Range Mgmt. & Agroforestry 38 (2) : 158-164, 2017
ISSN 0971-2070

Satellite and field radiometry for the estimation of biomass production in a grassland site in state of Durango, Mexico

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Received: 12th September, 2016 Accepted: 4th October, 2017

Abstract

The accurate and rapid estimation of biomass is important for the management of rangelands. The objective of this study was to find regression models to predict aerial biomass at a grassland site in the state of Durango, Mexico. For this purpose, samples of above ground biomass and normalized difference vegetation index values were obtained from two sources (NDVI-field radiometer and NDVI-MODIS) during the growing season of 2011 and 2013. Using 2011 data (n=180), the model Ln (Y) = $\beta_0 + \beta_1X + \beta_2X^2$ was found with the NDVI-field radiometer, $R^2 = 0.54$, and $Y^{0.3} = \beta_0 + \beta_1X + \beta_2X^2$ with NDVI-MODIS, $R^2 = 0.81$. Model validations were carried out comparing regression coefficients of 2011 and 2013 models, there was not significant difference with t (P>0.05). However, model with NDVI-MODIS had 77 outliers; therefore any prediction must be considered cautiously.

Keywords: Biomass, Field radiometer, MODIS, NDVI models

Introduction

The study of biophysical variables of vegetation grassland ecosystem is valuable for researchers and land managers especially when they are faced with a changing global climate that presents new threats to ecosystem stability (Wylie *et al*., 2012; Ghosh and Mahanta, 2014). The most important among the study parameters of vegetation is the production of biomass. Commonly accepted method for its measurement is to harvest and weigh plants directly in a given unit area (Sorensen *et al*., 2012). However, this technique is labor intensive and expensive, so it is necessary to implement the use of reliable technique for the determination of vegetation biomass (Casiano and Bolaños, 2010).

Primary productivity is a function of photosynthetically active radiation intercepted by vegetation (Monteith, 1977) and this variable can be estimated through the information captured at different wavelengths. Remote sensors allow acquiring radiometric images of the Earth's surface from aerial or spatial sensors (Chuvieco, 2010). The use of remote sensing in combination with the use of geographic information systems, allows the assessment of natural resources and can provide alternative sources of data collection for estimating biomass in large areas of grasslands (Chang *et al*., 2001; Di Bella *et al*., 2009). Another option for radiometric values of *in situ* vegetation is the use of field spectroradiometers, which allow information from objects at short distances from the ground without any material in contact (López, 2012). Traditionally, the main functions of the field radiometry have been serving as a link between laboratory measurements and reflectance gathered by sensors aboard aircraft and satellites. However, it has also gained importance itself for accuracy, reliability and the relative abundance of information generated and has led to numerous ramifications operating data (Vaughan, 2001).

In the last three or four decades, many vegetation indices (VI) calculated from spectral data from satellite and field remote sensing, have been developed in order to obtain information on the status of vegetation and its characteristics. A plant cover in good health, has a spectral signature that is characterized by the contrast between the band of the red (between 600 and 700nm), which is largely absorbed by the leaves, and the infrared (between 700 and 1100nm), which is mostly reflected (Carvacho and Sánchez, 2010). These indices do not directly measure vegetation productivity or forage availability, but have a close relationship with these variables that allows use for analysis (González *et al*., 2009).

Normalized Difference Vegetation Index (NDVI) has been widely used in agronomic explanations (Hunt and Miyake, 2006). It meets three important features for its implementations, mathematical simplicity, ease of interpretation and its power to normalize the spectral response of vegetation systems (Thoma *et al*., 2010). In addition achieves a high degree of correlation with various parameters of interest of vegetation, including grassland biomass (Gaitan *et al.*, 2013; Jin *et al.*, 2011; Ouyang *et al.*, 2012) which allow estimating the amount of forage at the end of the growing season and planning strategies for the dry season grazing (Medina *et al*., 2009).

The objective of this study was to develop models of annual linear regression between NDVI data obtained from imaging radiometer MODIS and NDVI data obtained from field spectroradiometer; both as predictor variables, and the production of biomass obtained by direct cutting as a response variable in northern state of Durango.

Materials and Methods

Study area: The research was conducted in the years 2011 and 2013. The study area was established on the site La Cieneguilla Hidalgo municipality located in north-central part of the state of Durango, 25 ° 39 ' 35" N and 104 ° 39' 23" W (Fig 1). The predominant climate in the area is steppe, semiarid temperate (BS1 kw) and semi-arid warm (BWhw), the annual average temperature is 20° C (Espinoza *et al*., 2000). The soil is sandy loam and clay-sandy loam with a slope of 1 to 8 percent. Hydrologically the study site is encompassed in the Hydrologic Region No. 35 Mapimí and RH 36 Nazas-Aguanaval.

Fig 1. Location of study area La Cieneguilla in northern Durango State, Mexico

The historical annual rainfall in the study area is 457 mm, about 80% of the rainfall occurs between the months of June to September irregularly, values accumulated rainfall for the years 2011 and 2013 was 139 and 382 mm, respectively (SAGARPA-INIFAP). The vegetation type is classified as medium open grassland with dominance of *Bouteloua gracilis* (Willd. Ex Kunth) Lag. ex Griffiths with different associations oak-juniper (*Juniperus* spp.- *Quercus* spp.) as part of the forest and mesquite (*Prosopis* spp.) as part of the bush (SEMARNAT, 2009). The site is used for the production of weaning calves under conditions of extensive pasture grazing by cow-calf system intended primarily for sale to feeders in the United States.

***Field radiometry*:** A permanent sampling site (PSS) was established using two perpendicular lines of 1,300 m each one. Nine sampling stations of 1 ha (SS) were distributed on these lines. The SS were spaced every 200 m in a sequence from north to south and from east to west. Each SS was divided into four quadrants measuring 50 by 50 m each quadrant (Fig 2). In each quadrant a sampling point was found randomly and a circumference of 1.6 m in diameter made of polyurethane was used to delimit the sampling area. Random points (36) were located in the PSS each sampling date. Measurements in 2011 were in April 27, July 04 August 02, September 06 and November 10 (n = 36 sampling date). In 2013 information in the same place on June 08 July 27, September 01, October 22 and November 28 with the same number of samples were recorded.

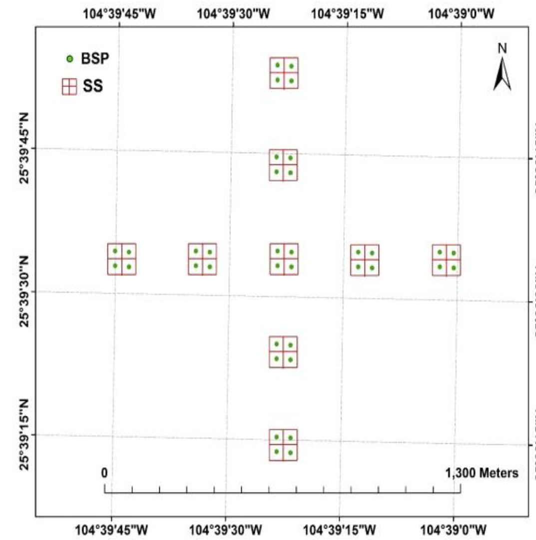

Fig 2. Schematic representation of the permanent sampling site (PSS) showing nine sampling stations (SS) and 36 biomass sampling points (BSP)

With the polyurethane circumference on the soil, a multispectral radiometer was located 3.20 m above of the center point of the circumference, and three observations were taken and an average was recorded. The radiometer was a crop scan Model MSR5 5-band of the electromagnetic spectrum 485, 560, 660, 830 and 1650 nm. Data were collected in the data logger of the radiometer. After the radiometric measurements were made, the above ground herbaceous biomass was harvested above 1 cm above the soil. At the same time, the closest images to the sampling dates of the NASA MODIS sensor were used. As it is known, these images have a spatial resolution of 250 m and taken in intervals of 16 days.

Calculation of NDVI: The design of the multispectral radiometer (MSR) allows almost simultaneous inputs of the flux of incident solar radiation on vegetation surface and the acquisition of the fraction of reflected solar energy (reflectance) by the object of study after the incidence of the same solar energy on the surface (Yao *et al*., 2013). From the reflectance values acquired in the five bands of the radiometer, only Band 3 (660 nm) and Band 4 (830 nm) were used for the calculation of the NDVI value by the equation of Rousse *et al*. (1974):

NDVI = (NIR - R) / (NIR + R)

Where:

NDVI = Normalized difference vegetation index

NIR = Near infrared (Band 4)

R = Red band (Band 3)

The surface reflectance MODIS (MOD 09) was calculated from the level of the bands 1, 2, 3, 4, 5, 6, and 7 (centered on 648, 858, 470, 555, 1240, 1640, and 2130 nm, respectively). Bands 1 and 2 were used to calculate MODIS-NDVI with the aforementioned formula. Once calculated NDVI values of each of the satellite images, the value was extracted by overlaying the corresponding number of point's georeferenced sampling points biomass of each of the sampling stations obtaining a total of 36 values.

Statistical analysis: For the analysis of the information obtained STATGRAPHICS XVII Centurion Version XVI.I program was used. Skewness and Kurtosis tests were used to determine normal distribution of the biomass samples. Since the normal distribution was not found in the data, Ln transformation was used or Y value raised to less than one in the regression models. Data of 2011 was used to find regression models, and data of 2013 was used to validate the models found in 2011. One model was where the dry weight of the aerial herbaceous biomass was the dependent variable and the NDVI estimated with radiometry data in the field was the independent variable. The other model had the herbaceous biomass as dependent variable and NDVI obtained from the MODIS radiometry was the independent variable.

Results and Discussion

Biomass production: The average biomass production was different in the two years of measurements (Table 1).The results were expected since there was a significant difference in precipitation in the two years of study. Yahdjian and Sala (2008) mentioned that the variation in the productivity of grassland is directly related to the high inter-annual variability in the amount and seasonal distribution of precipitation.

Table 1. Statistical summary of biomass production for 2011 and 2013 on the site La Cieneguilla, Durango, Mexico

Estimator	Biomass 2011	Biomass 2013
Count	180	180
Average (g m^{-2})	29.29	44.15
Standard deviation	22.47	30.02
Coeff. of variation (%)	76.72	67.98
Minimum	0	0
Maximum	93.20	109.95
Stnd. skewness	4.79	2.28
Stnd. kurtosis	-0.26	-2.25

The values of the Skewness and Kurtosis tests were found outside the range (-2 to +2) indicating significant deviations from normality. Tsutsumi *et al*. (2007) mentioned that although many studies may implicitly assume that samples can be approximated a the normal distribution, generally cannot apply the normal distribution to the biomass in pastures, since the frequency distribution of biomass shows a " long tail ", as was the case in our data.

NDVI-field radiometer regression model: The model Ln (Y) = $\beta_0 + \beta_1 X + \beta_2 X^2$ was found. Studentized residuals with the predicted values for each model were verified. The 2011 regression model had 30 outliers which were eliminated. In the 2013 regression, 25 outliers were eliminated. Regression models without outliers, both for 2011 and for 2013 data, met Gauss-Markov assumptions (Table 2; Fig 3).

Table 2. Parameters of the regression models of 2011 and 2013, the weight of aboveground biomass estimated using NDVI-field radiometer values in La Cieneguilla, Durango, Mexico

		Parameter	Error std	Statistical t	Value-P	Gauss Markov (Residual)	
	β_0	0.8888	0.3540	2.5102	0.0131	D. N.	Yes
Ln(Y_{2011})	$\beta_1 X$	11.8767	2.4155	4.9166	0.0000	I.	Yes
	$B_2 X^2$	-10.5460	3.7492	-2.8128	0.0056	H.	Yes
Adjusted R^2 = 0.5352							
Ln(Y_{2013})	β_0	0.7655	0.2076	3.6863	0.0003	D. N.	Yes
	$\beta_1 X$	12.6075	1.2875	9.7918	0.0000	I.	Yes
	$B_2 X^2$	-11.1926	1.7252	-6.4875	0.0000	H.	Yes
Adjusted R^2 = 0.8091							

D. N. = Distribution normal; I.= Independence; H. =Homoscedasticity

Table 3. Parameters of regression models of 2011 and 2013, the weight of aboveground biomass values estimated using NDVI-MODIS radiometry data in La Cieneguilla, Durango, Mexico

		Parameter	Error std	Statistical t	Value-P	Gauss Markov (Residual)	
	β_0	1.3324	0.1755	7.5915	0.0000	D. N.	Yes
Ln(Y_{2011})	$\beta_1 X$	8.7877	1.1931	7.3655	0.0000	I.	Yes
	$B_2 X^2$	-9.2276	1.8646	-4.9487	0.0000	H.	Yes
Adjusted R^2 = 0.8134							
Ln(Y_{2013})	β_0	0.684282	0.3528	1.9393	0.0544	D. N.	Yes
	$\beta_1 X$	9.02028	2.0849	4.3263	0.0000	I.	Yes
	$B_2 X^2$	-6.77787	2.8074	-2.4142	0.0170	H.	Yes
Adjusted R^2 = 0.6374							

D.N.=Distribution normal; I.=Independence; H.=Homoscedasticity

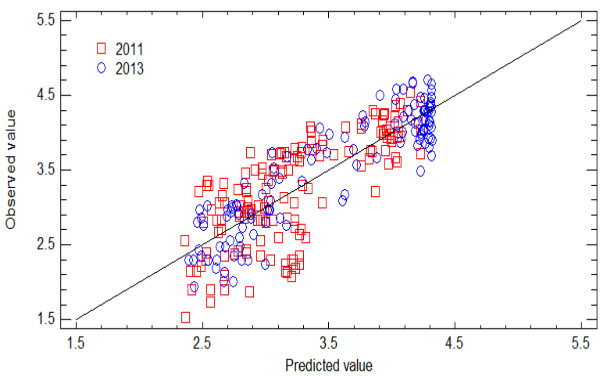

Fig 3. Relationship between predicted and observed values of the regression models for 2011 and 2013 estimated from NDVI-field radiometer values in La Cieneguilla, Durango, Mexico

The regression model found in this study was similar to that found by Psomas *et al*. (2011), which was generated with biomass data obtained at four sampling dates during the growing season and field radiometric data at dry pasture sites in central Europe, the best models were obtained from the multiple linear regression of the NDVI and the logarithm of biomass production, with the highest R2 value of 0.65. On the other hand, Deb *et al*. (2014) found that both dry fodder yield and grain yield of *Sorghum bicolor* can be estimated using nonlinear function through reflectance values based on the normalized difference vegetation index and aerial biomass, with the maximum positive correlation coefficient r = 0.61. These variations in the models found in the studies mentioned might be due to the variability conditions at different pasture sites, therefore, it suggests the generation of prediction models of biomass at particular level.

NDVI-MODIS regression model: The model found was $Y^{\wedge 0.3} = \beta_0 + \beta_1 X + \beta_2 X^2$. In 2011, outliers (35) were removed, by 2013 a total of 77 values were eliminated. Models without the aberrant data, both for 2011 and 2013 data met Gauss-Markov assumptions (Tables 3; Fig 4). Because there were a lot of eliminated aberrant data, the information of this regression model should be taken cautiously. The disadvantage of the NVDI-MODIS data was that the pixel scale was too large, and it gave the same value in an area of 62500 m^2.

The results found in this work for the conditions of this region were very similar to those found by other researchers. In a study in the Xilingol region of northern China, which is dominated mainly by the temperate desert steppe, among the statistical models established for the estimation of biomass and NDVI values, the power function model of the biomass with the best value of R^2 =

0.604 (Jin *et al*., 2014). In other study in the rangelands of Zacatecas, Mexico; on forage production related NDVI from images "SPOT Vegetation", Medina *et al*. (2009) adjusted a model of multiple regression for the three years together that lasted the experiment, they obtained an R^2 value of 0.66 ($P<0.01$), with which forage production for all areas of pasture were estimated by applying the generated model.

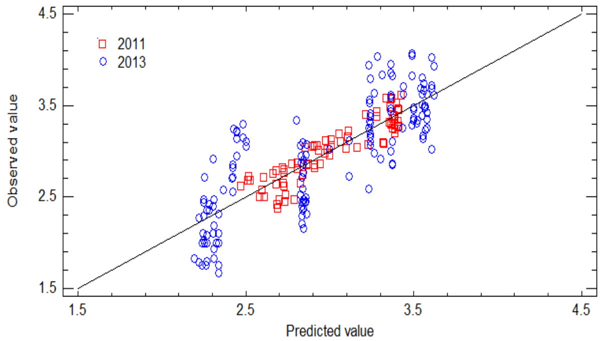

Fig 4. Relationship between predicted and observed values of the regression models of 2011 and 2013 using estimated values of the NDVI- MODIS, La Cieneguilla, Durango, Mexico

Models validation: A comparison was made between the regression coefficients of the models 2011 and 2013 for NDVI radiometry values estimating biomass and for NDVI-MODIS values estimating the same dependent variable. No significant difference was found in both years of study according to the "t" Student (Tables 4 and 5), showing that the 2011 models were validated with information taken in 2013. Again, the validation of the NVDI-MODIS regression model must be considered cautiously due to the large number of aberrant data taken away. However, this methodology and equation form used have to be contemplated in further studies using satellite radiometry with smaller scale.

Table 4. Comparison of the coefficients of the models 2011 and 2013 field radiometry with herbaceous biomass t (180 + 180-30-25-2 = 303, P<0.05) = 1.967

	β_0	$\beta_1 X$	$\beta_2 X^2$
2011	0.8888	11.8767	-10.5460
2013	0.7655	12.6075	-11.1926
t student	0.3004 n.s.	0.2669 n.s.	0.1566 n.s.

n.s.: not significant at P<0.05.

In previous to estimate the biomass of grassland by remote sensing attempts, through the NDVI, had the disadvantage that the rate was only sensitive to green vegetation, with the best results in the peaks of increased production (Tucker, 1979; Hunt and Miyake, 2006), also aboveground biomass of rangelands was changed very quickly within a few weeks, especially when livestock was used and was strongly influenced by rainfall (Baruch, 2005; Scanlon *et al*., 2005). In this study, the estimated biomass models indicated a good fit in terms of quality even when the biomass model and changes every year, models were developed using the annual fluctuation of two contrasting years. The models found in 2011 and 2013 were statistically equal. The difference in the amount of rain between one year and another was 243 mm (the average for the region is 475 mm). Gutiérrez-Guzmán *et al*. (2015) in a study on the site La Cieneguilla, used regression models to determine the relationship between biomass production herbaceous and estimated by using digital images, even when precipitation was different on vegetation cover and they found no statistical significance between the 2011 and 2013 models.

Table 5. Comparison of the coefficients of the models 2011 and 2013 MODIS radiometer with herbaceous biomass t (180 + 180-37-77-2 = 244, P<0.05) = 1.967

	β_0	$\beta_1 X$	$\beta_2 X^2$
2011	1.3324	8.7877	-9.2276
2013	0.6842	9.0202	-6.7778
t student	1.6447 n.s.	0.0967 n.s.	0.7268 n.s.

n.s.: not significant at P<0.05.

Using data from multi-temporal satellite to measure inter-annual changes in biomass of grasslands in semi-arid environments is common, although the selection of appropriate image acquisition dates is problematic for estimating biomass of grasslands (Casady *et al*., 2013). In our study, we ensured that the time of field sampling and remote sensing data acquisition was consistent to the maximum extent possible, this approach improved the sensitivity of remote sensing data to reflect the plant biomass information. When comparing models with the two sources of origin of NDVI, the field radiometer best explained the variability of biomass harvested MODIS data. Fitzgerald (2010) mentioned that the use of radiometers spectrum field ensured high spatial resolution for small scales of analysis. In the run to find suitable models, a greater number of observations of atypical MODIS-NDVI data were removed.

Conclusion

The regression models showed that it is feasible to estimate the dry weight of the biomass, even under conditions of inter-annual variability in the same pasture site. The use of the field radiometer ensured a high spatial resolution adequate for the scale of the analysis, finding an adequate prediction model. The regression model constructed with biomass data and NDVI-MODIS values, even with the limitation in spatial resolution, can serve as a basis for further studies with high spatial resolution satellite imagery.

References

Baruch, Z. 2005. Vegetation-environment relationships and classification of the seasonal savannas in Venezuela. *Flora* 200: 49-64.

Carvacho, B. L. and M. M. Sánchez. 2010. Comparison of vegetation indices from MODIS in the region of Libertador Bernardo O'Higgins, Chile, in the period 2001-2005. In: Ojeda, J., M.F. Pita and I. Vallejo. 2010. *Geographic Information Technologies: The Geographic Information in the service of citizens.* Secretariat of Publications of the University of Seville. Sevilla. pp. 728-737. http://age-tig.es/2010_Sevilla/ponencia3/CARVACHO.pdf (accessed on Jan. 5, 2015).

Casady, G., V. Leeuwen and B. W. Reed. 2013. Estimating winter annual biomass in the Sonoran and Mojave deserts with satellite and ground-based observations. *Remote Sensing* 5: 909–926.

Casiano, M. D. and M. Bolaños. 2010. Field Manual for the National Satellite Monitoring System Oriented Livestock SIMSOG. Texcoco, Mexico. pp. 30.

Chang, C. W., D. A. Laird, M. J. Mausbach and J. R. Hurburgh. 2001. Near-infrared reflectance spectroscopy-principal components regression analyses of soil properties. *Soil Science Society of America Journal* 65: 480-490.

Chuvieco, E. S. 2010. *Environmental remote sensing, earth observation from space*. Ed. Ariel. Barcelona, Spain. pp 528.

Deb, D., J. P.Singh and S. K. Rai. 2014. Usefulness of *in-situ* hyperspectral data to develop prediction model of dual purpose sorghum (Sorghum bicolor (L.) Moench) grown under semi-arid condition of India. *Range Management and Agroforestry* 35: 43-50.

Di Bella, C. M., I. J. Negri, G. Posse, F. R. Jaimes, E. G. Jobbágy, M. F. Garbulsky and V. A. Deregibus. 2009. Forage production of the argentine pampa region based on land use and long-term normalized difference vegetation index data. *Rangeland Ecology & Management* 62: 163-170.

Espinoza, C., A. L. Aguilar, E. Martínez, L. Gómez and E. Loa. 2000. Priority land regions of Mexico (CONABIO). http://www.conabio.gob.mx/conocimiento/regionalización/doctos/rtp_053.pdf (accessed on Jul. 24, 2014).

Fitzgerald, G.J. 2010. Characterizing vegetation indices derived from active and passive sensors. *International Journal of Remote Sensing* 31: 4335–4348.

Gaitán, J.J., D. Bran, G. Oliva, G. Ciari, V. Nakamatsu, J. Salomone, D. Ferrante, G. Buono, V. Massara, G. Humano, D. Celdrán, W. Opazo and F.T. Maestre. 2013. Evaluating the performance of multiple remote sensing indices to predict the spatial variability of ecosystem structure and functioning in Patagonian steppes. *Ecological Indicators* 34: 181-191.

Ghosh, P.K. and S.K. Mahanta. 2014. Carbon sequestration in grassland systems. *Range Management and Agroforestry* 35: 173-181.

González, L., P. Paredes and P. Rial. 2009. Severity of drought in Santa Cruz. Evaluation through vegetation indices of MODIS images. In: B. G. Díaz and Y P. Calviño (eds). *Regional conference on geographical information and territorial planning: Proceedings of the I and II Conference (2007 2008).* Ministry Secretary General of the Government of the Province of Santa Cruz. Argentina. pp. 146-153.

Gutiérrez-Guzmán, U.N., E. Castellanos-Pérez, J. J. Quiñones-Vera, J. S. Serrato-Corona, J. J. Martínez-Ríos, I. Orona-Castillo and I. Chairez-Hernández. 2015. Vegetal cover estimated by digital photographs related to biomass in a grassland site in northern Mexico. *Phyton-International Journal of Experimental Botany* 84: 312-318.

Hunt, R.E. and B. A. Miyake. 2006. Comparison of stocking rates from remote sensing and Geospatial Data. *Rangeland Ecology and Management* 59: 11-18.

Jin, Y.X., B. Xu, X. C. Yang, J. Y. Li, D. L. Wang and H. L. Ma. 2011. Remote sensing dynamic estimation of grass production in Xilingol, Inner Mongolia. *Science Si. Vitae* 41: 1185–1195.

Jin, Y. X, X. Yang, J. Qiu, J. Li, T. Gao, Q. Wu, F. Zhao, H. Ma, H. Yu and B. Xu. 2014. Remote sensing-based biomass estimation and its spatio-temporal variations in temperate grassland, northern China. *Remote Sensing* 6: 1496-1513.

López, P.M.S. 2012. Application of remote sensors to estimate net primary productivity in the grasslands of the state of Chihuahua. Master Thesis. Faculty of Animal Science and Ecology. Autonomous University of Chihuahua. Chihuahua, Chih; Mexico.

Medina, G.G., L. Gutiérrez, F. G. Echavarría,M. D. Amador, and J. A. Ruiz. 2009. Estimating forage production with satellite images in the grasslands of Zacatecas. *Revista Mexicana de Ciencias Pecuarias* 47: 135-144.

Monteith, J. L. 1977. Climate and efficiency of crop production in Britain. *Philosophical Transactions of the Royal Society of London, Series B* 281: 277-294.

Ouyang, W., F.H. Hao, A. K. Skidmore, T. A. Groen, A. G. Toxopeus and T. J. Wang. 2012. Integration of multi-sensor data to assess grassland dynamics in a Yellow River sub-watershed. *Ecological Indicators* 18: 163-170.

Psomas, A., M. Kneubühler, S. Huber, K. Itten and N. E. Zimmermann. 2011. Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats. *International Journal of Remote Sensing* 32: 9007-9031.

Rouse, J.W., R.H. Haas, J.A. Schell, and D.W. Deering. 1974. Monitoring vegetation systems in the Great Plains with ERTS, In: S.C. Freden, E.P. Mercanti, and M. Becker (eds) *Third Earth Resources Technology Satellite–1 Syposium. Volume I: Technical Presentations*, NASA SP-351, NASA, Washington, D.C. pp. 309-317.

SAGARPA-INIFAP. National Weather Network. http://clima.inifap.gob.mx/redinifap/historicos.aspx?est=41513&edo=9&m=1&an=2013 (accessed on Sep. 7, 2014).

Scanlon, T.M., K. K. Caylor, S. Manfreda, S. A. Levin and I. Rodrigues. 2005. Dynamic response of grass cover to rainfall variability: implications for the function and persistence of savanna ecosystems. *Advances in Water Resources* 28: 291-302.

SEMARNAT. 2009. Environment in Mexico 2009: Summary. Ministry of Environment and Natural Resources http://www.semarnat.gob.mx/informacionambiental/documents/sniarn/index_informes.html (accessed on Apr. 14, 2014).

Sorensen, G.E., D. B. Wester and S. Rideout-Hanzak. 2012. A nondestructive method to estimate standing crop of purple three awn and blue grama. *Rangeland Ecology and Management* 65: 538-542.

Thoma, D. P., D. W. Bailey, D. S. Long, G. A. Nielsen, M. P. Henry, M. C. Breneman and C. Montagne. 2010. Short-term monitoring of rangeland forage condition whit AVHRR imagery. *Journal of Range Management* 55: 383-389.

Tsutsumi, M., S. Itano and M. Shiyomi. 2007. Number of Samples Required for Estimating Herbaceous Biomass. *Rangeland Ecology and Management* 60: 447-452.

Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8: 127-150.

Vaughan, P. 2001. Estimating moisture content of vegetation by spectro-radiometer. http://www.investigacion.cchs.csic.es/espectroradiometria/sites/investigacion.cchs.csices.espectroradiometria/files/files/uploads/TESINA_VAUGHAN%20P_2001_0.pdf (accessed on Apr. 14, 2014).

Wylie, B. K., S. P. Boyte and D. J. Major. 2012. Ecosystem performance monitoring of rangelands by integrating modeling and remote sensing. *Rangeland Ecology and Management* 65: 241-252.

Yahdjian, L. and O. E. Sala. 2008. Climate change impacts on south American rangelands. *Rangeland Journal* 30: 34-39.

Yao, X., X. Yao, W. Jia, Y. Tian, J. Ni, W. Cao, and Y. Zhu. 2013. Comparison and intercalibration of vegetation indices from different sensors for monitoring above-ground plant nitrogen uptake in winter wheat. *Sensors* 13: 3109-3130.