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ANIMAL SCIENCE

Spatial and Temporal analysis (2008-2017) of droughts and their effects on livestock in the Brazilian semi-arid region

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Abstract: In this study a temporal analysis (2008-2017) was conducted to examine the occurrence of droughts and the spatial distribution of livestock herds in the Brazilian semi-arid region. Maps of vegetation cover, classes of normalized difference vegetation index (NDVI) and normalized difference drought index (NDDI) were used. Image processing took place on the Google Earth Engine platform along with QGIS Software (2.18). Two historical series were created to compare the variation between two herds and the dry monitoring, one called the 1st series (2008-2012) and 2nd series (2013-2017) which were compared using a paired t-test. The comparative analysis showed that the classes of extreme drought and exceptional drought covered the greatest land areas in the 2nd series, while abnormal drought covered the greatest land area in the 1st series. The analysis of herds, a reduction in the cattle herd and an increase in goat and sheep herds were noted. This study considers the efficacy of NDDI and NDVI indices to monitor the distribution of droughts in the Brazilian semi-arid region. The geoprocess of Sidra data enabled an analysis of the spatial distribution and temporal variation of the herds in the semi-arid region and how drought may have impacted livestock dynamics.

Key words: Environmental disasters, google earth engine, livestock analysis, remote sensing, spectral vegetation indices.

INTRODUCTION

Recently, climate change has had devastating effects around the world, not only on the environment, but also on the social and economic aspects of societies that seek sustainable development (Marzouk et al. 2021). Arid and semi-arid regions of the world face major problems of degradation due to human activities, climate change, natural disasters, and socioeconomic inequalities (He et al. 2005). These regions cover approximately 60.95 million km², corresponding to approximately 41% of the Earth's surface, with an estimated population of 2 billion inhabitants (Pinheiro & Nair 2019). In Brazil, there is a large land area classified as a semi-arid region, located mainly in the northeast of the country, where approximately 56 million people live (Albuquerque & Melo 2018). This area is considered as the most inhabited semi-arid region in the world (Maia et al. 2007). In comparison to other semi-arid regions over the world, Brazil has several extreme climatic characteristics, such as the intense radiation associated with increase of evapotranspiration from vegetation generating water scarcity (Marques et al. 2020), which challenges agricultural and livestock activities, leaving herds more vulnerable mainly due to fluctuations in the annual carrying capacity of rangelands. The production of ruminants is an important cultural, social and economic activity, playing a crucial role in the development of the Brazilian semi-arid region (Costa et al. 2008). However, droughts have caused changes in the population pattern of herds, mainly due to the different mechanisms of adaptation of livestock farmers to the dry environments that ruminant species are raised within this region.

Geoprocessing consists of operations necessary to manipulate geospatial data (Zhao et al. 2012). For the analysis of data through geoprocessing, it was necessary to use Geographic Information System tools, which are very useful in making cartographic products and in characterizing livestock production systems through spatial mapping. An example of the application of geoprocessing in livestock is the study carried out by Robinson et al. (2014), who used FAO statistical data (FAOSTAT) to create a model to represent the population density of herds on the globe (i.e., the Gridded Livestock of the World [GLW] database). The authors mapped high densities of cattle in regions of India, East Africa (mainly in Ethiopia), Northern Europe, and South America and concluded that the application of the tool can bring environmental, socioeconomic, and anthropogenic benefits, serving as an aid in defining the conference of the geographic distribution of the herds and informing public policies directed to the farmers.

A geoprocessing tool capable of consistently capturing the characteristics of large areas of the Earth's surface is remote sensing (Lu et al. 2016). Through this tool, it is possible to check water and vegetation conditions on a large scale, supporting sustainable development and the management of agricultural production, as well as the incidence of droughts (Shahabfar & Eitzinger 2011). Additionally, the combination of geographic information system tools with remote sensing data makes it possible to understand the phenomena that occur on the Earth's surface on a large scale, relating them to natural events or anthropic activity (Mendes et al. 2018). Moreover, studies of vegetation variation and its relationship to climate change and human activities constitute a fundamental theme of sustainable development research (Li et al. 2021).

Droughts are characterized by their duration, intensity, and spatial distribution, so evaluations to quantify their effects can be carried out through statistical analysis of historical rainfall data, soil moisture data, and an array of different spectral vegetation indices (Renza et al. 2010). Some spectral indices have been used to estimate information on the productivity and humidity conditions of vegetation and to relate them to the incidence of droughts, of which the normalized difference vegetation index (NDVI, Bajgain et al. 2015) and normalized difference drought index (NDDI, Gu et al. 2007) are very useful. Tavazohi & Nadoushan (2018) tested NDDI's ability to monitor the drought condition in the Isfahan region of Iran during the years 2000 to 2015 and found it to be very efficient and acceptable in making predictions since it relates the NDWI, which indicates changes in the plant water content of the vegetation to the NDVI, which is related to the vegetation cover and chlorophyll content. Thus, the aim of this study was to conduct a temporal analysis (2008-2017) of the distribution of droughts using remote sensing data and to relate it to the spatial distribution and variation in herd sizes of cattle, goat and sheep with the hypothesis that geoprocessing tools combined with remote sensing can be useful in detecting periods of drought, and that droughts have direct interference in livestock herds in the Brazilian semi-arid region.

MATERIALS AND METHODS

Study location

For this study, towns located in the Brazilian semi-arid region were analysed (Figure 1a). Delimitation of this semi-arid region according to the CONDEL (Deliberative Council of the Northeast Development Superintendence) resolution number 115 of 11/23/2017 was used. This delimitation established its limits with 1,262 towns distributed in ten states of the Federation, occupying an area of approximately 1,128,697 km², of which about 823,461 km² (72.95%) are from the *Caatinga* biome, 239,133 km² (21.18%) from the *Cerrado* biome and 91,913 km² (8.14%) of Atlantic forest (figure 1b). The elevation of the Brazilian semiarid region (Figure 1c) plays a key role in the organization and utilization of the region's

natural resources, as it creates microclimates that influence adaptation to adverse weather conditions.

Some important characteristics of the Brazilian semi-arid region are the high solar radiation and temperature throughout the year, with rainfall regime marked by scarcity and irregularity of precipitation, ranging from 750-800 mm in most towns (Ab' Sáber 2003). The rainy period lasts from 3 to 4 months in the semi-arid region when about 80% of the annual rainfall occurs (Araújo Filho 2013). Even during the rainy season, the amount of evaporation is comparatively higher than the amount rainfall, and this characteristic results in negative water balance during most part of the year (Da Silva et al. 2020).



Figure. 1. Regions of Brazil (a) Biomes (b) and Elevation (c, Obtained through shuttle radar topography mission -SRTM data) of the Brazilian semi-arid region.

One hundred sixty random points (yellow points in figure 2a) were created using the random points creation function within the polygon present in the QGIS software (2.18), considering as polygons the limits of the federal conservation units (blue polygons in figure 2a) of the Ministério do Meio Ambiente (Brasil 2019) for the sampling CHIRPS rainfall, NDDI, NDVI, and NDWI values to perform correlation. Federal Conservation Units (FCUs) are natural areas of ecological importance intended for environmental protection, thus maintaining the integrity of the local biological heritage with the present vegetation conserved. Average annual rainfall, obtained from CHIRPS (Climate Hazards Group Infrared Precipitation) precipitation monitoring, ranged from 531 to 1006 mm, and was collected in the monitoring points and years (figure 2b).

Google Earth Engine (GEE) was used to acquire remote sensing and climate data used in this study. GEE consists of a web platform that uses a large computational capacity for storing remote sensing data in the cloud with a large catalogue of images (Gorelick et al. 2017), enabling processing and classification of remote sensing data quickly and in an interactive environment, through algorithm (Xiong et al. 2017)

To assess annual precipitation across the study area, CHIRPS satellite rainfall data were used. CHIRPS rainfall data consists of daily precipitation information from more than 30 years of monitoring with geographical coverage of 50°S to 50°N, containing data from 1981 to the present date (Funk et al. 2015). CHIRPS data are: (I) The Climate Hazards Group's Precipitation Climatology (CHPClim); (II) Satellite observations (NOAA) with thermal infrared spectroscopy (Thermal Infrared, TIR); (III) precipitation fields of Coupled Forecast System (CFSv2) and (IV) precipitation through regional service weather stations (Funk et al. 2015).

CHIRPS data used in this study was obtained from the Google Earth Engine image catalogue. Daily precipitation images for the study area were extracted for the study area locations, and then daily data were summed to generate annual precipitation.



Figure 2. Polygons in blue represent the conservation units (CUs) of the semi-arid region and the yellow points (a) are the sampling sites for CHIRPS data and spectral vegetation indices. Average annual rainfall (b, standard deviation of 160 points) of the Brazilian semi-arid region.

Regarding the representativeness of CHIRPS data for the Brazilian semi-arid, Paredes-Trejo et al. (2017) validated the CHIRPS method of precipitation monitoring from rainfall data collected at meteorological stations in Northeast Brazil and concluded that this monitoring method has high reliability in representing precipitation with a correlation around 0.94, but with a trend of overestimation around 100 mm.

Analysis of the severity of drought in the Brazilian semi-arid region

To obtain annual maps representing the distribution of droughts in this region, classes of normalized difference vegetation index (NDVI) and normalized difference drought index (NDDI) were derived and extracted for the study area using Google Earth Engine platform (figure 3) and the QGIS Software (2.18).

The Moderate Resolution Imaging Spectroradiometer (MODIS) (Terra MOD09A1) satellite data were used to derive NDVI and NDDI time series. Terra MOD09A1 is an 8-day composite product with 500 m spatial resolution. The images are atmospherically corrected for the interference of gases, aerosols, and scattering (Vermote et al. 2011). Images for the study area were mosaiced in GEE and images collected during the dry season (June to December images) were used to create a yearly times series (2008 to 2017). An algorithm to add the MOD09A1 image collection in platform GEE was later used for generation of the annual images for each year of evaluation.

For the generation of the annual images, clouds in the 8-day images were removed by an algorithm that calculates a simple score of the probability that clouds are present in a range zero (no cloud cover) to one hundred (100% cloud cover), and derived using the combination of brightness, temperature and NDSI (Normalized Difference Snow Index) in each pixel. After identifying the pixel that corresponds to the cloud, the pixel was removed from the 8-day image and then the median of the pixels without the presence of clouds was calculated for each year. After the generation of the yearly median images, the spectral vegetation indices were calculated through map algebra algorithms within GEE (table I).



Figure 3. Simplified flowchart of the steps performed on Google Earth Engine and QGIS software.

The NDVI was calculated by normalizing the difference in the reflectance of the near infrared red spectrum (Table I). The NDVI varies between -1 and +1, so that the higher the NDVI value, the greater the presence of vegetation. However, for inland surface targets, index tends to vary between 0.0 and 1.0 (Aquino et al. 2018), with pixels with less presence of vegetation having values close to 0.0 and greater presence of vegetation at values close to 1.0. Based on this principle, the classification of vegetation cover as proposed by Aquino & Oliveira (2012) was applied to MODIS imagery in this study, to evaluate the temporal and spatial variation of vegetation cover in the semi-arid region (classification illustrated in table II).

To obtain the area corresponding to each NDVI cover class, the NDVI maps were reclassified using the GRASS r.recode command of the QGIS software (version 2.18), and following the reclassification, the GRASS r.report was used to obtain the report detailing the areas (km²) corresponding to each class. The Normalized Difference Drought Index (NDDI) was also used to analyse the spatial and temporal distribution of droughts in the semi-arid region. NDDI is an index composed of the normalization of the NDVI and the normalized difference water index (NDWI, table I) and was also calculated in the GEE platform (figure 3).

Annual NDDI images were exported from GEE and then classified into drought severity indicators according to the classes proposed by

Table I. Spectral vegetation indices used in this research.

Gu et al. (2007). NDDI is a very sensitive indicator of drought, as it associates the information of vegetation vigour (NDVI) and local plant water stress (NDWI) in its equation (Lee et al. 2016). High NDDI values indicate drought conditions, which would be indicative of NDVI and NDWI being low (usually NDVI <0.5 and NDWI <0.3). Low NDDI values indicate no drought conditions, as both NDVI and NDWI are high (usually NDVI> 0.6 and NDWI> 0.4) (Gu et al. 2007).

NDDI maps were reclassified using the GRASS r.recode command of OGIS (version 2.18). Classes ranged from the absence of drought (negative NDDI values) to exceptional drought, with values greater than or equal to 5.0 (Table III). After reclassification, the GRASS r.report command of the QGIS software (version 2.18) was used to obtain the report on the area (km^2) corresponding to each class.

Geographical distribution of livestock herds in the semi-arid region

An analysis of the spatial distribution and temporal variation of livestock herds in the semi-arid region was carried out using data obtained from IBGE Automatic Recovery System (SIDRA). The information was downloaded from on the IBGE website (https://sidra.ibge.gov.br/ pesquisa/ppm/tabelas), which contains census information survey of animal herds from 2008 to 2017. The SIDRA data were obtained regarding the population of goats, sheep and cattle from all towns within the semi-arid region (figure 1a).

| Spectral vegetation indices | Abbreviation | Formula | References |
|--|--------------|---|-------------------------|
| Normalized Difference Vegetation Index | NDVI | (<u>ρb2 - ρb1)</u> (<u>ρb2 + ρb1)</u> | Pearson & Miller (1972) |
| Normalized Difference Water Index | NDWI | $\frac{(\rho b2 - \rho b6)}{(\rho b2 + \rho b6)}$ | Gao (1996) |
| Normalized Difference Drought Index | NDDI | <u>NDVI - NDWI</u> NDVI + NDWI | Gu et al. (2007) |

Spectral bands MOD09A1: pb1- red surface reflectance; pb2 - near-infrared surface reflectance, pb6 - short-wave infrared surface reflectance (SWIR1).

For the construction of livestock population maps, the QGIS software was used (version 2.18). Initially, it was necessary to include data referring to the geocode of all towns. The geocode consists of a numerical identification that each Brazilian town receives from IBGE. to facilitate the mixing of data from different sources. From the geocode, the database obtained on SIDRA was joined to the shape database (shp.) of the towns using the table joining tool. From the pairing of the information, thematic maps of the distribution of the herds population were constructed for time series analysis with geographic distribution (expressed in head per km²) and change comparison of the 1st (2008-2012) and 2nd (2013-2017) historical series (expressed in percentage) of cattle, goats and sheep in the Brazilian semi-arid region.

Statistical analysis

The remote sensing, climate data, and livestock population data obtained during the 10 years of study were split into two historical series (2008 to 2012 vs. 2013 to 2017) for statistical comparison. Paired t-tests, with a significance level of 10% (P < 0.10) were conducted on the means of the two time periods using PROC TTEST procedure of the SAS software (SAS University Edition version). The choice of the paired t-test for the comparison of historical series was because the present study compares the time

Table II. Description of Normalized DifferenceVegetation Index classes for vegetation cover (Aquino& Oliveira 2012).

| Class | Classification criterion |
|--------------------|---------------------------------|
| Bare soil or water | NDVI ≤ 0 |
| Very Low | 0 < NDVI ≤ 0.2 |
| Low | 0.2 < NDVI ≤ 0.4 |
| Moderately Low | 0.4 < NDVI ≤ 0.6 |
| Moderately High | 0.6 < NDVI ≤ 0.8 |
| High | 0.8 < NDVI ≤ 1 |

period before and after, therefore presenting paired observations.

To analyze the correlation of CHIRPS precipitation with the spectral indices, the data collected in the 160 points in the conservation units were used. Initially, the normality of the data was analyzed, which was not confirmed. Thus, Spearman's correlation was adopted using the CorrPlot package (Wei et al. 2017) of the software R Studio, which was also used to plot the correlation matrix. For the numerical representation of the temporal variation of the data, graphical methods were used, with the aid of the SigmaPlot software (version 11.0).

RESULTS AND DISCUSSION

Analysis of the severity of drought in the Brazilian semi-arid region

The results suggest an interannual variation of NDDI (figure 4a) and classes of vegetation vigour (figure 4b). Possibly, the variation occurred due to oscillations in interannual rainfall (figure 2b), which is an important characteristic of the Brazilian semi-arid region and directly affects the incidence of droughts and vigour of the vegetation. The comparative statistical analysis of the two historical series through the paired t-test showed that the moderate and extreme drought classes did not present any difference (P > 0.10), while extreme drought (P = 0.0849)

Table III. Normalized Difference Drought Index categories and drought severity indicators (Gu et al. 2007).

| NDDI value | Description | |
|---------------|---------------------|--|
| ≤ - 0.49 | Non-Drought | |
| - 0.49 ~ 1.99 | Abnormally Dry | |
| 2.00 ~ 2.99 | Moderate Drought | |
| 3.00 ~ 3.99 | Severe Drought | |
| 4.00 ~ 4.99 | Extreme Drought | |
| ≥ 5.00 | Exceptional Drought | |

and exceptional drought (P = 0.0705) presented the largest area in the 2^{nd} series, and abnormal drought (P = 0.0910) presented the largest area in the 1^{st} series (figure 4c).

When comparing the two historical series in the vegetation cover class (figure 4d), it was noted that high and moderately high classes showed no difference (P > 0.10), while exposed soil or water (P = 0.0038), very low (P = 0.0376) and low (P = 0.0674) had larger areas in the 2^{nd} series, and the moderately high class (P = 0.0177) had the largest areas in the 1^{st} series.

Rainfall in the Brazilian semi-arid varies in space and time (Muir et al. 2019) and its behaviour directly affects the incidence of droughts. According to Marengo et al. (2018), droughts in the semi-arid region are caused by the *El Niño* effect and by the variation in the surface temperature of the North Atlantic, and in recent years they have occurred more intensively, with a direct impact on the local economy. Additionally, climate change has directly influenced temporal dynamics of the drought-pluvial seesaw Globally (Dore 2005, Trenberth 2011). These climate changes have been attributed to processes of gas emission by natural and anthropic actions, altering the energy balance, increasing temperatures and evaporation, modifying the rain cycle and decreasing soil moisture (Rufino & Silva 2017).

It was possible to verify through drought indicators maps (figure 5) the places where



Figure 4. Variation and statistical comparison of drought indicators classes (a-c) and vegetation cover (b-d). Values with different letters within the same class differ from each other by the paired t-test. *P <0.01; **P <0.05; ***P <0.10; ^{NS}P> 0.10.

droughts are more intense and frequent, and analysing geographically it can be inferred that there are towns more affected than others, as they presented red or yellow, in consecutive years, particularly in the towns of the central semi-arid region during the years 2015, 2016 and 2017. Therefore, livestock farming in these regions may have been more affected by the additive effect of years of drought.

According to Tavazohi & Nadoushan (2018), information on the dynamics of the vegetation is very important for carrying out drought monitoring and can assist in planning, monitoring, forecasting and assistance to the most affected areas, serving as indicators to estimate information on precipitation, soil moisture or water supply from a given location. These characteristics have made NDDI useful for monitoring areas susceptible to drought (Lee et al. 2016). Gu et al. (2007), analysed the NDDI to monitor rangelands in the Flint Hills region in the United States using MODIS data and concluded that NDDI proved to be an important indicator for monitoring droughts on a regional scale, however, it is necessary to expand NDDI studies as a drought monitoring tool applied to a greater diversity of vegetation.

It is noted through the geographic distribution of the cover vegetation maps based on NDVI (figure 6), that the denser vegetation is located more in the edges of the semi-arid, exactly in the regions where the predominance of vegetation is Atlantic Forest and *Cerrado* (figure 1b). NDVI maps indicate the regions with the most abundant vegetation, so it is suggested that in these regions there is a greater supply of forage to feed the herds, and consequently, the probability that livestock farmers have losses due to the lack of forage feed will be lower. A



Figure 5. Drought indicators maps based on Normalized Difference Drought Index obtained from MOD09A1 data.

low supply of forage to feed the herds is bad for animal production, which may result in weight loss, and affects animal performance and property production costs.

The indices showed a high correlation with each other, and even though they are different indices (figure 7a), all have the basic premise that as morphological changes occur in the canopy of vegetation. There are also variations in the fractions absorbed, transmitted and reflected from the incident solar radiation. It is important to note that da rangelands vigor has a high influence of the presence of humidity, or that justifies the high correlation between the NDVI and the NDWI. However, observing a medium correlation with the CHIRPS rainfall values (figure 7b), we attribute this result to the objective of monitoring the indices during the dry period, during this period it is common for shrubs and trees to perch their leaves to avoid evapotranspiration.

NDVI is one of the most used spectral indexes for carrying out analyses and studies of vegetations (Hott et al. 2016, Vrieling et al. 2011) This index is based on the principle that the wavelength in the red spectrum is almost completely absorbed by plant surfaces rich in biomass and that are photosynthetically active, while the near-infrared spectrum is reflected (Myneni et al. 1995). Aquino et al. (2018), carried out an analysis on the variation of classes of vegetation cover from 1985-2011 in Tauá (town located in the Brazilian semi-arid region) and associated the variations in NDVI to precipitation. They found that, that the Caatinga vegetation cover can response rapidly to the years of greatest rainfall. Results from this study show higher productivity and less drought in years of



Figure 6. Vegetation cover maps based on Normalized Difference Vegetation Index obtained from MOD09A1 data.

greater rainfall, especially in 2009 (figure 2b, 5, and 6).

As already described, the predominant vegetation of the semi-arid region is the Caatinga, which is composed of small herbaceous, shrub and tree species. An important characteristic of the plants of this vegetation type is that they are deciduous, that is, the plants lose their leaves in the dry season to prevent transpiration losses (Morais et al. 2021). As a result, there is a change in the chlorophyll content of the vegetation caused by water stress (Ceccato et al. 2001) and this combination of red, infrared and shortwaves infrared reflectance information may have been useful for monitoring the condition of drought in the region.

According to Barbosa et al. (2019), drought conditions during 2012 to 2015 were intense within the Brazilian Semi-arid Region, and these droughts brought impacts never seen before in this region, with estimated losses of up to 6 billion dollars. Added to this, Santana & Santos (2020) evaluated the impacts of the drought from 2012 to 2017 in the Northeast semi-arid region, and found a reduction of around 90% in the value of gross agricultural production, which caused greater economic damage in locations with livestock activity. Angelotti et al. (2011) state that, the Brazilian semi-arid region will be one of the most affected regions by climate change, because in addition to temperature increases, this region will have a tendency to become more arid, with an increase in frequency and intensity of droughts and the consequent reduction in the availability of water resources.

Geographical distribution of livestock herds in the semi-arid region

Cattle herd size reduced (figure 8b) and goat and sheep herds increased over the study period, with the increase in the goat and sheep herds (from 2008 to 2017) being 8.5 % for sheep (figure 8a), and 3.0% for goats (figure 8c). The reduction of cattle herd corresponded to a decrease from 17.3%, to 15.2% (figure 8b).

The cattle herd decreased by 2.1% or 1.7 head per km², while the goat herd increased by 3.0% or 1 head per km². The sheep herd showed the most significant increase (8.5%), which corresponds to 2.3 head per km². Even with the increase in



Figure 7. Annual mean and standard deviation of NDVI, NDWI and NDDI values collected at 160 sample points (a). Spearman's correlation coefficients between CHIRPS precipitation and the spectral vegetation indices (b).

the goat herd, the comparative analysis of the historical series by the paired t-test, showed that there was no statistical difference (P > 0.10) between the two series (figure 8d). The cattle herd showed a reduction (P = 0.0303) from the 1^{st} to the 2^{nd} series while the sheep herd showed increase (P = 0.0365).

The maps of the herds distribution (head per km2) and the change (%) of cattle (figure 9a and d), goats (figure 9b and e) and sheep (figure 9c and f), suggest the possibility of verifying the geographical distribution of reduction or increase in the herd size. Relating the maps in figure 9 to the maps in figures 5 and 6, it is noted that the regions where the droughts were more intense geographically concentrate the towns that had increase in the effective herd of sheep and goats.

Extreme variations in temperatures and precipitation patterns cause direct impacts on livestock activity, mainly due to the behaviour of precipitation directly interfering in the vigour of vegetation (Hermance et al. 2015), and, consequently, in the supply of forage to herds (Sayre et al. 2013). According to Nogueira et al. (2010), the instability of precipitation regimes in the semi-arid region is one of the main causes of the seasonality of livestock production, directly interfering in local livestock production, mainly because it compromises the supply of forage to the animals. Even though not very productive, livestock in the semi-arid region has been an



Figure 8. Sheep (a), cattle (b) and goat (c) herds variation, expressed as % of the Brazilian herd (vertical bars) and head per km² in the semi-arid region (lines), and statistical comparison of the 1st and 2nd historical series through the paired t-test (d).Values with different letters within the same class differ from each other according to the paired t-test. **P <0.05; ^{NS}P > 0.10

option in comparison to agriculture, as crops are more affected by the lack of rainfall in critical periods of growth, leading property owners to choose livestock because they are less sensitive to scarcity of water (Coutinho et al. 2013).

The increase in the number of sheep and goats possibly occurred because these species have different mechanisms of adaptation to dry environments, and it is known that the production of sheep and goats has great identity with the semi-arid region and has been recognized as an important economic activity for the region, demanding special attention to become increasingly competitive. According to Otaviano (2020), small ruminants are considered species more viable to be bred in regions of climatic vulnerability, as they have greater versatility in the composition of their diet in times of adversity than other animals, mainly due to their high selective capacity, where in an environment with high variation in forage availability between the herbaceous and woody strata such as the Caatinga, small ruminants are able to explore vegetation more efficiently.

Besides, some physiological characteristics that small ruminants have, such as the greater ease of heat dissipation, as they are animals of smaller body size, in addition to the characteristics of their faeces being drier (Araújo Filho 2006), promoting less dehydration when compared to cattle, allow small ruminants to better explore dry environments. Another possible explanation for this behaviour of herds is a change tendency in the profile of



Figure 9. Geographic distribution (expressed in head per km²) and change comparison of the 1st (2008-2012) and 2nd (2013-2017) historical series (expressed in percentage) of cattle (a and d), goats (b and e) and sheep (c and f) in the Brazilian semi-arid region.

production systems in the semi-arid region. cattle herd by g With the advance of drought periods there was a need to adopt more intensive systems, and consequently the permanence and selection of animals of high productive potential on the

consequently the permanence and selection of animals of high productive potential on the farm, knowing that sheep are more adapted to this production system than goats that are more explored in merely extensive conditions. Another explanation for this reduction is related to the reproductive cycle of sheep and goats, which are earlier when compared to cattle. This may reflect on buying power, as there is a greater supply of sheep and goats for sale during prolonged periods of drought.

The application of geoprocessing is a useful tool for research in the field of livestock, as it is able to characterize and demonstrate the various systems of animal production through cartographic products (Robinson et al. 2011). Also, the knowledge of the structure and geographic distribution through the mapping of livestock allows the definition of policies for infrastructure, transport, logistics, feasibility analysis of regional and sectoral development projects, and studies of the dynamics of the agriculture sector (Zoccal et al. 2006). Goat, sheep and cattle farming in the Brazilian semiarid region are largely extensive, which is based on rangeland feed, that allows for even moderate weight gains during the rainy season and weight loss during the dry season. Therefore, periods of drought cause economic losses to breeders because there is reduction in animal weight gain and increase in the age at slaughter, thus, the production of goats and sheep can be more economically viable due to the precocity of these animals.

Another important aspect is that the mapping of herds can provide information to support public policies to encourage breeders. Buggenhout (2008) carried out an analysis of the geographical distribution of the Brazilian cattle herd by geoprocessing data from IBGE. The results led the author to conclude that the increase in the cattle herd in the Midwest and North regions and the reduction in the South and Southeast regions suggest migration of cattle farming to the Midwest and North regions. From this analysis, a focus on investments and support can be directed to regions with the greatest demand for planning on an environmental, economic, and sanitary basis.

From the results obtained in this research, it is expected that mapping the distribution of herds on a temporal and spatial scale will provide useful and consistent information to support the necessary political decisions to improve the livestock sector in the semi-arid region. Although the results provide important indicators that will serve as a basis for the public sector and livestock farmers, a study of just 10 years may reflect trends or climate influences on rangelands and consequently on livestock, which makes future studies with longer time series important, and can reveal how droughts have historically affected herds.

CONCLUSIONS

The use of remote sensing data applied to natural phenomena is useful in the generation of cartographic products such as regional distribution of droughts. With the production of maps indicating the most affected places by droughts, it becomes possible to allocate benefits such as policies to support and make it possible to cope with drought in these regions, so that their populations can anticipate the occurrence of disasters.

The geoprocessing of SIDRA/IBGE data allowed an analysis of the spatial distribution and temporal variation of the herds in the semi-arid region and this analysis generated information about the places of greatest growth in sheep and goat farming in view of the risks of periods of climatic uncertainty. It is important to highlight the reduction of the cattle herd and the increase of the sheep herd in the analysis of the semi-arid region, however, this behaviour differed considering the different towns of the region, indicating that even though they are located in the semi-arid region, the drought more intensely affected some regions than others.

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GEOPROCESSING IN LIVESTOCK MONITORING

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L.F.M., R.N.F, D.N.A, and F.H.M.N contributed to the idealization of the methodology and the analysis in the Google Earth Engine and the QGIS software. L.F.M., A.G., A.C.R.C., and M.J.D were responsible for data curation, formal analysis, and downloading the data from Sidra for statistical analyses. All authors contributed to the editing and reviewing of the manuscript.

