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# Above ground biomass estimation of arid rangelands using irs p6 imagery (case study: Deylam, Iran)

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**Key words:** Rangeland, Biomass, Vegetation Index, Aridland.

**Abstract**

Ten vegetation indices (VIs) including Ratio, Normalized Difference Vegetation Index, Ratio Vegetation Index, Transformed Vegetation Index, Corrected Transformed Vegetation Index, Perpendicular Vegetation Index3, Difference Vegetation Index, Transformed Soil-Adjusted Vegetation Index2, Modified Soil-Adjusted Vegetation Index2, Weighted Difference Vegetation Index used for aboveground biomass estimation (AGB) were derived from Indian Remote Sensing Resource Sat (P6) imagery at an arid rangeland study site in Deylam south western of Iran. 100 sample locations (75 samples for model estimation, and 25 samples for model validation) were selected for the collection of AGB. Correlation coefficients between above ground biomass and VIs were calculated. The results demonstrate that biomass was linearly related to PVI3 (r= -0.491) and WDVI (r= 0.385). The higher bare soil is the main factor making the AGB estimation difficult. These results suggest that Distance Based VIs is useful and performed better than Slope Based VIs for estimating above ground biomass in arid rangelands of Iran.

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## Introduction

Rangelands around the world can have drastically different grazing management systems depending on the political, social, economic, and cultural settings. Rangelands cover approximately 40% of the earth's terrestrial surface and are important areas for livestock production and wildlife habitat (Huntsinger and Hopkinson, 1996). To effectively manage rangelands it is important to assess ecosystem productivity and biomass production (Running *et al.*, 2004). Remote sensing assessment is used along with field data to enhance sampling and site representation (Booth *et al.*, 2005).

Above Ground biomass (AGB) is related to many important components, such as carbon cycles, soil nutrient allocations, fuel accumulation, and habitat environments in terrestrial ecosystems. The increasing availability of satellite based remote sensing data extends the assessment of AGB to a broader spatiotemporal scale (Chen *et al.*, 2011). Biomass estimates represent the quantity of matter in a given area and are expressed either as the weight of organisms per unit area or as the volume of organisms per unit volume. Previous total above-ground biomass (AGB) research has demonstrated that vegetation indices (VIs) are sensitive to the biophysical and biochemical variations vegetation, and as a result are the most common parameters used to estimate AGB (Davidson and Csillag, 2001, Numata *et al.*, 2008, Chen *et al.*, 2011). A remote sensing–derived VI is a quantitative optical measure of canopy greenness (Tucker1979). Various VIs, such as the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and soil adjusted vegetation index (SAVI), have been correlated with AGB, and applied to predict AGB within a variety of biomes (Davidson and Csillag, 2001, Kogan *et al.*, 2004, Numata *et al.*, 2008, Cho and Skidmore, 2009).

Estimation of vegetation productivity using remotely-sensed information has generally followed two approaches, (1) establish direct empirical relationships between spectral reflectance and biomass (e.g. Tucker *et al.*,1983 and Wylie *et al.*,1995) or (2) use the spectral reflectance to estimate the amount of absorbed photosynthetically active radiation (Choudhury, 1987). The first approach has proven useful for estimating live biomass. AGB from VIs, many problems have been found. One problem is that an empirical relationship derived by a VI for the accurate prediction of AGB at one site or time period may not apply to other sites or even the same site at another time (Foody *et al.*, 2003). This problem is primarily due to variations in the natural environment (e.g., variable precipitation, soil-water content, and temperature conditions), viewing season (e.g., phenology during the growing season), and the sensor used in the study (e.g., differences in spatial resolution and other sensor characteristics) (Davidson and Csillag, 2001). Despite the confusion and conflicting viewpoints surrounding rangeland health, productivity estimates may be an important component for determining whether current management practices are improving, degrading, or sustaining ecological integrity (Pickup *et al.*, 1994). Some forms of site degradation may produce distinctive temporal and spatial in addition, because VIs have differing abilities to provide accurate estimates of AGB, it is difficult to determine an optimal VI for a specific study. The most research focuses on slope based indices such as NDVI to estimation of AGB in semiarid and humid rangeland, and estimation of AGB in aridland is difficult, so it is necessary to examine the application of slope based and distance based VIs in the arid land. The aim of the present research was investigating the relationship between VIs with aboveground biomass of rengeland vegetation for determining the more useful VIs in the study area, and estimating of AGB of arid rangeland of Iran using IRS P6 LISS III satellite data.

## Material and methods

*Study area*

The research was carried out in Deylam region located between 50° 05´ to 50° 6´ east longitude and

30° 03´ to 30° 13´ in Bushehr province of Iran (Fig. 1.). Studying area has dry Climate (Average annual precipitation is 224.6 mm) and located in the coastal region with 15915 hectare area. Rangeland covers 95.7% (15234 hectares) of the studying area. The area is steppe, consisting primarily of native and non-native species including grasses (*Aelorupus lagopoeides*, *Stipa capensis*), forbs (*Plantago cylindrical*, *Centaurea Bruguierana*), and many shrub (*Halocnemum strobilaceum*, *Gymnocarpus decandera*, *Astragalus fasiculifolius*). Sheep and goat grazing is the primary usage of the study area rangeland.

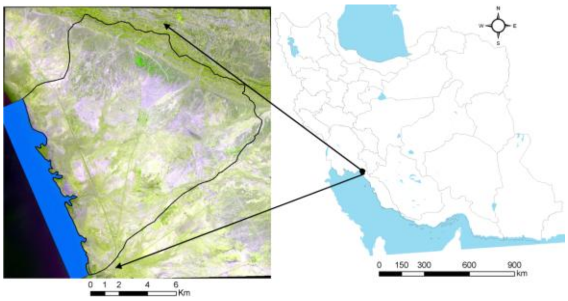


**Fig. 1.** Location of study area in southwest of Iran.

*Satellite data*

Indian Remote Sensing Resource-Sat (P6) LISS III multispectral imagery (23.5 m × 23.5 m pixels) was acquired for the study area on 01 March, 2011. Geometric corrections of image were applied using Ground Control Points and geo-referenced images with RMSE less than one pixel and projected in UTM Zone 39 North with WGS 1984 datum. All Atmospheric correction was performed with IDRISI Taiga (v16.03) using the ATMOSC module (Clark Labs, Worcester, MA). Image was corrected for atmospheric effects using the Cos(t) model (Chavez, 1996) and input parameters reported in the metadata supplied by IRS Image Corporation. Then ten VIs (Table 1.) including slope based (Ratio, NDVI, RVI, TVI, CTVI) and distance based (PVI3, DVI, TSAVI2, MSAVI2, WDVI) calculated with IDRISI. Most VIs used for AGB estimation are based on radiance or reflectance from a red band (RED) around 0.66 µm and a near infrared band (NIR) around 0.86 µm (Huete *et al.*, 2002, Chuvieco *et al.*, 2004). Slope and intercept values of the soil line are obtained by performing a simple linear regression on bare soil pixels in the red and infrared bands.

**Table 1.** Vegetation indices used to estimate above-ground biomass.

| Index | Formula | Reference |
|---|---|---|
| Ratio | NIR/RED | Rouse, *et al.*, 1974 |
| NDVI | (NIR-RED)/(NIR+RED) | Rouse, *et al.*, 1974 |
| RVI | RED/NIR | Richardson and Wiegand, 1977 |
| TVI | $\sqrt{}${(NIR-RED)/(NIR+RED)}+0.5 | Deering *et al.*, 1975 |
| CTVI | {(NDVI+0.5)/ABS(NDVI+0.5)}×$\sqrt{}$ABS(NDVI+0.5) | Perry and Lautenschlager, 1984 |
| PVI3 | aNIR-bRED | Qi, *et al.*, 1994 |
| DVI | bNIR-RED | Richardson and Wiegand, 1977 |
| TSAVI2 | {b(NIR-bRED-a)}/{RED+bNIR-ab+0.8+(1+$b^2$)} | Baret, *et al.*, 1991 |
| MSAVI2 | {2NIR+1-$\sqrt{}$(2NIR+1)$^2$-8(NIR-RED)}/2 | Qi, *et al.*, 1994 |
| WDVI | RED-bNIR | Richardson and Wiegand, 1977 |

a: intercept values of the soil line, b: slope values of the soil line.

*Field data*

This study presents results using AGB measurements, and does include measurements of all grasses, forbs, and shrubs biomass production. Available AGB was measured using a clearing and clipping methods (Milner and Hughes, 1968) in plots (1m×2m). All vegetation within the plot was clipped as close to the ground as allowed by the clipper (approximately 5 mm from the ground surface) and the samples were taken to the laboratory, and after drying, weighed (±0.01 g). Biomass was estimated and expressed in kilograms per hectare. AGB measured in four category including total AGB, AGB of class I plants (AGB I), AGB of class II plants (AGB II), and AGB of class I plants (AGB III). 100 sample locations (75 samples for model estimation, and 25 samples for model validation) were selected for the collection of AGB. Site selection criteria included the site being a homogeneous area at least 24 m × 24 m in size. At least distance between sample sites is 100 meter. In each site nine plots measured, then mean of AGB plots calculated (Fig. 2.). The location of each sample plot centre was recorded using a Garmin eTrex Vista CSX GPS receiver using latitude longitude (UTM WGS 84).

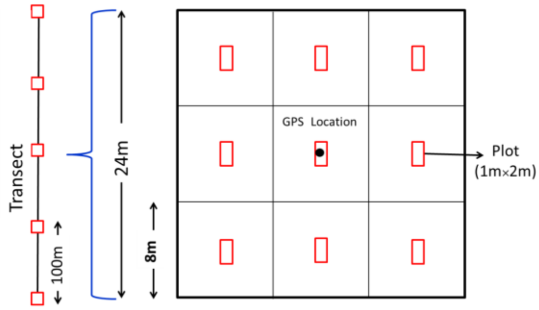


**Fig. 2.** Position of plots in each sampling site.

*Aboveground biomass estimation models*

In ABG estimation research, multiple regression is the most often used approach (Steininger, 2000, Zheng *et al.*, 2004), thus, it is also used in this study. In this research, all the sample data were linked to image variables (indices) to extract the value for each sample. After the image values for these samples were extracted, person's correlation coefficient was used to analyse relationships between AGB and remote sensing derived variables including LISS III vegetation indices. The total AGB, AGB I, AGB II, and AGB III, was used as a dependent variable, the VIs used as independent variables, and a stepwise regression analysis was used to AGB estimation models. Coefficient of determination ($R^2$) is used to evaluate a regression model performance because it measures the percentage of variation of variation explained by the regression model. Although validation of the estimated results is an important part in the AGB estimation procedure, it is difficult to collect a large amount of field-measured AGB data, and we used a relatively small sample size (25 samples) in this study.

**Results and discussion**

Field-based total AGB estimates ranged from 11.0 kg/ha to 297.8 kg/ha (mean = 123.71 kg/ha), AGB I ranged from 4.7 kg/ha to 128.1 kg/ha (mean = 53.19 kg/ha), AGB II ranged from 7.0 kg/ha to 190.5 kg/ha (mean = 79.17 kg/ha), and AGB III ranged from 9.8 kg/ha to 265.9 kg/ha (mean = 110.47 kg/ha), based on vegetation samples collected at 75 field locations. Using linear regression analysis between each VI and AGB measurements, the relationship between these variables were described (Table 2.). Based upon these results, it was noted that the relationships varied greatly and the strength of all correlations were strongly weak in slope based indices ($0.022 \le r \le 0.114$) and relatively weak to proper in distance based indices ($0.026 \le r \le 0.491$). The VIs provided poor estimates of herbaceous AGB. Furthermore, the prediction of AGB was acceptable explained using PVI3 (r= 0.491) and WDVI (r= 0.385). As a result, while NDVI is one of most widely used VIs for AGB prediction and other vegetation studies, in this study area rangeland, it was not considered a reliable predictor of AGB. NDVI might not be a useful estimate of vegetation cover or biomass in semi-arid rangelands, especially when bare soil cover is >20 % (Sanky and Weber, 2009).

Linear relationships were determined between VIs and AGB. Result of stepwise regression show that PV3, TSAVI2, Ratio, MSAVI2, and WDVI indices entered in final estimation model of AGB I and AGB II (table 3.) and other indices not entered in final model. No variables were entered in equation of Total AGB and AGB III model. Vegetation indices are not a direct measure of biomass or primary productivity, but are correlated with both the leaf area index and to plant biomass and are therefore useful for estimating these parameters (Weiser *et al.*, 1986). Validation of models with ground data (25 sample) show that the estimation model of AGB class I ($R^2$= 0.403), and AGB class II ($R^2$= 0.414) have proper accuracy in the study area. In arid regions bright soil background constitutes a large portion of pixel reflectance, and the interaction between vegetation and soil reflectance is assessing the potential effectiveness of remote sensing techniques to estimate biomass. In semi-arid regions, secondary soil influences, as well as soil-vegetation spectral mixing is a major concern. Soil, plant, and shadow reflectance components mix interactively to produce composite reflectance (Richardson and Wiegand, 1990). VIs correlation with vegetation cover and biomass might be greater in areas with various biomes and community types. Vegetation condition, distribution, and structure can affect the relation between biomass and spectral indices. However, our rangeland sites represent a single biome with little variability in vegetation cover and species distribution. This study area has specific condition in arid rangeland and the relationships discovered in this study should not be directly generalised to other regions.

**Table 2.** Pearson Correlation between VIs and Above Ground Biomass used in this study.

| Index | Pearson Correlation | | | |
|---|---|---|---|---|
| | **Total AGB** | **AGB I** | **AGB II** | **AGB III** |
| Ratio | 0.100 ns | 0.090 ns | 0.090 ns | 0.114 ns |
| NDVI | 0.092 ns | 0.023 ns | 0.022 ns | 0.106 ns |
| RVI | -0.086 ns | -0.034 ns | -0.034 ns | -0.100 ns |
| TVI | 0.089 ns | 0.027 ns | 0.028 ns | 0.104 ns |
| CTVI | 0.089 ns | 0.026 ns | 0.028 ns | 0.104 ns |
| PVI3 | -0.157 * | -0.491 ** | -0.490 ** | -0.136 * |
| DVI | 0.026 ns | 0.031 ns | 0.030 ns | 0.048 ns |
| TSAVI2 | 0.100 ns | 0.146 * | 0.145 * | 0.092 ns |
| MSAVI2 | 0.029 ns | 0.202 ** | 0.202 ** | 0.028 ns |
| WDVI | 0.102 ns | 0.385 ** | 0.383 ** | 0.068 ns |

**significant at p=0.01, *significant at p=0.05, ns not significant.

**Table 3.** Summary of ABG estimation models using VIs derived from LISS III image.

| Variable | Variables Entered | $R^2$ | SE |
|---|---|---|---|
| Total AGB | No variables were entered. | - | - |
| AGB I | PVI3, TSAVI2, RATIO, WDVI | 0.488 | 2.194 |
| AGB II | PVI3, TSAVI2, RATIO, WDVI | 0.487 | 3.266 |
| AGB III | No variables were entered. | - | - |

## Conclusion

This study demonstrates that Resource-sat LISS III image is successful for AGB estimation in arid rangeland. Distance based VIs play an important role in improving AGB estimation performance comparing slope based VIs in arid rangeland. The lower vegetation cover in other hand higher bare soil is the main factor making the AGB estimation difficult. Rangelands often have some amount of bare soil, especially in arid and semiarid environments such as our study area. Exactly how much bare soil can be present to warrant the successful use of VIs in rangelands, however, is not well documented. Different biophysical conditions significantly influence AGB estimation models to different study areas. Future work will seek to assess a more comprehensive on AGB estimations in semiarid rangelands.

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