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Technical Communication

Polarimetric Classification in a Tailings Deposition Area at the Timika Mine Site, Indonesia

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Abstract. Preliminary results indicate that polarimetric synthetic aperture radar (SAR) data can be useful in characterizing remote tailings sites in Indonesia. Recent launches of polarimetric radar satellites offer new opportunities to use such data. Wishart polarimetric radar classification was used to map tailings conditions and vegetative stress. We assessed the accuracy of our analysis and found that almost all scatterers could be discriminated properly, and that the technique was particularly useful in distinguishing saturated versus relatively dry tailings. Since tropical regions are subject to severe atmospheric disturbances, tailings stability is a major issue; there is thus high potential value in using radar remote sensing to aid revegetation and tailings stabilization.

Key words: Freeman-Durden decomposition; Indonesia; mining; SAR polarimetry; Wishart classification; tailings

Introduction

Tropical regions are a major focus for remote sensing research because of the difficulties of scale, cloud cover, and access. A wide range of sensors have been used, with a historic emphasis on optical remote sensing, but such data are affected by atmospheric conditions. In Indonesia, many areas are persistently cloud covered and optical data acquisition is difficult. Active systems such as synthetic aperture radar (SAR) provide a useful alternative, either as a complement to optical systems or to derive value-added information, such as a digital terrain model.

SAR data have mostly been delivered to users in single polarimetric form. Despite their all-weather capabilities, this has limited its utility. Fully-polarized data can be obtained from airborne systems such as AirSAR or ESAR, but this does not provide the continuous monitoring required in many applications, such as forestry or tailings management. Using fully-polarized airborne SAR data, researchers have used the approach in agricultural research (Skriver et al. 2005) and to study forest properties at different sites, including the Amazon (Quinones and Hoekman 2004). SAR data have also attracted hydrologists. An important example was presented by Paloscia et al. (2004) based on a multi-sensor dataset using AirSAR and Shuttle Imaging Radar SIR-C/X-SAR. Recently, efforts have been made to provide fully-polarimetric data from a spaceborne platform. This was initiated by the ESA Envisat program, and followed by the Japanese ALOS and Canadian Radarsat-2 programs.

SAR sensors have been designed to be sensitive to terrain. Hence, the imagery is useful for terrain-related applications, such as geology or mining. Most recent assessments of geology and mining have been limited to single polarimetric data, using SAR interferometry techniques (Smith 2002).

An application of particular interest is the management of mine tailings. A wide range of remote sensors have been exploited, frequently using airborne-mounted sensors. Spaceborne optical data such as Landsat have been used to extract environmental conditions near tailings deposition (e.g. Paull et al. 2006). Multi-spectral data have limited utility for tailings characterization, but several papers have reported successful use of hyperspectral sensors, which can discriminate diverse surface materials (Swayze et al. 2000).

Tailings deposition is a major issue in environmental management, particularly in Indonesia, where it often causes disputes about public health and the local economy. Paull et al. (2006) reported on such problems, focusing on the communities of Amungme and Kamoro, in the highlands and coastal regions, respectively. Local awareness of health issues associated with environmental degradation has increased since gold mining apparently caused an unknown skin disease that affected several people in Minahasa (North Sulawesi) in 2004. Heavy metal contamination of water and soil has also been associated with gold mining in other countries (Florea et al. 2005; Ogola et al. 2002). It is clear that monitoring the environmental impact of tailings benefits many stakeholders, including the mining companies. Where extensive in-situ monitoring is not feasible, remote sensing can be used to assess potential problems and to prepare for more detailed field surveys.

In Indonesia, the reclamation of mined land, especially for agricultural activities, can be improved by using updated spatial data. Information on soil moisture conditions is especially critical in remediation of tailings deposition zones; reclamation is much more likely to succeed in relatively dry conditions, where and when the effects of mine drainage are minimal, allowing suitable soil treatments. This paper evaluates the use of Wishart classification to assess vegetation conditions over time and the potential effect of mine water on revegetation efforts.

Polarimetric Radar Data Analysis

Scatterers Characterization

Characteristics of surface objects have been the key to data extraction from remotely-sensed radar data. Previously, earth surfaces were studied by means of statistical properties retrieved from backscatter data. Instead of only using statistical properties, polarimetric decompositions simultaneously account for both physical and statistical attributes of scattering objects.

One of the broadest decomposition techniques is the Cloude-Pottier algorithm, which decomposes natural scatterers into two basic features, entropy and alpha angle (Cloude and Pottier 1997). Polarimetric scattering entropy is a statistical parameter that defines a global measure of the component distribution of the scattering process. The alpha angle represents the different types of scattering.

Freeman and Durden (1998) observed that previous decomposition theorems, including Cloude-Pottier, tend to be mathematically-based, and may not easily correlate with physical scattering models. They published an alternative method to decompose target scattering matrix into volume, odd, and double bounce scattering components.

Polarimetric Classification

Polarimetric classification is an important development enabling the study of bio-physical properties from polarimetric data (Pottier 2005). Generally, classification approaches using polarimetric radar data involve two types of data. The first approach uses backscatter or amplitude radar data; hence, no complex data are involved. This approach is rather simple to implement and is mainly based on image processing. A number of reports using this approach have been presented, e.g. decision trees (Ferrazzoli et al. 1997). Since phase data contained in fully polarimetric data have proven to be useful, recent studies suggested using full and phase-preserved complex data.

The second classification approach represents complex data in covariance or coherence matrices to ensure that all information is kept. The Wishart classification algorithm (Lee et al. 1994) has been widely employed. The corresponding development of polarimetric decomposition techniques has opened a new perspective in classification procedures. Extension of Wishart classification incorporating polarimetric decomposition was presented by Lee et al. (2004).

Methodology

Data Set

During 2000, JPL launched the PACRIM tour to Pacific countries, including Indonesia. AirSAR was flown in two main sites in Indonesia, namely Sungai Wain (East Kalimantan) and Timika (Papua). The Timika site is interesting because of the range of surface scatterers included forests, tailings deposition areas, and agricultural fields. The tailings are on a mine site that has been operated by Freeport-McMoRan since the early 1970s. Mine waste is transported through a natural stream into the Ajkwa deposition area (ADA) at a rate of approximately 125,000 t/day (Brunskill et al. 2004).

Figure 1 is a map of the site location. The flight direction was east-west along the lowland region. Hence, it covered relatively flat terrain. Due to the large amount of data, we selected smaller regions to cover a forested and a tailings area. C-band data were chosen to allow us to compare our findings with data from the future Radarsat-2 sensor.

Data Processing

A preliminary assessment was made by visual analysis. This step was useful in identifying surface scatterers. Visual analysis involved the creation of a polarimetric composite image. We used the Pauli composite algorithm on a linear polarization (H, V) basis. Pauli decomposition has been widely used by previous researchers, e.g. Karathanassi and Dabboor (2004). We compared our results with Landsat ETM+ composite imagery for confirmation. Prior to image analysis, the data were filtered using Lee's polarimetric speckle filter. In order to maintain a low noise level and boundary preservation, we used a window size of 5x5.

The scattering matrix presented after raw data extraction was then converted into a coherence matrix.

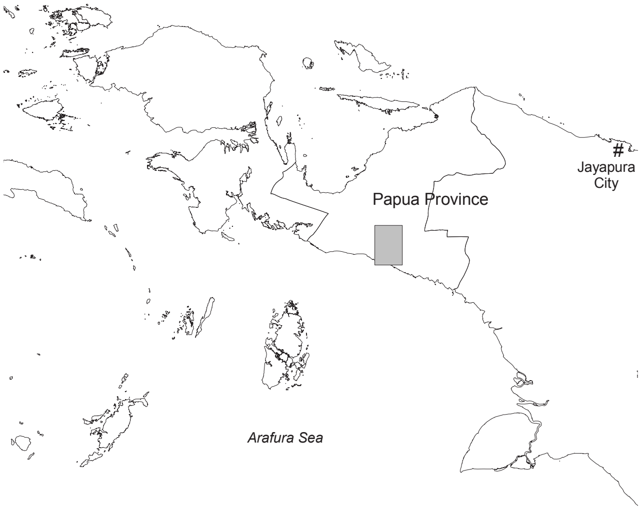

Figure 1. Site location; the Timika site is shown as a grey box.

Next, Freeman-Durden decomposition was applied to the data. This resulted in three derivative features, called three component scattering data. Again, visual analysis was taken in order to comprehend surface features and their relation to volume, odd, and double bounce scattering mechanisms. For quantitative analysis, the coherence matrix was then fed to the Wishart supervised classification algorithm. We extended this analysis using an accuracy matrix to evaluate the overall robustness of the method.

Results and Discussion

Polarimetric Characteristics in the Tailings Deposition Zone

The composite image created from Pauli decomposition was used to assess the region and to determine training sites. We selected five locations based on the image and confirmed by Landsat ETM+ and field data. Each location represented a distinct surface scatterer. Five classes were then considered: undisturbed forest, stressed vegetation, water, and dry and wet (largely saturated) tailings. Undisturbed vegetation in the Pauli image appeared bluish green, whereas stressed vegetation was in pale green. Different scattering components of these types of vegetation were indicated. Dark blue represented water bodies. Depending on the wetness, dry tailings were represented in reddish colors, while wet tailings were in purple. Keys of interpretation for forest and water bodies were then confirmed by comparing their polarimetric signatures with a previous result (van Zyl 1986). There were no available comparison data for the other three classes. However, we observed similar patterns between dry tailings and bare soil and between wet tailings and water. These suggested our development in key interpretation was quite reliable.

Freeman-Durden decomposition was one of the important steps used to derive meaningful information about each scatterer's characteristics. Three-component data were then presented as images (Figure 2). Vegetated areas were clearly discernible, and were best represented by the volume scattering component, as was observed by van Zyl (1986). In order to distinguish vegetation conditions, two scattering components can be used simultaneously, i.e. volume scattering and double bounce. Since stressed vegetation stands lose their leaves, such plants can be discriminated from healthy ones using data provided by the double bounce image. In C-band polarimetric data, healthy vegetation tends to have strong volume scattering and a relatively weaker response in the double bounce, due mainly to the fact that leaves are the dominant scattering object. On the other hand, stressed stands maintained strong backscatter in both components, allowing them to be discriminated. Thus, a combination of leaves and small branches contributed to the total signal received by the sensor.

Water bodies were best discriminated using odd bounce and/or double bounce. This scatterer showed a unique characteristic in that it reflected the signal away from the sensor. Hence, it showed up as a darker grey. Since the tailings were placed in a river catchment, the effect of water bodies had to be taken into account when identifying tailings condition. Separation was made based on either volume or double bounce components. By using odd bounce data, we were able to distinguish the soil moisture of the tailings.

Wishart Classification

In order to have a meaningful figure for mapping purposes, we fed the complex coherence matrix into a Wishart classification scheme. As we learned that the classes were successfully distinguished by the Freeman-Durden decomposition, it was necessary to prove the robustness of the Wishart classification. The result is presented in Figure 3.

A visually high degree of agreement was presented by the Wishart classifier relative to our understanding from both the Pauli and Freeman-Durden component images. However, higher resolution imagery revealed some texture information of the surface scatterer. AirSAR sensors produced high resolution data with a spatial resolution of less than 10 m, so that the texture property dominated the appearance. Hence, visual analyses that accommodate both tone and textural data can have different results from the purely tone-based scheme of the Wishart classification. Undisturbed forest suffered from this phenomenon.

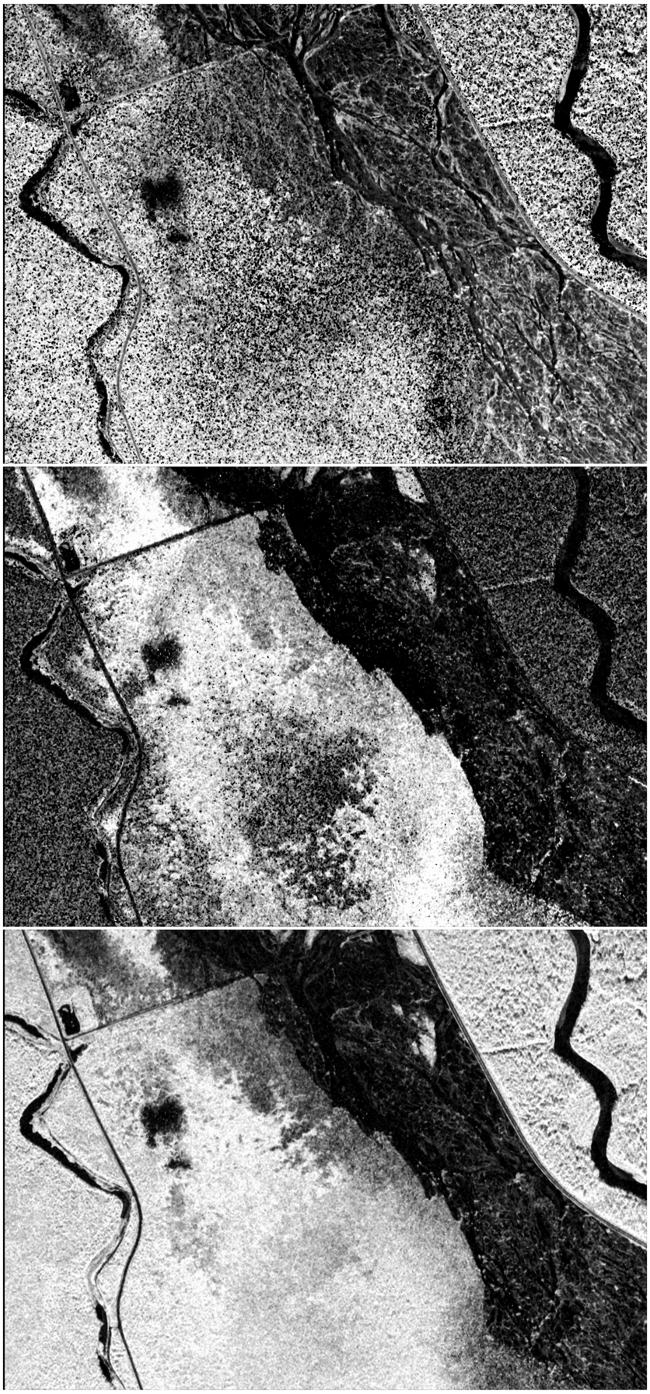

Figure 2. Three-component image of Freeman-Durden: top image = odd bounce; middle image = double bounce; bottom image = volume scattering.

Visual assessment indicated no occurrence of gaps within the forested site. However, undesirable patches were found, particularly in the eastern part (or right hand side) of the tailings zone.

In order to quantify the performance of the Wishart classification, we computed an accuracy matrix using the training regions (Table 1). Although this technique may not be adequate for mapping purposes, the matrix did reflect the general condition of the site.

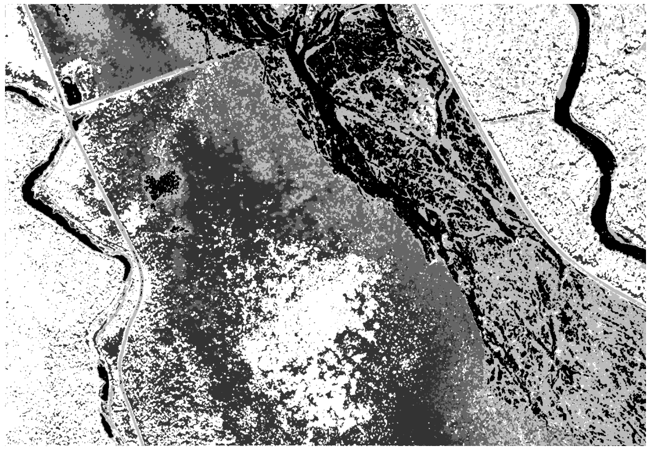

Figure 3. Classified image by Wishart algorithm: white = undisturbed forest; light grey = wet tailings; grey = dry tailings; dark grey = stressed vegetation; black = water.

Table 1. Accuracy matrix: C1 = undisturbed forest; C2 = dry tailings; C3 = stressed vegetation; C4 = water; C5 = wet tailings

	C1	C2	C3	C4	C5
C1	96.82	0.00	3.09	0.00	0.09
C2	0.00	91.90	7.69	0.00	0.40
C3	1.96	3.35	94.69	0.00	0.00
C4	0.00	0.00	0.00	99.50	0.50
C5	5.44	1.72	0.27	12.66	79.91

The rows indicate our defined grouping (training sites), whereas columns represent segmented clusters.

Generally, the matrix indicates acceptable accuracies of designated training sites. The forested site, however, required more attention due to its texture. There were some ambiguities in wet tailings. This was probably due to the fact that wet tailings were located at the side of streams and also had a very high moisture content. As a result, clear boundaries could not be resolved from the water bodies. Interestingly, dry tailings were clearly separated from other classes. The Pauli composite image exhibited similarity in reddish color between those types of tailings, which may lead to classification difficulties. The Wishart classification performed well in separating surface scatterers, especially similar objects.

Conclusion

In this paper, we presented a new application of polarimetric radar data. Within the cloud-prone areas, we demonstrated capabilities of fully polarimetric methods to extract useful information on a tailings deposition zone. Generally, the Freeman-Durden decomposition provided meaningful information for an initial site characterization. Surface scatterers were visually distinguished and comprehended. The Wishart statistic was shown to be a reliable approach for classification of the objects.

We found a higher degree of accuracy in discriminating dry tailings. This suggests that polarimetric radar data were sensitive to soil moisture conditions and can be used to provide reliable spatial data for reclamation purposes. While the overall accuracy was acceptable, especially for general mapping, the result suffered from skewing by textural characteristics of the targets. Nevertheless, this opens the way for a new approach to environmental and tailings monitoring using polarimetric SAR data.

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