Continuous Wavelet Transformations for Hyperspectral Feature Detection

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Abstract

A novel method for the analysis of spectra and detection of absorption features in hyperspectral signatures is proposed, based on the ability of wavelet transformations to enhance absorption features. Field spectra of wheat grown on different levels of available nitrogen were collected, and compared to the foliar nitrogen content. The spectra were assessed both as absolute reflectances and recalculated into derivative spectra, and their respective wavelet transformed signals. Wavelet transformed signals, transformed using the Daubechies 5 motherwavelet at scaling level 32, performed consistently better than reflectance or derivative spectra when tested in a bootstrapped phased regression against nitrogen.

1 Introduction

Recent advances in remote sensing have resulted in the development of high spectral and spatial resolution sensors. These sensors enable us to measure more objects more accurately. Recent work has shown the utility of hyperspectral data to detect foliar nitrogen (Kokaly 2000; Lilienthal et al. 2000; Ferwerda et al. 2005), phosphorous (Mutanga et al. 2003), chlorophyll (Haboudane et al. 2002; Coops et al. 2003) and phenolic compounds (Soukupova et al. 2002; Ferwerda et al. in press).

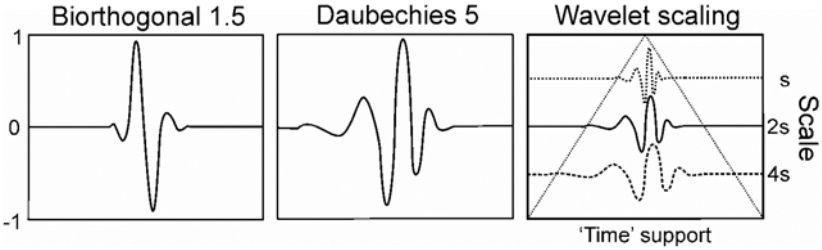

Fig. 1. Wavelets used for decomposition, and an illustration of the effect of scaling wavelets in the time-domain. With increasing scale levels the window of analysis, or time support, increases, and the frequency resolution decreases

With the development of high spectral resolution sensors, reflectance data has become near continuous. This has created an opportunity to treat individual measurements (in the case of field spectra) or the combined band values for individual pixels (in the case of hyperspectral images) as a continuous signal, where electromagnetic radiation reflectance is measured as a function of wavelength. Several methods, which were developed to detect absorption features in hyperspectral data, such as derivative analysis (Demetriades-Shah et al. 1990; Tsai and Philpot 1998) and continuum removal (Clark and Roush 1984), are based on the fact that the data forms a near-continuous signal. It is therefore surprising to note that studies using wavelet transformations for the analysis of absorption features in hyperspectral reflectance data are rare. Wavelet analysis is based on the Fourier transform, developed by Joseph Fourier in 1807. It decomposes a complex signal into component sub-signals. Each of these sub-signals is active at a different signal scale, or frequency. This makes it ideal for the detection of absorption features in complex signals

Wavelets look like small oscillating waves, and they have the ability to analyze a signal according to signal scale (frequency, see Fig. 1). In other words, during analysis the original wavelet, or mother wavelet, is scaled along the time-axis, to match signals at different frequencies. Thus a narrow wavelet (low scaling number) is used to match high frequency signals, irrespective of the underlying low-frequency changes. Low frequency signals are picked up using a wide wavelet (high scaling number), while high frequency signals (e.g., noise) is ignored.

The analysis of a signal is equivalent to computing all the correlations between the wavelet function at a certain scale and the input signal (Abbate et al. 2002, p 26). The results of the wavelet transform are the wavelet coefficients C, which are a function of scale and position of the transform. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal. This

can be repeated at different wavelet scales, to either match against low or high frequency signals in the input signals. A specific form of wavelet transformation, the continuous wavelet transformation, decomposes a signal into an output signal with the same length as the input signal. To provide the reader with a comprehensive technical background of wavelet analysis falls outside the scope of this paper. For more information on the mathematical and historical aspects of wavelet analysis, please see the work by Hernandex (1996), Abbate (2002) or Ogden (1997).

Although wavelet analysis is used in remote sensing, this is mainly for the purpose of data compression (Amato et al. 2000; Bjorke and Nilsen 2002) and edge detection (Gruen and Li 1995). Examples of the use of wavelet transforms to enhance absorption features in hyperspectral data originate predominately from the food industry, where quality control is performed using near infrared lab-based spectroscopy. Chen (2002) for instance improved prediction of oil content in instant noodles by applying a 4-scale Mallat wavelet transform to NIR reflectance spectra. Fu (2005) successfully applied a Daubechies wavelet transform to NIR spectra of vinegar to derive sugar content. In the environmental sciences, Koger (2003) used wavelet-based analysis of hyperspectral reflectance signals for early season detection of 'Pitted morning-glory' in soybean fields. A field where the unambiguous identification of the characteristics of absorption features is of critical importance is that of hyperspectral remote sensing of foliar chemistry. Chemical components in foliage result in distinct absorption features, with a specific spectral location, and a depth and width related to the concentration of that component (Curran 1989). Therefore, during data processing it is crucial to be able to quantify changes in the depth and width of absorption-features. For the project presented here we hypothesized that wavelet analysis might do just that. Since wavelet transformed signals represent a measure of resemblance between the mother wavelet stretched at a certain scale, and the input signal at each specific spectral location, we hypothesize that this match between wavelet and derivative spectra will provide us with an unbiased measure of the shape of the absorption feature at that spectral location. Typically only the information of one or a few bands is included in a model to predict the concentration of specific foliar components. However, since wavelet transformation matches a subset of the input signal against a scaled wavelet, the output signal combines information on the variation over a number of surrounding bands. Therefore it is expected that the wavelet transform is less sensitive to noise and will result in a better relation to the component of interest than pure reflectance or derivative signals.

The ability to predict chemical composition of plants using remote sensing is directly dependent on the selection of appropriate bands to use. When specific absorption features are unknown, most studies have used stepwise regression techniques to determine which wavebands are most appropriate to use. This may however result in over-fitting of prediction models. Principal component analysis is another method, which combines the information from several bands into one predictor variable, and reduces this problem. It however minimizes the understanding of the relation between absorption features and chemical composition, since the effects of individual bands are combined into one factor. Because it reduces the number of variables while maintaining most of the information, principal component analysis has also been used to compress data. Still, selecting the appropriate predictor bands, and managing the volume of this data remains a problem. Ferwerda et al. (in Press) suggested a method they referred to as *bootstrapped phased regression*, that partially overcomes this problem. In short, from the original dataset of n unique samples, a bootstrap dataset of n samples is selected, allowing duplicate samples to occur (Efron and Tibshirani 1993). This is repeated 10 000 times, a number comparable to that suggested by Potvink and Roff (1993) and Pitt and Kreutzweiser (1998) for bootstrapping routines. For each repetition, the waveband with maximum correlation to the component of interest is recorded, which results in a frequency table detailing the number of times that each waveband has maximum correlation with the component of interest. The band with the highest frequency after 10 000 iterations is selected, where the position of a band is defined as the central wavelength of that band.

This step is repeated in order to build a linear regression model with more than one predictor by calculating the regression goodness of fit between the component of interest and the already selected band combined with each of the other bands, again selecting the band with the highest frequency of maximum correlation for 10 000 random datasets. This routine deviates from a full stepwise regression within each bootstrap repetition because the aim is to select the best waveband to use with respect to already selected wavebands. This process is repeated until the required number of bands is reached or until the maximum frequency of maximum correlation drops below 5%.

This study explores the ability of wavelet transformation to enhance absorption features in reflectance signatures. Wavelet transformation was applied to derivative signatures of wheat of which the foliar nitrogen content was known. Subsequently a bootstrapped phased regression was applied to select the best bands for prediction of foliar N. The predictive power of wavelet factors was compared to that of reflectance and derivative spectra.

2 Materials and Methods

2.1 Field Data

Wheat was grown during the 2004-growing season in Horsham, Victoria, Australia (Sowing date: June 17th). As part of a larger experiment on the effects of nitrogen and water availability on the productivity of wheat in semi-arid systems, wheat was grown on a split-plot factorial design. The treatments consisted of irrigated (390 mm; decile 9 for Horsham) and rain-fed (270 mm; decile 5 for Horsham), combined with two plant densities (300 and 150 plants/m^2) and four levels of nitrogen applied as urea (0, 34, 84 and 354 kg urea/ha) in subplots with three replications.

2.2 Hyperspectral Measurements

At the end of the growing season (November 8th, 144 days after sowing) spectral properties were recorded. Approximately 1 m^2 of the canopy was recorded using an ASD Fieldspec FR field spectrometer. The FieldSpec® FR spectrometer combines three spectrometers to cover the 350 to 2500 nm range of the electromagnetic spectrum. This spectrometer uses a photo diode array to cover the 350 to 1000 nm spectral range with 1.4 nm sampling interval and 3 nm bandwidth. Two fast scanning spectrometers provide coverage for the wavelength range from 1000 to 2500 nm with 2 nm sampling interval and 10 nm bandwidth. The optic fiber was placed in a pistol grip and mounted on a steel boom 2.5 m above ground surface pointing downwards in a 900 angle to measure the up-welling radiance of the wheat. Absolute reflectance was calculated using a calibrated Spectralon Reflectance Target (Labsphere, Inc, North Sutton, New Hampshire) as a reference. The centre of the measured area was harvested (0.9 m^2) and a random sub-sampled was chemically analyzed to determine total canopy nitrogen content.

2.3 Data Processing

The reflectance spectra were very noisy between 1850 and 2500 nm. Therefore this part of the spectrum was excluded from further analysis. During wavelet transform, the wavelet used should represent the signal to be detected as closely as possible. In this paper it was decided to use two mother wavelets (e.g., Fig. 1): one which closely represented the derivative of a Gaussian distribution; the second of which represented a combination

of the derivative of multiple Gaussian absorption features. Therefore derivative spectra were calculated of the original reflectance spectra. An added advantage is the signal normalizing effect of calculating derivative spectra. Derivative analysis (Tsai and Philpot 1998) assumes that differences in the absolute reflectance do not affect the actual absorption features. Therefore derivative spectra are less affected by sun angle and structural variation than absolute reflectance spectra, and by using the slope of the spectrum instead of the absolute reflectance, the same signal is produced for samples with different absolute reflectance but the same absorption features.

Using the reflectance spectra, derivative spectra were calculated using an adjusted version of the seven band moving spline smoothing technique (Savitzky and Golay 1964; Tsai and Philpot 1998). Instead of smoothing the spectra first and then calculating the derivative spectra from the smoothed spectra, the parameters of the moving polynomial were used to directly calculate the derivative at the centre waveband of the moving spline window.

Reflectance and derivative spectra were averaged by individual treatments, and plotted against wavelength to visually analyze the differences in reflectance between treatments, and the effect of normalizing data through derivative calculation. To better understand the sources of variation in the dataset, A full factorial ANOVA was performed on a subset of wavebands (350 nm to 1250 nm, step 100 nm), with applied nitrogen level (n=4), irrigation (n=2) and planting density (n=2) as interacting factors. Similarly, the effect of individual treatments on the foliar nitrogen content was tested using a factorial analysis of variance with nitrogen level (n=4), irrigation (n=2) and planting density (n=2) as interacting factors. The concentration of nitrogen was recorded as a fraction of the dry weight. Since these values are typically low (< 10%), these concentrations require a log-transformation to meet requirements of normality (Zar 1999). After transformation groups did not deviate from normality (Shapiro wilks' W; $p > 0.05$).

2.4 Wavelet Transform

The Matlab environment was used to perform continuous wavelet transform on the derivative spectra, decomposing the derivative spectra at 7 scale levels, in 2^a step increments ($0 < a < 7$). Two mother wavelets were used for decomposition. The first is the biorthogonal wavelet 1.5 '(Bior.1.5, see Fig. 1), which represents the derivative of a Gaussian curve.

The other is the Daubechies wavelet 5 (DB.5) a basic ripple with 5 convolutions (see Fig. 1).

The 16 resulting datasets (Reflectance spectra, Derivative Spectra and 2 times 7 wavelet transforms) were tested for their relation foliar nitrogen content. To select the most robust wavebands for detecting nitrogen content, a bootstrapped phased regression was applied.

3 Results

3.1 Effects of Treatment

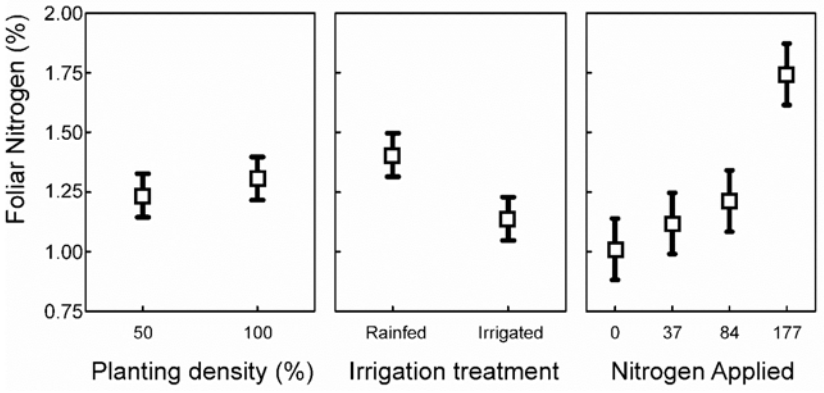

Fig. 2. Foliar nitrogen content in wheat samples, grouped by nitrogen treatment and irrigation treatment. Vertical bars denote 95% confidence interval for the mean

Foliar nitrogen concentration was affected by nitrogen application and irrigation treatment individually (ANOVA; $p \leq 0.001$; see Fig. 2) but not by sowing density (ANOVA; $p \geq 0.1$). Second degree interaction terms were not significant. Group sizes were too small to reliably calculate full factorial interaction terms.

The effects of irrigation and nitrogen treatments on reflectance spectra (see Fig. 3) were significant, but the effect of 'between planting densities' was not (ANOVA; $p \leq 0.001$). The interactions between treatments were not significant.

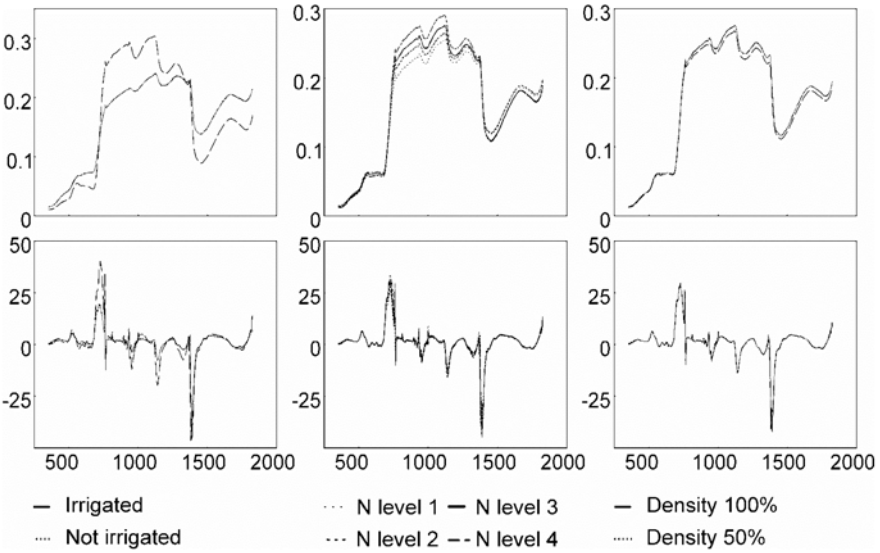

Fig. 3. Comparison of reflectance and derivative spectra averaged by treatments. N levels: 1: 0 kg urea/ha, 2: 34 kg urea/ha, 3: 84 kg urea/ha and 4: 354 kg urea/ha

Decomposition of spectra using a wavelet transform showed localized responses, in particular around 1000 nm and 1400 nm for lower scale transforms (matching higher frequency signals, see Fig. 4). Higher scale levels (Matching lower frequency signals) result as expected, in responses over wider regions of the signal (see Fig. 4).

Figure 5 depicts the regression goodness of fit (r^2) between foliar nitrogen concentration and reflectance spectra, derivative spectra, and wavelet transformed spectra for models with 1 to 6 predictor bands. Derivative spectra of wheat, transformed using a DB.5 wavelet transform at scale 32, show a stronger relation to foliar nitrogen concentration than the original derivative spectra (see Fig. 5). Figure 5 shows a mean regression r^2 of 0.54 between the best band for DB.5 scale level 32 transformed derivative spectra over 10 000 bootstrap iterations, whereas this is only 0.03 and 0.31 for the pure reflectance spectra, and derivative spectra respectively. For all models a maximum mean regression goodness of fit is achieved when derivative spectra are transformed using DB.5 at scale level 32 (see Fig. 5). Derivative spectra have a higher mean regression goodness of fit than reflectance spectra. Derivative spectra transformed using Bior.1.5 perform less good than the input derivative spectra (see Fig. 5).

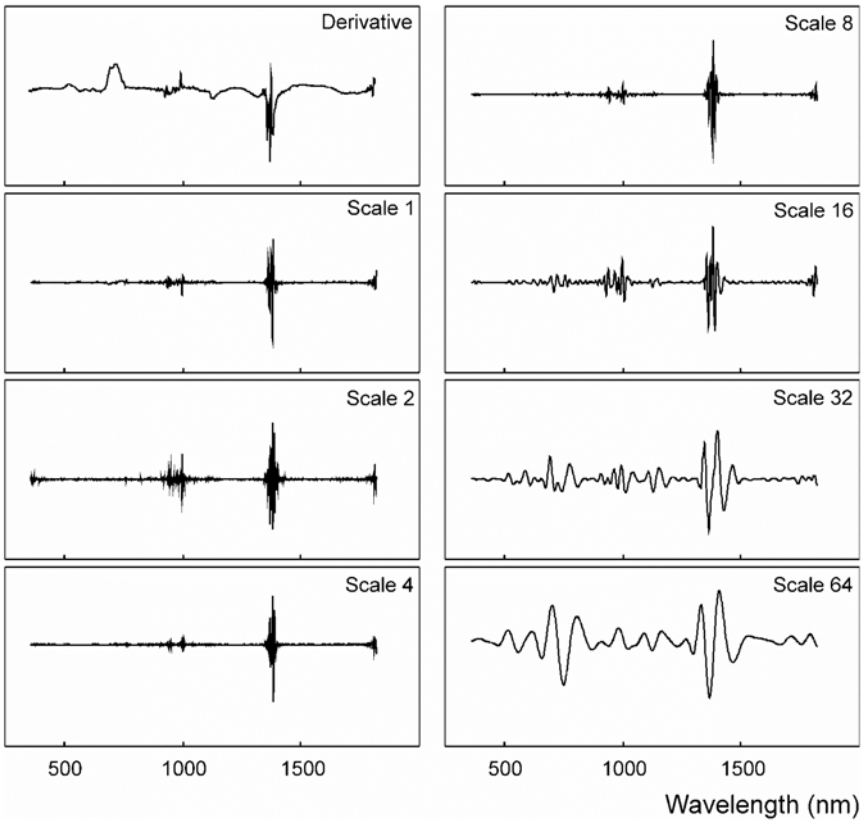

Fig. 4. Derivative spectrum of wheat and the 7 wavelet transforms using a Daubechies 5 continuous wavelet transform

4 Discussion

Transforming derivative spectra in the wavelet transformed signals resulted in an increased correlation with foliar nitrogen concentration. Low scale analysis uses a small window for analysis, in other words: the mother wavelet is stretched across only a small part of the spectrum during the analysis. Therefore it is well suited to detect high-frequency changes in the signal (absorption features). An increase scale results in a wider analysis window and the mother wavelet is scaled along a wider stretch of the spectrum. Wavelet transformations at higher scales are consequently more suitable for detecting changes in large absorption features. The graphs in Figure 5 show a steep increase in the relation between the Daubechies wavelet transformed signal and foliar nitrogen when moving from scale 2 to scale 32, for all regression models. At scale 64 the regression goodness of fit is

lower than at scale 32. This suggests that the optimal scale for detection of nitrogen using derivative spectra is located between 16 and 64.

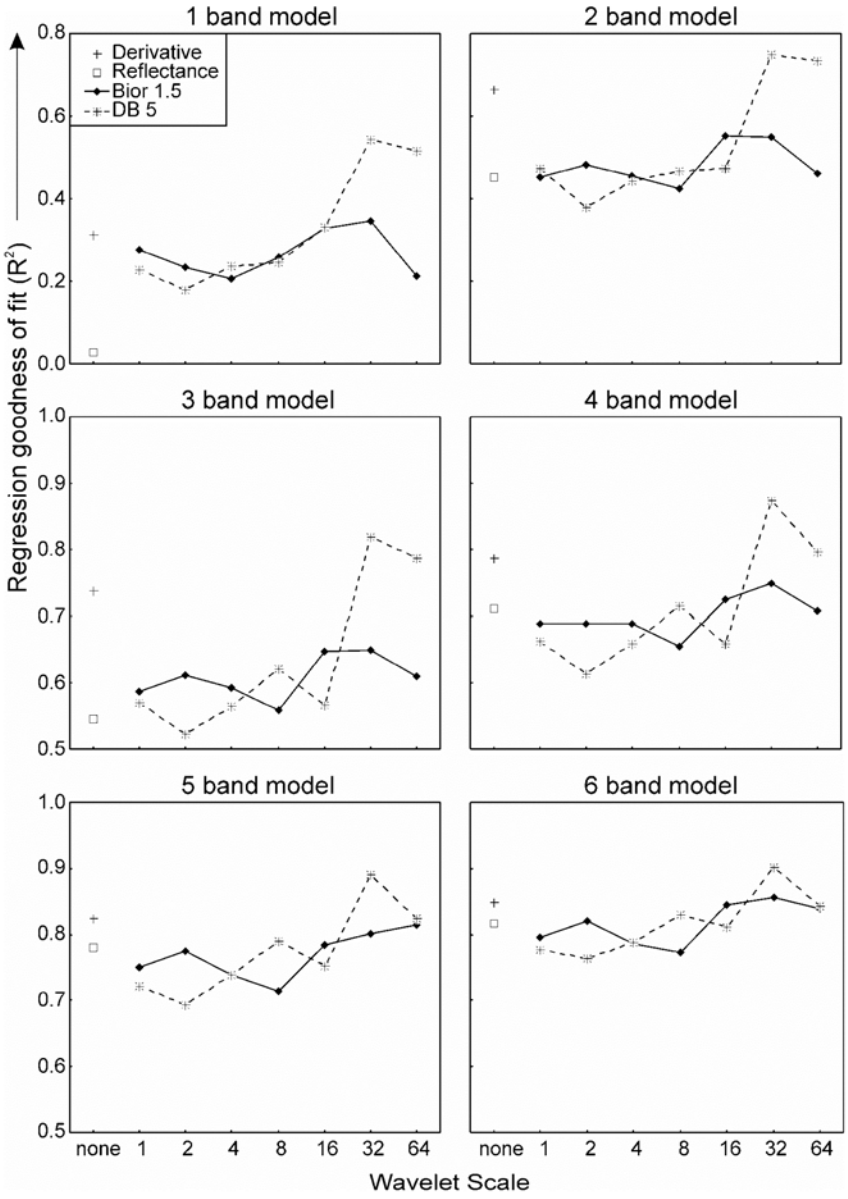

Fig. 5. Mean regression goodness of fit (r^2) over 10 000 bootstrap iterations for regression models with 1 to 6 predictors, in regression between nitrogen and reflectance, derivative and wavelet transformed spectra

The current work does not take into account the various aspects of remote sensing using imaging spectrometers, such as mixed signals, canopy shading and varying canopy architecture. Obviously these factors will affect the outcome of these results, and to fully understand whether wavelet transformations are appropriate signal processing tools for hyperspectral data, a subsequent study is required. This would ideally integrate the ideas presented here in a purpose designed image-based study.

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