Use of the ERS Coherence for Forest Classification

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December 9, 1999

1. Introduction

In this working note the use of the ERS coherence for determining forest classes with different levels of growing stock volume is investigated. The strategy is to find an appropriate model to describe the relationship between coherence and growing stock volume and to define a classifier based on this model.

2. Modelling ERS Coherence versus Growing Stock Volume

The visual analysis of the scatter plots of ERS coherence γ versus growing stock volume v shows that the functional relationship can be reasonable modelled with an exponential function of the form (Figure 2-1):

$$\gamma(v) = \gamma_\infty + (\gamma_0 - \gamma_\infty) e^{-\frac{v}{V}} \qquad (1)$$

where γ_0 is the coherence at V = 0 m^3/ha, γ_∞ is the coherence towards infinity, and V is the growing stock volume where the exponential function has decreased to e^{-1}. The physical interpretation is that γ_0 is the representative value for bare ground surfaces respectively surfaces with low vegetation cover, and γ_∞ represents dense forest.

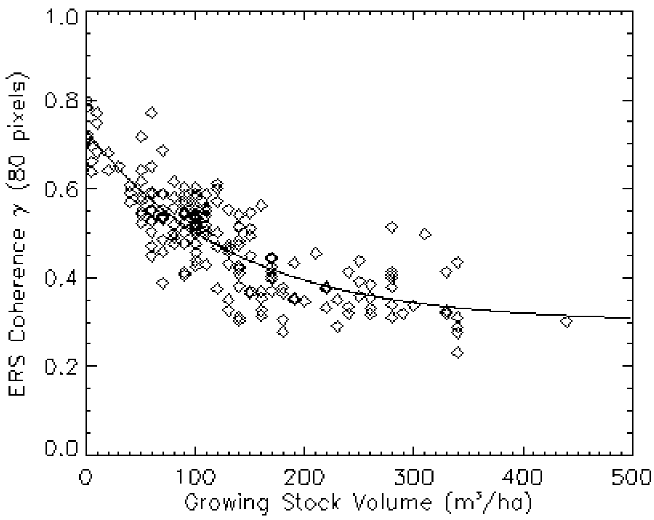

Figure 2-1: Observed and modelled relationship between ERS coherence γ and growing stock volume v in m^3/ha for Primorskii, subsite 3.

The results of fitting (1) to data from all sites are shown in Table 2-1. With some exceptions, the estimated parameters γ_0, γ_∞, and V are within the expected range. However, the estimated confidence interval of the parameters is large, often larger than the parameters itself. This indicates that model (1) has too many unknown parameters. To decrease the number of freedoms of the exponential model the parameter V is set equal to a constant value.

Enterprise	No.	Track	Frame	Prd.	Coherence γ_∞	Coherence γ_0	Volume V	StDev
Bolshemurtinskii	1	348	2457	GTC	0.27+0.30	0.56+0.27	47+160	0.12
Bolshemurtinskii	2	348	2457	GTC	0.29+0.11	0.75+0.15	73+106	0.20
Bolshemurtinskii	3	348	2457	GTC	0.25+0.27	0.46+0.41	99+496	0.09
Bolshemurtinskii	4	348	2457	GTC	0.20+0.16	0.60+0.12	200+150	0.17
Bolshemurtinskii	1	305	2457	GTC	0.25+0.12	0.50+0.15	41+93	0.17
Bolshemurtinskii	2	305	2457	GTC	0.23+0.11	0.44+0.54	46+229	0.09
Bolshemurtinskii	1	305	2457	GEC	0.24+0.12	0.49+0.15	45+102	0.16
Bolshemurtinskii	2	305	2457	GEC	0.23+0.13	0.43+0.57	51+278	0.10
Chunsky	1	491	2439	GEC	0.21+0.25	0.35+0.17	104+648	0.07
Chunsky	2	491	2439	GEC	0.21+0.23	0.57+0.09	103+220	0.21
Chunsky	3	491	2439	GEC	0.17+0.96	0.75+0.11	242+694	0.17
Ermakovsky	1	305	2529	GEC	0.20+0.71	0.24+0.36	118+5403	0.04
Ermakovsky	2	305	2529	GEC	0.20+0.44	0.23+0.45	115+4016	0.04
Ermakovsky	3	305	2529	GEC	0.11+4.67	0.23+0.17	601+29677	0.05
Ermakovsky	4	305	2529	GEC	0.19+0.19	0.38+0.42	66+287	0.08
Ermakovsky	1	33	2529	GEC	0.29+0.21	0.67+0.41	68+151	0.16
Ermakovsky	3	33	2529	GEC	-0.03+3.06	0.50+0.37	367+3125	0.15
Hrebtovsky	1	448	2421	GEC	0.24+0.07	0.38+0.15	9+40	0.07
Hrebtovsky	2	448	2403	GTC	0.41+0.39	0.70+0.25	162+560	0.12
Hrebtovsky	3	448	2403	GTC	0.37+0.51	0.64+0.38	164+794	0.10
Hrebtovsky	4	448	2385	GTC	-0.73+11.81	0.76+0.12	1504+13114	0.24
Irbeiski	1	491	2475	GTC	0.36+0.10	0.39+0.14	106+1072	0.14
Lake_Baikal_South	1	462	2565	GEC	-0.11+7.56	0.40+0.18	961+16616	0.09
Lake_Baikal_South	2	419	2565	GEC	0.20+0.11	0.59+0.21	23+51	0.19
Nishni_Udinskii	1	362	2511	GTC	0.36+0.16	0.66+0.10	47+95	0.23
Nishni_Udinskii	2	362	2493	GTC	0.25+0.27	0.81+0.10	150+192	0.35
Primorskii	1	47	2475	GTC	0.38+0.35	0.75+0.27	83+206	0.14
Primorskii	2	47	2475	GTC	0.30+0.40	0.72+0.27	137+320	0.16
Primorskii	3	47	2475	GTC	0.30+0.38	0.73+0.27	131+279	0.15
Primorskii	4	47	2475	GTC	0.30+0.20	0.70+0.32	102+228	0.17
Ulkanskii	1	147	2475	GEC	0.20+0.16	0.37+0.16	78+306	0.09
Ulkanskii	2	104	2493	GEC	0.19+0.35	0.43+0.22	159+560	0.12

Table 2-1: Estimated model parameters γ_0, γ_∞, and V of model (1) and their standard deviation. The last column shows the standard deviation of the residuals between the fitted model and the observations.

Enterprise	No.	Track	Frame	Prd.	Coherence γ_∞	Coherence γ_0	StDev
Bolshemurtinskii	1	348	2457	GTC	0.21+0.29	0.53+0.19	0.12
Bolshemurtinskii	2	348	2457	GTC	0.27+0.08	0.74+0.13	0.19
Bolshemurtinskii	3	348	2457	GTC	0.25+0.11	0.46+0.29	0.09
Bolshemurtinskii	4	348	2457	GTC	0.28+0.13	0.59+0.16	0.16
Bolshemurtinskii	1	305	2457	GTC	0.21+0.13	0.47+0.12	0.16
Bolshemurtinskii	2	305	2457	GTC	0.21+0.11	0.39+0.28	0.10
Bolshemurtinskii	1	305	2457	GEC	0.21+0.12	0.46+0.12	0.15
Bolshemurtinskii	2	305	2457	GEC	0.21+0.11	0.39+0.29	0.10
Chunsky	1	491	2439	GEC	0.22+0.08	0.35+0.16	0.07
Chunsky	2	491	2439	GEC	0.21+0.08	0.57+0.08	0.21
Chunsky	3	491	2439	GEC	0.35+0.11	0.78+0.10	0.18
Ermakovsky	1	305	2529	GEC	0.20+0.19	0.24+0.33	0.04
Ermakovsky	2	305	2529	GEC	0.20+0.13	0.24+0.36	0.04
Ermakovsky	3	305	2529	GEC	0.19+0.11	0.23+0.17	0.05
Ermakovsky	4	305	2529	GEC	0.17+0.13	0.35+0.24	0.07
Ermakovsky	1	33	2529	GEC	0.25+0.13	0.62+0.24	0.16
Ermakovsky	3	33	2529	GEC	0.24+0.12	0.55+0.35	0.15
Hrebtovsky	1	448	2421	GEC	0.22+0.08	0.34+0.11	0.07
Hrebtovsky	2	448	2403	GTC	0.46+0.08	0.72+0.21	0.12
Hrebtovsky	3	448	2403	GTC	0.42+0.08	0.67+0.30	0.10
Hrebtovsky	4	448	2385	GTC	0.53+0.06	0.79+0.11	0.19
Irbeiski	1	491	2475	GTC	0.33+0.11	0.39+0.15	0.14
Lake_Baikal_South	1	462	2565	GEC	0.29+0.09	0.42+0.18	0.09
Lake_Baikal_South	2	419	2565	GEC	0.12+0.14	0.51+0.18	0.19
Nishni_Udinskii	1	362	2511	GTC	0.28+0.13	0.65+0.10	0.23
Nishni_Udinskii	2	362	2493	GTC	0.31+0.07	0.83+0.09	0.33
Primorskii	1	47	2475	GTC	0.36+0.22	0.73+0.19	0.14
Primorskii	2	47	2475	GTC	0.35+0.13	0.75+0.21	0.16
Primorskii	3	47	2475	GTC	0.34+0.13	0.76+0.21	0.16
Primorskii	4	47	2475	GTC	0.30+0.09	0.71+0.24	0.17
Ulkanskii	1	147	2475	GEC	0.19+0.10	0.37+0.14	0.09
Ulkanskii	2	104	2493	GEC	0.23+0.09	0.45+0.17	0.12

Table 2-2: Estimated model parameters γ_0 and γ_∞ of model (2) and their standard deviation. The last column shows the standard deviation of the residuals between the fitted model and the observations.

It can be seen in Table 2-1 that most of the estimated *V* values fall within the range from 40 to 250 m^3/ha with a mean value of around 100 m^3/ha. Therefore, to allow only two degrees of freedom, *V* in model (1) is set equal to 100 m^3/ha:

$$\gamma(v) = \gamma_\infty + (\gamma_0 - \gamma_\infty) e^{-\frac{v}{100}} \qquad (2)$$

As can be observed in Table 2-2, the confidence intervals of γ_0 and γ_∞ are much smaller now and the values of the standard deviation of the residuals remain more or less the same. Therefore model (2) is selected for the development of a classification procedure.

Table 2-2 and Figure 2-2 show that most of the values of γ_∞ are within the range between 0.15 and 0.35. However, it is noted that γ_∞ values, which represent γ for dense forests, may be as large as 0.4 to 0.5. The observed γ_0 values range between about 0.2 and 0.8 demonstrating the importance of temporal decorrelation effects also over bare ground surfaces. The left hand side figure of Figure 2-2 shows that, as expected, γ_0 and γ_∞ are in general higher for GTCs than for GECs.

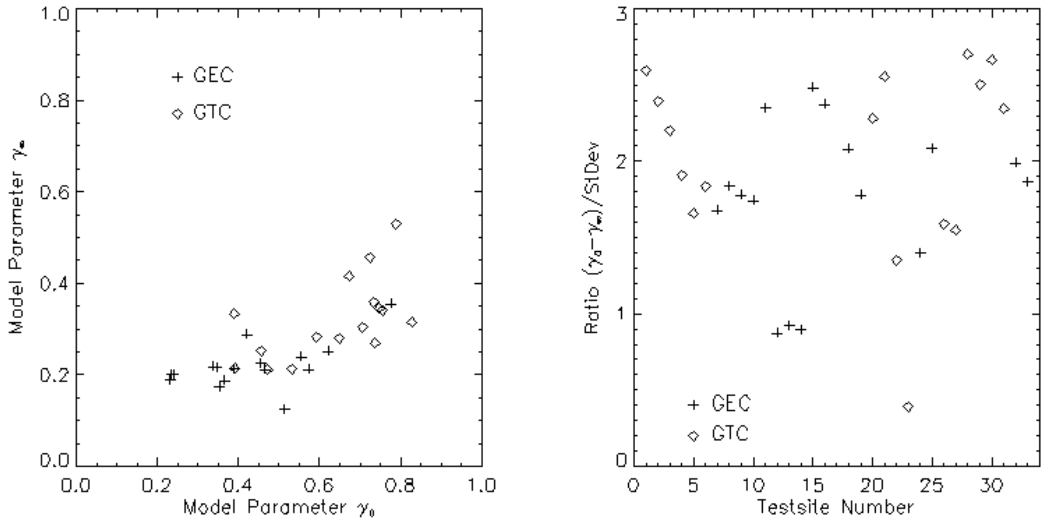

Figure 2-2: Graphical representation of estimated parameters of model (2) according to Table 2-2. The figure on the left side shows the scatter plot of the model parameters γ_∞ and γ_0. The right hand side figure shows the ratio of the difference γ_0 -γ_∞ and the standard deviation of the residuals. The two different symbols indicate a GEC or GTC.

3. Retrieving Growing Stock Volume Classes from ERS Coherence

In principle, if estimates of γ_0 and γ_∞ are available then the inverted model of (2) could be used to estimate growing stock volume from the coherence. However, this inversion of model (2) is not meaningful due to the large scattering of γ. To test how many growing stock volume classes can be determined the following ratio is calculated:

$$\text{Ratio} = \frac{\gamma_0 - \gamma_\infty}{StDev(\text{Residuals})} \qquad (3)$$

It can be seen in the right hand side figure of Figure 2-2 that some of the ratio values are below one, i.e. for these testsites no forest classes can be distinguished. The other ratio values are in the range between 1.5 and 2.5 which means that it should be possible two growing stock volume classes. Given that the scattering of the γ values is independent of forest density, the best threshold value v_{thres} between the two forest classes is where γ is equal to the arithmetic mean of γ_0 and γ_∞:

$$\frac{\gamma_0 + \gamma_\infty}{2} = \gamma_\infty + (\gamma_0 - \gamma_\infty) e^{-\frac{v_{thres}}{100}} \qquad (4)$$

Rewriting equation (4) gives:

$$v_{thres} = -100 \ln \frac{1}{2} = 69.3 \approx 70 \tag{5}$$

The two optimum forest classes are therefore a low density forest class with growing stock volumes smaller than 70 m^3/ha and a high density forest class with $v > 70$ m^3/ha.

The following simple classifier is proposed:

$$\text{if } \gamma < \frac{\gamma_0 + \gamma_\infty}{2} \text{ then low density forest class with } v < 70 \text{ m}^3\text{/ha} \tag{6a}$$

$$\text{if } \gamma \geq \frac{\gamma_0 + \gamma_\infty}{2} \text{ then high density forest class with } v \geq 70 \text{ m}^3\text{/ha} \tag{6b}$$

Of course, the problem is that the two parameters γ_0 and γ_∞ are not known and need to be estimated from the images. Two approaches could be pursued. The first one is to visually identify bare ground surfaces and dense forests in the image and to assume that γ_0 and γ_∞ are equal to the average γ values of these regions. The second approach is to use statistical parameters of the γ distribution to estimate γ_0 and γ_∞. The second approach is followed here.

Let us test the hypothesis that the percentiles $\gamma_{0.9}$ and $\gamma_{0.1}$ are estimates of γ_0 and γ_∞. The percentiles $\gamma_{0.1}$ and $\gamma_{0.9}$ are those γ values below which one respectively nine tenths of the data fall. Figure 3-1 shows the histogram of γ for one testsite of the Bolshemurtinskii forest enterprise which is based on all data values, irrespective of land cover class. This is important because this approach requires that also bare ground surfaces are represented in the data set. Figure 3-1 also shows the values of the model parameters γ_0 and γ_∞ and the statistical parameters $\gamma_{0.9}$ and $\gamma_{0.1}$. One can see that there is a relatively good agreement between the pairs $\gamma_{0.9}/\gamma_0$ and $\gamma_{0.1}/\gamma_\infty$.

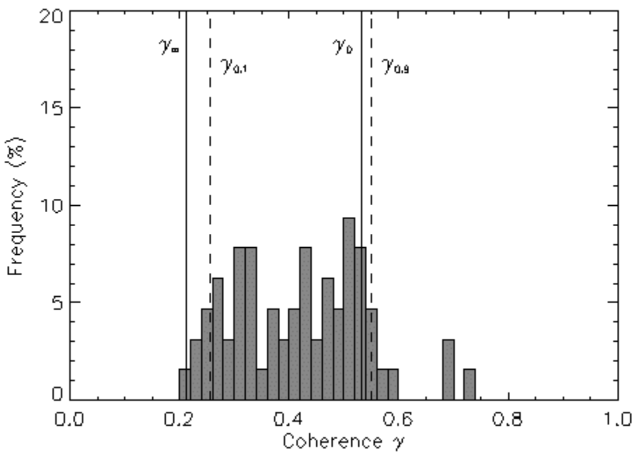

Figure 3-1: Histogram of coherence γ for Bolshemurtinskii (Subsite 1, ERS track 348, ERS frame 2457, GTC). The vertical lines indicate the estimated model parameters γ_0 and γ_∞ (solid lines) and the statistical parameters $\gamma_{0.1}$ and $\gamma_{0.9}$ (dashed lines).

Figure 3-2 summarises the results for all testsites. One can see that there is a relatively good agreement between $\gamma_{0.9}/\gamma_0$ and $\gamma_{0.1}/\gamma_\infty$ with R^2 equal to 0.84 for both cases. The correlation between the differences $\gamma_{0.9}$ - $\gamma_{0.1}$ and γ_0 - γ_∞ is somewhat less good, but still R^2 equals 0.65. Encouraging is the fact that the arithmetic mean of γ_0 and γ_∞ can be well estimated by using the arithmetic mean of $\gamma_{0.9}$ + $\gamma_{0.1}$ because this is the crucial value for separating the two forest classes.

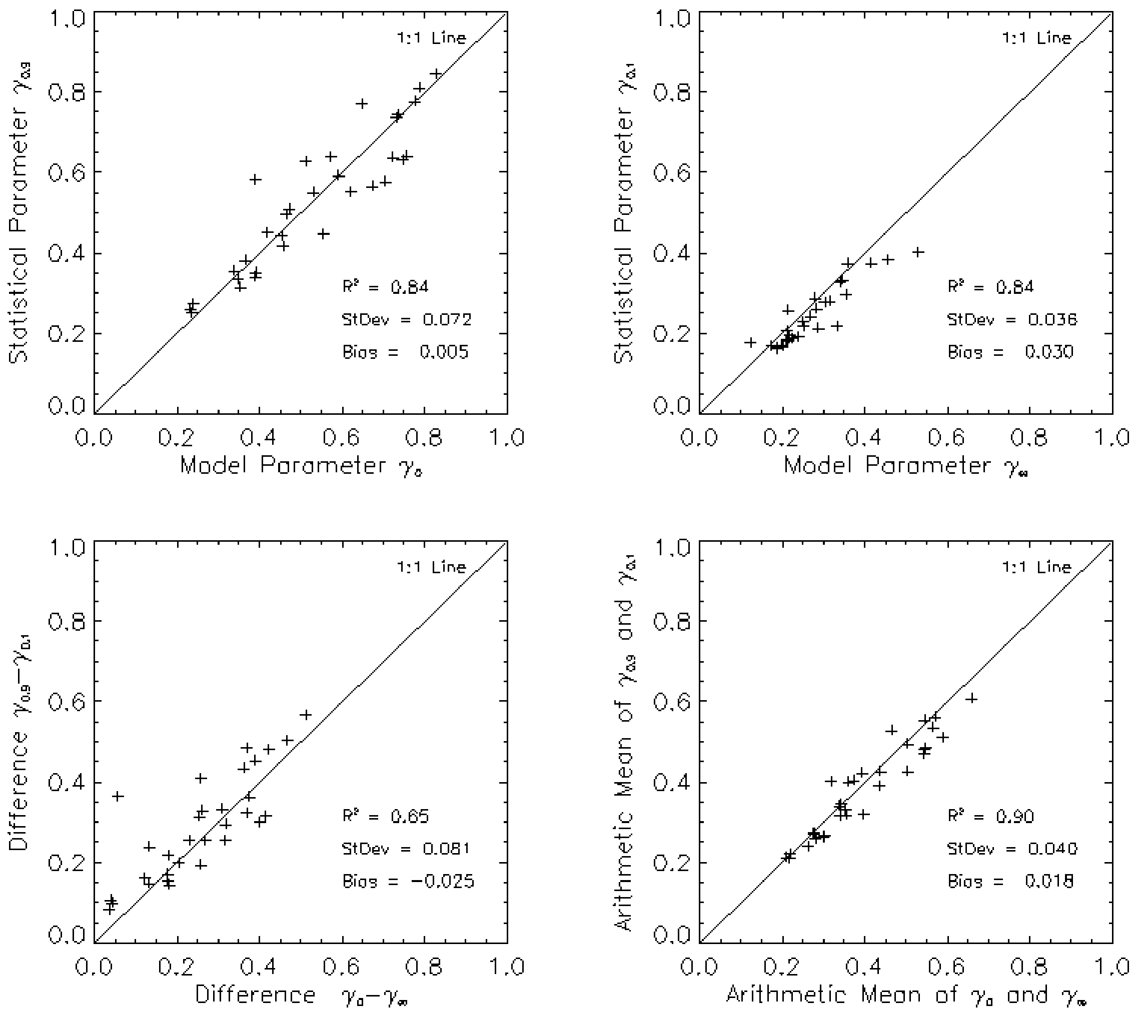

Figure 3-2: Comparison of parameters γ_0 and γ_∞ according to model (2) and percentiles $\gamma_{0.1}$ and $\gamma_{0.9}$.

4. Validation of Classification Approach

4.1. Two Forest Classes

In the last chapter it was demonstrated that the model parameters γ_0 and γ_∞ can be estimated through simple statistical parameters that can be directly derived from the coherence images. Therefore the classification rules (6) can be rewritten:

$$\text{if } \gamma < \frac{\gamma_{0.1}+\gamma_{0.9}}{2} \text{ then low density forest with } v < 70 \text{ m}^3\text{/ha} \qquad (7a)$$

$$\text{if } \gamma \geq \frac{\gamma_{0.1}+\gamma_{0.9}}{2} \text{ then high density forest with } v \geq 70 \text{ m}^3\text{/ha} \qquad (7b)$$

Table 4-1 shows the detailed results of the classification for all testsites. For example the column LL shows the percentage of polygons with $v < 70$ m^3/ha which were correctly classified using γ. Columns T and F show the percentage of correctly and wrongly classified polygons. The best results of 96.3 % classification accuracy is achieved for one of the subsites of the Bolshemurtinskii forest enterprise, the worst result of 54.5 % for one of the Ermakovsky sites. The average classification accuracy is 76.6%.

Enterprise	No.	Tr.	Fr.	Prd.	$\gamma_{0.1}$	$\gamma_{0.9}$	LL	HH	LH	HL	T	F
Bolshemurtinskii	1	348	2457	GTC	0.26	0.55	56.3	28.1	15.6	0.0	84.4	15.6
Bolshemurtinskii	2	348	2457	GTC	0.24	0.74	27.7	68.6	2.5	1.2	96.3	3.7
Bolshemurtinskii	3	348	2457	GTC	0.22	0.42	8.2	68.2	2.9	20.6	76.5	23.5
Bolshemurtinskii	4	348	2457	GTC	0.26	0.59	39.1	49.4	6.4	5.1	88.5	11.5
Bolshemurtinskii	1	305	2457	GTC	0.18	0.51	43.5	40.8	8.7	7.1	84.2	15.8
Bolshemurtinskii	2	305	2457	GTC	0.18	0.35	9.6	69.9	3.2	17.3	79.5	20.5
Bolshemurtinskii	1	305	2457	GEC	0.18	0.50	44.7	42.1	7.4	5.8	86.8	13.2
Bolshemurtinskii	2	305	2457	GEC	0.19	0.34	9.6	73.1	3.2	14.1	82.7	17.3
Chunsky	1	491	2439	GEC	0.18	0.33	11.4	67.2	2.4	19.0	78.6	21.4
Chunsky	2	491	2439	GEC	0.21	0.64	42.2	52.5	3.3	2.0	94.7	5.3
Chunsky	3	491	2439	GEC	0.30	0.78	51.8	37.2	0.8	10.3	88.9	11.1
Ermakovsky	1	305	2529	GEC	0.17	0.27	11.3	54.9	8.5	25.4	66.2	33.8
Ermakovsky	2	305	2529	GEC	0.17	0.25	3.8	60.5	2.5	33.1	64.3	35.7
Ermakovsky	3	305	2529	GEC	0.16	0.26	11.7	59.3	11.0	17.9	71.0	29.0
Ermakovsky	4	305	2529	GEC	0.17	0.31	15.8	63.7	4.2	16.3	79.5	20.5
Ermakovsky	1	33	2529	GEC	0.23	0.55	15.5	63.1	3.4	18.0	78.6	21.4
Ermakovsky	2	33	2529	GEC	0.27	0.46	27.3	27.3	0.0	45.5	54.5	45.5
Ermakovsky	3	33	2529	GEC	0.19	0.45	5.0	63.5	1.3	30.2	68.6	31.4
Hrebtovsky	1	448	2421	GEC	0.19	0.35	20.4	50.6	15.4	13.5	71.1	28.9
Hrebtovsky	2	448	2403	GTC	0.38	0.64	11.7	51.5	0.0	36.8	63.2	36.8
Hrebtovsky	3	448	2403	GTC	0.37	0.57	2.5	61.1	0.6	35.7	63.7	36.3
Hrebtovsky	4	448	2385	GTC	0.40	0.81	16.6	49.1	1.4	32.9	65.7	34.3
Irbeiski	1	491	2475	GTC	0.22	0.58	9.4	52.5	17.8	20.3	61.9	38.1
Lake_Baikal_South	1	462	2565	GEC	0.21	0.45	9.8	51.6	6.3	32.4	61.3	38.7
Lake_Baikal_South	2	419	2565	GEC	0.17	0.63	15.3	71.5	13.1	0.0	86.9	13.1
Nishni_Udinskii	1	362	2511	GTC	0.29	0.77	39.5	40.3	14.2	6.0	79.8	20.2
Nishni_Udinskii	2	362	2493	GTC	0.28	0.84	31.8	60.0	1.7	6.5	91.8	8.2
Primorskii	1	47	2475	GTC	0.37	0.74	44.6	33.0	12.5	9.8	77.7	22.3
Primorskii	2	47	2475	GTC	0.33	0.63	18.9	46.5	1.1	33.5	65.4	34.6
Primorskii	3	47	2475	GTC	0.33	0.64	18.9	45.9	1.1	34.1	64.9	35.1
Primorskii	4	47	2475	GTC	0.28	0.58	14.7	74.5	0.0	10.8	89.2	10.8
Ulkanskii	1	147	2475	GEC	0.16	0.38	22.1	65.7	2.3	9.9	87.8	12.2
Ulkanskii	2	104	2493	GEC	0.19	0.44	12.2	62.8	4.6	20.4	75.0	25.0
Average					0.24	0.53	21.9	54.7	5.4	17.9	76.6	23.4

Table 4-1: Accuracy of classification approach (7). Explanation of columns LL, HH, LH, and HL: The first character stands for the density class derived from the ground data base, and the second character for the density class derived from the coherence. L stands for the low density forest class ($v < 70\ m^3/ha$) and H for the high density forest class ($v \geq 70\ m^3/ha$). Column T shows the percentage of correctly classified polygons, and column F the percentage of wrongly classified polygons.

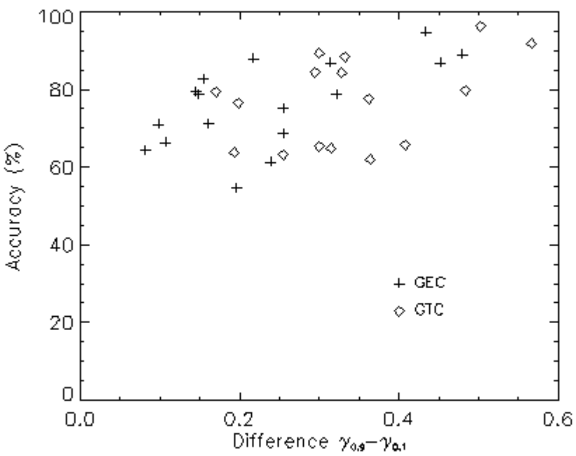

Figure 4-1: Accuracy in % of forest density classifier (two classes) versus the difference of the $\gamma_{0.9}$ and $\gamma_{0.1}$ percentiles of the coherence distribution.

The classification accuracy should be related to the spread of the γ values which is expressed by the difference $\gamma_{0.9}$ - $\gamma_{0.1}$, i.e. the higher the spread the more accurate the classification. Figure 4-1 shows the scatterplot of the accuracy versus the difference $\gamma_{0.9}$ - $\gamma_{0.1}$. Despite some scattering of the data point one can clearly recognise a relationship between these two values. Therefore $\gamma_{0.9}$ - $\gamma_{0.1}$ can be used to provide an indication of the expected classification accuracy:

$$\text{Accuracy}(\%) \approx 62 + 44 \cdot (\gamma_{0.9} - \gamma_{0.1}) \pm 10 \quad (8)$$

It should also be noted in Figure 4-1 that the classification results are equally good for GEC and GTC products. This is an important observation because it means that also GEC products can provide useful information.

4.2. Three Forest Classes

Given the encouraging results for the two forest classes, it is logical to ask if even three forest biomass classes could be distinguished. The two optimum thresholds would be:

$$\begin{aligned} \gamma^1_{thres} &= \frac{2}{3}(\gamma_{0.1} + \gamma_{0.9}) \Rightarrow v^1_{thres} = 40.5 \approx 40 m^3/ha \\ \gamma^2_{thres} &= \frac{1}{3}(\gamma_{0.1} + \gamma_{0.9}) \Rightarrow v^2_{thres} = 109.9 \approx 100 m^3/ha \end{aligned} \quad (9)$$

The results of the classification using the thresholds given in (9) are summarised in Table 4-2. The percentage of correctly classified polygons is on average only 36 %. Most of the estimated polygon classes, on average 61.2 %, are one class off the true growing stock volume class. It can be seen in Figure 4-2 that the classification accuracy increases quite strongly with increasing spread of the γ distribution. For $\gamma_{0.9}$ - $\gamma_{0.1}$ greater than 0.5 accuracies up to 70 % are achieved, however, this concerns only few testsites so that the use of three forest classes cannot be recommended.

Enterprise	No.	Tr.	Fr.	Prd.	Coh1	Coh9	T	F1	F2
Bolshemurtinskii	1	348	2457	GTC	0.26	0.55	43.8	56.3	0.0
Bolshemurtinskii	2	348	2457	GTC	0.24	0.74	71.5	28.5	0.0
Bolshemurtinskii	3	348	2457	GTC	0.22	0.42	15.9	80.6	3.5
Bolshemurtinskii	4	348	2457	GTC	0.26	0.59	48.1	51.9	0.0
Bolshemurtinskii	1	305	2457	GTC	0.18	0.51	58.7	37.5	3.8
Bolshemurtinskii	2	305	2457	GTC	0.18	0.35	19.2	76.9	3.8
Bolshemurtinskii	1	305	2457	GEC	0.18	0.50	53.7	42.6	3.7
Bolshemurtinskii	2	305	2457	GEC	0.19	0.34	14.7	81.4	3.8
Chunsky	1	491	2439	GEC	0.18	0.33	12.1	85.2	2.8
Chunsky	2	491	2439	GEC	0.21	0.64	58.3	40.9	0.8
Chunsky	3	491	2439	GEC	0.30	0.78	59.3	40.7	0.0
Ermakovsky	1	305	2529	GEC	0.17	0.27	19.7	78.9	1.4
Ermakovsky	2	305	2529	GEC	0.17	0.25	8.3	89.8	1.9
Ermakovsky	3	305	2529	GEC	0.16	0.26	12.4	84.8	2.8
Ermakovsky	4	305	2529	GEC	0.17	0.31	30.0	68.9	1.1
Ermakovsky	1	33	2529	GEC	0.23	0.55	35.9	62.1	1.9
Ermakovsky	2	33	2529	GEC	0.27	0.46	9.1	81.8	9.1
Ermakovsky	3	33	2529	GEC	0.19	0.45	30.8	57.9	11.3
Hrebtovsky	1	448	2421	GEC	0.19	0.35	26.7	72.0	1.3
Hrebtovsky	2	448	2403	GTC	0.38	0.64	16.5	82.3	1.2
Hrebtovsky	3	448	2403	GTC	0.37	0.57	9.6	89.5	1.0
Hrebtovsky	4	448	2385	GTC	0.40	0.81	21.8	74.5	3.8
Irbeiski	1	491	2475	GTC	0.22	0.58	34.2	52.5	13.4
Lake_Baikal_South	1	462	2565	GEC	0.21	0.45	25.4	70.3	4.3
Lake_Baikal_South	2	419	2565	GEC	0.17	0.63	67.9	27.0	5.1
Nishni_Udinskii	1	362	2511	GTC	0.29	0.77	41.6	57.5	0.9
Nishni_Udinskii	2	362	2493	GTC	0.28	0.84	73.4	24.4	2.2
Primorskii	1	47	2475	GTC	0.37	0.74	61.6	37.5	0.9
Primorskii	2	47	2475	GTC	0.33	0.63	50.3	49.7	0.0
Primorskii	3	47	2475	GTC	0.33	0.64	53.5	46.5	0.0
Primorskii	4	47	2475	GTC	0.28	0.58	27.5	71.6	1.0
Ulkanskii	1	147	2475	GEC	0.16	0.38	39.4	58.7	1.9
Ulkanskii	2	104	2493	GEC	0.19	0.44	36.9	58.5	4.6
Average					0.24	0.53	36.0	61.2	2.8

Table 4-2: Accuracy of classification approach for three forest classes. Column T shows the percentage of polygons which were correctly classified, column F1 the percentage where the class derived from γ is one class off the one obtained from the ground truth, and the last column shows the percentage where the class derived from γ is two classes off the one obtained from the ground truth.

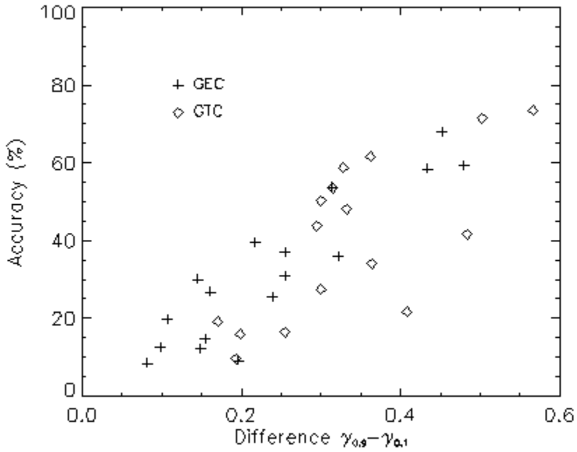

Figure 4-2: Accuracy in % of forest density classifier (three classes) versus the difference of the $\gamma_{0.9}$ and $\gamma_{0.1}$ percentiles of the coherence distribution.

5. Conclusions

A seemingly robust method for determining two forest classes based solely on the statistical properties of the coherence images was defined. The two classes represent low-density forest with growing stock volumes smaller than 70 m^3/ha and high density forest with growing stock volumes greater than 70 m^3/ha. The method works equally well for GEC and GTC products. Also, the expected classification accuracy can be estimated based on the image properties. The use of three forest classes cannot be recommended.