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demand, or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.
Mapping swamp timothy (*Crypsis schoenoides*) seed productivity using spectral values and vegetation indices in managed wetlands

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This work examines the potential to predict the annual seed productivity of swamp timothy (*Crypsis schoenoides*) in two Central California managed wetlands by correlating spectral reflectance values and associated spectral vegetation indices (SVIs) calculated from two sets of high-resolution aerial images (May and June 2006) to collected vegetation data. An object-based segmentation approach incorporating image textural properties was also investigated. The June image provided better predictive capacity relative to May, a result that underscores the importance of imagery timing to coincide with optimal vegetation status. The simple ratio (SR) derived from the June image proved to be the best predictor of swamp timothy dry seed productivity ($R^2 = 0.566$, standard error (SE) = 29.3 g m⁻²). Addition of object-based texture information did not significantly increase the accuracy of seed mass estimations. Using the SR-seed biomass model, a seed productivity map was created demonstrating the potential utility of this approach as a tool for resource managers.

1. Introduction

Prior to 1850, there were an estimated 5 million acres of wetlands in California. Today, less than 6% remain (Hartmann and Goldstein 1994). The remaining wetlands are now intensively managed to provide habitat for 19% of the wintering waterfowl in the continental USA and 60% of the waterfowl of the Pacific Flyway (Gilmer *et al.* 1982). In 1986, The North American Waterfowl Management Plan was drafted by the US Fish and Wildlife Service in cooperation with Canadian Wildlife Service. A goal of this plan is to increase waterfowl populations to their pre-1970 numbers *by improving and securing long-term protection of 6 million acres of habitat [nationally] in 34 areas of major concern* (US Fish and Wildlife Service 1986). Wetland health and productivity greatly affects growing waterfowl populations (Mushet *et al.* 1992, Fleskes *et al.* 2005), and better tools that assist wetland managers in efficiently assessing ecosystems’ status and changes are needed.

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The wetlands in California’s Central Valley are managed by controlled flooding in the late summer, maintaining water levels through the winter and then draining in the spring (Fredrickson and Taylor 1982, Naylor 1999). The timing and rate of the spring drawdown affects many aspects of habitat health, including vegetation composition. The varieties of annual plants that germinate on the exposed mudflats of the seasonal wetlands are collectively known as moist-soil plants. The seeds and tubers produced by moist-soil plants during these summer months feed the wintering waterfowl. Soil moisture, soil salinity and soil and air temperatures at the time of germination are affected by the timing and rate of drawdown and influence the overall moist-soil plant species composition (Naylor 1999).

Swamp timothy (Crypsis schoenoides), one of the key forage species in the managed wetlands of the Central Valley (Fleskes et al. 2004, 2005), is a fast-growing annual producing high-quality seeds in great quantities. It is tolerant of both temporary inundation induced by summer irrigation and moderate to high soil salinity levels inherent in Central California wetland soils (Fredrickson and Taylor 1982, Mushet et al. 1992, Rahilly 2008). Bird species that forage on swamp timothy seeds are primarily ducks such as pintails, gadwalls, mallards and teal (Hothem and Ohlendorf 1989, Burns et al. 2003, Fleskes et al. 2004, 2005). Wetlands managed for swamp timothy are also utilized by many shorebird species, such as dunlins, sandpipers and the American avocet, due to its low growth habit (Isola et al. 2000). A challenge facing wetland managers is to efficiently quantify the amount of seed mass produced annually. Current techniques are both field and lab intensive because they involve manual biomass harvesting and sorting of tiny seeds. Furthermore, because these labour-intensive methods can only be applied to representative vegetation stands within large wetland areas, they are prone to bias. Remote-sensing techniques have the potential to enable large-scale assessment of feed biomass in this wildland setting.

It is well documented that digital spectral reflectance values, as well as vegetation indices derived from these spectral values, can be used to estimate the total above-ground biomass produced on an annual basis (Asrar 1989). These techniques have been used to estimate crop yields (Richardson et al. 1982, Moran et al. 1997, Cheng et al. 2003, Godwin et al. 2003, Tao et al. 2005) and to quantify the areal extent of standing biomass in rangeland ecosystems (Everitt et al. 1989, Loris and Damiano 2006, Beeri et al. 2007, Cho et al. 2007). Moreau et al. (2003) used these techniques to successfully estimate the areal extent of Andean wetland forage grasses. However, no one has assessed the potential of these techniques to estimate annual seed mass production in a managed seasonal wetland.

While spectral values and indices have been successfully applied to vegetation mapping, more recently developed object-based approaches offer some advantages by enabling the integration of spatial information (e.g. plant community structure) into the analysis (Caridade et al. 2008, Sheeren et al. 2009). For example, textural properties, such as contrast, homogeneity and regularity, derived from image segments have been shown to improve the estimation of biophysical parameters in forests (Wulder et al. 1996, Franklin et al. 2001, Ruiz et al. 2004, Ozdemir et al. 2008, Kimothi et al. 2009, Mariz et al. 2009, Laba et al. 2010). However, the value of applying this approach in a relatively homogeneous, low-lying vegetative canopy, such as the wetlands of this study, has yet to be determined.

In this study, spatial vegetation data were collected and analysed to quantify total swamp timothy seed mass in a pair of managed wetland ponds. The objective was to assess the feasibility of using spectral reflectance values ($\rho_{\text{red}}$ and $\rho_{\text{NIR}}$ bands) to
derive vegetation indices to estimate swamp timothy seed productivity. In addition, the capacity of an object-based classification method incorporating image textural properties was investigated as a means to improve upon the spectral band-based and index-based approaches. The analysis here is based on two sets of aerial imagery taken approximately 4 weeks apart after pond drawdown in adjacent wetland units.

2. Site description and methods

2.1 Site description

An adjacent pair of privately owned wetland ponds within the Ducky Strike Duck Club, known as Ducky Strike North (DSN) and Ducky Strike South (DSS), was chosen for this project because these ponds are dominated by swamp timothy (figure 1). The ponds are located in the southwest part of Merced County, CA (36° 57' 40" N and 120° 43' 58" W), within the Grasslands Ecological Area (GEA). The areas of DSN and DSS are 32.2 and 36.5 ha, respectively. The mean annual precipitation is 21 cm and the mean annual temperature is 16.8°C (Western Region Climate Center 2006). The soil series underlying the sites is Britto clay loam, ponded, derived from mixed alluvium composed dominantly of ocean sediments. Some of the chemical characteristics of this series include 5% maximum calcium carbonate, 10% gypsum, electric conductivity of 1.0–11.0 dS m⁻¹, sodium adsorption ratio maximum of 30.0 and pH values ranging from 6.0 to 8.5 (NRCS 2007). As noted above, this area is no longer naturally flooded but now diked and levied for controlled flooding typically lasting from 1 September to the middle of March. Within the DSN pond, the water flows from south to north, following a swale located along the eastern edge of the field. DSS utilizes one inlet/outlet at the northeast corner of the field. The fields both slope gradually.

Figure 1. Aerial image of the study area in the near-infrared (NIR) band, Ducky Strike North (DSN) and Ducky Strike South (DSS). Image (a) taken on 11 May 2006 and image (b) taken on 9 June 2006.
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from west to east. Vegetation consists of C. schoenoides, Rumex spp., Eleocharis spp., Scirpus maritimus, Scirpus acutus, Juncus balticus, Typha spp. and Xanthium strumarium as the major components. The site is primarily managed for swamp timothy and often the emergent vegetation (rushes, tules and cattails) are disked under to maintain maximum swamp timothy productivity while leaving some emergent vegetation for wildlife cover.

2.2 Aerial imagery

Multiband high-resolution aerial photographs were taken using a Zeiss RMK® (Zeiss Inc., Thornwood, NY, USA) Top 15 Aerial Survey Camera System on 11 May 2006 and 9 June 2006 (figure 1). Images were taken at noon, zero degrees off nadir to minimize shadow effects. Missions were flown and imagery geo-rectified by HJW Geo-Spatial, Inc. (Oakland, CA, USA). Ground pixel resolution is 15 cm × 15 cm (maximum root mean squared error (RMSE) = 7.5 cm). The coordinate system used for the images is UTM zone 10 NAD 83. Aerial images responded to green (ρgreen, 500–600 nm), red (ρred, 600–700 nm) and near-infrared (NIR) (ρNIR, 700–900 nm) spectral bands. The scanner produced RGB digital images with 8-bit colour with pixels in each band ranging from 0 to 255.

Calculations of vegetation indices are primarily based on reflectance while the aerial photographs record the reflected radiation of ground objects as digital numbers (DNs). DNs need to be converted to reflectance values in order to calculate vegetation indices. As ground reflectance measurements were not made in 2006, a campaign was conducted in the study area in October 2008. Ground reflectance data were collected using a field spectrometer (ASD FieldSpec Pro FR; ASD Inc., Boulder, CO, USA) with a spectral range of 350–2500 nm. The ground hyperspectral measurements were taken under a clear sky. Twelve invariant targets (concrete and gravel surfaces) around the wetland ponds were selected. Data were collected using a sensor with a 15° field of view (FOV) held at a nadir angle about 1.0 m above each target, resulting in a 0.22 m radius footprint within a target. For each target, measurements consisted of 8–12 randomly distributed points within a circle with a radius of roughly 0.8 m. The spectral reflectance was calculated as the ratio of target radiance to the radiance of a white reference panel. Following each hyperspectral measurement, the corresponding coordinate was recorded using a Trimble GPS device (Trimble AG114; Trimble, Sunnyvale, CA, USA) connected to a handheld PC (Allegro Cx, Juniper Systems, Logan, UT, USA) with a determined 15 cm accuracy. The average coordinate for the above points was then assigned to the central position of the target. The hyperspectral data for spectral regions of 500–600, 600–700 and 700–900 nm were averaged and compared with the corresponding DN value of the pixels extracted from aerial images, and the DN value was converted to an apparent reflectance. The reflectance of 12 targets at green, red and NIR bands exhibited a highly linear correlation (R2 > 0.95) with brightness. Because reflectance from these surfaces is not expected to change with time (road gravel and concrete), we used these results to correct the 2006 aerial images, yielding the reflectance products used in subsequent analyses.

2.3 Vegetation sampling, processing and analysis

Vegetation sampling was conducted in August 2006 after the swamp timothy seeds had matured and the entire plant was desiccated. Sample locations were randomly generated using GIS software (ArcGIS v9.3, ESRI; Redlands, CA, USA) to select one
sample location per 0.41 ha (DSS, \( n = 73 \); DSN, \( n = 81 \)). The GPS system described above was used to identify each sample plot. At each plot, a 10 cm \( \times \) 10 cm core representing the 1 m \( \times \) 1 m area was removed from the pedon, allowing the entire aboveground biomass to be clipped and secured. Samples were oven-dried at 105\(^\circ\)C for 24 h. Dry masses of total biomass, total swamp timothy and swamp timothy seeds were determined gravimetrically for each sample.

From our field plot samples, total dry biomass was found to be strongly correlated with dry seed mass for swamp timothy as determined by lab assessments \((R^2 = 0.817, \text{ see figure 2(a)})\). Dry swamp timothy biomass, the main component of total dry biomass in samples, correlated even more strongly \((R^2 = 0.894, \text{ see figure 2(b)})\) with dry seed mass. Because remote-sensing techniques have been successfully applied to map vegetation biomass (Anderson et al. 1993, Moreau et al. 2003, Mutanga and Skidmore 2004), this finding suggested that swamp timothy seed mass could be estimated across our study sites using spectral values and vegetation indices.

### 2.4 Spectral reflectance, vegetation indices and object-based segmentation

We tested the feasibility of two spectral reflectance bands (\( \rho_{\text{red}} \) and \( \rho_{\text{NIR}} \)) and six vegetation indices as predictors of dry swamp timothy seed production. Vegetation indices for quantifying biomass or vegetative vigour were derived from spectral bands categorized as (1) intrinsic indices such as the simple ratio (SR) (Jordan 1969, Baret and Guyot 1991) and the normalized difference vegetation index (NDVI) (Kriegler et al. 1969, Rouse et al. 1974), which do not involve external factors other than the measured spectral reflectance; (2) soil-line-related indices, such as the soil-adjusted vegetation index (SAVI) (Huete 1988), the transformed soil-adjusted vegetation index (TSAVI) (Baret et al. 1989) and the modified soil-adjusted vegetation index (MSAVI) (Qi et al. 1994); and (3) the atmospheric-corrected index, global environment monitoring index (GEMI) (Pinty and Verstraete 1992). Mathematical descriptions of the indices are summarized in table 1.

To parameterize the soil-line-related indices, a linear relationship between the red (\( \rho_{\text{red}} \)) and NIR (\( \rho_{\text{NIR}} \)) reflectance values on bare soil (the soil line) was developed from base soil areas at a site (Fox and Metla 2004). From the May and June imagery, 113 and 104 bare soil pixels, respectively, were manually selected based on visual observation of high albedo. The selected pixels were then used to develop the following two soil-line models: \( \rho_{\text{NIR}} = 1.760 \rho_{\text{red}} + 0.041 \) \((R^2 = 0.792)\) and \( \rho_{\text{NIR}} = 1.742 \rho_{\text{red}} + 0.083 \) \((R^2 = 0.821)\) for the May and June images, respectively. These slope and intercept values \((a \text{ and } b \text{ in table 1})\) were used to evaluate the TSAVI and MSAVI expressions.

In addition to the vegetation indices, object-based approaches incorporating image texture data were explored as a means of improving upon the pixel-based approaches discussed above. To obtain the objects, segmentation was conducted using eCognition software (v2.0; Definiens Inc., Munich, Germany). Scale, colour and shape parameters were optimized to achieve realistic segmentation results by trial and error (Platt and Rapoza 2008). Satisfactory results were achieved with the following parameters: scale = 10, colour = 0.8, shape = 0.2, compactness = 0.3 and smoothness = 0.7. After segmentation, we obtained five main textures: standard deviation (SD), homogeneity, contrast (grey-level co-occurrence matrix (GLCM)), contrast (grey-level difference vector (GLDV)) and entropy from the three channels (green, red and NIR) of the aerial image resulting in 15 (3 channels \( \times \) 5 features) texture parameters (table 2). The sample plots were assumed to be representative of the segmented objects. Hence, the
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Figure 2. Relationship between swamp timothy dry seed mass and total dry biomass for both May (a) and June (b) images.

Samples were spatially joined to the corresponding objects with the texture features of objects. Stepwise multiple linear regression was employed to model the relationship between the dry seed mass of swamp timothy and the combination of vegetation indices and
Table 1. Summarized table with references for mathematical descriptions of vegetation indices used in this study.

<table>
<thead>
<tr>
<th>Vegetation index name</th>
<th>Abbreviation</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized difference vegetation index</td>
<td>NDVI</td>
<td>$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}}}$, where $\rho_{\text{red}}$ and $\rho_{\text{NIR}}$ stand for the spectral reflectance measurements acquired in the red and NIR regions, respectively</td>
<td>Kriegler et al. (1969) and Rouse et al. (1974)</td>
</tr>
<tr>
<td>Simple ratio</td>
<td>SR</td>
<td>$\text{SR} = \frac{\rho_{\text{NIR}}}{\rho_{\text{red}}}$, which is the NIR/red reflectance ratio</td>
<td>Jordan (1969) and Baret and Guyot (1991)</td>
</tr>
<tr>
<td>Soil-adjusted vegetation index</td>
<td>SAVI</td>
<td>$\text{SAVI} = \frac{(1 + L)\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + L}$, where $L$ is just a number that takes values between 0 and 1; 0 for very high vegetation cover and 1 for very low vegetation cover. In this study, ‘$L$’ represents a particular quantity, $L = 0.5$</td>
<td>Huete (1988)</td>
</tr>
<tr>
<td>Transformed soil-adjusted vegetation index</td>
<td>TSAVI</td>
<td>$\text{TSAVI} = \frac{a(\rho_{\text{NIR}} - a\rho_{\text{red}} - b)}{\rho_{\text{red}} + a\rho_{\text{NIR}} - ab}$, where $a$ and $b$ are, respectively, the slope and the intercept of soil line* ($\rho_{\text{NIR}} = a\rho_{\text{red}} + b$)</td>
<td>Baret et al. (1989)</td>
</tr>
</tbody>
</table>
| Modified soil-adjusted vegetation index    | MSAVI        | $\text{MSAVI} = \frac{(1 + L)(\rho_{\text{NIR}} - \rho_{\text{red}})}{\rho_{\text{NIR}} + \rho_{\text{red}} + L}$, 
$L = 1 - 2a \times \text{NDVI} \times \text{WDVI}$, 
$\text{WDVI} = \rho_{\text{NIR}} - a\rho_{\text{red}}$ | Qi et al. (1994) |
| Global environment monitoring index        | GEMI         | $\text{GEMI} = \frac{\eta(1 - 0.25\eta)(\rho_{\text{red}} - 0.125)}{1 - \rho_{\text{NIR}}}$, 
$\eta = \frac{2(\rho_{\text{NIR}}^2 - \rho_{\text{red}}^2) + 1.5\rho_{\text{NIR}} + 0.5\rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + 0.5}$ | Pinty and Verstraete (1992) |

Notes: NIR, near-infrared; WDVI, weighted difference vegetation index.
*Soil-line models for this work based on site imagery for May: $\rho_{\text{NIR}} = 1.760\rho_{\text{red}} + 0.041$ ($R^2 = 0.792$) and June: $\rho_{\text{NIR}} = 1.742\rho_{\text{red}} + 0.083$ ($R^2 = 0.821$).

texture parameters. In a stepwise regression, the predictor with the highest $t$-statistic is entered into the model until there are no predictors left that have $t$-statistics with significance values less than 0.05. Both May and June images were tested. All statistical analysis employed SPSS software (v16.0, SPSS Inc., IBM, Armonk, NY, USA).

2.5 Creating swamp timothy productivity maps

To properly relate dry seed mass to spectral reflectance and vegetation indices, the cell size of the spectral reflectance and vegetation indices must be consistent with the
Table 2. Description of the texture parameters.

<table>
<thead>
<tr>
<th>Texture features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy*</td>
<td>Highly correlated to energy. Measures the disorder of an image. Entropy is high when an image is not texturally uniform</td>
</tr>
<tr>
<td>Contrast*</td>
<td>Contrast measures the difference between the highest and lowest values of a contiguous set of pixels</td>
</tr>
<tr>
<td>Homogeneity*</td>
<td>A measure of image homogeneity. Sensitive to the presence of near-diagonal elements in a GLCM</td>
</tr>
<tr>
<td>SD*</td>
<td>Calculates the SD of the feature values of an image object and the objects in a specified surrounding, computing a value for the structural heterogeneity of the given feature without consideration of spatial distribution</td>
</tr>
<tr>
<td>Contrast†</td>
<td>Contrast based on the GLDV</td>
</tr>
</tbody>
</table>

Notes: SD, standard deviation.
*Based on the grey-level co-occurrence matrix (GLCM).
†Based on the grey-level difference vector (GLDV).

represents field plot scale (1 m^2). Hence, the cell size surrounding each sample coordinate was altered from the 15 cm × 15 cm pixel to an average cell size of 7 × 7 pixels, equivalent to 1.05 m^2. The NIR and red pixel reflectance values for each cell were then averaged and used to calculate the vegetation indices.

In preliminary data analysis for the June dataset, we found that the dependent variables had skewed distributions, and the residuals of the regression analysis were not normally distributed. Data transformation was employed to meet the regression assumption of normality of the error distribution. Employing the ladder of power transformation approach (Velleman and Hoaglin 1981), we found the square root transformation performed the best and applied this to the dependent variables in the regression analysis. As the data sets for May were not skewed, no data transformation was applied to the May dataset.

Linear regression models were tested for spectral reflectance and vegetation indices with total dry biomass, dry swamp timothy biomass and dry seed biomass. Determination coefficients (R^2) and SE of the estimation were used to differentiate model performance. To create swamp timothy seed mass maps, the best predictive models were used to assign swamp timothy seed mass to each 7 × 7 cell. Because the DSN and DSS ponds are not entirely swamp timothy inclusive habitat, non-swamp timothy areas, which were identified based on ground surveys and object-based image analysis using eCognition software, were assigned to zero swamp timothy seed mass values.

### Results

Coefficients of determination and SEs of estimate for all models tested are summarized in table 3. The best swamp timothy dry seed mass predictions were obtained using the June aerial image, with the best performance achieved using SR (R^2 = 0.565, SE = 29.3 g m\(^{-2}\)) TSAVI (R^2 = 0.561, SE = 29.9 g m\(^{-2}\)) and NDVI (R^2 = 0.554, SE = 30.0 g m\(^{-2}\)) in univariate linear models. Red, SAVI and MSAVI models yielded comparable but lower correlation coefficients, ranging from 0.401 to 0.465 (SE from 32.6 to 34.6 g m\(^{-2}\)), while the GEMI and NIR model fits were inferior. For the May aerial image, SR was also found to perform best, but poorer than for the June image (R^2 = 0.419, SE = 33.4 g m\(^{-2}\)). TSAVI, NDVI and \(\rho_{\text{red}}\) produced results for the May
Table 3. DS coefficient of determination $R^2$ and SE of estimate (SE with unit of g m$^{-2}$) for dry total biomass, dry ST biomass and ST seed mass (g m$^{-2}$) plotted against spectral reflectance and vegetation indices; all the models are calculated using univariate linear regression.

<table>
<thead>
<tr>
<th></th>
<th>$\rho_{\text{NIR}}$</th>
<th>$\rho_{\text{red}}$</th>
<th>NDVI</th>
<th>SR</th>
<th>SAVI</th>
<th>TSAVI</th>
<th>MSAVI</th>
<th>GEMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>May</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dry total biomass</td>
<td>$R^2$</td>
<td>0.066</td>
<td>0.412</td>
<td>0.463</td>
<td>0.468</td>
<td>0.135</td>
<td>0.438</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>201.7</td>
<td>160.0</td>
<td>152.9</td>
<td>152.3</td>
<td>194.0</td>
<td>156.4</td>
<td>197.1</td>
</tr>
<tr>
<td>Dry ST biomass</td>
<td>$R^2$</td>
<td>0.046</td>
<td>0.331</td>
<td>0.384</td>
<td>0.398</td>
<td>0.122</td>
<td>0.367</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>176.1</td>
<td>147.5</td>
<td>141.5</td>
<td>140.0</td>
<td>169.0</td>
<td>143.6</td>
<td>171.2</td>
</tr>
<tr>
<td>ST seed mass</td>
<td>$R^2$</td>
<td>0.056</td>
<td>0.312</td>
<td>0.391</td>
<td>0.419</td>
<td>0.112</td>
<td>0.370</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>42.6</td>
<td>36.4</td>
<td>34.2</td>
<td>33.4</td>
<td>41.3</td>
<td>34.8</td>
<td>41.9</td>
</tr>
<tr>
<td>June</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dry total biomass</td>
<td>$R^2$</td>
<td>0.100</td>
<td>0.445</td>
<td>0.599</td>
<td>0.610</td>
<td>0.498</td>
<td>0.605</td>
<td>0.430</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>199.6</td>
<td>152.9</td>
<td>128.6</td>
<td>125.6</td>
<td>145.5</td>
<td>128.2</td>
<td>155.5</td>
</tr>
<tr>
<td>Dry ST biomass</td>
<td>$R^2$</td>
<td>0.110</td>
<td>0.438</td>
<td>0.575</td>
<td>0.588</td>
<td>0.458</td>
<td>0.572</td>
<td>0.391</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>172.0</td>
<td>132.8</td>
<td>113.7</td>
<td>110.7</td>
<td>129.2</td>
<td>114.1</td>
<td>137.5</td>
</tr>
<tr>
<td>ST seed mass</td>
<td>$R^2$</td>
<td>0.085</td>
<td>0.401</td>
<td>0.554</td>
<td>0.566</td>
<td>0.465</td>
<td>0.561</td>
<td>0.403</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>42.4</td>
<td>34.1</td>
<td>30.0</td>
<td>29.3</td>
<td>32.9</td>
<td>29.9</td>
<td>34.6</td>
</tr>
</tbody>
</table>

Notes: DS, Ducky Srike; NDVI, normalized difference vegetation index; SR, simple ratio; SAVI, soil-adjusted vegetation index; TSAVI, transformed soil-adjusted vegetation index; MSAVI, modified soil-adjusted vegetation index; GEMI, global environment monitoring index; SE, standard error; ST, swamp timothy; $\rho_{\text{red}}$ and $\rho_{\text{NIR}}$, spectral reflectance values for red and near-infrared spectral bands.
image that were consistently better than that of $\rho_{\text{NIR}}$ and GEMI, which both exhibited weak correlation.

The best-fitting model for seed production (SR-based) is plotted in figure 3(a). A nonparametric Kolmogorov–Smirnov test (K–S test) was conducted to test the normality of the error distribution for the model. The error distribution did not deviate significantly from the normal distribution ($p = 0.981$). The predicted value of the

![Figure 3](image_url)

**Figure 3.** (a) Positive square root of seed mass plotted against simple ratio (SR) and (b) the error distribution of predicted values.
model is plotted against the error in figure 3(b), and we found that there is no evident violation of the homoscedasticity assumption for the regression analysis.

Linear regressions were also developed for vegetation indices with total dry biomass and dry swamp timothy biomass. In most cases, total dry biomass and dry swamp timothy biomass (primary properties) produced better model fits than did swamp timothy dry seed mass (secondary property). NDVI, SR and TSAVI were found to be consistently better indicators of these properties for both the May and June images. MSAVI and SAVI for the June image were good predictors, while these indices were relatively poorer for the May image. Again, GEMI and $\rho_{\text{NIR}}$ were found to be relatively weak indicators.

Models resulting from the May image generally performed poorly relative to those obtained from the June image. In both images, for all of the vegetation indices predicting total dry biomass, dry swamp timothy biomass and their dry seed mass, SR, NDVI and TSAVI were more consistent than other vegetation indices, with SR being the best vegetation index for the three biomass variables. The exception was the total biomass model obtained from the May image, which yielded determination coefficient values comparable with those obtained using the June image.

Object-based linear correlations between SR, texture features and dry seed mass (table 4) also supported SR as the best explanatory variable (Pearson correlation coefficient, $r = 0.648$ and 0.723 for May and June, respectively). For the May image, most of the texture parameters resulted in Pearson correlation coefficient values of less than 0.3, with the exception of three parameters associated with the $\rho_{\text{NIR}}$ bands:

<table>
<thead>
<tr>
<th>Texture feature</th>
<th>Correlation coefficient</th>
<th>Significance</th>
<th>Correlation coefficient</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>May</td>
<td></td>
<td></td>
<td>June</td>
<td></td>
</tr>
<tr>
<td>SR</td>
<td>0.648</td>
<td>$&lt;0.001$</td>
<td>0.752</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td>Std1</td>
<td>0.210</td>
<td>0.005</td>
<td>-0.094</td>
<td>0.123</td>
</tr>
<tr>
<td>Std2</td>
<td>0.165</td>
<td>0.021</td>
<td>-0.318</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td>Std3</td>
<td>0.331</td>
<td>$&lt;0.001$</td>
<td>-0.175</td>
<td>0.015</td>
</tr>
<tr>
<td>GLDV contrast1</td>
<td>0.185</td>
<td>0.011</td>
<td>-0.049</td>
<td>0.274</td>
</tr>
<tr>
<td>GLDV contrast2</td>
<td>0.186</td>
<td>0.011</td>
<td>-0.365</td>
<td>0.000</td>
</tr>
<tr>
<td>GLDV contrast3</td>
<td>0.438</td>
<td>$&lt;0.001$</td>
<td>-0.072</td>
<td>0.188</td>
</tr>
<tr>
<td>GLCM entropy1</td>
<td>0.061</td>
<td>0.228</td>
<td>0.014</td>
<td>0.432</td>
</tr>
<tr>
<td>GLCM entropy2</td>
<td>0.067</td>
<td>0.204</td>
<td>-0.347</td>
<td>0.000</td>
</tr>
<tr>
<td>GLCM entropy3</td>
<td>0.148</td>
<td>0.034</td>
<td>-0.073</td>
<td>0.184</td>
</tr>
<tr>
<td>GLCM contrast1</td>
<td>0.210</td>
<td>0.005</td>
<td>-0.094</td>
<td>0.123</td>
</tr>
<tr>
<td>GLCM contrast2</td>
<td>0.165</td>
<td>0.021</td>
<td>-0.318</td>
<td>0.000</td>
</tr>
<tr>
<td>GLCM contrast3</td>
<td>0.331</td>
<td>$&lt;0.001$</td>
<td>-0.175</td>
<td>0.015</td>
</tr>
<tr>
<td>GLCM</td>
<td>-0.185</td>
<td>0.011</td>
<td>0.022</td>
<td>0.394</td>
</tr>
<tr>
<td>homogeneity1</td>
<td>-0.126</td>
<td>0.060</td>
<td>0.392</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td>homogeneity2</td>
<td>-0.273</td>
<td>$&lt;0.001$</td>
<td>0.171</td>
<td>0.017</td>
</tr>
<tr>
<td>homogeneity3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The numbers 1, 2 and 3 in the ‘Texture feature’ and standard deviation (Std) represent the $\rho_{\text{green}}$, $\rho_{\text{red}}$ and $\rho_{\text{NIR}}$ bands, respectively. GLCM, grey-level co-occurrence matrix; GLDV, grey-level difference vector.
Table 5. Results of stepwise multiple linear regression for dry seed mass and SR combined with texture features.

<table>
<thead>
<tr>
<th>Data sets</th>
<th>Variables</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>SE</th>
<th>Significance, F</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>SR (June)</td>
<td>0.566</td>
<td>0.563</td>
<td>29.3</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>May</td>
<td>SR (May) + GLDV contrast of NIR</td>
<td>0.445</td>
<td>0.438</td>
<td>32.8</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Notes: SR, simple ratio; NIR, near-infrared; GLDV, grey-level difference vector; SE, standard error; $R^2$, coefficient of determination.

$\text{Std3} (r = 0.331)$, $\text{GLDV contrast3} (r = 0.438)$ and $\text{GLCM contrast3} (r = 0.331)$. For the June image, parameters with comparable contributions are associated with the red bands: $\text{Std2} (r = -0.318)$, $\text{GLDV contrast2} (r = -0.365)$, $\text{GLCM entropy2} (r = -0.347)$ and $\text{GLCM homogeneity2} (r = 0.392)$.

To evaluate the additional contribution of the textural parameters to the regression model, a stepwise multiple regression was conducted by incorporating the SR and 15 texture parameters. Table 5 summarizes the results from the best models based on the stepwise regression. For the May image, the resulting two-parameter model with SR and GLDV of $\rho_{\text{NIR}}$ outperforms the single variable SR model by only about 1.9% based on the SE of estimation. For the June image, all the texture parameters were excluded by the stepwise regression, which resulted in the SR only model.

Finally, the swamp timothy seed productivity map (figure 4) was created using the best model based on the SR and the June image. The areas of the wetland units with relatively high swamp timothy seed productivity match the areas with lower soil salinity and the lower elevation areas of the fields (Rahilly 2008), a result suggesting that future work is warranted with respect to remote sensing and plant–soil interactions in this system. An overall trend observed with respect to swamp timothy seed production is for greater abundance in the eastern portion of the field relative to that in the western portion. The southern portions of both fields contain relatively little swamp timothy. Note that the areas mapped in red indicate portions of the field that were determined to be non-inclusive swamp timothy habitat (e.g. tules, cattails and Baltic rush).

4. Discussion

The SR from both the May and June images exhibited the strongest correlation with seed productivity outperforming the NDVI model. While it has been noted that SR-based correlations with crop yield outperform NDVI-based models (Mutanga and Skidmore 2004), less has been written about mixed vegetation. In a somewhat related study, Loris and Damiano (2006) reported that SR was best for estimating meadow grass productivity from aerial imagery. Meadow grass is typically a diverse array of grasses and forbs analogous in structure to the present wetland moist-soil plant community. The degree of correlation observed here is reasonable considering within-field variability at the study sites, where soil moisture, salinity and vegetative composition all vary across the landscape. To improve this method's performance for diverse plant communities, additional vegetation information about community and canopy structure may need to be collected. In this context, it is worth noting that there may have been vegetation-specific causes for elevated red reflectance in the June imagery. Specifically, $\text{Rumex}$ spp., a common species that grows in these fields, is bright rust
red in colour and may bias the reflectance values by overwhelming the influence of the green chlorophylls. Where there are different chlorophylls and carotenoids, the use of the green band instead of the red band when calculating NDVI or SR may produce better results (Gitelson et al. 1996, Loris and Damiano 2006).

The addition of texture information did not significantly improve upon the single variable SR model for predicting dry seed mass. The results were somewhat ambiguous in that the contributions of the texture parameters for the May and June images resulted in opposite (positive vs. negative) correlation coefficients in all cases but the relatively uncertain case (GLCM entropy in red band). This may be a consequence of the seasonal differences between the two images, and suggests that further investigation of this approach may be warranted. Neglecting the May results, one may argue that the June images were reasonably representative of mature swamp timothy stands. If so, then our results for June should serve as a suitable test of the role of image texture in delineating swamp timothy biomass.

The observed lack of correlation with texture might then be due to the relatively flat and uniform topology of the swamp timothy canopy compared with more diverse
communities, such as forests, where information such as shadows, canopy cover, crown closure play an important role in the variation of texture characteristics. Inclusion of textures yielded a significant improvement on leaf area index (LAI) estimation, for instance (Wulder et al. 1996). However, for the wetland site in this study, lower correlation coefficients were observed between texture features and dry seed mass, and the added information did not improve the vegetation indices models. This finding may be a result of the relative uniformity of swamp timothy stands, which decreased the variation of texture information.

Issues with respect to the timing of sampling events in our investigation merit further discussion. First, our clip samples were collected in August 2006, nearly 2 months after the June aerial imagery event and at a time when the vegetation was desiccated. While this timing greatly facilitated seed collection, it precluded the preferred usage of wet and overdried biomass in relating vegetation indices to productivity (Tucker et al. 1983). A second and more crucial issue pertains to the timing of the aerial photography. By the time of the June imagery, the vegetation was highly stressed and wilting. Of course, if the images are taken too early in the season, the results will suffer from lack of vegetation cover resulting in high soil reflectance, as was the case with the May results. Thus, it is clear that more research is warranted with respect to the optimal imagery timing for this type of investigation. A related issue worth noting is that a separate investigation was undertaken on the north and south ponds, the results of which (not shown here) revealed that DSS estimation accuracy of seed productivity was inferior to that for DSN. This result is consistent with the fact that total aboveground biomass and swamp timothy seed mass productivity were not as strong in DSS as they were in DSN, suggesting that there are inherent differences between the two ponds’ soils which translated to differences in swamp timothy seed production. This argument is supported by electromagnetic (EM) surveys from the site, which have shown that the apparent soil salinity in DSS is greater than that in DSN (Rahilly 2008). Elevated salinity in DSS is most likely associated with less effective drainage in this pond due to isolated topographic depressions within the pond (Rahilly 2008). The NIR band image of the two ponds (figure 1) illustrates the poor and prolonged drainage time of DSS compared with DSN. The dark areas in the DSS May image are exposed mudflats where the annual plants have not yet begun to germinate. In comparison, DSN exhibits vegetation across the entire field at this time. While swamp timothy eventually germinates in DSS, the end result is less growth, probably due to the stressful growing conditions relative to those experienced in DSN. The more stressful growing conditions in DSS would force the swamp timothy to focus its energy on seed production rather than biomass production which may explain the weaker correlation between total swamp timothy biomass and seed biomass in DSS.

5. Conclusions

The results of this study suggest that the use of spectral reflectance-based vegetation indices to predict swamp timothy seed productivity in seasonally managed wetlands is feasible, while additional texture information from object-based analysis did not significantly improve the regression result. Accuracy of the resulting model depends on coordination of the imaging with the key management event (drawdown), which in turn triggers changes in the drivers of swamp timothy production, namely soil moisture, temperature and salt accumulation. The results suggest that a less intensive field sampling effort can be utilized to calibrate a model in order to create swamp
timothy biomass and seed productivity maps. Methods for more efficient assessment of wetland seed productivity will enable wetland managers to adaptively manage the wetlands in support of waterfowl.

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Mapping seed productivity using vegetation indices


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