

Use of ERS Backscattering Coefficient for Forest Classification

Wolfgang Wagner and Jan Vietmeier, DLR-DFD

February 18, 2000

1. Introduction

Preliminary experience with ERS intensity imagery in the SIBERIA project has suggested that these images appear to be of little use for forest classification. On the other hand some authors have recently suggested that even the C-band data can be used for detecting forest biomass (Kurvonen et al., 1999; Paloscia, 1999). The scope of this working paper is to provide a quantitative analysis of the SIBERIA common data base to get a better understanding about the usefulness and limitations of the ERS backscatter images for forest classification.

2. Topographic Effects on ERS Backscatter

The ERS backscattering coefficient σ^0 shows little dependence on tree species. Therefore, for individual ERS SAR acquisitions, σ^0 values of dense forest stands within one of the SIBERIA testsites should be relatively similar. This is indeed observed in some of the testsite specific scatterplots of σ^0 versus growing stock volume for growing stock volumes greater than about 100-200 m^3/ha . However, for other testsites the scattering of σ^0 is large (Figure 1). One reason for this high dispersion at some sites may be related to a more heterogeneous forest cover, but also topography may play a significant role. The topography respectively local incidence angle influences σ^0 in two ways. Firstly, the definition of σ^0 requires that for a correct calibration the local incidence angle must be known, which is the case for the GTC products but not the GECs. Secondly, σ^0 generally decreases with increasing incidence angle, the strength of the decrease being related to land cover (Figure 2).

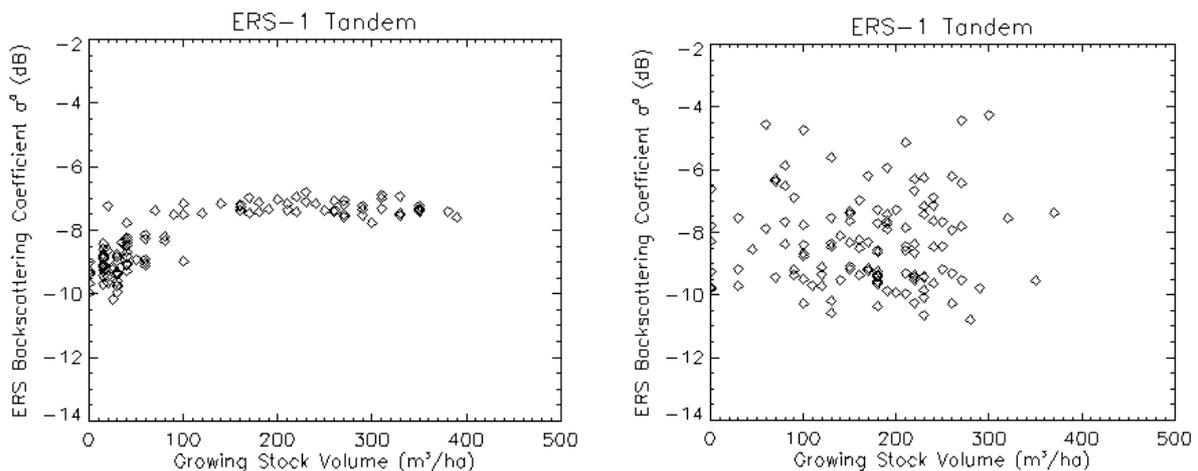


Figure 1: Scatterplots of ERS backscattering coefficient versus growing stock volume for two test sites. 1) Bolshemurtinskii (centre at 92.10°E , 54.30°N), track 348, frame 2457, orbit 32400, date 1997-09-25, GTC; 2) Lake Baikal South (centre at 103.59°E , 51.58°N), ERS track 462, frame 2565, orbit 32514, date 1997-10-03, GEC.

Without the introduction of land cover specific correction methods this may lead to variations in class specific σ^0 values in the order of several decibels. While for GEC products it is impossible to account for this effect, it may in principle be possible for the GTC products as the incidence angle is known. However, scatterplots of σ^0 versus the incidence angle (averaged over the polygons) do not show a consistent relationship between the two parameters (Figure 3) and therefore corrections methods can not be derived from this analysis. The reason for this could be that incidence angle effects should be

investigated on a pixel by pixel basis rather than using the current polygon based approach. But it also may be possible that there are problems with the incidence angle estimated from the InSAR DEM.

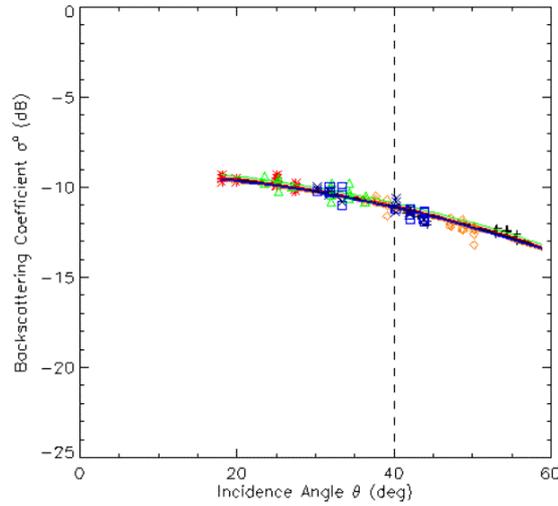


Figure 2: Incidence angle behaviour of σ^0 over Siberian forests from ERS Scatterometer observations during winter 1993 (frozen soil, dry snow cover).

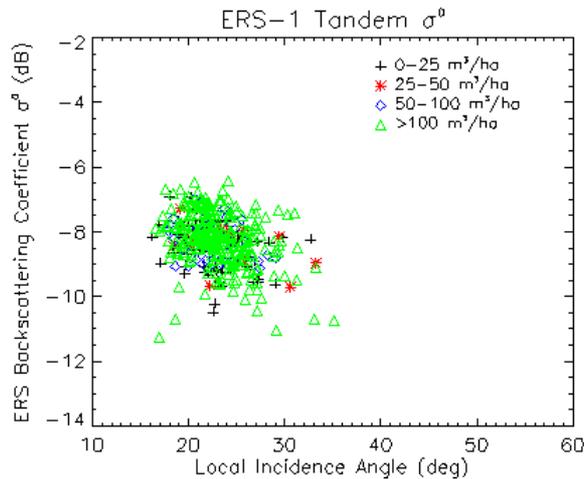


Figure 3: ERS backscattering coefficient versus local incidence angle for Irbeiskii (centre 55.56°N, 95.96°E), track 491, frame 2475, orbit 32543, date 1997-10-05.

Let us now investigate if the amount of dispersion of the σ^0 values is related to topography and product type (GTC versus GEC). As a measure of the spread of σ^0 values, the standard deviation of σ^0 is calculated for forest stands with growing stock volume greater than 100 m³/ha. On the left hand side of Figure 4 the standard deviation is plotted for all sites. For each testsite three SAR images are available and hence three values of StDev(σ^0) are obtained. The first observation is that the StDev(σ^0) values are similar for all three SAR acquisitions. From this follows that the degree of scattering is related to time invariant site characteristics such as topography or land cover, but not to highly variable geophysical parameters such as soil moisture.

The second observation is that while for all GTC products the standard deviation of σ^0 is less than 1 dB, it is higher for the majority of the GEC products. However, also for some of the GEC products StDev(σ^0) is lower than 1 dB which probably means that for those sites the terrain is relatively flat. This is confirmed by the graph on the right hand side of Figure 4 which shows how StDev(σ^0) increases with the area that would be masked out if Jan's masking algorithm would be applied. So far, the masked area is only known for the testsites of DLR, but already for this limited data set a clear trend can be observed.

Given that the limited sensitivity of σ^0 to changes in growing stock volume a small amount of topography related scattering is the precondition for using σ^0 images in the classification. Therefore all data sets where $\text{StDev}(\sigma^0)$ is greater than 1 dB are not considered in the following modelling exercise. This reduces the number of data sets from 42 to 26.

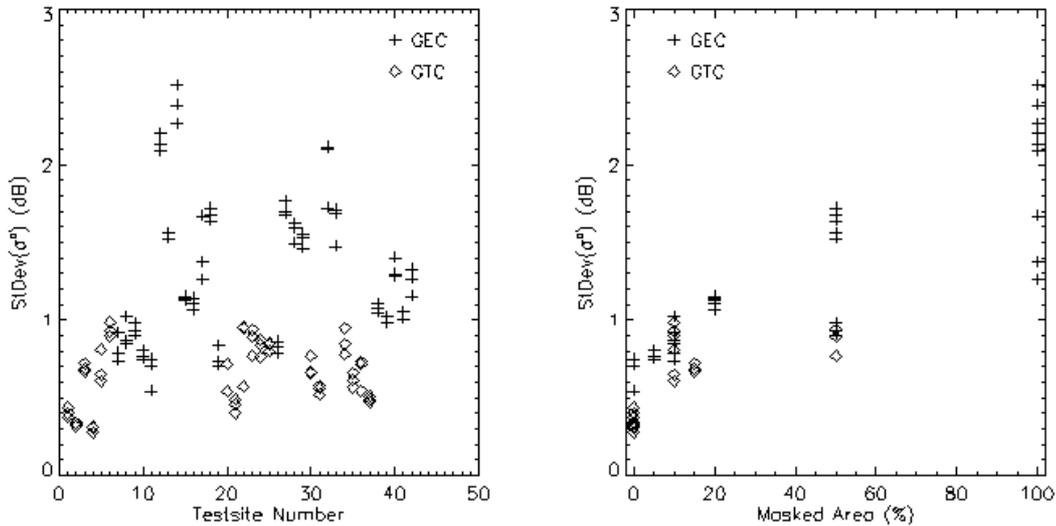


Figure 4: Standard deviation of ERS backscattering coefficient σ^0 for growing stock volumes greater than 100 m³/ha. On the left hand side the standard deviation of all three images is plotted versus testsite number, and on the right hand side versus the estimated percentage of the masked out test site area. Diamonds indicate GTC products and the crosses GEC products.

3. Modelling ERS Backscatter versus Growing Stock Volume

As the visual inspection of the scatterplots of σ^0 versus growing stock volume show there is no simple relationship between these two parameters. For one given testsite σ^0 may increase or decrease from one acquisition to the next, not just for low biomass areas but also for the highest forest biomass stands present in the study areas. Because these changes can occur from one day to the next, they are most likely related to changes in the dielectric properties of the ground surface (soil moisture, freezing), although changes in the vegetation canopy may also play a role. Another important observation is that σ^0 does not necessarily increase with increasing biomass levels. For wet conditions backscatter from non-forested areas may even be higher than from dense forests, so that σ^0 decreases with increasing growing stock volume (Figure 5).

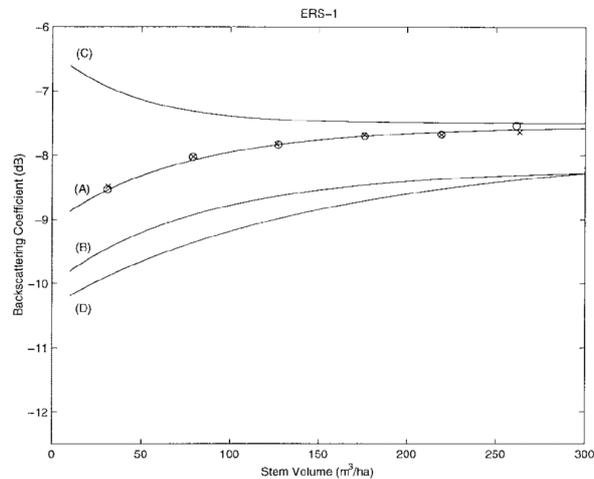


Figure 5: Variation of ERS backscattering coefficient with increasing forest stem volume under varying soil moisture conditions. From Kurvonen et al. (1999).

The relatively strong influence of soil moisture would call for a physically based modelling approach for the concurrent retrieval of vegetation and soil parameters from the σ^0 images, as was done in Kurvonen et al. (1999). Nevertheless, an empirical model may serve to explore the usefulness respectively limitations of the C-band data for forest classification.

The relationship of σ^0 on growing stock volume v can be described by the following model:

$$\sigma^0(v) = \sigma_0 + (\sigma_\infty - \sigma_0) \cdot \left(1 - e^{-\frac{v}{V}} \right) \quad (1)$$

where σ_0 is the backscattering coefficient at $v = 0 \text{ m}^3/\text{ha}$, σ_∞ is the saturation level for dense forest stands, and V is a characteristic growing stock volume. The model fit can be seen for two testsites in Figure 6.

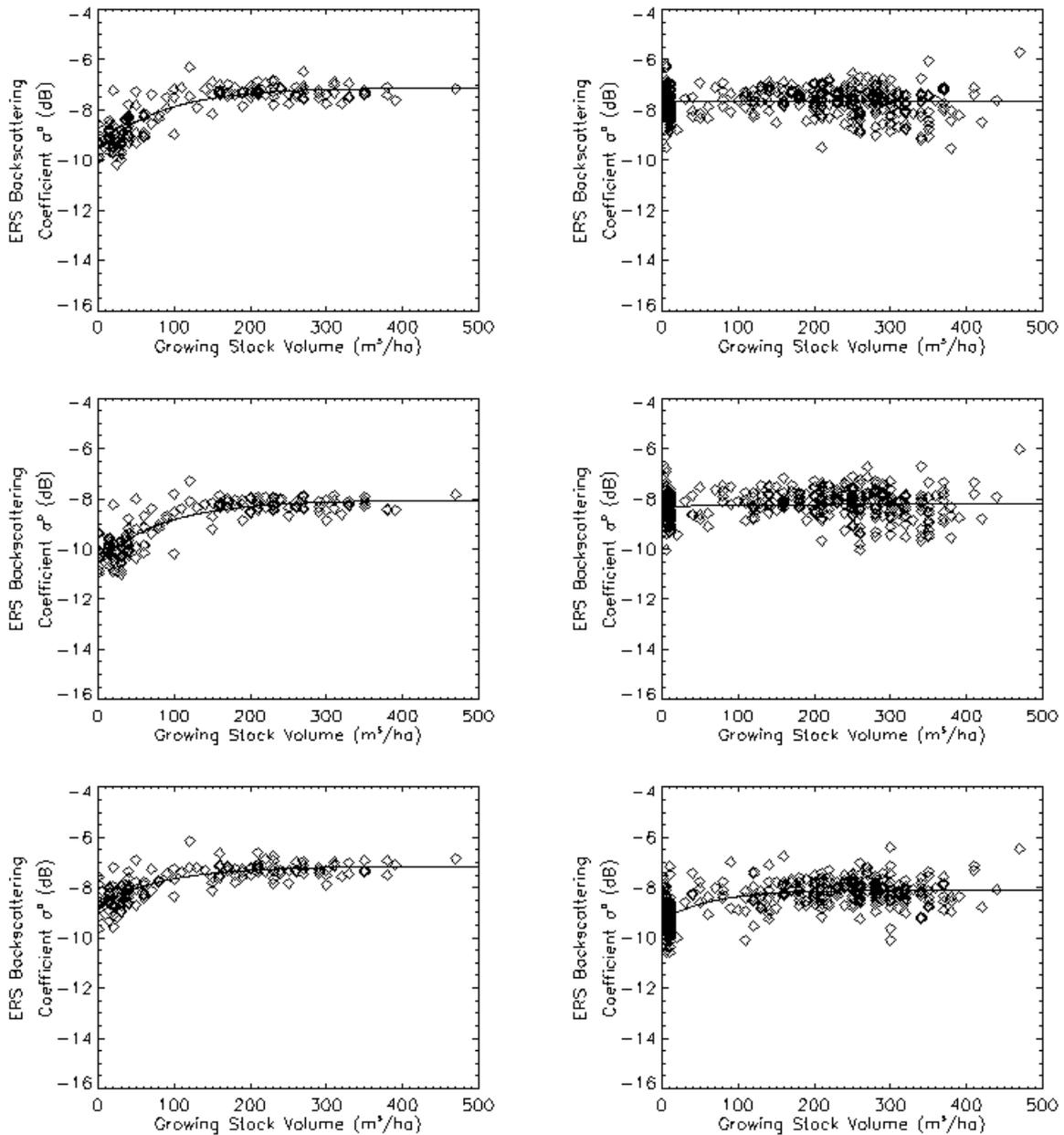


Figure 6: Fit of exponential model (1) to data from Bolshemurtinskii, 4 (left) and Nishni Udinskii, 2 (right). The images from top to bottom are the ERS-1 and ERS-2 tandem images from 1997 and the third image from summer 1998.

For several images (27 out of 78 = 26 image triplets) the fitting resulted in unrealistic values of the model parameter V . Also these images had to be excluded from the analysis. The statistics of the remaining 51 images can be seen in Table 1.

<i>No Forest</i> σ_0 (dB)	<i>Dense Forest</i> σ_∞ (dB)	V (m ³ /ha)
Mean = -8.47991	Mean = -7.42874	Mean = 115.222
StDev = 0.784470	StDev = 0.499842	StDev = 97.5958
Min = -10.5289	Min = -8.62532	Min = 3.62335
Max = -6.68413	Max = -6.31538	Max = 380.642

Table 1: Statistics of fitted model parameters.

In forested areas σ^0 can take on values between about -10.5 dB up to -6.5 dB for low biomass levels and between about -8.5 to -6.5 dB for dense forests. For dense forests the mean value of σ^0 is -7.5 dB. Since σ^0 of dense forest is more stable than σ^0 of low biomass areas, the backscatter difference between these two land cover classes is related to the backscatter level of the low biomass areas (Figure 7). The maximum separability of the two classes is about 2.5 dB, but for most images the separation is probably not high enough to obtain accurate classifications given that the standard deviation of σ^0 is rather high (Figure 7).

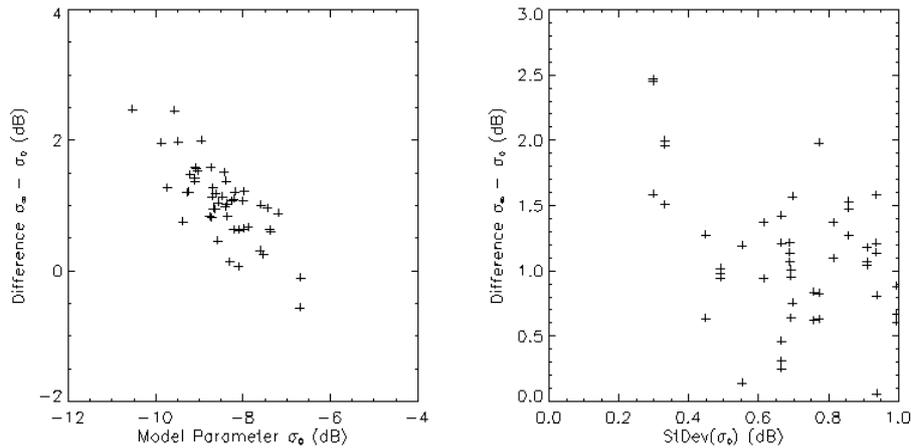


Figure 7: Relationship of extracted parameters of model (1). Left hand side: Difference $\sigma_\infty - \sigma_0$ versus σ_0 ; Right hand side: Difference $\sigma_\infty - \sigma_0$ versus $StDev(\sigma^0)$.

4. Separation of Forest/Non-Forest

Although the previous analysis has already shown that soil moisture and topography limit the usefulness of the σ^0 images for forest classification, a simple threshold approach to separate to forest classes is tested here. As shown in the last chapter, σ^0 for dense forests varies over a range of about 2 dB which means that a dynamic threshold should be used. Let us assume this threshold can be estimated from the images. Here is it determined by calculating the mean backscattering coefficient for $v > 200$ m³/ha and by subtracting 0.5 dB. Since the typical correlation length of the exponential model is about 100 m³/ha let us use the following rules:

$$\text{if } \sigma^0 < \sigma^0_{\text{thres}} \text{ then low density forest class with } v < 70 \text{ m}^3/\text{ha} \quad (2a)$$

$$\text{if } \sigma^0 \geq \sigma^0_{\text{thres}} \text{ then high density forest class with } v \geq 70 \text{ m}^3/\text{ha} \quad (2b)$$

The rules are applied to all testsites with each having the three images. The results are summarised in Figure 8. The scatterplot of κ versus testsites number shows that often the κ values of the three images are similar to each other. However, there are also instances where κ varies strongly from acquisition to acquisition. For example, for testsite number 31 (Nishni_Udinskii, 2) κ varies from about 0 to over 60

% . No distinct dependence on product type, i.e. GEC or GTC, can be established. The great majority of the κ values are below 40 %. The scatterplot of κ versus the area that would be masked out if Jan's masking algorithm would be applied shows the expected behaviour. Only for relatively flat areas good results may be achieved, but also over these areas κ may be low due to wet soil conditions. This is confirmed in the scatterplot of κ versus the $\text{StDev}(\sigma^0)$.

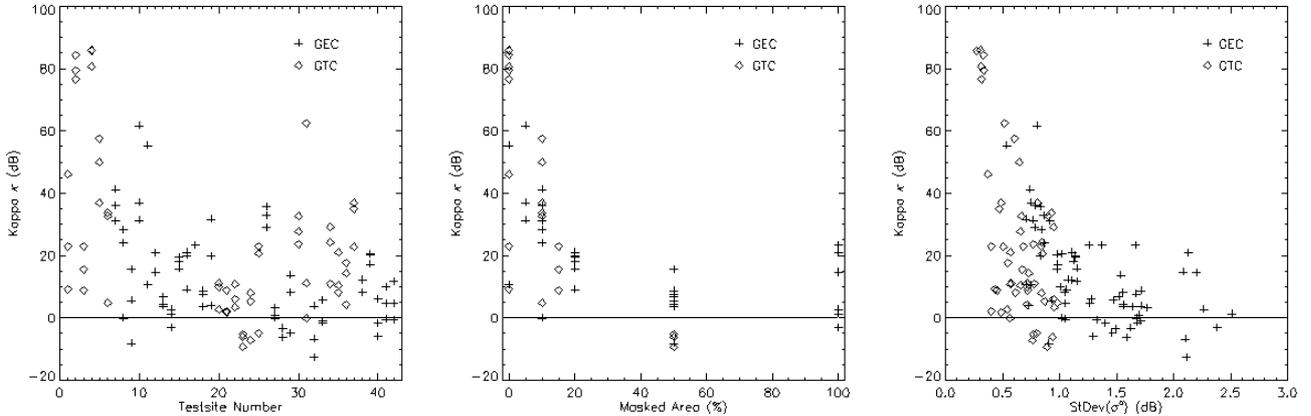


Figure 8: Accuracy coefficient κ versus testsite number, percentage of masked area, and standard deviation of σ^0 for $v > 100 \text{ m}^3/\text{ha}$.

5. Conclusions

The information content of ERS SAR images for forest classification was investigated. In the majority of cases a simple threshold method does not allow to distinguish forests from non-forested areas (without knowing the spatial context). High topography leads to rather strong erratic variations in σ^0 which means that over such areas the ERS intensity images cannot be used in the classification. Over relatively flat areas the information content depends on the wetness conditions. If it is dry or frozen, non-forested areas have a lower backscatter than dense forest areas which allows a certain separability. However, if it is wet σ^0 of forest and non-forest areas are similar. One suggestion to determine if it is dry/frozen or wet is to identify non-forest areas using the ERS coherence and extract the level of backscatter. If σ^0 is lower than about -9/-10 dB then the ERS σ^0 image could possibly be used in the classification.

6. References

- Kurvonen, L., J. Pulliainen, M. Hallikainen (1999) Retrieval of biomass in boreal forest from multi-temporal ERS-1 and JERS-1 SAR images, IEEE Trans. Geoscie. Remote Sensing, Vol. 37, No. 1, pp. 198-205.
- Paloscia, S., G. Macelloni, P. Pampaloni, S. Sigismondi (1999) The potential of C- and L-band SAR in estimating vegetation biomass: the ERS-1 and JERS-1 experiments, IEEE Trans. Geoscie. Remote Sensing, Vol. 37, No. 4, pp. 2107-2110.