UNCERTAINTIES ANALYSIS IN FOREST HEIGHT ESTIMATION USING POLARIMETRIC INTERFEROMETRIC SAR DATA

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ABSTRACT

Quantifying the uncertainty of forest height estimation is crucial for accurate global carbon computation. Forest height have been estimated by random volume over ground (RVoG) model using polarimetric interferometry synthetic aperture radar (PolInSAR) data in recent two decades. By far, RVoG derived forest height uncertainty estimation has been limited to comparison against "true" validation data, which then lead to the impossible use of uncertainties analysis at a national, continental or global landscape. In this paper, Bayesian theorem were introduced to RVoG forest height estimation procedure and used to estimated the uncertainties of the estimated forest height. The results revealed the feasibility of Bayesian method in forest height uncertainties estimation.

Index terms—Uncertainties, forest height, Bayesian theorem

1. INTRODUCTION

Forest height is one of the most important parameters for forest management, forest biomass estimation, and forest dynamics monitoring. Traditional forest height collection through ground survey is useful but time-consuming and labor-intensive. Moreover, it is impossible to measure large geographic areas [1]. In the last decades, an approach based on polarimetric interferometric synthetic aperture radar (PolInSAR) measurement has been established and widely explored for forest height measurement and mapping. Among these studies, random volume over ground (RVoG) model, which presents a good compromise between physical structure and model complexity, is widely used in PolInSAR data for forest height estimation [1-3].

For scientific application of forest height collection, the uncertainties estimate of forest heights are as crucial as the height estimates themselves [4]. For example, the uncertainties of forest height estimates may directed propagate to uncertainties of global carbon mapping and calculation when forest height derived forest biomass is used to quantify the global carbon storage [5]. Currently the forest height estimate uncertainties are quantified by Root mean square errors (RMSE), which is calculated by comparing model prediction to "true" forest height (LiDAR-derived heights and filed measured heights) values over a sample of forest plots. However, these "true" forest height may have errors which will affect the uncertainty of the forest height estimation from RVoG model using PolInSAR data. Meanwhile, the "true" data often unavailable for national, continental or global landscape. In addition, uncertainties on any estimated model parameters depend on the quality of the input observations, the model assumptions, and the appropriateness of the model used to relate observations to model parameter. Besides, it is also affected by investigated forest characterizations. While current uncertainty analysis method not only adds uncertainties in forest heigh estimates, but also is limited to distinguish the uncertainties sources, like coming from model parameters or from the observations [4,5]. A literature introduced Bayesian theorem to quantify these uncertainties [4]. However, it only considered the uncertainties coming from model parameters and observations. Furthermore, it only explored the uncertainties quantification at L-band. In this study, we applied Bayesian theorem in RVoG forest height inversion procedure and explored the uncertainties coming from model parameters, observations, forest types when using both L- band and P- band PolInSAR data.

2. TEST SITE

The test site, approximately 6700 ha in size, is located in Middle Sweden (64°24′N, 19°79′E; Fig.1). The land cover is comprised by boreal forest, the typical forest systems of Scandinavia. It is a managed forest with a mean forest height of 18 m. The site has a hilly topography and altitudes varies from 20 m to 400 m above mean sea level (AMSL). Mixed coniferous trees (Scots pine, *Pinus sylvestris*, and Norway spruce, *Picea abies*) are the dominated tree species.

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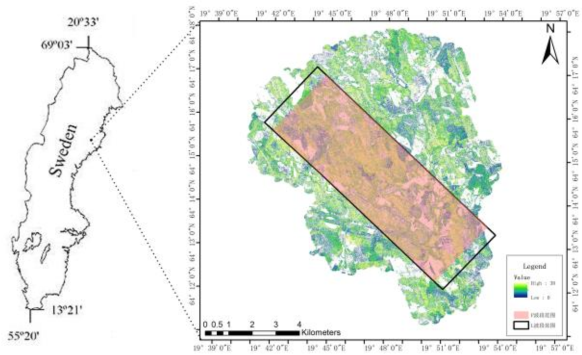


Fig.1. Location map of the test site in Middle Sweden described by the LiDAR-derived forest height map. The coverage of acquired L- and P-bands PolInSAR data showed in this fig as well.

3. MATERIALS AND METHODS

3.1 Materials

3.1.1. PolInSAR data

PolInSAR data over the study area were acquired in L-band and P- band during the BIOSAR II campaign and are summarized in Table I. The kz factor is computed as equation (1):

$$kz = \frac{4\pi B \sin(\theta + \xi)}{\lambda r \sin\theta} \tag{1}$$

where B is baseline length and ξ is baseline tilt from vertical, θ is look angle, λ is wavelength and r is range. ξ and θ are given by equation (2) and (3), respectively.

$$\xi = \tan^{-1}\frac{B_h}{B_v} \tag{2}$$

where B_h and B_v are horizontal and vertical baseline component.

$$\theta = \cos^{-1}\frac{h - h_{topo}}{r} \tag{3}$$

where h and h_{topo} are antenna height above geoid and local terrain elevation.

In this study, kz is 0.48 rad/m for both L- and P- bands PolInSAR data.

TABLE I. The details of L- and P-bands PolInSAR data

Band/Frequency	Parameters	Values
L/1300MHz	Image Id	0201(Master)/0209(Slave)
	Baseline (m)	24
	Incidence angle	25°– 55°
	Acquisition date	2008.10.15
	Range resolution (m)	8.33
	Azimuth resolution (m)	12
P/350MHz	Image Id	0103(Master)/0107(Slave)
	Baseline (m)	24
	Incidence angle	25°– 55°
	Acquisition date	2008.10.14
	Range resolution (m)	8.33
	Azimuth resolution (m)	12

3.1.2 Forest height derived from (Light Detection and Ranging) LiDAR

The laser mapping was conducted a couple of months earlier than the BIOSAR 2008 campaign took place. Forest height map (Fig.1) was created by LiDAR-derived canopy height model (CHM) and digital elevation model (DEM). The map is used for cross-validation of the estimated forest height by L- and P- bands PolInSAR data.

3.2 Methods

3.2.1 Random volume over Ground Model for forest height estimation

Random volume over Ground (RVoG) Model is a two-layer vegetation model, which was first derived in [2] and then extended for quad-polarimetric interpretation in [2,3], and currently were widely used for forest height inversion using PolInSAR data [6].

The equation of RVoG can be written as equation (4):

$$\Re(m) = \exp(i\phi_0)\frac{\gamma_v + \mu}{1+\mu} \tag{4}$$

where $\Re(m)$ represents the forward model vector output for a given scattering model and parameter m, here $\Re(m)$ means RVoG vegetation model, ϕ_0 is ground phase, μ is the ratio of effective surface-to-volume scattering, γ_v is the volumetric complex interferometric coherence and it is given as shown in equation (5):

$$\gamma_v = \frac{p_1(^{p_2 h_v} - 1)}{p_2(^{p_1 h_v} - 1)} \begin{cases} p_1 = \dfrac{2\sigma}{\cos\theta} \\ p_2 = \dfrac{2\sigma}{\cos\theta} + i \bullet kz \end{cases} \tag{5}$$

where h_v is forest canopy height, σ is the extinction coefficient, kz is the effective vertical interferometric wave number, θ is the local incidence angle.

3.2.2 Uncertainty estimation based on Bayes' theorem

The Bayesian framework ties together probabilities for any prior information we have for inversion model parameters, the error model for observations and the distribution we can expect for the inversion model given to the observed data. three key steps are involved in Bayesian methodology: 1) selecting a 'prior' distribution for the quantity of interest, 2) using the observed data to update the selected distribution in step 1), 3) converting the distribution to a 'posterior' distribution. The steps can be written as equation (6):

$$p(\theta \mid \mathrm{y}) = \frac{p(\mathrm{y} \mid \theta)\, p(\theta)}{p(\mathrm{y})} \tag{6}$$

where $p(\theta \mid \mathrm{y})$ is the posterior distribution function, $p(\mathrm{y} \mid \theta)$ is the likelihood function, $p(\theta)$ is the prior distribution function, and $p(\mathrm{y})$ is the marginal function.

3.3.3 Bayes' model based on RVoG

The Bayes' model based on RVoG applied in this study quantified the uncertainty coming from not only observation data, but also modeling errors and a priori knowledge. Moreover, the errors between observed and modeled coherence are affected by both errors in the data and errors in the model formulation, here we can use hierarchical Bayesian model to model the above-mentioned error. Then the Bayesian model based on RVoG and considering the errors between observed and modeled coherence are modeling as equation (7):

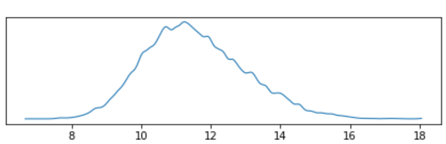
$$p\,(m,\sigma_r \mid \gamma,\Re(m)) \propto p\,(\gamma \mid m,\Re(m),\sigma_r)\bullet p(m)\,p\,(\sigma_r) \quad (7)$$

where $p\,(m,\sigma_r \mid \gamma,\Re(m))$ is the posterior distribution of the estimated values using RVoG, $p\,(\gamma \mid m,\Re(m),\sigma_r)$ is likelihood function, $p(m)$ is the priori distributions of h_v and σ, here we choose a Gaussian distribution for h_v and a uniform distribution for σ according their physical characteristics. $p\,(\sigma_r)$ is the priori distribution of observation errors, here an inverse gamma distribution is chosen for $p\,(\sigma_r)$.

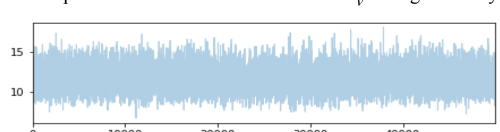
4. RESULTS AND DISCUSSION

4.1 Bayesian framework building for estimated h_v

The forest height h_v was computed with RVoG model and L-, P- bands PolInSAR data. The average values of the estimated h_v for L- and P- bands were selected as the average values of Gaussian distribution, the priori distribution function, and the standard value was set as 10 m. Then uniform priori distribution with bounds [0,1.5] were used for σ. Next, they were used to compute the posterior distribution of h_v, the calculated posterior distribution was shown as Fig 2. (a). Fig .2 (a) revealed that the posterior distribution of the estimated h_v looks like Gaussian distribution. Fig 2. (b) showed a generated h_v samples using the calculated posterior distribution at a single pixel, the time interval for sampling is 18 s.



(a) The posterior distribution of estimated h_v using RVoG by P-band

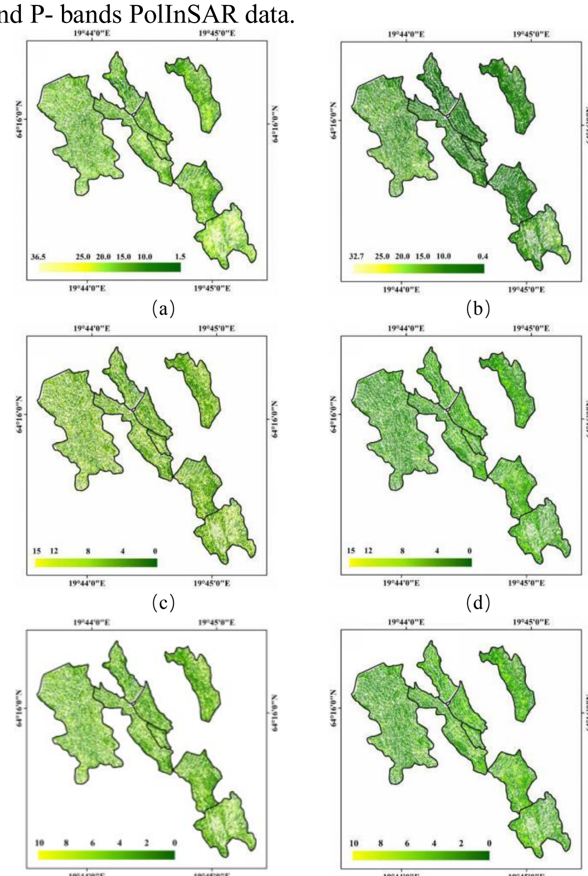


(b) Generated samples of h_v using the posterior distribution of (a)

Fig.2. Posterior distribution h_v of and the its generated samples

4.2 Uncertainties analysis

7 forest stands with different forest types were selected for uncertainties analysis of forest height estimation. The uncertainties were described by the absolute errors between estimated h_v by RVoG in Bayesian framework and the LiDAR derived forest height, and the standard deviation of the sampled h_v. Fig.3. shows the results acquired for both L- and P- bands PolInSAR data.



(a) (b) (c) (d) (e) (f)

Fig.3. Forest height estimation results in the study area. The maps show (a) estimated h_v using RVoG in Bayesian framework at L-band, (b) estimated h_v using RVoG in Bayesian framework at P-band, (c) absolute error between h_v and LiDAR derived heights for L-band, (d) absolute error between h_v and LiDAR derived heights for P-band, (e) standard deviation of the sampled h_v for L-band, and (f) standard deviation of the sampled h_v for P-band.

In general, areas associated with larger forest heights are associated with larger absolute errors and height standard deviations. Meanwhile, larger uncertainties also larger at stands covered with mixed forest tree species. Compared the results of L- band and P-band, the uncertainties of P-band shower greater than that of the L-band at the same pixels. It may result from the unsuitable bounds of σ for P-band. The bounds of the distribution of σ set in this study is [0,1.5], which is more consistent with the physical extinction phenomenon of L-band in forest area. It may not be consistent with the extinction of P- band in forest covered areas. Nonetheless, we found relatively good correspondence between our estimated tree height uncertainties (standard values in Fig.3 (e) and (f)) and the deviation between RVoG-derived and LiDAR-derived heights (pixel values in Fig.3 (c) and (d)).

To quantified the uncertainties of the estimated forest height, the scatter-plots of height uncertainty versus height were reported here as Fig.4. Fig.4 (a) show that height uncertainties increase with height monotonically at L- band, while at P-band, an obvious disturbance of uncertainties occurred at forests with lower height, its uncertainties show likely controlled by an inverse gamma posterior distribution. It may result from the complex scattering mechanisms of forest at P-band, which in turn resulted in the low coherences in P-band at the same areas compared with L-band. For L-band, most of the uncertainty values estimated for heights between 10 and 20 m lie in the interval of 0-2.5 m, indicating a similar uncertainty with the uncertainty of 10%-20% generally accepted in previous studies [4,7,8], which were reported in the PolInSAR forest height estimation community.

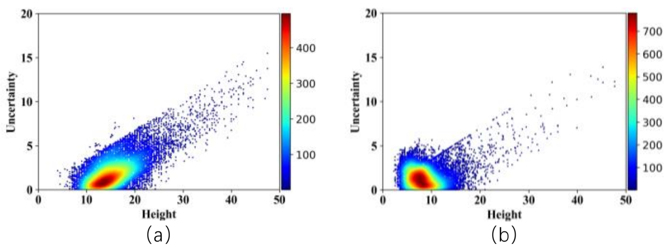


Fig.4. Scatterplots of height uncertainty versus height (a) for L-band, (b) for P-band,

5. CONCLUSION

In this paper, RVoG model in Bayesian framework is used for L- and P- band PolInSAR data forest height estimation and uncertainties analysis. Gaussian distribution and uniform distribution were selected as priori distribution function for estimated forest height and extinction coefficient, respectively. Then the posterior distribution of estimated forest height is computed and applied for sampling of each pixel in the estimated forest height maps for L- and P-band. The uncertainties of the estimated forest height were analyzed by compared with the LiDAR derived forest height. According to the comparison of absolute errors in RVoG-derived and LiDAR-derived heights with the uncertainties calculated by Bayesian framework (Standard derivation), we can conclude that the uncertainties of forest height estimation using RVoG model based on Bayesian framework is acceptable may effective than traditional uncertainties analysis ways. However, since we only considered the extinction effects in RVoG model, effects from other model parameters like temporal decorrelations or baselines on uncertainties of estimated results need further explored.

6. ACKNOWLEDGMENT

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