HYPERION STUDIES OF CROP STRESS IN MEXICO

David B. Lobell[1,2] and Gregory P. Asner[1,2]

1.0 INTRODUCTION

Satellite-based measurements of crop stress could provide much needed information for cropland management, especially in developing countries where other precision agriculture technologies are too expensive (Pierce and Nowak 1999; Robert 2002). For example, detection of areas that are nitrogen deficient or water stressed could guide fertilizer and water management decisions for all farmers within the swath of the satellite. Several approaches have been proposed to quantify canopy nutrient or water content based on spectral reflectance, most of which involve combinations of reflectance in the form of vegetation indices. While these indices are designed to maximize sensitivity to leaf chemistry, variations in other aspects of plant canopies may significantly impact remotely sensed reflectance. These confounding factors include variations in canopy structural properties (e.g., leaf area index, leaf angle distribution) as well as the extent of canopy cover, which determines the amount of exposed bare soil within a single pixel. In order to assess the utility of spectral indices for monitoring crop stress, it is therefore not only necessary to establish relationships at the leaf level, but also to test the relative importance of variations in other canopy attributes at the spatial scale of the remote sensing measurement. In this context, the relative importance of a given attribute will depend on (1) the sensitivity of the reflectance index to variation in the attribute and (2) the degree to which the attribute varies spatially and temporally.

In this study, we investigate the ability of spectral indices derived from data collected by the EO-1 Hyperion instrument to detect canopy stress in an agricultural region in Northwest Mexico. In particular, the objectives of this study were to: (1) determine the correlation between reflectance indices of canopy “structure” and “chemistry” within an agricultural landscape, and (2) quantify the extent to which information in chemical indices provide useful information for crop management. In essence, this equates to asking whether hyperspectral chemical reflectance indices provide any unique information on crop canopies, and, if so, whether this information is potentially useful for precision agriculture applications.

2.0 DATA AND METHODS

2.1 Site Description

The study was conducted in the Yaqui Valley, a region comprising roughly 225,000 ha of intensively fertilized and irrigated cropland on the west coast of Sonora, Mexico (Figure 1, after the references). A vast majority of this land is planted to wheat in November-December and harvested in April-May, with wheat yields among the highest in the world. Rising fertilizer prices, concerns about environmental pollution, and diminishing water supplies has increased the need for methods to improve nutrient and water use efficiencies of wheat production in this region. A particularly important time in the growing season is mid-January, when the first post-planting irrigation and fertilization is performed. At this time, detection of canopy nutrient or water stress could guide the timing and amount of water and fertilizer applications.

2.2 Data acquisition and processing

Hyperion data was acquired on January 14, 2002, one minute after an image was collected by the Landsat ETM+ sensor. The Hyperion image was roughly centered within the ETM+ image and covered a significant fraction of the irrigation district (see Figure 1). An additional ETM+ image acquired on March 16, 2002 was combined with the January image to estimate wheat yields using a previously validated methodology (Lobell, Asner et al. 2003). These yields were used to evaluate the eventual growth of fields observed by Hyperion in January, as described below.

Hyperion data were provided by the EROS Data Center (EDC) and processed to apparent surface reflectance using the ACORN 3 atmospheric correction model. A de-striping algorithm was then applied to correct for mis-calibration between cross track detectors. This algorithm determines the average noise in each column by summing all reflectance values by column and applying a Lee filter to the resulting 256 values. The column sums are divided by the filtered reflectance values to approximate the necessary gains for each column, which are then applied to the image. After this step, a cubic spline is fit to the water bands at 940 and 1140 nm in each pixel to reduce the effects of mis-calibration and modeling errors introduced by the atmospheric correction.

[1] Department of Global Ecology, Carnegie Institution of Washington, Stanford, California 94305
[2] Department of Geological and Environmental Science, Stanford University, Stanford, California 94305
(dlobell@globalecology.stanford.edu, gasner@globalecology.stanford.edu)

2.3 Reflectance Indices

Several indices drawn from the literature and shown in Table 1 were computed from the Hyperion data. The first two indices (NDVI and SR) are based on combinations of red and near infrared (NIR) reflectance that are known to capture variations in canopy structural attributes, such as canopy cover and leaf area index (LAI). The rest of the indices were designed to measure aspects of leaf chemistry, including contents of leaf pigments such as chlorophylls, carotenoids, and anthocyanin (PRI, SIPI, PSRI, R-Gratio); nitrogen (NDNI); and water (WI, NDWI, MSI, NDII). Many of these indices were defined by leaf-level studies and have not been widely tested at the canopy or landscape scales.

To determine the extent to which these indices provide unique information from each other in this agricultural landscape, Spearman's rank correlation coefficient (ρ_S) was computed for each combination of indices using all image pixels (n = 224,042). This non-parametric correlation was used to capture non-linear relationships between indices and to minimize sensitivity to extreme values. Two indices (PRI and WI) were judged to be too noisy using the Hyperion data and were therefore excluded from further analysis.

Table 1. Vegetation Indices Employed in this Study

Index	Index Name	Equation	Reference
SR	Simple Ratio	R800/R680	
NDVI	Normalized Difference Vegetation Index	(R800-R680)/(R800+R680)	
RG-Ratio	Red-Green Ratio	Σ(R600…R699)/ Σ(R500…R599)	Gamon and Surfus (1999)
SG	Sum-Green	ΣR500…R599)	
PRI	Photochemical Reflectance Index	(R531-R570)/(R531+R570)	Gamon et al. (1992)
PSRI	Plant Senescence Reflectance Index	(R680-R500)/R750	Merzlyak et al. (1999)
SIPI	Structure Insensitive Pigment Index	(R800-R445)/(R800-R680)	Peñuelas et al. (1995)
NDNI	Normalized Difference Nitrogen Index	[log(1/ R1510)-log(1/ R1680)]/ [log(1/ R1510)+log(1/ R1680)]	Serrano et al. (2002)
WI	Water band Index	R900/R970	Peñuelas et al. (1993)
NDWI	Normalized Difference Water Index	(R857-R1241)/(R857+R1241)	Gao (1996)
MSI	Moisture Stress Index	R1599/R819	Hunt and Rock (1989)
NDII	Normalized Difference Infrared Index	(R819-R1649)/(R819+R1649)	Hardinsky et al. (1983)

2.4 Quantile Mapping

There are several approaches to evaluating the utility of information in the chemical indices. One possibility is to define a suite of leaf chemistry variables of interest, measure these properties in various fields simultaneous to image acquisition, and then statistically test the ability of each index to predict each variable. In this study, we use an alternative approach that utilizes image data taken at a later point in the growing season. We refer to this procedure as quantile mapping (QM), which is illustrated in Figure 2 and can be described as follows:

1) To control for variations in canopy structure, which are shown to affect all indices (see below), we identify all pixels within a narrow range of NDVI values.
2) For these pixels, we compute the distribution of values for a selected index (e.g. RG-ratio), and identify all pixels falling below and above defined thresholds. In this case, we select pixels below the 25-percentile (group A) and above the 75-percentile (group B).

3) An image collected later in the season is used to define the eventual growth of each pixel. In this study, we used the yield estimates derived from Landsat ETM+, which rely on an image from March 16 (two months after the Hyperion image). By comparing the eventual yields of pixels in group A and group B, which possessed the same structural attributes (NDVI), we can evaluate whether the additional information in the selected index was predictive of canopy growth, and therefore indicative of canopy stress.
4) Steps (1)-(3) are repeated for each level of NDVI.

This procedure is called quantile mapping because pixels above and/or below a specified quantile are mapped and tracked through the growing season. To determine the sensitivity of this approach to sampling uncertainties, step (3) is repeated a large number of times (10,000), each time with random subsets of group A and B used in place of the entire groups. This provides a bootstrap estimate of sampling uncertainty (Efron and Gong 1983).

We see several advantages to this approach. First, it requires only image data and therefore can be used to test indices in any region where ground data is not available. Similarly, it can be used for retrospective studies of images acquired in previous years. Second, because it is based solely on image statistics, the entire process can be automated. For example, steps (1)-(2) effectively create maps of nutrient stress that can be quickly generated and potentially used for management applications. This is particularly important for agricultural applications, where quick turnaround times are essential. Third, the comparison of groups A and B is performed at various levels of NDVI, so that the effect of canopy structure on the information content of the selected index can be readily evaluated. For example, some aspects of leaf chemistry may only be retrievable at very high LAI (Asner 1998).

One drawback of this approach is that, because it relies on image statistics, it is only able to determine relative levels of stress within an image. For example, in cases where 50% of fields are stressed in reality, a procedure that selects only the top 25% will miss many fields. Alternatively, if only 5% of fields are stressed, then 20% will be falsely identified as stressed. However, by combining image statistics across several years, it should be possible to associate an absolute value with each quantile and therefore produce more robust measures of crop stress.

3.0 RESULTS AND DISCUSSION

Table 2 shows the correlation matrix for indices evaluated in this study. Given the high correlation of all indices with NDVI ($\rho_S > 0.9$, $p < 0.001$), it is clear that each index is highly impacted by variations in canopy cover and structure across the landscape. This is true even for indices designed to be “structure insensitive.” Therefore, no single index should be considered as a measure of solely canopy chemistry. In general, high correlations between all indices indicated that no two indices provided independent measures of plant canopies. However, the fact that all correlations were less than unity implies that there is some information (or potentially noise) unique to each index.

Figure 3 illustrates the result of the QM procedure for several of the indices. Some indices appear to provide little information beyond NDVI, implying that the only differences between the two indices are due to sensor noise or some attribute that does not measurably affect plant growth. However, several indices exhibit the ability to predict future canopy growth, implying that they provide a useful measure of canopy stress.

The QM results clearly show that some indices, such as NDWI, provide information only at high values of NDVI. This is consistent with previous studies that showed the relationship between NDWI and canopy water content improved greatly when limiting the study to pixels with high canopy cover (Serrano, Ustin et al. 2000). Other indices, such as RG-ratio, appear to provide useful information on canopy chemistry across a wide range of canopy structure.

The difference between the upper and lower quartile provides a quantitative estimate, in terms of yield, of the potential value of using a given index for crop management. For example, if fields below the lower quartile of RG-ratio could be managed and raised to the level of the upper quartile, then a potential gain of roughly 0.5 ton ha^{-1} could be realized. Yield gains of this magnitude would represent a significant increase in farmer income and regional productivity.

Table 2. Spearman's Rank Correlation Coefficients for Vegetation Indices in Jan. 14, 2002 Hyperion Image.

	NDVI	SumGreen	SIPI	PSRI	NDNI	RG-Ratio	NDWI	MSI	NDII
SR	1	-0.85	-0.99	-0.99	-0.93	-0.98	0.9	-0.96	0.95
NDVI		-0.85	-0.99	-0.99	-0.93	-0.97	0.89	-0.96	0.95
SumGreen			0.83	0.85	0.79	0.85	-0.74	0.77	-0.77
SIPI				0.98	0.93	0.98	-0.89	0.95	-0.94
PSRI					0.93	0.99	-0.88	0.95	-0.94
NDNI						0.92	-0.83	0.91	-0.91
RG-Ratio							-0.87	0.92	-0.91
NDWI								-0.94	0.94
MSI									-0.99

4.0 SUMMARY

Reflectance indices derived from Hyperion data were highly correlated across an agricultural landscape, indicating that all indices were impacted by variations in canopy structure and bare soil extent. A procedure termed quantile mapping was developed to combine structural and chemical reflectance indices in an attempt to identify attributes of canopy chemistry associated with stress. Some chemical indices were successful in identifying stress, as judged by the ability to predict future growth estimated from late-season Landsat ETM+ imagery, while others were not. Of those successful in predicting future growth, R-G ratio was successful at various levels of NDVI (canopy structure and extent) while NDWI was useful only at high values of NDVI. Moreover, these indices depicted stress in different fields (not shown here), indicating that each index provides information on a unique aspect of canopy chemistry. Future work is needed to better quantify canopy stress from hyperspectral measurements, with careful attention to sources of reflectance variability other than canopy chemistry.

5.0 REFERENCES

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6.0 ACKNOWLEDGEMENTS
The authors are grateful to A. Warner, K. Heidebrecht, and I. Ortiz-Monasterio for assistance with data processing and helpful discussions. This work was supported by NSF Graduate Research Fellowship, NASA New Investigator Program grant NAG5-8709, NASA New Millenium Program grants NCC5-480 and NCC5-481, and the Packard Foundation.

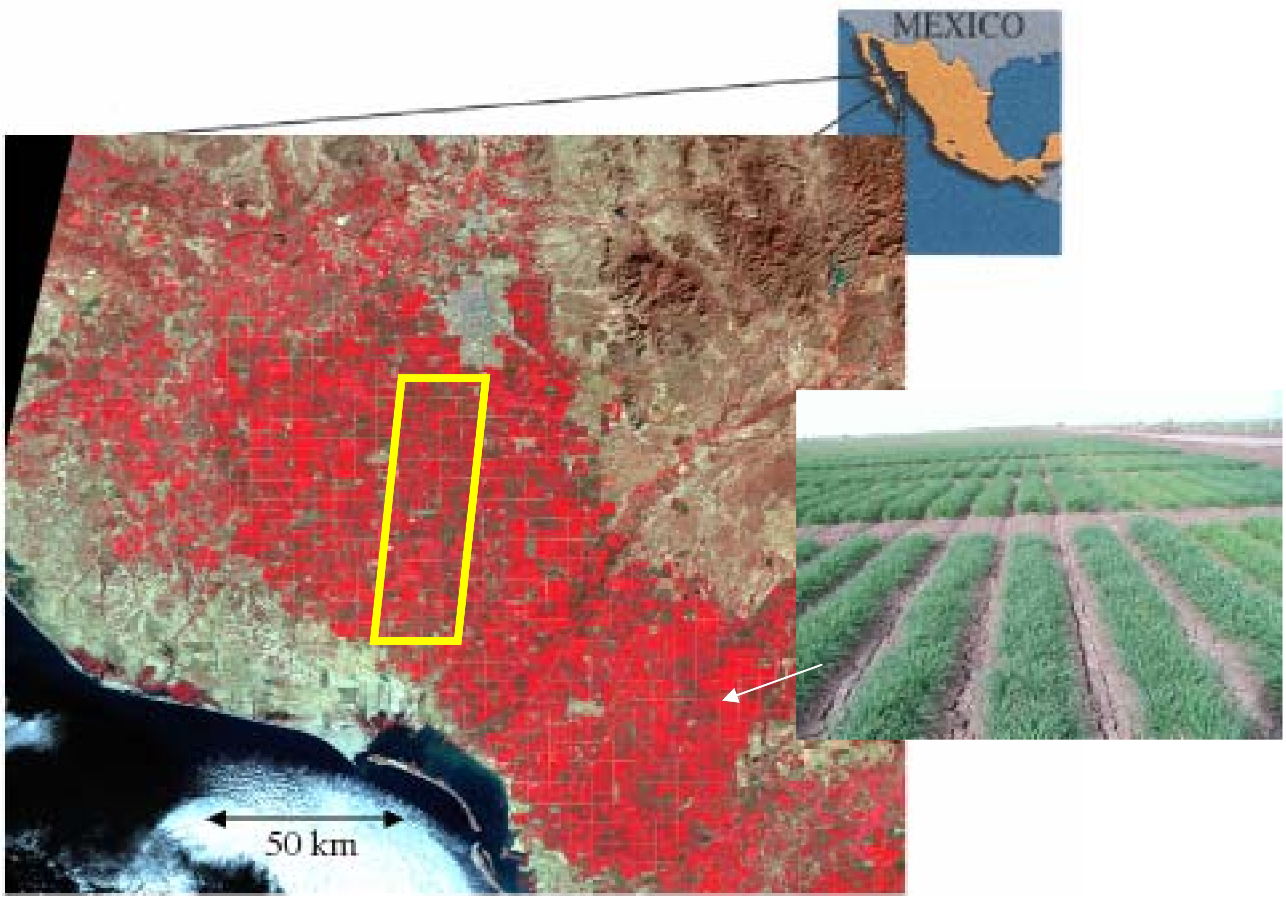

Figure 1. The Yaqui Valley study region. The satellite image is a color composite of Landsat ETM+ data (4-3-2) from January 14, 2002. The yellow box shows the swath of the Hyperion image used in this study, while the picture inset shows a typical wheat field at this time of year.

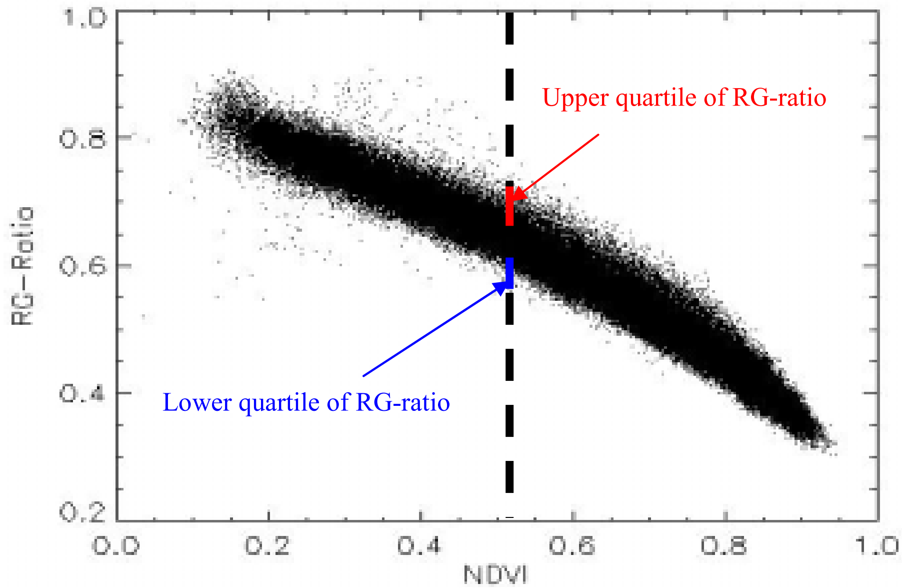

Figure 2. Schematic representation of the quantile mapping algorithm. At each value of NDVI, all pixels below and above prescribed quantiles of a selected reflectance index are identified and separated into two sets (high and low). The average states of these two sets later in the growing season, in this case as measured by Landsat-based yield estimates, are then compared to determine the ability of the given index to predict future growth, and thereby indicate stress.

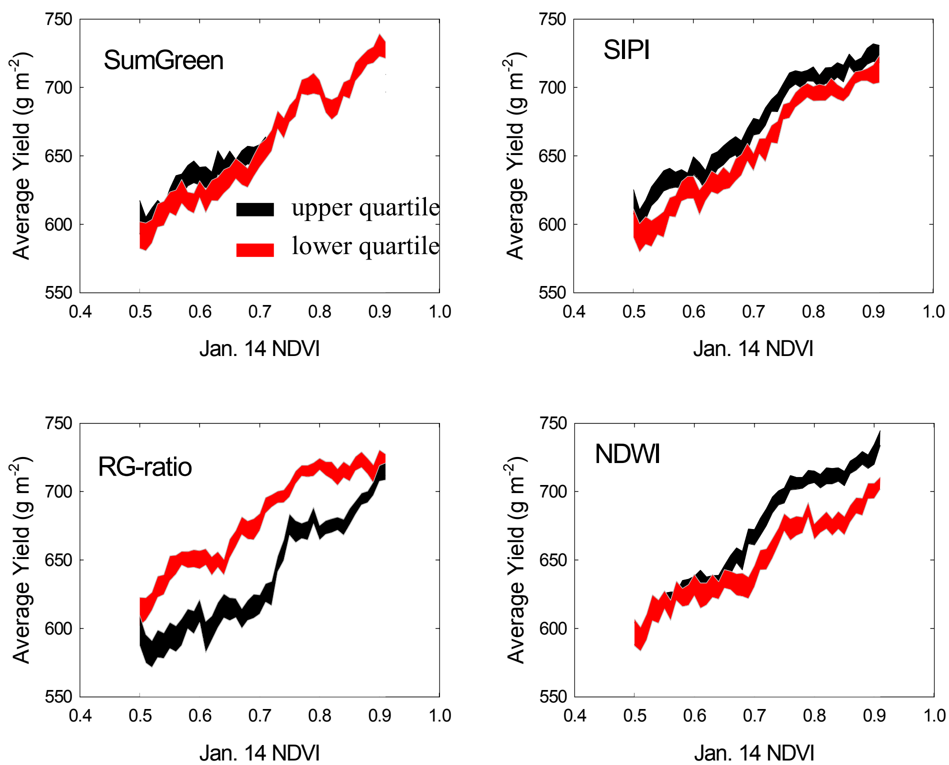

Figure 3. Average yield estimates for pixels in lower (red) and upper (black) quartiles of selected indices at each value of NDVI in Jan. 14 Hyperion image. Average yield is based on January and March Landsat images, and indicates the eventual growth of wheat. Width of line is a 95% confidence interval based on bootstrap estimates of uncertainty in average yield. Several indices appeared to offer little additional information beyond NDVI for predicting future growth (e.g. SumGreen and SIPI), while others were much more successful (RG-ratio and NDWI), with yield differences between the upper and lower quartile as high as 0.5 ton ha^{-1}.