Estimating biophysical variables of pasture cover using sentinel-1 data

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Abstract

Over the years, different optical remote sensing platforms and data have been used to estimate aboveground pasture biomass in a variety of landscapes, both heterogeneous and homogenous and at varying spatial scales. Optical methods are often confounded by target visibility, namely presence of cloud cover and haze, and are constrained to daylight conditions. In this study, we used the synthetic aperture radar data from the European Space Agency Sentinel-1 mission to estimate pasture biomass, sward height and leaf area index of a complex extensive grazing 'farmscape' comprising of a range of grass vegetation communities We observed that the quality of digital elevation model used in radar data pre-processing significantly influences the ability of eigenvector scattering decomposition in estimating biomass, sward height and leaf area index.

Background

Estimation of aboveground pasture biomass (AGB) does not only provide information on the primary plant productivity of the site or paddock but is useful for graziers managing that landscape in making decisions such as setting stocking rate, grazing rotation interval and rate of fertiliser application using variable rate technology. Several tools and methods have been used in estimating AGB at different scales spanning sub-paddock to landscape. The methods of AGB estimation can be broadly categorised into direct and indirect. The direct method which involves physically cutting and weight plant material from quadrats, provides the most accurate AGB estimation but is destructive and labour and time expensive, and it is logistically difficult to sample with a scale and resolution that reflects the scope of the landscape in question. Indirect methods such as the use of proximal active optical sensors have augment the conventional destructive method but, as with the destructive methods are infeasible when the study site is expansive, complex and requires long-term monitoring. Data from satellite-based optical (multispectral) remote sensing have been used for AGB estimation at landscape scale, for example Clarke et al. (2006); Donald et al. (2004) and Gherardi et al. (2004), the acquisition of optical satellite data is limited by cloud cover and haze, and daylight hours and thus makes their availability unreliable especially in tropical regions or during peak growing seasons which generally also experience season-dominant rainfall

Satellite-based, synthetic aperture radar (SAR) remote sensing is able to provide relatively high spatial resolution images (~ 10 m) without being affected by the presence or absence of solar illumination and presence of clouds and other weather conditions that obscures visible line of sight. This potentially makes the SAR an appropriate source of data for long term monitoring of AGB estimation especially at landscape scale. Optical satellite remote sensing methods are passive and rely upon solar illumination of the target. They tend to rely upon the photosynthetic activity of the plants in question and detection of the associated plant pigments. However, SAR responds to the physical structure of the plants and their associated canopy assemblages. Granted, optical reflectance methods are also influenced by the physical structure of plant canopies (for example LAI and leaf orientation), as it relates to the plant's ability to influence the reflected incident sunlight. However SAR relies solely upon such characteristics and more importantly, SAR is an active sensor using radiation that penetrates (and returns) through cloud, and that the return scattered signal is based upon the incident radiation provided by the sensor itself, hence is not reliant upon any form of solar illumination.

Leaf area index (LAI) and sward height (SH) are crucial biophysical or structural variables in estimating pasture biomass. They are functionally complementary in determining the light and water regimes of a pasture, as well as the canopy geometry and architecture (Haldar et al., 2014). The LAI and SH of pasture interacts with light energy (Baghdadi et al., 2016) and LAI is known to be sensitive to radar backscatter (Jiao et al., 2009).

The utilisation of satellite-based SAR scenes over hilly terrain demands extra caution (as compared to flat ground) as phenomena such as lay-over, fore-shortening, and radar shadow effects, all of which result from variations in the viewing geometry of the SAR system impact on the backscattered (hence detected) signal. Both of these effects are related to the 'relief' of the terrain; foreshortening occurs when the radar beam reaches the bottom of a tall feature before it reaches the top, and layover occurs when the radar beam reaches the top before it reaches the base. Both foreshortening and layover result in radar shadow; that is the radar beam is not able to illuminate a nearby portion of the ground surface and this confounds the interpretation of the backscattered signal. These effects can be minimised or eliminated depending on the quality of the digital elevation model (DEM) used when pre-processing the SAR data. The spatial resolution of the DEM used for radiometric terrain flattening, orthorectification and radiometric calibration (Small, 2011) is imperative in deriving polarimetric and interferometric information such as local incidence angle, polarimetric decomposition parameters and the precision of feature location in SAR scenes (Park, 2015).

The utilisation of SAR data in biomass estimation has been largely limited to trees and field crops (Bouman and van Kasteren, 1990) whereas its use in pasture has received little attention. In these previous studies, commercial SAR systems such as Radarsat-2 (Haldar et al., 2014), TerraSAR-X (Dhar et al., 2010; McNeill et al., 2010) and COSMO-SkyMed (Wang et al., 2013) were used. To our knowledge, no work has been reported on the use of the freely available Sentinel-1 C-band SAR (S-1) for pasture biomass estimation in grass lands. The S-1 is both a single and dual polarisation system that collects data in four different modes using a Terrain Observation with Progressive Scans SAR (TOPSAR) principle (Moreira et al., 2013). Furthermore, S-1 data are generated as ground detected (GRD) without phase information and simple complex look (SLC) where the phase is preserved. S-1 has a 12-day repeat cycle for one sensor but 6-days when using both sensors.

The radar sensor is characterised by its incidence angle, polarisation and frequency of operation; and these parameters influence the reflected radar signal. Further, the pasture canopy water content, shape, size and orientation of pasture blades, soil moisture and surface roughness all contribute to the measured radar backscatter. The radar backscattering coefficient can however be de-convolved into individual scattering mechanism, of which the dominant scattering type can be identified. Several radar scattering decomposition methods spanning coherent and incoherent targets have been used. In this study, the Cloude and Pottier scattering decomposition method which estimates three components; entropy (H), anisotropy (A) and alpha angle (α) on the basis of decomposing eigenvalues and eigenvectors of coherence matrices [T] (Cloude and Pottier, 1997). The entropy, H, and anisotropy, A, are of the range 0 – 1. The H is indicative of the type of scatterer and the number of dominant scattering mechanism; it in short describes the randomness of the scattering mechanisms. The entropy value is directly proportional to the degree of depolarisation (or random scattering). The anisotropy, A, is complimentary to the H in that it offers the interpretation of the extent of secondary scattering mechanisms through evaluation of the significance of the second and third eigenvectors (Cloude and Pottier, 1996); and it only becomes a useful parameter when $H > 0.7$. The alpha angle parameter, $0 \leq \alpha \leq 90$, is indicative of the mean (dominant) scattering mechanism. This study aims to investigate the extent of which the quality of a DEM has on polarimetric variables extracted over a number of grassland pasture calibration sites, and then to estimate LAI, SH and AGB exclusively on S-1 polarimetry of three different level of DEMs quality.

Methods

This study was implemented at the SMART Farm of the University of New England in Armidale, NSW Australia. The SMART Farm is a complex pasture landscape which comprises mainly of different tree and pasture species and characterised by hilly topography. Grazing livestock (e.g. sheep and cattle) are rotated onto the various paddocks throughout the year. In this study, ten different study sites, defined by variability in soil, pasture species and livestock grazing were sampled (Fig.1).

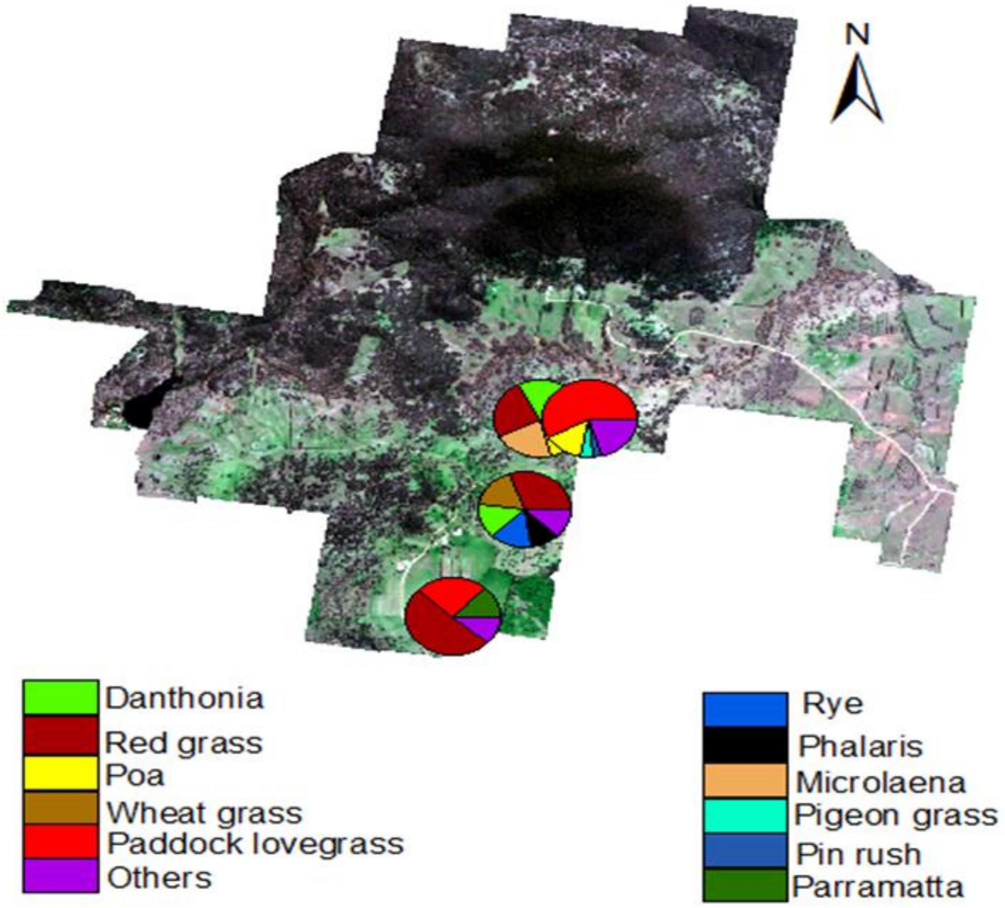

Figure 1. Location of the study area with a selection of the sites sampled and their mixed pasture species composition. Note, only four of the ten study sites are shown here.

Soil moisture sensors were located nearby to provide concurrent measurements (at 15 minute intervals) of soil moisture and soil and air temperature via the SMART Farm sensor telemetry network. Each of the 10 sites was 30 x 30 m to match the 10 x 10 m spatial resolution of the SAR satellite data, allowing for a 10 m radius buffer of the same pasture composition around the 'central pixel' location to allow for uncertainty in spatial registration of the image pixels. Each site was also selected on the basis of having an additional 50 m radius buffer region around it, again of the same pasture composition, to reduce mixed-pixel effects. Aboveground pasture biomass was measured using destructive sampling while sward height and leaf area index were measured using rising plate disk and AccuPAR LP-80 Ceptometer, respectively.

Sentinel-1A interferometric wide swath mode (IWS) data for GRD and SLC, with an observation date (13 February 2017) coincidental with field measurement were downloaded from the Scientific Data Hub (ESA, 2017). This S-1 IWS data was in the dual polarisation of VV (radar pulses transmitted in vertical polarisation and received in vertically polarisation) and VH (transmitted in vertical polarisation and received in horizontal polarisation). The GRD was pre-processed to extract the radar backscattering coefficients in both polarisations ($\gamma 0VV$ and $\gamma 0VH$) whereas eigenvector decomposition parameters entropy (H), anisotropy (A) and alpha angle (α), and local incidence angle were all derived from the SLC data. In SAR data pre-processing, three different spatial resolutions of DEM data were tested; SRTM 90 m, SRTM 30 m (Shuttle Radar Topography Mission, JPL-NASA) and a lidar derived 1 m. These were sequentially used for radiometric-terrain and geometric-terrain corrections. Polarimetric variables from these DEM data were visually and statistically analysed.

Finally, a second-order regression models were built to estimate AGB, SH and LAI using the derived polarimetric variables (γ0VH, H and α). Models were tested using the method proposed by Pena and Slate (2006) to ensure none of the assumptions of linear regression was violated. Further, we used the Breusch and Pagan (1979) test for heteroscedasticity in the models. Owing to limited size of trained data, leave-one-out cross-validation (LOOCV) was applied to the models. Only the best models were presented in this paper to assist in discussion.

Results

Quality of digital elevation model in SAR polarimetry

The three different DEMs used in pre-processing the SAR data generated different outputs for the polarimetric measures. The DEM with finest spatial resolution (1 m DEM) captured the most variability whereas the coarsest DEM (SRTM 90 m) showed the least variability in estimated local incidence angle as shown by their standard deviation, co-efficient of variation and equivalent number of looks values in table 1 and visually expressed in figure 2.

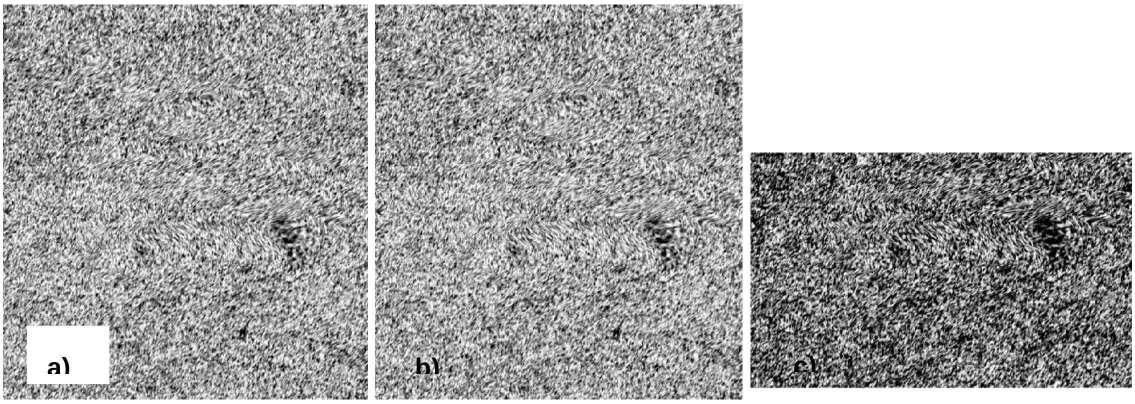

Figure 2. Images of entropy parameter of eigenvector scattering decomposition- a) SRTM 90 m DEM; b) SRTM 30 m DEM and c) LiDAR generated 1 m DEM for orthorectification. The entropy of the eigenvector scattering decomposition measures the statistical randomness of scattering by targets.

Table 1. Variability measures for the 1 m, 30 m and 90 m digital elevation models used in pre-processing radar data. The standard deviation (σ), coefficient of variation (CV) and equivalent number of looks (ENL) explain variability in the local incidence angle estimated for radiometric and geometric calibration of radar data.

DEM type	mean	standard deviation (σ)	coefficient of variation (CV)	equivalent number of looks (ENL)
1 m	38.6	10.7	0.84	1.4
30 m	37.5	6.7	0.34	8.8
90 m	37.4	6	0.3	11.1

Relationship between biomass, sward height and leaf area index and SAR polarimetry

Both polarisations of the S-1 (VV, VH) were negatively correlated to AGB, SH and LAI. Although the correlations were all weak (|r|< 0.55), the backscattering coefficient γ0 from the VH polarisation showed the strongest negative association with AGB, r = -0.55 (Fig.3). Of all the parameters of the eigenvector scattering decomposition related to AGB, SH and LAI; only the mean scattering parameter (alpha angle) offered the best results. AGB, H and LAI revealed a second-order polynomial relationship with the mean scattering mechanism. Although mean scattering mechanism was the most suitable parameter in estimating AGB, SH and LAI, the efficacy of the model is dependent on the size of the spatial resolution of DEM used for radar signal calibration and local incidence estimation.

It was observed that the ability of mean scattering mechanism in estimating AGB, SH and LAI directly relates to the pixel size of the DEM used in orthorectification of the SAR imagery. The 1 m DEM-enhanced mean scattering mechanism explained most of the variation in AGB, SH and LAI (R2 = 0.8, 0.72 and 0.59, respectively) compared to the 30 m and 90 m DEM-enhanced data (Fig.4a-c). The second-order, 1 m DEM enhanced model yielded a root mean squared error (RMSE) of 321 KgDM/ha, 1.48 cm and 0.34, in AGB, SH and LAI, respectively (Fig.4d-f). Furthermore, the models did not violate any of the linear regression assumptions and showed constant error variance as expressed by p-values of the score tests (chi-square values) in Table 2. Finally, the LOOCV for models estimating AGB, SH and LAI exhibited standard errors of 136, 0.138 and 0.764, respectively (Table 2).

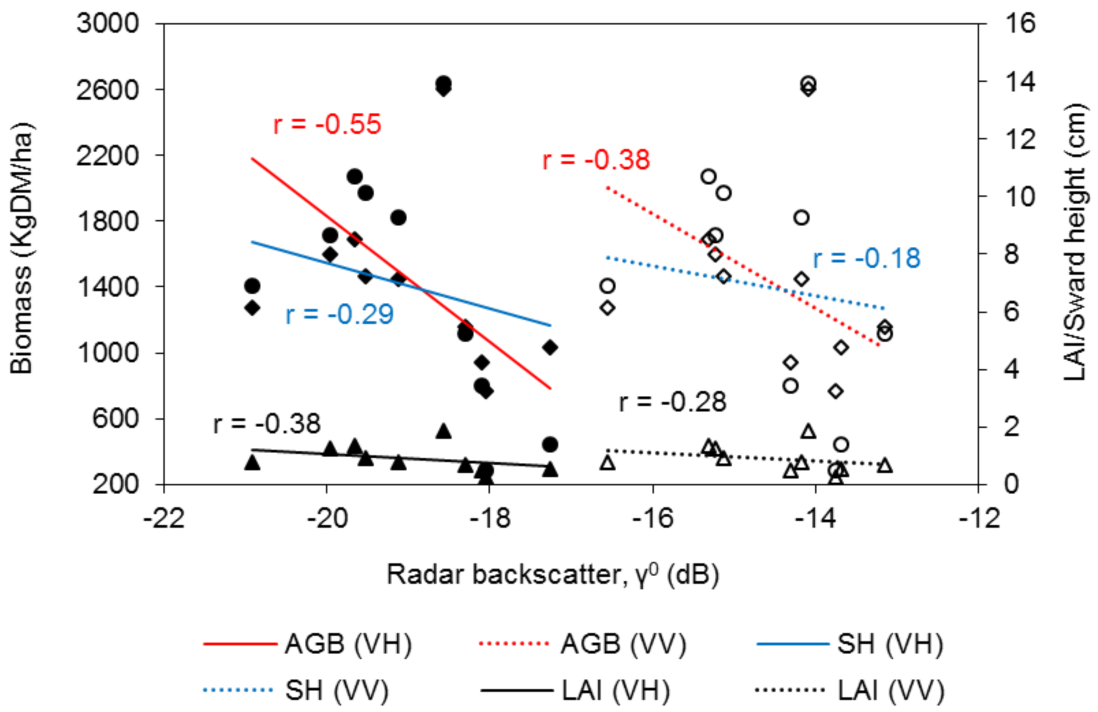

Figure 3. Correlation between backscattering co-efficient of Sentinel-1 VV and VH polarisation and aboveground pasture biomass (KgDM/ha), sward height (cm) and leaf area index (LAI). The solid and broken correlation lines represent VH and VV polarisations, respectively. The red, blue and black lines and their respective correlation values are for aboveground biomass, sward height and leaf area index, respectively.

Table 2. Homoscedasticity and leave-one-out cross validation analyses of models. Low chi-square values coupled with p>0.05 means the error of variance in models is constant whereas standard error is a performance measure for the LOOCV.

	Breusch and Pagan test		Leave-one-out cross-validation
	chi-square	p-value	standard error
AGB	0.00018	0.989	136
SH	0.266	0.606	0.138
LAI	0.03	0.86	0.764

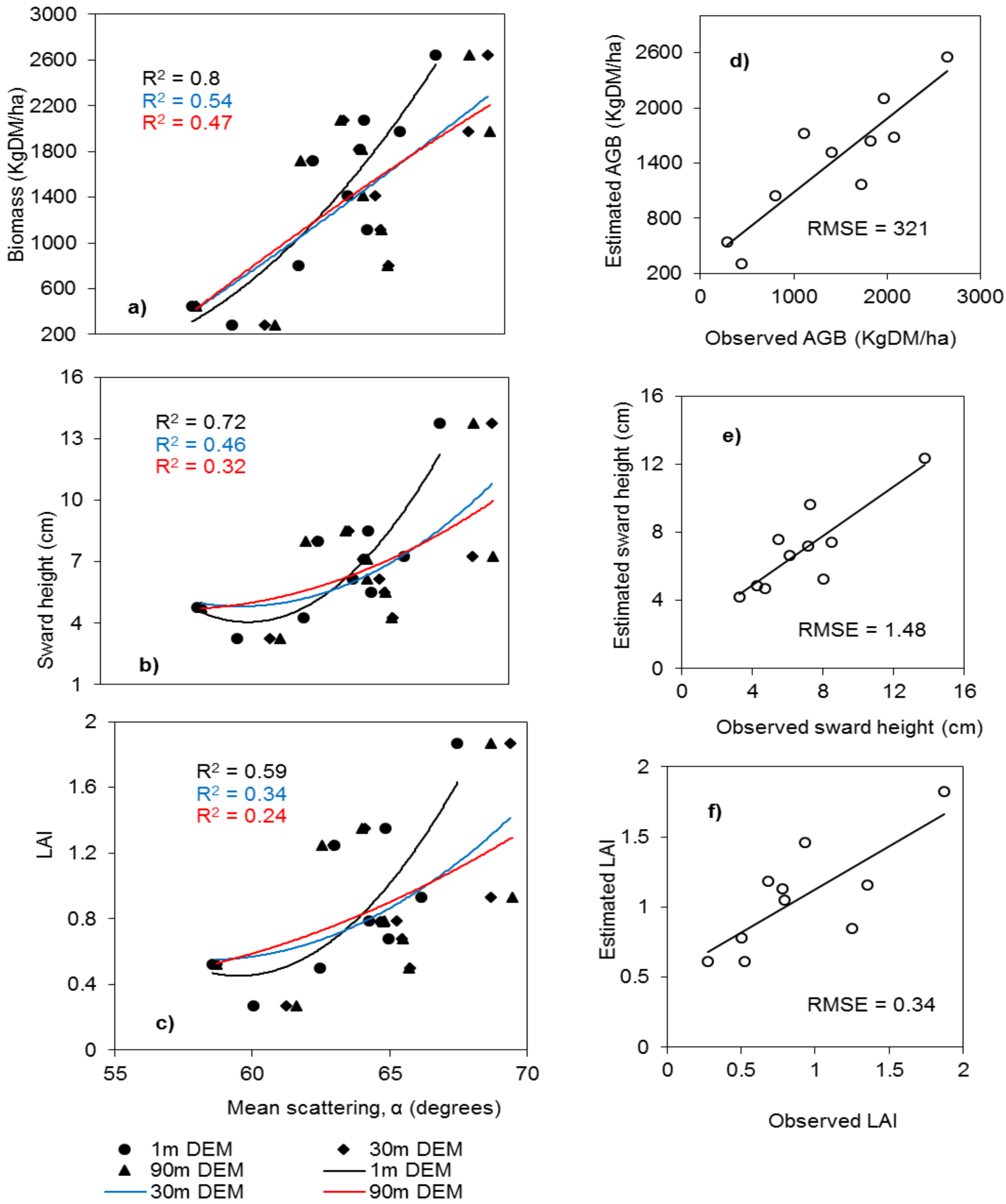

Figure 4. The relationship between mean scattering mechanism and aboveground pasture biomass, sward height and leaf area index (a-c) and the relationship between observed and estimated values for AGB, SH and LAI with their respective root mean square error (d-f).

Conclusion

This paper explored the role of digital elevation model in improving SAR polarimetry for the estimation of aboveground pasture biomass, sward height and leaf area index. We observed that DEM of fine spatial resolution is able to make the mean scattering mechanism of eigenvector decomposition a useful parameter in estimating biomass, sward height and leaf area index. In future analysis, data size will be increased so as to have independent data to sufficiently test or validate the model. Also, exclusively grazed and ungrazed tests will be conducted. In sum, this study pioneers the exclusive use of Sentinel-1 SAR data and scattering matrix decomposition to estimate biophysical variables of agricultural pasture cover in a complex landscape.

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