ISPRS Journal of Photogrammetry and Remote Sensing 65 (2010) 77–85

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Statistical information of ASAR observations over wetland areas: An interaction model interpretation

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ARTICLE INFO

Article history:
Received 30 January 2008
Received in revised form
7 August 2009
Accepted 25 August 2009
Available online 15 September 2009

Keywords:
Statistics
SAR
Ecology
Floods
Hydrology

ABSTRACT

This paper presents the results obtained after studying the relation between the statistical parameters that describe the backscattering distribution of *junco* marshes and their biophysical variables. The results are based on the texture analysis of a time series of Envisat ASAR C-band data (APP mode, VV + HH polarizations) acquired between October 2003 and January 2005 over the Lower Paraná River Delta, Argentina. The image power distributions were analyzed, and we show that the K distribution provides a good fitting of SAR data extracted from wetland observations for both polarizations. We also show that the estimated values of the order parameter of the K distribution can be explained using fieldwork and reasonable assumptions. In order to explore these results, we introduce a radiative transfer based interaction model to simulate the *junco* marsh σ^0 distribution. After analyzing model simulations, we found evidence that the order parameter is related to the *junco* plant density distribution inside the *junco* marsh patch. It is concluded that the order parameter of the K distribution could be a useful parameter to estimate the *junco* plant density. This result is important for basin hydrodynamic modeling, since marsh plant density is the most important parameter to estimate marsh water conductance.

1. Introduction

Areas near rivers, or in low-lying coastal places, are in risk of flooding. Periods of heavy rain, not necessarily in the area, can lead to increases in the water level of streams and rivers to a point where the main channels can no longer hold the volume of incoming water. In wetland areas, it is claimed that this excess of water can be taken by marshes located in the floodplain separated from the mainstream channel by island levees. These marshes are continuously exchanging water with the mainstream channel, but in extreme flood conditions, when the river overflows, the net flux goes in the marsh direction (Arihood and Sidle, 2006). When the river water level returns to normal, this excess of water moves back to the mainstream channel. This capability is usually called the ''marsh buffer effect'' because its effect is analogous to a low pass filter that ''smoothes'' the mainstream flux (Novitzki and Fretwell, 2002).

In the Lower Delta of the Paraná River in Argentina, marshes are the most extended autochthonous vegetation. The species that dominates the marsh vegetation is the *junco* marsh (*Schoenoplectus californicus*), and it covers up to 25% of the wetland area (~800 km^2). These marshes are mainly located in islands along the channels and they are responsible for the water buffer effect on this wetland.

Water storage in floodplains is also a governing parameter in continental scale hydrologic models (Keedy, 2000). Coe (2000) reported that a wetland component could provide up to 50% of the observed Nile River discharge in the Sudan. Furthermore, Richey et al. (1989) estimated that the Amazon floodplain-to-mainstream flux is about 25% of the annual discharge. These large percentages suggest that inaccurate knowledge of floodplain storage and discharge can lead to significant errors in hydrological models (Alsdorf, 2002).

In order to characterize this buffer effect, there are two important magnitudes to be estimated: the marsh water storage capacity and the marsh hydraulic conductivity. Marsh water storage capacity determination consists of the estimation of the volume of water inside wetland islands; this can be done using remote sensing data in several ways (Alsdorf, 2002; Coe, 2000; Keedy, 2000) and it has been estimated previously on the Paraná River wetland for flooded and non-flooded conditions using both field

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doi:10.1016/j.isprsjprs.2009.08.003

data and Envisat ASAR images (Grings et al., 2006, 2008, 2009). Characterization of hydraulic conductivity is a much more difficult task, which requires the estimation of the drag coefficient of the vegetation in different areas of the watershed (Järvelä, 2004a). Nevertheless, many authors have pointed out that the vegetation drag coefficient in herbaceous vegetation ecosystems (like *junco* marshes) depends mostly on the plant density (Järvelä, 2004a; Nepf and Koch, 1999; Stone and Hung, 2002). As a result, the estimation of *junco* plant density information at high spatial resolution and at a regional scale is critical in the hydrodynamic modeling of wetlands.

It was found that the mean σ^0 of a homogenous marsh area is mostly related to a few marsh biogeophysical variables (Grings et al., 2005, 2006, 2008). The question we address in this work is: is there other substantial information that is available in the marsh SAR image? In wetlands, it is common that inside a patch dominated by a single marsh species (homogeneous in terms of species), different marsh *conditions* are present. In the Paraná River Delta, these different conditions of the marsh are usually related to a non-homogeneous distribution of some biogeophysical variables, typically related to the different availability of water and nutrients. Therefore, it is reasonable to assume that some of the variability that is observed in an SAR image of a wetland patch may be related to spatial inhomogeneities of one or more of the main biogeophysical variables that determine the observed σ^0. This idea has already been addressed, and is the base of the interpretation of complex SAR image statistics of inhomogeneous targets (Oliver and Quegan, 1998). Moreover, it has been shown that most of the observed statistics can be interpreted as generated by two unrelated processes encapsulated in a product model (Oliver and Quegan, 1998). This product model states that the observed SAR image is the result of the product of the target backscatter with a speckle component. One underling hypothesis of the multiplicative model is that the parameters characterizing the backscattering distribution are related in some way to target parameters (Blacknell, 1994; Oliver and Quegan, 1998). The problem is that there is no general relation between the statistical distribution of SAR data and the underlying physical interaction between the wave and the ecosystem patch.

This hypothesis was further investigated recently (Wang and Ouchi, 2005). Data acquired over a forest by PI-SAR were fitted to a K distribution, and one of the estimated parameters was associated to the forest biomass. In (Wang and Ouchi, 2005), the authors demonstrated that there is a strong positive correlation between the K homogeneity parameter and the forest biomass, showing that there is some kind of relation between the statistical parameters that characterize forest patches and some of the biogeophysical variables of the terrain (biomass in this case). Furthermore, they also provided a sound speculative interpretation of this relation, which will be explored further in the present paper.

In this work, the SAR image power distributions of *junco* marshes were analyzed, and we show that the K distribution provides a good fitting of SAR data for both HH and VV polarization. We also show that the estimated values of the order parameter of the K distribution are related to the *junco* plant density distribution. Taking up the ideas in Lee et al. (1994); Oliver and Quegan (1998); Wang and Ouchi (2005), we modeled the SAR return of the *junco* marsh to show that there is biophysical information in all the statistical parameters that characterize a given marsh area.

The paper is structured as follows. In Section 2, we introduce the statistical model of SAR backscattering. In Section 3, we illustrate the method adopted to estimate the distribution parameters. In Section 4, we show the results obtained by analyzing an Envisat ASAR time series acquired over the lower Delta of the Paraná River for both HH and VV polarizations. In Section 5, we give a theoretical interpretation of the statistical model by using an interaction model of the marsh area based on radiative transfer theory. In Section 6, we discuss the results obtained in Section 4 taking into account the theoretical results developed in Section 5. Finally, in Section 7 we show a comparison between the statistical parameters estimated from ASAR images and simulated ones.

2. The statistical model

A multiplicative model is commonly adopted for SAR image interpretation (Oliver and Quegan, 1998). This model assumes that the observed intensity value in every pixel is the outcome of a random variable Z, defined as the product between the random variables X and Y, where X represents the random variable modeling the variations of terrain scattering properties and Y represents the random variable modeling the speckle; i.e. $Z = X \cdot Y$. Different distributions for X and for Y yield different models for the observed data Z. For homogeneous regions, the terrain scattering properties are constant. Therefore, the distribution of Z is a rescaled version of the distribution of Y, which is usually assumed, for intensity, as Gamma distributed with parameters $(n, 2n)$. In conventional notation, $Y \sim \Gamma(n, n)$, where n is the *equivalent number of looks* of the SAR image (Oliver and Quegan, 1998).

The basic hypothesis that governs the modeling of inhomogeneous regions is that their scattering properties are not constant, though they can be modeled by a convenient distribution. In this work, it will be assumed that $X \sim \Gamma(\alpha, \beta)$, where α is the shape or homogeneity parameter and β is the scale parameter. This assumption is not arbitrary, since Jakeman and Pusey (1976) show that an inhomogeneous SAR sample in which the number of scatterers per pixel N is itself a random variable distributed inverse binomial will present a Gamma distribution. In this way, this model includes two sources of image inhomogeneity: target spatial variability and speckle; the target variability is related to a fluctuation in the number of scatterers inside every pixel (Jakeman and Pusey, 1976).

The K-distribution model for a radar clutter arises (Oliver and Quegan, 1998) when a Gamma-distributed noise process modulates a Gamma-distributed radar cross-section. It is important to remark on an assumption of this model, which needs to be checked in order to be used: the fluctuation of the target scattering properties should have a greater spatial scale than the speckle, so that multilooking reduces the speckle without affecting the scattering fluctuations (Oliver and Quegan, 1998).

3. Estimation of the parameters of the intensity *K* distribution

The parameters that define a K distribution can be estimated in several ways (Blacknell, 1994; Frery et al., 1997; Lee et al., 1994; Oliver and Quegan, 1998; Yanasse et al., 1994). In this work we choose the straightforward estimation scheme presented in (Lee et al., 1994). The estimator of β based on the first sample moment of the data $X = \{x_1, x_2, \dots, x_n\}$ is

$$\hat{\beta} = \frac{1}{N} \sum_{i=0}^{N} X_i = \hat{m}_1. \tag{1}$$

This gives the sample mean. In order to obtain the moment's estimator of α it is necessary to use other moments of the measured distribution (1/2, 2, etc.). One estimator for α using the moment method is

$$\hat{\alpha} = \frac{\hat{m}_1{}^2 (n+1)}{n\,(\hat{m}_2 - \hat{m}_1{}^2) - \hat{m}_1{}^2}. \tag{2}$$

To estimate the variances of the parameters, we use the *bootstrapping* method (Cribari-Neto et al., 2002). This method consist of the estimation of the parameter (i.e. β), using a sub-sample X_k