

Prediction of cattle density and location at the frontier of Brazil and Paraguay using remote sensing

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Abstract

In this paper, we explore the potential of remote sensing to map pastures areas and by this way establish models for predicting cattle density and location. First, an object based classification (OB) was made in Landsat 5 images for three different municipalities to provide a land-cover map. Second, on the basis of Brazilian official livestock database, a statistical model to predict number of cattle in function of declared pasture area by the farmers was produced. Finally, this model was applied to the pasture areas detected by remote sensing to predict cattle density. Coefficient of determination of the model was 0.63. The results indicate that the methodology used for estimating cattle density has a potential to be applied in regions where no information about farm location and cattle density exists.

Key-words: cattle density, landsat 5 images, linear regression, object based classification, pasture areas.

1.Introduction

The meat production chain is the largest generator of jobs in Mato Grosso do Sul (MS) State, having the third largest beef herd in Brazil (22 million heads) according to the Brazilian Ministry of Agriculture, Livestock and Supply (2010). It has also the largest network of qualified exporters' slaughterhouses to the European Union. This, associated with the fact of having 1.131 km of international border, makes the State strategic for the control and prevention of diseases that are included in World Organization for Animal Health (OIE) list and affects international trades such as Foot and Mouth Disease (FMD).

As the frontier with Paraguay extends over a range around 1.100 km, there is a considerable change of landscape, soil and microclimates that leads to changes in agricultural practices and production systems. These different types of production systems are not very well documented and they play a significant role in terms of risk of the spread of FMD virus. Moreover, in Brazil farm cadastre is not georeferenced. By this means it is important to find another mean to characterize and spatialize cattle production systems in the frontier. By this reason, remote sensing could be potentially used to map and to monitor pastures areas and by this way establish models for predicting cattle density and location.

Maps of cattle density provided by FAO (2005) were produced from census livestock statistics but in a broad scale, not precisising location of pasture areas inside the municipality and the estimative are more generalized for the municipalities. The objective of this paper is to propose a methodology to predict cattle density and location from medium resolution satellite images using image oriented object classification.

2.Methods

2.1.Study area

The studied region comprehended three sites (municipalities) located in the frontier between Brazil and Paraguay in Mato Grosso do Sul State. The municipalities were chosen because they represent the differences that exists in the frontier and they are also well geographically distributed, Porto Murtinho in the extreme north, Ponta Porã in the center and Mundo Novo in the south (Figure 1).



Figure1. Map of Mato Grosso do Sul State, with the localization of the study areas (Porto Murtinho, Ponta Porã and Mundo Novo)

Mato Grosso do Sul State climate is classified, according to Köppen, as tropical-type Aw, with an average temperature of 24.4 °C in the warmer months (January and February) and 19.1 °C during the coldest months (June and July). The average annual precipitation is 1.470 mm. January is the wettest month (average of 243 mm of rain and 81% relative humidity) and August the driest (40 mm of rain and 60% relative humidity, on average).

Mundo Novo municipality is the smallest studied area, occupying an area of 480 km² with approximately 30,000 head of cattle, characterized by small producers, who mainly develop dairy farming and subsistence agriculture. Ponta Porã is potentially an agricultural region, with 5,328 km², where co-exist large farms and family farming, with around 3,000 properties of smallholder farming systems and approximately 231,000 cattle heads. Porto Murtinho is the largest municipality 17,734 km², mainly characterized by extensive livestock production, with a predominance of medium and large beef cattle farms with a herd of approximately 650,000 bovines.

2.2. Remote sensing data

Four Landsat 5 TM images from August and September 2010 with 30-meter spatial resolution were downloaded from Brazilian Institute for Space Research (INPE, www.inpe.br). Pre-processing included geometric correction, mosaicing and the creation of subsets for the study area. Geometric rectification of the imagery was undertaken using a first order polynomial with a nearest neighbor interpolation, incorporating ground control points taken from the GLCF 2005 orthorectified images, producing a Root Mean Square Error (RMSE) of less than 0.5. Ponta Porã site requested

the mosaicing of two images, both were taken in the same dates (August 18,2010). The pre-processing was undertaken with the use of the software ENVI, version 4.7.

2.3. Image classification

The object-based classification (OB) was undertaken using eCognition Developer version 7 software. Six bands of Landsat images were used, excluding thermal infra-red band. A total of seven land cover classes area were identified: water, forest, secondary forest, riparian forest, agriculture, marshes and pasture.

OB classification involved two sub-processes: (i) two segmentations, the first (L1) at the pixel level, and the second (L2) at the object level and (ii) classification.

The selection of segmentation scale parameters is often dependent on subjective trial-and-error methods (Meinel and Neubert 2004). After testing many possible parameters, we used the following: scale: 15, shape: 0.1 and compactness: 0.5. The resulting objects closely corresponded to the boundaries of fields, forests, riparian forests, water bodies and other elements of interest in the image.

After the first segmentation (L1), a hierarchy classification was conducted and several parameters were used: normalized difference vegetation index (NDVI), normalized difference water index (NDWI), shape index and mean difference between bands. The second segmentation (L2) took place in the object level and the parameters used were: scale (100), shape (0.1) and compactness (0.5).

Classification validation was done through a confusion matrix with 30 ground truth control regions of interest by class and by study area to validate OB classification. The confusion matrix was done with focus on pasture class which is our interest class.

2.4. Model for cattle prediction

Database provided from Brazilian Ministry of Agriculture, Livestock and Supply (MAPA) containing the number of farms, total animals per farm and pasture area declared by producers was used to build the prediction model for cattle density. The data from the three municipalities studied were used: Mundo Novo (n=591), Ponta Porã (n=3540) and Porto Murtinho (n=704). Data was treated in the opensource statistical package “R”.

The principle of linear regression is to establish a model linking a variable to be explained, in this study, the “number of cattle” (Nbcattle), by the explanatory variables, here, a single explanatory variable “pasture area” (Apasture). The variables were transformed in order to stabilize variance. It was assumed that the logarithm of response follows a normal distribution; by this way it was possible to construct a classic linear regression model. The second step was to verify the possibility of a linear relationship between Nbcattle and Apasture in each municipality. Farms with no cattle and/or no pasture in the database were excluded.

Comparison between predict value and observed value was made. The validation of the model was done in another data base from three other municipalities in the same region, which are: Caracol, Eldorado and Japorã.

2.5. Mapping cattle density

After the adjustment and validation of the model, the equation was applied to predict animal density in pasture areas detected by remote sensing using OB image classification. Data was treated in ArcGIS software version 10 and maps of cattle density were created. Validation was done through the comparison between cattle density obtained by remote sensing and data base provided by MAPA for each studied area.

3. Results

3.1. Land cover classification

Pasture area counts for 53% of Mundo Novo region, 28% of Ponta Porã and 49% of Porto Murtinho region. By the land cover classification it is possible to note the differences between three municipalities. In Mundo Novo and Porto Murtinho, the main activity is cattle production, in Ponta Porã, principal activity is agriculture, where 48% of the territory is occupied by agriculture areas and bare soil. Total area of Porto Murtinho is smaller than stated by IBGE this is because we used only one Landsat image for Porto Murtinho region, because of the size of municipality we would need three images and it was not the purpose of this study. The biggest part that was not comprised in this study represents the Indian area of 500 thousand hectares (Figure 2).

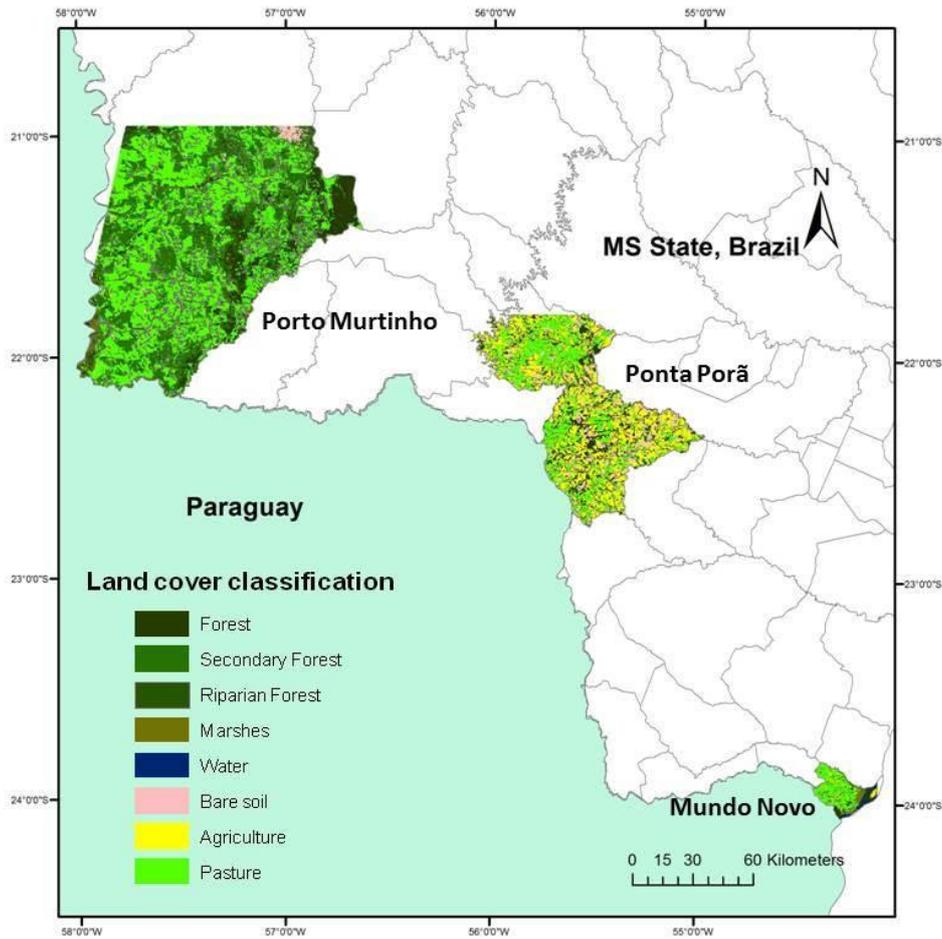


Figure 2. Geographic representation of the subsets of the three municipalities and land cover classification.

In this study we considered that the object-based classification had a good accuracy for the class that we were interested (pasture class) for the three sites studied (Table 1).

Table 1. Producers Accuracy (PA), Users Accuracy (UA) from OB classification from Mundo Novo, Ponta Porã and Porto Murtinho for pasture class and overall accuracy (Acc) and overall Kappa coefficient (KIA)

<i>Pasture class</i>	<i>Object-based classification</i>			
	PA %	UA%	Acc	KIA
Mundo Novo	99,8	79,9	75,1	0,69
Ponta Porã	84,2	89,9	74,4	0,66
Porto Murtinho	94,6	87,6	72,6	0,66

MAPA database containing number of cattle producers, total declared area and pasture declared area was confronted with pasture area detected by remote sensing (Table 2). We can observe that magnitude orders are respected for pasture areas even if

there is a small difference between them. For Ponta Porã, pasture area detected by remote sensing was underestimated in 11%, for Mundo Novo and Porto Murtinho were overestimated in 14%.

Table 2. Number of cattle producers, total declared area (ha), pasture declared area (ha) and pasture area detected by remote sensing in Mundo Novo, Ponta Porã and Porto Murtinho

Municipality	Number of producers	Declared total area (ha)	Declared pasture area (ha)	Pasture area detected by RS (ha)	Difference between declared and detected (%)
Mundo Novo	591	25.476	21.391	24.459	14%
Ponta Porã	3.540	259.332	165.292	147.457	-11%
Porto Murtinho	704	738.871	521.177	595.683	14%

3.2. Linear model for predicting cattle density

Porto Murtinho has the biggest pasture area and biggest cattle herd which largely differs from the two other ones (Table 3). Ponta Porã has a great number of familiar settlements (almost 3.000) what makes the average of farms and cattle herd decrease. It was important to select these municipalities that have differences in herd size and farm size in order to have a great heterogeneity for modeling cattle density.

Table 3. Summary of the official database from the three municipalities studied

Municipality	N. of producers*	Declared Pasture area (ha)	Pasture area per farm (ha)	N. of cattle	N. of cattle per farm	N. of cattle per ha
Mundo Novo	452	21.391	36.2	30.299	67	1.4
Ponta Porã	2831	165.292	46.7	230.754	81.5	1.4
Porto Murtinho	585	521.177	740	650.130	1,111	1.2

*Number of producers that had cattle in the year of 2010 and which were used to build the model.

The relationship between the two variables studied (Nbcattle and Apasture) was tested. Figure 3 shows that there is a linear relationship between these two variables. For Ponta Porã there is a concentration of the values between 0 and 4. For Mundo Novo, the values are between 0 and 6 and for Porto Murtinho the values are distributed between 0 and 10. This is because average size of farms is different between municipalities.

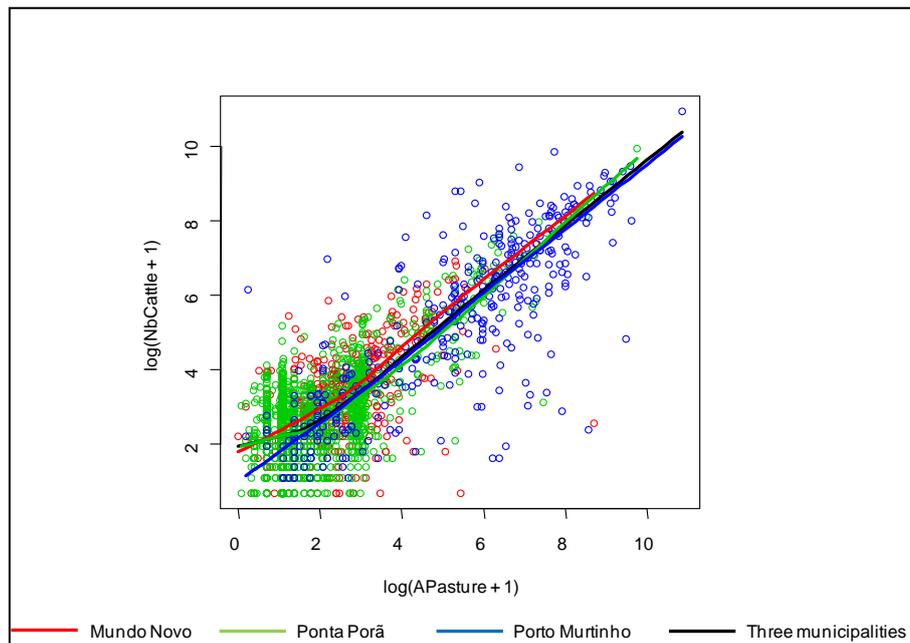


Figure 3. Relationship between pasture area (APasture) and number of cattle (Nbcattle) in the three municipalities studied (in logarithm).

As the number of cattle (Nbcattle) is related to the pasture area (APasture), the model built which analyses this relationship is:

$$\log(\text{Nbcattle} + 1) \sim \log(\text{APasture} + 1) + I(\log(\text{APasture} + 1))^2$$

where:

Nbcattle = number of cattle predict

APasture= pasture area (ha)

I = intercept

Determination coefficient (R^2) was 0.6683, it means that the model was able to predict 67% of the variability in the data set. Porto Murtinho had the biggest difference between observed and predicted (3%) but it can be considered a small difference.

Model validation was done with data from three other municipalities in the same region. There was no difference between predict and observed values ($P= 0.9122$). As there was no significant difference between observed and predicted for the municipalities used for validation, the model could be applied in other municipalities that exist in the region.

3.3. Applying the model in areas detected by remote sensing

After validation, the model was applied in pasture areas detected by remote sensing (OB) to calculate number of cattle existent in each polygon of pasture for each data subset (Figure 4).

The equation applied to areas detected by remote sensing, and the confident intervals were:

Nbcattle predict =

$$1.635912 + 0.495649 * \log (\text{Apastureremot} + 1) + 0.031114 * \log (\text{APastureremot} + 1) ^ 2$$

$$\text{Conf. Interval min} = \text{Nbcattle predicted} - 1.96 * 0.9162738$$

$$\text{Confidence interval max} = \text{Nbcattle predicted} + 1.96 * 0.9162738$$

Where:

Apastureremot = area of pasture polygons detected by OB classification

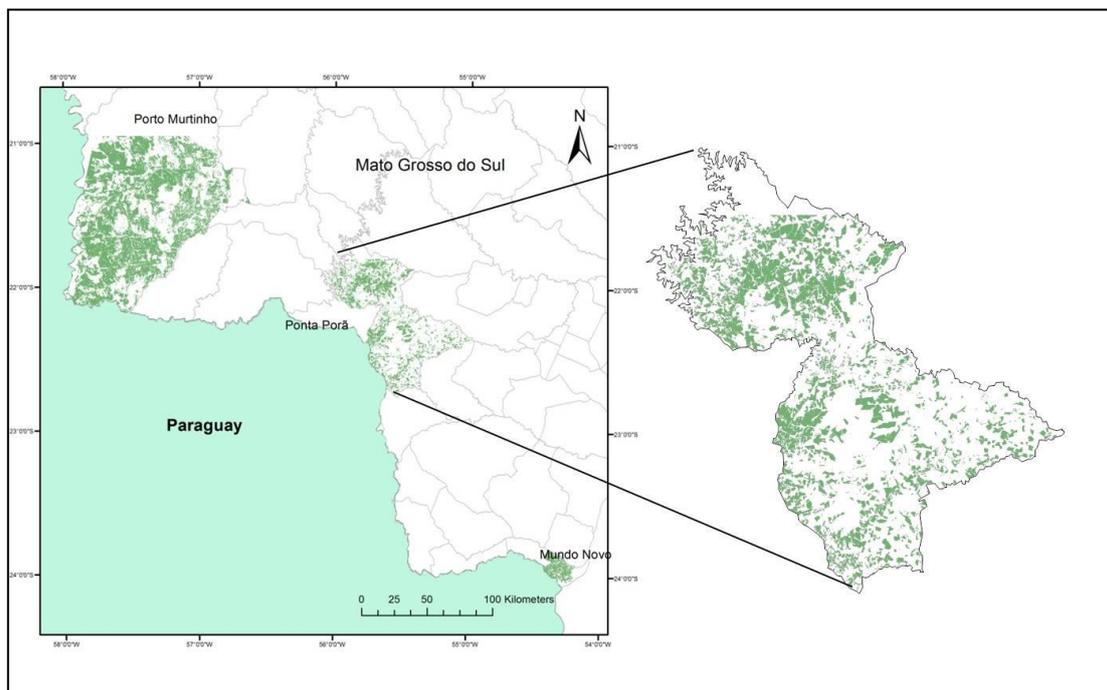


Figure 4. Pasture areas detected by OB classification with Ponta Porã site highlighted

Polygons from pasture area were regrouped in a second segmentation (L2), in order to have bigger areas of similar radiometry, and these areas could represent farms as the cadastre does not exist. Average L2 polygon area was bigger for Porto Murinho (608 ha), followed by Mundo Novo (436 ha) and Ponta Porã (221 ha). As agriculture is the main activity in Ponta Porã region (48% of land cover) pasture areas are more discontinuous and intercalated with agriculture. Farms usually have both activities, this is the reason why L2 polygons are smaller in Ponta Porã region. Another great difference between municipalities is the number of farms per polygon. In Mundo Novo region there are 10,5 and in the opposite side we have Porto Murinho with 0.71 farms per polygon. This indicator reflects the characteristic of the municipalities, Mundo Novo with small subsistence producers and Porto Murinho with extensive cattle areas. Mean pasture size was also bigger for Porto Murinho (28,5 ha), followed by Ponta Porã with 24,7 ha and Mundo Novo with 23,6. This indicator also reflects the difference between three municipalities in terms of land cover fragmentation.

Table 4 shows the application of the model in areas detected by remote sensing. For Mundo Novo site predicted value was 10% less than the observed value. Great differences in cattle density were seen in Ponta Porã region, 56% more predicted than observed and for Porto Murtinho site the difference between observed and predicted was 23%.

Table 4. Number of cattle observed and predicted by linear model applied in pasture areas detected by remote sensing

Municipality	Observed	Predicted	Min.	Max.
Mundo Novo	29,180	26,869	18,701	36,287
Ponta Porã	105,081	164,970	147,631	185,336
Porto Murtinho	490,370	643,869	587,544	704,512
Total	624,631	835,709	778,631	902,172

Figure 5 represent the map of cattle density (number of cattle per hectare) predicted by the model and applied in pasture areas detected by remote sensing. Average cattle per hectare for Mundo Novo, Ponta Porã and Porto Murtinho according to the prediction model was 1,32; 1,34; and 0,98 respectively, which does not differ from the indicator calculated based on number of cattle and pasture area declared by farmers (Table 2).

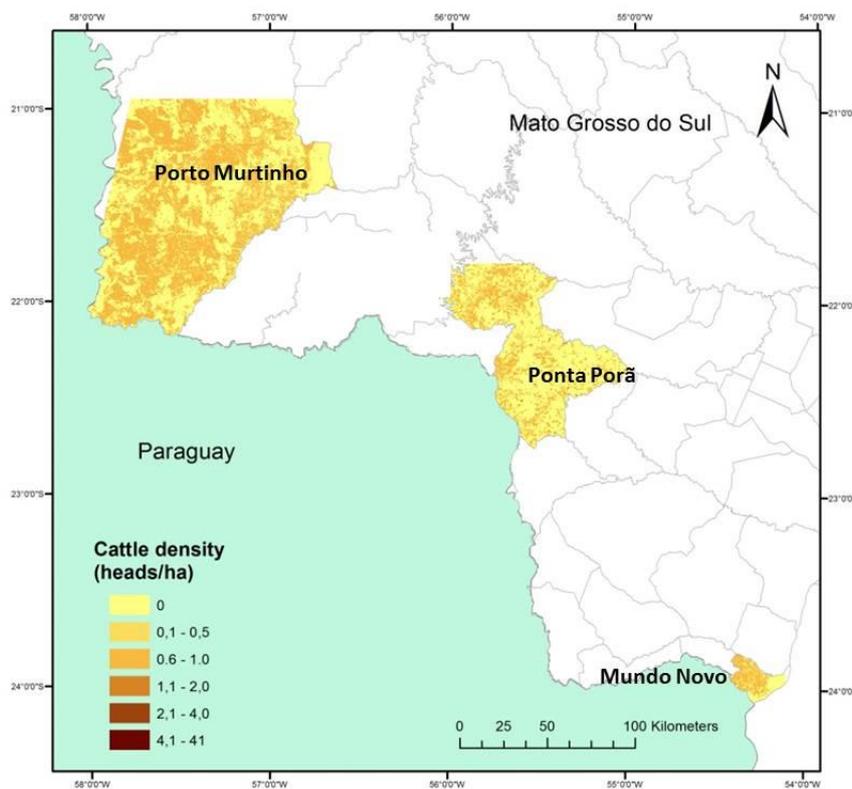


Figure 5. Map of animal density in the three studied sites

4. Discussion

The methodology proposed in this paper, to predict cattle density and location from medium resolution satellite images using object-based classification demonstrated to have good potential use.

OB classification showed good user's and producer's accuracy, as we were interested in extracting pasture areas, OB methodology fitted our purpose. Jobin et al., (2008) noted that one of the advantages of OB is the utility of a knowledge base that is beyond purely spectral information and includes object-related features such as shape, texture and context/relationship, along with the capability to include ancillary data. Myint et al. (2011), found that including principal component images and NDVI within an object-based rule-set classification produced significantly higher accuracy than maximum likelihood classification. The greater producer's and user's accuracy achieved for pasture class was probably due to the fact of using NDVI and NDWI as one of the indices in the hierarchy classification.

Differences between detected pasture areas by remote sensing and declared areas were observed (Table 2). In Ponta Porã region they were underestimated in 11%. This could have happened due to the common practice in the region that is rotation of cultures. Several farmers have both agriculture and livestock production and part of pasture areas are used in agriculture for one or two years in order to improve soil fertility and after this period they return with cultivated pasture. The overestimation for Porto Murtinho and Mundo Novo sites pasture area was expected. This occurred due to the user's accuracy, although it was high for all three municipalities, we could say that there was 20% in Mundo Novo and 12% of error of inclusion, where other classes such as agriculture or marshes for example were included in pasture class and they do not belong to it. Another factor that could influence these differences is also the database from MAPA. Farm and pasture area are declared by the farmers, Brazilian government has no georeferenced cadastre so declared areas could also be not accurate.

The linear model to predict cattle density ($R^2=0.66$) can be considered a good predictor because there are other factors associated to cattle density that are not possible to foresee such as economic situation of the farmers and also his decision of having more or less cattle in the farm due to market fluctuations and pasture quality. These factors would count for the others 33% of data variability.

Great differences between observed and predicted cattle density by remote sensing were seen in Ponta Porã region, 56% more predicted than observed. As the model was built based on declared pasture area and cattle number when it is applied to areas detected by remote sensing, it recognizes smaller areas as more populated. As Ponta Porã region has a discontinuous pasture area, and a smaller area of L2 polygons, the model overestimates cattle density.

Another factor associated with this difference is the fact that the model was built in logarithm, and when it is transformed to exponential, the errors are multiplied and when it is estimated the total cattle for each municipality the effect is a sum of exponential errors making the total number superior. For Mundo Novo this effect did

not appeared because total area of the municipality and the number of polygons were much smaller than for the other two municipalities. We can say that the model is good to predict cattle density inside the polygons, but not as good to count for the whole area, as the values are added, errors are added too.

Brazilian government is improving farm and cattle register by implementing farm georeference. The cadastre of all farms in Brazil is expected to be concluded by the year 2025. Even in this region which is considered a model for Brazil in terms of register, lot of work is still needed. In Ponta Porã, for example, from the 3540 farms 620 did not have GPS point location. In Porto Murtinho, from 704 farms, 187 did not have GPS location. In other regions of Brazil, this information does not exist.

As the density maps produced here have better spatial resolution than maps produced by FAO, they would have better usage for supporting public politics related to rural planning and a local development and also epidemiologic studies. The methodology developed here also has potential use for areas where no information is available.

5. Conclusions

Object based classification showed to be an interesting tool to detect and classify pasture areas in the tropics. The results of the study have a great potential to be used in areas where scarce information is available. Limitation of the use is that the model is restricted to the study area. More studies should be done in order to extrapolate the methodology to other regions or other countries which have the same characteristics of cattle grazing or production systems.

6. References

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