CREATION OF LARGE AREA FOREST BIOMASS MAPS FOR NORTHEAST CHINA USING ERS-1/2 TANDEM COHERENCE

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ABSTRACT

One of the objectives of the Forest DRAGON project is the generation of a forest biomass map for Northeast China based on ERS-1/2 tandem coherence. The ERS-1/2 tandem dataset consisted of 223 image pairs acquired in all seasons between 1995 and 1998. ERS-1/2 tandem coherence has been shown to provide accurate estimates of forest biomass but is also known to depend strongly on the meteorological and environmental conditions at image acquisition. For large-area mapping existing algorithms have not been able so far to classify forest biomass based on a multi-seasonal dataset. In this study a new classification approach, based on synergy between the optical remote sensing product MODIS Vegetation Continuous Field and ERS-1/2 tandem coherence, has been developed for automatic and seasonal-adaptive retrieval of forest biomass. The procedure integrates the semi-empirical Interferometric Water Cloud Model. With this procedure a forest biomass map of Northeast China (~ 1.5 Million km²) discriminating between four stem volume classes (0-20, 20-50, 50-80 and > 80 m³/ha) has been generated.

1. Introduction

The forests of Northeast China, which represent one of the most important wood supplies in China, have been undergoing constant pressure for several decades. The existing forest resources are not considered adequate for the needs of the Chinese economy and livelihood of the Chinese people. According to [1] the main problems are low total volume, low quality and sluggish growth of both naturally growing forests and plantations. The existing statistics about forest area, type and quality in China differ significantly [2], indicating a need to monitor the forests status and their development on a regular basis. This represents the background to the activities reported in this paper as part of the work carried out within the Forest DRAGON Project (FOREST-related Development of Radar Applications for Geomatic Operational Networks, id 2583). The Forest DRAGON Project has the aim of generating large scale forest biomass and forest cover maps for the main forested regions of China (NE China, South China, Central China and West China) using radar remote sensing techniques [3].

Radar remote sensing has been shown to allow the retrieval of forest area extent and forest resources in the form of growing stock volume. Several studies have shown that ERS-1/2 tandem coherence can be used to assess forest wood resources [4,5,6] with reasonable accuracy under ‘good’ (i.e. stable frozen) imaging conditions. The retrieval accuracy achievable is however related to the strong sensitivity of coherence to meteorological and environmental conditions. This variability makes in turn forest stem volume mapping strongly dependent on forest inventory data in order to correctly tune the models relating coherence to growing stock volume.

Large area applications of interferometric SAR techniques for forest mapping are scarce. Currently the only existing large-area forest cover map has been produced within the ‘SAR Imaging for Boreal Ecology and Radar Interferometry Applications’ SIBERIA project [7,8]. The result of this project was a forest cover map of a ~ 1 Million km² large area in Central Siberia, discriminating four stem volume classes (0-20, 20-50, 50-80 and > 80 m³/ha). The algorithm used for the estimation of the volume classes was fully-automated and could be applied without the need of forest inventory data in the model training phase. The model training was conducted based on histogram statistics for each image frame. The application of this algorithm, however, has narrow confines since it has been developed for ERS-1/2 tandem coherence acquired only in fall, i.e. for a limited set of imaging conditions. It also utilizes a simple empirical model. For example it does not consider tree height and baseline dependent volume effects, which can be considered significant for perpendicular baselines longer than 100 m [4]. One of the goals of the Forest DRAGON project was to

Proc. Dragon 1 Programme Final Results 2004–2007, Beijing, P. R. China
21–25 April 2008 (ESA SP-655, April 2008)
produce a forest biomass map based on ERS tandem data. However, due to the lack of full coverage multi-temporal data acquired under optimal conditions, the production of a SIBERIA type of map, i.e. a forest cover map, discriminating at least some low stem volume classes, was considered to be more realistic. For this an ERS-1/2 tandem dataset consisting of 233 image pairs was available. This dataset was acquired under a wide range of meteorological conditions in all seasons between 1995 and 1998 and with a wide range of perpendicular baselines between 0 and 400 m. The given dataset spanning different seasons and baselines length showed the limits of the SIBERIA approach. For this reason it was decided to develop a new retrieval algorithm that would be able to cope with multi-seasonal and multi-baseline data in an automatic retrieval procedure.

The development of the retrieval algorithm focused on two main aspects:

1) Utilization of a semi-empirical model, which also considers volume effects on coherence in order to describe the relationship between coherence and stem volume for a wide range of baselines.

2) Analysis of the feasibility of an automated model training for every frame without forest inventory data by means of the MODIS Vegetation Continuous Field product [9].

In the following, this paper illustrates the ground-truth and EO data used for this study, the development of the fully-automated algorithm for forest stem volume mapping, the production of a SIBERIA type of map for Northeast China and an assessment of the accuracy to be expected by such an approach. Finally, an outlook on possible future activities in the framework of the DRAGON project is given.

2. Test sites and ground data

The study area in China coincides with the Northeastern part of the country (for details it is referred to [15]). The Chinese Academy of Forestry provided inventory data for three test sites located in the Greater (53°8’ N, 123°4’ E) and Lesser Hinggan (47°10’ N, 128°53’ E) mountains and the Changbai area (42°60’ N, 128°10’ E). These represent the main forested areas in Northeast China and include the typical forest types for the area, i.e. the cold-temperate larch-dominated forests in the north and the temperate mixed broadleaved / Korean pine forests in the south and east. The data comprised information about stem volume and height for each stand and was provided together with stand-wise measurements of ERS-1/2 tandem coherence and backscatter.

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Since only three ERS-1/2 tandem pairs, all acquired under frozen winter conditions, were available for the three Chinese test sites, the methodological development was extended to five compartments of three forest enterprises located in Central Siberia: Bolshe-Murtinsky (57° 5’ N, 92° 55’ E), Chunksky (57° 45’ N, 96° 43’ E) and Primorsky (55° 46’ N, 102° 30’ E). These areas were chosen because of the availability of detailed inventory measurements and the long-standing experience gathered using coherence in previous studies [5,7,8,10]. The compartments are from now on referred to with an index describing their geographical location within the territories (Bolshe NE, Bolshe-NW, Chunksy N, Chunksy E, Primorsky E). Bolshe NW and NE are located at the western and eastern banks of the Yenisey River respectively with rather flat topography in the west and a hilly relief in the east. The northern part of Chunksy N and the whole area of Chunksy E, both located south of the Angara River, are rather flat as well, whereas the southern part of Chunksy N is characterized by steeper slopes. Primorsky is located on the southern banks of the Bratskove Reservoir. The topography is rather gentle with a few steep slopes along several riverbeds crossing the area mainly from North to South.
The forests in this part of the boreal zone are dominated by mature stands of coniferous species such as spruce, fir, larch, pine and cedar. When disturbance occurs, typically birch and aspen regenerate first and are generally replaced after 60-100 years by evergreen coniferous species. In larch forest, larch regenerates after disturbance (as e.g. in Chunsky). The maximum stem volume in the compartments is in the range of 400-470 m$^3$/ha.

The Siberian forest inventory data included stand-wise measurements of several forest variables (e.g. stem volume, height, dbh, age and relative stocking, RS) and digital forest stand boundary maps. Stem volume represents the tree trunk volume per unit area excluding branches and stumps and is accounted for all living species in a stand. RS is a measure of stand density with respect to an optimal stocked stand and was given from 0 to 100 % in steps of 10%. RS depends on site quality and cannot be related to stand density directly. As suggested in [5], RS was here used as a proxy for the structure of a forest, i.e. high RS indicates a more homogeneous type of forest. The stands in the digital forest mask were edge-eroded by a 50 m wide buffer zone along the stand boundaries in order to minimize the influence of mis-registrations between satellite and ground data.

3. SAR imagery

For the methodological development a multi-seasonal ERS-1/2 tandem dataset was available, consisting of five tandem pairs for Bolshe, two for Chunsky and one for Primorsky. The perpendicular baselines were between 65 and 313 m. The whole dataset covering Northeast China consisted of 223 coherence images with baselines <400m and acquired in two periods between winter 1995 and summer 1998. Three tandem pairs covered the Chinese test sites, i.e. one per test site. All three pairs were acquired under frozen conditions.

Interferometric processing was done on a frame basis (100 km x 100 km). It consisted of co-registration at sub-pixel level, multi-looking (1x5 for the Siberian dataset; 2x10 for the Chinese dataset), common-band filtering and adaptive coherence estimation using window sizes between 3x3 and 9x9 pixels. All coherence and backscatter images were geocoded using SRTM-3 DEM data. During geo-coding, the Siberia and the Chinese images were resampled to a pixel size of 25x25 m$^2$ and 50x50 m$^2$ respectively. For a more detailed description of the processing of the ERS-1/2 tandem coherence mosaic covering Northeast China it is referred to [11]. During geocoding, maps of slope angle, layover/shadow, pixel area normalization and local incidence angle were produced. These assisted in the interpretation of the coherence and the backscatter measurements.

Figure 1. ERS-1/2 tandem mosaic of Northeast China. Red – coherence, Green – ERS-1 intensity, Blue – ERS-1/2 intensity difference. The colour differences between the different tracks are caused by the seasonal variations of coherence and intensity.

4. Coherence measurements

One of the main challenges when dealing with ERS-1/2 tandem coherence for forest cover or biomass mapping is the ability to compensate for spatial and temporal variations of the coherence in the retrieval algorithm. These variations are caused by meteorological and environmental conditions at image acquisition, as well as by the interferometric geometry (i.e. the baseline).

Figure 2 illustrates the variability of the relationship between coherence and stem volume under different environmental conditions at acquisition. Forest stands larger than 3 ha have been considered to be able to clearly pick out the main trend. The two plots on the left correspond to image pairs acquired under stable frozen conditions. Coherence decreased significantly up to 250-300 m$^3$/ha. A similar situation was found for the image acquired at the test site Primorsky E under unfrozen but rain-free weather conditions. In all three cases the coherence of stands with very low stem volume was in the range of ~0.6-0.85 and the coherence of dense forest above 0.2. For images acquired under rainy conditions strong temporal decorrelation occurred. As exemplified by the plot in the bottom right corner, the coherence of open as well as dense stands was considerably lower and saturation of coherence with respect to stem volume occurred at ~100 m$^3$/ha. From Figure 2 it is clear that the temporal variability needs to be captured when aiming at forest cover mapping with a multi-seasonal dataset. It is also clear that the capability of discriminating among high stem volume classes is restricted to images acquired under stable conditions.
The model describes the coherence of a forest $\gamma_{gr}$ as a sum of a ground $\Gamma_{gr}$ and a vegetation contribution $\Gamma_{veg}$:

$$\Gamma_{gr} = \gamma_{gr} \frac{\sigma_0^{gr}}{\sigma_0^{tot}} e^{-\beta \sigma_{veg}}$$

$$\Gamma_{veg} = \gamma_{veg} \frac{\sigma_0^{veg}}{\sigma_0^{tot}} \left(1 - e^{-\beta \sigma_{veg}}\right)$$

The ground component (1) accounts for temporal decorrelation of the ground, weighted by the fraction of backscatter from ground $\sigma_{gr}$ and the forest transmissivity, expressed as a function of the stem volume ($e^{\beta \sigma_{veg}}$). $\beta$ represents an empirical parameter, which accounts for the fraction of gaps in the canopy as well as the transmissivity of the trees. The vegetation contribution (2) accounts for the temporal decorrelation of the canopy, weighted by the forest transmissivity and the fraction of backscatter from the canopy $\sigma_{veg}$ with respect to the total backscatter. The terms in the brackets account for volume decorrelation and the effect of the InSAR geometry. These two factors are expressed as a function of the two-way attenuation of the signal in the canopy $\alpha$, the tree height $h$, which is generally replaced with an allometric equation of the form: $h = (a^*V)^{\frac{1}{3}}$ [5,12], and the InSAR geometry coefficient $\omega$, where $B_x$ represents the perpendicular baseline, $R$ the slant range and $\theta$ the local incidence angle (3). The backscatter from a forest is modeled according to [13] (4).

$$\omega = \frac{4\pi B_x}{\lambda R \sin \theta}$$

$$\sigma_0^{veg} = \sigma_0^{gr} e^{-\beta \sigma_{veg}} + \sigma_0^{veg} \left(1 - e^{-\beta \sigma_{veg}}\right)$$

The model describes the coherence of a forest $\gamma_{gr}$ as a function of stem volume for four image pairs acquired over the Siberian test sites under different meteorological conditions.

5. Methodology

The semi-empirical model used in this study to retrieve stem volume from coherence was the Interferometric Water Cloud Model (IWCM) [12]. This model has been shown to be capable of describing the relationship between coherence and stem volume under a wide range of environmental and meteorological imaging conditions, i.e. varying temporal decorrelation, as well as for a wide range of baselines since it also accounts for baseline and tree height dependent volume decorrelation [4,5,12].

The IWCM includes five unknowns: $\gamma_{gr}$, $\gamma_{veg}$, $\sigma_0^{gr}$, $\sigma_0^{veg}$ and $\beta$ that should be determined via model training based on forest inventory data. Actually, $\alpha$ should be considered an unknown as well. Recent results, however, showed consistent modeling results using a value of 1 dB/m in case of frozen and 2 dB/m in case of unfrozen conditions [5]. The model reduces to the empirical model used for the SIBERIA project, when neglecting volume decorrelation ($B_x=0$) and assuming $\sigma_0^{gr}=\sigma_0^{veg}=\sigma_0^{tot}$.

The determination of the model unknowns has relied so far on the availability of forest inventory data (see e.g. [4,5]). The high spatial variability of coherence requires in theory a very high density of training sites, in order to be able to capture these variations and obtain a spatially consistent modelled coherence. For Northeast China this was not the case, hence a model training method independent from inventory data had to be developed.

In this respect we investigated the possibility to include the MODIS Vegetation Continuous Field (VCF) tree cover product [9] in the model training phase. The VCF product provides global sub-pixel estimates of tree cover at 500 m pixel size. As exemplified in Figure 3, a consistent relationship between coherence and VCF tree cover was found for all images covering the Siberian test sites. The basic idea therefore was to use the relationship between VCF and coherence information for the training of the IWCM. It was found that reasonable estimates of $\gamma_{gr}$ and $\sigma_0^{gr}$ were possible when calculating the most frequent value of coherence and intensity for all areas with low VCF tree cover <10%. Similarly, $\gamma_{veg}$ and $\sigma_0^{veg}$ were found to be related to the mode of coherence and intensity for all areas with high VCF tree cover, at least 70%. Here we considered a compensation for residual ground contribution and volume decorrelation, since $\gamma_{veg}$ and $\sigma_0^{veg}$ represent the temporal coherence and backscatter of ideally opaque canopies. While these parameters should be independent from stem volume, the estimated values for high VCF tree cover represent coherence and backscatter for a specific stem volume. Here we assumed this volume to be 400 m$^3$/ha. Tests with different (high) volumes showed that the model parameters did not differ substantially.
The empirical forest transmissivity parameter $\beta$ could not be estimated by means of the VCF product. Therefore it was analyzed by means of regression-based model training using inventory data whether a sort of generalized value could be used. Previous studies showed that the range of valid values for $\beta$ is between 0.003 and 0.007 for boreal forests [5]. Model training by means of least-squares regression revealed a range of $\beta$ between 0.0055 and 0.0073 for all images acquired over the Siberian test sites under stable imaging conditions and a fixed $\beta$ of 0.006 resulted in reasonable outcomes for the VCF-based model training. This was not the case when doing regression-based model training for all images acquired under unstable and rainy conditions. In this case $\beta$ varied between 0.0029 and 0.0279, exceeding by far the range of the physical meaning of the parameter. This wide range of values obtained can be interpreted as the consequence of the considerable spread of the measurements around the main trend as well as the very early saturation at 100 m$^3$/ha which cannot be explained with a decrease in forest transmissivity solely.

Actually, more stable estimates of $\beta$ were achieved, when neglecting volume decorrelation ($B_v=0$) and backscatter contributions ($\sigma_0^t=\sigma_0^v=\sigma_0^f$), i.e. when using the simple empirical model used in [7]. This is why the empirical model was used for the VCF-based approach in case of unstable imaging conditions together with a fixed $\beta$ of 0.015 in order to roughly describe the trend indicated by the measurements.

6. Results and Discussion

6.1 VCF-based model training
The results of the VCF-based model training are illustrated in Figure 4 for two tandem pairs acquired under frozen stable conditions and for two pairs acquired under unstable conditions affected by rain. Mostly a good fit to the trend in the measurements was achieved. However, some differences between regression- and VCF-based model training could be noticed. The regression-based model training consisted of parameters estimation using forest inventory data. A clear overestimation of ground coherence was found for example when using the VCF-based training approach for all coherence images acquired at the Bolshe NE test site. This was related to distinct spatial properties of the ground coherence for all images acquired after rain events in fall. Remarkable differences between the coherence of sandy soils predominant in the area of the Bolshe NW test site and of the peaty soils in the area of Bolshe NE were found [5]. A separate VCF-based training of the IWCM for the two soil zones, using a soil map, confirmed this assumption as VCF- and regression-based values for $\gamma_0$ were then of the same order. The difference in ground coherence for the image acquired over Bolshe NE in January could not be retraced this way, indicating that spatial variations of coherence are not necessarily distinct and cannot always be related to large-scale landscape units or landscape properties, e.g. soils. For example wind directional effects in temporal decorrelation for tree canopies cannot be retraced without detailed topographic and meteorological data [14].

6.2 Retrieval of growing stock volume
For the accuracy assessment of growing stock volume retrieval the inventory data of the test sites were divided into a training and a test dataset by sorting all stands for increasing stem volume and assigning every other stand to either the training or the test dataset. The training dataset was used for the regression-based model training whereas the test dataset was used for retrieval by means of both training approaches, i.e. regression- and VCF-based. The retrieval accuracy was determined for different thresholds of minimum relative stocking.

The analysis of the retrieval statistics revealed a relative rms error of ~ 25% as realistic accuracy level to be achieved for large homogeneous stands with high
6.3 Accuracy of forest cover mapping
Since the ERS dataset available for Northeast China comprised a considerable fraction of images acquired under unstable meteorological conditions, no discrimination of high stem volume classes was possible when aiming at obtaining a consistent forest biomass map of Northeast China. Therefore the accuracy of a SIBERIA-type of class discrimination, i.e. four stem volume classes 0-20, 20-50, 50-80 and >80 m$^3$/ha, was considered. Forest volume maps were generated for both the Siberian test areas and Northeast China. The classification was done by applying simple thresholds to the stem volumes retrieved by inverting the trained models.

The accuracy assessment of this type of map revealed results similar to those obtained for the SIBERIA forest volume map [8]. The general pattern can be summarized as follows: 1) The Producer’s accuracy of the highest stem volume class was always high in the range of 90%. The accuracy of the lowest class, i.e. 0-20 m$^3$/ha, was in the range of 80% as long as no overestimation of ground coherence occurred. In this case, e.g. for the image acquired over Bolshe NE at 22-23 September 1997 (Figure 4), the accuracy was almost 90%. The intermediate classes always had low accuracies in the range of 10-65%. The low accuracy of the intermediate classes was in line with the accuracy assessment carried out for the SIBERIA map. An independent ground survey of the SIBERIA map accuracy, however, found high accuracies (> 80%) for these classes as well, suggesting the error in the inventory data as the main cause for the low accuracy. In [8] an uncertainty model was used in order to quantify the influence of the error in the forest inventory data. The true stem volume was assumed to be in an interval between $V_{\text{Tr}}-2 \text{SD}$ and $V_{\text{Tr}}+2 \text{SD}$ with 95% certainty, with SD denoting the standard deviation and $V_{\text{Tr}}$ the volume reported in the inventory data. A classified pixel was considered correctly classified when the stem volume boundaries of the class it was assigned to overlapped with the fuzzy interval. For an uncertainty SD of 20 m$^3$/ha a $\kappa$ of 0.72 was reported in [8]. When applying this uncertainty model to the pooled data of all classified images acquired over the Siberian test sites for the VCF-based classification approach, a 20 m$^3$/ha uncertainty resulted in a $\kappa$ of 0.76. This coefficient was equal to 0.70 for the images acquired in fall and spring and 0.78 when only considering the winter data. According to these statistics, a SIBERIA-type of class discrimination seemed to be reasonable.

![Figure 6. Overall accuracy and $\kappa$ for different assumed uncertainties in the forest inventory data.](image)

6.4 Production of the forest cover map of NE China
By means of the VCF-based approach, training of the IWCM could be carried out for 76 out of the 223 coherence images available for Northeast China. For these images, a sufficient number of VCF pixels (>2%) reported a tree cover above 70%. For all other images the training had to be repeated, integrating neighbour image frames into the training procedure in order to keep the training as local as possible. In this way, model training could be carried out for all images covering the main forest areas. Only for very few tracks no model training was possible, e.g. for tracks covering the mostly un-forested grasslands of Inner Mongolia or the agricultural areas of the Northeast China plain. In these cases some rough estimates for $\gamma_{\text{veg}}$ and $\sigma_{\text{veg}}^2$ were established based on the relatively high correlation found for the estimated values of $\gamma_{\text{veg}}$ and $\sigma_{\text{veg}}^2$ and temperature measurements. Using data from 43 weather stations the Pearson correlation coefficients of -0.872 for $\gamma_{\text{veg}}$ and 0.932 for $\sigma_{\text{veg}}^2$ were obtained. Unstable weather conditions between the ERS-1 and ERS-2 acquisition were identified using the available meteorological data in order to decide when to use the IWCM with a physically relevant transmissivity expression or the simple empirical model. Also $\gamma_{\text{veg}}$ calculated by means of VCF gave good indication of the imaging conditions since it never exceeded a level of 0.25 for unfrozen conditions.

![Figure 7. $\gamma_{\text{veg}}$ calculated by means of the VCF-based approach, vs. mean temperature during the acquisition period and sum of rain in 10 days before the ERS-2 acquisition ($o$ denotes temperatures $>0^\circ$ C).](image)
A problem that did not occur in Siberia but needed to be faced in China was spatial decorrelation on sloped terrain. This aspect was quite relevant since the most important forest areas of Northeast China can be found in the Greater and Lesser Hinggan and the Changbai Mountains. Spatial decorrelation introduced through uncompensated topography in the interferometric processing is known to affect the estimation of coherence [14]. For this reason mountainous areas had to be masked before doing model training and classification. A simple exclusion of all mountainous areas as done for example for the production of the SIBERIA map would have prevented classification of large forested areas. Therefore a more selective masking had to be applied.

Figure 8 illustrates the strong influence of the perpendicular baseline on the coherence over un-forested mountainous terrain for three coherence images acquired with different baselines over the same area in the Liaoning province. For short baselines, only steep slopes facing the radar (aspect angle of ~100°) were affected. With increasing baseline, coherence decreased also for gentle slopes. Slopes tilted away from the radar (aspect angle > 190°) were mostly unaffected for baselines shorter than 100m whereas for 150m baseline even slopes of 5° showed lower coherence than flat areas. This can be explained in terms of non-perfectly compensated spatial decorrelation in the range common-band filter on sloped terrain for long baselines. Standard range common band filtering assumes a flat planar surface, resulting in non-common parts of the spectra not being removed over sloped terrain and thus spatial decorrelation being introduced. Since the overlap of the spectra decreases with increasing baseline, spatial decorrelation increases. In order to mask out as few areas as possible, only slopes steeper than 10° facing the radar were masked for very short baselines. For baselines longer than 100m, however, all slopes steeper than 10° were masked. The topographic mask was then widened by four pixels in order to account the window size used for the estimation of coherence. In this way, a negative influence of spatial decorrelation on the model training could be excluded. For the classification, however, a less strict topographic mask was applied, since especially for baselines between 100 and 200m, the topographic influence on slopes tilted away from the radar was considered moderate and at least the forest/non-forest information should have been relevant. Therefore in the final forest map only slopes facing the radar were masked. Additionally a quality flag map has been produced for the classified areas, indicating the possible spatial decorrelation dependent on baseline length and slope angle.

The final forest map of Northeast China is shown in Figure 9. When comparing it with the ERS data mosaic in Figure 1, the map does not seem to be affected by the clear striping effects due to seasonal conditions visible in the coherence mosaic. The distinct differences between the tracks can hardly be retraced in the forest map, which should mean that the VCF-based model training performed in a robust and consistent manner.

This map represents a forest base map for NE China for the mid 1990s. A similar product for the year 2004-2005 has been obtained by the Chinese partners of the Chinese Academy of Forestry using multi-temporal ENVISAT ASAR Alternating Polarization (AP) backscatter data. This product and the comparison to the ERS-based forest map are presented in [15].

### 7. Conclusions and Outlook

In this paper the generation of a forest biomass map for NE China using ERS-1/2 tandem coherence data has been presented. Many publications have indicated the high potential of ERS-1/2 tandem coherence for forest cover and forest biomass mapping. Despite the high potential, large area applications have been scarce. Even though the theoretical understanding of coherence over forest has increased in the last decade, the considerable and yet mostly unpredictable variability of coherence with environmental and meteorological acquisition conditions has hindered the operational use of coherence in forest monitoring. Most applications have therefore been restricted to small test areas with extended ground-truth databases available. This has been so far the only way to be able to model the coherence as function of biomass and cope with spatial and temporal variations of the coherence in a retrieval approach.
For large areas typically the inventory data are scarce, probably erroneous and/or obsolete. For this reason the retrieval methods based on ERS coherence appear limited when it comes to mapping large areas unless another source is identified for training the model on which the retrieval is based. In this study we have developed an automated method for forest biomass retrieval based on the Interferometric Water Cloud Model and on the MODIS Vegetation Continuous Fields (VCF) tree canopy cover product. The clear relationship between the ERS tandem coherence and the VCF product suggested that several model parameters can be derived by masking the coherence image for low and high VCF values. The methodological development of this approach has been carried out mostly for test sites in SIBERIA for which long-standing experience has been gathered in several studies and projects before.

The analysis confirmed that coherence acquired under stable frozen winter conditions has superior information content with respect to images acquired in other seasons. Consistent model parameters estimates were obtained for these images. For images acquired under unstable conditions (e.g. rainy conditions) the model parameters strongly varied. Nonetheless the automated procedure was able to obtain a reasonable description of the dependence of coherence upon the forest growing stock volume. The result has been shown in Figure 9. The forest biomass map (4 classes) for NE China (~ 1.5 Million km²) shows homogeneous and consistent estimates. The map does not show the striping effects due to seasonal conditions that are clearly visible in the coherence data (Figure 1).

The accuracy of the biomass map could not be assessed due to lack of large-scale reference data. It should be noted that the aim of Forest DRAGON was in fact the generation of a forest biomass map that could be used by the Chinese Academy of Forestry as reference for the mid-1990 period. A qualitative assessment gave an indication on the obtained product. Results from the Siberian test sites showed that for youngest and densest forest the classification accuracy obtained by using the retrieval algorithm is rather high. In [15] the map has been compared to similar products by ENVISAT ASAR AP data and Landsat TM data, showing a strong agreement. Based on these observations it is possible to conclude that the ERS coherence forest biomass map has an accuracy that can be considered sufficient for the large area. This was confirmed by the Chinese partners of the project that deemed the ERS-based forest map as satisfactory.

The positive results obtained for NE China have boosted preparatory activities for further mapping of other Chinese regions. An ERS-1/2 tandem mosaic consisting of approximately 500 tandem pairs is currently being produced for South China. A preliminary version of the mosaic consisting of 325 coherence images is shown in Figure 10. Although the environmental conditions in this region are not optimal for coherence-based retrieval of forest properties, still many features can be distinguished. This is a promising result indicating a potential application of ERS tandem coherence for forest mapping outside the boreal forest belt.

8. Acknowledgments

ESA and MOST are greatly acknowledged for establishing and managing the DRAGON Programme. All Forest DRAGON project partners are acknowledged for cooperation. Ground and satellite data were available from the EC-funded SIBERIA (ENV4-CT98-0743), SIBERIA-II (EVG1-CT-2001-00048) and Forest Dragon (C1P.2583) projects. Weather data were provided by DWD.

9. References

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Figure 4: Coherence and correspondent ERS-1 intensity vs. stem volume. Dashed lines represent the IWCM trained by means of inventory data. The solid lines represent the VCF-based IWCM coherence.
Figure 9. Forest biomass map of Northeast China based on 223 ERS-1/2 tandem coherence images acquired between 1995 and 1998.

Figure 10. Preliminary mosaic of Southern China based on 325 ERS-1/2 tandem coherence images.