

1 **Classification of environmental factors potentially motivating for dairy cows to access**  
2 **shade**

3

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**SUPPLEMENTARY FILE**

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## 18 **Materials and Methods**

### 19 *Experimental area and climate pattern*

20 This work was carried out in a silvopastoral system (SPS) on a commercial dairy farm in  
21 southern Brazil. Data collection was performed during summer (southern hemisphere); in four  
22 consecutive days with high temperatures, high solar radiation, and low cloudiness. According  
23 to Köppen classification, the climate of the region is subtropical humid mesothermic (Cfa)  
24 and presents hot summers with average annual temperatures between 18 and 20°C and  
25 relative humidity between 63 and 84% (INMET *et al.*, 2009; Alvares *et al.*, 2013).

26 The experimental area had 4 paddocks (1.550m<sup>2</sup>/ paddock) where each one was composed  
27 of a silvopastoral system. This system consisted of native trees (approximately 8 meters high)  
28 planted in wood with a distance of 14 meters, and provided a total shaded area of 5m<sup>2</sup>/ animal  
29 in each paddock (determined by Shading Vegetation Index) and a sunny area of 33m<sup>2</sup>/ animal  
30 in each paddock. At the farm, animals are raised permanently on pasture, mainly composed of  
31 plant species of *Axonopus catarinenses*, *Arachispintoi spp.* and *Paspalum notatum*. The  
32 pasture is managed under Voisin's Rotational Grazing system whereby animals are moved  
33 daily to a new paddock. Thus, as the paddocks and SPS distribution were uniform, this  
34 allowed us to evaluate one paddock per day.

35

### 36 *Animals and frequency at the shaded and sunny areas*

37 Lactating Jersey cows (n = 39), with similar coat colour (light brown), weight (mean ± SD) of  
38 450 ± 50kg were observed during four days, for 8h each day (from 09:00 to 16:50). All  
39 observations were performed in an area already known by the animals and began after the last  
40 animal entered at the paddock. To minimize research bias, after milking morning, animals  
41 were handled by farmers to the experimental area. Frequency of animals in each area (shaded  
42 and sunny) was recorded by scan sampling of 10 min. intervals (Altmann, 1974). The cow  
43 was considered to be in the shaded area when more than 50% of her body was in the shade of

44 the tree. The cow was considered to be in the sunny area when more than 50% of her body  
45 was in the sun (Kendall *et al.*, 2006; Giro *et al.*, 2019). All observations were made by  
46 researchers previously trained and with knowledge in the area of animal behaviour; in order to  
47 not interfere with the animals' behaviour, the observations were performed outside of the  
48 paddock with a safe distance. The reliability of simultaneous observations of a given  
49 individual by the observers reached 94.2% before the beginning of the data collection.

50

### 51 *Environment evaluation*

52 During the experimental period, environmental factors were collected in 120 points [fifteen in  
53 each area (shaded and sunny)]. Thus, in order to avoid temporal variations between the areas,  
54 data collection was carried out simultaneously in both areas. In shaded and sunny areas of the  
55 SPS, the following environmental factors were measured: air temperature (AT, °C), relative  
56 humidity (RH, %), solar radiation (SR, W/m<sup>2</sup>) and wind speed (WS, m/s).

57 Air temperature (°C) and relative humidity (%) measurements were performed (with solar  
58 radiation shield) with a thermo-hygrometer (humidity 0-100% scale; ± 2.5% accuracy; 0.1%  
59 resolution; temperature, -30 to 100°C scale; ± 0.8°C accuracy; and 0.1°C resolution). The  
60 solar radiation measurement was performed with a pyranometer (0 to 4000W/m<sup>2</sup>; ± 4%  
61 accuracy). Wind speed was measured with a thermo-anemometer (0.4 to 20 m/s scale; ± 2%  
62 accuracy). Data collection was carried out from 9:00 to 16:50 at a height of 1.3m from the  
63 ground (height average of the center of mass of Jersey adult cattle) with intervals of 10 min.,  
64 and averages were generated every 1 h.

65

### 66 *Data mining and statistical analysis*

67 Animal frequency at the areas and environmental data were used to build a database with  
68 29320 observations and 10 variables, one being the classification (Table S1). The database  
69 was built with each observation (frequency at the areas and environmental) synchronized by

70 date and time of day. Data mining technique was applied following CRISP-DM methodology  
71 (Klein *et al.*, 2020).

72

### 73 **Table S1**

74

75 Data mining was performed with the software Waikato Environment for Knowledge  
76 Analysis (WEKA<sup>®</sup>, 3-4), which classifies the data and build a classification tree using the J48  
77 algorithm, an implementation of the algorithm C4.5 that is a supervised machine learning  
78 tool. The J48 algorithm generates a model with semantic rules using the minimum  
79 information required for classification. The model result is expressed graphically in the form  
80 of an inverted tree; the first attribute is the one with the highest classification power (root  
81 node). From the root node, semantic rules are expressed as body → head. The rules body are  
82 logic connectors ( $\leq$ ,  $>$ , and  $=$ ) called as nodes that express the connection between the features  
83 that are capable to classify an event. The classification from a rule is the head that is  
84 represented in the graphic tree as the leafs. Each branch in the classification tree is one rule  
85 with their connectors in the body and a class on the head.

86 Classification tree was generated by ranking the cow's frequency at the areas (shaded or  
87 sunny), according to the environmental factors. The best model selection was based on the  
88 model accuracy, the precision of classes, and the interpretation of classification rules by  
89 experts with the minimum requirement of three years of expertise. In the analysis, were  
90 applied a ten-fold cross-validation, available in the J48 algorithm. Model accuracy, as well as  
91 class precision, were calculated by a confusion matrix (Table S2). The class precision ranges  
92 from zero to one and expresses the relation of true positive and true negative classifications in  
93 a specific class. The model accuracy expresses the percentage of instances that were correctly  
94 classified.

95

96 **Table S2**

97

98 In order to confirm the level of agreement of the data sets and classification accuracy, the  
99 Kappa statistical method was used (see more information in: Sim and Wright 2005; McHugh  
100 2012) was determined by equation (1) developed by Cohen (1960). In this study, when  
101 describing the relative strength of agreement associated with kappa statistics, the labels  
102 proposed by Landis and Koch (1977) were used. The relative strength values indicate:  $\leq 0$ :  
103 poor; 0.00 – 0.20: slight; 0.21 – 0.40: fair; 0.41 – 0.60: moderate; 0.61 – 0.80: substantial; and  
104 0.81 – 1.00: almost perfect.

105

$$K = \frac{P_o - P_c}{1 - P_c} \quad (1)$$

106

107 Where:

108 K is the kappa statistical,

109  $P_o$  is the proportion of observed agreements and,

110  $P_c$  is the proportion of agreements expected by chance.

111

112 As confirmatory analysis, the data (frequency at the areas and environment) were  
113 submitted to the normality test (Shapiro-Wilk), analyzed by Generalized Linear Models  
114 (GLM) and submitted to the Spearman correlation test. Experimental design of environmental  
115 factors was composed of four replicates (paddocks), 120 experimental units (30 collection  
116 points by paddock), two independent variables (shade and sun) and four dependent variables  
117 (air temperature, relative humidity, solar radiation and wind speed) following the model:

118

119

$$Y_{ij} = \alpha_j + \beta_{ij} + e_{ij}$$

120

121 Were:

122  $Y_{ij}$  are the microclimatic variables,

123  $\alpha_j$  are the fixed effect of the areas provided by the silvopastoral system,

124  $\beta_{ij}$  is the random effect,  $i$  corresponds to days;  $j$  corresponds to hours, and

125  $e_{ij}$  is the residual effect.

126

127 All analyzes were performed separately and each environmental factor obtained a GLM  
128 model. Gamma distribution and logarithmic bonding function were used for the  
129 environmental factors, at a 95% confidence level.

130 The analysis of frequency at the areas was composed of four repetitions (paddocks), 39  
131 experimental units (animals), two independent variables (shade and sun) and the dependent  
132 variable was the frequency of events recorded in shaded and sunny areas. Poisson distribution  
133 at a confidence interval of 99% was used. Animals, days and hours were defined as random  
134 effects following the model:

135

$$136 \quad Y_{ij} = \alpha_j + A_i + \beta_{ij} + e_{ij}$$

137 Were:

138  $Y_{ij}$  is the cow's frequency at the areas,

139  $\alpha_j$  are the fixed effect of the areas provided by the silvopastoral system,

140  $A_i$  is the random effect of animals,

141  $\beta_{ij}$  is the random effect,  $i$  corresponds to days;  $j$  corresponds to hours, and

142  $e_{ij}$  is the residual effect.

143

144 All analyzes were performed through the statistical software R (R Core Team 2019) and all  
145 statistical models were adjusted using the maximum likelihood-Laplace approximation  
146 method in the statistical package lme4 (Bates *et al.*, 2015).

147

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177 **Supplementary tables legends:**

178

179 **Supplementary table 1:**

180 Summary of data and variables of the final database.

181

182 **Supplementary table 2:**

183 Confusion matrix representation.

184

185

186 **Supplementary table 1**

187

| N° | Variable                      | Unit    | N° | Variable                             | Unit             |
|----|-------------------------------|---------|----|--------------------------------------|------------------|
| 1  | Day <sup>A</sup>              | Numeric | 6  | Air temperature                      | °C               |
| 2  | Hour <sup>B</sup>             | Numeric | 7  | Relative humidity                    | %                |
| 3  | Categorized time <sup>C</sup> | Numeric | 8  | Solar radiation                      | W/m <sup>2</sup> |
| 4  | Scan <sup>D</sup>             | Numeric | 9  | Wind speed                           | m/s              |
| 5  | Animals ID <sup>E</sup>       | Numeric | 10 | Areas: shaded/<br>sunny <sup>F</sup> | Class            |

188 <sup>A</sup>collection days; <sup>B</sup>hours of data collection (range: 1 to 8); <sup>C</sup>categorization of observation  
 189 hours in period (morning and afternoon); <sup>D</sup>observations of frequency at the areas in each  
 190 10min.; <sup>E</sup>individual identification by animal; <sup>F</sup>nominal classification of each event based on  
 191 the area used by animal.

192

193

194 **Supplementary table 2**

195

| Class          | Predict as C <sub>+</sub>            | Predict as C <sub>-</sub>            | Class precision                                     | Model accuracy <sup>A</sup>                   |
|----------------|--------------------------------------|--------------------------------------|---|---|
| C <sub>+</sub> | True positives<br>(T <sub>p</sub> )  | False negatives<br>(F <sub>n</sub> ) | T <sub>p</sub> / (T <sub>p</sub> + F <sub>n</sub> ) | [T <sub>p</sub> + T <sub>n</sub> ] / N] x 100 |
| C <sub>-</sub> | False positives<br>(F <sub>p</sub> ) | True negatives<br>(T <sub>n</sub> )  | T <sub>n</sub> / (F <sub>p</sub> + T <sub>n</sub> ) |   |

196 <sup>A</sup>N is equal to the number of instances in the test set.

197