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Non-ruminants

Factors affecting the performance of Pantaneiro horses

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ABSTRACT - This study aimed to assess the physical performance of Pantaneiro horses with and without equine infectious anemia (EIA) under functional conditions of cattle management. The horses were subjected to a performance test and split into two groups according to a completely randomized design: animals were chosen from populations testing positive and negative for EIA. Performance was measured as a function of a data envelopment analysis (DEA) model considering four outputs and one unitary input. The output measures were the distance achieved in the performance test, hematocrit as a weighted average over the test duration, respiratory rate as weighted average over the test duration, and the level of lactic acid at the test termination. Weights for the hematocrit and the respiratory rate output variables were determined by means of factor analysis. The performance score was a weighted average of the output variables with the weights defined by the averages of the optimum individual multipliers in the DEA analysis. Contextual variables of interest were age, horse weight, room temperature, and corporal temperature. Only groups and room temperature were statistically significant effects, as indicated by a bootstrap analysis. The performance of group positive for EIA is significantly lower than that of the group negative for EIA and room temperature has a negative effect.

Key Words: covariance analysis, data envelopment analysis, equine infectious anaemia, experimental design, multivariate analysis

Introduction

The Pantanal wetland in the central western region of Brazil (Pantanal for short) counts 9.63 million heads of cattle according to the 2015 Brazilian county livestock research. This livestock is of economic importance in this region. The use of the so-called Pantaneiro horses is critical for the appropriate management of cattle. Equines were brought to Brazil by the first European settlers and in the Pantanal, they have grown and multiplied without human interference for more than two centuries, giving rise to the Pantaneiro breed (Santos et al., 2016).

In recent years, the occurrence of equine infectious anemia (EIA) has become a serious drawback for the use of Pantaneiro horses in cattle management (Oliveira et al., 2011). Equine infectious anemia is an incurable and transmissible viral disease affecting equines (Craigo and Montelaro, 2008; Cook et al., 2009). It is endemic in the Pantanal and vaccines are not available to control the disease. The infected horses have their working capacity reduced or, if asymptomatic, may be a permanent source for the spread of the disease (Juliano et al., 2016).

Pantaneiro horses are generally not euthanized if they test positive for EIA. According to a Brazilian government web page, euthanasia is not required in endemic regions (Brasil, 2004). This fact leads to the investigation of whether infected horses perform satisfactorily when used in cattle management (Rezende et al., 2016). A growing number of cattle raisers use Pantaneiro horses in cattle management and are showing increased concern regarding this issue.

This study aimed to assess the physical performance of horses with and without EIA under functional conditions of cattle management. To this end, 16 male equines, equally split into two groups – EIA positive and EIA negative – were evaluated after a stress test. The performance was determined by multivariate methods and by data envelopment analysis (DEA) models with unitary inputs and further analyzed

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by nonparametric and bootstrap regression methods. The concept of DEA appears in the literature in the study of performance of decision-making units in a broader context. Decision-making units may be firms, schools, hospitals, airplane companies, farmers, or experimental units arranged according to an experimental design. Particularly in experimental design, the use of DEA is not new. Marlin and Sohn (2016) proposed a hybrid process that combines simulation, design of experiments, and DEA to study an educational system. Yang et al. (2016) applied DEA and design of experiment concepts to evaluate the emission of water pollutants. Leme et al. (2014) proposed a simulation approach based on the philosophy of design of experiments to test the impact of environmental variables on the DEA efficiency scores of Brazilian electricity companies. Grigoroudis et al. (2014) proposed a DEA model and optimal design to investigate biomass supply chain networks. Liu and Yang (2014) used DEA to obtain a robust design for the analysis of carbon filters. Gutiérrez and Lozano (2010) and Miranda et al. (2017) combined Taguchi's method (orthogonal arrays) and DEA to estimate the response of experimental units. Bezerra Neto et al. (2007, 2010, 2012) and Lima et al. (2014) used DEA models to evaluate the performance of intercropping production systems arranged according to different experimental designs. Gomes et al. (2008) proposed the use of DEA efficiency scores, with unitary input, in the multivariate analysis of variance. They discussed two examples of intercropping systems, where the experimental plots were arranged according to specific designs. The authors stated that this approach agrees with the standard analysis of variance (covariance) for univariate responses and simplifies the statistical analysis in the multivariate case.

The approach proposed here differs from the use of classical techniques, as for instance in Rezende et al. (2016). We borrowed the notion of performance from operational research, in which it is defined as a solution of optimization problems associated with production functions. Our view of performance is in close association with DEA, in a multicriteria decision analysis context (Gomes et al., 2008).

Material and Methods

The experimental design was completely randomized, with the choice of eight animals per treatment. Initial conditions of the animals differed. The following response variables were measured: lactic acid blood concentration, hematocrit (initial condition, immediately after the test, and 10, 30, and 60 min after the test), heart rate at four time periods, respiratory rate at three time periods, and distance achieved in the test. Contextual variables of interest were room temperature, horse age, horse weight, and horse superficial temperature (this is skin temperature measured in 11 different parts of the animal body, determined by a thermal imaging camera).

The objective of the statistical analysis was to compare the treatment effects (positive and negative for EIA), adjusted for the covariates. Having the same number of experimental units per treatment is a common choice in experimental design, which facilitates the consideration of type II probability errors in the design (Scheffé, 1959) and allows the same precision for the estimate of each treatment effect. As a performance vector, we initially considered a five-dimensional output vector with these components: distance achieved, lactic acid concentration, hematocrit score, heart rate score, and respiratory rate score (Tables 1 and 2). Later, the heart rate score was eliminated, given its negative rank correlation with distance and very low association with the remaining performance variables. Statistical methods considered here were descriptive statistics, standard nonparametric analysis with the use of ranks, standard multivariate analysis of variance, factor analysis, and regression analysis. Performance analysis is a modification of standard DEA models. We briefly summarize below only the most important topics for our analyses: multivariate factor analysis and DEA models assuming a unitary input.

Mardia et al. (1980) and Johnson and Wichern (2007) were referenced for the factor analysis. A vector of a p-dimension variable x with mean μ and variance-covariance matrix Ω satisfies the k-factor model if $x - \mu = \Lambda f + u$, $\Lambda = (\lambda_{ij})$ is a $p \times k$ matrix of constants. $f(k \times 1)$ and $u(p \times 1)$ are random. The common factors are the components of f. The components of u are the specific factors. The variance-covariance matrix of u is given by $\Phi = diag(\varphi_{11}, ..., \varphi_{pp})$. We then have $x_i - \mu_i = \sum_{j=1}^{k} \lambda_{ij} f_j + u_i$.

Under the factor model, the variance σ_i^2 of x_i is given by $\sigma_i^2 = \sum_{j=1}^{k} \lambda_{ij}^2 + \varphi_{ii}$. The term $h_i^2 = \sum_{j=1}^{k} \lambda_{ij}^2$ is called communality and represents the variance of x_i that is shared with the other variables via the common factors. $\lambda_{ij} = \text{Cov}(x_i, f_j)$ is the extent to which x_i depends on the j-th common factor.

The performance response score of horse i on the marginal dimension d of the output vector based on the k-factor model is defined, in our application, by a weighted average. The weights are the relative communalities as defined in (1). These scores differ from usual factor scores

and endow the weighting system with robustness relative to orthogonal transformations of the factor model.

$$y_i^d = \sum_{j=1}^{v} \theta_{jd} c_j^{id}, \ \theta_{jd} = h_{jd}^2 \Big/ \sum_{\tau=1}^{v} h_{\tau d}^2 \quad (1)$$

Data envelopment analysis models are defined by linear programming problems designed to measure performance under production assumptions or for benchmarking purposes. It is possible to consistently estimate a production function using DEA responses. Intuitively, a DEA measure estimates the maximum increase in production that can be achieved given input levels (see Cooper et al. (2011) for details about DEA modeling). In our application, the output-oriented notion is generalized to measure output performance when a vector of responses is characterized by marginal indicators. We assume unitary input for all experimental units to make the analysis consistent. This idea is not unusual in the DEA literature and can be seen, for instance, in Caporaletti et al. (1999), Lovell and Pastor (1999), De Koeijer et al. (2002), Leta et al. (2005), and Gomes et al. (2008, 2012).

In DEA modeling, it is necessary to define the units under evaluation – decision-making units – and the production variables (inputs and outputs). In an experimental design, the experimental units arranged according to the layout of the design are the decision-making units. The output vector is the non-negative response vector of each experimental unit. The issue under consideration is the

Table 1 - Experimental data – response variables

Experimental unit	Treatment	Lactic acid (mmol/L)	Distance (km)	Hematocrit (%)					Heart rate (beats per minute)				Respiratory rate (breaths per minute)		
				H_r	H_0	H_10	H_30	H_60	CF_r	CF_1	CF_2	CF_f	RF_r	RF_2	RF_f
1P	P	8.8	5.3	35	39	33	38	27	40	57	172	192.0	12	36	50.0
2P	P	10.7	6.0	34	42	34	35	29	40	101	149	205.0	12	56	88.0
3P	P	4.8	3.9	27	27	27	21	24	38	69	172	172.0	16	56	56.0
4P	P	17.2	5.2	28	34	29	28	28	37	100	111	158.0	16	52	72.0
5P	P	11.0	5.3	29	39	30	28	23	37	75	148	208.0	30	40	64.0
6P	P	6.1	4.0	32	40	35	32	25	45	106	202	202.0	20	56	56.0
7P	P	4.9	3.9	22	32	28	25	25	46	97	197	197.0	32	64	64.0
8P	P	5.3	3.9	33	34	30	30	29	38	96	167	167.0	30	56	56.0
1N	N	8.4	4.3	25	41	35	30	27	48	110	144	144.0	52	64	64.0
2N	N	19.8	5.3	26	45	31	30	25	50	74	178	178.0	48	96	84.0
3N	N	12.5	5.8	27	39	33	29	28	48	105	210	210.0	32	80	76.0
4N	N	8.1	5.8	25	41	32	29	42	48	92	130	130.0	30	53	53.0
5N	N	2.3	6.9	28	46	40	35	31	54	85	157	192.0	25	56	72.0
6N	N	17.8	5.4	34	44	40	35	35	54	85	204	204.0	28	60	60.0
7N	N	14.5	5.4	27	41	35	29	24	40	85	130	130.0	36	80	64.0
8N	N	10.2	5.6	27	40	33	31	32	52	105	161	161.0	36	60	84.0

P - testing positive for EIA; N - testing negative for EIA; H_r - hematocrit when resting; H_0 - hematocrit immediately after the stress test; H_10 - hematocrit 10 min after the stress test; H_30 - hematocrit 30 min after the stress test; H_60 - hematocrit 60 min after the stress test; CF_r - heart rate when resting; CF_1 - heart rate at time 1; CF_2 - heart rate at time 2; CF_f - final heart rate; RF_r - respiratory rate when resting; RF_2 - respiratory rate at time 2; RF_f - final respiratory rate.

Table 2 - Experimental data – contextual variables

Experimental unit	Room temperature (°C)	Horse weight (kg)	Horse age (years)	Horse superficial temperature (°C)										
				Tsg	Tsn	Tscx	Tsp	Tsc	Tspt	Tsa	Tsb	Tsj	Tsbp	Tspf
1P	26.6	370	22	35.8	34.2	35.5	34.7	35.4	35.0	34.7	34.3	35.8	34.9	34.7
2P	23.8	360	14	32.1	34.7	35.2	34.5	32.8	35.7	34.3	33.7	34.1	35.2	34.9
3P	26.6	385	15	36.3	34.4	37.4	35.6	37.0	34.7	35.4	35.8	36.9	35.5	35.3
4P	29.0	355	14	33.6	34.8	35.3	35.5	33.5	33.2	33.7	34.0	33.2	33.2	36.0
5P	30.5	362	14	34.7	36.5	37.0	36.0	35.6	37.1	37.0	36.2	34.7	36.7	35.0
6P	30.2	390	16	33.2	34.6	35.1	34.5	34.1	34.9	35.7	35.0	35.0	34.6	36.6
7P	33.6	359	15	39.3	39.7	38.5	39.1	38.6	37.6	37.8	37.9	37.4	37.3	37.5
8P	34.0	300	9	35.1	36.7	37.2	36.9	35.2	36.6	36.5	36.4	35.8	36.3	36.2
1N	36.1	360	10	35.7	37.5	37.8	37.3	36.8	37.5	37.5	37.1	36.8	37.5	36.8
2N	30.8	300	11	36.8	37.1	37.5	37.3	36.9	38.4	38.2	38.1	36.7	38.2	37.1
3N	32.1	310	11	33.2	35.9	35.5	35.3	34.0	35.7	36.0	35.0	33.6	35.0	36.4
4N	23.7	380	11	31.6	32.8	33.65	33.5	31.2	33.0	32.8	32.5	30.0	30.5	33.8
5N	27.6	388	11	35.8	34.8	36.7	35.5	35.2	36.4	36.7	35.9	35.1	36.8	36.1
6N	27.7	285	12	34.0	33.2	34.4	34.1	33.0	34.7	34.4	34.1	32.0	35.3	35.4
7N	30.9	355	9	33.3	35.5	36.0	35.4	34.1	36.4	36.8	35.9	34.7	36.6	35.9
8N	28.3	355	-	33.5	35.3	35.4	34.6	33.2	34.7	34.8	34.1	32.9	34.3	35.7

Tsg - croup; Tsn - buttocks; Tscx - gaskin; Tsp - legs; Tsc - cannons; Tspt - chest; Tsa - forearms; Tsb - arms; Tsj - knees; Tspb - neck; Tspf - nose.

assessment of treatment differences based on the output vector and unitary input. This is the approach suggested in Gomes et al. (2008).

Assuming unitary inputs is suitable for experimental design evaluation. Under this assumption, all experimental units are set on the same basis for comparisons. Therefore, the differences in the response vector are assumed to be due to error control variables (induced by the choice of the experimental design) and to the influence of contextual variables. These are qualitative or quantitative variables that affect the experimental units and which are under the control of the researcher. The effects of contextual variables are assessed in a second stage using a linear model and the DEA score as the response variable. In this context, we postulated the classical assumptions (Steel et al., 1996) of the analysis of variance (covariance).

The unitary input DEA model is presented in (2), in which h_o is the performance score (efficiency) of the experimental unit o, with production values $(1, y_o)$. Each experimental unit k, $k = 1...n$, produces s outputs y_{jk}, $j = 1...s$ (non-negative, not all zeros). The quantities u_j are the most favorable weights attributable to the response vector to calculate the performance score.

$$\begin{aligned} &\text{Max } h_o = \sum_{j=1}^{s} u_j y_{jo} \\ &\text{subject to} \\ &\sum_{i=1}^{r} v_i = 1 \\ &\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i \le 0, \quad k = 1,...,n \\ &u_j, v_i \ge 0 \quad \forall\, j,i \end{aligned} \tag{2}$$

We observed here that it is not necessary to assume an underlying production function (frontier) as a data-generating process for the output vector. We are interested here in a performance model instead of a production model. Data envelopment analysis also serves this purpose in general (Gomes et al., 2008; Cook et al., 2014). We assumed a data-generating process in which a population of DEA responses is determined by the experimental error, given that the values of covariates are fixed.

Results

The multivariate factor analysis for the performance indicators hematocrit, heart rate, respiratory rate, and superficial temperature of the horse (Table 3) indicated a one-factor model for each dimension (Table 4).

Scores of DEA and the corresponding weights assigned by the DEA model were computed in the optimal solution for each animal (Table 5). The average weights to be applied to each output variable were also determined (Table 5). The modified DEA score is a linear combination of the ranked output variables using these average weights, leading to the final performance scores and the corresponding rank transformation (Table 6).

Finally, we performed a nonparametric regression analysis of the final performance scores on the regressors treatment effect and room temperature (Table 7). The statistical model used is $R_{ij} = \mu + \tau_i + \beta t_{ij} + \varepsilon_{ij}$, $i = 1,2$ $j = 1,...,16$, in which R_{ij} is the rank of the performance score of horse j under treatment i, subject to rank of room temperature t_{ij}. The constants μ, τ_i, and β are parameters to be estimated. Parameter μ is an overall mean, τ_i are treatment effects, and β is the decrease in performance resulting from the increase in one unit of room temperature. The model does not include an interaction effect in room temperature. The error term ε_{ij} may be neither normal nor homoscedastic.

Table 3 - Multivariate factor analysis for hematocrit, heart rate, respiratory rate, and animal superficial temperature

Hematocrit		Heart rate		Respiratory rate		Superficial temperature	
Component	Communality	Component	Communality	Component	Communality	Component	Communality
H_r	0.3002	CF_r	0.1211	RF_r	0.4480	Tsg	0.7235
H_0	0.6842	CF_1	0.0001	RF_2	0.6620	Tsn	0.7967
H_10	0.7071	CF_2	0.6939	RF_f	0.2373	Tscx	0.9118
H_30	0.8605	CF_f	0.5228			Tsp	0.8794
H_60	0.1280					Tsc	0.8714
						Tspt	0.7916
						Tsa	0.8816
						Tsb	0.9629
						Tsj	0.7888
						Tsbp	0.8017
						Tspf	0.6004

H_r - hematocrit when resting; H_0 - hematocrit immediately after the stress test; H_10 - hematocrit 10 min after the stress test; H_30 - hematocrit 30 min after the stress test; H_60 - hematocrit 60 min after the stress test; CF_r - heart rate when resting; CF_1 - heart rate at time 1; CF_2 - heart rate at time 2; CF_f - final heart rate; RF_r - respiratory rate when resting; RF_2 - respiratory rate at time 2; RF_f - final respiratory rate; Tsg - croup; Tsn - buttocks; Tscx - gaskin; Tsp - legs; Tsc - cannons; Tspt - chest; Tsa - forearms; Tsb - arms; Tsj - knees; Tspb - neck; Tspf - nose.

Table 4 - Aggregate scores

Experimental unit	Hematocrit score (%)	Heart rate score (beats per minute)	Respiratory rate score (breaths per minute)	Superficial temperature score (°C)
1P	36.0748	167.8530	30.4847	34.991
2P	36.1248	161.0071	47.0040	34.286
3P	24.9302	159.8582	42.6989	35.875
4P	29.7957	122.6627	43.5510	34.161
5P	31.2093	161.3870	40.9012	36.100
6P	34.4997	187.7760	44.0290	34.825
7P	27.2426	183.3190	53.3591	38.257
8P	31.3095	155.3134	47.3543	36.288
1N	33.4243	135.3044	60.0097	37.148
2N	33.4066	166.4014	77.9254	37.508
3N	32.3367	195.3226	63.3342	35.048
4N	33.0279	122.5718	45.3518	32.306
5N	38.1525	161.3432	48.5092	35.914
6N	38.5050	190.4081	49.3591	34.028
7N	33.1840	121.8469	62.5511	35.532
8N	33.4251	151.1256	56.2458	34.392

Table 5 - Data envelopment analysis (DEA) scores and output weights

Experimental unit	DEA score	DEA weight			
		Lactic acid	Distance	Hematocrit score	Respiratory rate score
1P	0.8751	0.0157	0.1505	0.0059	0.0000
2P	1.0000	0.0137	0.1317	0.0052	0.0000
3P	0.5857	0.0244	0.2439	0.0000	0.0000
4P	1.0000	0.0180	0.1439	0.0000	0.0000
5P	0.9144	0.0187	0.1498	0.0000	0.0000
6P	0.7500	0.0000	0.0000	0.0833	0.0000
7P	0.7068	0.0000	0.1064	0.0000	0.0532
8P	0.6277	0.0000	0.1863	0.0000	0.0342
1N	0.9096	0.0000	0.0000	0.0397	0.0464
2N	1.0000	0.0625	0.0000	0.0000	0.0000
3N	1.0000	0.0000	0.0752	0.0000	0.0376
4N	0.9143	0.0156	0.1563	0.0000	0.0000
5N	1.0000	0.0000	0.0340	0.0510	0.0000
6N	1.0000	0.0000	0.0000	0.0625	0.0000
7N	0.9630	0.0144	0.1382	0.0028	0.0032
8N	0.9362	0.0148	0.1421	0.0029	0.0033
Mean		0.0124	0.1037	0.0158	0.0111

Table 6 - Final performance scores

Experimental unit	Final performance score (values normalized by the maximum)	Rank of the final performance score
1P	0.5702	8
2P	0.9849	15
3P	0.1400	1
4P	0.4417	5
5P	0.5233	7
6P	0.3595	4
7P	0.1983	2
8P	0.2115	3
1N	0.4519	6
2N	0.6709	9
3N	0.9010	14
4N	0.8221	12
5N	1.0000	16
6N	0.8158	11
7N	0.7625	10
8N	0.8279	13

Table 7 - Nonparametric regression – bootstrap replications

	Coefficient	Bias	Bootstrap standard error	Bias-corrected 95% confidence interval	
Treatment effect	6.0764	1.0000	1.5340	2.9489	8.9710
Room temperature	−0.4351	0.0073	0.2026	−0.8307	−0.0253
Constant	9.1605	−0.1399	2.6542	3.7820	13.9987

Discussion

Regarding the multivariate factor analysis, the hematocrit indicator had five components, heart rate had four, respiratory rate had three, and superficial temperature had 11 components. The likelihood ratio tests of orthogonality produced the statistics 43.05 ($P<0.001$), 13.23 ($P = 0.0395$), 11.45 ($P = 0.0095$), and 286.89 ($P<0.0001$) for the hematocrit, heart rate, respiratory rate, and superficial temperature, respectively. Under the null hypothesis of independence (non-factor model), the distributions are chi-square with 10, 6, 3, and 55 degrees of freedom, respectively. These statistical tests support the factor model. Models with more than one factor did not converge under maximum likelihood estimation. Therefore, we used the minimum eigenvalue equal to 1 as the choice criterion of the number of factors, which leads to one factor in all cases, implying average aggregated scores calculated using the relative communalities as weights (Table 4).

The performance vector, that is, the output variables for the DEA model, is defined by distance achieved, lactic acid blood concentration, hematocrit score, heart rate score, and respiratory rate score. It is important to emphasize here that these data were ranked before undergoing the DEA analysis.

We performed a multivariate analysis of variance using the ranked output variables as dependent variables. The independent variables were treatment (positive and negative for EIA), ranked room temperature, ranked animal weight, ranked animal age, and ranked animal superficial temperature score. Wilks' lambda test of treatment effect was not significant. In this context, DEA provides a better insight into the performance issue, discriminating the responses for treatments.

The output variables were subjected to a screening process before applying DEA. The very nature of DEA precludes negative correlations between the final performance achieved and the output components. This was the case with heart rate in our application, showing a rank correlation of −0.326 with the distance and low correlations with the hematocrit score, respiratory rate, and lactic acid concentration. For this reason, we opted to eliminate heart rate and use a four-dimensional output in the DEA model.

From the DEA results (Table 5), we understand that a null weight for a variable such as distance achieved is not acceptable in the calculation of a global performance score. An alternative within DEA models to avoid this drawback is to impose restrictions on the weights (Thanassoulis et al., 2004). Typically, these are achieved by introducing preferences (by means of value judgments) on the relative worth of the variables. We believe that a better approach in our case is to use average weights for each variable. The weights are normalized means of individual DEA solutions. Thus, our final performance scores were weighted averages of rank-transformed values (Table 6).

The box plots for rank-transformed final efficiency score by treatment effect (Figure 1) indicate a reduction of more than 60% in performance from negative EIA (11.5) to positive EIA (4.5) horses, measured by unadjusted (for covariates) median responses. The five-number summaries are: positive EIA – minimum = 1.0, Q1 = 2.5, median = 4.5, Q3 = 7.5, maximum = 15.0; negative EIA – minimum = 6.0, Q1 = 9.5, median = 11.5, Q3 = 13.5, maximum = 16.0.

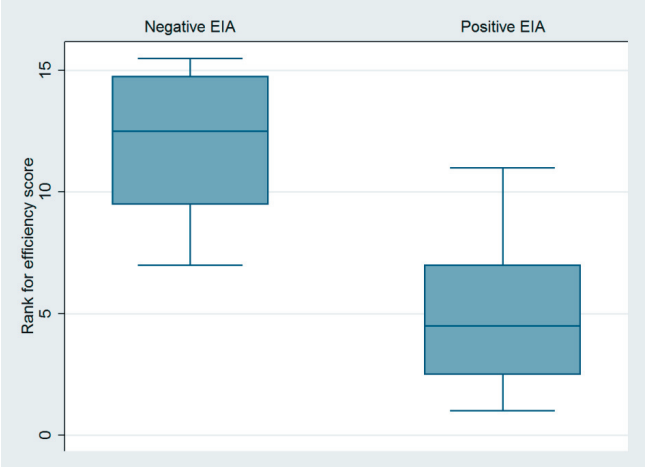

Figure 1 - Box plots: efficiency scores by treatments.

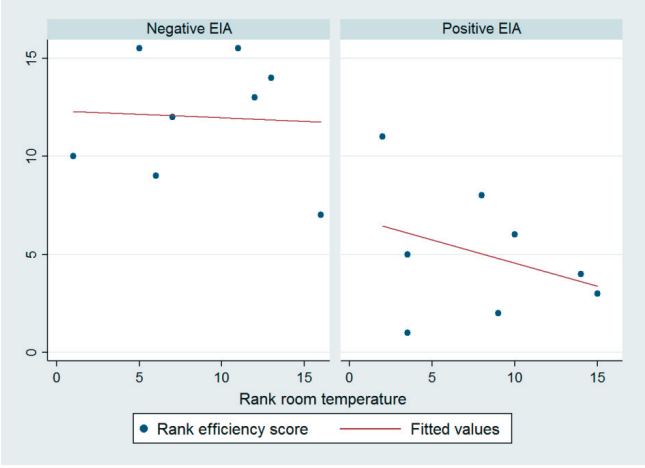

Figure 2 - Efficiency scores versus room temperature by treatment.

All covariates correlated negatively with the performance score. Together, they did not lead to a significant model. Included one at a time, they produced significant treatment effects and P-values of 0.0819, 0.6247, 0.6336, and 0.0320 for animal superficial temperature, animal weight, animal age, and room temperature, respectively. Including room temperature in the model was enough. The addition of any other covariate combinations was not statistically significant. Thus, the best parsimonious model used treatment and room temperature as covariates.

The behavior of the efficiency scores as a function of room temperature suggests a negative effect for both treatments (Figure 2), more intense for the positive EIA horses. The difference in slopes (Figure 2) was not sufficient to declare an interaction effect. Correlations induced by the computations among final performance scores of animals were handled by a nonparametric bootstrap (Table 7). We performed 2,000 replications using Stata 14.1 (Stata, 2015).

The main point we emphasize (Table 7) is the EIA effect on performance adjusted by room temperature. We assessed this effect using the intercepts in the cases of positive and negative EIA . The relative reduction in performance was, therefore, 6.0764 / 15.2369 = 39.9%.

Conclusions

Animal age, animal weight, and animal superficial temperature do not significantly affect the performance score. Given that room temperature and treatment have been fitted, these covariates do not increase model significance. There is a significant treatment effect and a significant negative slope regression coefficient for room temperature. Adjusted for room temperature, there is a decrease of almost 40% in performance of positive EIA horses compared with horses testing negative for EIA. Therefore, the control of this disease in the Pantanal wetlands is of importance, as it may reduce the performance of the horses, considering the functional conditions of cattle management.

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