# Use of Remote Sensing Techniques to Enhance Forage Management: Unmanned Aerial Vehicles

### TESIS FIN DE MÁSTER

Gustavo Togeiro de Alckmin

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# Máster en Planificación de Proyectos de Desarrollo Rural y Gestión Sostenible

Escuela Técnica Superior de Ingenieros Agrónomos



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# Use of Remote Sensing Techniques to Enhance Forage Management: Unmanned Aerial Vehicles

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#### Resumen

El uso de vehículos aéreos no tripulados (VANT) en la agricultura ha sido objeto de intensa investigación y desarrollo en el pasado reciente. Del mismo modo, el uso de cámaras digitales comerciales modificadas para capturar, además de las longitudes de onda visibles, el infrarrojo cercano (NIR) tiene abierto nuevas rutas y oportunidades para aplicaciones de teledetección en alta resolución espacial. Este estudio examina el uso de una plataforma VANT y cámaras digitales modificadas como herramienta - en una metodología sencilla - para la medición de la biomasa instantánea de forraje (materia seca por hectárea). El estudio se realizó en el Rannells 'Ranch (Estación Experimental de K-State) en Manhattan, Kansas. La precisión de un modelo de regresión entre datos de imágenes y la biomasa se evaluó: resultados mostraron que existe una relación lineal entre el índice de vegetación (GNDVI) y la biomasa (r²=.80) hasta un punto de ruptura de 3500 kg MS/ha. A partir de esto, los datos de imagen no coinciden más con los incrementos de biomasa.

Palabras clave: VANT; forages, teledetección, GNDVI, biomasa.

#### **Abstract**

The use of Unmanned Aerial Vehicles (UAVs) in agriculture has been the subject of intense research and development in the recent past. Likewise, the use of modified commercial digital cameras to capture, besides the visible wavelengths, near-infrared (NIR) spectra has open new venues of opportunities for remote sensing applications in high spatial resolution. This study examines the use of a UAV platform and modified digital cameras as a tool for instantaneous in a straightforward methodology for measurement of forage biomass (dry matter per hectare) – a key-point on forage management. The study was carried on at Rannells' Ranch (K-State Experimental Station) on the Flint Hills, aTallgrass Prairie at Manhattan, Kansas in the Great North American Plaines. The accuracy of a regression model between imagery data and biomass was assessed: results showed that there is a linear relationship (r<sup>2</sup>=.80) in between a vegetation index (GNDVI) and standing biomass up until a breakpoint up to 3.500 kg DM/ha. Afterwards, the imagery is not fit to estimate marginal increments on biomass

**Keywords**: Unmanned Aerial Vehicles; forages, remote sensing, GNDVI, biomass.

#### Introduction

Grazing land - as per the definition of (Allen et al. 2011)- occupies as much as 40.5% of the World terrestrial surface (World Resources Institute, 2000, based on IGBP data). These sites might be employed for forage-based livestock systems; consequently converting non-available resources (i.e. forages) to useful products for human consumption (e.g. milk, leather and animal protein). The study of rangelands, forage accumulation and its inherent management are a key point when addressing the sustainability of range and or grazing ecosystems. The main goal on this work was to address the accuracy and reliability of a

straightforward process that could provide actionable data and information for grazing management.

In addition, from an International Development perspective, approximately 70% of the 1 billion people, which still faces chronic hunger, are located in rural areas (IFAD, 2011). For these populations, a significant fraction (approximately 600 million people) rely on livestock production for subsistence and are thus, in many cases, capitalizing on grazing areas (e.g. pasturelands, rangelands etc.) to sustain their production systems.

From a Nature Conservation perspective, an equilibrated management of grazing lands can enhance positive ecological parameters, while the absolute contrary is also true (Savory, 2013). Therefore, grazing land degradation, whenever due to anthropogenic interference, is an outcome of poor management.

For producers within this scope (i.e. managing grazing lands), the main managerial decision is the balance of animal live weight, forage mass at one time (i.e. grazing pressure – Allen et al, 2011.) and, furthermore, to do so without compromising future levels of forage yield (i.e. carrying capacity – Allen et al, 2011.)

Thus, an accurate estimate of the aboveground forage mass or "available feed" is a critical information to support decision, consequentially, granting an optimal operation management and conservation of natural resources.

#### **Problem**

When and if well-informed forage-management decisions are taken into account, producers are faced with a trade-off between accurate estimations vs. laborious/costly sampling methods for feed availability estimation. The equilibrium between these three parameters (stock, feed-availability, time) is a complex and dynamic system, which is made even more difficult by the large spatial heterogeneity and the seasonal and inter-annual variability of forage resources. Traditionally, laborious and costly sampling methods (e.g. quadrant sampling, canopy height, plate meter) are then required in order optimally pilot the grazing system (Grigera et al, 2007.)

An alternative that could also provide general guidelines on forage-management is the use of yield-models. Nevertheless, the translation of it to production sites are often made difficult by many of the same constraints of sampling methods: laborious, costly, calibrations and, additionally, technical inputs that are not in the outreach of the average producer (Leaf Area Index "LAI", Photosynthetic Active Radiation "PAR" etc.) In addition, both solution (i.e.

traditional sampling methods and yield-models) normally do not take into account the intrinsic intra-plot heterogeneity.

As a result, forage-management is – in most cases - conducted through empirical and non-technical practices an can, consequentially, lead to overgrazing, its opposite as well as desertification (Savory, 2013.).

#### Supporting Research and Background

The employment of digital photography for measuring plant characters such as leaf area (Baker et al. 1996; Campillo et al. 2008, Hunt et al, 2010) as well as senescence of leaves (Ide and Oguma 2010) for agriculture practices and on field conditions has become more frequent in the recent past. Furthermore, a series of studies and analysis about the use of Unmanned Aerial Vehicles (UAV) and small and large frame cameras (Markelin et al 2008; Bergo, Calleri et al 2010; Laliberte et al 2011, Zarco-Tejada, P. J., V. Gonzalez-Dugo, et al. 2012) on agriculture, has made possible the large-scale employment of remote sensing techniques previously mainly applied on satellite data.

Nevertheless, despite the breakthroughs and recent interest of the scientific community, such equipment used on aerial imagery collection are usually high-cost and designed for scientific purposes more than a widespread commercial use.

The reasons for such are - in the one hand - from an engineering developer and scientific perspective, a series of challenges which are proposed and presented as an impediment for a straightforward use of modified digital cameras and UAV. In between many, is important to quote the non-linear response, spectral sensitivity, quantum efficiency of camera sensors; on the aerial platform side, one should cite as UAV operability, auto-pilot engineering etc.. As a recent innovation, these factors may not meet the accuracy and reliability standards or scrutiny of scientific review; thus not being consider trustworthy for widespread/commercial use.

In the other hand, from an amateur community and remote sensing enthusiasts, no rigorous scientific approach has been applied to off-the-shelf products. The extenuate task of quantifying how accurate the straightforward methods applied are have yet not been performed wide range of applications.

Nevertheless, the amateur community has played an important role on popularizing the idea of using modified commercial cameras as a sensor for vegetation status assessment and on engineering autopilots (e.g. Pixhawk) and on imagery analysis (e...g PublicLab).

#### Bottlenecks and challenges

As stated, the current commercial off-the-shelf UAVs and modified low-cost digital cameras for agriculture presents significant technical challenges in order to become a successful

solution – and, thus, be subject to the wide use of remote sensing techniques (e.g. multi-temporal analysis, deployment of different sensors).

Among such challenges, converting Digital Numbers (DN) to the values of spectral radiance (absolute calibration) is of paramount importance for the monitoring of biotic and abiotic plant stresses, yield models etc. Such challenge lies on an extensive knowledge of the sensor itself (i.e. digital camera), and on the environmental variables that influence light conditions, absorption and reflection.

As per the sensor itself, in between the set of variables that can create biased or inaccurate measurements, one should consider – in between many - the optical systems (e.g. lenses, sensors), the many possible settings (e.g. aperture, shutter speed), as well as factory-designed pre-processing compression algorithms. The bias created by these factors, thus, can lead to inaccurate and biased measurements, which consequentially would invalidate the linear radiometric response of targets and a straightforward imagery analysis.

Despite these challenges, Markelin et al (2008) analyzes large format CCD sensors and has found a linear radiometric response; thus, granting a linear assessment of target radiometric measurements when employing small format digital cameras.

In a literature review, Honkavaara et al (2009) summarizes the *state-of-art* on research for small-frame digital cameras radiometric calibration. He also reviews and proposes efforts to create an International Standard for radiometric calibration within these parameters. He concludes that – at the time - the calibration procedures for quantitative measurements (i.e. radiance) were insufficient to provide a straightforward methodology that could accurately respond to the several bias and error factors in question. Additionally, the possibility of employing cameras calibrated on laboratory to field conditions is questioned. The review concludes, however, that such scientific endeavor is promising.

Following a rather more empirical approach, Lebourgeois (2008) analyzes and corroborates the possibility of use of digital cameras to monitor crops. Nevertheless, is important to stress that the modified digital camera used in such research had undergone a spectral sensitivity calibration, to which a set of scientific instruments (goniometer, tunable light-source, integrating sphere etc.) are required. Such instruments are not available for the majority of commercial or industrial operations.

Equally, when assessing radiance values at canopy height (Incoming Radiation at the Canopy Level) and its behavior throughout the day and under different atmospheric conditions, there is no standardized procedure (e.g. Model of the Atmospheric Radiative Transfer, SMART) and how taking into account the variations on radiance composition and intensity (Honkavaara et al, 2009).

Usually, in experimental conditions, the method applied for standardization of DNs is the use of invariant targets (Collings et al, 2011; Clemens et al, 2012; von Bueren, 2014) .Also,

flight missions for data collection are executed in ideal weather conditions: no clouds, near the solar noon and in short periods of time.

Such limitations are – to a certain extent - an obstacle to the widespread use of this technology and its use in field conditions and especially on temporal analysis – that are the backbone for many techniques of yield modelling. For such kind of analysis, such radiometric calibration and data normalization is critical.

In that sense, the current commercial service provided by companies relies on calibrations and relative values and indices (e.g. EVI and NDVI), thus generating measurements that are valid for site and date specific. For such reason, these services are focused on abnormal physiological behavior as an indicator of stress. However, for forage production and biomass assessment, the assumption that a linear regression model may have a good fit is logic, as the assessment of "green material" is the one variable the manager is keen to measure. Following such rational, the employment of vegetation indices (VI) may be enough to overcome the absence of the challenges stated (radiometric calibration). This study aims, therefore, to assess the accuracy and the characteristics of a straightforward linear regression between a specific VI and biomass.

#### **Vegetation Index:**

A vegetation index is a proxy that assess plant vigor, photosynthetic activity, the relative density and health of vegetation for each picture element, or pixel, in a digital image. The Normalized Difference Vegetation Index (NDVI) is a simple graphical indicator that is commonly employed to analyze remote sensing measurements, typically but not necessarily from a space platform, and assess whether the target being observed contains live green vegetation or not. The NDVI is a ratio between Near Infrared (NIR) and one band of the visible wavelengths (VIS);

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$

#### Material and Methods:

#### Study Site:

The experimental site was the Rannells Ranch; located on Manhattan – Kansas and managed by the K-State University faculty members. This particular study-side is located at an specific area of the Mid-west United States of America (USA): the Great Plains; a rangeland area traditionally used for beef production and a habitat for wildlife. Moreover, this area of the Great Plains is known as the Flint Hills. The Flint Hills region includes over 1.5 million hectares encompassing much of eastern Kansas from near the Kansas-Nebraska border

south into northeastern Oklahoma. It possesses the largest remaining and last region of unplowed tallgrass prairie in North America.

Rangelands occupy over half the land area of the USA, i.e. approximately 311.7 million ha (Mitchell et al 2000). As in many parts of the World, such lands are habitually managed for multiple uses, providing natural habitat, forage, and leisure opportunities.

Within the Ranch, the paddocks are managed as different ecologic management units, and the paddocks chosen are managed in order to assess differences in grazing systems; thus is expected that no main agronomic difference (e.g. soil type, fertility, irrigation) may bias the long-term research. Therefore, it is expected that – due to applied treatment "grazed and ungrazed" – only the

#### Landscape

Given its pedologic characteristics – young, thus non-withered soils; having limestone and shale as parent material - soils in the Flint Hills should be chemically fertile and – as expected – present physical impediments due to its shallow A horizon yet with a hilly topography.

Such shallow topsoil, due to alternating layers of limestone benches, too rocky to plow - and shale, thus, forming slopes, giving the landscape a terraced shape.

These characteristics granted two important factor on remote sensing: no shadow due topographic effects and no soil color contamination, as there was no exposed apparent soil on the study site.

#### Forage Species:

The paddocks used on the experiment were largely dominated by grass mixtures (Figure 1). Grasses were in its vegetative or reproductive stage. Although there was a sparse presence of broad-leaves - mainly in the grazed paddock and possibly as a residue of previous grazing activity - no patch was exclusive formed by a single species. Additionally, no dead or senescent material was perceived as the main source of biomass, during data collection. Thus, no important differences within spectral behavior on plant material should be expected and





Figure 1- Landscape and Forage Assessment

differences the VIs should only be due to biomass levels (as all material is considered to be photosynthetic active).I

#### Material:

*UAV Platform* – A platform was built with the purpose to be used for imagery collection for this experiment and future EASAL's work. The chosen airframe was a Skywalker 2014 (1800)





Figure 2- Flight Take-off

mm wingspan). The complete description of the setup of the UAV given on Annex A. Take-off and landing were manually controlled (Figure 2), yet the data acquisition was executed within a pre-programmed flight plan loaded by an autopilot in order to have constant ground speed, allowing a grid pattern for data collection.

#### Camera and Conversion:

The camera used was a Sony S100 modified by MaxMax company. A brief explanation of the modification is giver bellow:

The camera Digital cameras can employ a specific type of sensor named charged-couple device. (CCD) or complementary metal-oxide-semiconductor (CMOS) A simple explanation of the functioning of such sensors is that when a light photon reaches the photoactive area (capacitor array), it causes each capacitor to accumulate an electric charge proportional to photon energy at that location, thus being able to measure total incoming energy per pixel.

Digital color cameras generally use a Bayer mask over the sensor. Such Bayer mask is grid filter for red, blue and green, which, thus, can register the spectral response of a point for each of the RGB bands. The camera modification consists on removing that filter and applying another that can block one of the visible wavelengths, thus the chosen channel will only capture the NIR band.

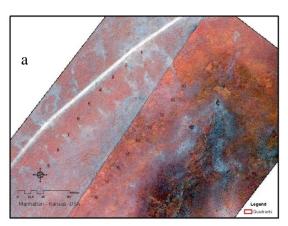
CMOS has an spectral resolution that ranges from  $\lambda$  300-1100 nm and a quantum efficiency (from 5 to 90%, depending on wavelength). When utilized as true color composite image, a filter is applied in order to remove the effect of Near Infrared (NIR,  $\lambda$  750-1400 nm). By

removing such filter and applying a different one, one could, thus, create a specific band for NIR.

Imagery Acquisition and Geo-referencing. The images are georeferenced based on the built-in GPS of the Canon S-100, the full control and setup of the camera was executed through a firmware name CHDK – Canon Hack Development Kit. The field of view of the camera is 73.3 degree and flight height was 130 meters. Image acquisition was executed through a built-in intervalometer on CHDK firmware (three seconds apart) and enough to have more than 75% overlap of each photogram. A table with the Exchangeable image file format (\*.exif) – camera setup information - is attached (Annex B).

#### Ground truth or sampling biomass process.

The data was collected at Rannells Ranch, on the 31<sup>st</sup> of July, 2014. In order to have access to the a biomass gradient, the sampling method consisted on 4 transects divided in between



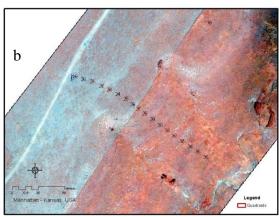


Figure 3-a) Transects 1 and 2; b) Transects 3 and 4

the grazed and Ungrazed paddocks. Two transects (Transects 1 and 2; Figure 3) were parallel to the fence and the other two were transversal to it (Transects 3 and 4, Figure 3).

The quadrants were built of two PVC tubes fifty centimeters long (0.5m) connected on a 90° angle, in order serve as marker at time of imagery data acquisition, subsequently the area (0.25 m²) was clipped to the ground level and the aboveground biomass was stored on paper

bags. The samples were dried during 72 hours at a temperature of 64°C, afterwards the now sample dry matter (DM) was weighted on a scale with an accuracy of +- 0.2 grams.









Figure 4 - Biomass Gradient and Sampling Method

#### Atmospheric Conditions

Data was acquired in a period of the day close to the solar noon (Fig.5) and within short interval. Second off, an invariant target was constantly assessed by taking photos throughout the mission. Pictures were taken from a close to nadir angle and in a frequent interval.



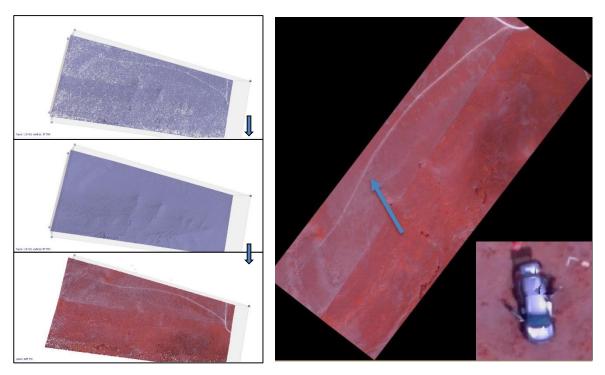
Figure 5 – Atmospheric condition at time of flight.

#### Data Processing

In order to to create a orthophoto mosaic, the images (n=410) were processed using Agisoft PhotoScan©. The following process was applied:

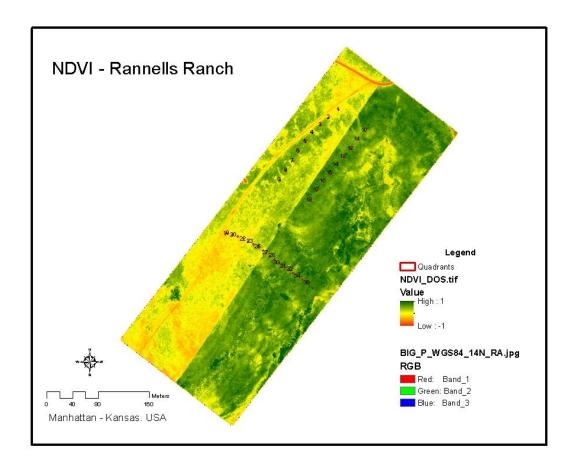
The GPS data was imported from the EXIF; Photos were aligned using the "High Accuracy Option, and Pair preselection as "Ground Control". Afterwards a Dense Cloud was built using the "High" Quality option.

The following process was to build the Texture under the "Mosaic" option of Blending Mode Texture, and Mapping Mode "Orthophoto".



Afterwards, the orthophoto was exported into ArcGis; the image was then enhanced using the "Image Analysis" tool, applying "Percent Clip" and "Bilinear Interpolation".

Subsequently the enhanced imaged was processed using the NDVI tool on the same Image Analysis. The NDVI values (Green NDVI) were then extracted with "Spatial Analyst Toolbox > Zonal Statistics". Dry matter and Mean Green NDVI values were statistically analyzed on Microsoft Excel and R.



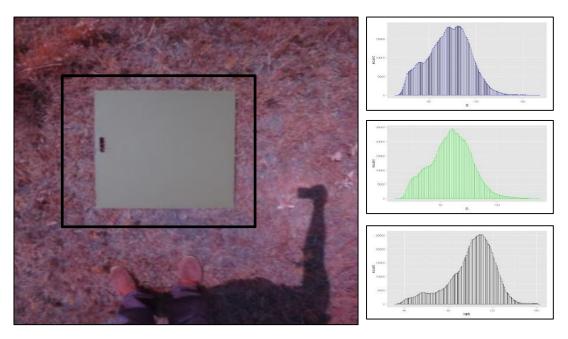
#### Results

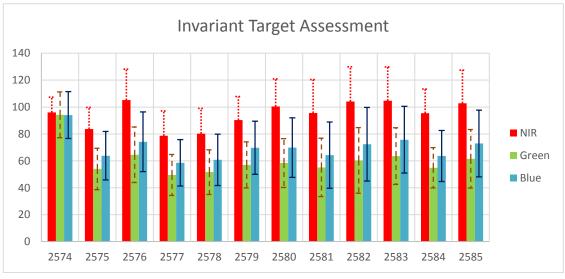
#### Invariant target Assessment:

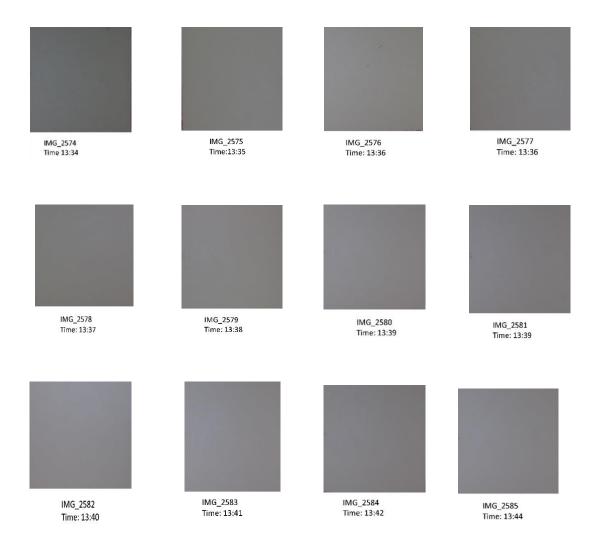
In order to be able to assess and normalize spectral response within and between a dataset as well as assess whether the Incoming Radiation was constant throughout the flight mission, a series of 12 pictures were taken.

Such pictures were taken while the embarked Canon S-100 was capturing imagery data. The hypothesis was that the targets would present a consistent and narrow response throughout the mission (as there was a clear sky),

These assumptions would be validated if the spectral analysis of the target had the same DN during flight mission.







The visual inspection of the twelve pictures taken from the target are sufficient, alongside with the histogram of one picture and the standard deviation presented for pixel values are an indicator that the targets employed may not be used as invariant targets. The reasons for such may be many: from the non-lambertian response of the target to the inherent non-monochromatic response of the paint used to manufacture the target.

For such reasons a reflectance value or color correction based on the target was not considered beneficial and, at the same time, showed itself to be a non-necessary task to be performed on this methodology

#### Estimation of Forage Biomass Based on Biomass

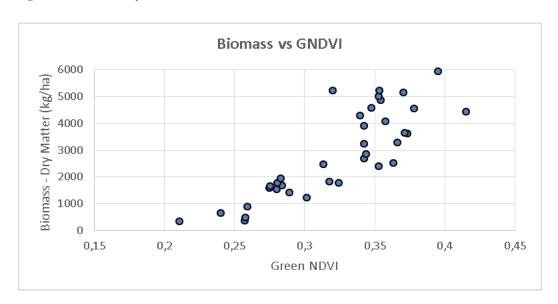
The basic assumption of this methodology that Green NDVI values and Biomass would be linearly correlated. In such way, this would be an applicable straightforward approach when assessing or estimating forage biomass. In this regards, mainly the Linear Regression and its characteristics and analysis were executed.

At the same time as other models were executed, the preference was given to the Linear Model.

The summary of data presented(Figure 6) shows the wide range of biomass values sampled (min:353, 3 to max: 5950 kg/ha).

Summary - Green NDVI and Biomass						
Mean GNDVI		Biomass (kg/ha)				
Min:	0,2106	Min:	353,2			
1 <sup>st</sup> Q	0,2824	1 <sup>st</sup> Q	1640,7			
Median	0,341	Median	2614,2			
Mean :	0,323	Mean :	2868,3			
3rdQ	0,3551	3rdQ	4320,9			
Max:	0,4151	Max:	5950			

Figure 6 - Data Summary



In this sense, a linear regression was executed on all the data set. In order to assess the goodness of fit, two other models (with different characteristics) were chosen as a comparison: a logarithmic and a power model.

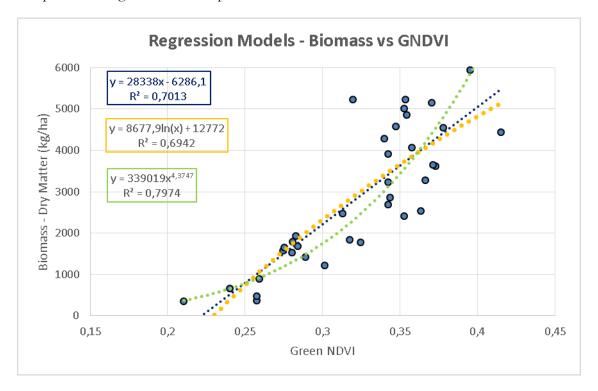


Figure 7 - Regression Models – Blue line: Linear Model; Yellow Line: Logarithmic Model; Green Line: Power Model

In this comparison, the coefficient of determination for a linear model was equal to .70; the logarithmic, .69 and the power model, .79. The power model had a better fit  $(r^2)$  as the Green NDVI values saturated at around .40, even when difference in biomass levels were in the order of 1000kg.

One of the desired properties in a model estimated by an Ordinary Least Square (OLS) method is that the residual (difference between fitted and actual values) is the residual homoscedasticity.

Homoscedasticity means that the variance of errors are the same across all levels of the Independent Variable. Therefore, in order to assess whether the model is valid or not, a first analysis that should be performed is the visual analysis/inspection of the model's residues

The inspection of residues showed that there was a possible heteroscedasticity issue (as there is a slightly evident growing pattern) on the linear regression model (Figure 7a).. The error is not randomly scattered neither the errors distribution were constant throughout the independent variable.

In order to confirm whether there was indeed a heteroscedasticity issue, the test "Heteroscedasticity Test of Breusch-Pagan-Godfrey" was run. Such is a hypothesis test,

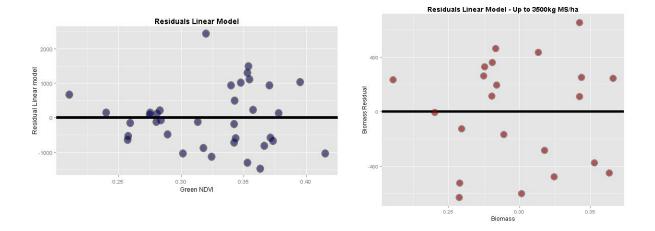


Figure 8 - Residuals Linear Model - (a) all dataset; (b) up to 3500kg DM/ha

which assess whether the independent variable has an effect on explaining the variance of the residue.

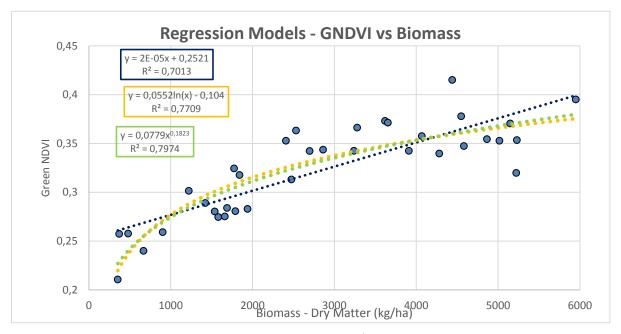
$$var(resid|Green NDVI)i = c + Beta1 * (Green NDVI)i$$

As a result, performing such homoscedasticity test, we have found a 11,57% significance that we should not reject the null-hypothesis (Beta1 equals to zero), i.e. the model is homoscedastic. Nevertheless, due to the size of the sample analyzed, a 11,57% significance may be seen as an indicator that the model has a trend for no random residual variance

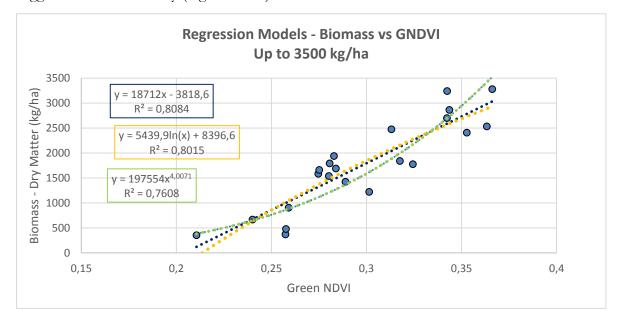
Heteroskedasticity Test: Breusch-Pagan-Godfrey				
Variable	Coefficient	Std, Error	t-Statistic	Prob,
С	-1222533	1240973	-0,98514	0,3315
Green NDVI	6135192	3801286	2	0,1158
R-squared	0,071163	Mean dependent var		759402,2
Adjusted R-squared	0,043845	S,D, dependent var		1098948
S,E, of regression	1074586	Akaike info criterion		31
Sum squared resid	3,93E+13	Schwarz criterion		31
Log likelihood	-550	Hannan-Quinn criter,		31
F-statistic	3	Durbin-Watson stat		2
Prob(F-statistic)	0,115776			

Also, when analyzing the determination coefficient of the logarithmic and power models, one can infer that the variance of the dependent variable is better explained - i.e. higher  $r^2$  - through a model that explains the saturation on Green NDVI values (i.e. power model).

When pivoting the axis, thus, stressing the dependent variable as the Green NDVI, a same approach can be validated, yet also allowing one to identify the plateau to which the vegetation index becomes saturated (around 3.500 kg DM/ha).



Running a linear regression up to a level of 3500 kg DM/ha, the r-square increases to a level of .81 and the additionally the assumption that there is a linear response in between biomass and GNDVI is fulfilled. Also, the visual inspection of the residual of such linear model suggests homoscedasticity (Figure 8-b).



#### Conclusions and discussion:

The analysis of the data and the regressions applied allow the following conclusions: there is a linear behavior up to a threshold which is close to 3.500 kg of DM/ha. After such level, the Green NDVI becomes saturated and the regressions breakthrough.

Nevertheless, it is important to remark that such is a high level of instantaneous biomass. In this sense, operationally, forage and range managers would in most cases assess levels of biomass beneath such threshold.

A possible explanation for such saturation level is that light interception, due to a high level of LAI has already reached its maximum, therefore an increase in biomass/LAI would not yield a different response as no sufficient incoming radiation is available to be absorbed or reflected.

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#### Annexe A -

Make Canon

Model Canon PowerShot S100

Aperture 2.5

 Exposure Time
 1/2000 (0.0005 sec)

 Lens ID
 Unknown 5–26mm

Focal Length 5.2 mm

**Flash** Off, Did not fire

File Size 2.6 MB
File Type JPEG

MIME Type image/jpeg

Image Width4000Image Height3000

Encoding Process Baseline DCT, Huffman coding

Bits Per Sample8Color Components3X Resolution180Y Resolution180

YCbCr Sub Sampling YCbCr4:2:2 (2 1)

YCbCr Positioning Co-sited

**Date and Time (Original)** 2014:07:31 13:17:15

Max Aperture Value 2

Metering ModeEvaluativeColor SpacesRGB

Sensing Method One-chip color area

Custom RenderedNormalExposure ModeManualWhite BalanceCloudy

Digital Zoom Ratio

Scene Capture TypeStandardContrastNormalSaturationNormalSharpnessN/AQualityFine

Sequence Number 1

F Number 2.5
Exposure Compensation N/A

Focus Mode Single

**ISO** 100

Digital Zoom None

CompressionJPEG (old-style)OrientationRotate 270 CW

#### .Annexe B

Project Fixed-wing for grassland survey

Airframe Skywalker 2014 1900 mm

Motor T-Motor AT2820 kv830 Brushless Motor

Prop size 12x6 APC like (HK)
ESC T-Motor 60A ESC(2-6s)

Servos Henge 12g 2.0kg 10sec MD933 Servos

Battery 1 DUPU 5200mAh 14.8v 25c nanometer lithium battery

Power Combo Motor + ESC + Servos

Autopilot 3DR Pixhawk+ GPS+Telemetry+digital airspeed sensor