10

Remote sensing applied to grassland ecosystems in regions with climatic vulnerability

Leonardo Fiusa de Morais
Universidade Federal do Ceará - UFC

Ana Clara Rodrigues Cavalcante
Embrapa Caprinos e Ovinos

Deodato do Nascimento Aquino
Instituto Nacional de Colonização e Reforma Agrária - INCRA

Magno José Duarte Candido
Universidade Federal do Ceará - UFC

doi 10.37885/221010540

SUMMARY

The aim of this review is to present the concepts and current research on the use of remote sensing in studies of pastoral ecosystems. The management of pasture plays an important role in the balance between biomass production and its regrowth so that the determination of biomass production is fundamental information to perform the adjustment of the number of animals. There are direct and indirect methods to obtain forage biomass in pastures. Generally the most used are direct methods, where there is the cutting of all forage present in a known area frame, and this requires the help of a variety of tools, requiring infrastructure, labor with long-term fieldwork. Remote sensing is an indirect way to determine biomass in pastures, which has a significant potential to monitor vegetation dynamics, besides predicting events such as the beginning or peak of vegetation growth. One of the ways to monitor the vegetation is through the use of vegetation indexes. There are several vegetation indexes, but soil adjusted vegetation index (SAVI) and normalized difference vegetation index (NDVI) are the most used in studies on pastoral ecosystems. Remote sensing used for pasture evaluation can contribute with relevant and complementary information on forage production, as well as the growth behavior of the forage plant, allowing to obtain information on large scales.

Keywords: Environmental Disasters, Livestock Analysis, Remote Sensing, Spectral Vegetation Indices.

INTRODUCTION

Remote sensing is a geoprocessing tool capable of consistently capturing the characteristics of large areas of the Earth's surface (Lu *et al.*, 2014). One of the benefits of this tool is to enable researchers to study large areas with a moderately large temporal and spatial resolution at a relatively low cost and in a short time (Salimon & Anderson, 2017). From a livestock point of view, the evaluation of exotic or native forage plants is of fundamental importance, since they are used in the formation of pastures and are the main source of energy in the diet of ruminant animals. However, the efficiency of forage utilization, which will be decisive in the economic return and performance of the animal, depends very much on the structural condition of the pasture, being of decisive character, the prediction of the phenological state of the forage plants for the adequate management of the pasture (Hermance *et al.*, 2015).

Livestock is an important source of income, especially for rural communities in Africa (Sibanda *et al.*, 2017), arid and semi-arid regions (He *et al.*, 2005), which are the main regions facing degradation problems caused by anthropogenic activities, climate change, natural disasters and socioeconomic inequalities. According to Verstraete *et al.* (2009), the arid and semi-arid lands of the world are closely related to global poverty, and livestock activity, even if not very productive, is an important source of income for the inhabitants of these regions. And it is precisely in these regions, where there is low pasture productivity, and therefore the low number of animals reared in large pastures (Sayre *et al.*, 2013).

The strategic management of pasture aims to improve the efficiency of the use of resources through the optimization of processes that involve plants, ruminants, and their interface, increasing productive efficiency and consequently becoming an ecologically correct practice (Congio *et al.* 2018). Based on this, control of grazing intensity plays a crucial role in the equilibrium of biomass production and regrowth of pasture (Chang *et al.*, 2016). However, pastures undergo crop fluctuations throughout the year (Magliano *et al.*, 2015), so that the understanding of the productive behavior is fundamental information to perform the adjustment of the number of animals, as a function of the fodder biomass offered. Generally, grassland degradation occurs due to the imbalance between the cycling of accumulated nutrients in the vegetal residue and the growth of the pasture, constituting an open door for the degradation, as there is the elimination of many points of growth and when new shoots appear, are rapidly consumed.

The amount of biomass supplied will represent animal support capacity, and to obtain this information, direct methods are usually used with the aid of a variety of tools, requiring infrastructure, labor with fieldwork long-term (Ran *et al.*, 2016). So, from these limitations, other methods have been studied, developed and improved in order to estimate the forage biomass indirectly, without the need for direct cutting of the forage, and to make it possible to relate characteristics that are easy and quick to measure.

Remote sensing consists of obtaining information about a particular target without having direct contact with it, mainly through the interpretation of the variation of the electromagnetic radiation that is reflected from the target, and captured by sensors that are usually aboard spacecraft orbital level. When we apply remote sensing in large areas, we can map the livestock production systems to a regional level (Robinson *et al.*, 2011). With this, the mapping allows providing information on the biomass condition of pastures in almost time, generating information necessary for the producer to estimate its stocking rate. In addition, the forage biomass estimation allows the cattle rancher to predict times of deficit or surplus of forage production, avoiding the overgrazing.

Based on the foregoing, the objective of this review article is to discuss the evolution of remote sensing in pasture ecosystems, in relation to the contextualization of the importance of livestock activity, methods for the determination of forage biomass and applications of remote sensing in studies on pastoral ecosystems.

Importance of Grasslands for livestock

According to Rao *et al.* (2015), four of the five agricultural commodities with the greatest global economic value come from livestock activity, and the action moves global economic values in order of at least 1.4 trillion dollars, being that, the grassland is the main food source of domestic herbivores, and grazing is the means by which these animals seek food in the 3.4 billion ha of existing pastures in the world. However, for Garnett *et al.* (2013) livestock must comply with the premises of sustainable intensification, through increasing food production with high production rates, food security, and environmental sustainability.

Historical changes in demand for livestock products have been driven largely by human population growth, income growth, and urbanization (He *et al.*, 2005), however, some quantitative assessments that relate food production to increased demand show that global agriculture will have to be technically evolving to meet this growth in demand (Tilman *et al.*, 2011). In addition, for Reshef *et al.* (2010), even if global agricultural production is increasing, there are pressures imposed by society, in order to ensure safe food and produce in a sustainable way for the population. Livestock activity is considered one of the fastest growing sectors in the industry, mainly due to the world demand for food of animal origin. Table 1 shows the growth trends expressed in consumption of meat and milk in developing countries and developed through estimates for the years 2015 to 2050 (Thornton *et al.*, 2010).

Table 1. Trends in meat and milk consumption in developed and developing countries.

		Annual per capita consumption		Total consumption	
		Meat (kg)	Milk (kg)	Meat (Mt)	Milk (Mt)
Developing	1980	14	34	47	114
	1990	18	38	73	152
	2002	28	44	137	222
	2015	32	55	184	323
	2030	38	67	252	452
	2050	44	78	326	585
Developed	1980	73	195	86	228
	1990	80	200	100	251
	2002	78	202	102	265
	2015	83	203	112	273
	2030	89	209	121	284
	2050	94	216	126	295

Source: Adapted from Thornton et al., (2010).

According to Thornton *et al* (2010), there is a large difference between the availability of meat and milk between developed and underdeveloped regions, and the future prospects of animal production, is a wide gap between developed and developing countries, due to the great existence of systems highly intensive and high technology production in developed countries and by systems based on extensive animal husbandry based on pasture-based and extensively managed livestock in underdeveloped countries. Moreover, a large increase in demand for animal products, but there is an expectation that changes in the global climate will directly affect the productive efficiency of agriculture. Tilman el al. (2011) forecast global food demand by 2050, and according to the authors, this global demand is growing rapidly and much of the world's agricultural areas are below productivity, and the current global expansion trajectory has serious long-term implications for the environment.

For Smith *et al.* (2013), there is an increase in animal production on pasture, both from grazing expansion and from intensification, and these dynamics of expansion and intensification can pressure the environment and compete for land with other uses, requiring socio-economic and environmental compensation.

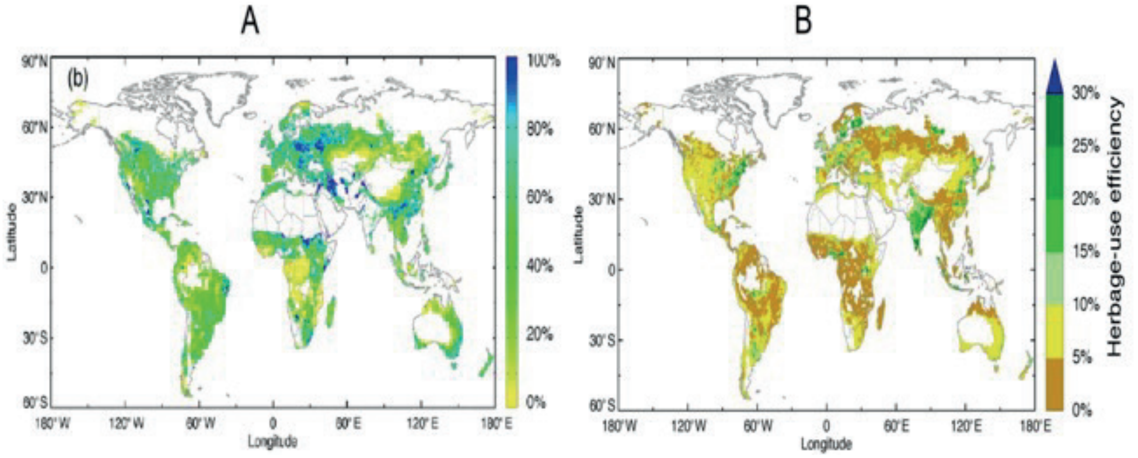
Grazing encompasses interactions between the animal and its environment (Provenza *et al.*, 2015), and this interaction depends essentially on the herbage supply present in the pasture. According to Allen *et al.* (2011), grazing management consists in the manipulation of animal grazing in search of a defined objective, so that this, objective seeks to maximize the transformation of forage present in the pasture in animal product, maintaining the perennial pasture, through the continuous emission of leaves and tillers after grazing, restoring the leaf area of the plant (Araújo *et al.*, 2015).

Livestock farming contributes directly to the livelihoods and food security of almost one billion people in the world (Robinson *et al.*, 2014), and when we think especially of ruminant production, these animals have the capacity to transform fiber in nutrient-rich foods of high quality for human consumption (Smith *et al.*, 2013), with pastures being the main source of feed for ruminants. Pastures also provide other services to the environment, such as fiber production, carbon sequestration, conservation of natural resources and recreation activities in some regions of the planet, mainly where natural pastures are cultivated. However, pastures continue to have their main importance in supporting livestock activity, so that approximately 30% of the world's human population is estimated to use livestock on pasture as a means of survival (Reynolds *et al.*, 2007).

Chang *et al.*, (2016), in his article: Combining livestock production information in a process-based vegetation model to reconstruct the history of grassland management, produced global maps of grazed areas of the globe (Figure 1).

For the construction of the maps, estimates were made using ORCHIDEE-GM (ORganizing Carbon and Hydrology in Dynamic Ecosystems grassland management). This model is calibrated to simulate the distribution of potential biomass harvested. Figure 1 includes pasture areas with high and low presence of grazing animals (0-100%), while the areas in blue there is a large presence of grazing animals, those of yellow there is a low presence. It can be understood that yellow areas have a low pasture consumption and therefore can be defined as extensively managed pasture.

Figure 1. Map of the areas grazed by ruminants (a) and efficiency of forage use (b) from data modeled by ORCHIDEE-GM model.



Source: Adapted from Chang et al., (2016).

In this same paper, Chang *et al.* (2016) developed maps of herbage-use efficiency. This variable found values between 2 and 20% in most regions, which usually follows the spatial pattern of ruminant density. The highest herbage-use efficiency utilization, that obtained above 20%, was found in regions with intensively managed pastures, while the lowest efficiency of forage use is obtained in the regions of Central Asia, Russia, Africa, Brazil, Australia and in the mountains of southwest China and Europe, the Alps. The author attributes this low efficiency to the extensive pasture management at these sites.

As the stocking rate increases, the individual performance of the animal decreases, while the production/area increases to a maximum, and then decreases as a result of a competition process that controls the production and use of the plant by the grazing animal (Carvalho & Batello, 2009).

Grazing management strategies that optimize forage utilization are alternatives to improve land use and reduce the emission of the main greenhouse gases in grassland systems, and this brings out, the great challenge of producing food of animal origin in a sustainable way without the degradation of grazing by overgrazing. And to obtain the efficient management of the pastures, the control of the variation of the biomass and its components is a decisive point in the planning of a rational management, that is, it represents to adjust an availability of forage at a suitable stocking rate.

Determination of Above Ground Biomass in Grassland

There are direct and indirect methods for estimating forage mass in pastoral environments, however, indirect methods are being further studied, mainly because the direct method is based on total forage cutting (Morais *et al.*, 2018), however, harvesting by direct cutting of forage is time-consuming and requires very intensive labor, which makes it difficult to evaluate large areas, especially when it is difficult to access regions (Zhang *et al.*, 2016). Therefore, it is of fundamental importance to develop reliable systems of biomass monitoring in pastures that are practical, easily accessible to producers and of high cost-benefit ratio (Sibanda *et al.*, 2017).

The variability of pasture structural characteristics, limitations of human resources and materials, causes difficulty in choosing the most appropriate method to be used. The trends is for indirect methods to be used instead of a direct method, since the direct method is a costly process with respect to labor.

From the biomass present in this frame, and provided that the location chosen for sampling is representative of the pasture area, the value obtained for kg/ha of dry matter produced can be extrapolated.

Another alternative for forage biomass estimation is modeling (Silva Neto *et al.*, 2016), and satellite-based remote sensing combined with modeling tools can provide large-scale, timely information with sufficient spatial details and reasonable costs. Generally, the models are based on edaphoclimatic variables, defined from the basic information necessary for the plant to reach a certain stage of growth (Almeida *et al.*, 2011).

Modeling for the estimation of biomass in pastures has some particular characteristics (Snow *et al.*, 2014): Pastures are biologically diverse, so interactions among plant species should be considered; economic return requires the inclusion of the animal as an additional trophic level; the interaction between the animal and the pasture is complex, influenced by the environment, plant species and animal behavior; There is nutrient transfer between animals and pasture; and data to generate simulation models depend on farm management, becoming complex when it comes to a pasture production system.

Bryant & Snow (2009), cite some important models for the simulation of pastoral ecosystems: APSIM, EcoMod, FaSSET, GRaZPLaN, GPFaRM, Hurley Pasture, IFSM, LINCFaRM and WFM, which are the most commonly available and widely used models in articles in the field of pasture modeling. Another model with research reports in the pasture area is the CROPGRO model. Pequeno *et al.*, (2018) compared the performance of the CROPGRO perennial forage (CROPGRO-PFM) model to simulate the yield of three tropical grass species (Urochloa cv Marandu, Urochloa decumbens, Tifton 85) and concluded that harvest frequency 28 and 42 days, provided better adjustment to the model, adjusting the simulation of leaf and stem weight, and biomass production of these grasses. From an appropriate adjustment of this model, it could be used to carry out simulations of forage biomass production, especially in a tropical environment.

Despite the importance and dissemination of modeling knowledge in the simulation of pasture growth, few studies have evaluated the application of models in pastures (Andrade *et al.*, 2016), which, according to Marin and Jones (2014), is partially explained lack of understanding of the capabilities and limitations of this tool, little experience in the evaluation, calibration and use of models, in addition to the low credibility of the models created. However, regardless of the difficulties of its use, it is expected that this tool will have a greater use, knowing that, the models need to be well calibrated, providing information that has a great representation and that are accurate with low cost of operation and good accuracy on the biomass conditions of pastures.

■ REMOTE SENSING APPLIED TO PASTORAL ECOSYSTEMS

Obtaining Images from Satellites and Image Processing

Remote sensing data have significant potential to monitor vegetation dynamics, and this allows monitoring of events such as the onset or vegetation growth maximum. Currently, from the ease of access to the internet, it has become more accessible (Ferreira *et al.*, 2008), and high-resolution satellite imagery are increasingly available to be used free of charge in many applications for both small and large-scale studies (Forkuor *et al.*, 2017), and is an effective tool for estimating and monitoring different types of vegetation.

The contrast of the vegetation response at the different wavelengths makes the vegetation of the pasture stand out in relation to the other targets, facilitating its identification and its monitoring. In this way, the information collected by satellite images can contribute to obtain data faster and in regions of difficult access. Major remote sensing platforms include satellites, airplanes, balloons, helicopters, and a variety of sensors such as optical and near-infrared, Radar and sensors are installed on these platforms for remote sensing applications (Zhang and Kovacs, 2012)..

However, the success of remote sensing of vegetation depends on many factors, including soil type, plant structure, water and nutrients, phenological cycle and cultivation practices (Bégué *et al.*, 2018). According to Lu *et al.* (2014), for biomass estimation through remote sensing, it is necessary to select suitable variables for the development of biomass estimation models: data from the optical sensor suffer the saturation problem with high biomass density; spectral variables are unstable and influenced by external factors such as atmosphere, soil moisture, phenology and vigor, so high-quality optical sensor data depend on weather conditions when satellites pass; and lack of adequate methods to identify the most appropriate variables for the modeling of biomass estimates.

According to Ferreira *et al.*, (2008) a major advance in vegetation studies through remote sensing was the launch of the Modis sensor (Moderate Resolution Imaging Spectroradiometer), in the spatial resolution versions of 250, 500 and 1000m, released on board Earth satellite in December 1999 and aboard the Aqua satellite in May 2002. This sensor, the flagship of the Earth Observing System (EOS - NASA), combines features of the AVHRR and Landsat TM sensors, while bringing important advances such as more spectral bands, higher spatial resolution and better (less subject to atmospheric contamination and more sensitive to photosynthetically active vegetation).

An important satellite, and one of the most used in remote sensing of vegetation, is the Landsat series. The LANDSAT program, which is managed by National Aeronautics and Space Administration (NASA) and NOAA (National Oceanic and Atmospheric Administration), which was initially named ERTS-1 (Earth Resources Technology Satellite 1), which was released in 1972 The program was renamed to LANDSAT, and is currently on the 8th satellite of this series in orbit. Landsat 8 has an OLI sensor which is a multispectral sensor composed of 11 bands and with a temporal resolution of 16 days.

Another commonly used satellite in vegetation studies is the Sentinel. The Sentinel-2 mission is designed to provide multispectral Earth observation data for a wide range of remote sensing applications such as land-use mapping or land cover, land-use identification, agriculture and forest monitoring, water monitoring, monitoring of natural hazards and monitoring of water stress (Du *et al.*, 2016). Sentinel-2, consisting of a mission of two satellites, with MSI sensor of 10 meters of spatial resolution, and with a capacity of 5 days of revisit.

Studies that use vegetation indices need to minimize the main sources of noise that affect vegetation response, which according to Ferreira *et al.* (2008), are: variations in solar irradiance; atmospheric effects; the contributions of non-photosynthetically active vegetation; the contributions of the substrate; the effects of canopy composition and structure. Generally these atmospheric corrections are necessary due to the reflection, refraction or absorption of the radiation after the direct contact with the target, causing the scattering of the radiation, and as a result of the correction is to obtain the reflectance spectral.

Application of vegetation indexes in grassland

The interpretation of remote sensing of vegetation occurs through canopy reflectance processes. The basic premise of applying remote sensing to vegetation assessment is that differences in crop growth and soil condition can be identified through variations of spectral responses (Warren and Metternicht, 2005). This happens because vegetation represents the reflection or biosphere response of the radiation emitted on Earth (Zhang *et al.*, 2003).

As morphological changes occur in the forage canopy, there are also variations in the absorbed, transmitted and reflected fractions of the incident solar radiation, and these variations allow monitoring of the vegetation. Through this principle, vegetation indices have been created and are widely used to monitor crop development and are generally used as input data in models to predict yield (Morais *et al.*, 2021), as well as to study the photosynthetic potential of a vegetation, canopy pigments, water content in the canopy and the cover of green vegetation and senescent (Hill *et al.*, 2013).

There are several vegetation indexes, however, the normalized difference vegetation index (NDVI) is the most used for studies in pasture ecosystems (Hermance *et al.*, 2016; Hott *et al.*, 2016). According to Vrieling *et al.* (2011), NDVI derived from large-scale satellite images provides observations on a short time scale, allowing frequent updates of vegetation status. This index is based on the principle that the wavelength in the red band is almost completely absorbed by plant surfaces rich in green and photosynthetically active biomass, whereas the infrared band is reflected. As the region of the electromagnetic spectrum corresponding to the photosynthetically active radiation, is used by the plants in the physiological processes of photosynthesis, there is a great relation of the NDVI with the accumulation of biomass. Another important feature of this index is the almost linear relationship between the interception of photosynthetically active radiation, and the latter can be an indication of productivity (Atzberger, 2013).

The Soil-Adjusted Vegetation Index (SAVI) is an important index created to describe soil-vegetation dynamics in remote sensing studies (Ha *et al.*, 2001). According to Andrade *et al.* (2013), the basis of the SAVI is also based on the antagonistic behavior of vegetation reflectance in the Red and Infra red bands. However, the Savi has an adjustment (L) of the index that is variable with the degree of canopy closure (variable from 0 to 1), which allows an improvement in the interpretation of vegetation variables. In order to obtain NDVI and SAVI, the red and near infrared bands are used using the following formulas: NDVI = (B8-B4) / (B8 + B4) and SAVI = (1 + L) * (B8-B4) / (B8 + B4 + L), where L is the soil adjustment factor.

Remote Sensing In Livestock Early Warning System

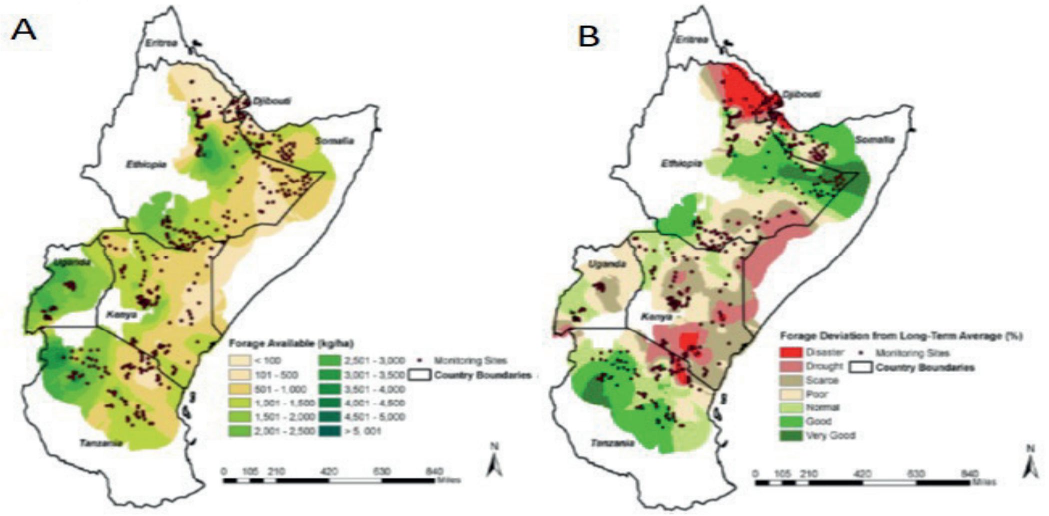
According to Adams *et al.* (2003), meteorological agencies around the world are looking at methods to determine how weather disturbances can be detected early enough to allow for decisions to be taken and to avoid losses from environmental events. Climate variability has been mainly attributed to greenhouse gas emissions and is one of the main causes that increase uncertainties and risks in animal production in pastures (Angerer *et al.*, 2013). But, advances in the use of computational tools, geographic information systems, satellite imagery, biophysical modeling, and near-real-time availability of weather data have become an opportunity for technologies to assess the impact of emerging forage production for livestock production, particularly in short-term projections (Alhamad *et al.*, 2007).

The Livestock Early Warning System (LEWS) project develops feed and livestock production monitoring systems throughout the eastern African continent (Kaitho *et al.*, 2007), Mongolia (Angerer, 2012), the United States (Angerer, 2008) and in Puma in Peru (Gutiérrez *et al.*, 2014). This project continuously seeks to provide information on forage production and cattle market price forecasting, enabling cattle ranchers to identify adverse moments by triggering appropriate and timely decision making (Stuth *et al.*, 2005). In some regions of Africa, where farmers are nomadic, this system enables them to be free to move (Moritz *et al.* 2013), always looking for places where there is a supply of fodder for your animals.

To estimate forage biomass, this system uses the Phytomass Growth Simulator (PHYGROW) as the primary model to estimate pasture biomass conditions. The Phygrow model requires field data, collected at different monitoring sites, for calibration and validation. In addition, the simulations are driven from climatic data based on almost real-time information, which provides representations of the rainfall and temperature of the monitored sites. There is geostatistical interpolation through co-kriging to create forage maps in real time (Figure 2A and B).

Forage difference maps (Figure 2B) indicate that the worst conditions were located in southern Kenya, where conditions were classified as dry and disastrous. These com maps are available to livestock farmers via the web (Angerer, 2012). According to Angerer *et al.* (2013), the future efforts of the early warning systems will focus on the development of a support tool that will represent a complete integration of the assessment of the quantity of fodder in almost real time, forecasting the production of fodder in the short and long term, water conditions on the farms and market information

Figure 2. Early warning map of total forage available to breeders in northern and southern Kenya during August 2009.



Source: Adapted from Angerer et al. (2013).

FINAL CONSIDERATIONS

Remote sensing tools associated with biophysical modeling to generate early warning maps contribute relevant information and additional to forage production and to forecast possible disasters resulting from drought, enabling measures or obtain information on large scales.

The development and refinement of these methodologies can assist the government in developing public policies to recommend and region times more likely to promote the conservation of fodder and to use it in times of scarcity. Added to this, this tool enables the adjustment of stocking rate throughout the year and it provides subsidies to farmers, so there is the rational and sustainable use of his pasture, preventing the degradation of the same.

Ackowlegments

To the Coordination for the Improvement of Higher Education Personnel (CAPES), the Federal University of Ceará (UFC) and the Brazilian Agricultural Research Corporation (EMBRAPA).

BIBLIOGRAPHY

1. Adams, R. M. et al., The benefits to Mexican agriculture of an El Niño-southern oscillation (ENSO) early warning**. Agricultural and forest meteorology**, vol. 115, no. 3-4, pag. 183-194, 2003.

2. Alhamad, M. N. et al., Biophysical modelling and NDVI time series to project near-term forage supply: spectral analysis aided by wavelet denoising and ARIMA modeling. **International Journal of Remote Sensing**, vol. 28, no.11, pag. 2513-2548, 2007.

3. Allen V.G. et al., An international terminology for grazing lands and grazing animals. **Grass and Forage Science**, vol. 66, no. 1, pag. 2–28, 2011.

4. Almeida, A.C.S. et al., Simulação do crescimento do capim Tanzânia irrigado com base na unidade fototérmica, na adubação nitrogenada e na disponibilidade hídrica do período. **Acta Scientiarum. Agronomy**, vol. 33, no. 2, pag. 215-222, 2011.

5. Andrade, A.S. et al., Simulating tropical forage growth and biomass accumulation: an overview of model development and application. **Grass and Forage Science**, vol. 71, no.1, pag. 54-65, 2016.

6. Andrade, R.G. et al., Uso de Técnicas de Sensoriamento Remoto na Detecção de Processos de Degradação de Pastagens. **Engenharia na Agricultura**, vol. 21, no. 3, pag. 234-243, 2013.

7. Angerer, J. P. et al., Gobi Forage Livestock Early Warning System. **In: Conducting national feed assessments**. Rome, Italy: Food and Agriculture Organization. vol.15, pag. 115-130, 2012.

8. Angerer, J. P. et al., Reducing Risk in Pastoral Regions: The Role of Early Warning and Livestock Information Systems. **Revista Cientifica de Produção Animal**, vol. 15, no. 1, pag. 9-21, 2013.

9. Angerer, J. P. **Examination of high resolution rainfall products and satellite greenness indices for estimating patch and landscape forage biomass.** 2008, pag. 129. PhD Dissertation, Department of Ecosystem Science and Management. College Station, Texas, Texas A&M University.

10. Araújo, D.L.C. et al., Características morfogênicas, estruturais e padrões demográficos de perfilhos em pastagem de capim-andropógon sob diferentes ofertas de forragem. **Semina. Ciências Agrárias**, vol. 36, no. 5, pag. 3303-3314, 2015.

11. Atzberger, C. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. **Remote Sensing**, vol. 5, no. 2, pag. 949-981, 2013.

12. Bégué, A. et al., Remote Sensing and Cropping Practices: A Review. **Remote Sensing**, vol. 10, no. 1, pag. 1-32, 2018.

13. Carvalho, P.C.F. and Batello C., Access to land, livestock production and ecosystem conservation in the Brazilian Campos biome: the natural grasslands dilemma. **Livestock Science**, vol. 120, no. 1-2, pag. 158-162, 2009.

14. Chang, J. et al., Combining livestock production information in a process-based vegetation model to reconstruct the history of grassland management. **Biogeosciences**, vol. 13, no.12, pag. 3757-3776, 2016.

15. Congio, G. F. S. et al., Strategic grazing management towards sustainable intensification at tropical pasture-based dairy systems. **Science of The Total Environment**, vol. 1, no. 15, pag. 872-880, 2018.

16. Du, Y. et al., Mapping from Sentinel-2 Imagery with Modified Normalized Difference Water Index at 10-M Spatial Resolution Produced by Sharpening the SWIR Band. **Remote Sensing**, vol. 8, no. 4, pag. 1-19, 2016.

17. Ferreira, L.G. et al., Sensoriamento Remoto da Vegetação: Evolução e Estado-da-Arte. **Acta Scientiarum. Biological Sciences**, vol. 30, no.4, pag. 379-390, 2008.

18. Forkuor, G. et al., Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso. **GIScience & Remote Sensing**, vol. 55, no. 3, pag. 331-354. 2017.

19. Garnett, T. et al., Sustaina-ble intensification in agriculture: Premises and policies. **Science**, vol. 341, no. 6141, pag. 33–34, 2013.

20. GUTIÉRREZ, A. P. A. et al., Drought preparedness in Brazil. Weather and Climate Extremes, v. 3, n. 6, p. 95-106, 2014.

21. Ha, K. et al., Inter – Annual and Intra – Annual Variabilities of NDVI, LAI and Ts Estimated by AVHRR in Korea. Korea Journal of Estimated by AVHRR in Korea. **Korea Journal of Remote Sensing**, vol. 2, pag. 111-119, 2001.

22. He, C. et al., Zoning grassland protection area using remote sensing and cellular automata modelling - A case study in Xilingol steppe grassland in northern China. **Journal of Arid Environments**, vol. 63, no. 4, pag. 814-826, 2005.

23. Hermance, J. F. et al., Predicting intra-seasonal fluctuations of NDVI phenology from daily rainfall in the East Sahel: a simple linear reservoir model. **International Journal of Remote Sensing**, vol. 37, no. 14, pag. 3293-3321, 2016.

24. Hermance, J. F. et al., Quantifying characteristic growth dynamics in a semi-arid grassland ecosystem by predicting short-term NDVI phenology from daily rainfall: a simple four parameter coupled-reservoir model. **International Journal of Remote Sensing**, vol. 36, no. 22, pag. 5637-5663, 2015.

25. Hill, M.J. Vegetation Index Suites as Indicators of Vegetation State in Grassland and Savanna: An Analysis with Simulated SENTINEL 2 Data for a North American Transect. **Remote Sensing Environment**, vol. 137, pag. 94–111, 2013.

26. Hott, M.C. et al., Vegetative growth of grasslands based on hyper-temporal NDVI data from the Modis sensor. **Pesquisa Agropecuária Brasileira**, vol. 51, no. 7, pag. 858-868, 2016.

27. I. Rao, et al., LivestockPlus – The sustainable intensification of forage-based agricultural systems to improve livelihoods and ecosystem services in the tropics. **Tropical Grasslands – Forrajes Tropicales**, vol. 3, no. 2, pag. 59-82, 2015.

28. Kaitho, R.J. et al., Forage and livestock marketing information analysis and forecasts. **Outlook on Agriculture**, vol. 36, no. 4, pag. 267–272, 2007.

29. Lu, D. et al., A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. **International Journal of Digital Earth**, vol. 9, no. 1, pag. 63-105, 2014.

30. Magliano, P. N. et al., Precipitation Event Distribution in Central Argentina: Spatial and Temporal Patterns. **Ecohydrology**, vol. 8, no. 1, pag. 94-104, 2015.

31. Marin, F.R. and Jones J.W. Process-based simple model for simulating sugarcane growth and production. **Scientia Agricola**, vol. 71, no. 1, pag. 1–16, 2014.

32. MORAIS, L. F. et al., Spectral responses in rangelands and land cover change by livestock in regions of the Caatinga biome, Brazil. **Scientific Reports**, v. 11, n. 1, p. 1-10, 2021.

33. Morais, L.F. et al., Avanços na avaliação de pastagens cultivadas com forrageiras tropicais no Brasil: Uma revisão. **Pesquisa Aplicada & Agrotecnologia**, vol. 11, no. 2, pag. 125-136, 2018.

34. Moritz, M. et al., Open access, open systems: pastoral management of common-pool resources in the Chad Basin. **Human Ecology**, vol. 41, no.3, pag. 351–65, 2013.

35. Myneni, R.B. et al., The interpretation of spectral vegetation índices. **IEEE Transactions on Geoscience and Remote Sensing**, vol. 33, no. 2, pag. 481-486, 1995.

36. PEQUENO, D. N. L. et al. Species-genotypic parameters of the CROPGRO Perennial Forage Model: Implications for comparison of three tropical pasture grasses. **Grass and Forage Science**, v. 73, n. 2, p. 440-455, 2018.

37. Provenza, F.D. et al., Synthesis: foraging decisions link plants, herbivores and human beings. **Animal Production Science**, vol 55, no. 3, pag. 411-425. 2015.

38. Ran, Y. et al., Spatial representativeness and uncertainty of eddy covariance carbon flux measurements for upscaling net ecosystem productivity to the grid scale. **Agricultural and Forest Meteorology**, vol. 230-231, no. 15, pag. 114-127, 2016.

39. Reshef, I. B. et al., Doorn, Monitoring global croplands with coarse resolution earth observations: The Global Agriculture Monitoring (GLAM) project. **Remote Sensing**, vol. 2, no. 6, pag. 1589-1609, 2010.

40. Reynolds J.F. et al., Global desertification: Building a science for dryland development. **Science**, vol. 316, no. 5826, pag. 847–851, 2007.

41. Robinson, T.P. et al., Global livestock production systems. **In: Food and Agriculture Organization of the United Nations (FAO) and International Livestock Research Institute (ILRI)**, pag. 152, 2011.

42. Robinson, T.P. et al., Mapping the Global Distribution of Livestock. **PLoS ONE**, vol. 9, no. 5, pag. 1-13, 2014.

43. Salimon, C. and Anderson L. How strong is the relationship between rainfall variability and Caatinga productivity? A case study under a changing climate. **Anais da Academia Brasileira de Ciências**, vol. 90, no. 2, pag. 1-7, 2017.

44. Sayre, N. F. et al., Earth Stewardship of rangelands: coping with ecological, economic, and political marginality. **Frontiers in Ecology and the Environment**, vol. 11, no. 7, pag. 348-354, 2013.

45. Sibanda, M. et al., Estimating Biomass of Native Grass Grown under Complex Management Treatments Using WorldView-3 Spectral Derivatives**. Remote Sensing**, vol. 9, no. 55, pag. 1-21, 2017.

46. Silva Neto, S.P. et al., Variabilidade espacial da biomassa da forragem e taxa de lotação animal em pastagem de capim Marandu. **Revista Agrogeoambiental**, vol. 8, no.2, pag. 119-130, 2016.

47. Smith, J. et al., Beyond milk, meat, and eggs: Role of live-stock in food and nutrition security. **Animal Frontiers**, vol.3, no. 1, pag. 6-13, 2013.

48. Snow, V.O. et al., The challenges – and some solutions – to process-based modelling of grazed agricultural systems. **Environmental Modelling & Software**, vol. 62, 420-436, 2014.

49. Stuth, J.W. et al., Livestock early warning systems for Africa's rangelands. **In: Monitoring and Predicting Agricultural Drought: a global study.** Oxford University, Press, NY. Pag. 283-294, 2005.

50. Thornton, P.K. Livestock production: recent trends, future prospects. **Philosophical Transactions of the Royal Society B: Biological Sciences**, vol. 365, no. 1554, pag. 2853–2867, 2010.

51. Tilman, D. et al., Global food demand and the sustainable intensification of agriculture. **Proceedings of the National Academy of Sciences**, vol. 108, no. 50, pag. 20260 – 20264, 2011.

52. Verstraete, M. M. Climate and desertification: looking at an old problem through new lenses. **Frontiers in Ecology and the Environment**, vol. 7, no.8, pag. 421–28, 2009.

53. Vrieling, A. et al., Variability of African farming systems from phenological analysis of NDVI time series. **Climatic Change**. vol. 109, no. 3-4, pag. 455–477, 2011.

54. Warren, G. and Metternicht, G. Agricultural applications of high-resolution digital multispectral imagery: Evaluating within-field spatial variability of canola (Brassica napus) in Western Australia. **Photogrammetric Engineering and Remote Sensing**, vol. 71, no. 5, pag. 595–602, 2005.

55. Zhang, B. et al., Application of Synthetic NDVI Time Series Blended from Landsat and MODIS Data for Grassland Biomass Estimation. **Remote Sensing**, vol. 8, no. 10, pag. 1-21, 2016.

56. Zhang, C. and Kovacs, J.M. The application of small unmanned aerial systems for precision agriculture: a review. **Precision Agriculture**, vol. 13, no. 6, pag 693–712, 2012.

57. Zhang, X. et al., Monitoring vegetation phenology using MODIS. **Remote Sensing Environment**, vol. 84, no. 3, pag. 471–475, 2003.