Mapping the Potential for Hay Making in the Rangelands: A Methodological Proposition

Makuma-Massa, H [4, 5*]; Bemigisha, J[1], Kyasimire, B[1], Nyiramahoro, E.[1], Begumana, J[1], Swidiq, M.[2, 4], Egeru, A[4,5], and Cho, M[3]

1: ESIPPS International Ltd, P. O. Box 33011, Kampala Uganda
2. National Livestock Resources Research Institute, P. O. Box 96, Tororo, Uganda
3: Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa
4: Makerere University, Department of Environmental Management, P. O. Box 7062, Kampala, Uganda
5. Regional Universities Forum for Capacity Building in Agriculture (RUFORUM), P.O Box 16811 Wandegeya, Uganda

Abstract

Hay production and harvesting is one of the viable adaptation measures to climate change and variability in semi-arid areas. The paucity of data on hay availability and production over vast rangelands has stymied strategic engagement in taking the opportunities that the rangelands present in Uganda. This study presents work on developing a hay geo-information system by use of remote sensing and geographic information system for enhancing hay production as an adaptation to climate change stresses in the rangelands of Uganda. The study determined the optimum period for hay harvesting and available hay using remote sensing data and secondly to detailed methodological processes and steps for modeling hay quantity at peak vegetation productivity. Freely available satellite imagery including Landsat 8 and MODIS were utilised in this study. Findings revealed that peak biomass (potential time for hay harvesting) production period occurred on 130th and 320th day of the vegetation growing season. The study also established eight key steps of producing herbaceous biomass spatial variability maps from Landsat 8 imagery and MODIS imagery. This study has demonstrated that using freely available satellite data livestock managers, extension workers and ultimately cattle farmers in climate stressed range lands are in position to timely and accurately determine the optimum hay harvest period, estimate total hay yield at peak productivity and identify high potential hay locations in the vast rangelands. This methodological proposition ought to be scaled up in the rangelands areas of East Africa where climate change and variability present a potent challenge.

***Corresponding Author:** Makuma Massa Henry; henrimassa@yahoo.com

Key words

Climate change; grasslands; pastoralists; rangelands; geographic information system; remote sensing

INTRODUCTION

Global environmental change has been on the international agenda for many decades. Climate change, as an 'undesirable' consequence of increased concentration of greenhouse gases in the atmosphere has remarkably undermined agricultural productivity translating into alarming levels of food insecurity[1]. The devastating effects of climate change on agricultural productivity are more pronounced in arid and semi-arid ecosystems. With or without climatic changes, the climate of rangeland ecosystems is characterized by stochastic rainfall events on spatial and temporal scale, high atmospheric temperatures and evaporation rates[2]. Climate change is thus exerting more pressure on the functionality and resilience of rangeland systems. Yet, rangelands support a significant number of the livestock around the world, putting the sustainability, productivity and competitiveness of livestock production systems in rangelands at a threat. In Uganda, rangelands account for 43% of the total land area and livestock production is the major source of livelihood to over 60% of households in the rangelands of Uganda. Livestock production in these locations is largely constrained by climatic changes with devastating effects on forage and water availability leading to variable milk and meat outputs[3].

Further, climate change and variability has been shown to have negative impacts on livestock birth rates, mortality rates and meat quality in Uganda[4, 5]. The rapidly increasing population, changes in land use as well as alterations in policies towards pastoralism are constraining pastoral movements leading to increased transhumant pastoralism, transitions to livestock-crop integration and commencement of permanent grazing areas[6, 7]. Pastoralists in Uganda depend on rain-fed pastures find challenges maintaining herds during prolonged droughts and yet they will have burned the previous season pasture in belief that better pastures will sprout in the next rainy season[5].

In the face of climate change and variability with dwindling grazing land, areas the available grazing areas would have to be effectively managed to ensure sustainable supply of pasture resources. The trends observed in the pastoral production systems have led to discourse on how to ensure sustainable livestock production amidst pressing climate change and variability patterns. Consequently, hay production has been identified as a key leverage action that will not only allow pastoral communities to increase livestock productivity and quality but at the same time ensure sustainable income streams and build their resilience to impacts of climate change and variability[8, 9]. Hay making is advantageous in a way that forage, which would have been wasted by burning and rotting, is available in the next season of feed shortage. Hay production also has potential to enhance income, wealth and livelihoods of the producer communities if production is stepped up to realize surpluses. The production of hay promotes environmental conservation and sustainable use of rangelands for improved livelihood and set guidelines for development of appropriate feed resources which is a key objective of the rangeland policy[9, 10]. Stimulating community engagement and promotion of adoption of hay production offers an opportunity to livestock farmers to cope with climate change induced forage scarcity but this requires explicit description of the hay production potential in such areas.

Hay production can be optimized when grasses are at their most productive period, and this may become more pressing in the advent of unpredicted climate/weather patterns in African rangelands. However, the lack of sufficient data on hay availability and production in most areas has limited decision making in the livestock sector in Uganda and Africa at large. There is a paucity to information regarding the hay production potential in the rangelands of Africa. Several studies[11, 12] have highlighted the role of earth observation data, particularly remote sensing data acquired using space borne platforms as a cost effective and rapid means of providing data on pasture quality and quantity at any given period of the year[11, 12]. Information on suitable sites for hay production, the temporal and spatial variations in quantity and quality of hay is particularly deficient. Therefore, the study sought to employ remote sensing (RS) and geographical information system (GIS) to determine the hay production potential and dynamics developing a methodology for rapidly mapping and establishing the potential of hay productions in rangelands.

STUDY AREA

The study was conducted in the districts of Nakasongola, Nakaseke and Luwero in the Cattle Corridor of l Uganda. The Cattle Corridor of Uganda stretches diagonally from the southwest to northeast of the country (Figure 1). Nakasongola, Nakaseke and Luwero are located at 00 57’ 44.89” N and 310 58’ 03.77” E; at the central part of the cattle corridor of Uganda. The districts receive a bi-modal rainfall regime with the first rainy season occurring in the months of March–May while the second in September-November. The mean annual rainfall ranges between 500 mm and 1600 mm with seasonal variations and prolonged droughts with a return period of 8 – 12 years. The mean daily minimum temperature ranges between 15.0^0C and 20.9^0C while the mean daily maximum temperature ranges between 25.4°C and 33.7°C. Average humidity ranges from 80% in the morning to 56% in the afternoon. The potential evapotranspiration remains high throughout the year (~130 mm/month and ~1586 mm/annum) and shows less variability unlike the rainfall.

Figure 1: Location of study area

METHODS

Methodological structure and interrelationship

This study set out to determine the optimum period for hay harvest that is; the peak vegetation production and the method for assessing the available hay at peak production that is; herbaceous grass biomass. Uganda has a tropical climate with two rainy seasons (March to May and September to November) and two dry periods. The three districts that make up the project area do experience this bimodal seasonal calendar. Figure 2 presents a summary of the methodological logical structure and interrelationship that were undertaken to achieve the study’s focus. This methodology was used to monitor vegetation production throughout the four seasons and to then determine the period of peak vegetation production, which constitutes the best period of hay harvest in the project area.

Figure 2: A methodological approach that can help determine the period for hay harvest and potential quantity (biomass) of hay was developed

Modelling peak herbaceous biomass production

A time series of 8 day-composite Normalized Difference Vegetation Index (NDVI) derived from Moderate Resolution Imagery Spectrometer (MODIS) imagery was used to determine the peak/optimum production period. MODIS imagery is recommended for this purpose because it provides a higher temporal resolution (one day revisit time) than Landsat 8 (16 days). On the other hand, the higher spatial resolution of Landsat 8 is better suited to determine variability of herbaceous biomass and quality at peak production in the rangelands because of the patchiness often associated with these locations.

NASA launched the MODIS sensor into space in 1999 on board the TERRA satellite and in 2002 on board the AQUA satellite. MODIS provides data at various spatial resolution including 2 bands (red and near-infra red – NIR) at 250 m and 5 visible-to - Short-wave Infrared (SWIR) bands at 500 m. MODIS 2-band image at 250 m resolution (MOD09Q1 products – surface reflectance, i.e. atmospherically corrected 8-day composites) is proposed for this project. The images can be downloaded from http://earthexplorer.usgs.gov/. The 250 m resolution is better than the 500 m to capture the spatial variability of grass patches in the project area whose sizes are generally smaller than 500 m by 500 m.

The Normalized difference vegetation index – NDVI (NIR-R) / (NIR+R), a well-established remote sensing index or indicator for vegetation productivity was computed from the MODIS image to determine the peak production. NDVI images for the year e.g. 2014 were stacked to generate a time series that could be used to monitor the trend in vegetation production. The time series are usually noisy due to the presence of clouds. Therefore, smoothing was required to tease out the trend in vegetation productivity. The Savitzky-Golay filter was used to smoothen the NDVI time series). A two-stage smoothing process is proposed – 1^{st} using a straight line model (1 degree polynomial) and followed by a 2^{nd} degree polynomial smoothing function.

Profiles of hundreds of 350 randomly selected pixels were extracted from the time series and the following statistics computed: mean and standard deviation of the profiles (e.g. see figure 3 for 2014 NDVI profiles). The peak production period was determined from the mean profiles i.e. the period of maximum NDVIs. The first derivative of the NDVI time series or profile can be used to monitor the changes in NDVI. At peak production (i.e. maximum turning point of the time series), the first derivative is equal to zero. The first derivative profile can be produced using the first difference transformation of the NDVI profile.

Modelling hay quantity (spatial variability) at peak vegetation productivity

An 8-steps approached was established for assessing grass biomass maps (spatial variability of biomass) at the peak production period of the vegetation in the cattle corridor: Landsat 8 image acquisition; Landsat 8 atmospheric correction; cloud removal; vegetation type cover classification; field sampling of leaf area index (LAI) and grass biomass; Radiative transfer modelling and developing predictive equation for LAI; predicting LAI on the Landsat image; and predicting grass biomass.

RESULTS

Part I: Best period for hay harvesting and available hay using remote sensing data

A first derivative profile of the mean NDVI profile for 2014 was used to determine the maximum production (maximum turning point of the NDVI profile) date i.e. where the profile cuts the horizontal axis i.e. at slope = 0. Potential hay harvesting (NDVI/biomass) was found to peak on the 130^{th} day and 320^{th} day (Figure 3). Vertical lines in the graphs indicate dates of maximum vegetation productivity within the project site. Graph 2 of figure 3 shows the evolution of NDVI profile for 2015. Monitoring the evolution of the 2015 NDVI profile can be used to determine the maximum turning point or peak production for this year. .

Figure 3: Graph 1 is the 2014 NDVI time series analysis and 2015 NDVI time series analysis

In summary, determining the best period for hay harvest includes image acquisition and pre-processing and creating NDVI time series images and determination of peak production.

Part II. Process of modelling hay quantity (spatial variability) at peak vegetation productivity

Step 1 – Landsat 8 Image acquisition

LANDSAT 8 OLI images were proposed for this modelling of grass biomass. Landsat 8 was launched on February 11, 2013. This is a medium resolution sensor (30 m) consisting of 11 bands in the visible, NIR, SWIR and thermal infrared (TIR). The TIR is not required for this project. Landsat 8 images for the peak production period were downloaded from[13] http://earthexplorer.usgs.gov/. Two main scenes made up the area (171059 and 172059) Images of different dates were used because of the possible presence of clouds.

Step 2 – Landsat 8 atmospheric correction

The images required cloud removal and atmospheric correction. Atmospheric / Topographic Correction for Satellite Imagery (ATCOR 2/3) was used for atmospheric correction.

Step 3- Cloud removal

Band maths in ENVI was used to find the sum of the blue, red and NIR bands. A threshold value was applied to mask out the cloud free portions of the image (see Figure 4 for the detail process).

Figure 4: Cloud removal using thresh-holding of sum of red, green and blue bands (RGB) (picture on the right)

After the cloud removal from various image scenes of the region, the new cloud free scenes are mosaicked as shown in Figure 5.

Figure 5: Mosaic of two image scenes acquired on 29 October and 16 November 2014 after cloud removal

Step 4 – Vegetation type cover classification

Maximum likelihood, Support vector machine (SVM) or Random forest (RF) algorithm was used to classify the image into grass and tree pixels. We recommend the use of SVM or RF because of the high intra-class variability. The area was classified into pasture (grasslands) which included crop areas and seasonal flooded wetlands and woodlands. Training and validation was obtained from field sampling and Google Earth.

The classification using Support Vector Machine classifier produced an overall accuracy of 82%: Grasslands and farms (producer = 97%, user accuracy = 60%, Woodlands (producer accuracy = 91%, User accuracy = 99%, vegetated riverbeds (Producer accuracy = 73%, user accuracy = 95%). The low accuracy of grassland was due to the classification of vegetated riverbeds as grassland, which was understandable as most of the riverbeds were grasslands.

Figure 6: Vegetation type classification in the project site

Step 5 NDVI images

To highlight patterns in vegetation and grass condition, the traditional NDVI (NIR-R)/(NIR+R) and green NDVI or GNDVI (G-R)/(G+R), where G and R are the reflectance in the green and red bands, respectively, were calculated from the Landsat mosaic. The vegetation index value increases with increasing vigour e.g. amount of leaf chlorophyll of the vegetation. It is also well established that the nutrient (e.g. leaf N) content of grass generally increases with increasing chlorophyll.

Figure 7: Patterns of NDVI and GNDVI at peak vegetation production (November 2014) in the cattle corridor of Uganda

Step 6 – Field sampling of leaf area index (LAI) and grass biomass

Fieldwork was conducted in the area to collect data on LAI, fresh and dry biomass. LAI was measured using the plant canopy analyser (LAI 2200; LI-COR Inc.), a hand held optical device. Aboveground fresh biomass was harvested and immediately weighed. A sensitive balance (at least +/- 10 grams) was used for the measurement.   The fresh grass for each sample was placed in paper bag and oven dried at 60 to 70 degrees for 24 hours before measurement of the dry biomass.

Field LAI data was collected for only 10 randomly selected plots because the LAI 2200 was available for only one day. The fresh and dry biomass data was measured for five other plots. The data was used to establish the relationship (predictive model) between LAI and fresh or dry biomass in the region (see figure 8 for November 2014). We assumed that these relationships were generic in nature and were used to convert LAI measurements to biomass. The power functions (predictive models) in the Figure 8 were preferred to the linear predictive models because they could be extrapolated to predict realistic values for biomass below LAI of 1. The linear model for LAI values predicted negative biomass values. The mass of the dried grass was about half the mass of fresh grass. The relationship between the fresh and dry mass was also established (Figure 9).

Figure 8: Relationship between field measured LAI using plant canopy Analyzer (LAI 2200) and fresh grass biomass or dry (oven dry) grass biomass

Figure 9: Relationship between fresh grass biomass and dry biomass

Step 7 - Radiative transfer modeling and developing predictive equation for LAI

The PROSAIL-5 radiative transfer model was used to simulate 3000 spectral reflectance, mimicking the Landsat 8 reflectance spectral of the project area. PROSAIL had a combination of PROSPECT (a leaf optical properties model) and SAIL (a four-stream canopy RTM) [14, 15]. Figure 10 shows the input parameters used to into the forward modelling of PROSAIL. PROSAIL-5 and were downloaded from:[16] http://teledetection.ipgp.jussieu.fr/prosail/. The simulated models were achieved in Matlab.

NDVI (NIR-R)/(NIR+R) and GNDVI (G-R)/(G+R) values were derived from the simulated spectra. A predictive model between LAI and NDVI or GNDVI was made using simulated data. The green NDVI derived from the green and red bands provided a better fit ($R^2 = 0.70$) when compared to the traditional NDVI derived from the NIR and red reflectance ($R^2 = 0.35$). The predictive equations are shown on the graphs in Figure 11 below. These predictive models were used to predict LAI on the satellite image.

Figure 10: Parameter ranges for forward modelling of PROSAIL i.e. for the simulation of synthetic spectra

Figure 11: Predictive model of LAI derived from simulated spectra using PROSAIL radiative transfer model.

Step 8 – Predicting LAI on the Landsat image

First, a GNDVI image (the green NDVI in this project provided higher accuracies when compared to the traditional NDVI) which was derived from the Landsat data. Second, we used grass class mask derived from the vegetation type map established in step 4 to mask out the grass areas on the NDVI image. The LAI predictive model developed from the PROSAIL data (Step 6) was inverted on the Landsat GNDVI image to predict LAI from the Landsat 8 image.

Figure 12: Leaf area index (LAI) map of the region

The LAI map was produced by inverting the predictive model between the green NDVI derived from the simulated data using the PROSAIL model:

$$\mathbf{Y = 1.437e^{4.108x},} \quad \text{-------------------------Eq.1}$$
$$\mathbf{R^2 = 0.6984} \quad \text{----------------}$$

LAI was predicted with a root mean error (RMSE) of 1.28 (39% of the mean), i.e., the error between the predicted LAI using the PROSAIL RTM and the field measured LAI. We recommend the use of many more points to validate the predicted LAI.

Figure 13: Coloration between measured and predicated LAI

Step 9 – Predicting grass biomass

A grass biomass map was produced from the LAI map by applying the biomass/LAI model established between the field measured biomass and LAI (figure 8). The units were converted from g/m^2 to kg/ha by multiplying g/m^2 by 10 (i.e. 1 $g/m^2 \rightarrow$ 10 kg/ha). The strength of the relationship between the predicted LAI and field measured fresh or dry mass was assessed as shown in figure 14. A stronger relationship was observed for the dry mass (R^2 = 0.60) when compared to the fresh mass (R^2 = 0.47).

Figure 14: Grass biomass maps derived for the project area

Figure 15: Fresh and dry (oven dry) grass biomass of the region

Accuracy estimation

The RMSE between the predicted biomass and field-measured biomass was assessed. The RMSE was lower for the dry mass (121 kg/ha i.e. 39%) as compared to the fresh biomass was (323 kg/ha i.e.45%) and for dry biomass was.

The grass biomass map was binned into several classes e.g. low, medium and high biomass classes as shown in Figure 16 below to highlight the regions of high production. The central and western region showed the highest biomass during the month of October to November 2014.

Figure 16: Three biomass classes (Vector map)

DISCUSSIONS

Best period for hay harvesting and available hay using remote sensing data indeed coincides with the rainfall season in the cattle corridor of Uganda. Most of the areas in the cattle corridor including the study area largely receives a bi-model rainfall[17]. This implies that harvest of hay in the cattle corridor should be shortly after the rainfall peaks in May and towards the end of November and beginning of December in the seasonal calendar year. This trend again agrees with studies done in the cattle corridor of Uganda, which receives substantial rainfall, which receives rainfall between 500-1000 mm annually[3, 6]. However, the issue is that the rainfall is highly variable. What we are seeing in the cattle corridor now is more a sedentary life style. This presents an opportunity for haymaking but also presents a challenge of placing pressure on resources that are available.

Modelling hay production quantity brings out the importance of importance of Geographic Information System (GIS) and remote sensing (RS) in mapping of potential hay areas. Use of geospatial technology (GIS and RS) in haymaking highlights the importance of optimizing hay production in rural rangelands and the findings indeed substantiate the findings presented in the paper. This shows the usefulness of such tools and if integrated with different spatial environmental and socio-economic variables such as climate, topography, geology, soils, drainage patterns, road networks, population presents an important tool doe decision making and investment. [11]Provides similar observation from recent research in ecological informatics involving remote sensing and GIS. We needs to focus on a selected range of issues including topics such as the nature of remote sensing data sets, issues of accuracy and uncertainty, data visualization and sharing activities as well as developments in aspects of ecological modelling research. Indeed considerable advances have been made over recent years and foundations for future research established.

This methodology (steps by step modelling) also does provide a rapid tool for data collection, minimising field work hence reducing the cost of obtaining critical information with minimal costs. The steps of modelling hay quantity present a new methodology for monitoring biomass production in the cattle corridor of Uganda. This can be used to plan when to harvest, how much to harvest and also highlights where to harvest. This methodology provides an adaptation approach to the increased changes in climate in the cattle corridor of Uganda. From the findings and field observations, there is high spread of woody species that affect grasslands. Other findings have observed the same thing that one major challenge in the management of rangeland ecosystems of Uganda is the perceived wide spread encroachment of woody species, which reduce grazing area, suppress palatable grass species and increases production costs[18]. Woody encroachment is often associated with alteration of above and below ground productivity, litter quality, altered hydrology, and changes in microclimate and earth's surface albedo among others [19]. Moving forward the need to move beyond mapping biomass quantity is to map species type and nutrient value of these species. There are a couple of technologies and satellite data that have been developed that can be used to map hay species type and quality in this case nutritive content.

CONCLUSIONS

In conclusion, this study presents a methodology that may guide livestock managers, extension workers and farmers on (i) determining the best period for hay harvest corresponding to peak productivity of the vegetation in rangelands, (ii) estimating the amount of hay available (biomass) at peak productivity, using commonly available satellite imagery and (iii) highlighting the best areas for hay production based on grassland availability. It is recommended that this methodology what we are calling a monitoring framework for hay mapping be scaled up to regional scales so we are able to map biomass areas hence potential hay making areas over wider areas.

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On Ground

- The information presented in this article is useful to various stakeholders including land managers, agency personnel, practitioners, researchers as it presents methodology for:
    - Determining the best period for hay harvest corresponding to peak productivity of the vegetation in rangelands.
    - Estimating the amount of hay available (biomass) at peak productivity, using commonly available satellite imagery
    - Highlighting the best areas for hay production based on grassland availability.
- All this is done by employing readily available tools of remote sensing (RS) and geographical information system (GIS).

Key words

Climate Change; grasslands; pastoralists; rangelands; geographic information system; remote sensing