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Capitalizing on opportunities provided by pasture sudden death to enhance livestock sustainable management in Brazilian Amazonia

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Highlights

Livestock is the main driver of deforestation in the Brazilian Amazon

The Sudden Death Disease (SDD) affects Brazilian pastures

SDD has promoted the overall reduction in the greenhouse gas emissions

Digital images of orbital sensors are able to detect pasture problems

ABSTRACT

Brazil has the largest commercial beef cattle stock on Earth, and most of the cattle produced in the country is bred and finished on pastures. The cattle ranching sector represents a significant source of the country's greenhouse gas (GHG) emissions. Agricultural intensification has been highlighted as one of the main strategies in reaching global food security and reducing deforestation. The Sudden Death Disease (SDD) of pastures, which affects the most planted cultivar of *Urochloa brizantha*, is degrading pastures in the Amazon, contributing to low production yields and high emission rates. This paper discusses the intensification of pasture production systems and SDD, to examine the potential for pasture renovation to address livestock productivity and GHG balance, emissions and potential sinks. Does SDD represent a blessing or a curse to climate change mitigation in the Brazilian Amazon? A collection of pasture samples were assessed to measure wet and dry weight in areas with and without SDD, which were related to remote sensing data to provide an overall estimate of the total area affected by the SDD in Alta Floresta, a municipal county of southern Brazilian Amazonia. We found that 77.1% of all pastures had been committed to the syndrome, which has forced farmers to renew their pastures. This also has great potential in increasing soil carbon stocks, effectively reducing the CO_2 footprint of meat production in those areas. Therefore, we firmly believe that SDD management has provided an opportunity to rebalance the emissions/sequestration equation associated with meat production by the cattle ranching sector in this Amazonin frontier.

KEYWORDS

Pasture intensification; land use change; GHG emission; land sparing; *Urochloa* spp.

INTRODUCTION

The world population is expected to reach 9.3 billion by 2050 and production will have to increase by 200 million tones to meet future demand for meat livestock (FAO, 2018). The livestock sector plays an important role in climate change, contributing to the release of 14.5% of all human-induced greenhouse gases; estimated to be 7.1 Gt of CO_2-eq annually (IPCC, 2014). The production of beef cattle contributes with most (41%) of the emissions in the sector, or a total of 2.9 Gt of CO_2-eq (Gerber et al., 2013). Currently, livestock production occupies about 30% of all the ice-free terrestrial surface of the planet (Steinfeld et al., 2013) and Brazil has the largest commercial cattle herd in the world, estimated at 212.8 million head in 2011 (de Figueiredo et al., 2017). Due to increased beef demand, the Brazilian cattle herd grew from 147 million head in 1990 to over 217.7 million in 2017 (Mapa, 2017). Some 83% of this expansion occurred in the Amazon biome and most cattle in Brazil are raised on pastures, which now occupies over 220 million hectares across the country (Bowman et al., 2011).

Pasture expansion in Brazil principally presents two interconnected challenges: emissions from land use change and deforestation, and greenhouse gas (GHG) emissions from the agricultural sector including enteric and manure emissions, as well as those associated with other sources (Latawiec et al., 2014). Both sources can be exacerbated by the spread of degraded pastures within many of the country's key pasture regions (Pedreira et al., 2014). In response, renovation and intensification of pasture agriculture has been presented as a critical tool (Martha et al., 2012), as well as the conversion of degraded areas into other production scenarios, as cropland expansion and vegetation restoration (Strassburg et al., 2017).

Agricultural intensification is done by increasing agricultural inputs and management to improve yield per unit of area. This has been highlighted as one of the main strategies to reach global food security targets and reduce deforestation (Latawiec et al., 2014). Intensifying pasture-based cattle systems results in higher beef mass per unit area, in addition to mitigating GHG emissions from the sector, as has been shown in both simulation and empirical studies (Latawiec et al., 2014; Carneiro et al., 2014). This mitigation has been obtained either to promote mass gains or to incorporate soil and biomass carbon in the CO_2 balance of those production systems.   Changes from extensive to intensive cattle ranching has also been driven by increased national and international interest given to deforestation in Brazil, and the traceability of meat trade chains and production status.

Livestock GHG emissions and mitigation options have been studied to estimate the main emission sources, which are related either to production activities or land use change (de Figueiredo et al., 2017; Bellarby et al., 2012; Herrero et al., 2016; Styles et al., 2018). In Europe and most of western countries, the highest emissions are located in the production phase (i.e. use of feed additives, enteric fermentation and manure emissions) while in countries like Brazil they are also related to land use change (LUC) and deforestation (de Figueiredo et al., 2017; Herrero et al., 2012), primarily in beef production areas. Estimates based on inventory techniques in several European countries have indicated policies to reduce GHG emissions per kg of livestock products, particularly those dealing with food waste (Bellarby et al., 2012). On the other hand, in South America, especially in Brazil, estimates of

GHG emissions from beef production are extremely dependent of LUC. In Brazil, for example, this varies from 41 kg CO_2e kg^{-1} without LUC to 298 kg CO_2e kg^{-1} when LUC in accounted for in the Legal Amazon region (Cederberg et al., 2011), especially in years of intensive deforestation. As beef and milk production have more than doubled over the past decades, the intensification of production is a need to reduce emissions especially related to LUC (Herrero et al., 2012; Smith, 2015). Practices that increase livestock and pasture productivity have been shown to be beneficial to biomass and soil carbon accumulation, increasing the land-occupation factor, and consequently reducing the carbon footprint of beef (de Figueiredo et al., 2017; Herrero et al., 2012; Smith, 2015). Hence, in order to reconcile increasing demand for meat with reductions in emissions and environmental impacts caused by the sector, practices to mitigate emissions point to intensifying pasture systems or reduce the production cycle by shortening the cattle lifespan, especially in the Amazon region of Brazil (Hoffmann et al., 2016).

There are ~71 Mha of cattle pastures across the nine states of Brazilian Amazonia, which contain ~81 million head of bovine cattle (IBGE, 2015) and cattle ranching has been seen as the main driver of deforestation in the region (Barona et al., 2010). Due to the high emissions from cattle ranching, this sector represents one of the largest GHG mitigation potential in the Brazilian economy (Silva et al., 2018). An event has inadvertently contributed to this in the Amazonia by decimating vast pasture areas and forcing farmers to renew their pastures. This is the Sudden Death Disease of pastures (SDD), which is affecting the most popular forage type used for pasture cultivation in the country; *Urochloa brizantha* cv. Marandu (Carneiro et al., 2014). The disease is killing off cattle pastures across the Amazonian states of Mato Grosso, Pará, Rondônia, Acre, Amazonas, Tocantins e Maranhão (Dias-Filho, 2011), and given time, will lead to complete pasture degradation (Dias-Filho, 2015). This disease has been attributed to low soil fertility coupled with climatic, physiological, entomological and phytopathological drivers (Teixeira-Neto *et al.* 2000) and occurs during the rainy season. The reduction of forage mass results in lower beef mass per hectare, and because cattle have to graze for longer periods to reach slaughter weight. In addition, this prolonged bovine lifecycle until the slaughter threshold weight releases more carbon than degraded pastures are able to store in the soil (Lal, 2010) and foliage biomass. The only viable way to deal with SDD has been to restore the affected areas and replant with a new forage type. Here, we hypothesize that introducing further intensification measures to renovate pastures and increase production would result in GHG mitigation in the livestock sector. Our research explores whether the spread of SDD in pastures in Alta Floresta, a municipal county of southern Amazonia, represents a blessing or a curse in GHG mitigation in Amazonia. In order to achieve this, we quantitatively surveyed pasture areas that were either affected or remained unaffected by SDD in the Alta Floresta region of northern Mato Grosso. We then explore the benefits of SDD in terms of its potential in GHG mitigation, by intensifying pasture systems in the affected areas.

MATERIALS AND METHODS

Field sampling of pasture areas was designed to map different types of tropical pastures using a remote sensing technique (Alves de Aguiar 2013). The field-research for this study was initiated in mid to late June 2016, in the municipality of Alta Floresta, state of Mato Grosso, southern Brazilian Amazonia. The climate of the region is Awi type, i.e. tropical rainy with clear dry season from June to August, according to the *Köppen-Geiger* classification. The average annual temperature is 26ºC and a maximum of 40ºC, with precipitation around 2,500 mm yr^{-1} of highest intensity in January - March with annual average relative wetity around 70% (Alvares et al., 2014). The soil is classified as dystrophic Red-Yellow Latosol (EMBRAPA, 2013), with medium texture and medium depth, with good drainage and slopes lower than 2%.

A total of 148 samples were collected, 74 from pastures affected by the SDD, and 74 from pastures without SDD (see Figure 1). Out of the sampled pastures with no signs of the disease, 46 had been renovated. GPS coordinates were taken at each sample point, in addition to searching for indicators of SDD and general signs of pasture degradation. The information from each point regarding pasture quality and GPS positional data were added to Google Earth Pro. These coordinates were later used to classify all sampled pastures using remote sensing techniques based on satellite images, in order to estimate the total area (ha) of pasture affected by SDD. The pastures sampled, and the estimate of their total hectare size were used in order to discuss the research questions. It is important to point out that the study area does not represent the region of Alta Floresta as a whole, but rather paints a picture of the current situation in this municipal county.

Insert Fig 1.

Methodology of pasture sampling

A 1-m^2 quadrant of hard plastic was used to mark the sampling point. According to Salman et al. (2006), a 1-m^2 quadrant is recommended when sampling heterogeneous pastures, pastures containing a high density of weeds, where exposed soil is present or when sampling degraded pastures (Salman et al., 2006); when sampling both, this was a viable method of marking sample points. The GPS points were taken standing in the middle of the quadrant, using a GARMIN GPS. Sampling points were at least 300 m apart in order to maximize spatial independence. The sampling point was randomly selected by taking 20 steps into the pasture, and from there throwing the quadrant into the field. However, if the spot where the quadrant landed was not representative of the pasture (fully bare soil, for example), it was moved to a more representative patch, using the overall aspect of the pasture to determine a representative location. The forage type was identified at each site. It was determined whether or not there were grazing cattle, using indicators such as the presence of dung piles, indicators of grass height and whether or not forage had been consumed. Most pastures planted with the *U. brizantha* cv. Marandu showed signs of SDD, but some areas did not. Pastures affected by SDD often showed general signs of degradation, in addition to having some parts of the forage slightly red coloured, with the presence of surface rocks, termite nests, tree trunks and invasive ruderal plants.

Wet and dry weight

All grass within the 1 m^2 quadrant was cut down, using a large knife or saw, depending on forage density. The grass was cut from the soil level, excluding all dead grass and roots in order to weigh only what bovine cattle would consume (Salman et al., 2006). The forage was then placed into a large bag (formally used for animal feed, cleaned and pre-weighed before samples were collected), and weighed in situ using a portable scale, to determine wet weight. Three scales were used, ranging from 0-300 g, 0-1000 g, and 0-2500 g. The scale used was determined depending on the total volume of grass collected. To estimate dry-weight, each of the samples was oven-dried for 48 hours in paper-bags straight after collection. Oven-drying an also be used to obtain dry-weight of samples, but conventional kilns is the traditional way of drying samples (Alves de Aguiar, 2013; Lacerda et al., 2009). After 48 hours the samples were removed and weighed using a digital scale, subtracting the weight of the paper bags. When assessing these samples, it should be considered that the fieldwork for this research was conducted only a few months after the wet season (October to May) when most of the forage is produced (Carneiro et al., 2014). Due to this, dry-weights obtained here are not representative of year-round forage production. The samples function as an indicator of the differences in forage production at both pasture types. In addition, the grass biomass sampled in the 1-m^2 quadrant was removed from the bottom, excluding all roots and dead forage.

Remote Sensing Analysis

Images of the Operational Land Imager (OLI) orbital sensor onboard the Landsat-8 satellite were used. Scenes (path/row) 227/67, 228/67, and 228/66 were obtained from the United States Geological Survey (USGS) database of 2016. The OLI/Landsat-8 sensor records multispectral measurements in spatial resolution (15 m for panchromatic and 30 m for the other bands) of the terrestrial surface in the following spectral regions: Band 1 (coastal aerosol) of 0.43 to 0.45 µm; Band 2 (blue) of 0.45 to 0.51 µm; Band 3 (green) of 0.53 to 0.59 µm; Band 4 (red) of 0.64 to 0.67 µm; Band 5 (NIR) of 0.85 to 0.88 µm; Band 6 (SWIR-I) of 1.57 to 1.65 µm; Band 7 (SWIR-II) of 2.11 to 2.29 µm; and Band 9 (cirrus) of 1.36 to 1.38 µm. Another advantage is the free availability of Landsat series data, which provides opportunities for the analysis of land-use change at multiple time scales (Silva Junior et al., 2014). By means of the radiometric calibration process in the ENVI 5.1 system, all bands of the scenes were transformed from digital numbers (DN) to spectral radiance measurements at the top of the atmosphere (TOA). Such a conversion is only possible for scenes that present metadata files (MTL), ensuring the process described in Equation 1 (EXELIS, 2014).

$$L\lambda = \text{Gain} * \text{pixel}\ DN\ + offset \qquad (1)$$

To convert radiance in the TOA ($L\lambda$) to planetary reflectance ($\rho\lambda$), Equation 2 was applied.

$$\rho\lambda = \text{M}\rho\ \text{Q}_{\text{cal}} + \text{A}\rho \qquad (2)$$

where: $\rho\lambda$ is the planetary reflectance in the upper atmosphere without solar angle correction; $\text{M}\rho$ is a multiplying factor rescaling the reflectance for any specific band; Q_{cal} is the digital pixel number; and $\text{A}\rho$ is an additive factor rescaled given the reflectance for any specific band.

The corrected planetary reflectance was then obtained by Equation 3:

$$\rho\lambda = \frac{\rho\lambda'}{sen(\theta_{SE})} = \frac{\rho\lambda'}{\cos(\theta_{SZ})} \qquad (3)$$

where: $\rho\lambda$ is the exoatmospheric reflectance; ΘSE is the local solar elevation angle equivalent to the ESUN value (obtained in each METADATA file of the scenes used); and θ_{SZ} is the local zenith solar angle.

After the conversion of digital numbers to reflectance factor, the OLI image processing was performed in the Atmospheric Correction stage by the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) model, with initial conditions including a 70-km visibility, the tropical atmosphere, and the continental aerosol model. FLAASH operates in the spectral range between 0.4 and 2.5 μm, and the processing is carried out pixel by pixel. The model starts from the radiance image that arrives at the sensor and ensures acquisition of surface reflectance data from the derivation of atmospheric parameters such as albedo, surface altitude, vapor column and water, the optical depth of aerosols and clouds, in addition to the surface temperature in the atmosphere (Kruse, 2004). Following the above-mentioned correction, a linear contrast was assigned to better target discrimination and some vegetation indices were applied (Table 1).

Insert Table 1.

In order to classify vegetation, bare soil, watercourses, and other land-uses, based on OLI/Landsat-8 images (bands 1, 2, 3, 4, 5, and 6) and vegetation indices, we performed an Artificial Neural Network (ANN) approach. Regarding the training of ANN, the settings of the samples and their spectral signatures were maintained, architecture definition and training of ANN, network application and obtaining the classified map. In relation to the ANN architecture, the classification module by artificial neural networks of the MLP type (Multi-Layer Perceptron) was executed. The elements of the output layer were defined based on the number of classes to be defined in the image. The artificial neural network was trained using the backpropagation algorithm (Haykin, 2008; Fausett, 1994). Strictly, backpropagation refers to the method calculating the sum gradient, according to the quadratic error function related to the weights for a feedforward network, which is a simple application that is efficient in the chain rule elemental (Chen, 2005). For this, it is assumed that there are n classes, and m neurons in the hidden layer and a neuron in the output layer. This network is assumed to consist of behavioural neurons as described in Silva Junior et al. (2014).

With the images processed, thematic maps of pasture areas were generated, one of which were monotemporal OLI images with vegetation indices. The accuracy of thematic maps with the spatialization of the vegetation areas was evaluated by the Kappa (Equation 4) and Overall Accuracy - OA (Equation 5) metrics, as well as errors and accuracy from the perspective of the producer and user. These metrics ensure a better evaluation of the final classification of areas with and without SDD on pastures.

$$\kappa = \frac{N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k}(x_{i+}.x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+}.x_{+i})} \tag{4}$$

$$\mathrm{OA} = \left(\frac{\sum_{i=1}^{k} x_{ii}}{N}\right) \tag{5}$$

where: κ= estimated value Kappa; k =number of row; x_{ii}= number of observations on row i and column i; $\sum_{i=1}^{k} x_{ii}$ = sum of the elements of the matrix in its main diagonal; x_{i+} = total sum of the observations for the lines; x_{+i} = is the total sum of observations for columns; and N is the total number of observations.

Laboratory measurements of both dry and wet forage biomass with and without SDD were submitted to linear regression analysis according to the vegetation indices described in Table 1. Pearson correlations between the variables assessed with and without SDD were then estimated. The correlation network was used to graphically express the results, in which the proximity between the nodes (traces) is proportional to the absolute value of the correlation between them. Edge thickness was controlled for by correlation estimates, where positive correlations were highlighted in green, while negative correlations were represented in red. Response surface plots and regression coefficients obtained by the Shapiro-Wilk normality test were generated using the SigmaPlot software (v. 11).

RESULTS

Our study area across the Alta Floresta landscape indicate an overall estimate of 42,672 hectares of pastures affected by SDD, out of a total of 55,360 ha. Out of a total of 74 pastures sampled without SDD, 46 had been renovated, while four were dominated by *U. brizantha* cultivar Marandu (Figure 2). In the year in which areas with pasture cultivation in the region were monitored, there was a predominance of areas exhibiting clear signs of the syndrome.

Insert Fig 2.

Some key areas were identified for visualization of the classification made possible by ANN using OLI data and vegetation indices. These identifications with their respective details are presented in Figure 3. The areas in which they were occupied by other land uses were classified and used as a mask for the exclusion of the final class, considering only those with or without SDD. For an adequate visualization of the areas and interpretation of the final data, high spatial resolution OLI images were also allocated using Google Earth. Note that the ANN classifications were effective in separating the classes using the aforementioned sensor (both with spectral bands and vegetation indices), in which pixel-by-pixel details were examined by the algorithm.

Insert Fig 3.

The relationship between the data collected in situ for pastures with or without SDD are presented in Table 2. Our overall dataset achieved an overall accuracy of 94% and a Kappa parameter of 92%. The highest reliability was observed in areas classified as without SDD, where 55 sample points coincided with the reference data, representing 87% of commission set. A 100% and 84% data accuracy was observed when related to the omission of the data with SDD and without SDD, respectively. The classes considered as other uses (water, bare soil, urban center, forest, and annual agricultural crops) yielded a 100% accuracy for either omission or commission.

Insert Table 2.

Figure 4 presents the dry weight of surface grass density which is an indicator of the total forage available for consumption, but this does not take into account the actual nutritional values of the forage. In order to estimate nutritional values, the forage needs to be laboratory-tested to establish protein, fiber and general nutritional contents. The measurements of dry weight serve as an indicator of pasture quality and forage quality at the sampled pastures. Mean values of dry weight biomass in SDD-affected and renewed pastures were 127.44 and 318.97 g m^{-2}, respectively, indicating an 150% increase in biomass after pasture renovation in the Alta Floresta region. Therefore, the overall increase in dry biomass of 1,915 ton ha^{-1} would correspond to an increase in 0.632 ton ha^{-1} of carbon content in biomass, whenever SDD pastures could be restored. Adding the benefits of soil biomass and, above all, long-term soil carbon accumulation would result in an increase of 7.2 ton C ha^{-1} at the end of a 15-year period, a mitigation potential equivalent of 26.5 ton CO_2eq ha^{-1} if SDD-affected areas are converted into renovated pastures.

Insert Fig 4.

The linear relationship between the wet and dry matter as a function of reflectance through the EVI2, GNDVI, NDVI, and OSAVI indices were calculated and presented in Figure 5. Positive relationships were found between biomass production and all indices in areas without SDD (Figure 5). Comparing the dry matter ratio in areas without SDD and the EVI2 and GNDVI indices, the data presented the highest predictive power, with absolute R^2 values ranging from 0.73 and 0.84, respectively, followed by the NDVI and OSAVI indices (0.64 to 0.65). A higher linear relationship was also found for the GNDVI index when correlating with data on dry matter in areas affected by SDD ($R^2 = 0.80$). In contrast, the other indices related to wet matter in areas without SDD showed a weak linear relationship with the biomass, with a maximum R^2 value of 0.68 (EVI2).

Insert Fig 5.

The relationship between vegetation production (dry and wet matter) and vegetation indices (which are the arithmetic combination of spectral reflectance in bands ranging from green to near infrared wavelength), was investigated using regression analysis (Figure 6). The results indicated that there was a significant positive linear relationship between spectral indices and vegetation production, with 91% of the variation in production explained by EVI2 and NDVI. The relationship between GNDVI and OSAVI in areas with SDD, although significant, had a lower R^2 value between dry and wet matter. Vegetation indices as a function of SDD pasture areas showed negative values, which was also expected in areas lacking SDD. However, this possibly occurred due to lignin in plants in areas without SDD which were affected by no interference of fungi attacks of the cellular structure, leaving it intact and more resistant to water loss, thereby having little influence on the near-infrared wavelengths.

Insert Fig 6.

DISCUSSION

The high performance of neural networks in the classification of images of remote sensors is already expected compared to other methods, such as the maximum likelihood algorithm (Erbek et al., 2004; Chagas et al., 2009). Silva et al. (2014) using Landsat-derived vegetation indices based on a classification using ANN (MLP), concluded that Land Use and Land Cover (LULC) mapping with a high diversity of flora and occupation classes in southeastern Brazil was highly effective. Data extracted from the Landsat system were efficient in the classification of LULC, mainly in distinguishing cultivation areas, pastures and natural vegetation (Müller et al., 2015). The same authors reported an adjusted overall accuracy of 93%, with a 95% confidence interval ± 2%, which is considered to be excellent (Congalton and Green 2009).

SDD has strongly affected pastures in Alta Floresta. In a total of 55,360 ha of pastures assessed, 77.1% had succumbed to the syndrome and the remaining 22.9% were either free of the disease or had already been renovated. The presence of the SDD results in high levels of invasive weeds, exposed soils, and reduced forage production as observed by several authors. Lower forage production and poor soil quality cause these pastures to release carbon, contributing to a reduction in carbon sequestration potential (Braz et al., 2013; Carvalho et al., 2010).

Declines in overall pasture productivity do not only pose a threat to production, but it also affects the amount of carbon stored both above and below ground (de Figueiredo et al., 2017; Corazza et al., 1999; Silva et al., 2004). Carbon is stored both in plant biomass and soil, but the majority is stored within the soil (Amézquita et al., 2010). Different soil types have a different capacity of storing C, depending on temperature, precipitation rates, and vegetation in the area (Guo and Gifford, 2002). How much the soil is able to sequester from the atmosphere is dependent on how the soil and biomass are managed, including pasture management in areas allocated to ruminant livestock (La Scala et al., 2012; Cerri et al., 2009; Peters et al., 2012).

Degraded pastures affected by SDD emit more carbon than they are able to store in the soil and plants (Lal, 2002). A recent soil CO_2 emissions study contrasting degraded vs well-managed pastures in Brazil showed a significantly higher emission from degraded soils, despite smaller soil carbon stocks in those areas (de Figueiredo et al., 2017). This is due to less forage cover which results in lower biomass that reduces the uptake of soil residues, affecting the carbon accumulation potential suggested at a typical rate of 0.44 Mg C (1.464 kg CO_2eq) accumulated in the soil per hectare per year. Once managed appropriately, considering the carbon footprint of degraded versus managed pasture systems, an overall reduction from 18.5 to 9.4 kg CO_2eq per kg of meat produced has been shown. There is an additional reduction from 18.5 to 7.6 kg CO_2eq per kg of meet produced if soil carbon accumulation of managed pastures is taken into account (Bordonal et al., 2012).

Pasture quality and how well pastures are able to nutritionally support bovine cattle will determine the production rates of the system (Salman et al., 2006). Where forage quality is low, production will be reduced accordingly (IBGE, 2015). Cattle grazing on degraded pastures and pastures affected by SDD can be six times less productive than cattle grazing on renewed pastures with well-functioning grazing management practices (IBGE, 2015).

Recent studies have pointed to higher efficiency in integrated systems, rather than degraded pastures, in terms of GHG emissions (Cerri et al., 2007; Carvalho et al., 2014; Euclides et al., 2010; Salton et al., 2014; IPCC, 2014). This has been widely adopted by the IPCC as a mitigation option in the livestock sector (Moraes et al., 1996). Emission reductions are achieved mainly in terms of CO_2eq per kg of meat produced, as the increase in number of cattle head would benefit the lower footprint (IPCC, 2014). In addition, most studies indicate an increase in soil carbon (La Scala et al., 2012; Carvalho et al., 2010; Maia et al., 2009; Bustamante et al., 2006; Neill et al., 1997; Cerri et al., 2003; Fearnside et al., 1998). However, some have shown a depletion of soil C stocks in newly converted forest areas (Euclides et al., 2010; Hughes et al., 2000; Bustamante et al., 2012). In particular, yield increases due to improved efficiency results in lower pressure on natural forest areas, avoiding further deforestation especially in the Amazon (Silva et al., 2018).

Cattle ranching on pastures affected by SDD can be maintained for a certain amount of time but this land-use revenue option will continue to decline, if not collapse, if pastures fail to be renovated. Due to declining production on pastures affected by SDD, cattle ranchers experience significant losses of income which could trigger deforestation (Dias-Filho, 2015). Historically, low farm yields have contributed to higher deforestation rates in order to expand land tenure under cultivation (IBGE, 2017).

According to Silva et al. (2018), the stocking density of pastures in the Alta Floresta region would be roughly 2 head/ha in SDD-degraded areas, amounting to a slaughter time of ~40 months. After pasture renovation, those same pastures can sustain 3.25 heads/ha and the slaughtering period drops to 30 months. This represents a 62.5% increase in pasture support capacity, including each head of cattle reaching live target weights at slaughter. This is very meaningful in terms of enhanced support capacity, considering Amazonian pastures typically support a very low average stocking density of only 1.14 head/ha (Silva et al., 2018).

As described above, the total estimated area of 42,672 ha affected by SDD in the Alta Floresta region currently represents a curse for farmers due to low livestock production. Conversely, this represents a mitigation potential of 26.5 ton CO_2eq ha^{-1} once those areas are converted to renewed pastures, which amounts to an important mitigation potential in reducing the carbon footprint in that region. Considering the potential for biomass and carbon sequestration in the first three years after conversion from SDD-affected to renewed pastures, and intensifying meat production per hectare, both would significantly reduce the carbon footprint of livestock operations and their GHG emissions per kg of meat produced. For a stocking density of 4 head/ha, instead of 0.5 head/ha in degraded areas, emissions are intensified per unit area, assuming a methane emission factor of 52 kg CH_4 $head^{-1}$ $year^{-1}$ this would result in enteric emissions of around 4.4 ton CO_2eq $year^{-1}$. The mitigation potential of 26.5 ton CO_2 ha^{-1} in 15 years would correspond to a 1.76 ton CO_2eq ha^{-1} $year^{-1}$, or around 40% of the estimates associated with enteric emissions at those sites. This would amount to a significant mitigation option, further reducing the carbon footprint per kg of meat produced across the Brazilian Amazon. Considering all SDD-affected pastures area sampled, only two pasture sites had been renovated. The possibilities for improving carbon accumulation in the soil also declines as the overall forage cover declines (Peters et al., 2012; Mello et al., 2014). In order to increase the levels of successfully renovated pastures, knowledge on how the disease spreads, the reasons for SDD infection in the first place, and how pastures should be best renovate are essential. Avoiding further deforestation, increasing carbon stocks in the plant biomass and soils have shown to contribute enormous benefits and a blessing towards sustainable livestock production in the southern Amazon.

CONCLUSIONS

Sudden-death disease severely affects pastures wherever it occurs in the Amazon. In Alta Floresta, 77% of all pastures sampled had been affected. Our research was restricted to only one municipal county so further sampling in other Amazonian states is necessary to examine the environmental gains incidentally could be brought about by this syndrome. This high incidence rate limits the financial viability of cattle ranches and forces them to either sell out to other land-use options or renew their pastures. It is also necessary to quantify the *in situ* carbon balance of both pastures affected by SDD and renewed pastures. Renewal implies an increase in the green pasture mass and also an increase in pasture support capacity. Renewed pastures serve as carbon sinks in both the phytomass and the soil, higher stocking densities per hectare, and shorter lifespans, so that cattle grazing on renovated pastures results in much lower CO_2eq per kg of final product. Moving from an extensive system with low yields and high emissions towards a more intensive system including renovated pastures would benefit both production yields and the carbon footprint of the animals produced, while also contributing to increased C sequestration from the atmosphere. In the absence of SDD, farmers ranching on extensively non-degraded pastures in Alta Floresta and elsewhere may not adopt intensive practices, and therefore lose the associated benefits. The spread of SDD therefore represents a 'bitter pill' and a window of opportunity in climate change mitigation options, in terms of lower GHG emissions from the cattle ranching sector. The Brazilian government should therefore capitalize on this momentum, and direct strong policy incentives to promote renovation of Amazonian pastures conditioning the release of financing for livestock initially with the renewal of pastures.

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FIGURE CAPTIONS

Figure 1: Overview of the Alta Floresta region, and the sampling areas. Red dots indicate test sites where SDD was detected in situ, light green dots indicates pastures where SDD was not detected.

Figure 2: Classification results of pastures affected by SDD (with SDD), those where SDD was absent (without SDD) and other land use classes based on the benchmark dataset. Red squares indicate subsets enlarged in Figure 3.

Figure 3: Spatial patterns of the ANN for three subsets in the study area and the two datasets (spatial data). High-resolution imagery from Google Earth is shown for visual comparison (imagery acquisition date of subsets 16 July 2016). Geographic locations of subset can be found in Figure 2.

Figure 4: Weight of the 50 sampled pastures in Alta Floresta. In this figure, pastures without SDD refer to those where the disease was not detected. Sudden death indicated the weight of pastures in areas where SDD was detected.

Figure 5: Correlation coefficients between dry and wet matter (biomass g m^{-2}) and the orbital reflectance expressed by vegetation indices in areas without SDD.

Figure 6: Correlation coefficients between dry and wet matter (biomass g m^{-2}) and orbital reflectance expressed by vegetation indices in areas with SDD.

Table 1. Vegetation indices applied to the OLI image as a reflectance factor to reduce the dimensionality of the data for interpretation.

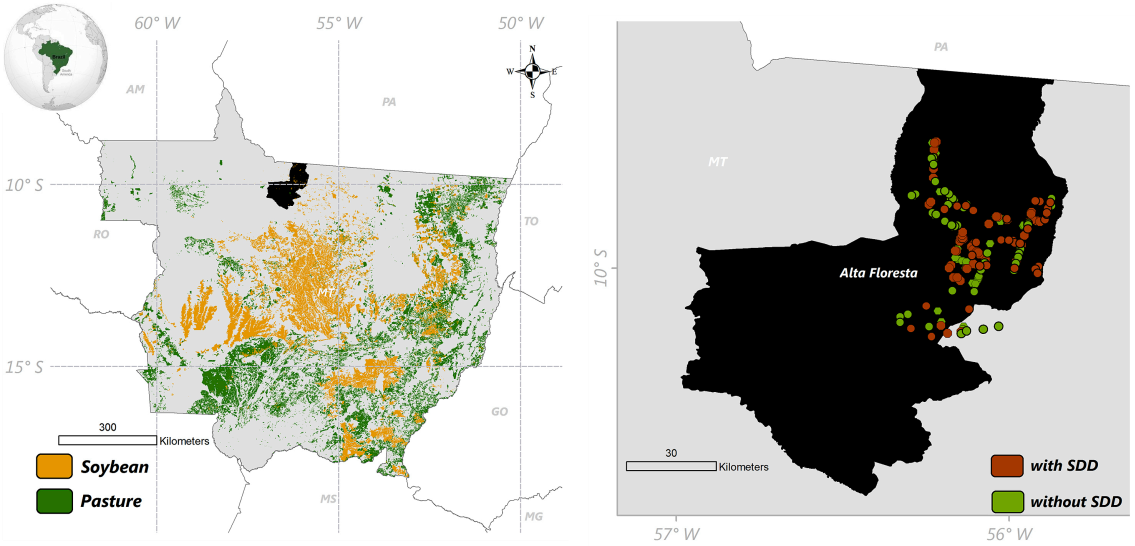
Equations**	**Indices***	**Reference**
$(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R)$	NDVI	Rouse *et al.* (1973)
$(\rho_{NIR} - \rho_G)/(\rho_{NIR} + \rho_G)$	GNDVI	Gitelson *et al.* (1996)
$2.5(\rho_{NIR} - \rho_R)/(\rho_{NIR}+2.4\rho_R+1)$	EVI2	Jiang *et al.* (2008)
$(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R + 0.16)$	OSAVI	Rondeaux *et al.* (1996)

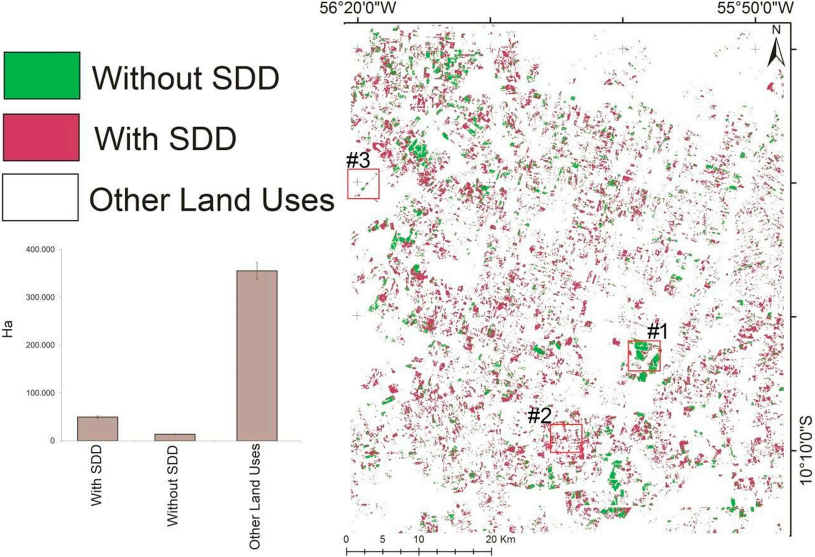
*NDVI: Normalized Difference Vegetation Index; GNDVI: Green Normalized Difference Vegetation Index; EVI2: Enhanced Vegetation Index 2; OSAVI: Optimized Soil Adjusted Vegetation Index. ** ρ_G: reflectance in green; $\rho_{R:}$ reflectance in red; $\rho_{NIR:}$ reflectance in near infrared.

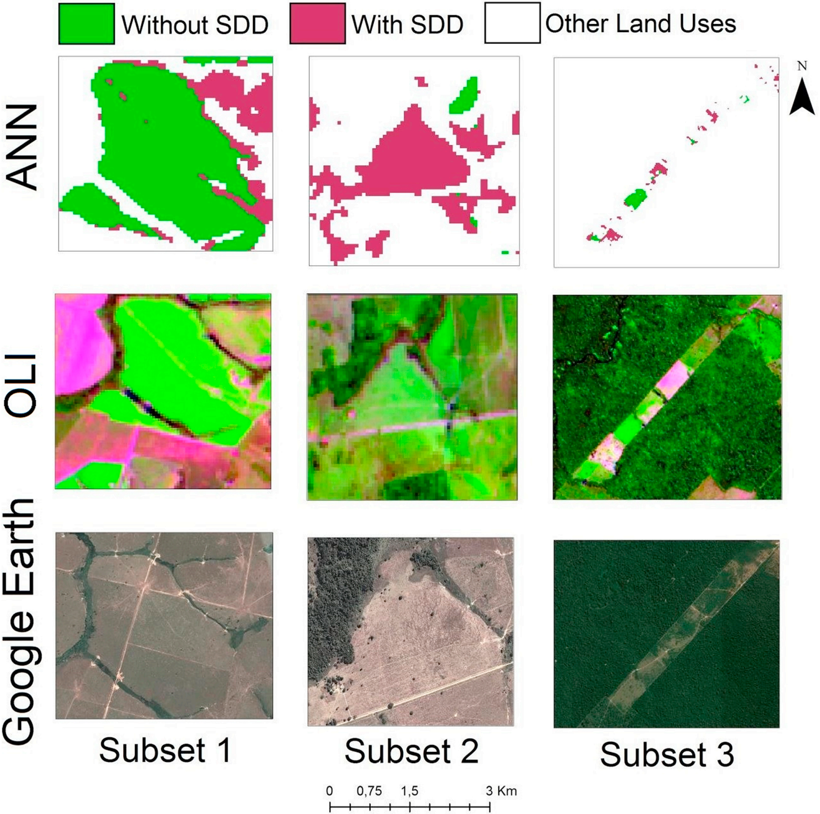
Table 2. Confusion matrix of validation results for the classes evaluated.

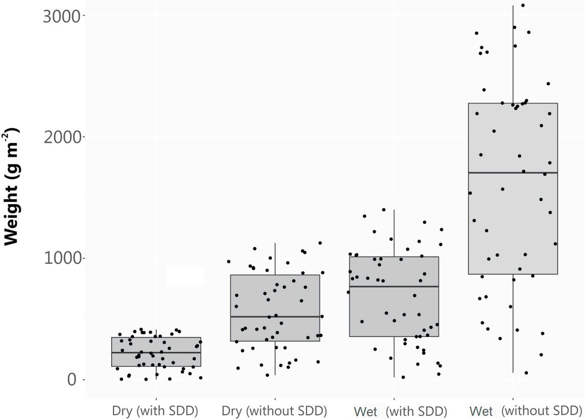
Classified data (ANN)	Reference data				
	With SDD	Without SDD	Other Land Uses	Σ	User's accuracy
With SDD	55	8	0	63	0.87
Without SDD	0	43	0	43	1.00
Other Land Uses	0	0	42	42	1.00
Σ	55	51	42	148	
Producer's accuracy	1.00	0.84	1.00		

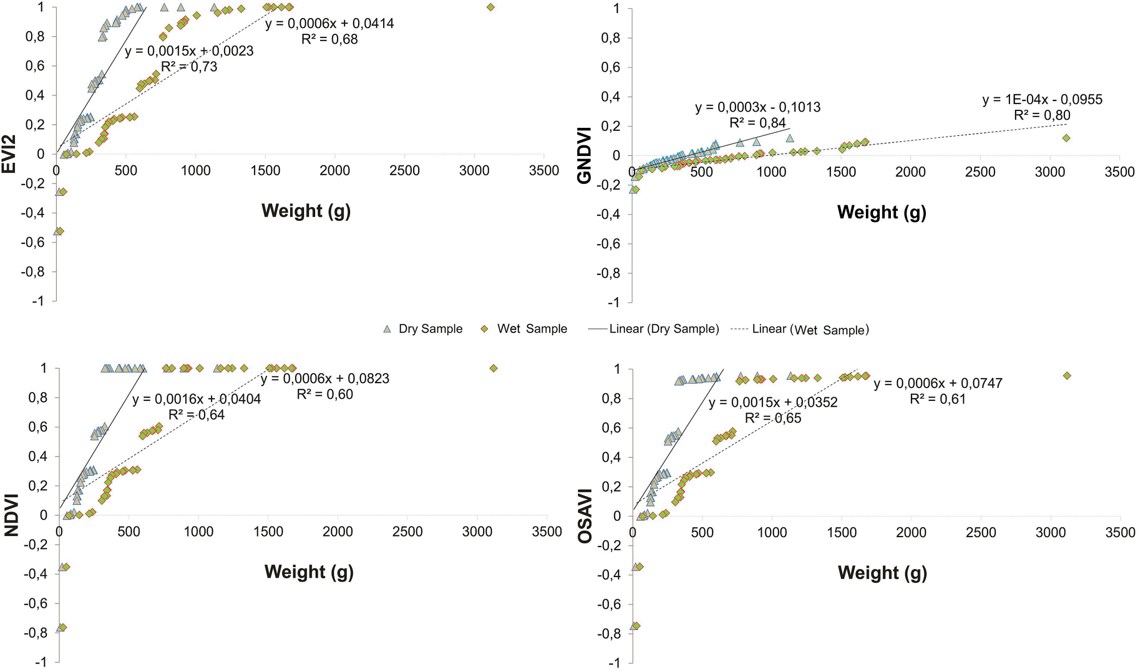
User's and producer's accuracy is normalized between 1 (100%) and 0 (0%). Parameters: κ = 0.92, OA = 0.94, Z = 32.67, p-value = 0.00 (α 0.05).

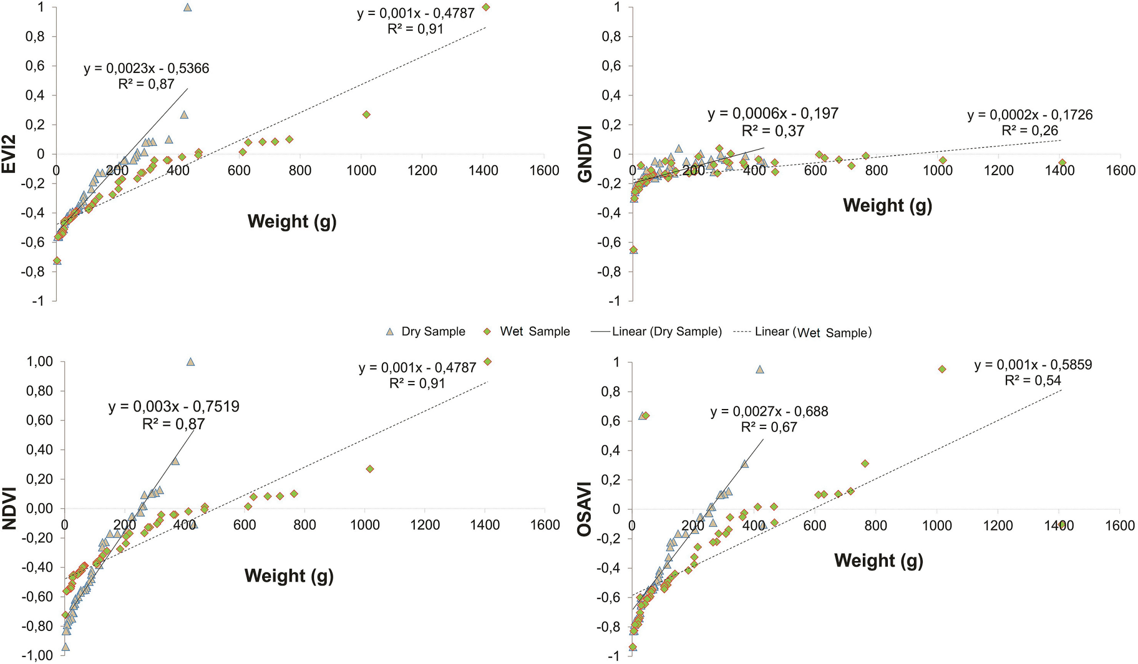

Brazil
South America
60° W
55° W
50° W
N
W
E
S
AM
PA
RO
TO
MT
GO
MS
MG
10° S
15° S
300
Kilometers
Soybean
Pasture
PA
MT
Alta Floresta
10° S
30
Kilometers
with SDD
without SDD
57° W
56° W


Without SDD
With SDD
Other Land Uses
400.000
300.000
200.000
100.000
0
Ha
With SDD
Without SDD
Other Land Uses
56°20'0"W
55°50'0"W
10°10'0"S
N
#1
#2
#3
0
5
10
20 Km


Without SDD
With SDD
Other Land Uses
N
ANN
OLI
Google Earth
Subset 1
Subset 2
Subset 3
0
0,75
1,5
3 Km


Weight (g m^{-2})
3000
2000
1000
0
Dry (with SDD)
Dry (without SDD)
Wet (with SDD)
Wet (without SDD)


EVI2
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
-1
0
500
1000
1500
2000
2500
3000
3500
Weight (g)
y = 0,0015x + 0,0023
R² = 0,73
y = 0,0006x + 0,0414
R² = 0,68
GNDVI
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
-1
0
500
1000
1500
2000
2500
3000
3500
Weight (g)
y = 0,0003x - 0,1013
R² = 0,84
y = 1E-04x - 0,0955
R² = 0,80
Dry Sample
Wet Sample
Linear (Dry Sample)
Linear (Wet Sample)
NDVI
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
-1
0
500
1000
1500
2000
2500
3000
3500
Weight (g)
y = 0,0016x + 0,0404
R² = 0,64
y = 0,0006x + 0,0823
R² = 0,60
OSAVI
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
-1
0
500
1000
1500
2000
2500
3000
3500
Weight (g)
y = 0,0015x + 0,0352
R² = 0,65
y = 0,0006x + 0,0747
R² = 0,61


EVI2
y = 0,001x - 0,4787
R² = 0,91
y = 0,0023x - 0,5366
R² = 0,87
Weight (g)
GNDVI
y = 0,0006x - 0,197
R² = 0,37
y = 0,0002x - 0,1726
R² = 0,26
Weight (g)
Dry Sample
Wet Sample
Linear (Dry Sample)
Linear (Wet Sample)
NDVI
y = 0,001x - 0,4787
R² = 0,91
y = 0,003x - 0,7519
R² = 0,87
Weight (g)
OSAVI
y = 0,001x - 0,5859
R² = 0,54
y = 0,0027x - 0,688
R² = 0,67
Weight (g)
0
200
400
600
800
1000
1200
1400
1600
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
-1
1,00
0,80
0,60
0,40
0,20
0,00
-0,20
-0,40
-0,60
-0,80
-1,00

Author Statement

The authors declare that this manuscript is not under review in another Journal and has not been published in other languages.

Conflict of Interest Declaration

The authors declare no conflict of interest.