Temporal Variations of the Microwave Polarization Difference Index and Its Relationship to the Normalized Difference Vegetation Index in a Densely Cropped Area

William L. Teng, Paul C. Doraiswamy, and James R. Wang

Abstract

The Microwave Polarization Difference Index (MPDI) for densely cropped areas contains information about the moisture and vegetation status of the ground surface. The surface parameters affecting MPDI and the relationship of MPDI to the Normalized Difference Vegetation Index (NDVI) vary seasonally. To better understand this seasonal variation, MPDI derived from the Special Sensor Microwave/Imager and NDVI derived from the Advanced Very High Resolution Radiometer were geo-registered and compared with ground data and with each other. Analysis of MPDI time series showed that moisture effects dominated at the beginning of the growing season, vegetation effects dominated during the period of peak canopy cover, and both effects were present at other times. MPDI was found to have an inverse, non-linear relationship with NDVI. MPDI varied more during the early part of the season, and NDVI varied more during the latter part of the season. Results were basically consistent with recent questions raised about the MPDI-vegetation relationship. The synergism between MPDI and NDVI is important for soil moisture and vegetation studies.

Introduction

The Microwave Polarization Difference Index (MPDI) and the Normalized Difference Vegetation Index (NDVI) have been used as vegetation indicators in many soil moisture studies (e.g., Choudhury and Golus, 1988; Teng *et al.*, 1993). Whether the soil moisture information is used in global process models or applied to agriculture, one must first account for the commonly occurring, natural or agricultural vegetation and its temporal variations.

Satellite microwave brightness temperatures (T_B) have been shown to correlate well with the antecedent precipitation index (API), an indicator of soil moisture, in sparsely vegetated areas (Blanchard *et al.*, 1981; Wang, 1985; Wilke and McFarland, 1986; Choudhury *et al.*, 1987a; Choudhury and Golus, 1988; Teng *et al.*, 1993). These studies used data from the Skylab radiometer, the Nimbus-5 Electrically Scanning Microwave Radiometer, the Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR), and the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave/Imager (SSM/I). The results showed that vegetation significantly affected the correlation.

Previous studies have also shown, based on ground measurements and satellite observations, that NDVI was highly correlated with the amount of vegetation cover (Tucker et al., 1979; Holben et al., 1980; Asrar et al., 1984) and the seasonal variations in vegetation extent (Goward et al., 1985; Justice et al., 1985). NDVI was shown to be useful in classifying land-cover types (Tucker et al., 1985) and in monitoring crop development and the length of the growing season (Gallo and Flesch, 1989). The NDVI seasonal time series generally followed crop growth and senescence. Although soil moisture conditions could not be directly inferred from the NDVI, the maximum NDVI value attained at mid-season has been related to crop moisture conditions (Doraiswamy and Hodges, 1991). A rapid decrease in the NDVI during the crop grain fill stage could also be an indicator of a lack of soil moisture.

The relationship between MPDI and NDVI is also important, because the indices provide complementary information on vegetation. Previous studies have shown that MPDI was inversely and non-linearly related to NDVI. In general, MPDI was more sensitive to vegetation cover in sparsely vegetated areas, whereas NDVI was more sensitive in densely vegetated areas (Choudhury and Tucker, 1987; Choudhury et al., 1987b; Becker and Choudhury, 1988; Townshend, 1989; Choudhury et al., 1990). These results were based on monthly or annual composites of satellite data covering selected regions of Africa, Australia, India, and the U.S., with climates ranging from arid to humid. More recently, Tucker (1992) has critically re-examined some of the data from arid and semi-arid Africa and Australia and found that the MPDI-vegetation relationship was weaker than had previously been shown. It should be noted that these previous studies all used the SMMR data, which were only available for four to five days per month. The SSM/I data used in this study were acquired daily.

In contrast to previous work, the current study focused on

0099-1112/95/6108-1033\$3.00/0 © 1995 American Society for Photogrammetry and Remote Sensing

W.L. Teng is with Hughes STX Corporation, Goddard Space Flight Center, Code 902.2, Greenbelt, MD 20771.

P.C. Doraiswamy is with the U.S. Department of Agriculture, Agricultural Research Service, Beltsville, MD 20705.

J.R. Wang is with the Goddard Space Flight Center, Code 975, Greenbelt, MD 20771.

Photogrammetric Engineering & Remote Sensing, Vol. 61, No. 8, August 1995, pp. 1033–1040.

a portion of the temperate, densely cropped U.S. Corn Belt in the Midwest (Figure 1), where climatic and soils conditions as well as cropping patterns and practices were quite different. In addition, daily satellite data and detailed ground data were available. The study aimed to better understand the ground surface parameters affecting MPDI and to determine if the seasonal variations of the MPDI-NDVI relationship found in previous work were also valid in a densely cropped area.

Methods

 $T_{\rm B}$ data used to calculate MPDI were acquired from the DMSP's SSM/I, a seven-channel, four-frequency, linearly polarized, passive microwave radiometer (Hollinger *et al.*, 1990; DMSP SSM/I Cal/Val Team, 1991). The original daily antenna temperature tapes were obtained in the "Wentz format," and Wentz-provided software was used to convert antenna temperatures to $T_{\rm B}$'s (Wentz, 1991). The SSM/I $T_{\rm B}$'s for each day were geo-registered and averaged to a grid base with a cell size of 1/4° latitude by 1/4° longitude. Footprint values were assigned, without weighting, to cells based on their latitudes and longitudes. MPDI was then calculated from the 1/4° cell $T_{\rm B}$'s of the two 37-GHz, vertically (V) and horizontally (H) polarized channels as

$$MPDI = (37 \text{ GHz}, \text{ V}) - (37 \text{ GHz}, \text{ H}).$$
(1)

For plotting time series (Figures 2 to 5), these cells were first averaged to $3/4^{\circ}$ quadrants (Figure 1). The data spanned the period from July 1987 (when SSM/I data became available) through 1990, although only the descending (afternoon) paths during the main growing season from May through September were used. Spatial resolution of the 37-GHz channels was about 33 km.

NDVI was calculated from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer-Local Area Coverage (AVHRR-LAC) as

$$NDVI = \frac{\text{channel } 2 - \text{channel } 1}{\text{channel } 2 + \text{channel } 1},$$
 (2)

where the wavelengths of channels 1 and 2 were from 0.58 to $0.68~\mu m$ and from 0.725 to $1.05~\mu m,$ respectively. Al-





though the 1.1-km resolution AVHRR data were acquired daily, cloud cover and the large scan angle limited the usable data frequency, ranging from one every few days to one every few weeks. For this study, data for the middle onethird of Iowa (34 counties) in 1988, also May through September, were used because of availability and the presence of a uniform mix of vegetation cover (mostly corn and soybeans). The data were calibrated following NOAA procedures (Kidwell, 1991). Each NDVI image was derived from an AVHRR image that was registered to the Digital Line Graph mapping data, Albers projection, acquired from the U.S. Geological Survey (USGS, 1990). A registration error of less than 1 km was achieved. County NDVI averages were obtained by overlaying a mask of the county boundaries on the NDVI images. The seasonal time series of the NDVI data was then derived by fitting the data to a Gaussian function, to filter out noise from various sources, and extracting five-day averages from the fitted data.

MPDI and NDVI values were stratified by API, crop stage,





and percent crop cover. API was calculated from precipitation and temperature history and potential evapotranspiration (Saxton and Lenz, 1967; Choudhury and Blanchard, 1983). It is given by

$$API_{i+1} = K_i (API_i + P_i)$$
(3)

where API_j and API_{j+1} are values (mm) at the beginning and end of day *j*, respectively, P_j is the total precipitation (mm) during day *j*, and K_j is the recession coefficient (dimensionless) for day *j*, given by

$$K_i = \exp\left(-E_i/W_m\right) \tag{4}$$

where E_j is the potential evapotranspiration (mm) for day jand W_m is the maximum depth of soil water (mm) available for evapotranspiration (Choudhury and Blanchard, 1983). Daily meteorological station data were obtained from NOAA's National Climatic Data Center and also registered and averaged to the $1/4^\circ$ latitude-longitude grid base. The $1/4^\circ$ cell



was initially used to better reflect the spatial variability of the meteorological data. Precipitation and temperature values for a cell that did not contain any weather stations were interpolated by averaging its nearest neighboring cells that contained data. API values were then calculated from the gridded meteorological data and averaged to 3/4° quadrants (for plotting Figure 7).

Phenological and percent crop-cover data of counties were obtained from the U.S. Department of Agriculture (USDA). In addition, for May and June, 1988 to 1990, weekly Crop Moisture Index (CMI) values for two NOAA climatological divisions were obtained from the USDA. A large part of each of the two divisions, in southwest central Illinois and central Iowa, coincided with quadrants $\boldsymbol{\mathsf{A}}$ and $\boldsymbol{\mathsf{B}},$ respectively (Figure 1). A division is a more or less climatologically homogeneous geographical unit within a state. There are usually five to ten divisions per state (Palmer, 1968). Illinois and Iowa each have nine divisions. CMI uses weekly average temperatures and precipitation as inputs and measures the degree to which moisture needs of growing crops are met by available moisture, for a division as a whole. CMI reflects the balance between evapotranspiration and soil moisture recharge (Palmer, 1968).

To register the MPDI and API data sets to the NDVI, the 1/4° cell values of the MPDI and API were first converted to rastor images. Each image represented a five-day average within the May through September period, corresponding to the five-day averages of the NDVI. The images were registered to the NDVI images by using control points selected from an MPDI image. Each MPDI and API 1/4° cell was then divided into units corresponding to the 1.1-km NDVI pixel size. All units within a cell were given the value of the cell. Finally, county boundary masks were used to extract county averages of the MPDI and API images.

Results and Discussion

Temporal and Spatial Variations of MPDI

MPDI time series curves were constructed from monthly averages of daily 3/4° quadrant values (Figures 2 to 5). Because the focus of the study was on seasonal trends, monthly averages were used to minimize the noise present in daily timeseries curves. The May values corresponded to field moisture conditions, increasing from the 1988 drought year to the 1989 "normal" year, to the 1990 wet year. In 1990, heavy precipitation during May and June led to significant planting delays as well as the flooding of many fields. The minimum in the MPDI curves in July-August was fairly constant from year to year. However, the minimum in 1990 was reached about a month later than that of other years, the curve still showing the effect of planting delays earlier in the season (Figures 2 to 4).

In general, MPDI curves had a maximum at the beginning of the crop season (May), a steep decrease towards a minimum at peak canopy cover (July-August), and a much gentler increase during maturation, senescence, and harvesting (August-September). These trends accorded with expectations, i.e., polarization difference increased with an increase in soil moisture and decreased with an increase in vegetation cover. In May, with most of the croplands bare, moisture effects should dominate, and MPDI should be high. During the period of peak canopy cover, vegetation effects should dominate, and MPDI should be low. Between May and the period of peak canopy cover and thereafter, there is a mixture of bare and vegetated ground surfaces and a corresponding mix-



ture of moisture and vegetation effects. Finally, the reduction in canopy during senescence is more gradual than the increase in canopy during earlier crop stages; thus, the MPDI curve should be steeper before than after peak canopy cover. A dry latter part of the crop season would also contribute to the slow rise in the MPDI curve after peak canopy cover. There were other factors which possibly contributed to the MPDI, such as atmospheric effects, clouds, and surface roughness (Tucker, 1989; Paloscia and Pampaloni, 1992; Tucker, 1992). However, despite these possible contaminants and recent questions raised about the MPDI-vegetation relationship, the above explanation for the MPDI, vegetation, and soil moisture trends still seemed to be reasonable, based on the clear relationships observed between MPDI values and documented ground conditions.

To check the dominance of moisture effects during May and June, CMI values for climatological divisions roughly corresponding to quadrants A and B as well as API values for



these quadrants were compared with MPDI values. In Figures 6a and 6b, the first and second halves of the plots approximately corresponded to weeks in May and June, respectively. For quadrant A (Figures 2 and 6a), both MPDI and CMI were higher in May than they were in June, for 1988 to 1990. This was also the case for quadrant B (Figures 3 and 6b) for 1988 and 1989. For quadrant B in 1990, both indices were lower in May than they were in June. The May and June API values for quadrants A and B showed similar trends (Figures 7a and 7b, respectively). At near peak canopy cover and beyond, however, both CMI and API varied inconsistently with MPDI, as vegetation effects became dominant.

Differences between MPDI curves of different quadrants seemed to reflect the differences in the mix of cover types. Vegetation cover types in quadrant B (central Iowa, Figure 3), quadrant C (northeast Missouri, Figure 4), and quadrant D(southern Missouri, Figure 5) were, respectively, mostly corn and soybeans, a mix of summer crops and winter wheat, and mostly forest. These figures show the decrease in soil moisture effects with an increase in vegetation cover. In areas of mixed summer and winter crops (e.g., quadrant C), there are



GHz channel of the SMMR and that NDVI values were curve fitted with a Gaussian function.

usually some cropped areas throughout the season. However, in mostly summer cropped areas, there is a majority of bare soil during the early part of the season. Notably, in all cases, the relative positions of the 1988 to 1990 curves were mostly preserved for the first half of the season. That is, the 1990 wet year had the highest values, and the 1988 drought year had the lowest values.

MPDI-NDVI Variations

To determine the relationship between MPDI and NDVI for a densely cropped area, 1988 data of 34 counties in central Iowa for both indices were compared. As Figure 8 shows, the relationship was inverse and non-linear (curve B), similar to that found in earlier studies (e.g., Choudhury and Tucker (1987), curve A in Figure 8). However, curve A represented data points collected from many different geographical and climatic regions, whereas data points for curve ${\bf B}$ were from the same geographical region but represented different local meteorological conditions and crop phenology. There were also many differences, such as soil types, associated with different climatic regions. In curve A, the data points ranged from the extremely dry Sahara (upper left) to the humid central Africa (lower right). Although the time period and geographical area of averaging for data points of A and B were also different, the most significant difference was that in climatic and associated conditions. The range of NDVI values (near 0 to 0.5) for both curves was similar. The range of MPDI values (2 to 15) for curve B, however, was only about onehalf that of curve A. This difference was likely related to vegetation density, vigor, and/or water content. The large range of MPDI at low NDVI values was due to the mixture of bare soil and emerged crops during the early part of the growing season as well as due to soil moisture differences.

The phenological effect for curve B can be better seen in Figure 9 (a to d), where the data points have been partitioned into four stages of the growing season. As indicated, the partitioning was by the date of peak NDVI (around the end of July to early August) and by the value of one-half peak NDVI. Note that the MPDI-NDVI relationship was not symmetrical about the date of peak NDVI; that is, MPDI varied more during the early part of the growing season (Figures 9a and 9b) than during maturation and senescence (Figures 9c and 9d). This seasonal variation was likely due to greater soil moisture and vegetative changes during periods of crop growth than during periods of crop senescence. These results were consistent with findings from earlier studies that showed a higher MPDI sensitivity in sparsely vegetated areas and a higher NDVI sensitivity in densely vegetated areas (e.g., Becker and Choudhury, 1988; Townshend et al., 1989). Again, Tucker (1992) has questioned the MPDI-vegetation relationship; however, the result from this study indicating that MPDI did not provide much information for densely cropped areas was basically consistent with Tucker's conclusion.

The seasonal variations of the MPDI-NDVI relationship was also evident from a time series of the indices (Figure 10). Again, MPDI varied more during the early part of the season (before around Julian day 180), whereas NDVI varied more during the latter part of the season (after around Julian day 210). Note again the inverse relationship between the two indices.

In addition to being partitioned by crop stage, the data points for curve **B** in Figure 8 were separately stratified by API or percent crop cover as well as by different combinations of the three factors. However, analysis thus far has not yielded significantly different information than that from stratifying by crop stage alone.

Summary and Conclusions

Time series analysis of MPDI derived from SSM/I data for parts of the densely cropped U.S. Midwest provided useful regional information about the moisture and vegetation status of the ground surface. Within-year seasonal variations of MPDI curves were mostly a function of moisture and crop phenology. Between-year variations were mostly a function of moisture and crop condition. Geographical variations were mostly related to differences in the mix of vegetation types.

A comparison of MPDI with AVHRR's NDVI showed an inverse, non-linear relationship, consistent with most previous results. However, the latter corresponded to geographical and climatic differences, whereas the former corresponded to local meteorological and crop phenological changes. In all cases, MPDI varied more in sparsely vegetated areas or during the early part of the crop growing season, and NDVI varied more in densely vegetated areas or during the latter part of the season. Despite recent questions raised about the MPDIvegetation relationship, the MPDI was shown to be useful during the early part of the crop season, notably for providing information on soil moisture condition at planting.

The seasonal variations of MPDI and NDVI indicated that a synergistic use of the two indices should be very beneficial, whether to account for the vegetation effect in soil moisture studies, to monitor vegetation condition and dynamics for global models or agricultural applications, or to assess episodic weather events such as droughts and floods. Thus, MPDI would be more useful during the early part and at the very end of the growing season, and NDVI would be more useful for the period in between. Similar conclusions on synergism were reached in previous studies with satellite





data (e.g., Townshend *et al.*, 1989) and with ground and aircraft data (e.g., Paloscia and Pampaloni, 1992). As an example, areas severely affected by the 1988 drought in the U.S. Midwest were indicated by NDVI very early in the season. However, for areas less severely affected, drought detection was not possible until the latter part of May or early part of June (Gutman, 1990; Teng, 1990). For the latter areas, MPDI could have provided a much earlier indication of the onset of drought. It is of interest to note that Tucker (1989), using SMMR-derived MPDI, found the NDVI to be a better indicator of drought conditions than MPDI in areas of the Sahel and northeastern Brazil.

Acknowledgments

The authors thank D. Gilra, B.L. Markham, J. McMurtrey III, and J.C. Shiue for their helpful comments and R. Strub and K.S. Rao for their assistance in producing the figures.

References

Asrar, G., M. Fuchs, E.T. Kanemasu, and J.L. Hatfield, 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat, *Agronomy Journal*, 76(2):300-306.

Becker, F., and B.J. Choudhury, 1988. Relative sensitivity of normal-

ized difference vegetation index (NDVI) and microwave polarization difference index (MPDI) for vegetation and desertification monitoring, *Remote Sensing of Environment*, 24(2):297-311.

- Blanchard, B.J., M.J. McFarland, T.J. Schmugge, and E. Rhoades, 1981. Estimation of soil moisture with API algorithms and microwave emission, *Water Resources Bulletin*, 17(5):767-774.
- Choudhury, B.J., and B.J. Blanchard, 1983. Simulating soil water recession coefficients for agricultural watersheds, *Water Re*sources Bulletin, 19(2):241-247.
- Choudhury, B.J., and R.E. Golus, 1988. Estimating soil wetness using satellite data, *International Journal of Remote Sensing*, 9(7): 1251-1257.
- Choudhury, B.J., M. Owe, S.N. Goward, R.E. Golus, J.P. Ormsby, A.T.C. Chang, and J.R. Wang, 1987a. Quantifying spatial and temporal variabilities of microwave brightness temperature over the U.S. Southern Great Plain, *International Journal of Remote* Sensing, 8(2):177-191.
- Choudhury, B.J., C.J. Tucker, R.E. Golus, and W.W. Newcomb, 1987b. Monitoring vegetation using Nimbus-7 scanning multichannel microwave radiometer's data, *International Journal of Remote Sensing*, 8(3):533-538.
- Choudhury, B.J., and C.J. Tucker, 1987. Monitoring global vegetation using Nimbus-7 37 GHz data, some empirical relations, *International Journal of Remote Sensing*, 8(7):1085-1090.
- Choudhury, B.J., J.R. Wang, A.Y. Hsu, and Y.L. Chien, 1990. Simulated and observed 37 GHz emission over Africa, International Journal of Remote Sensing, 11(10):1837-1868.
- DMSP SSM/I Cal/Val Team, 1991. DMSP Special Sensor Microwave/ Imager Calibration/Validation (J.P. Hollinger, coordinator), Final Report, Volume II, Naval Research Laboratory, Washington, D.C., pp. 9-65 to 9-93.
- Doraiswamy, P.C., and T. Hodges, 1991. Assessment of crop condition over large areas by satellite and ground based models, *American Society of Agronomy Abstracts*, p. 16 (presented October, 1991, Denver, Colorado).
- Gallo, K.P., and T.K. Flesch, 1989. Large-area crop monitoring with the NOAA AVHRR: Estimating the silking stage of corn development, *Remote Sensing of Environment*, 27(1):73-80.
- Goward, S.N., C.J. Tucker, and D.G. Dye, 1985. North American vegetation patterns observed with the NOAA-7 advanced very high resolution radiometer, *Vegetatio*, 64:3-14.
- Gutman, G.G., 1990. Towards monitoring droughts from space, *Journal of Climate*, 3(2):282-295.
- Holben, B.N., C.J. Tucker, and C-J. Fan, 1980. Spectral assessment of soybean leaf area and leaf biomass, *Photogrammetric Engineer*ing & Remote Sensing, 46(5):651-656.
- Hollinger, J.P., J.L. Peirce, and G.A. Poe, 1990. SSM/I instrument evaluation, *I.E.E.E. Transactions on Geoscience and Remote* Sensing, 28(5):781-790.
- Justice, C.O., J.R.G. Townshend, B.N. Holben, and C.J. Tucker, 1985. Analysis of the phenology of global vegetation using meteorological satellite data, *International Journal of Remote Sensing*, 6(8): 1271-1318.
- Kidwell, K.B. (editor), 1991. NOAA Polar Orbiter Data Users Guide, NOAA/National Environmental Satellite, Data, and Information Service, Washington, D.C.
- Palmer, W.C., 1968. Keeping track of crop moisture conditions, nationwide: The new Crop Moisture Index, Weatherwise, 21:156-161.
- Paloscia, S., and P. Pampaloni, 1992. Microwave vegetation indexes for detecting biomass and water conditions of agricultural crops, *Remote Sensing of Environment*, 40(1):15-26.
- Saxton, K.E., and A.T. Lenz, 1967. Antecedent retention indexes predict soil moisture, Journal of the Hydraulics Division (Proceedings of the American Society of Civil Engineers), 93:223-241.

Teng, W.L., 1990. AVHRR monitoring of U.S. crops during the 1988

drought, Photogrammetric Engineering & Remote Sensing, 56(8): 1143-1146.

- Teng, W.L., J.R. Wang, and P.C. Doraiswamy, 1993. Relationship between satellite microwave radiometric data, antecedent precipitation index, and regional soil moisture, *International Journal of Remote Sensing*, 14(13):2483-2500.
- Townshend, J.R.G. (guest editor), 1989. Special issue: Comparison of passive microwave with near-infrared and visible data for terrestrial environmental monitoring, *International Journal of Remote* Sensing, 10(10):1575-1690.
- Townshend, J.R.G., C.O. Justice, B.J. Choudhury, C.J. Tucker, V.T. Kalb, and T.E. Goff, 1989. A comparison of SMMR and AVHRR data for continental land cover characterization, *International Journal of Remote Sensing*, 10(10):1633-1642.
- Tucker, C.J., 1989. Comparing SMMR and AVHRR data for drought monitoring, International Journal of Remote Sensing, 10(10): 1663-1672.
- —, 1992. Relating SMMR 37 GHz polarization difference to precipitation and atmospheric carbon dioxide concentration: a reappraisal, *International Journal of Remote Sensing*, 13(2):177-191.
- Tucker, C.J., J.H. Elgin, Jr., J.E. McMurtrey, III, and C-J. Fan, 1979. Monitoring corn and soybean crop development with hand-held radiometer spectral data, *Remote Sensing of Environment*, 8(3): 237-248.
- Tucker, C.J., J.R.G. Townshend, and T.E. Goff, 1985. African landcover classification using satellite data, *Science*, 227(4685):369-375.
- USGS, 1990. Digital Line Graphs from 1:2,000,000-Scale Maps, Data Users Guide 3, U.S. Geological Survey, Reston, Virginia, 70 p.
- Wang, J.R., 1985. Effect of vegetation on soil moisture sensing observed from orbiting microwave radiometers, *Remote Sensing of Environment*, 17:141-151.
- Wentz, F.J., 1991. User's Manual SSM/I Antenna Temperature Tapes (Rev. 1), RSS Technical Report 120191, Remote Sensing Systems, Santa Rosa, California, 70 p.
- Wilke, G.D., and M.J. McFarland, 1986. Correlations between Nimbus-7 Scanning Multichannel Microwave Radiometer data and an antecedent precipitation index, *Journal of Climate and Applied Meteorology*, 25(2):227-238.
- (Received 5 November 1992; revised and accepted 12 October 1993; revised 9 November 1993)

William L. Teng

William L. Teng received the B.S., M.S., and Ph.D. degrees in civil and environmental engineering (1974, 1976, and 1984, respectively) from Cornell University, Ithaca, N.Y. His work at the U.S. Department of Agriculture, the National Air and Space Museum, the U.S. Department of Transportation, and Cornell University involved the application of remote sensing to the fields of agronomy, the geosciences, and engineering. He is currently a principal scientist with Hughes STX Corporation, Goddard Space Flight Center, Greenbelt, Maryland. His research interest is in the remote sensing of soil moisture, vegetation, and other terrain characteristics.

Paul C. Doraiswamy



Paul C. Doraiswamy received the B.S. degree in physics (1967) from Madras University, India, the M.S. degree in agricultural meteorology (1971) from the University of Nebraska, Lincoln, Nebraska, and the Ph.D. degree in forest meteor-

ology (1977) from the University of Washington, Seattle, Washington. He is currently an agricultural meteorologist with the Remote Sensing Research Laboratory, Agricultural Research Service, U.S. Department of Agriculture, Beltsville, Maryland. His research interest is in the integration of various types of remotely sensed data with climatic and crop information in models to assess crop conditions and predict crop yields.

James R. Wang

James R. Wang received the B.S. degree in physics (1963) from the University of Washington, Seattle, Washington, and the M.S. and Ph.D. degrees in physics (1964 and 1969, re-

spectively) from the University of Chicago, Chicago, Illinois. He is currently a senior scientist with the Microwave Sensors and Data Communication Branch (Code 975), Laboratory for Hydrospheric Processes, Earth Sciences Directorate, Goddard Space Flight Center, Greenbelt, Maryland. His research interest is in the application of passive and active microwave techniques for remote measurements of geophysical parameters such as soil moisture, vegetation, water vapor, and precipitation.

TWO NEW REMOTE SENSING TITLES IN THE ASPRS STORE

NEW

Decision Support - 2001

1995. 2 volume set. 1158 pp. \$70 (softcover); ASPRS Members \$40. Stock # 4541.

This set of papers has bought together a multitude of technologies that compose an integrated and more holistic approach to decision support. Split into two volumes, these proceedings are a valuable source of information for those who require or develop decision support technologies.

Volume 1 papers are technology oriented and topics include: Emerging Techniques for Decision Support Systems; GIS in Decision Support Systems; Knowledge-Based Systems; Data Visualization; Remote Sensing Developments and Applications; GPS/Control Survey; etc.

Volume 2 contains papers that are resource discipline-oriented. Subjects include: Forestry Applications; Natural Resource Decision Support; Requirements for DSS for Sustainable Development; Decision Support Systems in Agriculture; Decision Support Systems in Ecosystem Management; etc.

NEW 1995 Mobile Mapping Symposium

1995. 274 pp. \$55.00 (softcover); ASPRS Members \$30. Stock # 4540.

The 35 papers in this volume of proceedings show the potential applications for the mobile mapping technology to be limitless. Showing how mobile mapping systems are being used to map and inventory various transportation routes and utility systems and support natural resource management, these papers display the wide range and diversity of this industry.

Topics include: Imaging; Sensors; Sensor Integration; GPS Theory; GIS Theory; GIS Applications; Mobile Mapping Requirements; and Mobile Mapping Applications.

For ordering information, see the ASPRS Store.



