MEDIUM RESOLUTION IMAGE FUSION, DOES IT ENHANCE FOREST STRUCTURE ASSESSMENT

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ABSTRACT:

This research explored the potential benefits of fusing optical and Synthetic Aperture Radar (SAR) medium resolution satellite-borne sensor data for forest structural assessment. Image fusion was applied as a means of retaining disparate data features relevant to modeling and mapping of forest structural attributes in even-aged (4-11 years) *Eucalyptus* plantations, located in the southern Kwazulu-Natal midlands of South Africa. Remote sensing data used in this research included the visible and near-infrared bands of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), as well as a fine beam (6.25 m resolution) RadarSAT-1 image. Both data sets were collected during the spring of 2006 and fused using a modified discrete wavelet transformation. Spatially referenced forest inventory data were also collected during this time, with 122 plots enumerated in 38 plantation compartments. Empirical relationships (optimized multiple regression) were used to test whether fused data sources produced superior statistical models. Secondary objectives of the paper included exploring the role of scale in terms of forest modelling at the plot and extended plot levels (Voroni diagrams). Results indicated that even an optimized multiple regression approach did not return accuracies suitable for plantation forestry applications (adjusted R^2 of 0.55 and 0.6 for basal area and merchantable volume respectively). No significant difference was found between fused and non-fused data sets, however optical and fused data sets produced superior models when compared to SAR results. No significant difference was found between field enumerated plot level modelling and Voroni level modelling with both data sets producing similar goodness of fit statistics. Findings indicate that the spatial resolutions of both sensors are inappropriate for plantation forest assessment. The frequency of the *C*-band Radarsat-1 image is for instance unable to penetrate the canopy and interact with the woody structures below canopy, leading to weak statistical models. The lack of variability in both the optical and SAR data lead to unconvincing results in the fused imagery, where in some cases the adjusted R^2 results were worse than the single data set approach. It was concluded that future research should focus on high spatial resolution optical and LiDAR data and the development of automated and semi-automated forest inventory procedures.

1. INTRODUCTION

1.1 Motivation

The timber industry in southern Africa is managed based on a short rotation scheme where single tree species are grown as part of a mono-culture agricultural crop (Owen, 2000). The short rotation scheme used in South Africa requires an inventory programme that constantly updates inventory databases with relevant information that is primarily used for the planning of silviculture and harvesting activities (Uys, 2000). Collection of this information constitutes a time consuming manual process that requires a large amount of logistical and financial support. Increasing competition from international growers and decreasing profit margins have highlighted the need for streamlining forest management activities, in particular, the assessment of forest structure through inventory procedures. Remote sensing tools have long been identified as a means of streamlining this process and already play an important role in forest management (Norris-Rogers *et al.,* 2006).

Short rotation forestry of the type practiced in southern Africa, requires particularly accurate estimates of forest variables. While past research seems to provide operational solutions to the industry there are however, documented problems associated with the use of both passive and active medium resolution sensors. For instance, it has been shown that empirical models developed using optical data are site (Foody *et al.,* 2003) and species (Zheng *et al.,* 2004) specific and that empirical relationships are stronger in successional forests ($R^2 > 0.7$) (Lu 2005) as opposed to mature forests ($R^2 < 0.5$) where saturation causes weak empirical models (Castro *et al.,* 2003). Saturation has also been identified as a problem when using radar data, with radar frequency identified as being a primary contributing factor (*P*- 200 t/ha^{-1}; *L*- 40 t/ha^{-1}; *C*- 40 t/ha^{-1}) (Imhoff, 1995; Ramsey, 1999, Castel *et al.,* 2002) along with the age and biomass of the forest in question (Austin *et al.,* 2003). Recently it has been suggested that the fusion of multiple sensor systems may negate the impact of saturation and provide analysts and forest managers with accuracies suitable for operational planning and forest management (Holmgren and Thuresson, 1998). Image fusion has been used operationally in the military and defence and has distinct potential benefits in forestry and sensor-web technology (Pohl and van Genderen, 1998).

It has been postulated that application-relevant details from each sensor can be combined into one data set which will result in the value of the combined data being more than the sum of the individual images (Ehlers, 2005). This argument is based on the fact that both systems collect different types of information. Tanaka *et al.* (1998) showed that by using optical and radar data, they were able to predict both species type and structural parameters with a high degree of accuracy (r > 0.75). Magnusson and Fransson (2004) reported similar outcomes when assessing the accuracy of combined optical and radar data sets for stem volume estimates in Sweden. The authors reported that Root Mean Square Errors (RMSE) improved by up to 15% using regression techniques when compared to results derived from single sensor analysis. A study using an alternative method (*K*-NN; Nearest Neighbours) in the same area also reported significant improvements in the estimation of forest variables (Optical RMSE = 50 m^3/ha^{-1}, Optical+SAR = 37 m^3/ha^{-1}) (Holmstrom and Fransson, 2003). Furthermore, optical data provided more robust estimates at lower stem volumes while the inverse was true for SAR, which lead to the result where the combination of both sensors provided robust estimates throughout the age range (optical RMSE = 66 m^3/ha^{-1}, SAR RMSE = 51.9 m^3/ha^{-1}, Optical+SAR = 38 m^3/ha^{-1}). The combined use of SAR and optical data has thus shown potential for forest inventory applications. However, it is not known whether image fusion will have the same impact in the southern African forestry industry where largely homogenous stands of mono-culture timber species are grown on relatively short rotation schedules.

1.2 Aim

This study investigated the use of optical remote sensing and synthetic aperture radar (SAR) systems for forest structural assessment in managed, even-aged, short rotation plantations. It also explored the potential benefits of using a combined optical-SAR data set for forest structural assessment. Empirical models were computed between remote sensing data and field enumerated inventory data to determine the applicability of both active and passive remote sensing tools. The enumerated data included basal area (*ba*) and merchantable volume (*mvl*). Independent variables included the SAR and optical bands as well a fused data set. A sub-theme of the paper explored the scale at which modelling was most successful. Typically, remote sensing data are extracted from the images based on the size of the plots. The argument is that this reflectance data should characterize the inventory data sampled in the field. Our research extended this concept through the use of Voroni diagrams derived from the centre of each field plot and the boundaries of each compartment. The above analysis was also stratified into young (4-6 yrs) and mature (7-11 yrs) plots.

2. STUDY AREA & DATA

2.1 Study Area

The study was conducted in the Kwazulu-Natal province located in eastern South Africa. The sampled plantation stands were located approximately 50 km south of the town of Pietermaritzburg (figure 1). The area is known locally as the southern Natal midlands. Rainfall is predominantly in the summer months with cold dry winters and warm wet summers. Mean annual rainfall ranges from 746-1100 mm (Schulze, 1997) and is associated with either frontal systems originating from the south or from thunderstorms generated from convection activity. Temperatures range from high 20°C values in summer to below 10°C in the winter. Extreme temperature changes are a function of altitude and proximity to the warm Indian Ocean. The topography of the study area is flat with undulating hills and is classified by Schulze (1997) as being low mountains. Altitude ranges from 362 m amsl to over 1500 m amsl with an average altitude of approximately 874 m amsl.

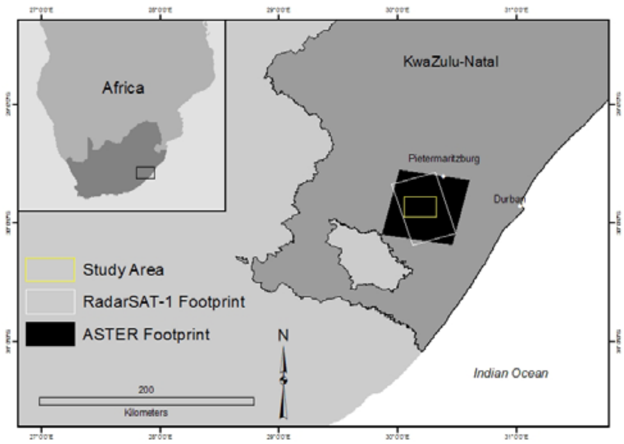

Figure 1. Location of study area

2.2 Data

Enumeration data: Recent aerial photographs were used in conjunction with commercial timber stock maps to identify potential sample plot locations prior to field enumeration. Plot locations were located in the field using a hand held Global Positioning System (GPS). Canopy entry points into the compartments were recorded with distance and bearing measurements collected for the plot centres relative to the entry points, thereby negating poor and inaccurate GPS reception under canopies. Distance and bearing measurements were digitised in a GIS and used to locate the centre of each sample plot. The number of plots per compartment was determined based on the size of the compartment; the total area of the sample plots was more than 5% of the total surface area of the compartment, with at least two plots sampled regardless of compartment size. Fifteen meter fixed-radius plots were established once the plot centres had been identified. Inventory measurements collected during the field campaign included diameter at breast height (dbh), tree height (tht), and stems per hectare (spha). A total of 122 plots were sampled in 38 compartments.

Remote Sensing data: Two data sources were used in this study which included an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) scene collected on the 20th of November 2006 and a RadarSAT-1 scene collected on the 17th of October 2006. Pre-processing of the ASTER data began with the geometric correction of the level 1B data. Geometric correction was only applied to the three VNIR bands of interest. Orthorectification was undertaken using the ORTHOENGINE module of PCI Geomatica (Version 10.1). A 20 m digital elevation model (DEM), produced by the Chief Directorate of Surveys and Mapping (CDSM), was used to correct for terrain-induced error. GCP root mean square error (RMSE) was 3.85 m. Atmospheric correction was undertaken using the Fast Line of Sight Analysis of Spectral Hypercubes (FLAASH) algorithm (Felde *et al.,* 2003).

The SAR data were delivered in Hierarchical Data Format (HDF), Georeferenced Fine Resolution (SGF) imagery (path orientated). GCPs used in the ASTER geometric correction were also employed to correct the SAR image. The data were corrected and projected to a common coordinate system (Gauss

Conformal, central meridian 31° East, WGS 84) using the CDSM DEM and the 21 SAR GCPs. The SAR image required substantial radiometric processing following orthorectification; terrain error was corrected by using a built in SAR model with speckle suppression and a 7x7 Kuan filter (Zhenghao and Ko, 1994). The final image was converted to radar backscatter (sigma nought) and rescaled to 8 bit grayscale (0 – 255).

3. METHODS

3.1 Image Fusion

Following preliminary assessments of several image fusion procedures, a hybrid image fusion procedure that incorporates the IHS transformation into a dwt fusion procedure was recently described by Amolins *et al.* (2007) and has been used in this study. The approach is as follows: (i) The RGB optical data set is converted to IHS colour space; (ii) the SAR image is stretched to match the Intensity image; (iii) a dwt is then performed on the SAR and Intensity images; (iv) following decomposition, the detail and approximation coefficients from the SAR and Intensity image are combined using a substitution approach; (v) once combined, an inverse IHS-to-RGB transformation is performed using the modified Intensity band with the result being the fused optical and SAR channel.

3.2 Analysis Methodology

Three distributional measures were extracted for each plot, namely mean, range, and standard deviation. These values were extracted from the remote sensing data on a band-by-band procedure for areas coincident with the field plot locations. The area covered by each plot varied due to slope differences and in some cases only 5 or 6 pixels were extracted. The scale of the study therefore was increased, with the goal of ensuring viable statistical variability and subsequent increased variable ranges for the independent variables. Voroni diagrams were constructed using plot centres, after which inventory data were assigned to the larger Voroni plots based on spatial association. Remote sensing data were subsequently extracted based on the area of the Voroni diagrams with the mean, range, and standard deviation extracted for each Voroni plot (See figure 2).

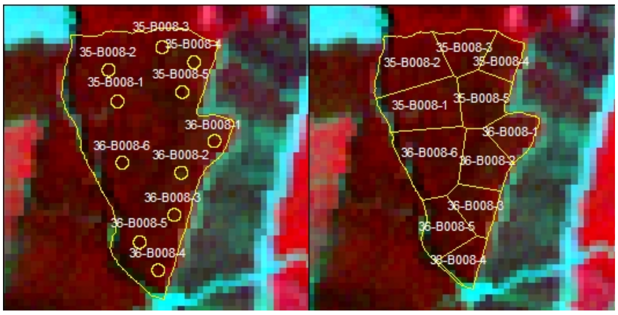

Figure 2. Plot and Voroni level data extraction

Unfused and fused data sets were compared using regression-based statistical models. Plot- and Voroni plot level variable mean, range, and standard deviation were used in multiple regression models. Output statistics used to compare the models included R^2, adjusted R^2, and Root Mean Square Error (RMSE). Two important inventory variables were modelled, namely basal area and merchantable timber volume. Three data sets were used (Optical, SAR, Fused optical+sar) to predict both basal area and merchantable volume at varying scales for 98 plots- and Voroni-plots, where each of these data sets consisted of three bands consisting of either optical, radar, or pseudo-optical bands (fused data sets). All input bands plus their distributional measures (range and standard deviation) were used to predict inventory measures using a multiple regression approach. Cook's distance was used to identify and remove outliers (Cook, 1977). Statistical procedures were implemented using the SAS 9.1 (SAS Institute Inc) statistical software package. The adjusted R^2 approach was selected above regular stepwise approaches as the procedure assess each and every combination of input variables and selects the best combination based on a measure (adjusted R^2). It was argued that optimization of models based on a measure that produces the smallest number of variables with the highest adjusted R^2, would facilitate an accurate comparison of the goodness of fit for each approach. The comparison between optical, SAR, and fused data sets was stratified according to scale using plots and Voroni plots. Within each scale, the analysis was once again stratified according to age, which, included all the data (n=98), young (4-6 yrs old; n=50) and mature plots (7-11 yrs old; n=48).

4. RESULTS

4.1 Basal Area: Plot level

Plot level results for *ba* regression models are shown in table 1. Goodness of fit statistics indicate that when using all plots for modelling purposes results are poor, with the SAR data set explaining less than 30% variance in enumerated *ba*. Results improved when the data were split into young (4-6 yrs old) and mature (7-11 yrs old) plots. Multiple regressions show that optical data lead to improved results over the SAR data in the younger stands (4-6 yrs old), with the inverse being true in the mature stands (7-11 yrs old). Fused data sets return lower R^2 and adjusted R^2 values in the "all" and young age group while in the mature age group the fused data return improved models.

Data	All		
	R^2	Adj- R^2	RMSE (m^2/ha^{-1})
Optical	.0718	.0412	5.86
SAR	.2860	.2337	5.83
Fused	.1137	.0730	6.24
	4-6 yrs		
Optical	.502	.4078	3.06
SAR	.2575	.2075	3.75
Fused	.3992	.3113	5.41
	7-11 yrs		
Optical	.4876	.4022	1.62
SAR	.5804	.5222	3.75
Fused	.4890	.4366	5.39

Table 1. Plot level Basal Area results

4.2 Basal Area: Voroni level

A significant difference exists between the young and mature age groups when comparing the multiple regression results, with the latter returning improved statistics (Table 2). The SAR data set exhibited similar results, although the goodness of fit statistics were distinctly lower than the optical data, implying that at this scale the optical data provided improved models when compared to SAR data. The fused data set followed the pattern of superior models with the mature group returning higher multiple R^2 and adjusted R^2 results than the 4-6 year old data sets. The Voroni-plot results were generally similar to the plot level results, save for marginally higher RMSE values, which indicated that modelling based on Voroni-plots were less precise than those developed at the plot level.

Data	All		
	R^2	Adj- R^2	RMSE (m^2/ha^{-1})
Optical	.0810	.0493	6.38
SAR	.0834	.0403	5.44
Fused	.1840	.1371	6.05
	4-6 yrs		
Optical	.4191	.3483	3.05
SAR	.2497	.1799	3.73
Fused	.3324	.2673	5.71
	7-11 yrs		
Optical	.5544	.4974	3.67
SAR	.4174	.2939	3.57
Fused	.5418	.4552	6.68

Table 2. Voroni level Basal Area results

4.3 Merchantable Volume: Plot level

Plot level results for *mvl* multiple regression models are shown in table 3. Similar to *ba* when all plots are used to model *mvl* results are poor with the SAR data returning the highest R^2 and adjusted-R^2. Results improved when the data set was subdivided into young and mature plots. Once again there appears to be a disparity between optical and SAR models with respect to age. In the young age group optical data return far superior models while in the mature age group the difference between the two was smaller. SAR data consistently return higher R^2 and adjusted R^2 values when modelling *mvl* in mature stands. Following from this the fused data sets also return improved models in mature stands, where nearly 50% enumerated *mvl* variance was explained compared to less than 10% and less than 30% in the all age group and young group respectively.

RMSE results shown in table 3 reflect the goodness of fit statistics mentioned above - an interesting result was that while the models developed with the mature data set return higher R^2 and adjusted R^2 values, the RMSE results in the young data set were in some cases lower than those reported for the mature data sets. This indicated that while modelling plot level volume in the older stands produced superior models, they may not be that precise when compared to the younger stands.

Data	All		
	R^2	Adj- R^2	RMSE (m^3/ha^{-1})
Optical	.1026	.0730	109.33
SAR	.2014	.1298	94.507
Fused	.0925	.0503	244.811
	4-6 yrs		
Optical	.5679	.4770	33.84
SAR	.2729	.1898	44.075
Fused	.4376	.3690	38.246
	7-11 yrs		
Optical	.4832	.4454	75.54
SAR	.4958	.4093	73.55
Fused	.4906	.4369	76.42

Table 3. Plot level Volume results

4.4 Merchantable Volume: Voroni level

Table 4 presents the results from the Voroni level *mvl* modelling. Analogous to results already presented in tables 1-3, when all plots are used to model inventory attributes results are poor. Goodness of fit statistics improved when the data were subdivided into young and mature plots. Once again optical models returned superior goodness of fit statistics in the younger age group when compared to the SAR results. SAR results did, however, improve in the mature age group but still remain inferior when compared to the optical data. Combining the optical and SAR data using the DWT-IHS transformation produced superior models in both the mature and all age groups. While results in the all age group explained less than 15% variance in enumerated *mvl* data, this value increased to just below 60% in the mature stands. Once again the precision of the mature stand models was called into question when observing the RMSE results. Younger plots seem to return more precise models regardless of the independent variables used.

Data	All		
	R^2	Adj- R^2	RMSE (m^3/ha^{-1})
Optical	.0702	.0495	101.07
SAR	.0867	.0437	99.10
Fused	.1498	.1208	103.26
	4-6 yrs		
Optical	.5970	.5317	29.83
SAR	.3250	.2426	44.09
Fused	.3025	.2131	40.20
	7-11 yrs		
Optical	.4987	.4309	71.83
SAR	.4871	.4040	80.21
Fused	.5716	.5167	69.65

Table 4. Voroni level Volume results

5. DISCUSSION

Both optical and SAR data returned poor results when compared to those in the published literature. Foody *et al.* (2001) used artificial neural networks and multiple independent variables to model above ground biomass, explaining 80% variance in field enumerated data. Zheng *et al.* (2004) used multiple regressions and achieved an R^2 of 0.67 for both pine and hardwood species. Lu (2005) found significant differences between mature and successional forests reporting R^2 values of 0.50 and 0.76, respectively. The major difference between the present study and those cited above is that the present study occured in plantation forests, while research in the case of Foody *et al.* (2001), Zheng *et al.* (2004), and Lu (2005) were conducted in natural forests where forest canopies display significantly more spectral variability, associated with structural variability. In contrast, plantation forests do not display as much canopy spectral variability, thereby making it more difficult to use reflectance from these canopies to explain structural variability. The very same observation was evident when investigating the SAR results.

Past studies have shown that saturation of the relationship between SAR backscatter is common with asymptotes usually determined by wavelength (Dobson *et al.,* 1992; Rauste *et al.,* 1994; Imhoff, 1995; Ramsey, 1999; Fransson and Israelsson, 1999) and to some extent the polarisation (Van de Griend and Seyhan, 1999; Santos *et al.,* 2003). It proved impossible to determine when and if saturation occurred in this study - older plots (7-11 years old) returned higher adjusted R^2 values than the younger plots (4-6 years old), which is counter-intuitive to established relationships. Low R^2 and adjusted R^2 values were a function of wavelength (Paloscia *et al.*, 1999); the RadarSAT-1 system uses a C-band HH sensor with a wavelength of approximately 5.6 cm. This relatively small wavelength, when compared to *L*- and *P*-band sensors (Dobson *et al.*, 1992), rarely penetrates the canopy with most of the backscatter originating from the top of the canopy. This characteristic severely restricted the modelling of basal area and timber volume in plantation forests.

Results presented above indicate that models developed using the fused data were not necessarily better than the optical data (tables 1-4). In most cases the fused data sets produced models that were comparable to the optical data and were consistently better than the SAR models. The only exception to this was the plot level basal area modelling, where the SAR data explained in excess of 50% of dependent variable variance. This result confirmed that the C-band data are not suitable for assessing forest structure and that it would be more appropriate to employ either an airborne or satellite platform collecting data in the *L*- or *P*-band frequency. Such data would provide more information regarding the variability of trunk size as opposed to the variability of the canopy structure.

A sub-theme of the paper explored the impact of the scale at which remote sensing data are extracted from imagery. The approach also attempted to mitigate any additional errors associated with the location of field plots (Halme and Tomppo, 2001; Patterson and Williams, 2003) Results presented in tables 1-4 show that regardless of the scale at which data were extracted, no improvement in model accuracy was observed.

6. CONCLUSION

Principle findings indicated that medium resolution data (6-100 m spatial resolution) are able to explain a limited amount of the variance in enumerated inventory variables. However, this is only achievable with an optimised multiple regression model. Fused and unfused data sets exhibited no significant difference when comparing goodness of fit statistics. A lack of spatial resolution, coupled to a microwave sensor frequency not suited to canopy penetration, are some of the reasons for the weak statistical models. It could be argued that errors in plot location could have contributed to the results; however, the scale analysis showed that even when a larger representative area was used, results remained unsatisfactory.

Results reported here were disappointing when compared to those in the published literature. R^2 and adjusted R^2 values were distinctly poorer than that of published papers in many cases. However, the type of forest being studied plays a central role in this outcome: The relatively homogenous nature of the plantation canopy in this case did not contain sufficient variability, as related to structural variability, for modelling purposes. Explanation of such variability requires a sensor with a higher spatial resolution than the 6.25 m (RadarSAT-1) and 15 m (ASTER) data sets used in this study. These sensors are thus not suitable for operational assessment of even–aged, homogenous, mono-culture plantation forests. Further research is required to test and assess various other data sources and approaches, which are cognisant of the inherent homogeneity of plantation forests. Possible alternative sensors include high resolution satellite imagery or aerial photography with a spatial resolution < 4 m. *P*- and *L*-band SAR sensors, combined with polarimetric data, furthermore are recommended for these conditions. Data fusion of LiDAR and high resolution optical sensors has shown promising results (Hudak *et al.*, 2002; McCombs *et al.*, 2003; Coops *et al.*, 2004) and it is suggested that such an approach should be assessed in plantation forest conditions.

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