Monitoring Glacier Changes Using Multitemporal Multipolarization SAR Images

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Abstract—This paper presents a processing chain for the change detection of Arctic glaciers from multitemporal multipolarization synthetic aperture radar (SAR) images. We produce terrain-corrected multilook complex covariance data by including the effects of topography on both geolocation and SAR radiometry as well as azimuth slope variations on polarization signature. An unsupervised contextual non-Gaussian clustering algorithm is employed for the segmentation of each terrain-corrected polarimetric SAR image and subsequently labeled with the aid of ground-truth data into glacier facies. We demonstrate the consistency of the segmentation algorithm by characterizing the expected random error level for different SAR acquisition conditions. This allows us to determine whether an observed variation is statistically significant and therefore can be used for the postclassification change detection of Arctic glaciers. Subsequently, the average classified images of succeeding years are compared, and changes are identified as the detected differences in the location of boundaries between glacier facies. In the current analysis, a series of dual-polarization C-band Environmental Satellite (ENVISAT) Advanced Synthetic Aperture Radar (ASAR) images over the Kongsvegen glacier, Svalbard, is used for demonstration.

Index Terms—Matrix log-cumulant diagram, multilook product model, polarimetric synthetic aperture radar (PolSAR), postclassification change detection, radiometric terrain correction (RTC), unsupervised contextual non-Gaussian segmentation.

I. INTRODUCTION

Changes in the Arctic glaciers and ice caps provide a visible manifestation of climate change. Being recognized as potentially the largest short-term contributors to sea level rise and having been observed to be one of the fastest warming areas on the planet [1], the present state of the Arctic ice masses and the changes over time are of scientific and social importance.

As the climate changes, so too do the variables affecting glaciers. Identifying and monitoring fluctuations in glacier facies provide a means to track climate change. The only feasible method to obtain good spatial and temporal coverage of the Arctic glaciers is through the use of satellites. Spaceborne synthetic aperture radar (SAR) instruments, operating independently of weather and daylight, are a particularly valuable tool in Arctic areas. SAR has an added advantage over higher frequency instruments (visible and laser) because the signal penetrates some distance into the glacier such that the return signal is influenced not only by the surface but also by the shallow subsurface. Another advantage of SAR in glacier monitoring is its sensitivity to moisture content and surface roughness, which enables it to detect different glacial zones. The multipolarization SAR may provide the additional information and thus is a better tool for glacier monitoring than single-polarization SAR sensors.

It is appreciated that a difference in radar backscattering between multitemporal multipolarization SAR data may be caused by several factors such as actual land cover change, differences in viewing geometry, surface topography, differences in polarization configuration, and differences in meteorological conditions. These considerations motivate us to develop a processing chain for glacier change detection which consists of five major steps: 1) multilooking; 2) terrain correction; 3) probability density function (pdf) selection; 4) unsupervised segmentation; and 5) postclassification change detection. Models accounting for temporal variation in multitemporal multipolarization SAR images should separate useful temporal variation, i.e., land cover or seasonal changes from variation arising due to other factors mentioned earlier.

Spaceborne SAR instruments have proven to be a very useful tool for multitemporal image analysis. However, terrain topography has significant impact on the geometric and radiometric qualities of SAR images. For the geometric correction of topographic effect, the precise terrain geocoding of SAR data is required. This can be accomplished by using a digital elevation model (DEM) and precise satellite state vector. In addition to geometric distortions, surface slopes modulate SAR backscatter which can be split into two main effects. The first effect is the changes in radar cross sections (RCSs) per unit image area [2], [3], and the second effect is that polarization states are also affected since the terrain slopes, particularly azimuthal slopes, induce polarization orientation changes [4], [5]. Hence, before analyzing the data, terrain correction is a prerequisite for intercomparisons of multitemporal SAR images. This paper therefore addresses the precise geocoding and geometric terrain correction (GTC) of SAR data and then the radiometric terrain correction (RTC) of multipolarization SAR data that utilizes the pixel size normalization on each element of the sample covariance matrix [6]. Moreover, orientation angle compensation (OAC) is included immediately following after the RTC [7]. Accurate backscatter estimates enable more robust use of the retrieved values for our task of change detection, as well as other applications such as land cover classification, monitoring of changes, edge detection, and retrieval of geophysical parameters.
The scaled Wishart distribution, denoted by $sW_{d}^{C}$, is the simplest pdf to model multilooked polarimetric SAR data in homogeneous areas. Non-Gaussian probability distributions provide better representation of the data for areas with pronounced heterogeneity or high texture. Such distributions can be obtained using a matrix version of the product model. The product model describes the covariance matrix as the product of a positive scalar texture component and a Wishart matrix speckle component [8], [9]. Several statistical models have been proposed in the literature to describe the texture term. For textured areas, the $K_{d}$ model is commonly used (e.g., [10]). However, the analysis shows that this model does not always represent the data well. The $G_{d}$-distribution is another multivariate distribution [11] to model extremely heterogeneous data. The two-parameter Kummer-U distribution has been introduced by Bombrun et al. to model the polarimetric vector data [12]. We use its multilook extension, named the multivariate $U_{d}$-distribution, for multilook covariance matrix data. The flexibility of this model with respect to $K_{d}$ and $G_{d}$ with an extra texture parameter encourages the authors to use this model for multitemporal multipolarization SAR data. It is expected to yield improved results because of its flexibility to model more varied textures. Using the matrix log-cumulant diagram [13], we demonstrate the capability of the multivariate $U_{d}$-distribution to model multipolarization SAR data.

In this paper, we use an unsupervised contextual non-Gaussian clustering algorithm, named $U$-MRF in [14], to segment each terrain-corrected SAR scene. This contextual non-Gaussian clustering algorithm uses a Markov random field (MRF) model that integrates the $U_{d}$-distribution for the multipolarization SAR data statistics conditioned to each image cluster and a Potts model for the spatial context. The parameters of the $U$-MRF model are estimated by the iterative expectation–maximization (EM) algorithm [15] and Besag’s algorithm [16] in the segmentation process. Contextual information can improve the accuracy and robustness of the image segmentation and hence leads to improved change detection results. The theoretical approach proposed in this paper is general for multipolarization SAR data and applicable to dual-polarization and single-polarization SAR data, although with some restrictions.

The analysis utilizes several Environmental Satellite (ENVISAT) advanced synthetic aperture radar (ASAR) dual-polarization scenes over the Kongsvegen glacier, Svalbard, from spring 2004, 2005, and 2006, together with some ground-based field observations. Ground-truth data are used to label segmented images and to investigate the accuracy of classifications. We demonstrate consistency by comparing classified scenes taken on the same day and from different acquisition parameters (e.g., look angle). The surface of a glacier can be roughly divided into accumulation and ablation areas, separated by the equilibrium line (the dividing line between the accumulation and ablation areas) [17]. Monitoring the firm line position over time is of interest because there are indications that this line is correlated with the equilibrium line. Hence, we demonstrate the consistency of the classification results as firm area total variation between chosen no-change pairs to obtain the expected variation of the firm area boundary with the superimposed ice (SI) zone. Subsequent yearly classifications are discussed in terms of postclassification change detection, and changes are identified as the detected difference in the locations of boundaries between glacier facies.

This paper is organized as follows. In Section II, we define the backscatter quantities measured by a polarimetric synthetic aperture radar (PolSAR), namely, the scattering matrix, radar backscatter, and area normalized scattering vector. Section III describes the processing chain of time series analysis, including multilook processing, terrain correction, pdf selection, unsupervised segmentation, and postclassification change detection. Section IV introduces the study area and describes the example data. Section V demonstrates the results. Finally, conclusions from the presented research are given in Section VI.

II. Measurements from SAR Sensors

A full-polarimetric imaging radar measures the amplitude and phase of backscattered signals in the four combinations of the linear receive and transmit polarizations: HH, HV, VH, and VV. These signals are used to form a complex scattering matrix, denoted by $S = [S_{ij}] \in C^{2 \times 2}$, associated with each resolution cell in the image, which relates the incident and the scattered electromagnetic fields as follows [18]:

$$
\begin{bmatrix}
E_{h}^s \\
E_{v}^s
\end{bmatrix} = \frac{1}{R} \begin{bmatrix}
S_{hh} & S_{hv} \\
S_{vh} & S_{vv}
\end{bmatrix} \begin{bmatrix}
E_{h}^t \\
E_{v}^t
\end{bmatrix}.
$$

(1)

Here, $k$ denotes the wavenumber, $R$ is the (radial) distance between the radar antenna and target, and $j = \sqrt{-1}$ is the imaginary unit. The superscript of the electromagnetic field components indicates the incident ($i$) or scattered ($s$) wave. The term $(e^{-jkR}/R)$ takes into account the propagation effects both in amplitude and phase. The scattering matrix $S$, which holds the scattering coefficients in (1), can be vectorized and represented as the scattering vector $\mathbf{S}$,

$$
\mathbf{S} = [S_{hh}, S_{hv}, S_{vh}, S_{vv}]^{T} \in C^{4}
$$

(2)

where the superscript $T$ denotes the transpose of a vector or a matrix. Assuming that the target reciprocity condition is satisfied (i.e., $S_{hv} = S_{vh}$), the lexicographic scattering vector $\Omega$ with dimension $d = 3$ can be extracted from the scattering matrix as

$$
\Omega = [S_{hh}, \sqrt{2}S_{hv}, S_{vv}]^{T} \in C^{3}
$$

(3)

where the elements represent the complex backscattering coefficients in the three polarimetric channels and $\sqrt{2}$ arises from the requirement to conserve the total scattered power. The vectors $\mathbf{S}$ and $\Omega$ are single-look complex (SLC) format representations of polarimetric SAR data. Single- and dual-channel polarimetric data can be treated in a similar way as subsets of lesser dimension, and, most likely, proportionally less information.

The radar backscatter ($\beta$) of a given target measured in the range–azimuth coordinates for linear polarizations $r$, $t \in$
Multitemporal Multipolarization SAR Data

- Multilooking
- Terrain Correction
- PDF Selection
- Unsupervised Segmentation
- Postclassification Change Detection

Fig. 1. Processing chain of time series analysis for postclassification change detection.

\[ \{H, V\} \] can be obtained from the elements of the scattering matrix in (1) as follows [19]:

\[ \beta_{rt} = 4\pi |S_{rt}|^2. \] (4)

Both \( S_{rt} \) and \( \beta_{rt} \) are functions of spatial position, wave frequency, viewing geometry, wave polarization, geometrical structure, and dielectric properties of the object [18]. Expressions (1)–(4) represent the quantities which are directly measurable by a SAR sensor. The area normalized scattering vector in the slant range plane (subscript \( \beta \)) is defined as

\[ \Omega_{\beta} = \frac{\Omega_0}{A_\beta} \] (5)

where \( A_\beta \) represents the reference area of the \( \beta^0 \) backscatter coefficient that contributes to the recorded signal.

Fully polarimetric data are not always available because the wider coverage of dual-polarization or single-polarization modes are often preferred for monitoring purposes such as change detection. The different possible configurations of the dual-polarization mode systems are as follows: HH/HV, VV/VH, or HH/VV. Therefore, only a reduced version of \( \Omega \) is available. Single channels are also possible, generally in HH or VV.

**III. PROCESSING CHAIN FOR POSTCLASSIFICATION CHANGE DETECTION**

The time series analysis of multitemporal multipolarization SAR data for postclassification change detection in this paper consists of a processing chain with five stages, as depicted in Fig. 1, which can be used for both single-channel and multichannel SAR data. These stages are explained in detail hereinafter. The inputs are multitemporal multipolarization SAR images with different configurations.

**A. Stage 1: Multilooking**

To utilize the multitemporal polarimetric acquisitions, the scattering vectors for all acquisitions have to be coregistered. These scattering vectors are transformed into the form of multilooked sample covariance matrices in order to reduce speckle noise at the expense of spatial resolution [18], i.e.,

\[ C = \frac{1}{L} \sum_{\ell=1}^{L} \Omega_{\ell}\Omega_{\ell}^H \] (6)

where \( L \) is the nominal number of looks used for averaging and \( (\cdot)^H \) means the Hermitian transposition operator. Hence, after multilooking, each pixel in the image is a realization of the \( d \times d \) stochastic matrix variable denoted by \( C \), and the image is referred to as the multilook complex (MLC) covariance image. Note that the multilooking is performed as a type of speckle filtering, a simple boxcar filter. Some of the more advanced speckle filters cannot be applied because they invalidate the statistical modeling that is performed in the next stages.

**B. Stage 2: Terrain Correction**

Terrain topography influences both the placement of each observed point on the Earth’s surface and the brightness of the radar return in radar geometry [20], [21]. In this stage, we implement a three-step method to generate terrain-corrected polarimetric SAR images for time series analysis. The procedure consists of the following steps:

1) GTC;
2) RTC;
3) OAC.

1) **GTC:** The objective of SAR geocoding is to find the corresponding position on the Earth for each image pixel, thereby transforming from the SAR coordinate image into an Earth-based coordinate image. Since the satellite state vector is known from the orbit information, the position of each SAR pixel is estimated for a given earth model by solving the so-called range-Doppler equations [22]. Due to geometrical distortions caused by the side-looking geometry and rugged terrain, a one-to-one relation does not always exist between the radar and the geographic map coordinates [3]. Those pixels that are located in layover and radar shadow regions have to be masked out in this step. The importance of accurate geocoding of multitemporal imagery is obvious because largely spurious results of change detection will be produced if there is misregistration. In cases of misregistration, a number of false alarms, particularly in the region of rapid intensity change such as edges, occur. This necessitates the use of precise terrain geocoding of SAR data that not only registers the images to a standard map projection but also performs the GTC.

2) **RTC:** The normalization of SAR imagery for systematic terrain variations is required for meaningful single-sensor multitrack intercomparisons and postclassification change detection. Although the position of the backscatter estimate has after multilooking, each pixel in the image is a realization of the \( d \times d \) stochastic matrix variable denoted by \( C \), and the image is referred to as the multilook complex (MLC) covariance image. Note that the multilooking is performed as a type of speckle filtering, a simple boxcar filter. Some of the more advanced speckle filters cannot be applied because they invalidate the statistical modeling that is performed in the next stages.
on the covariance matrices. Provided that the data are already calibrated with respect to the elevation antenna pattern, range spreading loss, and channel-to-channel calibration, all elements of the covariance matrix in (6) can be simultaneously radiometrically corrected to the ground range area by

\[
C_{\text{RTC}} = \frac{\cos(\Psi)}{L} \sum_{\ell=1}^{L} (\Omega_{\beta^0})_{\ell} (\Omega_{\beta^0})_{\ell}^H = \cos(\Psi) \cdot C_{\beta^0} \quad (7)
\]

where \( \Psi \) is the projection angle between the surface normal and the image plane normal, which is assumed to vary between 0° and 90° and exclude layover areas [2].

All covariance matrix values now correspond to the \( \sigma^0 \) backscatter coefficient, which is equivalent to \( \sigma^0 = \beta^0 \cdot \cos(\Psi) \). The conventional radiometric normalization method, which relies on the local incidence angle only, is adequate for flatlands or for pixels with zero slope. The expected results are radiometrically “flattened” SAR images. The required parameters for performing the RTC are estimated in the geocoding step using an available DEM and satellite state vector. In cases of unavailable DEM, ellipsoidal based radiometric correction is achieved over an earth model such as WGS-84.

3) OAC: Since different scattering mechanisms (double bounce, surface scattering, and volume scattering) have different sensitivities to terrain topography, RTC is not sufficient for polarimetric applications to produce reliable results for scattering characteristics [6]. The last step of terrain correction is to compensate the polarization signature which is due to topography effects, specifically azimuth slope variations. Polarization orientation angle (POA) shifts are introduced by terrain topography slopes in the azimuth direction. These shifts make the covariance matrix reflection asymmetric and can be compensated based on the derived POA by DEM in [5]. When a DEM is not available, target decomposition-based methods are an alternative to estimate the azimuth slope-induced POAs directly from polarimetric SAR data [23]. After deriving the POA, the compensation can be done on all elements of the covariance matrices by

\[
C_{\text{OAC}} = R(\theta)C_{\text{RTC}}R^T(\theta) \quad (8)
\]

where \( \theta \) is the shift in the POA required to achieve the maximum copolarization response, \( R(\theta) \) denotes the rotation matrix [7], and \( C_{\text{RTC}} \) and \( C_{\text{OAC}} \) are the covariance matrices before (after the RTC) and after rotation, respectively.

For most natural backscatter media, reflection symmetry holds, meaning that the copolarized and cross-polarized channels are uncorrelated. However, azimuth slope variations may induce correlation between these channels. Subsequently, the OAC over images leads to reflection symmetric covariance matrix data. The data are now ready for quantitative image analysis, such as surface cover change detection.

C. Stage 3: PDF Selection

1) Multilook Product Model: The multilook polarimetric product model describes the terrain-corrected covariance matrix \( C \) as the product of two independent stochastic variables [8], [11] as

\[
C = ZW \quad (9)
\]

where the strictly positive unit mean scalar random variable \( Z \) models texture and represents the backscatter variability due to the heterogeneity of the RCS. The texture term is scalar because of the assumption of equal textural variations for all polarimetric channels. The second contribution, the speckle term \( W \), follows a scaled complex Wishart distribution [13], denoted by \( s\mathcal{W}_d^L(L, \Sigma) \), with parameters \( L \), the number of looks, and the scale matrix with \( \Sigma = E[Z] \). The marginal distribution for \( C \) may be derived by integrating the conditional pdf over the prior distribution of \( Z \), i.e.,

\[
p_C(C) = \int_{0}^{\infty} p_{C|Z}(C|z)p_Z(z)dz, \quad C|z \sim s\mathcal{W}_d^L(L, z\Sigma). \quad (10)
\]

The pdf of \( C \) depends on the specific model for the scalar texture variable \( Z \) [8], [9]. The simplest multilooked PolSAR model for the pdf of \( C \) is achieved with a constant texture parameter (i.e., the pdf of \( Z \) is the Dirac delta function, \( \delta(z - 1) \)) which is justified only for homogeneous regions of the image, and leads to the scaled complex Wishart distribution [13]. For areas with pronounced texture, non-Gaussian probability distributions provide better representation of the data. If the texture random variable is gamma distributed, the covariance matrix \( C \) follows the well-known \( \mathcal{K}_d \)-distribution [8], [24]. The \( \mathcal{G}_d^0 \)-distribution is another multivariate distribution [11], [25], which implies an inverse gamma distributed texture. The two-parameter multivariate Kummer-U distribution has been introduced in [12] to generalize the aforementioned pdfs to model PolSAR vector data, which implies a unit mean Fisher–Snedecor (FS) distributed texture with pdf given by [26]

\[
p_Z(z; \xi, \zeta) = \frac{\Gamma(\xi + \zeta)}{\Gamma(\xi)\Gamma(\zeta)} \xi^{-1} (\xi + z^{-1})^{\xi-1} (\zeta + 1)^{\zeta+1} \quad (11)
\]

\( \xi > 0 \) and \( \zeta > 0 \) are called the shape parameters. The flexibility of the FS distribution is controlled with these shape parameters to steer between the heavy head and heavy tail distributions. Lower values of \( \xi \) and \( \zeta \) represent significant texture, and higher values represent low texture. The resulting \( U_d \)-distribution for \( C \) is parameterized \( U_d(L, \Sigma, \xi, \zeta) \) and is given in closed form as [27]

\[
p_{C}(C) = \frac{L^d}{\Gamma_d(L)} \left| C \right|^{L-d} \frac{\Gamma(\xi + \zeta)\Gamma(Ld + \zeta)}{\Gamma(\xi)\Gamma(\zeta)} (\frac{\xi}{\xi + 1})^{\xi-1} \left( \frac{\zeta}{\zeta + 1} \right)^{\zeta+1} \times U \left( \frac{Ld + \zeta}{Ld + \xi + 1}, Ltr(\Sigma^{-1}C) \right) \quad (12)
\]

where \( \text{tr}(\cdot) \) and \( |\cdot| \) denote the trace and determinant operators, respectively, \( d \) is the number of polarimetric channels, and
Fig. 2. SAR intensity image of field site Kongsvegen (shown on a universal transverse mercator coordinate system) located on the northwest of Svalbard (inset). The three zones of interest, GI, SI, and firn, can be visibly identified by their dark, medium, and bright intensities, respectively. The green frame shows the area of interest to be analyzed further. The glacier center line extends from the (lower right) firn area into the (upper left) GI zone.

Fig. 3. Daily air temperature and precipitation observed in Ny-Ålesund between 2004 and 2006. Data are from the Norwegian Meteorological Institute. The black/red bars between the temperature and precipitation represent the times of SAR acquisition. The black bars indicate the chosen SAR images based on the temperature and precipitation constraints, listed in Table I, for time series analysis.

\[ \Gamma_d(L) = \pi^{\frac{d(d-1)}{2}} \prod_{i=1}^{d} \Gamma(L - i + 1). \]  

(13)

\( \Gamma_d(\cdot) \) is a normalization constant, the multivariate gamma function of the complex kind in [13], while \( \Gamma(\cdot) \) is the standard Euler gamma function. \( U(\cdot, \cdot, \cdot) \) denotes the confluent hypergeometric function of the second kind (KummerU). \( L \geq d \) ensures that \( C \) is nonsingular.

2) Parameter Estimation of the \( \mathcal{U}_d \)-Distribution: Based upon the Mellin transform theory, in [13], the method of matrix log-cumulants (MoMLC) has been proposed to estimate the shape parameters of the FS distribution pdf. It has proved to be an effective estimation approach associated with the multilook product model. More details on the MoMLC for the parameter estimation of the \( \mathcal{U}_d \) model can be found in [13]. It is essentially a minimum distance search in the log-cumulant domain.

3) Evidence for \( \mathcal{U}_d \)-Distribution: The matrix log-cumulant diagram, which was proposed by Anfinsen and Eltoft in [13]
as a visualization tool for textured multilook multipolarization SAR data, is used to compare data with the potential distribution models. It is expected that $U_d$ can be a suitable pdf for polarimetric SAR scenes because of its flexibility to capture highly varied textures and to model both the heterogeneous and the homogeneous clutter. In addition, it includes the $sW_d, K_d$, and $G_0^d$ as asymptotic cases as follows:

$$\lim_{\zeta \to \infty} U_d(L, \Sigma, \xi, \zeta) = K_d(L, \Sigma, \alpha)$$

$$\lim_{\xi \to \infty} U_d(L, \Sigma, \xi, \zeta) = G_0^d(L, \Sigma, \eta)$$

$$\lim_{\xi \to \infty, \zeta \to \infty} U_d(L, \Sigma, \xi, \zeta) = sW_d^c(L, \Sigma)$$

where $\alpha$ and $\eta$ denote the texture parameters of the $K_d$ and $G_0^d$ distributions, respectively.

D. Stage 4: Unsupervised Segmentation

An unsupervised non-Gaussian contextual segmentation method is used that combines an advanced statistical distribution with spatial contextual information for MLC data. It is based on an MRF model that integrates a $U_d$-distribution for the polarimetric SAR data statistics conditioned to each image cluster and a Potts model for the spatial context [14], [28]. Specifically, the proposed algorithm is constructed based upon the EM and Besag’s algorithms. The resulting algorithm works in an iterative manner to jointly address the parameter estimation of the $U_d$-distribution and the spatial context model and also the minimization of the energy function [29]. More details about the clustering algorithm can be found in [14]. We obtain unlabeled segmentation results which then need additional knowledge to align classes for comparison. Therefore, ground-truth data are used to label segmented images and also to obtain overall classification accuracies.

E. Stage 5: Postclassification Change Detection

Postclassification change detection can be viewed as a particular case of the multitemporal image classification problem. This approach for change detection requires very high accuracy of the classification results from the previous stage. We believe that using the unsupervised contextual non-Gaussian segmentation method on terrain-corrected SAR scenes results in a robust segmentation which improves also the reliability of change detection. Since the class labels match on all images, we investigate changes for consistency and postclassification comparison change detection. The consistency of the segmentation method is characterized by comparing segmentation results of scenes taken on the same day (assumed “no change”) with different acquisition parameters. This allows us to determine whether an observed variation is statistically significant and therefore can be used for postclassification change detection of Arctic glaciers. Subsequently, the classified images of succeeding years are compared, and changes are identified as the detected differences in the location of boundaries between glacier facies.

### TABLE I

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<td>IS3</td>
<td>des</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_29</td>
<td>17 May 2005</td>
<td>IS2</td>
<td>des</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_30</td>
<td>21 Feb 2006</td>
<td>IS2</td>
<td>des</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_31</td>
<td>15 Apr 2006</td>
<td>IS6</td>
<td>asc</td>
<td>HH/HV</td>
</tr>
<tr>
<td>I_32</td>
<td>16 Apr 2006</td>
<td>IS2</td>
<td>des</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_33</td>
<td>17 Apr 2006</td>
<td>IS2</td>
<td>asc</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_34</td>
<td>19 Apr 2006</td>
<td>IS4</td>
<td>asc</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_35</td>
<td>20 Apr 2006</td>
<td>IS2</td>
<td>asc</td>
<td>VV/VH</td>
</tr>
<tr>
<td>I_36</td>
<td>20 Apr 2006</td>
<td>IS3</td>
<td>des</td>
<td>VV/VH</td>
</tr>
</tbody>
</table>

The differences between classified pairs can only be considered significant change when compared to that of the classification total variation.

IV. STUDY AREA AND DATA SET DESCRIPTION

The glacier Kongsvegen situated at approximately 78° 50' N and 13° E in the northwest of Spitsbergen, Svalbard, close to the meteorological station Ny-Ålesund is selected for the workflow presented in Section III. Kongsvegen is a surge-type glacier about 25 km long, covers an area of approximately 100 km², and is oriented in a northwest–southeast direction extending from an elevation of 800 m above sea level to sea level. The glacier has a flow velocity of < 4 m a⁻¹ and is thus a very slow moving glacier.

The satellite data set consists of a time series of correctly calibrated acquired SAR images for the period 2004–2006 over the glacier. The images are generally collected under different acquisition configurations. The series consists of dual-polarization C-band ENVISAT ASAR images in alternating-polarization mode from both ascending and descending orbits
and in both HH/HV and VV/VH polarizations, over a large range of look angles from 14° to 43° (swath angles IS1 to IS7). As seen in Fig. 2, the satellite flight path is across the glacier with the SAR looking down the glacier for a descending orbit. In ascending orbits, the satellite track is approximately parallel to the glacier center line; thus, the SAR look direction is across the glacier. The initial resolution of the raw SAR SLC images is 7.8 m in the slant range and 3.2 m in the azimuth direction. The SAR intensity image in Fig. 2 shows the spatial variability of the three different distinct zones across the glacier. Each zone has specific backscatter characteristics. In the upper parts of the glacier where firn accumulation occurs, layers dominated by large firn grains and ice layers cause considerable volume scattering on the ENVISAT SAR wavelength, leading to high backscatter [30]. The SAR signature in the ablation area is dominated by backscatter from the previous summer surface. In the SI area, varying fractional volumes of bubbles cause the coherent and the incoherent scattering, likely causing medium backscatter values. Although the previous summer surface still contributes, the increase in total backscatter, which determines glacier ice (GI) from SI, is caused by the air bubbles [17]. The GI does not reflect much of the incoming SAR signal back to the sensor, resulting in low backscatter values.

A DEM of 20-m pixel resolution covering all of Svalbard was also available, which was produced by the Mapping Section of the Norwegian Polar Institute (NPI). Ground-truth data are derived from a network of C-band ground penetrating radar (GPR) profiles oriented parallel to the glacier center line collected by the NPI in 2005 under the same spring conditions as the ASAR images. GPR is commonly used in glaciology for mapping layers within the glacier such as internal accumulation layers and the previous summer surface, as well as bedrock topography [31]. The differential GPS was used to determine the position of the GPR profiles with a horizontal accuracy within 10 cm. The C-band GPR is a step-frequency continuous-wave radar operating at 4.8–5.8 GHz. The center frequency of 5.3 GHz is the same as the ASAR instrument on board ENVISAT [32]. Details of the GPR data are given in [32] and [33]. The along glacier profiles have been manually classified into three zones of interest, i.e., GI, SI, and firn.

Meteorological conditions also affect the backscatter in addition to the SAR imaging geometry and surface topography effects as discussed in Section III-B. Therefore, from the temperature and precipitation observations of the Ny-Ålesund station, located at sea level about 15 km west of the terminus of Kongsvegen, we select only SAR images collected in spring under cold and dry conditions on the glacier surface (see Fig. 3). In cases of wet conditions, scattering occurs only at the wet-snow surface, and the underlying GI has no influence on the measurements. When just a small amount of liquid water is present in the upper layer of snow and firn, the radar backscatter properties change significantly [30]. However, in early spring, the snow pack on the glacier surface is mostly dry, and the previous summer surface at the base of the winter snow pack

![Fig. 4. Terrain correction parameters of the covered area in the map geometry. (a) Slope angle map in degrees. (b) Shadow/layover mask produced from the geocoding step. (c) Projection factor. (d) DEM-derived POA in degrees.](image)
gives the strongest return. Thus, this is the time of the year that the SAR signal incorporates the longer timescale signal recommended to collect the SAR data for monitoring temporal changes of the glacier [33]. We refer readers to [34] for more details on the influence of wet conditions on radar response. The authors demonstrated a good example image coinciding with the onset of rain in the meteorological records, and an image taken after the onset of rain clearly showed significant change compared to the day before. The suitable SAR images are chosen based on the temperature and precipitation constraints. The remaining images for the time series analysis are listed in Table I.

V. EXPERIMENTAL RESULTS

We now use the proposed workflow in Section III to analyze multitemporal dual-polarization SAR data for glacier change detection.

The raw SLC data are geocoded and multilooked simultaneously to a final geocoded resolution of approximately $30 \times 30$ m. The SLC image pixels were multilook averaged with two looks in the range direction and 12 looks in the azimuth, giving 24 looks in total. We have chosen 24 looks for the multilooking because it is a moderately large degree of multilooking and would achieve a high degree of speckle reduction. The 30-m ground resolution is good enough for the monitoring purpose in glacier areas.

The reconstruction of radar geometry with the help of DEM, the known orbit data vector, and image-line timing is done for each ASAR image. This stage derives not only the geocoding lookup tables but also various geometrical parameters for each ground point that are required for terrain corrections, such as local incidence angle, and also generates the layover-shadow mask. The pixels affected by the geometrical distortions are mainly located at slopes larger than $40^\circ$. The Kongsvegen glacier has a gentle surface slope of $0.5^\circ$–$5^\circ$, and therefore, such geometric corrections will be minimal over the glacier region.

The radiometric normalization of the covariance matrix data was then applied for each scene. Although the glacier slopes are generally small, if left uncorrected, they may manifest as misclassification of the glacier class boundaries. The projection factor is shown in Fig. 4(c) as an example. The backscatter coefficient is reduced when using the projection factor to radiometrically correct the covariance matrix data. The negative projection factors (the projection angles larger than $90^\circ$) correspond to the dark blue areas in Fig. 4(c) and red areas in the slope map. These areas are mostly affected by layover and, in the geocoding step, have to be masked out, as seen in Fig. 4(b). The DEM-derived POAs are used to correct for the azimuth
slope effect on the polarization signature. By estimating the POA for the data [see Fig. 4(d)], we observe that, for the rugged-terrain areas surrounding the glacier, the polarization shifts are more significant. Subsequently, the OAC over images leads to reflection symmetric covariance matrix data sets.

To demonstrate the effect of both RTC and OAC on the covariance matrix data, the profile along the glacier center line was plotted for the four images with different geometries. It should be mentioned that the middle of the three GPR ground-truth lines in Fig. 6 follows the glacier center line extending from the firn area into the GI zone. The original backscatter coefficient, RTC, and OAC values are shown with red, green, and blue lines, respectively. The reduction of the backscatter coefficient is geometry dependent, which shows the suppression of the SAR geometry effects on the data such that the images are comparable for the monitoring purpose. For example, the offset between original backscatter and RTC backscatter for the look angle IS1 is larger than that for the look angle IS7 (see Fig. 5).

The total backscatter power ($\text{Span} = C_{11} + C_{22}$) in Fig. 5 does not change significantly after OAC except some small changes for the pixels located at the higher azimuth slopes. For those pixels, the total power increased after the OAC.

To evaluate the capability of the $U_d$ pdf to model the variable texture of the polarimetric SAR data set, the second and third sample log-cumulants ($\kappa_3, \kappa_2$) are computed on a sliding window of size $5 \times 5$ [26]. Matrix log-cumulant diagrams are plotted for each scene of the multitemporal data (see Fig. 6). In the diagrams, the $K_d$ and $G_0^d$ are represented by the red and blue curves, respectively. The junction of two curves is the point which represents the nontextured $sW_d$ pdf. The $U_d$-distribution covers the light yellow space between the red and blue curves. The Whittaker $W$ and $M$ pdfs are not considered in this paper. The clusters of sample matrix log-cumulants plotted in Fig. 6 represent targets that have been selected from four example scenes with different configurations. In the diagrams, the collection of sample matrix log-cumulants for...
The firm, SI, and GI samples are shown as yellow, blue, and red dots, respectively. The variation in the clusters for each zone in the different scenes reveals that the statistical texture properties are dependent on external factors like the acquisition geometry. The cluster centers, and hence the data model, seem to fall within the $U_d$-distribution region, even though some of the elliptical scatter clouds fall outside the region. This indicates that $U_d$ pdfs can suitably model the entire multitemporal multipolarization data set and are good fits to the data classes, resulting in improved segmentation results. The observed elliptical scatter for each class is caused by natural variation and estimator inaccuracy for the finite/small sample sizes being measured.

A mask is applied to mask out mountains and isolate the glacier pixels for classification. The segmentation algorithm was working with $2 \times 2$ covariance matrix data. Unsupervised contextual non-Gaussian segmentation was then performed using the $U_d$-MRF classifier on the terrain-corrected dual-polarization data set. We fix the number of clusters to three for the segmentation. Fig. 7 shows the segmentation results for three SAR images as candidates from each year of the study period. In Fig. 7, the bottom figures depict class histograms and fitted model pdfs of the entity trace$(\Sigma^{-1} \mathbf{C})$ for all classes produced by the $U_d$-MRF classifier and give a visualization of the goodness of fit of the models. In all cases, the model fit of the class histograms is good. Since the three surface types (GI, SI, and firm) have distinct backscatter characteristics, they can be reliably discriminated in the segmented images. The firm line, i.e., the boundary between SI and firm, is detected in all segmentations. The boundary between SI and GI is also detected. The segmentation results are now validated using in situ observations. The three GPR ground-truth lines acquired in 2005, shown in Fig. 6, are used to label the segmented images into glacier facies and to validate the classification results. The validation is only performed on scenes acquired in spring 2005 that are within a few weeks of the GPR data. Table II reports the overall classification accuracies and omission errors of the glacier zones for the 2005 images. The classification accuracies for the scenes indicate overall accuracies higher than 80% for all cases. We did not find any obvious preference among different configurations because the geometric and radiometric terrain corrections should suppress the effects of both SAR
After consistency characterization, the classified images are compared and analyzed on a pixel-by-pixel-based analysis to form a change matrix which describes the mapping of classes between the images. From this matrix, we can extract a simple map of change versus no change and also more detailed information on the nature of the change. We take the average of several yearly classified images of the study period for change detection analysis. Fig. 8 shows the change images of the glacier within the periods of study (2004–2005, 2005–2006, and 2004–2006). It illustrates changes in the locations of boundaries between glacier facies. The firm line monitoring is important for glaciologists; thus, we concentrate only on the variation of the firn area boundary with the SI zone in the quantitative analysis. The total variation of the firm line in terms of both PGM and TCAE (firm to SI) and ELD for change detection pairs are estimated to verify whether significant changes occur for the periods. Table IV indicates the measure of variations of the firn/SI boundary for those periods. The differences between averages of yearly classified images can only be considered significant when compared to that of the classification total variation. By taking the average classification result over each year, the expected variation of 128 m (between scene pairs with differing configurations) will decrease by \( \sqrt{N} \) for the mean, where \( N \) is the number of scenes used in the averaging. Therefore, we obtain the reduced variation in the mean of 52.24, 26.72, and 47.58 m for the years 2004, 2005, and 2006, respectively, to be used when testing significance. The total variation of this boundary found between 2004 and 2005 exceeds the expected classification variation, which indicates significant change for this period. The same is found for the periods 2005–2006 and 2004–2006. The total movement of approximately 200 m toward the top of the glacier is obtained for the whole period.

VI. CONCLUSION AND DISCUSSIONS

This paper addressed glacier change detection from multitemporal multipolarization SAR images. A robust algorithm for firm line monitoring was developed. This suggests that we have a tool for glacier change detection and monitoring that is applicable over the Arctic region on a timescale of a few years. The recent findings may form the basis for more operational monitoring of Arctic areas, which may be even more successful with more capable satellite sensors.

It is noted that, when a difference in radar backscattering between multitemporal data is taken as a change indicator, the difference may be due to several factors such as actual land cover change, viewing geometry, surface topography, and other external factors (such as meteorological conditions that are minimized by using radar frequencies and choosing the scenes wisely). These considerations were the main reason for developing a complete workflow for postclassification change detection from the time series of polarimetric SAR images and where we also choose our SAR images to avoid the wet weather conditions.

The algorithm has been tested on dual-polarization ENVISAT ASAR images for the period 2004–2006 over the Arctic glacier, Kongsvegen, Svalbard. The images are first corrected for geometry and surface topography on the covariance matrix data sets.

Next, the images that have been taken on the same day with different geometries are chosen as pairs for the consistency investigation of the classification results. Table III is a list of the total variation of the firm line for given pairs and is an indicator of the variability of this boundary in terms of the percentage of the glacier mask (PGM), the total change area error (TCAE), and the equivalent linear displacement (ELD) along the glacier. Among these three indicators, the ELD may be a very robust indicator because the other two depend on the size of the glacier and the accuracy of its mask. An average ELD error of 128 m is obtained between the pairs which is for the worst case variation between different configurations. This variation may include the effect of different collection geometries, the segmentation algorithm, and other processing errors. Similar geometries and the segmentation itself should have much reduced variability. Basically, if we have a collection of a time series using data acquired from similar geometries (i.e., interferometric pairs), then we could anticipate reduced variation and better change detection ability. In such cases, we may not need to perform RTC for change detection.

<table>
<thead>
<tr>
<th>Image 1</th>
<th>Image 2</th>
<th>PGM</th>
<th>TCAE (m²)</th>
<th>ELD (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I₂</td>
<td>I₃</td>
<td>1.36%</td>
<td>763200</td>
<td>120.74</td>
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<tr>
<td>I₁₃</td>
<td>I₄</td>
<td>0.63%</td>
<td>354600</td>
<td>57.70</td>
</tr>
<tr>
<td>I₁</td>
<td>I₂</td>
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<td>1017000</td>
<td>179.52</td>
</tr>
<tr>
<td>I₂₄</td>
<td>I₂₅</td>
<td>1.55%</td>
<td>869400</td>
<td>153.20</td>
</tr>
</tbody>
</table>

This table lists the consistency characterization of the Kirkenes glacier study area for the period 2004–2005, 2005–2006, and 2004–2006. For the study, the average of yearly classified images can only be considered significant when compared to that of the classification total variation. By taking the average classification result over each year, the expected variation of 128 m (between scene pairs with differing configurations) will decrease by \( \sqrt{N} \) for the mean, where \( N \) is the number of scenes used in the averaging. Therefore, we obtain the reduced variation in the mean of 52.24, 26.72, and 47.58 m for the years 2004, 2005, and 2006, respectively, to be used when testing significance. The total variation of this boundary found between 2004 and 2005 exceeds the expected classification variation, which indicates significant change for this period. The same is found for the periods 2005–2006 and 2004–2006. The total movement of approximately 200 m toward the top of the glacier is obtained for the whole period.
for terrain effects by thoroughly reducing topographic effects on both geolocation, radiometry and polarization signature, and subsequently stacked into proper time series for further analysis. This is an important step for a meaningful time series analysis.

We showed in [28] that the $K_d$ distribution can be used to model SAR image texture. However, the analysis shows that this model does not always represent the data well. We then use a more flexible model, the multivariate $U_d$-distribution, for multilook covariance matrix data. The flexibility of this model with respect to $K_d$ and $G_0$ with an extra texture parameter is evident, which covers more of the space of the matrix log-cumulant observed in multitemporal dual-polarization SAR images. It is expected to yield improved results because of its flexibility to model more varied textures. The matrix log-cumulant diagram was demonstrated for each scene to visualize the capability of the $U_d$-distribution to model texture observed in multitemporal dual-polarization SAR data over this glacier.

We then applied an unsupervised contextual non-Gaussian clustering method, named $U_d$-MRF, over the terrain-corrected SAR scenes. The unsupervised segmentation algorithm, together with the DEM-based terrain correction, is reliable and robust enough to give consistent change detection results. It should be mentioned that the example glacier was only a very slow moving glacier and the annual change is small. A faster glacier, or other more drastic change examples like deforestation, would likely work much better. Ground-truth data are used to label segmented images into the three major classes of glacier facies, i.e., firn, GI, and SI, and to investigate the classification accuracies.

We then characterized the consistency of the classification as the total variation of the firn/SI boundary between two no-change images to obtain the expected variation just due to processing errors in the processing chain. Finally, we did post-classification change detection analysis based on the classified images on a pixel-by-pixel-based analysis. The variations of the boundaries between glacier facies were clearly detected within the period of study. The variation for the two-year period, 2004–2006, exceeds the measured classification variation and thus shows significant change for this period, although one year differences were not significant. The fact that we only detect a significant change over two years (with respect to the ELD) is clearly glacier specific. Glaciers in other areas that undergo significant changes may lead to results over a single year.

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REFERENCES


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