Measuring Efficiency on Milk Production Farms on the Cities of the Agreste Region of Pernambuco

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ABSTRACT

The present paper intends to conduct an efficiency analysis of cow milk production in the farms of the "Agreste" region of the Brazilian state of Pernambuco. The efficiency scores are obtained using Data Envelopment Analysis (DEA) methodology, and the size of the produced unit is given by the amount of milk produced. The results obtained show the relationship between size and their efficiency scores.

Key-words: Efficiency Analysis; Milk Production; Data Envelopment.

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1. INTRODUCTION

For the efficiency analysis, it will be used the Variable Return to Scale, proposed by Charnes, Cooper, and Rhodes (1978), measuring efficiency a La Farrell (1957) modeled with the R package “Benchmarking” by Bogetoft and Otto (2011). Some hypothesis tests and Bootstraps were made using the R package “FEAR” by Wilson, Paul W. (2008).

2. LITERATURE REVIEW

The modeling chosen relies on the input-output approach, required for the formulation of an efficiency frontier. The following papers have a series of elaborated analyses on which this article will be inspired:

Table 1: Efficiency modeling on literature

Authors	Year	DMUs	Outputs
Yuping Bai et. Al	2019	Meat Production Households	Total meat production of pigs, cattle and sheep
Hinrich D. Schultea et. Al	2018	Milk Production Households	Milk production per cow
S.H. Evers et. Al	2021	Milk Cow’s Milk Production	Milk solid production; Mid-lactation bodyweight
Hasan Yilmaz; Fekadu Gelaw; Stijn Speelman	2020	Milk Production Households	Milk production
Geraldo da Silva e Souza; Eliane Gonçalves Gomes	2020	Brazillian Cities	Production gross income
Ruxin Zhanga et. Al	2020	Multi-Household Livestock Farms	Livestock income; Grassland condition
Souhil Harchaoui; Petros Chatzimpiros	2017	Livestock Production Farms	Meat beef, sheep and goat; Meat pork; Meat chicken; Eggs; Milk
Zhaomin Hu et. Al	2019	Cattle Raising Farms	Livestock value

Wei Huang; Bernhard Bruemmer; Lynn Huntsinger	2016	Yak Production Farms	Yak meat; Revenue of other outputs
Katarina Labajova et. Al	2016	Pig Production Farms	Income from pig production; Income from production not related to pigs

Some papers to put in evidence here are Souza e Gomes (2020) and Schultea et. al.(2018), which put some intriguing factors in evidence to observe while modeling for efficiency, specifically for milk production.

In summary, both papers approach the efficiency of milk production by the quality of life of the cattle, but in two different ways. The first one goes about the amount and variety of the grass and the area available for pasture, while the second paper mentioned correlates the quality of life with the time spent on grazing, and some other factors, like the quality of the water.

3. DATA

3.1. Descriptive statistics

The data reviewed in this article was collected from the Brazillian Institute of Geography and Statistics (IBGE) and contains data from the Agriculture Census of 2017, the chosen subject was the production of milk for each city in the “agreste” region of the state of Pernambuco.

This data contains three missing values, all of which are associated with the city of Sairé, for that reason, this city will be disregarded from every further analysis in this paper. On the table below, are the descriptive data from the chosen dataset:

Table 2: Discriptive statistics

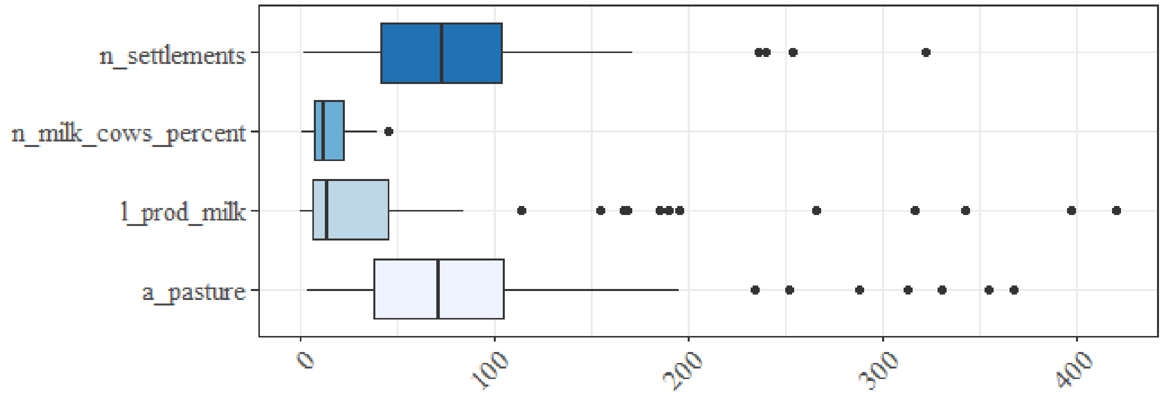
Variables	Mean	SD	1st Quartile	Median	3rd Quartile
l_prod_milk	5643.84	9654.70	657.50	1379.00	4540.25
n_settlements	831.41	597.42	419.25	736.00	1040.50
a_pasture	9306.26	8348.71	3828.13	7171.40	10452.69
n_milk_cows_percent	15.39	11.10	7.99	12.28	22.12

Source: IBGE, own elaboration

The variable "city" indexes the data for each following variable, "l_prod_milk" shows the production of milk in the city in liters, "n_settlements" is for the number of settlements that part or all production is destined for milk production, "a_pasture" is for the number of the total area destined for pasture in the cities (hectare), "n_milk_cow_percent" shows the percentage of the number of milk cows to the total cattle population of the city.

One peculiarity of this data set is on the distribution of all variables being very similar, with clustering of small values and less than 20 observations with high values, as outliers.

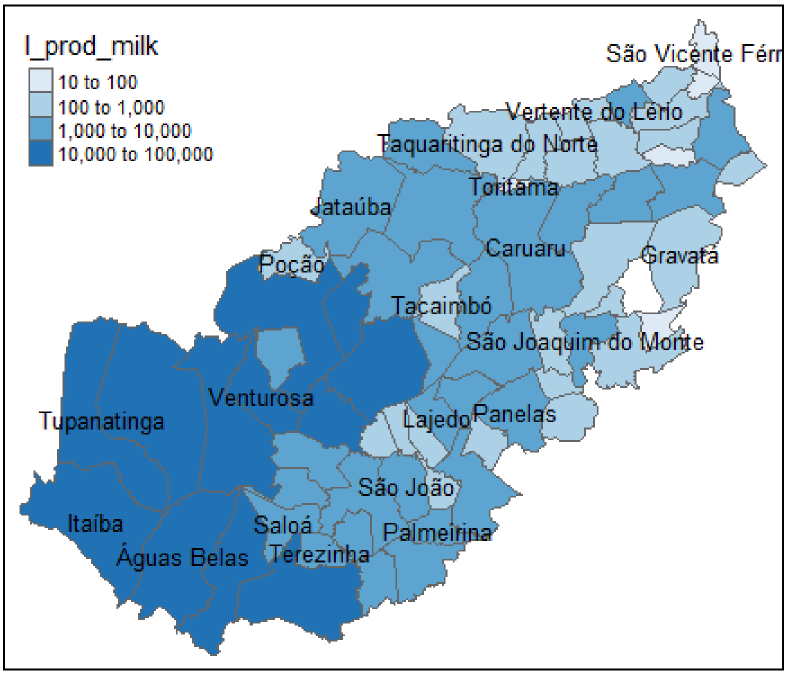
Figure 1: Boxplot of the data



* "a_pasture", "l_prod_milk" and "n_settlements" in 100
Source: IBGE, own elaboration

These outliers are also geographically clustered, it might have some connection with their geographic clustering, as can be observed in the map below:

Figure 2: Geographic allocation of milk production



From the distribution of liters of milk produced ("l_prod_milk"), it's possible to distinguish a few outliers, that represent the cities where most of the milk is produced for this region, these cities will be considered major producers and, for this article, their efficiency benchmark will have higher importance.

Table 3: Biggest and smallest milk producing units

City	Milk Produced (liters)	Total milk production
Itaíba	42042	10.64%
Pedra	39711	10.05%
São Bento do Una	34195	8.66%
Buíque	31689	8.02%
Venturosa	26598	6.73%
Tupanatinga	19520	4.94%
…	…	…
João Alfredo	126	0.03%
Cupira	114	0.03%
Machados	73	0.02%
Barra de Guabiraba	58	0.01%

Toritama	50	0.01%
Salgadinho	36	0.01%
São Vicente Férrer	14	0%

Source: IBGE, own elaboration

The cities of Itaíba, Pedra, São Bento do Una, Buíque and Venturosa are the main milk producers in Pernambuco, with historical tradition of cattle raising in the region. Together, they produce 44,1% of all the cow milk. While amongst the cities that produces less milk are Cupira and Toritama, this can be explained by their production systems being focused in clothes and fabric.

Table 4: Correlation Matrix

	l_prod_milk	**n_settlements**	**a_pasture**	**n_milk_cows_percent**
l_prod_milk	1.0000000	0.6530965	0.7323288	0.7861810
n_settlements	0.6530965	1.0000000	0.6453945	0.4238180
a_pasture	0.7323288	0.6453945	1.0000000	0.4331127
n_milk_cows_percent	0.7861810	0.4238180	0.4331127	1.0000000

Another interesting thing to notice is the correlation between the area for grazing and the amount of milk produced (0.73), but between the inputs, even though it was taken care that the correlation wasn’t too high, there where found a relatively strong correlation between most of the inputs. This condition might make it difficult to indicate the variable that should change to increase efficiency.

4. METHODOLOGY

4.1. Choosing the Efficiency Model

Before choosing a model, it was necessary to evaluate the assumptions with R’s FEAR package by Wilson, Paul W. (2008). The two tests, developed by Kneip et al. (2016) and Simar and Wilson (2020), approach the hypothesis of constant return to scale and convexity of the production, respectively, in which both were rejected.

Based on the given results, the first model selected was Free Disposability Hull (FDH), which, according to Lawrence et. al (2017), is more robust to less substitutable inputs and creates a frontier based only on actual observations, instead of weighted averages.

Given the hypothesis of constant return to scale being rejected, as a second option, the Variable Return to Scale (VRS) model will be tested too, yet this is one of the most common, given that neoclassic economics defaults to the assumption of convexity of input requirement and output possibilities (LAWRENCE et. al, 2017), which was rejected by the previous statistical tests.

4.2. Directional Model Hypothesis

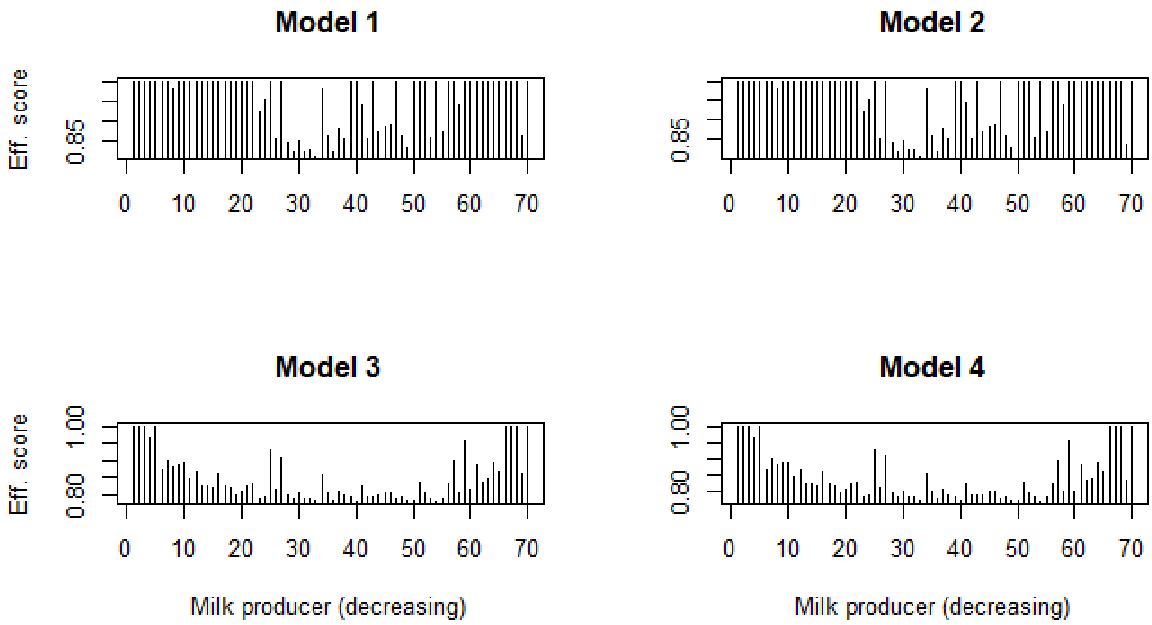
According with Lawrence et. al. (2017), the directional parameters are usually defined by specialists, because they may be able to tell which values should be assigned, given the disposal of inputs and outputs, and their theoretical relationship.

However, it is possible for a non-specialist on the field to assign non-discretionary variables to the data envelopment model, for the efficiency scores to be compatible with the assumption that, whether the input can be reallocated to increase efficiency or not.

For this study, the impossibility of reallocating the number of settlements will be taken into consideration. This means that the city governments cannot increase or decrease the number of milk farms in their territory to increase efficiency, but the other variables, which are controlled by the farmers, can all be reallocated, including the area available for grazing.
On the other hand, it will be tested for output to be discretionary, for whether it's best to leave the amount of milk collected to be decided by the inputs, or if the farmers should decide the amount of milk collected as a proxy for the number of milkings made.

Figure 2 shows the efficiency scores for each model, where "Model 1" and "Model 2" are set up as FDH, but the first leaves the output as discretionary, as the opposite of the latter, the same goes for "Model 3" and "Model 4", but considering the variable return to scale assumption (VRS model), the observations are ordered by the amount of milk produced by the unit (decreasing).

Figure 3: Efficiency Scores

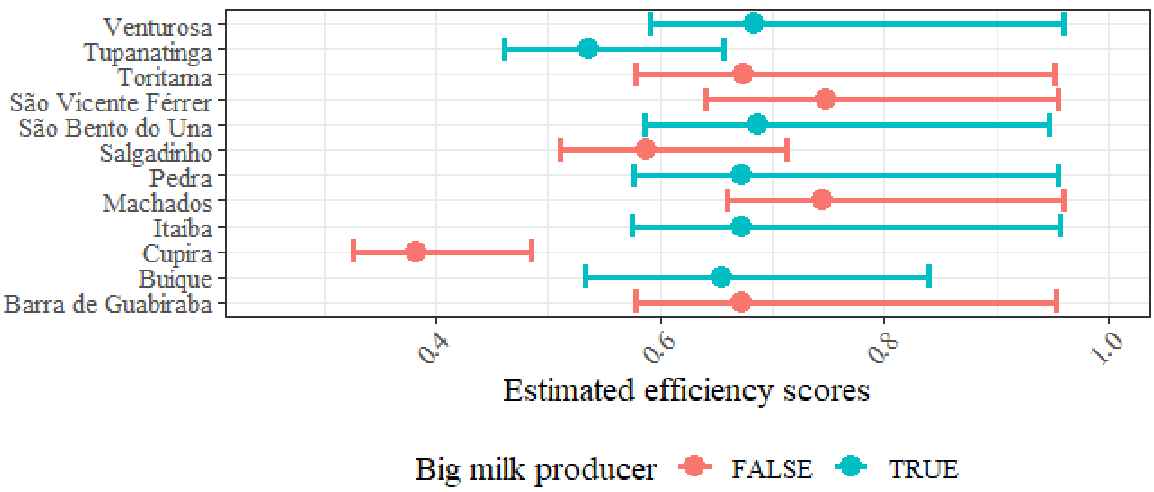


The FDH models oddly leave high-efficiency scores for most of the observations, so it doesn't seem to be a good choice for evaluating efficiencies, the model kept for every further analysis will be the "Model 4", using Variable Return to Scale (VRS) and keeping output as not discretionary.

4.3. Bootstrapping and Separability

Bootstrapping can be very useful for estimating the statistical significance of the estimated efficiencies as well as for obtaining unbiased efficiency scores:

Figure 4: Estimated efficiency scores for the most important DMUs



In Figure 3, the DMUs with the highest efficiency scores were the same highlighted in Figure 4. Most of them have displayed efficiency score values equal to or next to one, but the bootstrapped results showed values next to 0.7 with confidence intervals that do not reach 1, this indicates the presence of bias and possible omitted variables.

5. ASSESSMENT AND DISCUSSION

Only a few of the studied cities produced high-efficiency scores, and these units were significantly divided between the largest producers and the smallest ones. Figure 3 and Table 5 endorse this statement, the latter one displays the number of units peered by each performance reference unit. The results obtained in Figure 3 raise a question about how statistically significant are the difference of the actual (bootstrapped) efficiency scores of the major and lesser milk producers.

Table 5: Most efficient cities and their peering benchmark

City	Peered	Milk Produced (liters)
Itaíba	52	42042
Barra de Guabiraba	44	58
São Vicente Férrer	24	14
São Bento do Una	19	34195
Machados	12	73
Pedra	6	39711
Venturosa	3	26598
Toritama	2	50

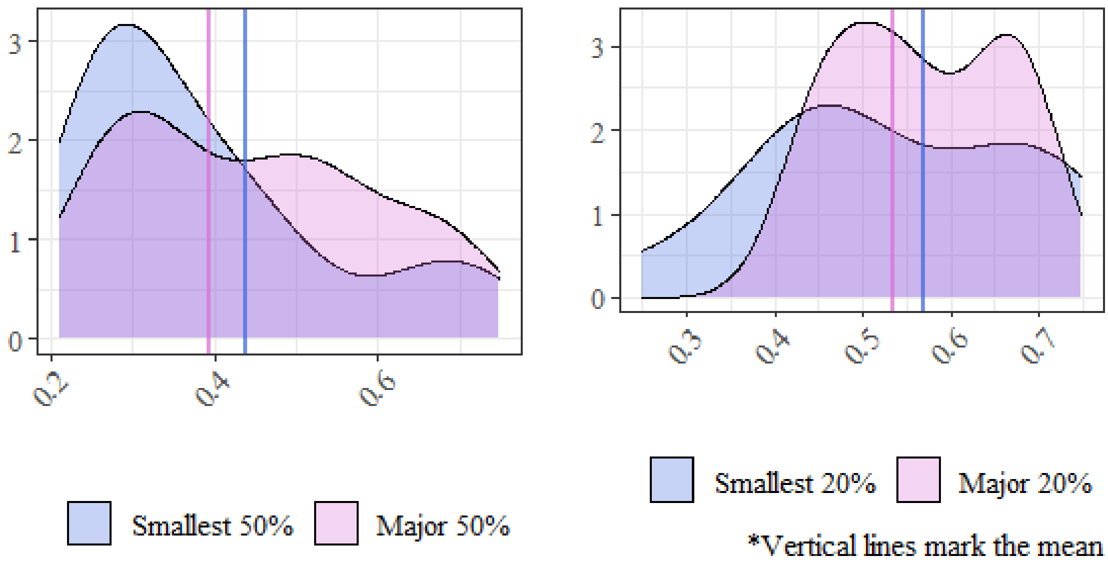
The acceptability of a set of tests depends on the distribution shape of the data, the central limit theorem could not be applied trivially because the data does not come from a population sample but a set of estimated statistics. Before proceeding with any tests, the dataset was to be evaluated for its distribution's shape in this case, so the bootstrapped efficiency scores were tested for normality with the Shapiro-Wilk test, in which the null hypothesis was rejected.

Since the normality hypothesis was rejected and the central limit theorem would not be applied, the differences tested in the data must be non-parametric in this case, the chosen test was Mann-Whitney for true location shift hypothesis, which uses Wilcoxon's statistic, but modified to involve two samples. The samples' were chosen by size, based on their available number of observations, their size between tests would differ by at least ten observations, and this number would also be the minimum amount for each sample.

Table 6: Statistical tests for bootstrap results

Test	P-Value	Null hypothesis
Shapiro-Wilk	0.0000700	Normality
Mann-Whitney (Major and Smallest 50%)	0.1767593	True location shift is not zero
Mann-Whitney (Major and Smallest 20%)	0.5052568	True location shift is not zero

Figure 5: Density plots for tested bootsrap results



The p-values displayed in Table 6 tell that the hypothesis of true location shift is equal to zero could not be rejected, which means that there were significant differences between the samples selected. Figure 5 shows their distributions for checking over, it is possible to notice that the mean bootstrapped estimates of the smallest producers (vertical orchid lines) are placed to the right in comparison to the mean bootstrapped estimates of the major producers (vertical blue lines) in both cases, which means that the smallest producers have, in general, higher efficiency scores.

Classical reference in the academy such as Gooding et. al (1985) suggests a non-significant or negative relationship between the size of the organization and its efficiency. However, most recent studies have somewhat different conclusions, like a non-linear relationship (HELFAND; LEVINE, 2004), or no clear relationship (ARAGON; RESTUCCIA, 2021).

According to Helfand and Levine (2004), the non-linear correlation between efficiency and farm size is negative along with the small and average-sized units, but positive between the average and big sized ones, although this conclusion comes very close to what is observed in

Figure 3, this affirmation cannot be perfectly related to the data of the present study, since the DMUs used are cities, instead of milk production households.

But some resemblance is to be kept since the cities that produce more milk in this dataset have more traditional cattle raising farms, as this production sector plays a big role in those cities' economy, meanwhile, cities that show the least milk production have other preponderant production sectors, as already mentioned before. So it's expected that the cities that produce more milk will have, on average, larger livestock farms.

6. CONCLUSIONS

In this study, the efficiency models showed high-efficiency scores and a high amount of peered units concentrated among the major and the lesser milk production units considered. These results were confirmed after the bootstrap, even though every efficiency score was reduced, with the mean of the scores going from 0.5255 to 0.4157 after the bootstrap.

The relationship between efficiency and size found here corroborates the findings of Helfand and Levine (2004), but with a slight addition, that the smallest units tend to show higher efficiency scores. There are still limitations to this conclusion, since the study was performed with a single region of one state, so to elaborate a definitive conclusion, more regions should be observed.

With that said, it is also possible that the higher efficiency scores for smaller units can be related to the increasing complexity of the production system, which makes it difficult to make tight adjustments to the production process. But this hypothesis cannot be tested with the present data and will remain as a suggestion to future studies.

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Appendix A: Commented Routines used in R for data analysis.

Annexed.

Appendix B: Complete dataset

Main variables

city	l_prod_milk	n_settlements	a_pasture	n_milk_cows_percent
Águas Belas	18514	1505	33017.815	28.6917715
Buíque	31689	3217	35434.980	29.3557204
Itaíba	42042	2533	36697.738	33.2957860
Pedra	39711	1026	31271.435	39.9533051
Tupanatinga	19520	1273	14988.553	37.3742828
Venturosa	26598	806	9410.087	45.3767561
Bom Jardim	541	1689	3900.496	4.4110855
Cumaru	1874	1134	12417.716	11.8964454
Feira Nova	154	369	2225.897	3.7152581
Frei Miguelinho	656	572	8049.638	10.2961485
João Alfredo	126	1357	4888.937	1.7932489
Limoeiro	1417	647	8741.973	4.7657952
Machados	73	177	1101.537	2.1950190
Orobó	167	1253	4119.845	3.1070021
Passira	1405	871	8169.474	9.9346898
Salgadinho	36	303	1164.231	6.3015027
Santa Maria do Cambucá	208	373	1425.683	9.4020797
São Vicente Férrer	14	164	2421.991	1.0204082
Surubim	990	915	6726.665	10.5152716
Taquaritinga do Norte	668	507	14013.199	4.3575064
Toritama	50	25	414.792	9.4339623
Vertentes	834	394	7685.518	9.9934146
Alagoinha	8480	593	5790.443	33.3606222
Belo Jardim	4406	762	5409.878	25.4802415
Bezerros	367	549	7375.079	5.8814567
Brejo da Madre de Deus	1819	792	10628.315	11.1707596
Cachoeirinha	3748	470	3584.314	16.7546174

Capoeiras	16902	1697	9925.832	30.9210936
Caruaru	2311	685	10633.599	10.8466099
Gravatá	914	478	5393.512	9.1775731
Jataúba	1176	532	3168.088	12.8947368
Pesqueira	16702	1036	13552.313	27.4724624
Poção	826	347	4820.298	13.5030303
Riacho das Almas	1353	738	5471.743	15.1688974
Sanharó	11433	519	5971.409	38.2096070
Santa Cruz do Capibaribe	1168	268	9185.361	17.0738887
São Bento do Una	34195	2359	14283.434	35.0873177
São Caitano	1571	591	6648.881	14.9062049
Tacaimbó	611	349	2489.086	18.2845041
Agrestina	898	416	9490.974	7.9425711
Altinho	6109	1715	23390.117	12.6584411
Angelim	604	341	5232.486	9.2678180
Barra de Guabiraba	58	43	4030.350	0.9433962
Bom Conselho	19013	1318	28810.530	26.3059562
Bonito	293	372	9342.638	1.3739594
Brejão	1845	429	7171.510	15.7745681
Caetés	8396	2393	7171.291	28.1188766
Calçado	880	892	2803.204	14.2294322
Camocim de São Félix	455	76	982.464	13.1341601
Canhotinho	2070	1046	25182.785	3.9003250
Correntes	3549	920	19541.945	11.2825588
Cupira	114	335	5054.105	2.1869874
Garanhuns	4822	1206	15008.551	15.5474603
Iati	15478	741	17977.759	36.4715006
Ibirajuba	7133	829	7528.410	25.2133012
Jupi	662	734	2266.262	10.3614458
Jurema	899	851	3766.383	8.1139404
Lagoa do Ouro	3805	1042	8790.110	17.1233535

Lagoa dos Gatos	196	679	7721.784	1.9355463
Lajedo	4585	838	3804.014	20.1925800
Palmeirina	1316	533	9496.238	10.8148988
Panelas	1040	1100	13814.458	5.7453301
Paranatama	1761	761	5764.958	15.0036066
Saloá	3387	629	8226.388	20.7938014
São João	1337	1093	7249.491	8.4141233
São Joaquim do Monte	2369	336	3716.596	4.3905747
Terezinha	3538	532	6645.813	24.7580393
Casinhas	1471	844	3758.768	18.4337738
Jucati	932	962	3521.312	10.6245090
Vertente do Lério	785	318	1557.048	22.5600000

Ommited or transformed variables

city	n_milk_cows	l_prod_milk	n_rep_heads	l_prod_milk/cow	n_heads/a
Águas Belas	5722	18514	7545	3235.66	0.60
Buíque	11277	31689	14224	2810.09	1.08
Itaíba	11528	42042	15924	3646.95	0.94
Pedra	10952	39711	12286	3625.89	0.88
Tupanatinga	5537	19520	4912	3525.30	0.99
Venturosa	7106	26598	7738	3742.97	1.66
Bom Jardim	382	541	1295	1415.80	2.22
Cumaru	1158	1874	2471	1618.09	0.78
Feira Nova	131	154	1124	1176.08	1.58
Frei Miguelinho	671	656	1426	977.53	0.81
João Alfredo	136	126	1005	923.41	1.55
Limoeiro	525	1417	2818	2698.64	1.26
Machados	52	73	267	1407.12	2.15
Orobó	205	167	614	812.61	1.60

Passira	791	1405	1517	1775.71	0.97
Salgadinho	130	36	191	274.14	1.77
Santa Maria do Cambucá	217	208	489	957.34	1.62
São Vicente Férrer	32	14	369	439.19	1.29
Surubim	902	990	1892	1097.67	1.28
Taquaritinga do Norte	274	668	941	2439.69	0.45
Toritama	30	50	88	1657.77	0.77
Vertentes	607	834	1680	1374.74	0.79
Alagoinha	2445	8480	2813	3468.32	1.27
Belo Jardim	1857	4406	2486	2372.88	1.35
Bezerros	386	367	2188	950.73	0.89
Brejo da Madre de Deus	978	1819	2709	1859.83	0.82
Cachoeirinha	1524	3748	1579	2459.08	2.54
Capoeiras	4965	16902	6155	3404.30	1.62
Caruaru	1171	2311	3413	1973.64	1.02
Gravatá	568	914	1735	1609.07	1.15
Jataúba	637	1176	1410	1845.94	1.56
Pesqueira	4639	16702	5723	3600.28	1.25
Poção	557	826	865	1483.62	0.86
Riacho das Almas	952	1353	1426	1420.97	1.15
Sanharó	3325	11433	3789	3438.50	1.46
Santa Cruz do Capibaribe	580	1168	1166	2013.45	0.37
São Bento do Una	10729	34195	12058	3187.20	2.14

São Caitano	1033	1571	1297	1520.52	1.04
Tacaimbó	518	611	600	1180.34	1.14
Agrestina	603	898	1453	1490.00	0.80
Altinho	3006	6109	6000	2032.24	1.02
Angelim	381	604	1199	1586.40	0.79
Barra de Guabiraba	26	58	1317	2224.04	0.68
Bom Conselho	7040	19013	9144	2700.78	0.93
Bonito	170	293	4396	1726.08	1.32
Brejão	1114	1845	1842	1655.94	0.98
Caetés	3444	8396	4072	2437.80	1.71
Calçado	614	880	969	1433.44	1.54
Camocim de São Félix	233	455	690	1953.73	1.81
Canhotinho	972	2070	6508	2129.37	0.99
Correntes	2508	3549	6572	1415.17	1.14
Cupira	120	114	1081	950.26	1.09
Garanhuns	2262	4822	4522	2131.95	0.97
Iati	4703	15478	4637	3291.12	0.72
Ibirajuba	2305	7133	3092	3094.50	1.21
Jupi	387	662	427	1711.82	1.65
Jurema	564	899	1190	1594.49	1.85
Lagoa do Ouro	1781	3805	2654	2136.67	1.18
Lagoa dos Gatos	200	196	2051	979.28	1.34
Lajedo	1426	4585	2256	3215.03	1.86
Palmeirina	1144	1316	2303	1150.62	1.11
Panelas	772	1040	3567	1347.53	0.97
Paranatama	624	1761	962	2821.49	0.72
Saloá	1315	3387	1879	2575.39	0.77
São João	703	1337	1044	1901.18	1.15

São Joaquim do Monte	259	2369	1662	9146.95	1.59
Terezinha	1586	3538	2271	2230.83	0.96
Casinhas	1144	1471	1600	1285.76	1.65
Jucati	541	932	1108	1722.92	1.45
Vertente do Lério	564	785	699	1391.26	1.61

Other variables, used for separabilty test

city	city_cod	longi	latit
Águas Belas	2600500	-35.93193	-8.441255
Buíque	2602803	-37.02117	-9.086871
Itaíba	2607505	-36.75820	-8.531098
Pedra	2610806	-36.07081	-8.484560
Tupanatinga	2615805	-36.27863	-8.846004
Venturosa	2616001	-35.62545	-8.391531
Bom Jardim	2602209	-36.42518	-8.277592
Cumaru	2604908	-35.81962	-8.261253
Feira Nova	2605400	-36.63801	-9.199287
Frei Miguelinho	2605806	-35.58606	-7.774995
João Alfredo	2608107	-35.69812	-8.501608
Limoeiro	2608909	-36.55959	-9.031039
Machados	2609105	-36.21730	-8.064194
Orobó	2609709	-37.12415	-8.741809
Passira	2610509	-36.30825	-8.540338
Salgadinho	2612109	-36.62810	-8.824035
Santa Maria do Cambucá	2612703	-36.31432	-8.796035
São Vicente Férrer	2613800	-35.76789	-8.347853
Surubim	2614501	-36.18280	-8.907091
Taquaritinga do Norte	2615003	-36.56098	-8.706014
Toritama	2615409	-36.04107	-8.167072
Vertentes	2616209	-35.71119	-7.765413

Alagoinha	2600609	-36.32030	-9.127190
Belo Jardim	2601706	-35.73508	-8.028774
Bezerros	2601904	-35.91151	-8.574514
Brejo da Madre de Deus	2602605	-35.39871	-7.931283
Cachoeirinha	2603108	-35.88557	-7.945344
Capoeiras	2603801	-36.53501	-8.913998
Caruaru	2604106	-35.51552	-8.216893
Gravatá	2606408	-36.94500	-9.172441
Jataúba	2608008	-36.15905	-8.617977
Pesqueira	2610905	-37.28785	-8.959855
Poção	2611200	-36.58565	-8.067116
Riacho das Almas	2611705	-35.59054	-7.863113
Sanharó	2612406	-36.47526	-8.745254
Santa Cruz do Capibaribe	2612505	-36.37154	-8.776315
São Bento do Una	2613008	-36.14216	-8.780628
São Caitano	2613107	-36.48367	-9.173228
Tacaimbó	2614709	-35.87582	-8.678416
Agrestina	2600302	-36.27565	-8.642683
Altinho	2600807	-35.42313	-7.868799
Angelim	2601003	-35.52001	-7.711933
Barra de Guabiraba	2601300	-35.59090	-7.705082
Bom Conselho	2602100	-36.23351	-9.018449
Bonito	2602308	-36.05391	-8.651783
Brejão	2602407	-36.67825	-8.898715
Caetés	2603207	-35.55572	-8.001495
Calçado	2603306	-36.90193	-8.603818
Camocim de São Félix	2603504	-36.75440	-8.401055
Canhotinho	2603702	-36.72007	-8.216857
Correntes	2604700	-35.83202	-8.062915
Cupira	2605004	-35.58898	-7.920343
Garanhuns	2606002	-36.71991	-9.024430
Iati	2606507	-36.52336	-8.288093
Ibirajuba	2606705	-36.32506	-7.906627

Jupi	2608305	-35.89344	-7.813225
Jurema	2608404	-36.45768	-8.527385
Lagoa do Ouro	2608602	-36.16633	-8.329515
Lagoa dos Gatos	2608701	-36.38580	-8.858299
Lajedo	2608800	-35.84634	-8.461434
Palmeirina	2610103	-35.49286	-7.591698
Panelas	2610202	-35.75465	-7.880133
Paranatama	2610301	-36.24029	-8.323998
Saloá	2612307	-36.11211	-7.876909
São João	2613206	-36.60957	-9.084016
São Joaquim do Monte	2613305	-36.05154	-7.996630
Terezinha	2615102	-37.21153	-8.786949
Casinhas	2604155	-36.81917	-8.568307
Jucati	2608255	-35.81438	-7.784137
Vertente do Lério	2616183	-35.99208	-7.904511