U.S. DEPARTMENT OF THE INTERIOR

U.S. GEOLOGICAL SURVEY

Spectral Analysis Workshop on the Use of Vegetation as an Indicator of Environmental Contamination

Proceedings of a Workshop
Desert Research Institute, Reno Nevada
November 9-10, 1994

by

Nancy Milton, U.S. Geological Survey
Judith Lancaster, Desert Research Institute
Editors

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A workshop entitled *Spectral Analysis Workshop on the Use of Vegetation as an Indicator of Environmental Contamination* was held at the Desert Research Institute in Reno, Nevada in November 1994. The workshop was sponsored by the U.S. Navy NAVFAC Engineering Service Center and brought together researchers from Federal agencies, academic institutions, and industry. A list of attendees is shown in figure 1. The purposes of the workshop were to discuss present research efforts and issues in the use of vegetation spectra for environmental applications, and to explore ways to keep in better touch with colleagues in the geobotanical remote sensing field for information exchange and possible collaborative work.

The first day of the workshop was primarily devoted to presentations of recent and ongoing research efforts. The agenda of the meeting (figure 2) shows the breadth of current research and the centers of teaching and applications of plant spectroscopy for environmental applications. The presentations may be generally grouped as follows:

- greenhouse studies of the effects on metal contamination on vegetation spectra
- analytical techniques to discriminate stressed vegetation, especially in hyperspectral data sets
- descriptions of field experiments using data from the Advanced Visible and InfraRed Imaging Spectrometer (AVIRIS) for identifying and mapping vegetation stress

Six of the presentations have been included in these proceedings as extended abstracts with figures (appendix 2).

Figure 1. List of participants

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Figure 2. Meeting agenda.

Spectral Analysis Workshop on the
Use of Vegetation as an Indicator of Environmental
Contamination

AGENDA

<u>Wednesday, November 9</u>

9:00am	Assemble at DRI Maxey Conference Room	
9:15am	Welcome to DRI	C. Fox
9:20am	Introduction	
9:30am	*Differentiation of Effects of Various Stresses on Vegetation Spectra* J. Zamudio, EG&G	
9:50am	*The Spectral Effect of Varying Concentrations of Arsenic on Greenhouse-Grown Soybean and Loblolly Pine* D. Mouat, EPA	
10:15am	***BREAK***	
10:30am	*Development of Band Selection and Analysis Techniques to Improve Environmental Applications of Hyperspectral Data* H. Foote, D. Beaver, Battelle PNL and T. Warner, W. Virginia Univ.	
10:50am	*Comparison of Multivariate Statistical Techniques for Estimating Vegetation Parameters* J. Pinzon et al., Univ. of California, Davis	
11:10am	*Research Strategies in Developing Synoptic Indicators of Salt Marsh Functioning in San Pablo Bay, CA.* Sanderson, et al., University of California, Davis	
11:50am	*Derivative-Based Green Vegetation Index (DGVI) Derived from Hyperspectral Data: Potential Use of Monitoring Vegetation Health with Higher Accuracy* Z. Chen, Lockheed-Stennis Space Center and C. Elvidge	

DRI/NOAA

12:15pm	***LUNCH*** Tour of Great Basin Environmental Research Laboratory
1:30pm	*Assessing Vegetative Indicators of Hazardous Waste Problems Using Texture Analysis of Remotely Sensed Data* J. Irvine, Environmental Research Institute of Michigan
1:50pm	*Using Hypertemporal Data to Assess Vegetation and Environmental Change* W. Jansen, WTJ Software
2:15pm	Tour of DRI's Laboratory for Spatial Analysis
2:45pm	Discussion Groups
5:00pm	Adjourn
6:00pm	Group Dinner at Olive Garden

Thursday, November 10

9:00am	Assemble	
9:15am	Discussion Groups	
11:15am	Group 1 Presentation	
11:30am	Group 2 Presentation	
11:45am	Group 3 Presentation	
12:00noon	Workshop Summary	N. Milton

At the conclusion of the presentations, the attendees selected three topics and divided into three groups to discuss each topic and the issues related to it. The topics selected were:

- software and analysis methods
- applying leaf chemistry studies to higher canopy and ecosystem scale, particularly for wetland and coastal studies
- hyperspectral data applications

The objectives of each work group were to identify current major issues and problems, define ways of solving these, and design some collaborative studies to compare and highlight methodologies (figure 3).

Figure 3. Discussion group objectives.

Identify major issues and problems

- e.g. how do we go from the lab to the field?

What improvements can be made

- what can we deliver?
- when?
- how will it help?
- who will it help?

How can data users communicate their needs and interests?

- do researchers have goals and priorities based on user needs?

Instrumentation

- what do we have?
- what do we need?

Ideas for case specific studies

- collaborative efforts
- proposal development

Each group discussed their topic, prepared viewgraphs highlighting the key points of the discussion, and presented their conclusions to the entire workshop (appendix 1).

The conclusions of the three work groups can be summarized in the following four points:

- we need to facilitate collaboration and communication among the institutions and scientists who use vegetation spectra for monitoring contamination
- a common field site is needed to serve as a test case for methodologies and instrumentation
- we recognize that because of the subtle nature of spectral changes, detection of plant stress resulting from contamination requires hyperspectral data
- scaling from laboratory to plant canopy to ecosystem levels requires additional technical developments

Nancy Milton closed the workshop with a brief summary of accomplishments of the workshop, two immediate action items, and a word of encouragement to maintain the momentum from this workshop. The two action items were:

- institute an email newsletter to share information, work in progress, and meeting schedules. Judith Lancaster of DRI agreed to edit such a newsletter for the community
- implement an annual or biannual meeting of the geobotanical remote sensing community

In addition to these two action items, participants strongly supported the establishment of a common field site for collaborative work. Members of the community who were not present at the meeting were to be contacted for inclusion in the email newsletter. Final comments focussed on the importance of communication and collaboration, especially on enhancing the dialogue among academia, government, and industry, both scientists and the user community.

Appendix 1

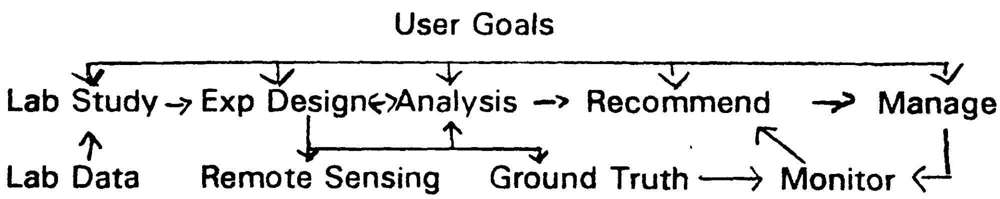
Summary of "Software Analysis Methods" Group Presentation
Presenter: Quinn Hart

The group agreed that deciding what to do with the data is the critical issue; writing the software is easy. The first viewgraph (viewgraph 1-1) of the presentation depicted the key elements used to solve a problem with remotely sensed data, and the group discussed which of these elements need to be enhanced or are completely lacking. One of the most important gaps noted is that user goals do not necessarily feed directly into laboratory studies, experimental design, and analysis. Other weak areas include a potential lack of connection between management on the one hand and experimental design and data gathering on the other.

The group concentrated on designing a technique to help users and researchers decide what their goals should be, thereby enabling development of better experimental designs. The proposed technique uses a series of focussed workshops (viewgraph 1-2). The first workshop is a steering group meeting in which the problem is defined, participants and data are identified, and any constraints are examined. The second workshop brings together the appropriate scientists, managers, and regulators to jointly examine user needs, develop goals, and produce an experimental design. At the end of the project, a final review workshop is conducted to discuss successes and weaknesses, transfer technology, and provide recommendations to management.

Group 1 believed that this process would enhance communication among all participants, e.g. site managers and scientists, which in turn would help in the development of the best-suited experimental design. Implicit in this collaborative effort are legal, technical, and transferability issues (viewgraph 1-3). For example, how do you share data? Are there legal constraints that will restrict sharing of data? How do you set standards, and how do you encourage adoption and implementation of these standards?

Viewgraph 1-1. Key elements in solving problems



Viewgraph 1-2. Focussed Workshops

Identify User
- Problem, site, $
- DOE, DOD, EPA, Indus, etc

Solve Problem

Vertical integration proposals

Steering Group
- Data collection
- Problem definition
- Constraints
- Identify participants

Design Workshop
- User needs
- Archival work
- New work
  - Lab, field, RS
- Monitor
- Outline recommendations
- Management tactics

Review Workshop
- Identify: success, weakness
- Tech transfer
- Continue
  - recommend
  - manage
  - monitor

Site Data

Viewgraph 1-3. Implicit Collaboration

How do we share data?
- within the community
- outside the community

How do we set standards?
- adopt broad standards
- standardize data collection

How do we encourage standards?
- tie to funding
- tie to journals
- tie to workshops

Possible constraints
- Legal issues
- Technical issues
- Transfer issues

Summary of "Applying Leaf Chemistry Studies" Group Presentation
Presenter: Nancy Milton

This group developed a list of the key issues which need to be addressed to improve vegetation spectral studies. The group also developed a list of action items for the workshop participants. The key issues discussed (viewgraph 2-1) include availability of data, instrumentation, scaling, and the need for collaboration.

Data availability encompasses the availability of remote sensors such as AVIRIS, mid-scale data on canopy characteristics, and individual plant physiological, chemical, and spectral reflectance information. Expense is the primary reason that data availability is such a large issue. Analyses of vegetation chemistry, especially non-routine analyses, are costly. AVIRIS data sets have thus far been relatively inexpensive, because NASA has subsidized data collection. However, with the impending federal government cuts, AVIRIS data costs may well increase. Plant reflectance spectra are not widely available primarily because no one has initiated the development of this database.

Funding is also an issue for instrumentation. It is virtually impossible for any one research institution or contractor to own all of the equipment necessary to conduct leaf chemistry studies and apply them to remote sensing analysis of environmental contamination. Most researchers are fortunate if they have state-of-the-art computer workstations on which they can perform remote sensing data analyses. However, scientists or institutions can keep up-to-date and have access to unique equipment by leasing or renting. It is typically easier to get funding agencies to approve usage fees than equipment purchases. In addition, it is easier to upgrade leased equipment. Collaborative sharing is also a potential solution to this problem.

The scaling issue is not a single problem. Numerous factors must be considered when scaling leaf spectral and chemical data to the canopy or plant community level. A few groups are attempting to develop models that will account for effects such as canopy geometry, chemical composition, sun angle, shadows, cover mixes, and backgrounds. However, a significant amount of research still needs to be conducted to fully address scaling.

Collaboration is an issue only because researchers have not had to collaborate to get funding in the past, or have been too busy with their own research. The apparent scarcity or competitiveness of present funding programs plus the need for interdisciplinary expertise now almost mandate collaboration. In addition, there are some efforts that require collaboration in order to complete the effort, for example, the development of a plant spectral database. To improve collaboration and research in general, it is important to improve communication among researchers with common interests. In particular, communication between remote sensing scientists and plant- and eco-physiologists needs to be improved. During the first day of the workshop, the U.C Davis participants presented initial research on coastal wetlands located near and within a former Naval base. This research may be an ideal collaborative effort between U.C. Davis and the U.S. Navy.

The list of action items developed by the group is shown in viewgraph 2-2. As shown, individuals and institutions were identified to be responsible for each of these action items.

Viewgraph 2-1. Issues

Availability of Data

- AVIRIS, etc.
- mid-scale
- chemistry
- plant reflectance database

Instrumentation

- leasing versus buying
- how to stay at state-of-the-art level

Scaling

- laboratory to image
- leaf to canopy to ecosystem

Collaborations

- database of plant spectra
- Navy and U.C. Davis on wetlands
- communications in general
- need expertise in plant- and eco-physiology

Viewgraph 2-2. Action Items

- Letter to NASA HQ regarding continuing availability of AVIRIS data (Lynn Shaulis)
- Get NASA and NSF to discuss joint funding of a plant spectral database (Susan Ustin & Nancy Milton)
- Workshop on data standards for plant spectra (followup from above)
- Make instrument/expertise/software list (everyone - DRI lead)
- email mailing list (DRI)

Summary of "Hyperspectral Data Applications" Group Presentation
Presenter: Bob Satterwhite

This group felt that the primary issue facing hyperspectral data applications was the lack of a study integrating laboratory and remotely acquired hyperspectral data. Therefore, they focussed on designing the ideal integrated study. The objective of this study would be an integration of ground spectra, geophysics, and plant geographical and physiological data with high spatial resolution hyperspectral data to detect environmental contamination. In particular the focus would be to detect early stress or premature senescence to permit mitigation prior to irreversible impacts.

The key to successfully completing this research is the selection of an appropriate site. Obviously, the site must be vegetated and in a high interest area. The environmental problem must be appropriate to or compatible with the sensor, and baseline characterization data must already exist for the site to reduce project cost. In addition, it would be easier if the site were not tied to any political problems. Once the site is identified, the major elements of the research would include:

- collection of hyperspectral data at various spatial and spectral resolutions
- additional field work and laboratory analyses as needed
- laboratory characterization of the contaminants if this has not been previously done
- an interdisciplinary team will be needed to address all aspects of the problem
- the robustness of existing models should be tested and models compared

Viewgraph 3-1. Objectives

Integration of ground level spectral, geophysical, and plant data with high spatial resolution for detection and location of environmental stressed areas

Detection of premature senescence of vegetation or other changes in healthy or stressed vegetation for possible mitigation

Viewgraph 3-2. Components

- Hyperspectral data at various spatial and spectral resolutions
- Field work/laboratory analysis
- Laboratory characterization of contaminants
- Interdisciplinary collaboration effort at a demonstration site
- Test robustness of theoretical models

Viewgraph 3-3. Site Characteristics

- Known site with high potential for success
- Vegetated site
- Problem consistent with sensor capability
- High interest area
- Not confounded by other problems
- Baseline data available

Appendix 2 Abstracts

ASSESSING VEGETATIVE INDICATORS OF HAZARDOUS WASTE PROBLEMS USING TEXTURE ANALYSIS OF REMOTELY SENSED DATA[1]

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EXPANDED ABSTRACT

A major environmental concern today is the characterization, remediation, and monitoring of Federal waste sites, such as those operated by the Department of Energy. Remotely sensed imagery data offers a rich source of information for characterizing and monitoring these sites. This paper explores the use of texture analysis of the imagery data as a technique for identifying and classifying features within the sites. Texture measures are derived from the spatial covariances, higher order moments, and estimates of the fractal dimensions of the imagery data. Application of classification procedures to these texture measures offers a way to identify features of interest, such as vegetative stress, surface contaminants, subsidence, and soil moisture. This paper applies the procedures to two specific environmental waste problems:

> <u>Vegetation recovery at the Coal Ash Pond at Oak Ridge National Labs</u>: The texture analysis can be used to correctly classify features within the image, distinguishing recovering vegetation from unaffected vegetation with approximately 90 percent accuracy.
>
> <u>Surface contaminant effects at Savannah River:</u> Although the surface oil patches at the site were not obvious based on visual inspection of the imagery, the texture analysis could correctly identify the oil features much of the time.

An additional area of study was the use of remote sensing for detection and location of buried waste trenches at the Solid Waste Storage Area 4 (SWSA-4) at Oak Ridge. The site contains a number of covered trenches where low-level radioactive waste was buried in the 1950s. The study indicated that three sources of information are valuable:

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[1] This project was supported under the Strategic Environmental Research and Development Program (SERDP). The Dystal artificial neural network was developed by ERIM under NIH grants NOINS02389 and NOINS32304 and ONR grants N00014-88-K-0659 and N00014-92-C-0018.

- Historical aerial photography acquired during the period of burial activity can reveal the locations of specific trenches and may give some indications of burial practices.

- High resolution multispectral imagery collected by the Daedalus 1268 indicates changes in vegetation vigor associated with the trench locations. These vegetative indicators may be attributable to differences in soil moisture caused by subsidence or altered drainage at the trenches.

- Thermal imagery collected by the Daedalus 1268 indicates differences in the apparent temperature of the trenches.

A composite map of the trench locations was constructed, using all three sources of data. This information is being used by the Environmental Restoration Program at Oak Ridge to plan remedial actions for the site.

The study demonstrates that imagery data are useful in the characterization and monitoring of various hazardous waste problems. Furthermore, it is evident that no single sensor provides all of the relevant information; a mix of sensors (including historical data) is desirable. We recommend that future study explore how widely these techniques can be applied, considering a variety of waste problems, climates, terrains, vegetative conditions, and soil types. Finally, it is imperative to develop studies in concert with ongoing clean-up activity to insure that the results are applicable in practice.

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QUANTIFICATION OF VEGETATION STRESS USING CANOPY REFLECTANCE MODELS

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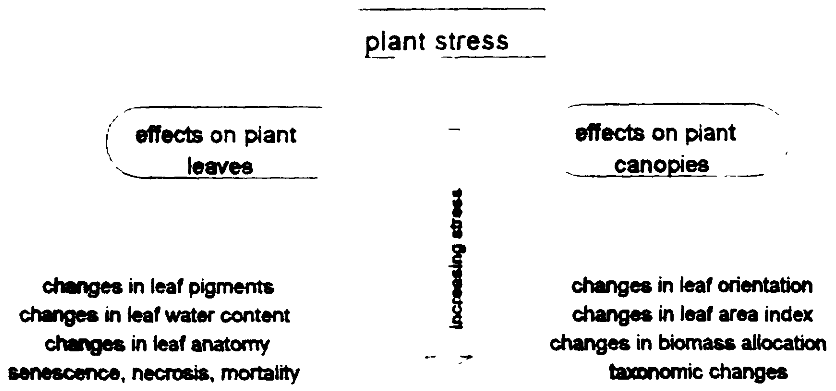
Environmental contamination (air, soil, water) may strongly disturb natural ecosystems, in particular vegetation by inducing stress phenomena. Stress, defined by Jackson (1986) as any disturbance that adversely influences plant growth, results in physiological and anatomical changes within plants potentially detectable by remote sensing techniques. For example, air pollution (O_3, SO_2, NO_x), ions (Na_2SO_4, $CaCl_2$, NaCl) and heavy metal (Cu, Zn, Co, Ni, etc.) toxicities are usually exhibited through abnormal leaf color, leaf burning, or defoliation that are sometimes followed by plant death. In fact, these changes are the visible expression of changes in leaf pigment concentration, leaf water content, or canopy architecture which are all correlated with variations in canopy spectral and directional reflectance properties. Most studies that analyze the effect of the above pollutants on leaf or canopy reflectance are rather descriptive. However, remote sensing offers the possibility of quantitatively assessing abiotic plant stress, for instance by using models.

Effects of stress on plant radiative properties



Can we detect plant stress by remote sensing techniques? At leaf level, changes in leaf pigment concentration or leaf water content are correlated with variations in leaf optical properties. For instance, an increase of the ozone concentration leads to a destruction of chlorophyll and a loss of water, inducing an increase of reflectance in the whole spectrum (Runeckles and Resh, 1975, Gausman et al., 1978; Schutt et al., 1984; Ustin and Curtiss, 1990; Carter et al., 1992). Heavy metals may change the chlorophyll a / b ratio and decrease the total chlorophyll content, inducing an increase of reflectance in the visible region and a blue shift of the red-edge (Horler et al., 1980; Schwaller and Tkach, 1985; Milton et al., 1989, 1991). At canopy level, changes in canopy architecture are also correlated with variations in canopy spectral and directional properties. For example, atmospheric pollution (e.g., ozone) may accelerate senescence and abscission of plant leaves or needles (defoliation), producing a decrease of canopy reflectance due to the increasing parts of shadow and to the growing influence of the soil background (Koch et al., 1990). In consequence, canopy reflectance changes resulting from an environmental contamination should be detectable by remote sensing techniques. The question is now: how to extract canopy biophysical parameters and therefore how to quantify these changes?

Extraction of canopy characteristics from remote sensing data

Two different approaches may be considered (Jacquemoud, 1993):

The semi empirical approach consists in using statistical techniques to obtain a correlation between the target and its spectral signatures. A first method, called spectral mixture analysis, reduces the spectral information of a complex target into independent sources of variability, the end-members, which can be chosen among a library of reference spectra acquired in the laboratory (leaves, mineral powders) or in the field on well known surfaces (vegetation types, rocks). The Forground/Background Analysis described by Pinzon et al., (1995) is an alternative multivariate statistical technique that has been used to determine leaf and canopy chemistry (Pinzon et al., 1995). Vegetation indices (NDVI, PVI, SAVI, TSAVI, GEMI, MSI, etc.) built as combinations of broad band reflectances have been also related to some biophysical characteristics of the canopy. High spectral resolution sensors permited the development of specific tools based on shape analyses of reflectance spectra: the spectral shift of the red edge, a region where the reflectance greatly increases from the red (650 nm) to the near infrared (800 nm), has given rise to a lot of literature.

A second approach consists, first, in describing the interactions between the sun light and the canopy (leaf+soil) through an analytical reflectance model. Second, that model is inverted using nonlinear optimization techniques (Figure 1). The use of a leaf-level radiative transfer model like the PROSPECT model, should help us to understand and quantify in terms of leaf biochemistry (chlorophyll, water, nitrogen or carbon content) and leaf mesophyll structure. The coupling of that model with a canopy reflectance model (IAPI, Kuusk, Myneni, SAIL, etc.) should later permit the evaluation of other consequences of an environmental contamination such as a modification of canopy architecture. The input parameters of such a model are: the leaf structure parameter (N), the leaf biochemical content – chlorophyll a+b (C_{ab}), water (C_w), nitrogen (C_N), and carbon content (C_C) – and the canopy architecture – Leaf Area Index (LAI), leaf orientation (θ_l), and hot spot size parameter (S_l). As seen before, these parameters may change, individually or all at once when a vegetation stress appears. Model inversion is the only way to separate the specific effects of each of them and consequently to better characterize the type of stress.

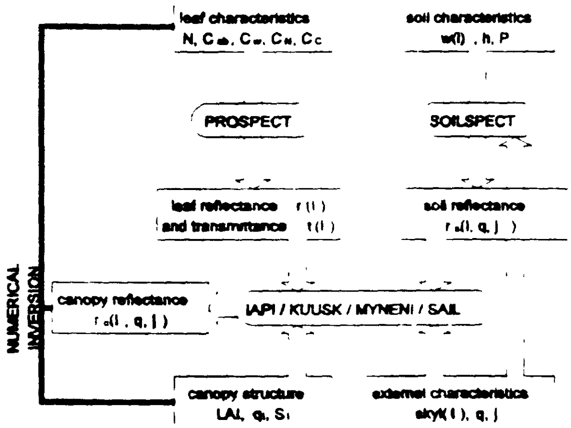


Figure 1: Schematic representation of model inversion.

The PROSPECT model

Leaf spectral reflectance and transmittance may be derived from the PROSPECT model (Jacquemoud and Baret, 1990; Jacquemoud et al., 1995) which idealizes the leaf as a stack of N identical elementary layers defined by their spectral refractive index $n(\lambda)$ and an absorption coefficient $k(\lambda)$. In the abstract, N relates to the cellular arrangement within the leaf: N ranging between 1 and 1.5 corresponds to monocotyledons with compact mesophyll; dicotyledons characterized by differentiated tissues - a compact palisade parenchyma and a spongy parenchyma with air cavities - have N values between 1.5 and 2.5 (Figure 2). The absorption coefficient depends on the leaf constituents concentrations: chlorophyll a+b concentration C_{ab} expressed in $\mu g.cm^{-2}$, water depth C_w expressed in cm, protein C_p and cellulose+lignin C_{c-l} concentrations expressed in $g.cm^{-2}$. For simplicity, these constituents are assumed to be distributed homogeneously in the leaf. The validation of PROSPECT was carried out using experimental data acquired at leaf level. The values estimated by the model inversion are plotted in Figure 3 against measured values: the high correlation for pigments and water shows that the procedure is successful in retrieving major leaf components whose effects predominate. Concerning minor ones, we notice that there is no sensitivity for protein but that cellulose+lignin is well estimated. In terms of reflectance and transmittance reconstruction, we showed that the PROSPECT model was able to accurately synthesize the whole leaf spectrum for widely different kinds of plant leaves using only 5 parameters.

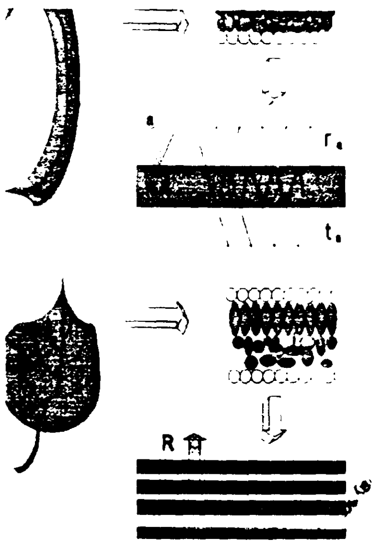


Figure 2: The PROSPECT model

Figure 3: Comparison between measured and estimated leaf biochemical parameters

nopy reflectance models

The topic of this paper is not to describe in detail canopy reflectance models because an excellent review has been done by Goel (1987) Some geometrical models and turbid-medium models have been inverted using reflectance measurements in order to estimate the canopy biophysical variables. Two methods of inversion can be distinguished: the first one uses directional data and allows estimation of physical variables describing the canopy architecture. The second one uses spectral data acquired for example at nadir and permits extraction of canopy biochemistry. Until now, the number of wavebands available on satellite sensors was smaller than the number of canopy parameters that determine the reflectance, making inaccurate any inversion using nadir reflectances in several wavelength bands, but the development of imaging spectroscopy offered the prospect of using such a method. The best results would be obtained by combining both spectral and directional reflectance measurements on the same target.

Conclusions

The detection and quantification of an environmental contamination are a tricky task. When affected by air, water or soil pollution, plant canopies tend to wither. As compared to the multitude of possible attacks, the vegetation shows up a small number of physiological and morphological changes detectable by remote sensing. Detecting a stress and estimating the level of contamination may first involve textural analyses of the image: the spatial pattern of affected canopies differs from that of healthy canopies (Irvine, 1995), and the more its differs, the more the vegetation is affected. Using the radiometric properties of the target is another way characterize a plant stress: vegetation indices have been developed in the past to quantify some of the canopy variables but they are not specific. For instance, in areas of recent environmental contamination, architectural changes may be more important than changes of leaf reflectance or leaf area index: that situation requires bi-directional reflectance measurements and model inversion to detect. The next generation of satellites such as MISR or POLDER which combine both several wavebands and several measurement angles should allow us to extract by this way accurate information on plant canopies, therefore to quantify a plant stress.

However, remote sensing cannot do miracles. Plant stresses or taxonomic changes require sometimes a long time to develop: this means that temporal information is necessary and that implies a requirement to correct the canopy reflectance for atmospheric and the sun zenith angles effects. Further, there are no direct effects of air pollution or metallic elements on spectral reflectance but only indirect influences related changes in chlorophyll or water content: detection may create possible confusion with other stress sources (Ex: O3 ↔ virus diseases, SO2 ↔ natural senescence). Finally, spectral detection of stress is often demonstrated when the vegetation is already very senescent or dead. Development of early stress detection methods and those related to detection of specific stress responses remains a challenge.

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Using Foreground/Background Analysis to Determine Leaf and Canopy Chemistry

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I. ABSTRACT

Spectral Mixture Analysis (SMA) has become a well established procedure for analyzing imaging spectrometry data, however, the technique is relatively insensitive to minor sources of spectral variation (e.g., discriminating stressed from unstressed vegetation and variations in canopy chemistry). Other statistical approaches have been tried e.g., stepwise multiple linear regression analysis to predict canopy chemistry. Grossman et al. (1994) reported that SMLR is sensitive to measurement error and that the prediction of minor chemical components are not independent of patterns observed in more dominant spectral components like water. Further, they observed that the relationships were strongly dependent on the mode of expressing reflectance (R, –log R) and whether chemistry was expressed on a weight (g/g) or area basis (g/m^2). Thus, alternative multivariate techniques need to be examined. Smith et al. (1994) reported a revised SMA that they termed Foreground / Background Analysis (FBA) and permits directing the analysis along any axis of variance by identifying w vectors through the n-dimensional spectral volume orthonormal to each other. Here, we report an application of the FBA technique for the detection of canopy chemistry using a modified form of the analysis in which the projections of each spectra along the vector *w* are its respective chemistry content. The study used two datasets representing a wide range of species having divergent foliar adaptations and conditions. These datasets were the LOPEx (Leaf Optical Properties Experiment) obtained from the Joint Research Centre in (Jacquemoud et al., 1994), and a similar but smaller dataset from the Jasper Ridge Biological Preserve at Stanford University (Grossman et al., 1994). The range of variation - several orders of magnitude - depended on the dataset and the specific chemistry (Jacquemoud et al., 1995). The variance structure is especially critical for variables like nitrogen that are in low concentration and do not express a wide range of variance between species.
The FBA was performed to define the best vector for discriminating each chemistry measured on the JRC and Jasper Ridge fresh leaf datasets, and on the JRC dry leaf dataset using R, –log R,and other non-standard transformations, like the squared reflectance (R^2). We calculated the multiple correlation coefficient (r^2), to compare the predicted values to the measured chemical concentrations. The best fit overall (0.94) was found for predicting water content (g/g), see Table 1.

These results show that the highest r^2 are found for spectra having high chemical variance (Figure 1). Low r^2 values correspond to chemistry variables that have limited variance. These

FUNCTION	CHEMISTRY										
	NITROGEN			CELLULOSE			CARBON			WATER	
DATA	JRC fl	JRC dl	JR	JRC fl	JRC dl	JR	JRC fl	JRC dl	JR	JRC fl	JR
R2	0.69	0.60	0.33	0.38	0.29	0.81	0.40	0.27	0.63	0.94	0.91
R	0.68	0.54	0.31	0.31	0.27	0.79	0.40	0.39	0.71	0.94	0.89
Log(1/R)	0.60	0.34	0.30	0.20	0.22	0.64	0.42	0.39	0.82	0.94	0.87
Filter(R)	0.62	NO	0.32	0.50	NO	0.65	0.44	NO	0.83	0.92	0.90

results also show that spectra are dominated by the mean reflectance response (related to albedo) rather than variability due to minor absorptions. Clearly this is undesirable for detection of canopy chemistry. We can try to improve detection by considering additional transformations that reduce the effect of variance around the continuum reflectance and maximize shape differences. Such transformations might improve predictions and provide a better basis for predicting canopy biochemistry of minor constituents.

The first operation was to normalize the spectra and remove albedo differences.

The next step applied a Discrete Fourier Transform (DFT) to the 211 band spectrum to remove high frequency response (typically related to noise) and a low frequency filter to alleviate the dc response. The best-fit predicted and measured chemistry is shown in Figure 2 and Table 1. The effects of these operations are shown in Figure 3. Normalization of the reflectance spectrum does not affect the shape although it does affect the wavelength dependent variance structure. The DFT filtering step clearly changes the shape of the spectrum (mean reflectance information is lost), but enhances other desirable characteristics of the variance structure. The r^2s of the FBA analysis on the normalized DFT dataset are shown in Table. The r^2s of the chemistry variables that have low sample variance (e.g., nitrogen and cellulose) are improved using the squared spectrum, while those with high concentration or having high intra-sample variability (like water) maintain an acceptable level of prediction. Thus, these preliminary results support the possibility of developing direct detection of canopy chemistry using imaging spectrometry.

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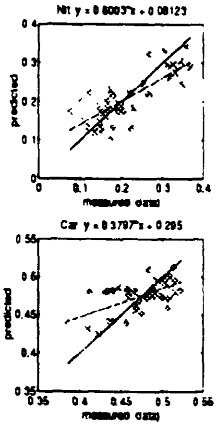

Fig. 1. Best fit by standard methods

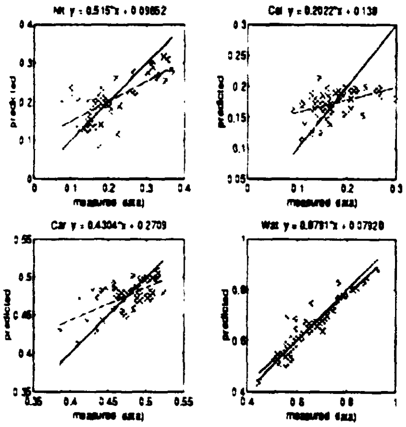

Fig. 2. Best fit by filtering spectra

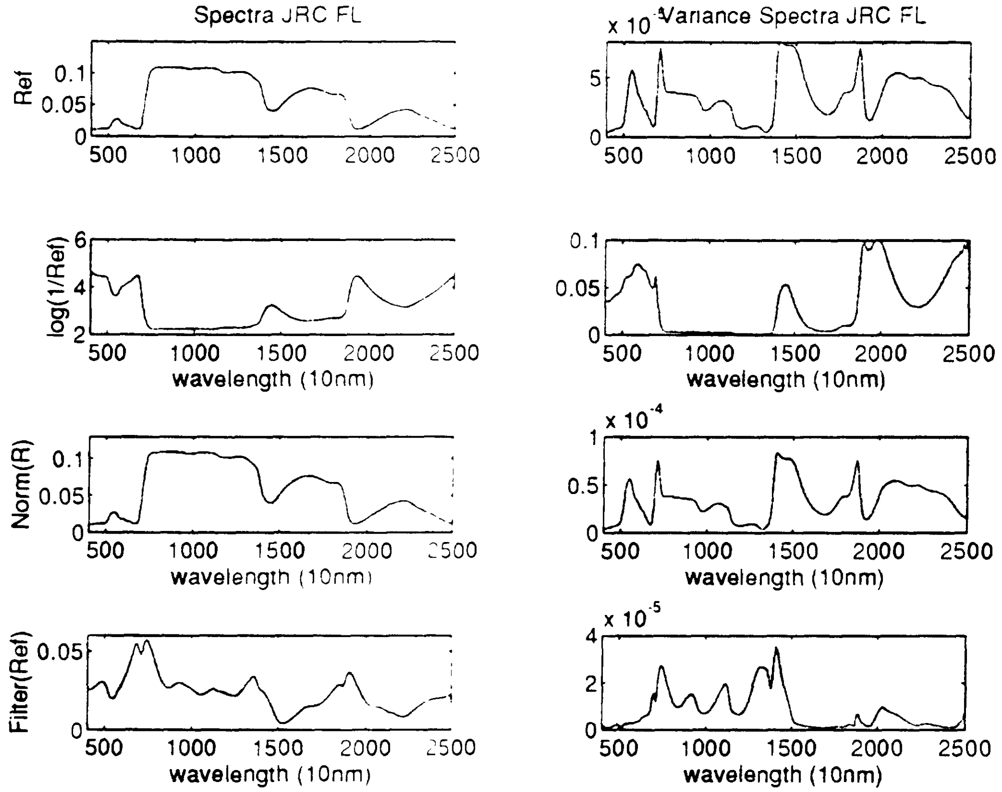

Fig. 3. Effects of the transformations for spectra and variance.

Mapping complex vegetation classes using hyperspectral visualization and classification tools

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The Arid Lands Ecology preserve (ALE) is a 312 square kilometer section of the Department of Energy's Hanford Site. Hanford is located in the semi-arid interior region of south central Washington, and the vegetation is dominated by sagebrush communities. ALE was set aside in 1967 to preserve shrub-steppe habitat and vegetation, and remains the largest Research Natural Area (RNA) in Washington State. Hyperspectral remote sensing is an important tool for monitoring and studying this large area. However, due to the complex and variable nature of the vegetation communities at ALE, it is difficult to develop automated methods to map the vegetation. A major cause of this problem is that there are few pure classes; most communities are mixtures. In addition, variability in plant architectures and rapid changes in plant phenological state make many of the spectral library-based methods developed for geological remote sensing inappropriate. Identifying the various community mixtures, and even small changes in these mixtures, is important in studying ecosystem response to the invasion of alien species, habitat changes for threatened species, or changes associated with stress from local contamination or regional climate change.

Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) imagery was collected over the Hanford Site on May 24, 1993. One of the tools we are using for mapping vegetation communities with this data is the n-Dimensional Probability Density Functions (nPDF), a suite of programs for data visualization, enhancement and classification (Cetin and Levandowski, 1991, Cetin *et al.*, 1993). The essence of the nPDF approach is in projecting the hyperdimensional data onto two-dimensional plots, which can be used to display data distribution or relative class position. Each axis of the plot is the hyperspectral distance from selected corners in the potential data space to the measurement vector of each pixel These plots provide an excellent representation of the spectral distribution of cover types and can also be used as look-up tables for a non-parametric classification. The only difficulty in using nPDF is in choosing the corners in the original data space from which the perspective plots are developed. For data sets of low spectral dimension, a combination of a knowledge of the spectral classes present and experimentation normally results in an adequate choice. However, with hyperspectral imagery this approach is generally not so successful. This is due to the large number of corners to select from. With each additional band the number of potential corners doubles, because hyperspectral distances can be calculated from the origin (0 Digital Number, or DN) or the maximum (255 in 8 bit data) in each band.

One automated approach for corner selection is to use a variation on the spectral maximization method of Cetin and Levandowski (1991). In spectral maximization, corners are chosen such that they result in a maximum hyperspectral distance to a cover-class of interest, compared to the distance to some other chosen class, normally a class with which it is being confused This is done by comparing the average DN for the two classes for each band: if the class of interest has a higher DN than the other class, then the corner is determined by the origin of that band, 0 DN. Alternatively, if the class of interest has a lower DN than the other class, then the corner is determined by the maximum in that band. Remotely sensed data tends to be highly correlated, and the maximization approach will tend to favor corners that measure albedo (i.e. the origin in all bands) or the opposite of albedo (i.e. the maximum in all bands). However, often albedo/illumination geometry variations will cause the class variance to be greatest in this direction. Thus, even though the maximization approach will chose corners that give the maximum separation of the means of the two classes, it may be better to suppress a solution that is dominantly albedo/illumination geometry

Pouch and Campagna (1990) have shown that spectral information can be separated from albedo/illumination effects by projecting each measurement vector onto a hypersphere. The albedo/illumination geometry component is the radius vector, calculated by taking the square root of the sum of the squared DN values in each band. In nPDF terminology this is an nPDF component calculated from the corner which represents the origin in all bands. The spectral information is represented by the hyperspherical direction cosines, which are calculated by dividing each band by the radius vector. This is in effect a normalization to the average reflectance for that pixel. Figure 1. shows the Hyperspherical Direction Cosine (HSDC) spectra calculated for two cover types from the ALE AVIRIS scene. It must be emphasized that because the data were not calibrated to ground radiance, these spectra cannot be related directly to field spectra and can only be used for comparing data within this image. Although the two spectra exhibit many similar features, the cheatgrass/Sandberg's bluegrass has a lower HSDC value than hopsage over wavelengths shorter than 1140 nm, a small region near 2100 nm, and at long wavelengths greater than 2260 nm. If we now choose a corner such that we calculate the hyperspectral distance from the maximum DN in these spectral regions, and from the minimum DN in the remaining bands, the resulting hyperspectral distance will be greatest for the cheatgrass/Sandberg's bluegrass and give the largest separation of the two spectra.

The results of an nPDF plot for selected cover types using such a corner selection are shown in Figure 2. The horizontal axis of the figure is the hyperspectral distance from the origin, and the vertical axis is the distance from the corner which will maximize the cheatgrass/Sandberg's bluegrass community HSDC spectra. Although this corner was chosen based on HSDC spectra, the data plotted here are determined from the original spectra, since albedo/illumination differences may provide additional spectral information. In figure 2, three spectral classes have been plotted, including the two classes used in the corner selection process (the hopsage class, and the cheatgrass/Sandberg's bluegrass class). The third class, big sagebrush/hopsage/Sandberg's bluegrass, has elements of both of the first two classes, as well as an additional species, big sagebrush. The fact that the third class plots on a mixing line between the two classes despite the presence of big sagebrush suggests that this represents a good transformation for estimating mixed classes of the type chosen. Previous work has shown that such transformations can be used as empirical estimates of the compositions of mixed pixels (Cetin *et al.*, 1993, Warner *et al.*, 1994).

Additional plots of mixing lines between other communities such as big sagebrush and bluebunch wheatgrass allow further investigation of the spectral separation of the various communities at ALE. Because nPDF is an absolute classifier, and therefore highly suited to multiple classifications with the different classes identified in different plots, we are able to combine the various classifications to produce a single map. This map includes both pure classes dominated by one cover type, as well as mixed classes.

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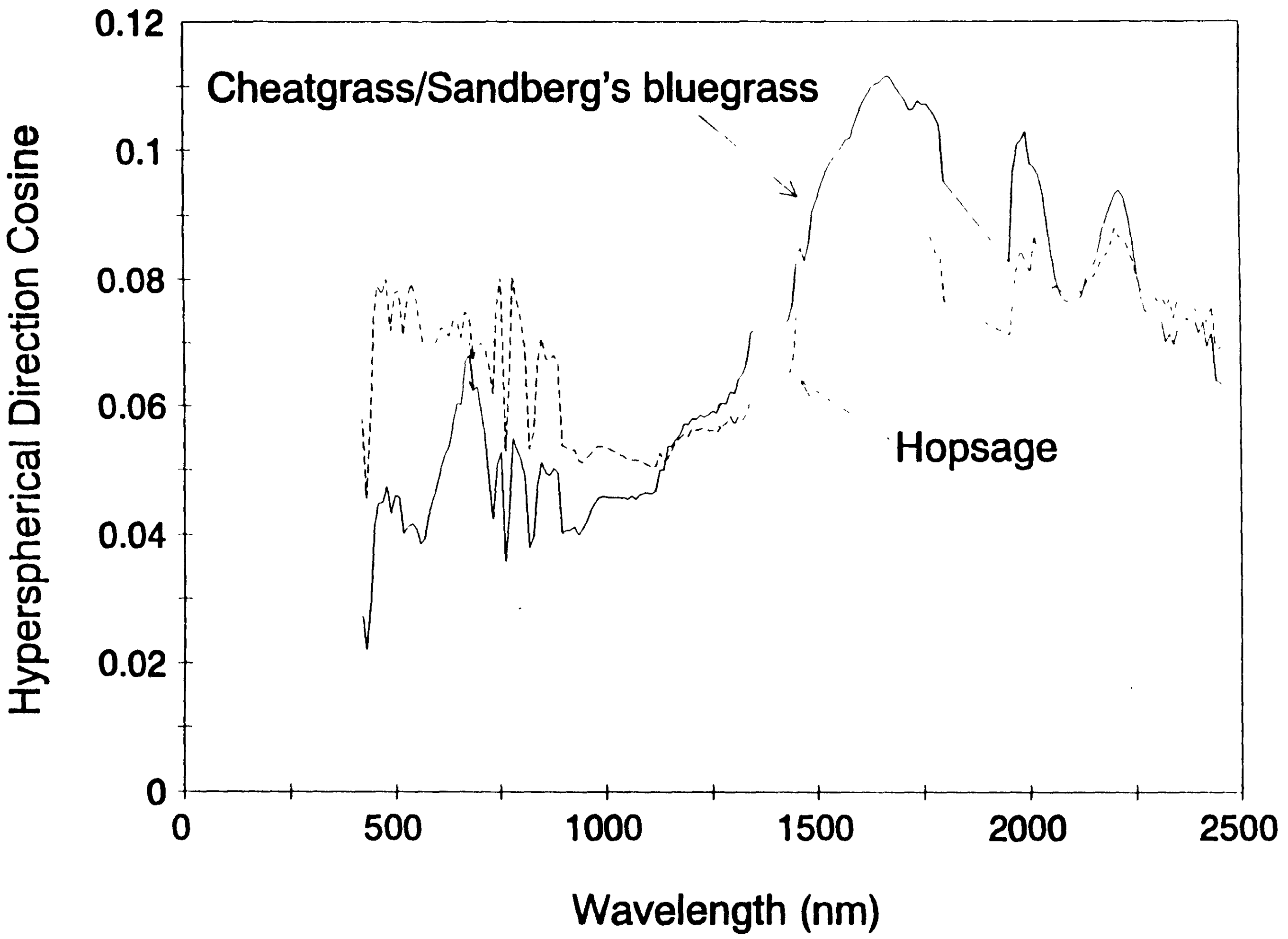

Figure 1. Hyperspherical direction cosine spectra of selected vegetation communities.

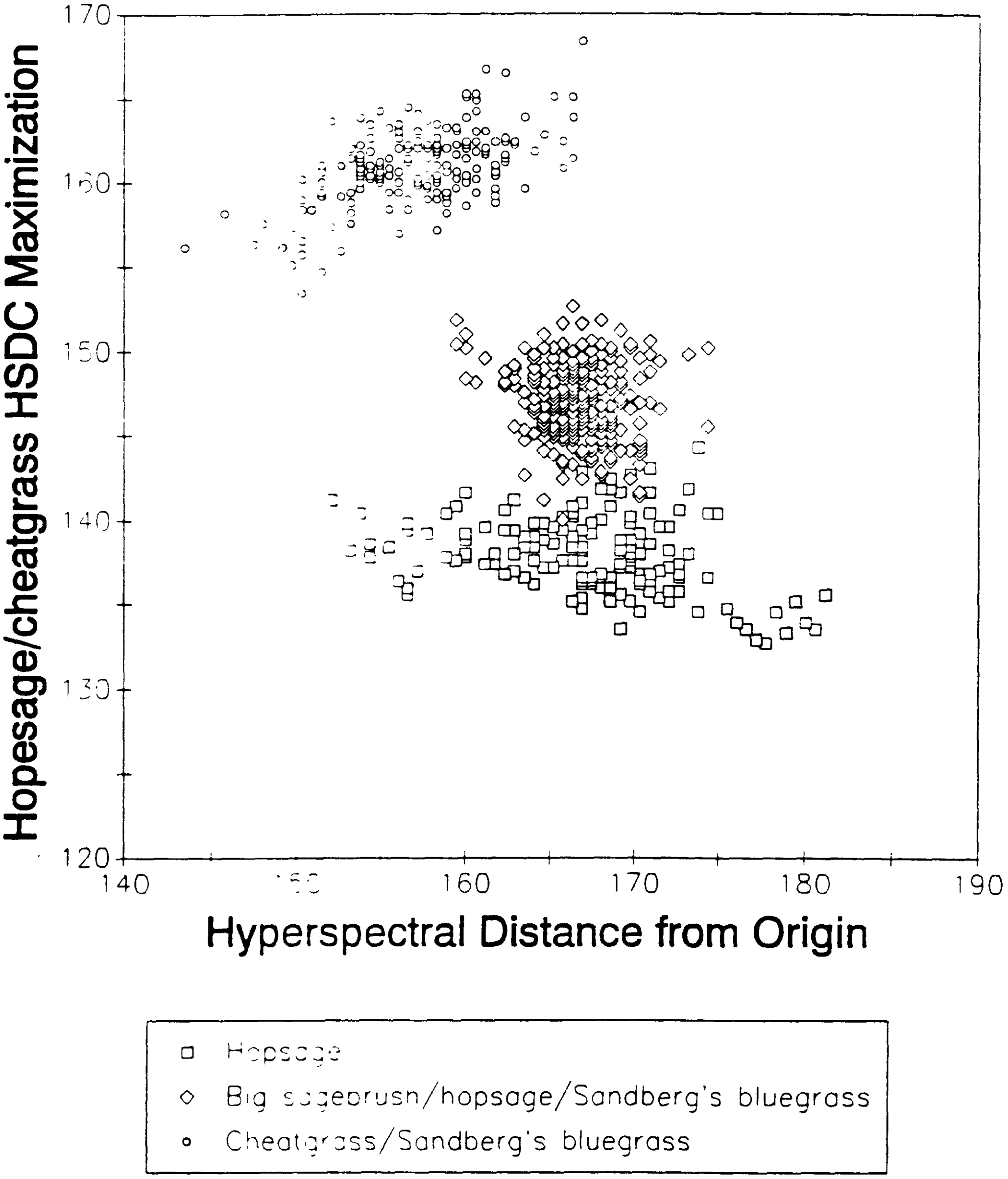

Figure 2. nPDF distribution of selected vegetation classes.

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DERIVATIVE-BASED GREEN VEGETATION INDEX (DGVI) DERIVED FROM HYPERSPECTRAL DATA: POTENTIAL USE FOR MONITORING VEGETATION HEALTH WITH HIGHER ACCURACY

Environmental contamination may concentrate trace elements in soils. Plants that absorb these trace elements at higher-than-normal levels may display abnormal spectral signatures, such as "blue-shift". Moreover, contamination can change geochemical constituents and reactions in the soils. The change can directly influence the character and amount of nutrients available for overlying plant growth. Either insufficient nutrients caused by this geochemical process or absorbed damaging trace elements would influence plant health, therefore affect reflection characteristics of plants. Variations in cover density and vigor of plants can be monitored by remote sensing data.

Vegetation health or cover status is usually monitored by using the conventional broad-band vegetation indices (e.g. NDVI, PVI, RVI, and SAVI). Our experiment, conducted by high spectral-resolution PS-2 data with bandwidth of ~4 nm, showed that the narrow-band conventional vegetation indices have higher accuracy than the corresponding simulated broad-band vegetation indices in quantifying vegetation cover, especially the low (≤30% green cover) and very low (≤10% green cover) green cover conditions. However, derivative-based green vegetation indices (DGVI) derived from continuous PS-2 spectra were proven to be the best among all of the tested broad- and narrow-band vegetation indices. The DGVI concept has been successfully applied to the AVIRIS datasets acquired at different seasons for mapping vegetation distribution variations and dynamic changes.

The derivative-based green vegetation indices (DGVI) were developed, by utilizing continuous spectra of the high spectral-resolution data, to minimize background impacts on green vegetation signals centered at the chlorophyll red-edge. The derivative technique was applied to the smoothed reflectance to enhance the green vegetation signals and to suppress low frequency noise caused by background variations in brightness and slope. The derivative spectra were then integrated across the chlorophyll red-edge to derive derivative-based green vegetation indices (DGVI).

In the experiment, five gravel backgrounds with different colors were prepared. A systematic series of spectral measurements were made of a pinyon pine over the five backgrounds with the PS-2. Seven green cover levels of the pinyon pine canopy were artificially made by manually removing green leaves during the measurements. The green cover levels were ranging from level 1 (Percent green cover: 17.75%, LAI: 0.2858) to level 7 (completely defoliated). The first order and second order derivative spectra were then derived from the smoothed PS-2 reflectance using the following equations:

$$\rho'(\lambda_i) = \frac{\rho(\lambda_{i+1}) - \rho(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}} \tag{1}$$

$$\rho''(\lambda_i) = \frac{\rho'(\lambda_{i+1}) - \rho'(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}} \tag{2}$$

In Equations 1 & 2, $\rho(\lambda_i)$ is the smoothed PS-2 reflectance, and λ_i represents the ith spectral band. The reflectance and the 2nd order derivative spectra at green cover level 1 and level 6 are displayed in Figures 1 & 2.

Among developed DGVIs, the 1st order DGVI-local was defined as the integration of the area under the 1st order derivative curve in reference to a local rock-soil baseline value set at λ_1. The 2nd order DGVI-zero was calculated by integrating the absolute values of the 2nd derivatives of the reflectance spectra in reference to the zero baseline. The two types of the DGVIs can be expressed in the following equations:

$$1st\ Order\ DGVI\text{-}local = \sum_{\lambda_1}^{\lambda_n} [\,|\rho'(\lambda_i) - \rho'(\lambda_1)| \times \Delta\lambda_i] \tag{3}$$

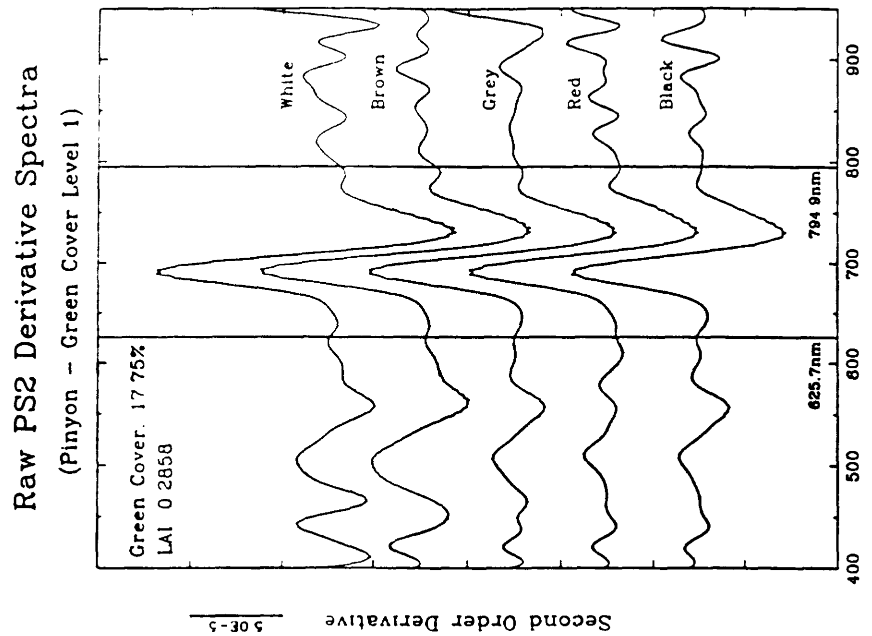
$$2nd\ Order\ DGVI\text{-}zero = \sum_{\lambda_1}^{\lambda_n} [\,|\rho''(\lambda_i)| \times \Delta\lambda_i] \tag{4}$$

Figure 3 graphically illustrates a comparison between all tested broad- and narrow-band vegetation indices (VI) in terms of their predictive power. The predictive power of the VIs was determined by the standard error of estimate ($S_{Y.X}$ or dimensionless $S_{Y.X}/\bar{Y}$) in estimating green cover levels. The standard error of estimate ($S_{Y.X}$) was calculated by the equation shown below:

$$S_{Y.X} = \sqrt{\frac{\sum (Y_i - \hat{Y}_i)^2}{n-2}} \tag{5}$$

Y is the actual green cover level. $\bar{Y}$ and $\hat{Y}$ represent the arithmetic mean Y and estimated green cover, respectively. Figure 3 exhibits that both the 1st DGVI-local and the 2nd DGVI-zero have lowest $S_{Y.X}$ values. On the contrary, broad-band NDVI and RVI show worst performance for predicting either the LAI or percent green cover levels. By applying the 2nd order DGVI-zero concept to the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired on October 3, 1990 over a Monterey pine plantation in Jasper Ridge, CA, the pine cover conditions, which were ranging from 0 to 32%, were quantified by the 2nd DGVI values. According to the existing strong linear relationship between the pine cover density and the 2nd order DGVI values, the percent green cover levels were inversely estimated and encoded in colors (Figure 4). Minor green cover variations in the Monterey pine plantation can be clearly identified in the 2nd DGVI map.

In summary, the high spectral-resolution data increased the detection limit of low-covered green vegetation based on the chlorophyll red-edge feature. The derivative-based green vegetation indices (DGVI) greatly enhanced green vegetation signals and optimally minimized background impacts. The 1st order DGVI-local and 2nd order DGVI-zero demonstrated the best performance for estimating green cover levels because of higher accuracy of estimate. Our inference is that the DGVI could be a useful method for monitoring vegetation health status with higher accuracy in arid and semi-arid regions.



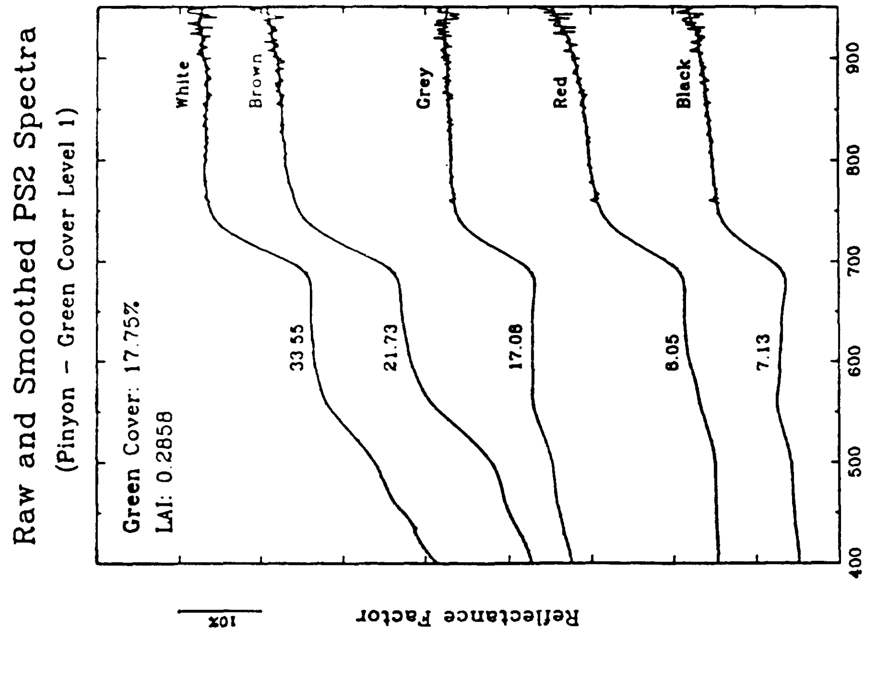


Figure 1. PS-2 reflectance and 2nd order derivative spectra of a pinyon pine with five backgrounds at green cover level 1. The reflectance value at 600 nm is provided for each reflectance spectrum. Two vertical lines at 625.7 nm and 794.9 nm indicate the integration interval for calculating the Derivative-based Green Vegetation Index (DGVI). Curves have been offset vertically to avoid overlap.

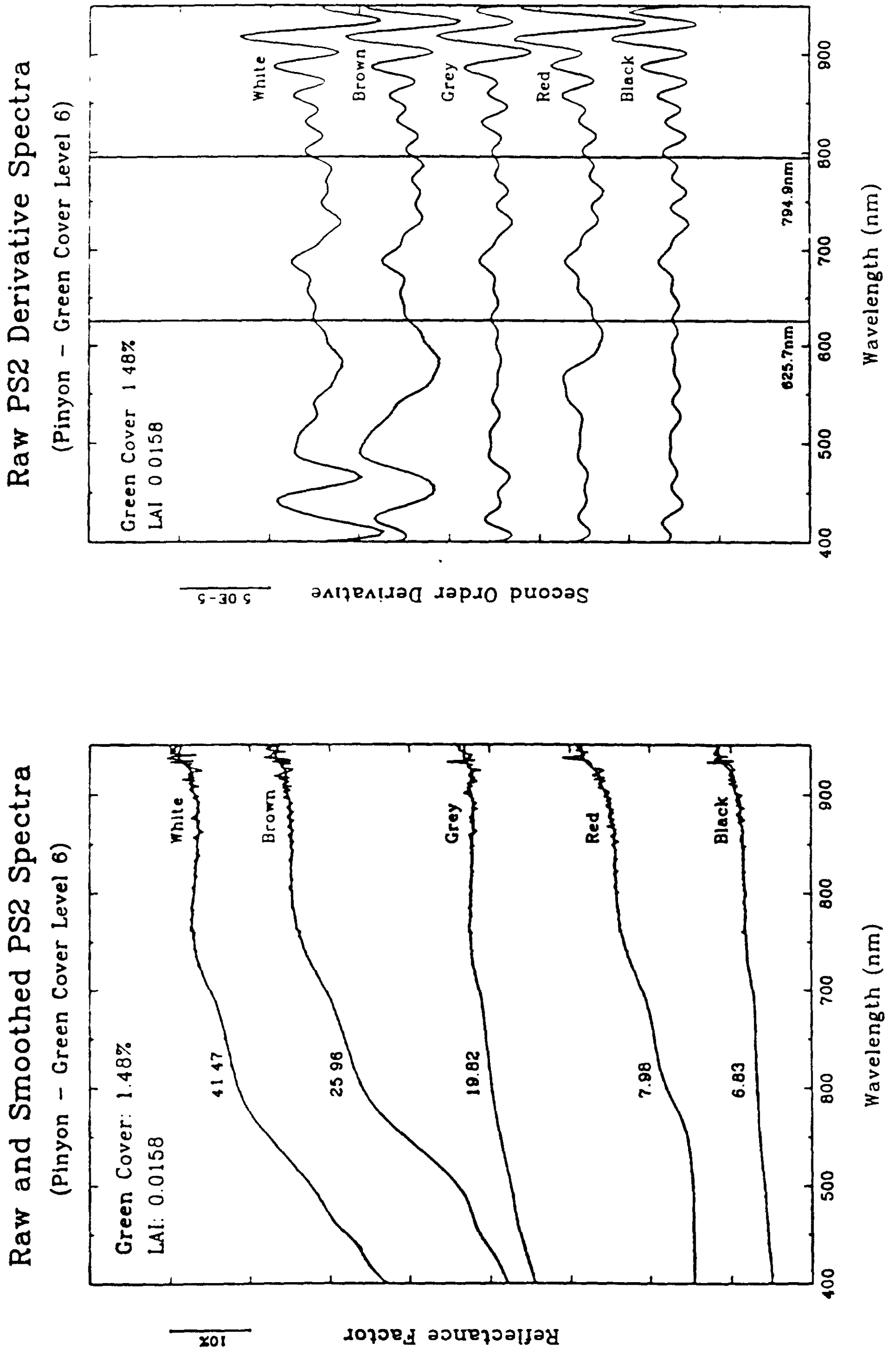
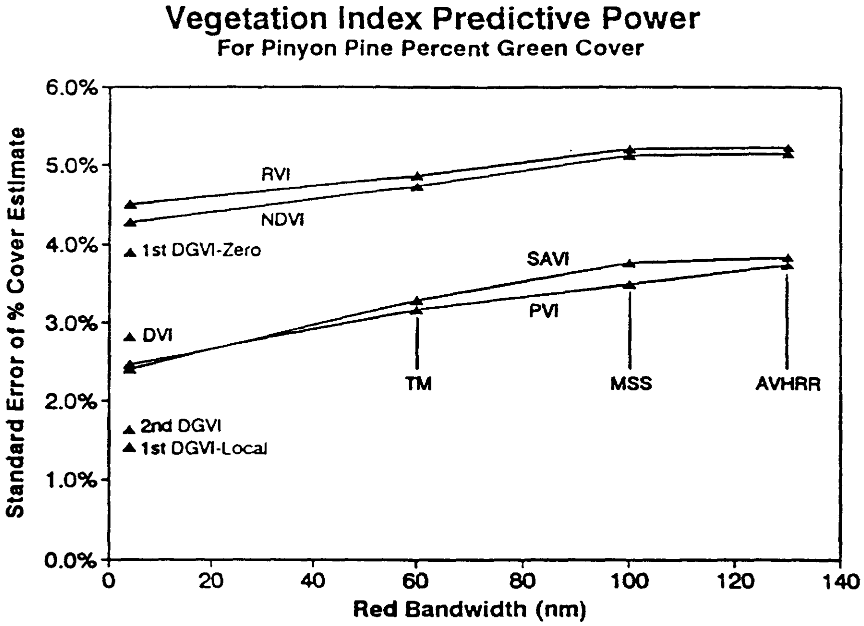


Figure 2. PS-2 reflectance and 2nd order derivative spectra of a pinyon pine with five backgrounds at green cover level 6. The reflectance value at 600 nm is provided for each reflectance spectrum. Two vertical lines at 625.7 nm and 794.9 nm indicate the integration interval for calculating the Derivative-based Green Vegetation Index (DGVI). Curves have been offset vertically to avoid overlap.



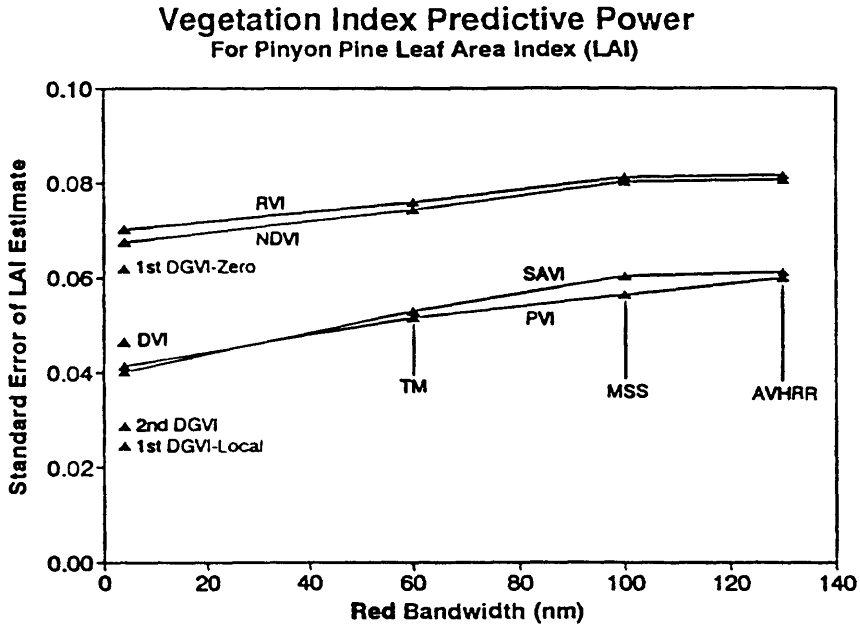
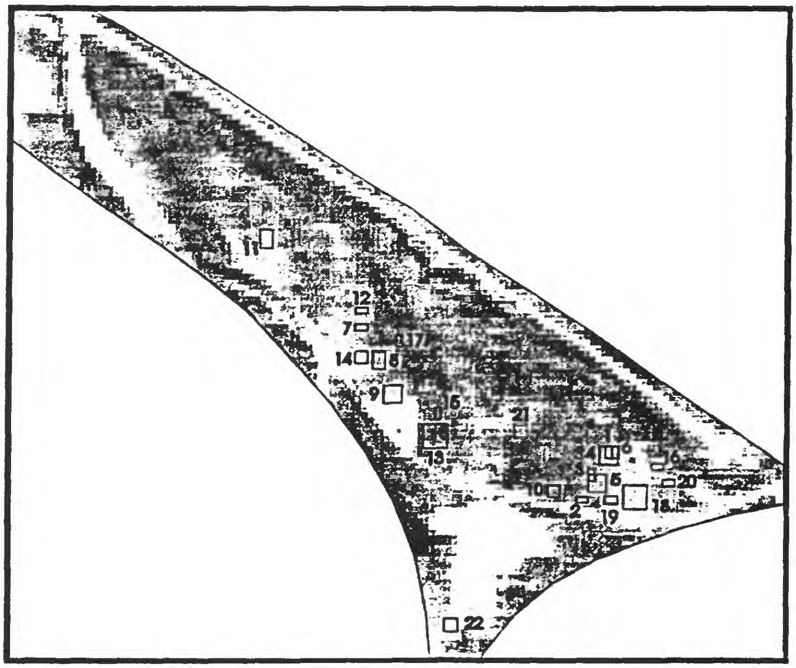


Figure 3. Standard error of estimate for predicting percent green cover and Leaf Area Index (LAI) of a pinyon pine against red bandwidth. Reducing the bandwidth improved the performance of NDVI, PVI, RVI, and SAVI. The best results were obtained for the 1st order DGVI-local and the 2nd order DGVI-zero.

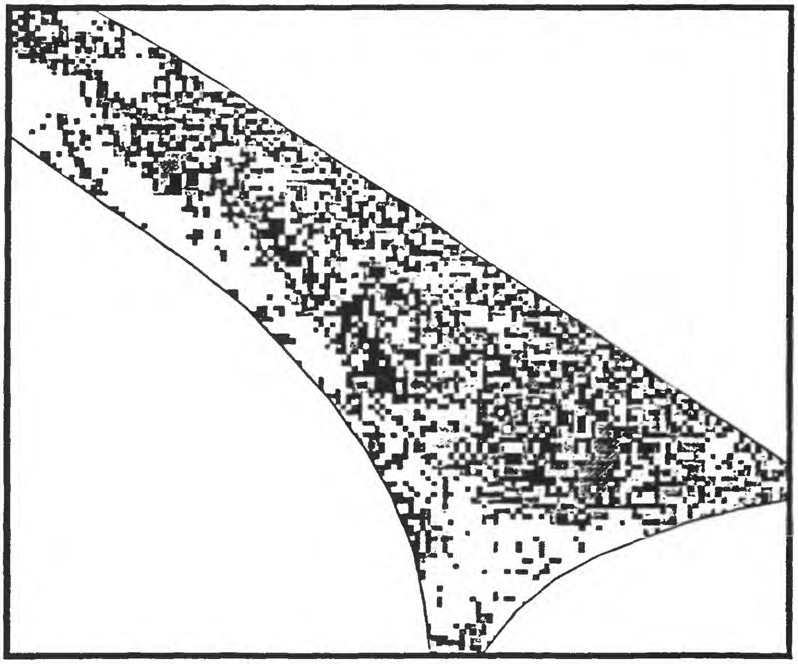
Monterey Pine Plantation (Jasper Ridge, CA)



AVIRIS
October 3, 1990

Red: 805 nm (CH. 46)
Green: 557 nm (CH. 17)
Blue: 450 nm (CH. 6)

2nd Order DGVI Distribution
(Derived From Reflectance Spectra Using Zero Baseline)



Green Cover Level (%)

White:	< 1
Cyan:	1 - 4
Blue:	4 - 7
Green:	7 - 10
Light Green:	10 - 15
Red:	15 - 20
Orange:	20 - 30
Yellow:	> 30

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Figure 4. TOP: Raw AVIRIS image of the Monterey pine plantation in Jasper Ridge, CA; BOTTOM: Percent green cover inverted from the 2nd order DGVI-zero values.

Research Strategies in Developing Synoptic Indicators of Salt Marsh Functioning in San Pablo Bay, CA

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Optical remote sensing applications have identified the relationship between biomass productivity and spectral signatures (Gross et al 1989) using a vegetation index based approach. Productivity in wetlands is of primary concern because of its potential as an indicator of ecosystem processes (Mahall and Park 1976). Health of intertidal wetlands is of concern for evaluating the sustainability of estuarine ecosystems, many of which are threatened by excessive nutrient loading from upstream agriculture and urban activities and from multdiple sources of point pollution. Locating and assessing contaminated sites as well as defining general wetland condition is often difficult because of limited physical access into the habitat. Remote sensing applications provide an excellent tool for this purpose by using vegetation as an indicator for the enviornmental contamination and/or condition. Innovations using high spectral resolution optical remote sensing (e.g. Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)) have indicated that it may be further possible to detect relative concentrations of foliar biochemicals, particulary water, plant pigments, carbon and nitrogen (Grossman et al, 1994; Jacquemoud et al., 1995; Pinzon et al., 1995). This note describes our research approach to developing indicators of ecosystem health in salt marsh ecosystems and demonstrates some of the preliminary results. We are using a multi-scale program combining airborne hyperspectral remote sensing and ground based measurements at three sites which vary in terms of edaphic factors.

Methods

Simultaneous top-down and bottom-up approaches were used to scale traditional ecological measurements at submeter scale to pixels scales (approximately 400 sq m) and to the landscape scale, covering several kilometers. At three different wetland sites, measurements were made of canopy reflectance spectra, vegetation distribution, biomass, canopy structure and height, and of soil nitrogen levels and type (nitrate vs. ammonia), salinity and redox potential. Leaf samples from the field were analysed for major pigment concentrations and total carbon and nitrogen levels. Each measurement was located using Global Positioning System (GPS) technology and incorporated into a Geographical Information System (GIS) database of each site. Our sampling strategy is designed to allow exploration of different geostatistical techniques (Englund and Sparks 1988, Rossi et al 1992) for interpolation from small scale field measurments to remotely sensed pixels. Maps generated from the GIS will be compared to AVIRIS imagery to develop pixel scale relationships between spectra and ecological factors for use in ecosystem evaluation at the landscape level.

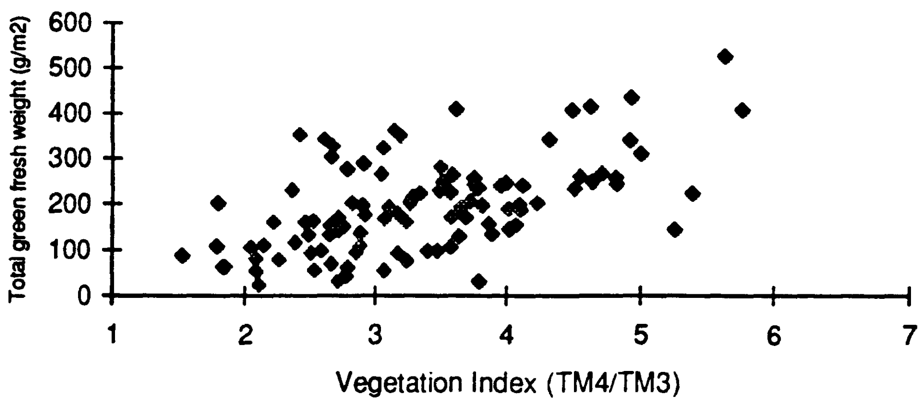
These comparisons are being made for three sites which differ in fresh water input and tidal flooding along the Petaluma River. Each site has unique features in terms of vegetation distribution and environmental gradients. They were chosen because they exhibit large variation in edaphic characteristics, including salinity, nutrients and soil water content. Three dominant species, *Salicornia virginica*, *Spartina foliosa* and *Scirpus robutus* are found under different conditions within the sites selected for study.

Preliminary Results and Discussion

Differences in dynamics of canopy structure and biomass result in differences in reflectance signatures of the vegetation. By developing indicators of foliar water content, relative pigment concentrations, and canopy architecture using remote sensing, and knowing how these parameters respond to the controlling influences of salinity and nitrogen, we hope to gain insight into overall wetland functioning on a landscape scale. We believe this research will have direct application for monitoring of natural and restored wetlands and for further ecological research on large scales.

Preliminary results showed that NDVI (Normalized Difference Vegetation Index) and VI (Vegetation Index) based on Landsat Thematic Mapper satellite band ratios of red and near infrared reflectances varied with biomass. These indices are related to the amount of green foliar biomass and indirectly to estimates of productivity. The correlation coefficient in our field data was found to be highest for the relationship between VI and green fresh weight (aboveground biomass). Therefore, it may be possible to use the VI to predict the green fresh weight from satellite image data for the salt marshes of San Pablo Bay. The regression equation of green fresh biomass and vegetation index indicated that 51% of variation of green fresh biomass was explained by the vegetation index (Figure 1).

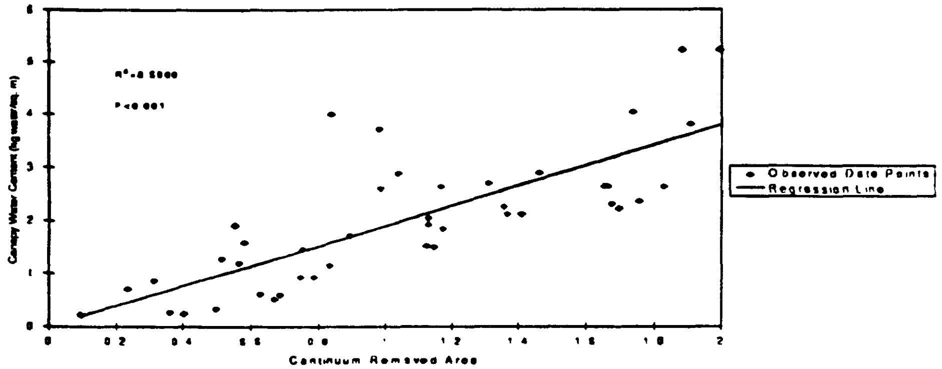
Figure 1: The Relationship between Total Green Fresh Weight and Vegetation Index



The water content varies between and within species. *Salicornia* dominated sites have the greatest water content, more than 86% water by fresh weight. *Spartina* and *Scirpus* foliage have lower water contents than *Salicornia.* Incident photons in the infrared portion of the solar spectrum are absorped by water in the leaves and changes in water content can be detected by changes in spectral reflectance in these wavelength regions. One of these regions occurs between 900 to 1040 nm wavelengths. Therefore, the foliar water content can be estimated as a function of this reflectance. If the area of the absorption feature under the continuum spectral shape (i.e., the reflectance on both sides of the feature), can be calculated using a "continuum removal" analysis (Clark and Roush 1984) then the water content can be linearly related to the area (Figure 2). Using this relationship, we can estimate the spatial distribution of canopy water from remote sensing data if the scale is appropriately understood (Sanderson et al., 1995). Assuming an environmental contaminant could be related to variations in the vegetation water content, then the degree of the contamination could be indirectly predicted using remote sensing data. Other relationships between environmental conditions and canopy spectra can be derived in an anologous fashion and used to evaluate ecosystem health.

	Salicornia virginica		*Spartina foliosa*	*Scirpus robustus*		*Frankenia grandifolia*
	Green	Woody		Green	Woody	
Mean Water Content (kg/m^2)	1.034	0.750	0.718	0.145	0.057	0.061
Standard Deviation	0.854	0.561	0.415	0.260	0.039	0.041
Mean Relative Water Content (%)	86.5	52.5	78.3	65.4	32.7	60.9

Figure 2 Regression of Continuum Removed Area from Water Absorption Band at 980 nm Against Observed Canopy Water Content



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