Understanding the multi-seasonal spectral and biophysical characteristics of reedbed habitats in the UK

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1. Introduction

Leighton Moss Nature Reserve is dominated by vast distribution of Phragmites australis (Phragmites) existing alongside the reedmace (Typha) plant species. The reserve is classified as a site of special and scientific interest and a protected area of high conservation interests in the UK. The Phragmites is a perennial plant that grows up to a maximum height of three meters with a thick mass of roots called the rhizomes. The height, density, and stem thickness (i.e. diameter) are some of the major biophysical measures used in estimating the quality of the reedbed canopy (Hawke and José 1996).

Remotely sensed data have been widely used in quantifying biophysical properties of different vegetation types (Liu et al. 2007; Wang, Huang, and Wang 2008). The use of high-resolution field spectral data has also been shown to assist in the effective differentiation of plant species and an in-depth understanding of vegetation physiology over time (Bork, West, and Price 1999; Bork et al. 1999; Schmidt and Skidmore 2003; Armitage, Kent, and Weaver 2004; Gao and Zhang 2006). Gao and Zhang (2006) investigated the spectral characteristics of four plant communities (Phragmites australis community, Spartina alterniflora community, Scirpus maritimus community, and Carex scabrifolia community) in the seasons of spring, summer, and autumn at the Chongming Dongtan Nature Reserve in Shanghai using a ground FieldSpec Pro JR spectroradiometer. The results of the study showed that the spectral characteristics of the four plant communities were unique during the three seasons studied and the near-ground spectral reflectance varied with the growing season, community type, and its phenology.

In addition to the use of only spectral information, both spectral characteristics and biophysical measures have been used as parameters for investigating the conditions of diverse vegetation canopies (Elvidge and Chen 1995; McDonald, Gemmell, and Lewis 1998; Blackburn and Pitman 1999; Blackburn and Steele 1999; Cochrane 2000). Blackburn and Steele (1999) investigated the relationships between spectral reflectance characteristics, concentrations of photosynthetic pigments, and biophysical attributes for semiarid bush land canopies. They derived relationships between spectral features and biophysical properties of the matorral vegetation type and identified the factors influencing such relationships. The relationships between spectral reflectance and biophysical measures were determined using empirical methods of data analysis based on mathematical regression models such as linear, logarithmic, exponential, or power functions. The first derivative and red edge reflectance...
properties of vegetation canopies were shown to have strong correlations with increasing vegetation cover. Shaw, Malthus, and Kupiec (1998) established a clear potential for monitoring changes in vegetation canopy cover using very high-resolution indices in the red edge spectral region. The relative proportion of two derivative red edge maxima \((D_{719}/D_{700})\) and derivative red edge shoulders \((D_{730}/D_{700})\) were shown to contain vital information about the proportion of species compared to the red edge position or single-wavelength indices. Apart from vegetation indices (VIs) calculated by multiple single bands within the red edge region, indices are derived by different simulated sensor images from ground-acquired spectral data. Previous studies have developed correlations between the leaf area index (LAI) and red edge parameters in the first derivative reflectance region (Horler, Dockray, and Barber 1983; Filella and Penuelas 1994; Shaw, Malthus, and Kupiec 1998). Armitage, Kent, and Weaver (2004) used simulated Compact Airborne Spectrographic Imager (CASI) sensor to calculate series of VIs. The derivations of different VIs employ a variety of spectral information and relate these measures with different biophysical measures was investigated in this study.

The study aims at investigating the multi-seasonal spectral variation of Phragmites australis, a dominant species of the reedbed wetland habitats in the UK. The specific objectives of the study are as follows:

1. To investigate the relationship between different biophysical properties of reedbed sample sites of varying canopy structure over summer, winter, spring, and autumn;
2. To analyze the seasonal properties in spectral reflectance of varying reedbed canopy sample sites; and
3. To compare the relationships between biophysical measures and spectral reflectance derivatives (such as VIs derived by broad band, narrow band, or single wavelengths; and red edge derivative reflectance) of different sample plots observed over the four seasons.

2. Materials and methods

2.1. Study site

The site used for this study was Leighton Moss Nature Reserve (2°47′W, 54°10′N) situated in the northern part of Lancashire county, north-western England (Figure 1). The study site covers an area of 175 ha in a wide shallow basin confined by limestone ridges and the high salt marshes of Morecambe Bay to the southwest (Middleton et al. 1995). At present, the basin is occupied by a large reedbed site, the largest in the north-western region (Ratcliffe 1977). Leighton Moss Nature Reserve is known to maintain suitable wetland habitat for endangered

![Figure 1. Study area.](image-url)
species such as the bitterns and other wildlife that continue to depend on its ecological diversity for continued existence.

2.2. Selection of sample plots

The sampling plots were selected based on the variation of reed canopy heights and habitat conditions. Most of the canopies had a homogenous floristic pattern of Phragmites across the reserve. Randomly selected sampling plots were located between the dry reedbed and willow carrs and in the wet reedbed habitats (Kent and Coker 1992). It was observed that the height of the Phragmites situated between the dry reedbed and willow carrs were smaller compared to those in the wet and dry reedbeds. During the study, field campaign to acquire spectral response readings and biophysical measurements were implemented in this order: summer (June–August 2008), winter (December 2008–February 2009), spring (April–May 2009) and autumn (September–October 2009). The coordinates of each sampling plot were taken by a Garmin eTrex handheld GPS.

2.3. Collection of biophysical measures

The biophysical measures of 63 randomly sampled plots were acquired over winter, autumn, summer, and spring. Field measurements included LAI, average diameter of reed stems per sample plot ($D$), canopy height (CH) of reed stems per sample plot, and the number of reed stems per sample plot ($n$). The calculated biophysical measures included the reed density ($RD = 4 \times n$) and basal area ($BA = \pi r^2$, where $r = D/2$) Here, the multiplier factor of four was used to derive measures for 1 m$^2$ from sampling plots of 0.25 m$^2$. The LAI measurements were performed employing the Li-COR LAI-2000 Plant Canopy Analyzer and processed by the FV2000 software. The LAI-2000 estimates LAI through radiation transmission values obtained by ratioing radiation measured at the top and the bottom of the canopy. A measurement with the LAI-2000 consists of a minimum of 10 numbers: five of the numbers are signals from the five detectors when the optical sensor is above the vegetation, and the remaining five are the readings made with the sensor below the vegetation (Li-COR, Inc 1992).

2.4. Spectral reflectance measurements and processing

For each sample plot, a GER 1500 spectroradiometer was used to measure the spectral reflectance of the reedbed canopies. The instrument has a spectral range of 350–1050 nm covering the ultraviolet (UV), visible and near infrared (NIR) wavelengths. It has a bandwidth of 1.5 nm and 512 channels. The spectroradiometer was used in standalone mode with a notebook interface. The sensor head of the instrument had a field of view of 15° and every measurement was made from a nadir position with the sensor head above the canopy. The measurements were made between 10:49 and 14:10 local time under clear sky and sunny weather conditions in order to obtain consistent spectral readings (Milton 1987; McCoy 2005). A Spectralon panel, SRT 99-050, was used as the reference panel when making measurements. All the spectral data were converted to reflectance values using the GER 1500 Version 1.30 Software and the results analyzed. For each sample plot, a minimum of 10 spectral readings were taken and the mean obtained to eliminate any potential source of variation (Blackburn and Pitman 1999; Gao and Zhang 2006). After processing the high-resolution field spectroradiometric readings obtained by the GER 1500, the percentage reflectance values were simulated to represent the Landsat ETM+ (bands 1, 2, 3, and 4) and the CASI used by the UK Natural Environment Research Council (Armitage, Kent, and Weaver 2004). Details of the bandwidth settings of both simulated sensors are shown in Table 1. Landsat and CASI bands were generated by the average values of field-measured spectral reflectance and subsequently used to derive the VIs. The relationship between biophysical measures and VIs were derived by high-resolution field reflectance spectra data. The broadband and narrow-band VIs were computed by simulated Landsat ETM+ and CASI bands, respectively. The single reflectance wavelength VIs was based on correlation peaks derived from a correlogram of all biophysical and

| Sensor | Band no. (region) | Wavelength (nm) | Field spectrometer wavelength (nm) | Field spectrometer channel no. |
|--------|------------------|-----------------|-----------------------------------|-------------------------------|
| Landsat ETM+ | 1 (Blue) | 450–515 | 450.24–514.54 | 40 |
|          | 2 (Green)       | 525–605 | 524.45–605.09 | 90 |
|          | 3 (Red)         | 630–690 | 629.54–690.69 | 139 |
|          | 4 (NIR)         | 750–900 | 750.58–900.49 | 99 |
| CASI    | 1 (Blue)        | 441–461 | 440.40–460.10 | 13 |
|          | 2 (Green)       | 546–557 | 547.57–557.46 | 7 |
|          | 3 (Red)         | 666–674 | 666.70–674.72 | 6 |
|          | 4 (Red)         | 694–703 | 693.88–703.41 | 7 |
|          | 5 (Red)         | 705–711 | 704.99–711.32 | 5 |
|          | 6 (NIR)         | 736–744 | 736.51–744.33 | 6 |
|          | 7 (NIR)         | 746–753 | 745.90–753.69 | 6 |
|          | 8 (NIR)         | 775–784 | 755.25–784.70 | 20 |
|          | 9 (NIR)         | 815–824 | 815.42–824.59 | 7 |
|          | 10 (NIR)        | 860–870 | 859.59–870.21 | 8 |
The process of continuum-removal analysis entails choosing specific parts of the spectrum where it is believed that there is useful information for a particular study area. Different matrices (such as band depth and band depth normalized by area) are calculated and investigations are made to determine which biophysical measure best relates with the calculated matrix. The continuum-removal analysis pulls out more of the intricate differences in the spectra between the plots. For this study, the empirical methods of data analysis based on mathematical regression models (such as linear, logarithmic, exponential, or power functions) were used as demonstrated by Blackburn and Steele (1999).

The spectral readings of the Phragmites obtained for each season were averaged. The first derivative of the spectral reflectance curve was computed in order to identify the red edge characteristics of the Phragmites vegetation by \( R'(\lambda_i) = \frac{R(\lambda_i) - R(\lambda_{i-1})}{2\Delta\lambda} \), where \( \lambda_i \) is the wavelength, \( R'(\lambda_i) \) is the first derivative amplitude at \( \lambda_i \), \( R(\lambda_{i+1}) \) is the reflectance at the wavelength \( \lambda_{i+1} \) and \( \Delta\lambda \) is the wavelength interval between \( \lambda_{i+1} \) or \( \lambda_{i-1} \) and \( \lambda_i \).

### Table 2. Vegetation indices used in the study.

| Acronym | Name                     | Vegetation index | Reference |
|---------|--------------------------|------------------|-----------|
| SR      | Simple ratio             | SR = \( \frac{R}{L} \) | (Jordan 1969) |
| NDVI    | Normalized difference vegetation index | NDVI = \( \frac{(R_{nir} - R_{vis})}{(R_{nir} + R_{vis})} \) | (Rouse et al. 1974) |
| TNDVI   | Transformed normalized difference vegetation index | TNDVI = \( \sqrt{\frac{(R_{nir} - R_{vis})}{(R_{nir} + R_{vis})} + 0.5} \) | (Deering and Rouse 1975; Richardson and Wiegand 1977) |
| DVI     | Difference vegetation index | DVI = \( \rho_{nir} - \rho_{vis} \) | (Tucker 1979) |
| SAVI    | Soil adjusted vegetation index | SAVI = \( \frac{(R_{nir} - R_{vis})}{(R_{nir} + R_{vis})} + (1 + L) \) | (Huete 1988) |
| RDVI    | Renormalized difference vegetation index | RDVI = \( \sqrt{\text{NDVI} \times \text{DVI}} \) | (Roujean and Breon 1995) |

Note: \( \rho_{nir} \) is the near infrared band, and \( \rho_{vis} \) is the red band. The \( L \) term (soil adjustment factor) in the SAVI equation ranges from 0 to 1 and is typically set to 0.5.

Figure 2. Scatter plot showing the power regression model for estimating CH by LAI input.

\( p < 0.01 \). Further analysis using logarithmic, exponential, and power function mathematical models indicated that the power model \( y = 1.4946x^{0.2755} \) \( R = 0.58 \) could best describe the relationship between CH and LAI (as shown in Figure 2). The significant correlation between LAI and CH of reedbed canopies is similar to results of Yuan et al. (2013), which demonstrates the existence of significant correlation between both aforementioned vegetation biophysical measures. It is also demonstrated that as LAI increases, so does CH and vice versa (Yuan et al. 2013). The poor correlation between LAI and other biophysical measures (namely BA and RD) could be attributed to seasonal variation of reedbed canopies over different phenological stages and the physical structure of reed stands. Sampson, Vose, and Allen (1998) noted that the relationship between BA and LAI was strongly linear during early stages of tree canopy growth, but at latter stages of phenological development this relationship declines. The result of this study showed a negative correlation between LAI and BA \( R = -0.15 \) and RD \( R = -0.15 \). Considering LAI was the most significant factor of all biophysical measures, subsequent analyses of this study focused on its relationship with different spectral properties. Accurate estimates of the LAI are important in ecosystem analysis because of the importance of canopy structure on gas, water, carbon, and energy exchange (Gower and Norman 1991).

3. Results and discussion

3.1. Relationships between different biophysical measures

The results of a linear correlation matrix showed no significant relation between most measured biophysical measures with the exception of LAI and canopy height (CH) (correlation coefficient \( R = 0.56, p \)-value...
The spectra reflectance of the Phragmites at the NIR and red edge region (around 750 nm) was the highest in site 2B (summer) which had a reflectance percentage of 87% at wavelength of 750.58 nm (Figure 3(b)). The reflectance percentage of the other sites at the same wavelength were site 2A (summer) 48%, site 2B (autumn) 39%, site 3A (autumn) 38%, site 3A (summer) 37%, site 2B (spring) 33%, site 3A (winter) 31%, site 2B (winter) 23%, site 2A (winter) 22%, site 2A (autumn) 21%, site 2A (spring) 19%, and site 3A (spring) 18%, respectively (Figure 3(a)–(c)). The mean reflectance spectra for all the sampling sites over the four seasons (Figure 3(d)) revealed that the spectral reflectance curves of the Phragmites during winter and spring were quite similar. The spectral reflectance curves for summer and autumn had pronounced changes in the visible and NIR regions. The “green peak” around 550 nm was obviously

3.2. Characteristics of multi-seasonal reedbed spectral reflectance

Figure 3(a)–(c) show the multi-seasonal mean reflectance spectra of the Phragmites acquired over summer (June–August 2008), autumn (September–October 2009), winter (December 2008–February 2009), and spring (April–May 2009) for three sampling sites 2A, 2B, and 3A. The results show the mean reflectance spectra of all across monitored sites tend to vary depending on the canopy structure and timing of the spectra data acquisition. The shape of the mean reflectance for the sample sites is presented in Figure 3(d). Figure 3(e) and (f) present the varying LAI of derivative spectra curves over the four seasons (summer, autumn, winter, and spring). The derivative spectra revealed a clear distinction in plots of varying LAI. On average, LAI of the monitored sites over the four seasons varied from 1.2 in winter to 4 in summer.

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Figure 3. Multi-seasonal mean reflectance spectra for sampling plots (a): Site 2A, (b): Site 2B, (c): Site 3A, and (d): All sampling plots. First derivative curves of Phragmites over two wavelength regions (e): 400–1000 nm and (f): 600–800 nm.
3.3. Relationship between broad-band Landsat-derived spectral indices and LAI

The correlations between Landsat-derived VIs and biophysical measures indicated that the best linear relationship was with LAI. Pearson's correlations of Landsat-derived VIs by linear regression model were as follows: 0.716 (SR), 0.742 (NDVI), 0.738 (TNDVI), 0.532 (DVI), 0.741 (SAVI), and 0.658 (RDVI). As indicated in the aforementioned R values, NDVI was most correlated with LAI. Further analysis of curve fitting for NDVI with LAI revealed that the power-based model could pronounce in the summer spectra reflectance curve but diminished in the autumn, winter, and spring reflectance curves.

The red edge was determined using the first derivative curve in order to identify more subtle changes within the vegetation spectra (Figure 3(e) and (f)). Results of the field experiments indicated that the “red edge peak” was highest in summer (late June), followed by autumn (early October), spring (early May), and lowest in winter (early February). The spectral characteristics of reedbeds appeared to be related to the phenology of plants (Pu and Gong 2000), which in turn determine the canopy structure, growth stage, water content, and chlorophyll content of reedbed canopies. These results indicate that the architecture of the reedbed canopy and the seasonal variations affect the spectral reflectance of the Phragmites.

Figure 4. Scatter plots of LAI vs. CASI-derived VIs by power regression models (a) TNDVI-15, (b) NDVI-15, (c) SAVI-15, (d) RDVI-15, (e) SR-5, and (f) DVI-14.
3.4. Relationship between narrow-band CASI-derived spectral indices and LAI

Figure 4 presents scatter plots of LAI vs. six CASI-derived VIs: TNDVI (a), NDVI (b), SAVI (c), RDVI (d), SR (e) and DVI (f) respectively. All scatter plots were modeled best predict the LAI (regression model $y = 3.9803x^{0.8032}; R = 0.78; p < 0.001$).

Past studies have demonstrated the NDVI values generated by broad-band multispectral satellite sensor could be used to estimate LAI for wetland and grassland vegetation (Cayrol et al. 2000; Fernandes et al. 2003).

**Figure 5.** (a) Correlograms constructed by correlation coefficient values (of percent reflectance against LAI, CH, BA and RD) against variations with wavelength and scatter plots showing power regression models that best predicts the LAI using (b) SAVI ($R_{602}$ and $R_{1037}$), (c) NDVI ($R_{602}$ and $R_{1037}$), (d) ($R_{700}$ and $R_{1037}$) and NDVI ($R_{700}$ and $R_{1037}$).
by power regression equations. The simulated CASI bands used to calculate the vegetation indices were band 5 (705–711 nm) and band 10 (860–870 nm) (Table 1). The CASI-derived VIs most correlated with LAI were TNDVI (0.8126), NDVI (0.8126), and SAVI (0.8125) (Figure 4(a)–(c)). The least correlated VIs with LAI were RDVI \( (R = 0.7729) \), SR \( (R = 0.7677) \), and DVI \( (R = 0.7013) \) (Figure 4(d)–(f)). The poor performance of the DVI in comparison to TNDVI or NDVI was attributed to effects of topography, shadow, or atmosphere (Akkartal, Türü'dúa, and Erbekb 2004). In a study by Fu, Wang, and Jiang (2010), both exponential and power curve models of TNDVI and NDVI were proved to be useful inputs in estimating LAI of Masson pine vegetation. In comparison to the broad-band Landsat-derived NDVI, the narrow-band CASI-derived TNDVI and NDVI were demonstrated to be more effective in this study.

### 3.4.1. Relationship between single-wavelength indices and biophysical measures

In order to identify spectral regions most strongly related to the biophysical measures, correlograms were constructed by sequentially regressing the value of percentage reflectance at each GER1500 channel \( (R) \) against the biophysical measures and plotting the coefficient of correlation \( (R^2) \) against wavelength (Blackburn and Steele 1999). Figure 5(a) shows a correlogram that illustrates how the correlation between percentage reflectance and biophysical measures changes with wavelength. The correlation coefficients for each biophysical measure was plotted against the wavelengths of a reference spectrum, showing the reflectance of a well-developed reedbed canopy in summer. The correlograms showed that the LAI had a similar form to the reedbed reflectance spectrum, with little correlation in the visible region and high correlations in the NIR regions. Blackburn and Steele (1999) discovered that for matorral vegetation there was a positive relationship between the LAI and NIR reflectance at 783.2 nm \( (R_{783.2}^2) \). A prominent peak was observed at wavelength 760 nm \( (R_{760}^2 = 0.51) \) against wavelength \( (R = 0.23) \) in the red region. In the near infrared region, the maximum peak was at wavelength 1036 nm \( (R_{1036}^2) \) with \( R = 0.27 \)–0.11 similar to the LAI pattern in the same region of the correlogram. The correlation coefficients gently increase from the bottom peak \( R_{691} \) in the blue region to \( R_{529} \) in the chlorophyll absorption green region. The peak correlation in the green region was at wavelength \( R_{560.76} \) \( (R = 0.20) \). A prominent peak was observed at wavelength \( R_{700.23} \) \( (R = 0.23) \) in the red region. In the near infrared region, the maximum peak was at wavelength 1036 nm \( (R_{1036}) \) with \( R \) value of 0.47. Generally, the percentage reflectance of the sample plots was poorly related to most of the biophysical measures with the exception of the LAI. From the correlograms (Figure 5(a)), the red and NIR peak wavelengths were used to generate the VIs and correlated with the biophysical measures (LAI: \( R_{501} \), \( R_{680} \), and \( R_{783} \); CH: \( R_{501} \), \( R_{565} \), and \( R_{702} \); RD: \( R_{565} \), \( R_{700} \), and \( R_{1032} \); and BA: \( R_{533} \), \( R_{602} \), and \( R_{113} \) respectively).

The results indicated that for CH, BA, and RD, the \( R \) value was quite low. However, the LAI showed some correlation with SAVI and NDVI generated by the red \( (R_{62} \) and \( R_{700} \) and NIR \( (R_{1032}) \) reflectance channels, respectively. Results of further analysis based on other mathematical models indicated the power regression

### Table 3. Selected red edge reflectance spectra and LAI derived using linear regression model.

| Wavelength | \( R \) | \( p \) | Region |
|------------|-------|-------|-------|
| \( R_{780} \) | -0.501* | 0.01498 | Red |
| \( R_{781} \) | -0.498* | 0.01566 | Red |
| \( R_{783} \) | -0.494* | 0.01649 | Red |
| \( R_{784} \) | -0.490* | 0.01771 | Red |
| \( R_{785} \) | -0.486* | 0.01885 | Red |
| \( R_{788} \) | -0.480* | 0.02031 | Red |
| \( R_{789} \) | -0.474* | 0.02224 | Red |
| \( R_{790} \) | -0.464* | 0.02560 | Red |
| \( R_{791} \) | -0.451* | 0.03071 | Red |
| \( R_{792} \) | -0.435* | 0.03812 | Red |
| \( R_{793} \) | -0.415* | 0.04905 | Red |
| \( R_{794} \) | 0.551** | 0.06838 | NIR |
| \( R_{795} \) | 0.697** | 0.00022 | NIR |
| \( R_{796} \) | 0.800** | 0.00000 | NIR |
| \( R_{794} \) | 0.801** | 0.00000 | NIR |
| \( R_{795} \) | 0.802** | 0.00000 | NIR |
| \( R_{797} \) | 0.797** | 0.00001 | NIR |
| \( R_{798} \) | 0.796** | 0.00001 | NIR |
| \( R_{799} \) | 0.801** | 0.00000 | NIR |

*Correlation is significant at the 0.05; **Correlation is significant at the 0.01.

### Table 4. Regression models that best predicted LAI using red edge indices.

| VI | Band combination (Red and NIR) | \( R^2 \) | Equation | Regression model |
|----|--------------------------------|-------|---------|-----------------|
| DVI | 695 and 758 | 0.88 | 0.72 | \( y = 1.1097e^{0.0224x} \) | Exponential |
| RDVI | 681 and 758 | 0.85 | 0.72 | \( y = 1.0326e^{0.0196x} \) | Exponential |
| TNDVI | 695 and 758 | 0.79 | 0.63 | \( y = 2.5610e^{0.0016x} \) | Power |
| SAVI | 695 and 758 | 0.79 | 0.63 | \( y = 0.2744e^{0.0194x} \) | Power |
| NDVI | 695 and 758 | 0.79 | 0.62 | \( y = 1.0958e^{0.0307x} \) | Power |
| SR | 695 and 749 | 0.75 | 0.56 | \( y = 1.3357e^{0.0178x} \) | Power |
model relating LAI to both SAVI-4 ($R = 0.804$) and NDVI-4 ($R = 0.803$) were most significant (Figure 5(b) and (c)). Though NDVI and SAVI show strong correlation with foliage density, the effects of sensitivity to external factors such as solar and viewing geometry, soil background, and atmospheric effects are compensated in SAVI (Rondeaux, Steven, and Baret 1996).

### 3.4.2. Relationship between biophysical measures and red edge reflectance

The red edge spectral reflectance ($R_{680–760}$) was compared with the biophysical measures using a linear regression mathematical model. The results showed that the only biophysical measure related to the red edge spectra was the LAI. Table 3 shows selected red edge spectral reflectance wavelengths that most correlated with LAI ($p < 0.05$). The selected red (680–695 nm) and NIR (749–760 nm) wavelengths within the red edge region were subsequently used to calculate the six VIs and compared with LAI for correlation. The red edge spectral values with $p$ values less than 0.05 were selected and used for calculating the VIs. The selected wavelengths in the red edge region were used to develop six vegetation indices (SR, NDVI, TNDVI, DVI, SAVI, and RDVI) and the

| Red edge parameter | $R$  | $R^2$ | Equation | Regression model |
|-------------------|------|-------|----------|------------------|
| $R_{719}/R_{703}$ | 0.741** | 0.55  | $y = 0.9394e^{0.8335x}$ | Exponential |
| $R_{720}/R_{719}$ | 0.738** | 0.54  | $y = 0.9041e^{0.8826x}$ | Exponential |
| $R_{706}/R_{719}$ | 0.731** | 0.53  | $y = 0.7705e^{0.5444x}$ | Exponential |
| $R_{724}/R_{719}$ | 0.724** | 0.53  | $y = 0.0828e^{0.7066x}$ | Exponential |
| $R_{718}/R_{719}$ | 0.718** | 0.52  | $y = 2.8922x - 0.9327$     | Linear     |
| $R_{715}/R_{719}$ | 0.715** | 0.51  | $y = 3.1641x^{0.323}$     | Power      |
| $R_{710}/R_{703}$ | 0.714** | 0.51  | $y = 2.8922x - 0.9327$     | Linear     |
| $R_{699}/R_{719}$ | 0.699** | 0.49  | $y = 2.6199x - 0.3451$     | Linear     |
| $R_{702}/R_{703}$ | 0.690** | 0.48  | Logarithmic               |
| $R_{706}/R_{703}$ | 0.678** | 0.46  | Logarithmic               |
| $R_{722}/R_{703}$ | 0.678** | 0.42  | Exponential               |

*p < 0.05; **p < 0.01.

![Figure 6. Scatter plots of the LAI against the four most effective red edge parameters for accurately predicting the LAI. Ratios between: (a) $(dr_{719}, dr_{703})$, (b) $(dr_{719}, dr_{705})$, (c) $(dr_{721}, dr_{703})$ and (d) $(dr_{708}, dr_{703})$.](image-url)
most effective VI for predicting LAI was selected. Table 4 presents regression models that best predict LAI by red edge-derived VIs. The exponential regression model relating DVI calculated by wavelengths $R_{705}$ and $R_{758}$ had the best relationship with LAI ($R = 0.88$).

### 3.4.3. Relationship between biophysical measures and amplitude of first derivative in red edge region

Table 5 summarizes the results of the correlation coefficients between LAI and amplitude of the first derivative in the red edge region. In this experiment, the maximum $R$ value for first derivative in the red edge region was used to determine variations to reedbed biophysical measures. The relative ratios ($R_{719}/R_{703}$), ($R_{719}/R_{705}$), ($R_{721}/R_{703}$) and ($R_{708}/R_{703}$) contain useful information for estimating LAI of reedbed canopies by comparing them with other red edge derivatives. Figure 6 presents the four most effective red edge parameters used for accurate prediction of LAI in the study area. However, the orthogonal and hybrid VIs, DVI, and RDVI computed using the red edge reflectance (Table 4) had a stronger correlation with the LAI when compared to these ratios.

### 4. Conclusions

The results of this study show that there is no strong relationship between the different biophysical measures evaluated with the exception of LAI and canopy height. The mean spectral reflectance of all the monitored plots varied depending on the canopy structure and season when the reflectance spectral data were acquired. The mean reflectance and spectral derivative graphs revealed a clear distinction in sample plots of varying LAI. Notable changes were in the NIR, green and red wavelength regions caused by chlorophyll absorption in the region. The spectral reflectance of the Phragmites during winter and spring were quite similar, unlike the summer and autumn reflectance curves, which had pronounced changes in the visible and NIR regions. The experiments also indicated that the amplitude of the first derivative in the red region was the highest in the summer (late June), followed by autumn (early October), spring (early May), and lowest in winter (early February). Table 6 summarizes the reflectance features that best predicts the LAI derived in the study. The orthogonal and hybrid VIs, DVI and RDVI, computed using the red edge reflectance at specific wavelengths (i.e. 681, 695, and 758 nm) had the strongest correlation with the LAI. For biophysical measures with VIs, the performance of the narrow band red edge-derived DVI using wavelengths $R_{705}$ and $R_{758}$ outperformed all simulated broad-band Landsat, narrow-band CASI or first derivative features investigated in the study. The results show that DVI is a good predictor of deciduous plantations and considered more sensitive to vegetation density than other indices (Franklin 2001). Considering the valuable information contained in the red edge region of the electromagnetic spectrum, subtle information of chlorophyll content in vegetation cover can be effectively utilized in developing models that predict accurately biophysical measures such as LAI. The development of space-borne sensors with high spatial, temporal, and spectral (particularly in the red edge region) resolutions could be used to generate valuable information needed in management of reedbed or similar wetland habitats and agricultural applications such as quantifying nitrogen content through understanding chlorophyll content (Eitel et al. 2007) and forestry management (Eitel et al. 2011).

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