ASSESSING NATURAL DISASTER IMPACTS AND RECOVERY USING MULTIFREQUENCY, FULLY-POLARIMETRIC SYNTHETIC APERTURE RADAR (SAR)

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Many natural disasters involving landslides, volcanic eruptions, fires, or floods entail terrain resurfacing, followed by subsequent recovery. Modern satellite and airborne remote sensing technologies, which combine broad spatial coverage and high spatial resolution with time-sequential site revisit capability, can provide important information on the extent and duration of major landscape disturbance. In humid climate settings, these hazards temporarily remove or replace a natural vegetation cover and in doing so, modify the physical properties of the land surface. In optical remote sensing, removal of vegetation alters surface albedo in the visible - near infrared (V-NIR) waveband, particularly the high reflectance from vegetation in the NIR. For SAR remote sensing, removal of vegetation cover causes a change in dominant microwave scattering mechanism for the areas affected. SAR has operational advantages over optical sensors for rapid disaster assessment because of its day/night acquisition capability, the ability to “see through” smoke, clouds and dust, and the side-looking viewing geometry, which is an advantage whenever data collection directly above the site would prove dangerous. We show how multifrequency, fully-polarimetric airborne SAR data can be “inverted” for parameters that reflect scattering mechanism signatures diagnostic of different surface cover types. We apply a uniform approach to map landslides resulting from the 1999 $M_w$ 7.6 Chi-Chi earthquake in Taiwan and volcanic flows from the major 1996 eruption of Manam volcano in Papua New Guinea. In addition, earlier work has shown that multifrequency SAR polarimetric backscatter is sensitive to total above-ground biomass. This attribute can be exploited to calculate vegetation loss during a disaster and for assessment of regrowth during the recovery phase.

1 INTRODUCTION

We present two case studies illustrating the usefulness of fully polarimetric, multifrequency SAR to map the surface after a major disaster or ecological disturbance. These cases are 1) the Tsaoling landslide following the Chi-Chi earthquake in Taiwan on Sept 20, 1999 and 2) the eruption of Manam Volcano, Papua New Guinea in 1996. Scattering mechanism information on a per-pixel basis is extracted by decomposing matrices formed as the outer product of the complex scattering vector measured for each resolution cell. We compare the SAR processing results to the available optical imagery.

2 SCATTERING MECHANISM INVERSION

We can express the backscattered electric field $E^s$ received at the radar antenna as a linear transformation of the electric field $E^i$ incident upon target material:

$$E^s = \frac{e^{ikr}}{r} S \cdot E^i,$$

or, explicitly in terms of horizontal $h$ and vertical $v$ components of the electric fields, as

$$\begin{bmatrix} E^s_h \\ E^s_v \end{bmatrix} = \frac{e^{ikr}}{r} \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} \begin{bmatrix} E^i_h \\ E^i_v \end{bmatrix}$$

[e.g., 1]. In Eq. 1 and Eq. 2, $k$ denotes the wavenumber of the illuminating wave and $r$ is the distance of the target from the radar. The complex $2 \times 2$ scattering matrix $S$ describes how scatterers transform an incident electric field $E^i$ into the backscattered field $E^s$ received by the antenna. The elements $S_{pq}$ of $S$ depend on the geometry, roughness and electrical properties of the target material.
There is an advantage in many applications to expressing target scattering properties in terms of a complex vector $\vec{t}_i$, comprising three elements in the monostatic backscatter case. This vector is related to the scattering matrix $S$ by

$$\vec{t}_i = \begin{bmatrix} A \\ B \\ C \end{bmatrix}^T = \frac{1}{2} \text{Trace}(S \cdot \Phi),$$

where $A$, $B$, and $C$ stand for the vector elements, and $\Phi$ denotes a complete set of $2 \times 2$ complex basis matrices [2]. It is sufficient for our purposes to consider one choice for $\Phi$: one that provides a straightforward lexicographic ordering of the elements of $S$, in which case the scattering vector becomes

$$\vec{t}_i = \begin{bmatrix} S_{hh} \sqrt{2}S_{hv} \\ S_{vv} \end{bmatrix}^T.$$  

The numerical factors in the expression for the scattering vector (Eq. 4) arise because of conservation of the total power scattered by the target [2,3].

The strength of imaging SAR polarimetry is its potential for discriminating among different types of scattering mechanisms. Recall that the elements of the scattering matrix $S$ (or the scattering vector $\vec{t}_i$) measured for each resolution cell represent the coherent superposition from all scattering centers within the cell illuminated by the incident wave. Methods have been developed for attempting to separate multiple scattering mechanisms occurring within each cell, with the aim of extending structure in scattering mechanism patterns spatially over a region of neighboring cells. First, correlation among the scattering coefficients for a cell is determined by forming a matrix $Z_i$ defined as the expected value of the outer product of the generic scattering vector $\vec{t}_i$ (Eq. 3):

$$Z_i = \langle \vec{t}_i \cdot \vec{t}_i^+ \rangle = \begin{bmatrix} \langle AA^* \rangle & \langle AB^* \rangle & \langle AC^* \rangle \\ \langle BA^* \rangle & \langle BB^* \rangle & \langle BC^* \rangle \\ \langle CA^* \rangle & \langle CB^* \rangle & \langle CC^* \rangle \end{bmatrix},$$

where $\langle \cdot \rangle$ denotes spatial (ensemble) averaging, $^*$ denotes the complex conjugate, and $^+$ the transpose of the conjugate. In the SAR literature, this “correlation” matrix $Z_i$ (Eq. 5) is called the covariance matrix $C$ when using the scattering vector $\vec{t}_i$ expressed in the linear basis (Eq. 4) [3,4].

Next, an eigenvalue/eigenvector decomposition of Eq. 5 is performed for the covariance matrix $C$:

$$Z_i = \lambda_1 \kappa_1 \cdot \kappa_1^+ + \lambda_2 \kappa_2 \cdot \kappa_2^+ + \lambda_3 \kappa_3 \cdot \kappa_3^+$$

(6)

allowing us to partition a resolution cell’s scattering properties into as many as three orthogonal (or independent) scattering mechanisms given by the eigenvectors $\kappa_i$, whose relative importance is determined by the eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3$. The challenge lies in relating the scattering mechanisms represented by the eigenvectors to polarimetric backscatter from common surface cover types like rough surfaces, water bodies, and vegetation.

The scattering entropy $H$ is obtained from the eigenvalues in Eq. 6 and characterizes the relative importance of the scattering mechanisms found from the decomposition of Eq. 5:

$$H = \sum_{n=1}^{3} -P_n \log_3 (P_n), \quad 0 \leq H \leq 1,$$

(7)

where $P_n = \lambda_n / \sum_{m=1}^{3} \lambda_m$, is a measure of the randomness or disorder of scattering. For entropy $H = 0$, there is only one eigenvector associated with a non-zero eigenvalue, and thus the resolution cell of the data is characterized by a single, discrete scattering mechanism. At $H = 1$, the three eigenvalues are equal, indicating superposition of three equally important scattering mechanisms within the resolution cell, and therefore no discrimination.

We use elements of the simplified covariance matrix $C$ to develop empirical criteria for discriminating among scattering mechanisms using L-band polarimetry obtained for the Taiwan and Papua New Guinea study areas. First, we make the simplifying assumption of reflection symmetry, so that the co- and cross-polarized scattering coefficients of the covariance matrix $C$, are uncorrelated, i.e. $\langle S_{hh}S_{hv}^* \rangle = \langle S_{vv}S_{hv}^* \rangle = 0$ [5]. The remaining elements of the covariance matrix are related to polarimetric radar cross-sections and correlation coefficients $\sigma_{pqrs}$:

$$\sigma_{pqrs} = \lim_{\Lambda_c \to \infty} \frac{4\pi}{\Lambda_c} \langle S_{pq} S_{rs}^* \rangle,$$

(8)
where \( A_c \) is resolution cell area [5]. In particular, when \( p = r \) and \( q = s \), we obtain the co- and cross-polarization radar cross-sections from the elements on the leading diagonal of the covariance matrix \( \mathbf{C} \).

For the mapping problems, our objective is to classify three types of terrain: a) bare surfaces (landslide scar, debris apron, water surfaces, lava flows), b) forest, and c) other (including cells without data). Previous work has shown that scattering from slightly rough, bare surfaces can be described by the following two relations among the coefficients \( \sigma_{pqrs} \):

\[
\text{Re}(\sigma_{hhvv}) > \sigma_{hvhv}, \quad \text{and} \quad \sigma_{vvvv} > \sigma_{hhhh} \tag{9}
\]

[6-9]. Three scattering properties are implied by the conditions in Eq. 9. First, the co-polarized returns are in phase, indicating single-bounce scattering. Second, the co-polarization backscatter cross-section is larger than the cross-polarization counterpart. Third, for bare surfaces the vertical backscatter cross-section is larger than the horizontal cross-section.

Forest covered cells are identified where threshold values for entropy \( H \) (Eq. 7), and two new parameters, radar vegetation index \( V \) and pedestal height \( \Psi \), are exceeded. Radar vegetation index is given by

\[
V = \frac{8 \sigma_{hvhv}}{\sigma_1}, \tag{10}
\]

where \( \sigma_1 = \sigma_{hhhh} + \sigma_{vvvv} + 2\sigma_{hvhv} \) is the total backscatter power. Radar vegetation index weights the contribution of the cross-polarized returns to total power. It will be relatively high where there is diffuse, volume scattering from vegetation branches and leaves. Pedestal height \( \Psi \) is derived from the eigenvalues (Eq. 6) of the decomposition of the simplified covariance matrix:

\[
\Psi = \min (\lambda_1, \lambda_2, \lambda_3) / (\lambda_1 + \lambda_2 + \lambda_3). \tag{11}
\]

Pedestal height measures the amount of depolarized energy in the return signal [10]. Forest, like most types of vegetation cover, is a depolarizing medium. Lastly, entropy \( H \) is very high for forest cover.

Forest covered areas are identified where \( V > V_{\text{min}}, \Psi > \Psi_{\text{min}}, \) and \( H > H_{\text{min}} \). Values for \( V_{\text{min}}, \Psi_{\text{min}}, \) and \( H_{\text{min}} \) are thresholds determined empirically from areas of known forest cover [9].

### 3 THE TSAOILING LANDSLIDE, TAIWAN

On September 2000, as part of the PacRim II mission, the AIRSAR flew three flightlines in central Taiwan over terrain that sustained kilometer-scale landslides generated by the September 1999 Chi-Chi earthquake. Full SAR polarimetry was collected at L- and P- bands (0.25 m and 0.68 m wavelength). C-band (0.06 m) was used for cross-track interferometry to produce a digital elevation model of the terrain, and consequently, C-band backscatter is restricted to a single (vertical) polarization. We will focus on the L-band polarimetry collected over the Tsaoling mega-slide to show how SAR polarimetry can readily be used to distinguish slopes affected by landsliding from slopes that are not.

Fig. 1a shows the surface cover classification of the Tsaoling landslide area based on decomposition of the simplified L-band covariance matrix, and the empirical threshold values for forest cover. Areas that have experienced landsliding show as predominantly single-bounce scattering from bare surfaces, as do water surfaces from the impounded lakes. Except for textural differences, the large landslide area is difficult to recognize in the Cvv backscatter data. Fully polarimetric SAR, however is able to map landslides (Fig. 1a), because we can extract information on changes in microwave scattering mechanisms caused by landslide resurfacing of the terrain.

The L-band classification map is compared to optical satellite data over the Tsaoling landslide in Fig. 1c and d. The landslide is very well depicted as the high albedo area in the IRS panchromatic data obtained on 31 October, 1999, six weeks after the Chi-Chi earthquake (Fig. 1d). Note that although the 5 m pixel size of the IRS data is the same as the resolution cell size of the AIRSAR polarimetry, the speckle present in all SAR data makes the radar results appear lower in resolution.

Landsat 7 data shown in Fig. 1c were acquired in February 2001, five months after the AIRSAR data, and 18 months after the Chi-Chi earthquake. Although the Landsat data are coarser resolution (28.5 m pixels) than both the AIRSAR and IRS data (5 m resolution), the Tsaoling landslide area and the impounded lakes are readily identified. Notice vegetation regrowth on the landslide toe area that occurred between the time
of the landslide and the Landsat data take, as indicated by the green areas (Fig. 1c) between the two lakes. Re-vegetation of the landslide debris apron is also apparent from the L-band polarimetry (Fig. 1a) where we observe a higher percentage of green pixels over the debris apron than over the landslide source area. Comparison with the Landsat data eliminates the possibility that the green pixels in the L-band classification map are due to vegetation debris in the slide runout material.

4 MANAM VOLCANO, PAPUA NEW GUINEA

During November 1996, as the NASA/JPL DC-8 conducted the PacRim I AIRSAR mission in the southwest Pacific, Manam volcano entered its largest eruption sequence since 1992. The aircraft, which was operating over northern Australia and Papua New Guinea, was diverted on the 17th of November to collect two TOPSAR flightlines over the erupting volcano. Two weeks after the airborne SAR data were acquired, the eruption culminated in a paroxysmal phase on the 3rd of December. Many large pyroclastic flows, some captured on video, swept down the SE and SW Valleys from South Crater, causing 13 deaths and forcing the evacuation of thousands. L-band polarimetric SAR data from one of the Manam Island flightlines (ts469, Manam 135-1) are analyzed below. The objective of our analysis is to show that scattering mechanism signatures obtained from inversion of the polarimetry data provide a way to distinguish recent or fresh lava flows from those of previous eruptions.

For volcanic eruptions in humid climates, lava and pyroclastic flows replace vegetated surfaces with bare surfaces. Radar scattering mechanisms will therefore change from primarily volume scattering from vegetation to primarily single-bounce scattering from bare surfaces. With time following eruption, the bare flow surfaces will become re-vegetated. Polarimetric SAR data and technology can play a significant role in rapid identification and mapping of lava and pyroclastic flows during and after disastrous volcanic eruptions.

Fig. 2a shows a three-dimensional perspective image of the surface classification of Manam Island viewed from

![Figure 1](image_url)

Figure 1: a) Surface classification map made from radar scattering mechanisms obtained through analysis of airborne L-band SAR polarimetry. Purple - bare surface, green - forest, black - other (including missing data). b) Grayscale L-Band image of the Cvv backscatter c) False-color image of Landsat 7 Thematic Mapper (TM) data (February 2001). Green areas are forested, the purple areas are the landslide source area and debris apron, dark areas in the lower half of image are lakes impounded by landslide. d) Indian Research Satellite visible band panchromatic data (October 31, 1999) obtained six weeks after the landslide. The landslide is the light colored area, and the vegetated slopes are dark. The IRS and AIRSAR data both have 5 m pixels. The Landsat TM data have 28.5 m pixels.
the east based on decomposition of the simplified L-band covariance matrix. Areas that have experienced recent lava flows show a predominantly single-bounce scattering from bare surfaces, as does the sea surface surrounding the island. A comparison of the RGB composite of AIRSAR data for an area on the lower slopes of the NE Valley (Fig. 2b) with the surface classification (Fig. 2c) allows us to map the youngest flow in the lower left-hand quadrant. This flow stands in contrast to the rest of the flows that are now re-vegetated and apparent in Fig. 2b. The handheld photo (Fig. 2d) shows an example of a typical recent lava flow juxtaposed with an older, re-vegetated flow.

5 CONCLUSIONS

We have demonstrated that SAR can be a useful tool for disaster response and assessing landscape recovery. Rapid response is key to saving lives and assessing property damage when natural disasters strike. Darkness, clouds or smoke over devastated areas can delay urgent relief efforts. Radar is not hampered by these conditions and can provide the needed information in a timely manner. We are therefore developing radar-based approaches for rapid response to natural disasters. Hazards such as floods, fires, volcanic eruptions and landslides essentially “resurface” parts of the terrain, and in doing so, alter the dominant radar scattering properties of the areas affected. The overall goal is to develop radar-based systems that can be deployed for rapid assessment of the extent and severity of many different kinds of natural disaster. Time series data acquisition after a resurfacing event provides the means to study re-vegetation and recovery of the landscape. Such information can help us better understand the natural and human dimensions of landscape changes.

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Figure 2: a) Three-dimensional perspective image of Manam Island viewed from the east. Yellow arrows denote recently erupted lava flows on the lowermost valley slopes (see c). For a and c: Purple - bare surface; Green - vegetated surface; Black - not classified based on decomposition of the simplified target covariance matrix. b) RGB composite of the AIRSAR data in the area of recent lava flow (NE Valley); Red - Phv, Green - Lhv and Blue - Cv. c) NE Valley surface classification using same method as in a). d) Handheld photo of a recent flow.
References


