the highest number of 244 significant correlations with other genera from milk. In contrast, *Faecalibacterium* didn't correlate with

- any genera in the milk from mastitis cows (Figure 3d).
- 246

247 3.5 Quantification of microbial in cows milk by ddPCR and construction of Udder Health Index

248	To verify the sequencing results, ddPCR was done to quantify the number of La. lactis and B. cereus, as
249	they were the most abundant species in the healthy and mastitis groups, respectively. For the healthy
250	group, there were significantly more <i>La. lactis</i> $(2.16 \times 10^3 \text{ copies/ml})$ compared with <i>B. cereus</i> (<i>P</i> < 0.01),
251	and B. cereus was only detected in the sample C17 (healthy group). An opposite trend was observed for
252	the mastitis group, with a significantly higher abundance of <i>B. cereus</i> $(3.25 \times 10^4 \text{ copies/ml})$ compared
253	with La. lactis (9.00×10 ² copies/mL; $P < 0.001$) (Figure 4a). These results were consistent with those

found by DNA sequencing.

255 The Random Forest regression model was applied to predict the udder health of cows. The relative 256 abundances of bacterial species detected in milk were regressed against each cow's health status. The top 257 nine mastitis-discriminatory marker species were selected based on the minimum 'CV error', and an 258 Udder Health Index was constructed (Figure 4b,d). Udder Health Indices for the healthy and mastitis 259 groups were calculated; a higher value represented a healthier status. As expected, the Udder Health 260 Index was significantly higher for the healthy compared with the mastitis group (P < 0.001, Figure 4c). 261 To verify the accuracy of the constructed model, the SCC of the healthy milk samples was measured 262 (Table 1). But this was not possible for the mastitis group due to the milk flocs were obvious and the 263 granules were large, accompanied by blood and different degree of coagulation. However, the SCC 264 associated well with the predicted Udder Health Index of the healthy cows, validating the current model.

266 4 DISCUSSION

267	Mastitis is a common disease among dairy cows; symptoms include shortening of lactation period and
268	milk production, increase in leukocytes in the milk, and lesions in mammary tissues (Paster, Dewhirst,
269	Olsen, & Fraser, 1994). Since bovine mastitis results in huge economical losses, its prevention and
270	treatment have attracted wide attention. Bovine mastitis can also increase the microbial load in milk
271	resulting in rapid changes in the quality and shelf life of raw milk and related products (Murphy, Martin,
272	Barbano, & Wiedmann, 2016). Pathogenic bacteria in raw milk from mastitis cows are a serious food
273	safety issue as they may lead to human disease. In addition, clinical mastitis is a serious animal welfare
274	concern because mastitis is debilitating and painful (Fromm & Boor, 2004; Halasa et al., 2007). Milk is
275	produced by the mammary tissues of lactating cows; the appearance, texture, and quantity of secreted
276	cow milk are indicative of the health of the mammary tissue and thus serve as indicators for clinical
277	mastitis. This study used PacBio SMRT sequencing technology to reveal the community composition of
278	microbiota in milk from dairy cows, and identified differences in the milk microbiota of healthy and
279	mastitis cows, and cows at different stages of lactation. We observed a significantly higher microbial
280	diversity and richness in milk from healthy compared with mastitis cows, as reported in other
281	studies (Braem et al., 2012; Kuehn et al., 2013). Our data also showed that the microbial diversity and
282	richness of milk also increased significantly during late lactation. On the other hand, the increase in
283	microbial diversity could indicate a healthy state of the cows, as the mastitis milk might be dominated by
284	certain pathogens, which would be reflected by the diminished microbiota diversity. Moreover, changes
285	in milk microbiota at different lactation stages could be associated with changes in the nutritional content

286	of the milk, e.g. the total concentration of milk oligosaccharides was found to decrease in the early and
287	mid lactation stages. The anionic oligosaccharides including N-glycolylneuraminic acid decreased more
288	rapidly than the neutral oligosaccharides in lactation (Nakamura et al., 2003; Tao, DePeters, German,
289	Grimm, & Lebrilla, 2009). Therefore, when cows suffer from mastitis, the mammary tissues may be
290	overwhelmed with harmful bacteria; this could induce localized immune responses that suppress the
291	healthy resident microbiota and reduce microbial diversity and richness in the mammary gland (Kuang et
292	al., 2009).
293	We found that the distribution of bacterial taxa present in milk also varied greatly between healthy
294	and mastitis cows, as found in other studies (Falentin et al., 2016; Oikonomou, Machado, Santisteban,
295	Schukken, & Bicalho, 2012). The predominant genera detected in this work included Lactobacillus,
296	Streptococcus, Acinetobacter and Bacillus, which are known to be common in milk (N. Li et al., 2018).
297	We found significantly more Lactobacillus, Lactococcus and Acinetobacter in milk from healthy
298	compared with mastitis cows. The relative abundance of Lactobacillus in milk is known to be negatively
299	associated with milk SCC, an indicator of the seriousness of mastitis; thus, these bacteria are crucial in
300	maintaining the health of the mammary tissues and suppressing local infection and inflammation (Yu,
301	Ren, Xi, Huang, & Zhang, 2017). In contrast, Lactococcus is known to be able to cause bovine
302	mastitis (Rodrigues, Lima, Higgins, Canniatti-Brazaca, & Bicalho, 2016). Acinetobacter is widely
303	distributed in nature and is often detected in milk, soil and water. It is also considered as an opportunistic
304	pathogen associated with wounds and skin infections (Dortet, Legrand, Soussy, & Cattoir, 2006; L. Li et
305	al., 2016). Results of the Spearman correlation analysis in our study indicated a negative correlation
306	between Lactococcus and Acinetobacter, suggesting that there may be a competition inhibition

307	relationship between them. Bacteroides are typical milk bacteria that may also have a role in maintaining
308	healthy mammary tissues (Quigley et al., 2013). Differences in the correlation patterns between the milk
309	microbiota from healthy and mastitis cows may suggest an important role of milk microbiota in
310	protecting cows from mastitis. Our data revealed an increase in the relative abundances of Bacillus,
311	Clostridium and Streptococcus in milk from mastitis compared with healthy cows. Staphylococcus has
312	been reported as the most common cause of mastitis in cows worldwide, followed by
313	Streptococcus (Moroni et al., 2006). Clostridium species have been reported to cause abscesses in
314	mammary tissues of sows and humans as well as gangrene in cows (Durojaiye, Gaur, & Alsaffar, 2011;
315	Osman, El-Enbaawy, Ezzeldeen, & Hussein, 2009). The Bacillus genus includes some important
316	causative agents of mastitis, e.g. B. cereus (Parkinson, Merrall, & Fenwick, 1999); in this study B. cereus
317	increased in relative abundance (up to 27.55%) in milk from mastitis compared with healthy cows. By
318	ddPCR, we confirmed the elevated abundance of <i>Bacillus cereus</i> in the mastitis group $(3.25 \times 10^4$
319	copies/mL); it was practically absent in the healthy group. These results suggest a possible link between
320	B. cereus and bovine mastitis.
321	Another spectrum of mastitis-associated bacterial sequences detected in this study was the anaerobes,

including *F. necrophorum* and *B. dorei*. Although these bacteria are unlikely to be causative agents of clinical bovine mastitis, they are known to be associated with summer mastitis and may interact with other pathogens such as *Trueperella pyogenes* (Oikonomou et al., 2012; Pyorala, Jousimies-Somer, & Mero, 1992). Significantly more *P. heparinolytica* and *H. ovis* sequences were detected in milk from cows at the early lactation stage in this study, both *P. heparinolytica* and *H. ovis* are potential pathogens that have previously been isolated from mammary gland wounds causing localized infection (Paster et

328	al., 1994). It is suspected that the presence of <i>H. ovis</i> in cows milk indicates involvement in the
329	pathogenesis of mastitis (Schwaiger et al., 2012). The relative abundances of La. lactis, A. johnsonii and
330	B. dorei were higher during late lactation compared with the early and middle lactation stages. B. dorei
331	can suppress the production of lipopolysaccharides by intestinal gut microbes and thus reduces
332	pro-inflammatory immune responses (Yoshida et al., 2018). Furthermore, changes in susceptibility to
333	mastitis might be coupled with changes in community composition of the milk microbiota, such as
334	increases in <i>B. dorei</i> and <i>La. lactis</i> (Xu et al., 2017).
335	Cows suffering from subclinical mastitis can easily develop clinical mastitis if they are not spotted
336	early enough and managed appropriately. Therefore, it is important to predict the likely risk of mastitis
337	developing. Current practice defines subclinical mastitis using a cut-off SCC threshold level of 200 000
338	cells/mL. However, the determination of milk SCC is widely used to monitor udder health, but there are
339	still some limitations: (1) it may take a longer time for the SCC to return to that of a healthy state after
340	pathogen clearance, so there is a window period when the diagnosis based on SCC level would not be
341	accurate; (2) the SCC value fluctuates largely with individual milk yield and other environmental factors;
342	(3) diagnosis based purely on SCC is mainly applicable to mastitis cows caused by contagious pathogens,
343	while mastitis caused by environmental factors would be hard to detect due to the relatively small
344	changes in SCC (Pyorala et al., 1992; Sharma, Singh, & Bhadwal, 2011). In this study we used the
345	Random Forest model identified the 9 top marker species that were indicative of bovine mastitis, and
346	constructed an Udder Health Index based on the relative abundances of these species. We validated the
347	model by associating the index with the SCC of healthy cows. Our results showed that the accuracy of the
348	model was 88.89%. Thus, this index would be a good complementary indicator that helps detect early

- 349 changes in cow health. One limitation of the current model is the small sample size, therefore, larger
- scale future works will be necessary to optimize and verify this model.
- 351
- 352 5 CONCLUSION
- 353 The results of this study showed great variation in the microbiota in milk from healthy and mastitis cows.
- 354 Overall there was a high relative abundance of commensals in healthy milk and a high relative abundance
- of potential pathogens in milk from mastitis cows. Finally, the Udder Health Index constructed is helpful
- 356 for early identification of mastitis risk and has the potential to be used to prevent mastitis from developing,
- and prompt measures should be taken to prevent further development of clinical mastitis.
- 358

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544 TABLES

Cow milk sample	Udder Health Index	SCC (x10 ⁴ cells/mL)	Total bacteria count $(x10^4)$
			CFU/mL)
C2	0.142	12.2	0.863
C4	0.253	14.8	0.948
C14	0.846	13.8	0.882
C13	0.849	13.3	1.050
C18	1.334	12.9	0.819
C17	2.180	12.0	0.796
C15	4.062	11.1	0.859
C20	5.545	10.7	0.671
C12	9.753	9.9	0.698

545 Table 1 Udder Health Index, somatic cell count (SCC), and total bacterial count of cow milk samples

547 FIGURE LEGENDS

548	Figure 1 Comparison of the number of observed OTUs and Shannon diversity index for the microbiota
549	in milk. The healthy and mastitis cows (a, b); early, middle and late lactation (c, d). Healthy and mastitis
550	cows are represented by 'HC' and 'MC', respectively. Early, middle, and late lactation stages are
551	represented by 'EL', 'ML' and 'LL', respectively. Single and triple asterisks represent $P < 0.05$ and $P <$
552	0.001, respectively.
553	
554	Figure 2 Community composition of the bacterial microbiota in milk from healthy and mastitis cows.
555	Milk bacterial community at the genus (a and b) and species (c and d) levels. Healthy and mastitis cows
556	are represented by 'HC' and 'MC', respectively.
557	
558	Figure 3 Principal coordinates analysis (PCoA) and correlation networks of the bacterial microbiota in
559	milk from healthy and mastitis cows. They are grouped based on mastitis status (a) and lactation stage
560	(b). The co-occurrence relationship was calculated using Spearman's rank correlation analysis of the
561	microbiota in milk from healthy (c) and mastitis (d) cows. Only major genera of average relative
562	abundance $> 0.5\%$ are included in the analysis. The diameter of the circles represents the abundance of
563	the genera. Healthy and mastitis cows are represented by 'HC' and 'MC', respectively. Early, middle, and
564	late lactation stages are represented by 'EL', 'ML' and 'LL', respectively.
565	
566	Figure 4 Quantification of <i>La. lactis</i> and <i>B. cereus</i> in cows' milk by ddPCR and construction of Udder

567 Health Index. (a) The prevalence of *La. lactis* and *B. cereus* in milk from healthy and mastitis cows. (b)

- 568 Model marker species selected based on minimum CV error. (c) The nine selected marker species of the
- 569 model. (d) Udder Health Indices in the healthy and mastitis groups. Healthy and mastitis cows are
- 570 represented by 'HC' and 'MC', respectively. Single and triple asterisks represent P < 0.05 and P < 0.001,
- 571 respectively.
- 572
- 573







