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The Use of Imaging Radars for Ecological Applications—A Review

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At the behest of NASA's Mission to Planet Earth, the National Research Council recently conducted a review on the current status and future directions for earth science information provided by spaceborne synthetic aperture radars. As part of this process, a panel of 16 scientists met to review the utility of SAR for monitoring ecosystem processes. The consensus of this ecology panel was that the demonstrated capabilities of imaging radars for investigating terrestrial ecosystems could best be organized into four broad categories: 1) classification and detection of change in land cover; 2) estimation of woody plant biomass; 3) monitoring the extent and timing of inundation; and 4) monitoring other temporally-dynamic processes. The major conclusions from this panel were: 1) Multichannel radar data provide a means to classify land-cover patterns because of its sensitivity to variations in vegetation structure and vegetation and ground-layer moisture. The relative utility of data from imaging radars versus multispectral scanner data has yet to be determined in a rigorous fashion over a wide range of biomes for this application. 2) Imaging radars having the capability to monitor variations in biomass in forested ecosystems. This capability is not consistent among different forest types. The upper levels of sensitivity for L-band and C-band systems such as SIR-C range between <100 t ha^{-1} for complex tropical forest canopies to ~250 t ha^{-1} for simpler forests dominated by a single tree species. Best performance for biomass estimation is achieved using lower frequency (P- and L-band) radar systems with a cross-polarized (HV or VH) channel. 3) Like-polarized imaging radars (HH or VV) are well suited for detection of flooding under vegetation canopies. Lower frequency radars (P- and L-band) are most optimal for detecting flooding under forests, whereas higher frequency radars (C-band) work best for wetlands dominated by herbaceous vegetation. 4) It has been shown that spaceborne radars that have been in continuous operation for several years [such as the C-band (VV) ERS-1 SAR] provide information on temporally dynamic processes, such as monitoring a) variations in flooding in nonwooded wetlands, b) changes in the frozen/thawed status of vegetation, and c) relative variations in soil moisture in areas with low amounts of vegetation cover. These observations have been shown to be particularly important in studying ecosystems in high northern latitudes.

INTRODUCTION

The past decade has seen a significant growth in research activities focused on developing approaches to use synthetic aperture radar (SAR) to study ecological processes. During this time, a number of advanced airborne SAR systems have been developed, and five separate spaceborne SAR systems have been successfully deployed: ERS-1, ERS-2, JERS-1, Radarsat, and SIR-C/X-SAR. It is anticipated that additional satellite SAR systems will be developed and launched throughout this decade and into the next, ensuring the availability of radar imagery for a wide range of applications.

The deployment of the multi-frequency, polarimetric Shuttle Imaging Radar-C and X-band Synthetic Aperture Radar (SIR-C/XSAR) instruments on two Space Shuttle missions (STS 59 and STS 68) in April and October 1994 represents one of the key milestones in the recent history of imaging radars. The articles in this special issue present examples of how multifrequency, multipolariza-

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tion SAR imagery can be used to determine specific surface characteristics important in ecological studies.

Ecologists are aware of the utility of remote sensing data for studying a number of processes at landscape scales. A wide range of approaches have been developed to exploit remote sensing data collected in the visible, near-infrared, and thermal infrared region of the electromagnetic spectrum to study terrestrial ecosystem processes (Hall et al., 1991; Kasischke et al., 1995a; Matson et al., 1994; Pierce et al., 1994a; Running and Nemani, 1988; Tucker et al., 1991). However, imaging radar data have received less attention than data from optical systems. Hindrances to use of SAR data have included: 1) difficulty in understanding the information content of the complex phase and amplitude information recorded in multifrequency, polarimetric SAR data; 2) the lack of available, calibrated data over sites of interest; 3) the lack of accessible computer software to exploit the information present in the data; and 4) unique characteristics of SAR data, including topographic effects and image speckle. In recent years, computer software and hardware have been developed to the point where most of the technological constraints of using SAR data have dissipated. In addition, much calibrated SAR imagery now exists and is being collected by a significant number of airborne and satellite systems. The focus of this review, therefore, is our current understanding of the information content of SAR imagery with respect to ecological applications based on recent research results.

The organization of this article is derived from the results of a working group of scientists who met on the campus of the University of California (Santa Barbara) to perform a critical review of the status of using imaging radars to estimate surface characteristics important for the study of terrestrial ecosystem processes.[1] The consensus of this group was that the ability of imaging radars to detect ecologically important characteristics of vegetated landscapes is well founded in both theory and observation (Evans et al., 1995). The working group felt the demonstrated capabilities of imaging radars for investigating terrestrial ecosystems could best be organized into four broad categories: 1) classification and detection of change in land cover; 2) estimation of woody plant biomass; 3) monitoring the extent and timing of inundation; and 4) monitoring other temporally dynamic processes.

This review complements a recent similar review by Waring et al. (1995) on the utility of radar for ecosystem studies. We feel our article differs from the Waring et al. (1995) effort in that a significant amount of research has emerged since this earlier review. Specifically, the workshop which resulted in consensus presented in Waring et al. (1995) was held in the fall of 1992, only 1 year after the launch of the current generation of spaceborne imaging radars (e.g., ERS-1 and JERS-1). A significant amount of research using data from these systems is included in this review. In addition, we also review the recent results from the SIR-C/X-SAR mission.

In this review, we first present a brief review of the origins of the signatures recorded in a SAR image collected over a vegetated terrain. Then, we discuss each of the four topical areas, including an overview of the scientific importance or application of the topic area and a review of the demonstrated capabilities of SAR to provide information necessary to provide specific inputs. Next, we discuss the optimum system configuration for specific ecological applications and make an assessment of the capabilities of existing SAR systems (including SIR-C/X-SAR) and those scheduled for launch in the near future to provide information required for each of the application areas. Finally, we present the major conclusions resulting from the workshop.

While we cover some basic principals of microwave scattering theory in the next section, we do not go into a detail on the basic principles of imaging radar systems. For this information, the reader is referred to Brown and Porcello (1969), Elachi (1987), Nuesch and Kasischke (1989), or Waring et al. (1995).

BACKGROUND

Because of their high moisture content, individual components of forest canopies and other vegetation (e.g., leaves, branches, trunks, etc.) represent discrete scattering and attenuating elements to the microwave energy transmitted by imaging radars. Variations in the microwave dielectric constant of vegetative elements or ground surface play a central role in determining the intensity and phase of the microwave energy scattered from a vegetated surface and recorded and processed into a SAR image. Factors influencing the dielectric constant of vegetated surfaces include temperature of the scattering medium, relative moisture content of vegetation, soil, and snow cover, and the presence of water on vegetation.

The frequency and polarization of microwave scattering from land surfaces is strongly dependent on the size and orientation of the different elements comprising the vegetation. In this article, we follow the standard convention of using bands to represent frequencies or wavelengths of imaging radar systems. P-band radars op-

[1] Members of this working group included the authors of this review and Malcom Davidson (University of Bonn), Frank Davis (University of California), Laura Hess (University of California), W. Kubach (University of Bonn); Anthony Milne (University of New South Wales); Leslie Morrissey (NASA Ames Research Center); Kevin Pope (GeoEcoArc Research); Sasan Saatchi (NASA Jet Propulsion Laboratory); JoBea Way (NASA Jet Propulsion Laboratory); F. Weber (U.S. Forest Service); Diane Wickland (NASA Headquarters); and Cynthia Williams (U.S. Forest Service).

erate at a center frequency of approximately 440 MHz and have a wavelength of 65 cm. L-band radars operate at a center frequency of 1.25 GHz and have a wavelength of 24 cm. C-band radars operate at a center frequency of 5.3 GHz and have a wavelength of 5.6 cm. X-band radars operate at a center frequency of 10 GHz and have a wavelength of 3.0 cm.

Imaging radar systems in operation today transmit either horizontally (H) or vertically (V) polarized electromagnetic (EM) energy and then receives either of these polarizations. The frequency transmit/receive configuration of an imaging radar is typically denoted by a three-letter code, with the first letter designating the band of the radar and the last two letters designating the polarization configuration. There are four distinct polarization combinations in use: HH, HV, VH, and VV. Thus, an L-VH radar is an L-band system that transmits vertically polarized EM energy and receives horizontally polarized EM energy.

At longer radar wavelengths (P- and L-bands), microwave scattering and attenuation result from interactions with the tree boles and larger branches found within forests, as well as the ground surface. At these wavelengths, the smaller woody stems and the foliage act mainly as attenuators. At shorter radar wavelengths (C- and X-bands), microwave scattering and attenuation result from interactions with smaller branches and leaves and needles in the canopy. The presence of a water-saturated or flooded surface leads to an increased double-bounce scattering that enhances the strength of the ground–vegetation interaction term. Finally, the polarization state of the received radar backscatter is strongly dependent on the polarization state of the transmitted microwave energy and on the horizontal and/or vertical orientation of the scattering elements present in the vegetation.

Theoretical models show the differential dependence of radar backscatter on the overall structure of vegetation canopies and on the variations in the characteristics of the ground layer. These models treat a forest stand either as a set of continuous horizontal layers (Richards et al., 1987; Sun and Simonett, 1988a; Durden et al., 1989; Ulaby et al., 1990; Chauhan et al., 1991) or as a discontinuous layer with individual trees acting as distinct scattering centers (Sun et al., 1991; McDonald and Ulaby, 1993). Both model classes are similar in that they calculate the same major scattering terms: 1) surface and volume scattering from the tree overstory (e.g., the branches and leaves/needles); 2) direct ground scattering; 3) direct trunk scattering; 4) ground-to-trunk scattering; 5) ground-to-crown scattering; and 6) ground-to-crown-to-ground scattering. Most models use formulations which assume the tree trunks and branches can be modeled as lossy dielectric cylinders, and the leaves or needles as dielectric discs.

Theoretical scattering models have been validated using SAR and scatterometer data collected over a wide range of forest types (Sun and Simonett, 1988b; Durden et al., 1989; McDonald et al., 1990; 1991; Moghaddan et al., 1994; Way et al., 1994; Ranson and Sun, 1994a; Wang et al., 1993a, b; 1994; 1995a). Because of their complexity, however, these models cannot be inverted to estimate surface and canopy characteristics needed to study specific ecological features or processes. The value of these models lies in their utility to better understand the dependence of microwave scattering on system and imaging parameters (frequency, polarization, and viewing geometry) and the basic geometric characteristics of the vegetated canopies being studied. In addition, these models have been useful in developing an understanding of some of the effects of temporally varying factors which influence radar backscatter, including responses to air temperature (Rignot et al., 1994a), soil moisture[2] (Wang et al., 1994), and monitoring degree of flooding in forested and nonforested wetlands (Dobson et al., 1995a; Wang et al., 1995b; Bourgeau-Chavez and Kasischke, 1997). This understanding has proven critical in developing approaches to using SAR data in algorithms to estimate specific surface characteristics (Rignot and Way, 1994; Dobson et al., 1995b; French et al., 1996a; Kasischke et al., 1995b, c; Wang et al., 1995b).

THE ROLE OF REMOTE SENSING IN TERRESTRIAL ECOSYSTEM STUDIES

Remote sensing has both direct and indirect applications in ecology. Remote sensing data are used directly in ecological studies to: 1) interpret landscape patterns; 2) examine correlations among physical, chemical, and biotic parameters; and 3) extrapolate known relationships over wider geographic areas or longer time periods. Indirect applications involve using remote sensing data to study processes that themselves directly affect specific ecosystem processes.

As an example of a phenomenon that is readily detected on remote sensing imagery and has both direct and indirect effects on ecosystem processes, consider forest fires in boreal regions. The results of these fires can be detected and monitored on satellite remote sensing systems. The information derived from remote sensing data can directly be used in a variety of ecosystem process models, including providing information on patterns

[2] Because liquid water strongly attenuates the microwave energy, radars are sensitive to volumetric moisture variations in the upper regions of the soil horizon. In this review, the term soil moisture refers to the volumetric moisture in the upper 5–10 cm of the soil horizon. Typically, imaging radars are used to monitor soil moisture in areas with little vegetation, such as agricultural fields (DuBois et al., 1995).

of disturbance through the detection of fire scars on visible, near-infrared, and radar imagery (Bourgeau-Chavez et al., 1996; Cahoon et al., 1994; Kasischke et al., 1993; Kasischke and French, 1995), spatial and temporal variations in soil temperature on thermal infrared imagery (French et al., 1996b), and spatial and temporal variations in soil moisture on radar imagery (French et al., 1996a; Kasischke et al., 1995c).

Satellite data sets can be used to estimate the amounts of gaseous carbon released into the atmosphere during biomass burning (Cahoon et al., 1994; Kasischke et al., 1995a; French et al., 1995b), which in turn are used as inputs into general circulation models (GCMs). The outputs from the GCMs are used as inputs into models to to predict the effects of climate change on a variety of ecosystem processes (Bonan and VanCleve, 1992; Smith et al., 1992; Kasischke et al., 1995d; Kasischke, 1996). This latter case represents an indirect application of remote sensing data to ecosystem studies.

LAND-COVER CLASSIFICATION

Many ecologists use remote sensing data as a basis for land-cover classification of the area under study. Many applications require the classification of the land surface into discrete land-cover types, specifically focusing on the delineation of the structural and compositional boundaries of vegetation communities, and the distribution of these communities throughout the landscape being studied.

With the widespread availability of satellite remote sensing data from systems operating in the visible and infrared regions of the electromagnetic spectrum, as well as a wide range of computer software to process these data into land-cover classifications, why consider using imaging radar for this purpose? There are two answers to this question. First, the origin of the signatures detected by imaging radars are fundamentally different than those detected by visible and infrared systems. Discrimination of land-cover categories from imagery collected in different regions of the EM spectrum is based upon different characteristics of the surface and vegetation cover; therefore, the information content of the classified images may be fundamentally different. For example, in tropical forests it is often difficult to discriminate between riparian and upland forests on visible/near-infrared imagery because the canopies of these two forest types are extremely dense and exhibit the same spectral signature. However, radar imagery can detect flooded forests, and be used to discriminate between these two distinct ecosystems (Hess et al., 1995).

A second reason for using radar imagery is the presence of cloud cover, either continuously (e.g., in most tropical and boreal regions) or during time periods when vegetation growth is optimal for discrimination with visible/near-infrared systems (e.g., in areas with distinct dry/rainy seasons, such as subtropical savannas). In these cases, imaging radars may provide the only means to collect imagery to monitor and map vegetated surfaces reliably. In addition, they provide information which in many cases is complementary to that provided from visible and near-infrared sensors (Rignot et al., 1997; Saatchi et al., 1997).

Image classification algorithms discriminate based on features extracted from the spectral, spatial, or temporal domains. Two general image classification approaches have been applied to SAR data: 1) maximum-likelihood classifiers including supervised and unsupervised cluster analysis and 2) knowledge-based techniques such as hierarchical decision trees and those based upon determination of dominant scattering mechanisms from electromagnetic theory. A key issue for either of these basic approaches is the consistency or stability of the classifier when applied to new regions or the same region at different times.

A summary of the demonstrated capabilities of SAR-derived image-classifiers is given in Table 1. This information is not intended to be all inclusive, but draws examples from analyses of a number of ecosystems as recently reported in the literature.

Manual classification of airborne SAR imagery provided the first comprehensive mapping of many tropical areas in the 1970s. The most notable of these was project RADAM in Brazil. Unsupervised classification of digital SAR imagery is a useful tool for characterizing landscapes without adequate vegetation maps (e.g., Pope et al., 1994). Most recent classification efforts have used supervised maximum likelihood approaches, which lead to high classification accuracy (>90%) for a given scene (de Grandi et al., 1994; Lemoine et al., 1994; Ranson and Sun, 1994a; Rignot et al., 1994b). When applied to temporal sequences of images, this technique implicitly incorporates ancillary knowledge such as phenologic development or cropping calendars. The extendibility of supervised maximum likelihood techniques to regional or global scales is impaired by the need for localized training. The knowledge-based techniques may overcome this limitation by first classifying on the basis of explicit relationships between radar backscatter and structural attributes (Dobson et al., 1996; Pierce et al., 1994b; van Zyl, 1989). These structural classes can then be relabelled locally on the basis of known linkages between structure and floristic community. At present, such classifiers have been successfully tested locally, so that their robustness in application to other areas have yet to be determined. In addition, the relative utility of SAR-based classifiers versus classifiers using MSS data has not been examined thoroughly.

Compositional variations within major vegetation types (physiognomic types) are not easily discriminated

Table 1. Recent Examples of Land-Cover Classification Approaches Using Radar Imagery

Ecosystem	*Purpose*	*Classifier*[a]	*Data Source*	*Number of Classes and Types*[b]	*Accuracy*[c]	*Frequency/ Polarizations*	*Reference*
Tropical floodplain forest	Map forest flooding	Decision tree	SIR-C	5 W,fH,H,F,fF	High	LHH,LHV, CHH	Hess et al. (1995)
Northern U.S. forest	Forest cover, biomass	Decision tree	SIR-C	10 W,B,H(2),F(6)	High	X-VV,L and C, all polarizations	Dobson et al. (1996)
Boreal forest	Forest cover, biomass	MLE	SIR-C	9 W,S(3),F(5)	Medium to high	L and C, all polarizations	Ranson et al. (1995)
Subtropical forest and wetlands	Ecosystem mapping	MLE Cluster	AIRSAR	7 W,B,C,H,S,F(2)	Medium	P,L,C, all polarizations	Pope et al. (1994)
Temperate floodplain forest	Wildlife habitat mapping	Decision tree	AIRSAR	5 W,fH,H,F,fF	High	PHV,PHH, CHH,CHV	Hess and Melack (1994)
Temperate coniferous forest	Forest age classes	MLE	AIRSAR	6 U,A,F(4)	Medium to high	PHH,PVV,PHV	de Grandi et al. (1994)
Boreal forest	Successional stage, biomass	MLE	AIRSAR	6 W,H,S,F(3)	High to low (F)	P,L,C, all polarizations	Rignot et al. (1994b)

[a] Classification approaches: Maximum likelihood estimator (MLE), cluster analysis (unsupervised classification), and decision tree.
[b] Agriculture (A), water (W), bare soil (B), crops (C), urban (U), herbaceous (H), shrubs (S), forest (F), flooded (f). Number of types in a cover class is indicated by the number in parentheses.
[c] High indicates >90% classification accuracy, medium indicates 70–90% classification accuracy and low indicates <70% classification accuracy.

on a single-date, single-frequency/single polarization SAR imagery, but usually require the use of multitemporal imagery (Ahern et al., 1993; Dreiman, 1994; Kasischke and Bourgeau-Chavez, 1997) or multifrequency/multipolarization data. A number of studies have shown that using multidate, multichannel SAR imagery leads to enhanced classification (Ranson and Sun, 1994a; Way et al., 1994). Orbital SARs have proven themselves to be very reliable for provision of multidate data because they are insensitive to local weather conditions. The good calibration stability of existing satellite SARs makes it possible to incorporate time-dependent ancillary information, such as phenological development and cropping calendars, into classification.

One complication to SAR-derived land-cover classification is that imposed by topographic relief. In severe cases, the layover[3] and shadowing produced by mountainous terrain makes classification inappropriate for these regions unless azimuth and viewing geometries have been carefully considered in the SAR data collection strategy. In less severe cases, ancillary digital elevation data can be used to generate approximate corrections for terrain effects prior to classification (Wivell et al., 1992).

A second limitation in image classification is the spatial resolution of a given SAR. Individual landscape patches cannot be unambiguously discriminated and classified unless they are much larger than the spatial resolution of the radar system. This limitation is due to the presence of image speckle or radar fading, which results in the "grainy" appearance of unsmoothed radar imagery. This phenomenon is due to the fact that radars use coherent electromagnetic energy, which results in constructive and destructive interference when the transmitted energy interacts with features (such as trees) present on the Earth's surface. To reduce the influence of radar speckle, a number of pixels from the same cover type are averaged (Porcello et al., 1976). In general, classification of patch sizes <200 m by 200 m is not practical from spaceborne SAR.

Finally, a variety of surface characteristics uniquely detected by SAR can lead to an improved capability to map not only land cover, but specific land-cover characteristics. Recent studies have shown that SAR data can be used to: 1) detect changes such as inundation (Orsmby et al., 1985; Morrissey et al., 1994; Hess et al., 1990; 1995; Bourgeau-Chavez and Kasischke, 1997), the presence of intercepted precipitation (Ulaby et al., 1983), and freeze/thaw status of vegetation (Rignot and Way, 1994; Way et al., 1994); 2) differentiate major structural differences in land-cover such as forest versus clear cuts or marshes versus flooded forests (Beaudoin et al., 1994; de Grandi et al., 1994; Dobson et al., 1995a; Drieman, 1994; Hess and Melack, 1994; Lopes et al., 1993; Lozano-Garcia and Hoffer, 1993; Pierce et al., 1994b; Ranson and Sun, 1994a); and 3) discriminate crop cover on the basis of structural attributes (Foody et al., 1994; Lemoine et al., 1994; van Zyl and Burnette, 1992). Many of these applications of SAR data are discussed in the following sections.

[3] In regions with steep topography, the positions of the tops of hills and mountains are detected by radar systems prior to the bottoms of hills. This results in these features appearing to be slanted or laid over towards the nadir position of the radar.

MEASURING ABOVE-GROUND, WOODY PLANT BIOMASS

The amount and distribution of biomass over the Earth's land surface is one of the major uncertainties in our ability to understand the global carbon cycle and how it may change in the future (Post, 1993). The living and dead biomass in both above- and below-ground storage pools constitutes a major terrestrial store of carbon. The physiological activity of living biomass and the fate of dead biomass determine the fluxes of carbon from the terrestrial biosphere to the atmosphere and the accumulation or removal of important greenhouse gases (primarily carbon dioxide and methane) in the atmosphere. These processes are dynamic and subject to change in response to a variety of environmental factors (e.g., temperature, moisture, nutrient availability) and patterns of disturbance, both natural (e.g., fire, windthrow, insect-induced mortality) and anthropogenic (e.g., deforestation, land degradation, atmospheric deposition) (Solomon and Cramer, 1993).

The knowledge of the biomass density in the Earth's terrestrial biomes is limited by the difficulty in obtaining sufficient high quality observations that are representative of a region or ecosystem type (Smith et al., 1993; Dixon et al., 1994). Ground-based measurements of biomass are very time-consuming and labor-intensive and are often constrained by lack of access. Numerous studies have demonstrated that approaches using optical remotely sensed data are not appropriate for most terrestrial ecosystems because there is a saturation effect at very low levels of biomass. Currently, radar remote sensing appears to offer the greatest promise for obtaining estimates of biomass via remote sensing techniques.

The dependence of microwave backscatter on total above-ground biomass has been documented in monospecific pine forests found in the southeastern United States and France (Dobson et al., 1992; Harrell et al., 1996; Kasischke et al., 1994a; 1995a; LeToan et al., 1992), mixed deciduous and coniferous forests of Maine, northern Michigan, and Alaska (Ranson and Sun, 1994a, b; 1996; Dobson et al., 1995b; Harrell et al., 1995; Rignot et al., 1994c; Ranson et al., 1995), coniferous forests of the Pacific Northwest (Moghaddam et al., 1994), and tropical forests (Rignot et al., 1995; 1997; Yanesse et al., 1997). These studies all show the same results: 1) The sensitivity of radar backscatter at a single polarization/frequency to variations in biomass saturates after a certain biomass level is reached; and 2) the biomass dependency of radar backscatter varies as a function of radar wavelength and polarization. In summary, the saturation point is higher for longer wavelengths and the HV polarization is most sensitive and VV the least.

A conclusion drawn by some scientists is that these single frequency/polarization saturation levels represent the upper limit of SAR's ability to monitor changes or differences in above-ground biomass in forests (Imhoff, 1995; Waring et al., 1995). However, this conclusion overlooks the fact that radar backscatter is correlated not only with total biomass, but also with the various components of biomass such as branch biomass, needle biomass, and bole biomass (Kasischke et al., 1995b) or with other physical tree-stand characteristics such as tree height and basal area (Dobson et al., 1995b; Hussin et al., 1991). Since microwave scattering at different radar frequency and polarization combinations often originates from separate layers of a forest canopy, it may be possible to use multiple channels of SAR data to estimate total above-ground biomass.

Recent research supports this viewpoint. Kasischke et al. (1995b) used a two-stage approach to estimate biomass of southern pine forests using JPL AIRSAR data. In step one, total branch biomass was estimated as a function of several different radar frequencies/polarizations. Total biomass was then estimated from branch biomass based upon allometric equations, and resulted in a relative error on the order of 20% for biomass levels up to 400 t ha^{-1}. Using SIR-C data over the same test site, Harrell et al. (1997) showed that biomass levels up to 300 t ha^{-1} could be estimated using L-HV data with the rms variations from test stands of less than 50 t ha^{-1}. Ranson and Sun (1994b) used a ratio of P-HV and C-HV to estimate total biomass (up to 250 t ha^{-1}) in mixed coniferous/deciduous forests in Maine. Finally, Dobson et al. (1995b) used a multistep, semiempirical approach to estimate above-ground biomass from a combination of channels from SIR-C data collected over a mixed coniferous/deciduous forest in northern Michigan. In this approach, different SAR frequency/polarization combinations were used to estimate canopy-layer biomass, total height, and total basal area, which were then used to estimate total biomass. Biomass estimates up to 250 t ha^{-1} with an uncertainty (standard error) on the order of 16 t ha^{-1} were achieved.

In spite of these recent results, a consensus on the overall utility of imaging radar data for estimating above-ground biomass is still evolving. As so aptly phrased by one of reviewers of this article, there are two camps in this debate: those who take the view the glass is half empty, for example, the saturation level for biomass in radar imagery is fairly low (Waring et al., 1995; Imhoff, 1995); and the view expressed in this review that the glass is half full, for example, the single-frequency/polarization saturation levels can be overcome using multichannel data or multistep approaches. In defense of both viewpoints, we would like to point out that previous reviews of this subject did not fully take into account the full range of research on this subject, some of which has only recently been published (Dobson et al., 1995b; Harrell et al., 1995; 1997; Kasischke et al., 1995b; Ranson and Sun, 1996; Ranson et al., 1995; Rignot et al., 1994c; 1995; Yanesse et al., 1997).

In summary, we present the following conclusions based on these recent results: 1) Using multiple-channel radar imagery or multiple-step approaches allows for estimating higher biomass levels with better precision than relying on correlations between total biomass and radar backscatter from a single frequency/polarization system (Dobson et al., 1995b; Harrell et al., 1997; Kasischke et al., 1995b; Ranson et al., 1994b); 2) the complexity of these methods is higher and the uncertainties are greater in landscapes where there are a number of different forest ecosystems with multiple tree species [e.g., the northern mixed coniferous/hardwood forests studied by Dobson et al. (1995b) and Ranson (1994b) and the boreal forest studied by Ranson et al. (1995)] than in forested areas where the successional chronosequence is dominated by single tree species [e.g., the old-field pines chronosequence studied by Harrell et al. (1997) and Kasischke et al. (1995b)]; and 3) regardless of the method being used or the forest ecosystem being studied, there will be a need to a) calibrate the radar imagery using ground-based techniques to quantify the patterns of biomass distribution in the forests of interest using valid sampling approaches (Kasischke et al. 1994c) and b) stratify or classify the land surface containing the forests under study into different cover categories (e.g., forested versus nonforested, deciduous versus nondeciduous) prior to application of the radar-based biomass estimation algorithms.

DELINEATION OF WETLAND INUNDATION AND VEGETATIVE COVER

One of the unique applications for imaging radars occurs because a significant portion of the energy transmitted by these systems penetrates to the ground surface. When standing water is present under a vegetated surface, the resultant interactions with the microwave energy are much different than in nonflooded regions, producing characteristic radar signatures. Depending upon radar frequency and polarization and vegetation type, flooding or inundation of an ecosystem can lead to significant increases or decreases in the radar backscatter. For example, in forested canopies, the presence of water over the ground layer results in a significant increase in ground-trunk/two-bounce scattering, which, in turn, results in an increase in radar backscatter. This increased ground-trunk scattering is typically detected using only longer wavelength (L-, and P-bands) (Hess et al., 1990). Attenuation of microwave energy by the forest canopy results in no enhancement at shorter wavelengths (C- and X-band) except when no leaves are present (Ustin et al., 1991). In wetland ecosystems with no woody plants, the increase in specular (forward) scattering caused by standing water under a vegetated surface results in a decrease in radar backscatter for the Earth Resources Satellite (ERS) SAR, which is a C-VV system (Dobson et al., 1995a; Bourgeau-Chavez and Kasischke, 1997; Tanis et al., 1994).

For study of ecological processes, the characteristic radar signatures imagery from inundated ecosystems have two major applications: improvement of land/vegetation-cover classification and monitoring of the timing and spatial extent of flooding. Here we will focus on this latter use, specifically on four different processes unique to wetland ecosystems: estimating the rates of exchange of biogenic trace gases; monitoring sea-level rises; monitoring disease vectors habitats; and monitoring hydroperiod.

Uncertainties in the spatial and seasonal extent of methane source and sink areas remains one of the greatest unknowns in the global methane budget (Bartlett and Harriss, 1993). Since wetlands comprise the largest natural source of atmospheric methane (Aselmann and Crutzen, 1989: Fung et al., 1991), characterization of their areal and temporal extent on a global basis would greatly extend the understanding of trace gas exchange from these ecosystems.

Two recent studies have focused on developing techniques to use spaceborne SAR data to monitor patterns of methane flux from wetlands. Studies by Morrissey et al. (1994) showed that backscatter signatures from the C-band ERS-1 SAR acquired over Arctic tundra at Barrow, Alaska were strongly related to the position of the local water table and thus to methane exchange rates. Morrissey et al. (1994) showed that backscatter: 1) from noninundated sites was low; 2) from herbaceous inundated sites was high; and 3) from sites with the water table at the surface was intermediate. The patterns of inundation were highly correlated with methane exchange rates for the region. Furthermore, the temporal patterns of ERS-1 SAR signatures in this region can be used to further discriminate between wetland and nonwetland vegetation types (Kasischke et al., 1995c).

SIR-C SAR data (C- and L-band) are also being used to monitor methane fluxes in river floodplains in tropical forest regions (Hess et al., 1995). In this case, higher rates of methane emission are observed during the flooding of these river floodplains (Melack et al., 1994). Recent studies using SIR-C data collected over the Amazon River in Brazil show that not only could L-band radar imagery be used to map the areas of flooded forests, but that the multiple-polarization C- and L-band data could be used to discriminate different vegetation communities, which themselves have different methane fluxes (Hess et al., 1995).

Recently, the average level of the world's oceans has been rising at a rate of 1–2 mm yr^{-1}, and it is expected that this rate will increase slightly as the climate warms during the next century (Warrick and Oerlemans, 1990). These slowly rising sea levels may eventually inundate many coastal regions of the world and accelerate erosional processes in areas exposed to littoral currents and waves. Such a sea-level rise would ultimately affect the distribution and composition of vegetation in coastal estuaries, where many ecosystem processes are linked to tidal flow as well as sea level. Studies by Tanis et al. (1994) and Ramsey (1995) have shown that ERS-1 SAR data (C-band) can be used to monitor changes in water inundation in coastal estuaries associated with tidal cycles. Tanis et al. (1994) showed that the maximum water inundation extent during various tidal cycles could be determined on ERS-1 SAR imagery, something not possible using Landsat data (Ramsey, 1995). Thus, the changes in the boundaries of coastal estuaries associated with changes in sea level can be monitored using ERS-1 SAR imagery.

Insect-borne viruses cause diseases outbreaks throughout much of the developing world (Davies et al., 1985; Hoogstraal et al., 1979; Rejmankova et al., 1993). Many of these diseases are carried and transmitted by various species of mosquitos. In regions with distinct wet and dry seasons, mosquito vector populations increase dramatically with the flooding of breeding sites during prolonged episodes of high rainfall. Accurate maps of vegetation inundation are needed not only for identifying breeding grounds for disease vectors, but for predicting and monitoring outbreaks of a variety of diseases. Remote sensing data provides an important tool for monitoring breeding areas for disease vectors (Linthicum et al., 1987; 1990). Pope et al. (1992) showed that C- and L-band SAR data could be used to monitor flooding in sedge and grass-covered mosquito breeding habitats in Kenya. In a similar study, Pope et al. (1994) demonstrated that multifrequency, polarimetric airborne SAR data collected over the wetlands in Belize were capable of mapping *Eleocharis* sp. dominated marshes, which are important breeding habitats of the malaria vector mosquito *Anopheles albimanus* (Rejmankova et al., 1993).

Finally, in seasonal tropical regions, many wetlands are inundated only during the wet season. The timing and length of this inundation (the hydroperiod) controls many ecosystem processes. Recent studies by Bourgeau-Chavez and Kasischke (1997) have shown that ERS-1 SAR data can be used to monitor the hydroperiod in the wetland ecosystems found in southwestern Florida. In addition, these studies showed that ERS-1 SAR imagery can be used to monitor the effects of man-made structures on patterns of water flow in this region. Pope et al. (1997) demonstrate the utility of SIR-C data for discriminating different wetlands in the Yucatan Peninsula as well as detecting flooding in these ecosystems during the wet season.

MONITORING OF DYNAMIC PROCESSES IN HIGH-LATITUDE ECOSYSTEMS

The ERS-1 SAR data collected at the Alaskan SAR Facility and Canadian receiving stations have provided a unique opportunity to study high-latitude terrestrial ecosystems found in North America. In addition to monitoring flooding in tundra biomes (as discussed above), ERS-1 SAR imagery has been used to study boreal forests. Specifically, research has centered on how the changes in the length of growing season affect net seasonal fluxes of CO_2 (Way et al., 1994) and how rates of biogenic carbon flux are affected by fires in boreal forest (French et al., 1996b).

A number of remote sensing instruments may be used to estimate growing season length, and it is likely that a combination of sensors will provide the information necessary for long-term ecological studies. The Advanced Very High Resolution Radiometer (AVHRR), for example, provides good estimates of leaf-on period, thus bounding the growing season length for deciduous species. For coniferous species, the growing season does not correspond to changes in the leaf area index detected by the AVHRR, but typically photosynthetic processes are halted when air temperatures drop below -2°C. For closed canopy forests, canopy temperatures are within a few degrees of air temperatures (Luvall and Holbo, 1989), and can be estimated using thermal infrared emissions detected by AVHRR. Use of this instrument in boreal regions is limited by cloud cover. A third technique is to measure the length of the growing season by monitoring freeze/thaw transitions using imaging radar data (Kwok et al., 1994; Way et al., 1990; 1994; Rignot et al., 1994a; Rignot and Way, 1994). At microwave frequencies, freezing results in a large decrease of the dielectric constant of soil and vegetation because the ice crystal structure prevents the rotation of the polar water molecules contained within the soil and vegetation. This phase change results in a significant lowering (by a factor of 2–4) of the radar image intensity.

Over the past several years, scientists have developed a greater understanding of the role of biomass burning in boreal forest in the global carbon cycle and the need to monitor these fires on a continuing basis (Kasischke et al., 1995d). Because of the large sizes and remote locations of fires, satellite sensing systems are now recognized as the only reliable means to locate and estimate the areal extent of fires in boreal forests continuously on a regional scale (Cahoon et al., 1994; Kasischke and French, 1995; Bourgeau-Chavez et al., 1996). In 1990 and 1991, over 2 million ha of land surface was affected by fire in Alaska, with most (1.85 million ha) occurring in forested regions. Studies have shown that these recent fires resulted in characteristic signatures on ERS-1 SAR imagery (Kasischke et al., 1992; 1994b).

Bourgeau-Chavez et al. (1996) demonstrated that>80% of the fires that occurred in 1990 and 1991 in Alaska resulted in a characteristic signature on SAR imagery. In some regions, fires that occurred in 1979 still had a characteristic bright signature present on the ERS-1 SAR imagery. A recent examination of ERS-1 SAR imagery collected over Canada revealed that recent fires in Quebec, Ontario, and the Northwest Territories had bright signatures on ERS-1 SAR imagery similar to those observed in Alaska, demonstrating that this is not a localized phenomena (Eric S. Kasischke, N. H. F. French, and L. L. Bourgeau-Chavez, unpublished data, 1996).

Field research (Kasischke et al., 1995c; French et al., 1996a) has shown that the spatial and temporal signatures present on the ERS-1 SAR imagery of recently burned forests are highly correlated with variations in the moisture found in the top 5–10 cm of the soil.[4] Furthermore, rates of aerobic decomposition in black spruce forests are directly proportional to both temperature and soil moisture (Schlenter and VanCleve, 1985). Since soil temperatures increase significantly after fires in boreal forests, the rates of soil respiration in these fire-affected forests should also increase. Recent field measurements (French et al., 1996b) have shown this to be true in fire-disturbed black spruce forests in Alaska, where fluxes of CO_2 were greater from burned sites than from unburned sites. In addition, CO_2 fluxes were shown to be proportional to soil moisture in the burned areas. The ability of ERS-1 SAR to monitor soil moisture variations in fire-disturbed boreal forests may provide the means to monitor patterns of biogenic emissions in these ecosystems.

SAR SYSTEM CONSIDERATIONS

The wide range of applications discussed in this review illustrates that there is probably no one ideal system configuration in terms of frequency and polarization. For some applications, existing single-frequency/polarization SARs (ERS, JERS, and Radarsat) may provide an adequate data set. For others, these systems are inadequate. To assess SAR system considerations for ecological applications, we take the approach of first defining the optimal system parameters for a specific list of applications, and then discussing the potential of existing or planned SAR systems for these applications.

Optimum System Parameters

The SAR parameters which define the utility of a specific system for ecological applications include microwave frequency, polarization, incidence angle, resolution, and sampling frequency. Most spaceborne SAR systems today have a fixed center incidence angle between 20° and 50° with images covering only a few degrees from near edge to far edge. The exception is Radarsat, which operates in a SCANSAR mode, with image swaths covering a 10–25° range in incidence angles. Most spaceborne SARs have relatively fine spatial resolution (20–40 m), narrow swath widths (60–100 km), and long sampling frequencies (20–40 days). SCANSAR systems such as Radarsat have the ability to cover wide areas at lower resolutions (up to 500 km swaths with 100–200m resolution) and higher sampling frequencies (every 2–4 days).

Table 2 lists seven ecological or land surface applications for imaging radar systems and summarizes the optimum SAR parameters for each application.

One important distinction to be made in planning for future imaging radar systems is the distinction between polarimetric and multipolarization systems. Polarimetric SARs preserve the phase coherence between the different radar channels and can be used to recreate any transmit/receive combination, including circular polarizations. On the other hand, multipolarization radars do not preserve this phase coherence, and only produce the intensity of the backscattered radar signature. In terms of system design and fabrication, polarimetric radars are much more complex and costly to build than multiple-polarization radars.

For terrestrial ecology applications, there are only two areas which require polarimetric SAR systems. First, most radar image classification algorithms achieve their optimum performance when polarimetric data are available (Van Zyl, 1989; Van Zyl and Burnette, 1992). This should not be used as an outright justification for the need for polarimetric radars, however, because detailed studies on the relative utility of polarimetric radar data for image classification purposes versus data from MSS systems (such as Landsat) have yet to be performed.

The second area where polarimetric radar data are needed is for soil moisture estimation regions in order to account for variations in surface roughness. Dubois et al. (1995) demonstrated that the phase difference between the HH and VV channels provided a more than adequate means for soil moisture estimation in agricultural regions. By not using the HV channel, calibration problems associated with system noise and channel cross-talk were eliminated.

A strong requirement for polarimetric radar data to

[4] These correlations should not be taken as a demonstration of the overall ability of SARs to detect soil moisture, but representative of a special case. In their study, French et al. (1996a) examined variations in relative soil moisture from a single site throughout several growing seasons. In this case, there was virtually no variation in surface roughness between collection dates, and vegetation cover was minimal. In terms of using SAR to estimate soil moisture in an absolute sense over broad areas, variations in surface roughness and vegetation density have to be accounted for. Dubois et al. (1995) showed that polarimetric SAR data are needed to account for variations in surface roughness, and that when vegetation density reached a certain point (e.g., NDVI>0.4), the SAR-based algorithm began to underestimate soil moisture.

Table 2. Optimal SAR System Parameters for Monitoring Land-Surface Characteristics

Application Area	*Radar Frequency*	*Polarization*	*Incidence Angle*[a]	*Resolution*[b]	*Sampling Frequency*[c]
Vegetation mapping	Multiple frequency data optimal—as a minimum, two frequencies (one high, one low) required	Multipolarization and polarimetric data desired, especially with single frequency systems	Both low and high desired	High resolutions desirable for mapping smaller sampling units	Low for multiple channel systems, high for single channel systems
Biomass estimation	L- or P-band optimal, as a mimimum L- and C-band required	Cross-polarization data most sensitive; multipolarization data improve biomass algorithms	Low	For small forest stands, fine resolution; for larger area studies, low resolution	Low can be used—sampling at proper phenologic stage and under optimum weather conditions important
Monitoring flooded forests	L- and P-band optimal, but some sensitivity at C-band if no leaves present and HH polarization used	HH polarization most sensitive, but VV polarization can be used	Lower required	Higher resolutions may be important for mapping narrow features	High sampling frequencies usually important
Monitoring coastal/ low stature wetlands	X or C-band	HH or VV	Low	High or low, depending on ecosystem patch size	High
Monitoring tundra inundation	X or C-band	HH or VV	Low	High or low, depending on ecosystem patch size	High
Monitoring fire-disturbed boreal forests	X or C-band	HH or VV	Low	High or low, depending on ecosystem patch size	High
Detection of frozen/ thawed vegetation	Multiple frequencies	Multiple polarizations	Low or high	High or low, depending on ecosystem patch size	High

[a] Low incidence angles=20–40°, high incidence angles=40–60°.
[b] High resolution=20–40 m, low resolution>100 m.
[c] High sampling frequency=once every 2 weeks; low sampling frequency=once per year.

study ecological processes has yet to emerge for most ecological applications. However, there is a need for multiple-polarization radar data for some applications, such as estimating biomass.

Utility of Existing SAR Systems

Five spaceborne imaging radar systems are now in operation or were recently deployed: ERS-1, ERS-2, JERS-1, Radarsat, and SIR-C/X-SAR. The ERS-1 and ERS-2 SARs are operated at C-band and have a vertical transmit polarization/vertical receive (VV) polarization. ERS-1 was launched in the summer of 1991, and ERS-2 was launched in the spring of 1995. This system has a 25-m resolution and 100-km swath. The orbit of these systems provides a 35-day, exact repeat orbit during the northern hemisphere summer and fall (which means it can image the same ground location every 18 days or so), and a 3-day exact repeat orbit during the winter and spring in order to obtain frequent coverage of the polar ice cap.

The JERS-1 SAR is an L-band, horizontal transmit/horizontal receive (HH) polarized system launched during the summer of 1992. It has a 40-m resolution and a 75-km swath. The exact repeat orbit of this system is once every 48 days.

The SIR-C/X-SAR System was flown onboard NASA's Space Shuttle on two 10-day missions in April and October 1994. This system consisted of a C- and L-band SAR system that was fully polarimetric (e.g., it collected HH, HV, VH, and VV imagery) and an X-band SAR which collected HH and VV data. The resolution of this system ranged between 10 m and 40 m, and it collected image swaths between 15 km and 90 km wide. The ground coverage of this system was limited in order to image specific test sites during its two missions.

The Canadian Radarsat consists of C-band SAR with horizontal transmit/horizontal receive (HH) polarization, and was launched in November 1995. It has a variety of modes for resolution/swath width. The SCANSAR mode can yield swath widths up to 500 km with a spatial resolution of 100 m. This wideswath mode will allow imaging of the same geographic location once every 2–3 days.

Table 3 summarizes the potential or demonstrated capabilities of these systems relative to applications of ecological interest.

CONCLUSIONS

While airborne (and to a limited extent) spaceborne radar imagery have been collected since the mid-1970s, the early radar systems largely collected analog data (imagery only), had a limited number of channels, and collected data over a limited number of geographic regions for short periods of time. It has only been recently that well-calibrated, digital SAR data have become available for a large number of test sites. These data sets were provided primarily by the JPL AIRSAR (since 1988), the ERS-1 SAR (since 1991), and the SIR-C/X-SAR (1994 only).

In spite of the relatively short time period these data have been available, we feel research has demonstrated that radar imagery provide spatial and temporal information for the study of ecological processes. In some cases, this information is redundant to that provided by visible and infrared remote sensing systems. In many cases, the information provided by imaging radars is unique and complimentary to that provided by optical methods. Our primary conclusions on the potential utility of radar imagery for ecological applications are:

1. Multichannel radar data provide a means to classify land-cover patterns. Whereas data from multispectral scanner systems use characteristics related to reflected solar illumination or surface temperature as a basis of discrimination of land cover, imaging radar systems use information related to variations in the surface roughness, vegetation structure, and moisture conditions as a primary basis for discrimination. For land-cover classification, optimum performance is achieved using multifrequency, polarimetric radars. The relative utility of data form imaging radars versus multispectral scanner data has yet to be determined in a rigorous fashion over a wide range of biomes for this application. This evaluation is essential for decisions concerning the design of future radar systems.
2. Imaging radars have the capability of monitoring variations in biomass in forested ecosystems. This capability is not consistent among different forest types. The upper levels of sensitivity for L-band and C-band systems such as SIR-C range between <100 t ha^{-1} for complex tropical forest canopies to ~ 250 t ha^{-1} for simpler forests dominated by a single tree species. Best performance for biomass estimation is achieved using lower frequency (P- and L-band) radar systems with a cross-polarized (HV or VH) channel. The most practical use of this capability is for monitoring forest regrowth and succession following disturbances.
3. Like-polarized imaging radars (HH or VV) are well suited for detection of flooding under vegetation canopies. Lower frequency radars (P- and L-band) are most optimal for detecting flooding under forests, whereas higher frequency radars (C-band) work best for wetlands dominated by herbaceous vegetation.
4. It has been shown that spaceborne radars that have been in continuous operation for several

Table 3. Demonstrated or Potential Applications of Existing Spaceborne SAR Systems

Application Area	*ERS-1/ERS-2*	*JERS-1*	*Radarsat*	*SIR-C/X-SAR*
Vegetation mapping	Poor overall, improvement with multitemporal data	Somewhat better than ERS-1, but still poor overall; multitemporal data may improve	Probably poor without using multi-temporal data	Near optimum configuration
Biomass estimation	Poor except for low biomass levels	Good for lower biomass levels, but still limited	Poor except for very low biomass levels	Provides good estimates, but lower frequency (P-band) still optimum
Monitoring flooded forests	Poor except when no leaves present	Good for flood detection, but poor for monitoring because of low sampling frequency	Will be better than ERS-1, but limited to leaf off conditions or low density stands	Near optimum in terms of frequency/ polarization, poor in terms of repeat frequency
Monitoring flooding in coastal/low stature wetlands	Very good	Poor	Better than ERS-1 because of higher repeat frequency and HH polarization	Near optimum in terms of frequency/ polarization, poor in terms of repeat frequency
Monitoring tundra inundation	Very good	Poor	Potential high, especially with wide-swath mode	Orbital ephemeris does not reach high latitudes; data not applicable
Monitoring fire-disturbed boreal forests	Very good	Poor, sensitivity to variations in soil moisture low	Potential high, especially with wide-swath mode	Excellent potential for lower-latitude boreal forests
Detection of frozen/ thawed vegetation	Fair for this application; repeat frequency limits system somewhat	Poor, repeat frequency too low	Potential high, especially with wide-swath mode	Can study processes on a limited basis with existing data

years [such as the C-band (VV) ERS-1 SAR] provide information on temporally dynamic processes, such as monitoring: a) variations in flooding in non-wooded wetlands; b) changes in the frozen/thawed status of vegetation; c) relative variations in soil moisture in areas with low amounts of vegetation cover. These observations have been shown to be particularly important in studying ecosystems in high northern latitudes.

Significant challenges still exist in order for radar imagery to achieve its full potential for ecosystem monitoring. From the remote sensing perspective, a number of issues need to be addressed. The full range of factors which result in temporally varying signatures on SAR imagery still have to be quantified, with the influence of rain and dew, and plant phenology being the principal uncertainties. Techniques to account for the effects of topography have to be developed. For estimating aboveground, woody biomass, the upper limits of sensitivity on radar imagery as well as error bounds have to be developed for the full range of forest types. The relative utility of polarimetric, multifrequency radar data versus multispectral scanner data for land-cover classification has to be determined.

Remote sensing scientists and ecologists must continue to work together in developing products from radar imagery that are useful for studying specific terrestrial processes. In accomplishing this task, however, ecologists must realize that radar imagery offers more than just a surrogate for observations that can be obtained from ground sampling. Like data from other remote sensors, radar imagery provides the opportunity to monitor a wide range of surface and vegetation characteristics in a synoptic, continuous fashion. The challenge ecologists face is developing new approaches to capture the information available from this class of sensors, recognizing both their advantages and limitations.

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