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Abstract. Vegetation biomass was estimated for ungrazed pastures in two grassland ecoregions of Alberta, Canada, using multispectral 20 m SPOT satellite imagery and vegetation indices (VIs) for multitemporal imagery acquired throughout the growing season with associated field validation data at four study areas. Eight VIs were tested as well as four different types of transformations (linear, log, exponential, power) to ascertain the best predictive model. The Renormalized Difference Vegetation Index and Transformed Vegetation Index provided the best overall prediction ($r^2 = 0.68$) of the amount of above-ground green biomass production, but only marginally better than the Normalized Difference Vegetation Index, Modified Simple Ratio, and other indices tested. When assessed by subregion, the Foothills Fescue study areas had higher discrimination ($r^2 = 0.72$) and from more VIs than for Dry Mixedgrass ($r^2 = 0.61$). In almost all cases a power function best described the form of the relationship between biomass and imagery variables. Compared with green biomass (current-year growth), the predictive power was lower when nonphotosynthetic vegetation (NPV, or carryover: dry, dead matter primarily from the previous year) was included in the analysis (total biomass = green biomass + NPV). The six VIs that used red and near infrared bands consistently outperformed the two VIs that used the green band. There was no clear preference for a specific VI from this battery of tests, likely owing to the functional equivalence of many VIs. ANOVA and Tukey tests showed significant variation between region and by sampling date for six imaging dates and field sampling periods throughout the growing season, with a possible mid-season change in the rate of biomass production evident for both green and total biomass. It was concluded that for regional studies elsewhere, a variety of VIs should be considered and that transformations are recommended to improve statistical predictive capabilities. Other methods such as spectral mixture analysis may be required to achieve improved results, particularly when including the important NPV component of biomass. The ability of SPOT satellites to acquire imagery every 2–3 days enabled a more comprehensive multitemporal study using high-spatial resolution data throughout the growing season, with important implications in terms of operational monitoring programs.

Résumé. La biomasse végétale a été estimée pour des prairies non soumises aux activités de pâturage dans deux écorégions de prairies en Alberta, au Canada, à l'aide d'images multispectrales de SPOT à 20 m de résolution et d'indices de végétation (IV) dérivés d'images multidates acquises durant la saison de croissance en conjonction avec des données de terrain sur quatre sites d'étude pour la validation. Huit indices de végétation ont été testés de même que quatre types différents de transformations (linéaire, log, exponentielle et puissance) pour déterminer le meilleur modèle prédictif. L'indice RDVI (Renormalized Difference Vegetation Index) et l'indice TVI (Transformed Vegetation Index) ont donné la meilleure valeur globale de prédiction ($r^2 = 0{,}68$) de la production de biomasse aérienne verte, bien que leur performance ne soit que légèrement supérieure à celle de l'indice NDVI (Normalized Difference Vegetation Index), de l'indice MSR (Modified Simple Ratio) et des autres indices testés. Une évaluation par sous-région a montré que les zones d'étude de la Prairie à fétuque affichaient une discrimination supérieure ($r^2 = 0{,}72$) et cela pour plus d'indices de végétation que dans le cas de la Prairie mixte sèche ($r^2 = 0{,}61$). Dans la plupart des cas, une fonction de puissance a permis de mieux décrire la forme de la relation entre les variables de la biomasse et celles des images. Comparativement à la biomasse verte (croissance de l'année en cours), le pouvoir prédictif était plus faible lorsque la part de végétation non-photosynthétique (NPV ou matière sèche et morte datant principalement de l'année précédente) était incluse dans l'analyse (biomasse totale = biomasse verte + NPV). Les six indices de végétation qui utilisaient les bandes du rouge et du proche infrarouge affichaient de façon constante une meilleure performance que les deux indices utilisant la bande verte. Aucun indice de végétation en particulier ne se distinguait clairement lors des nombreux tests effectués, vraisemblablement à cause de l'équivalence fonctionnelle entre plusieurs des indices de végétation. Des tests d'ANOVA (analyse de variance) et de Tukey ont montré des variations significatives entre les régions et selon les dates

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d'échantillonnage pour six dates d'acquisition et périodes d'échantillonnage sur le terrain durant la saison de croissance, avec un changement possible observé en mi-saison dans le taux de production de biomasse évident pour la biomasse verte et la biomasse totale. En conclusion, pour des études régionales réalisées ailleurs, plusieurs indices de végétation différents devraient être pris en considération et il est recommandé de procéder à des transformations pour améliorer le potentiel prédictif des statistiques. D'autres méthodes, comme l'analyse des mélanges spectraux, peuvent s'avérer nécessaires pour atteindre de meilleurs résultats, en particulier lorsque l'on inclut la composante importante qu'est la NPV de la biomasse. La capacité des satellites SPOT d'acquérir des images à tous les 2–3 jours a permis de réaliser une étude multitemporelle plus détaillée en utilisant des données à haute résolution spatiale tout au long de la saison de croissance, ce qui constitue un atout important en termes des programmes opérationnels de suivi.
[Traduit par la Rédaction]

Introduction

Rangeland and pastures are important because they provide forage for livestock grazing as well as benefits such as grassland cover that reduces erosion, provides habitat for threatened species, supports important biodiversity, and provides a variety of other ecosystem services. Grasslands are also the largest of the Earth's four major types of vegetation (Sims, 1988), are among the most productive agricultural lands on Earth (Guo et al., 2000), and are important in the carbon cycle (Li et al., 2004; Black and Guo, 2007). Satellite remote sensing is advantageous for regional-scale grassland assessment owing to its spectral domain, temporal archives, and large area coverage (Inoue, 2003; Guo et al., 2000; Zhang and Guo, 2007; Piwowar, 2009). Satellite imagery has also been used effectively in studies of biosphere–atmosphere functioning, for example the First ISLSCP (International Satellite Land Surface Climatology Program) Field Experiment (FIFE) in the tall-grass prairie of Kansas, USA (Hall et al., 1992; Sellers et al., 1992). In southern Alberta, drought is frequent in this semi-arid region and results in reduced productivity and economic loss. Species composition and rangeland biomass vary as a function of climatic conditions associated with subregions within the six natural regions of the province. Monitoring and prediction of a variety of grassland biophysical variables (Rahman and Gamon, 2004) such as vegetation biomass (Boutton and Tieszen, 1983; Davidson and Csillag, 2001; Mutanga and Skidmore, 2004) is thus critical, as well as for large jurisdictional monitoring programs (e.g., national, provincial or state, county).

In the context of operational monitoring programs encompassing large areas, it is important for remote sensing image analysis methods to be feasible and cost effective in terms of imagery (appropriate and available), field data requirements (minimal – preferably validation only), processing complexity (low), and speed (fast). Vegetation indices (VIs) are common and straightforward image analysis procedures (Tucker, 1979) that are suitable for rangeland and grassland applications (Duncan et al., 1993; Guo et al., 2000; Price et al., 2002; Henderson and Piwowar, 2006; Zhang and Guo, 2008; He et al., 2009). Although other more sophisticated approaches exist such as spectral mixture analysis (SMA) and other forms of modeling that address issues such as subpixel scale mixing, spatial variability and physical–structural interactions, it is important to first test VIs to assess their viability, which is the focus of this study. VIs offer the advantages of computational simplicity and rapid processing, and some VIs require little or no associated inputs other than image data.

The theoretical and physical bases for VIs (Rouse et al., 1973) are driven by the different spectral response of vegetation at certain portions of the electromagnetic spectrum (Gates et al., 1965), with the most commonly used spectral regions being at red and near-infrared (NIR) wavelengths. The primary biophysical controls on the interaction of energy with plants (McCoy, 2005) involve plant pigments in the visible portion of the spectrum and cell structure in the NIR. Healthy vegetation with abundant chlorophyll absorbs energy at blue and red wavelengths, with high reflectance in the green (thus its green colour). In contrast, at NIR wavelengths reflectance is determined primarily by cell structure and is much greater than even the peak visible reflectance attributed to pigmentation. The spectral response variation by plant type and species is much greater in the NIR due to differences in cell structure, even for plants that have similar pigment levels (and are thus difficult to distinguish using visible wavebands only). Mathematical indices based on the overall contrast in reflectance from visible (usually red) and NIR wavelengths have thus been devised and have been linked to various attributes such as leaf area index (LAI), biomass, vegetation health, and productivity.

There is a wide variety of VIs available as well as methods for deriving statistical predictive models, yet the appropriateness of these in the context of a large-area regional scale biomass monitoring program in Alberta using high-resolution (e.g., SPOT) satellite imagery has not been sufficiently assessed. Therefore, the objective of this study was to perform rigourous tests of different VIs and predictive model transformations in this context and to recommend a VI and predictive models for deriving grassland biomass in southern Alberta rangeland using satellite imagery that may be applicable throughout the region and possibly elsewhere. To achieve this validation ground data were collected to compare actual amounts of vegetation on rangeland fields against results obtained from eight VIs and with four different transformations as derived from remotely sensed satellite imagery throughout a growing season at different study areas representative of regional scale variability. Results were assessed with respect to VI requirements, statistical modeling and predictive power, and quality of derived information.

Methods

Study areas

Four study areas in southern Alberta were assessed, comprising grass pastures that were named based on the nearest community: Nanton, Granum, Barnwell, and Onefour (**Figure 1**). The four sites were selected within two natural subregions: Foothills Fescue (Nanton and Granum) and Dry Mixedgrass (Barnwell and Onefour). The Dry Mixedgrass study areas are located in the eastern and central portions of southern Alberta and had warmer temperatures, less precipitation, and less biomass during the 2005 field season (**Table 1**) compared with the Foothills Fescue study areas to the west, closer to the Rocky Mountains. Further details regarding each study area and all pasture sites are contained in Goosen (2005). The two natural subregions also had different dominant plant species (**Figure 2** and **Table 1**). Within the study areas, a series of nine rangeland pastures sites were identified for sampling based on ungrazed areas that were accessible. For rangeland biomass, nonphotosynthetic vegetation (NPV, also referred to in this paper as carryover) – typically dead litter material from the previous growing season – can be an important consideration (Frank and Aase, 1994; Gamon et al., 1995; He et al., 2006) and therefore was included in this study.

Vegetation sampling

Above-ground biomass samples were collected at all sites every two weeks from late May until early August, 2005. Both green biomass (current year growth) and NPV were collected and sorted then separated, allowing both green biomass and total biomass (green + NPV biomass) to be assessed and compared. For each sampling date, a total of 20 biomass samples were taken at randomized points along transects located within a 50 × 20 m area (**Figure 3**), ensuring that the same location was sampled only once (including all dates throughout the growing season). At each pasture site, the biomass samples were collected using a 0.25 m^2 metal frame (quadrat). All of the herbaceous vegetation was clipped as close to the ground as possible using hand shears, dried (60°C

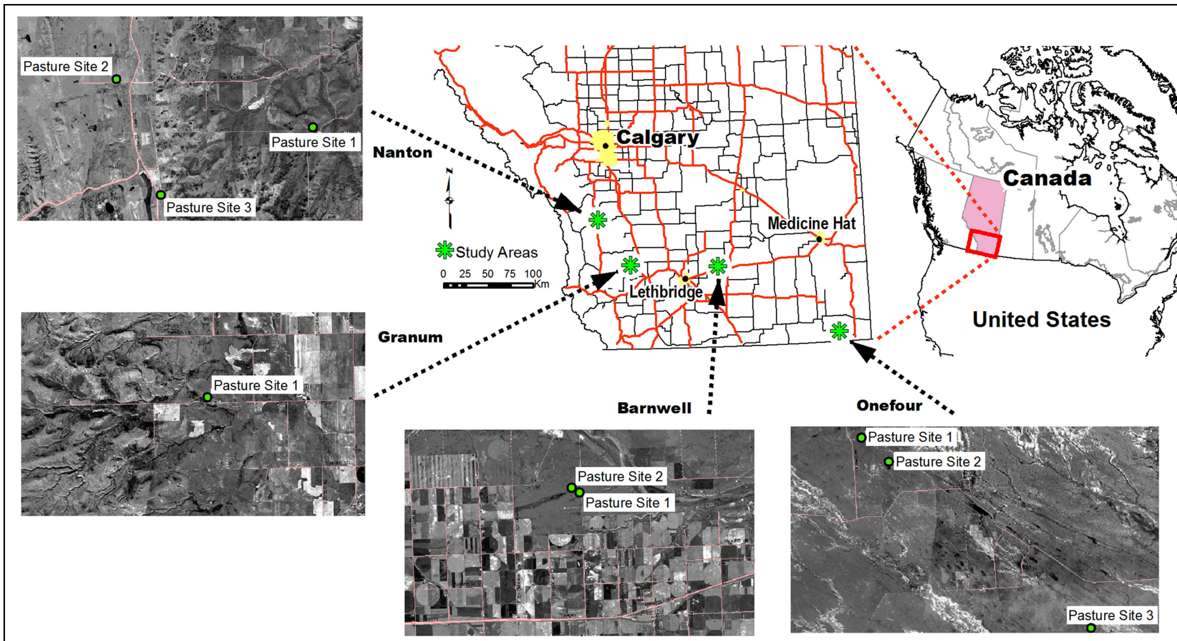

Figure 1. Study areas in southern Alberta, Canada. Individual pasture sites in each study area shown on SPOT panchromatic images.

Table 1. Natural subregion, climate data, major plant type, and biomass ranges for the four study areas.

Study areas	Natural subregion	Average precip. (mm)	Average temp. (°C)	Plant community	Biomass range (with carryover) (kg/ha)
Nanton (area 1)	Foothills Fescue	183.4	10.7	*Festuca**/*Stipa*	1707–3905 (1707–3905)
Granum (area 2)	Foothills Fescue	109.7	14.0	*Festuca**/*Stipa*	648–1231 (843–1392)
Barnwell (area 3)	Dry Mixedgrass	63.3	15.0	*Stipa*/*Bouteloua*†	556–1815 (899–2728)
Onefour (area 4)	Dry Mixedgrass	41.8	16.0	*Stipa*/*Bouteloua*†	163–640 (426–1431)

*Foothills Fescue grassland is dominated by rough fescue (*Festuca scabrella*).
†Dry Mixedgrass regions are dominated by needle-and-thread grass (*Stipa comata*) and blue grama grass (*Bouteloua gracilis*).
Note: Temperature and precipitation values are the average over the four-month study period in 2005.

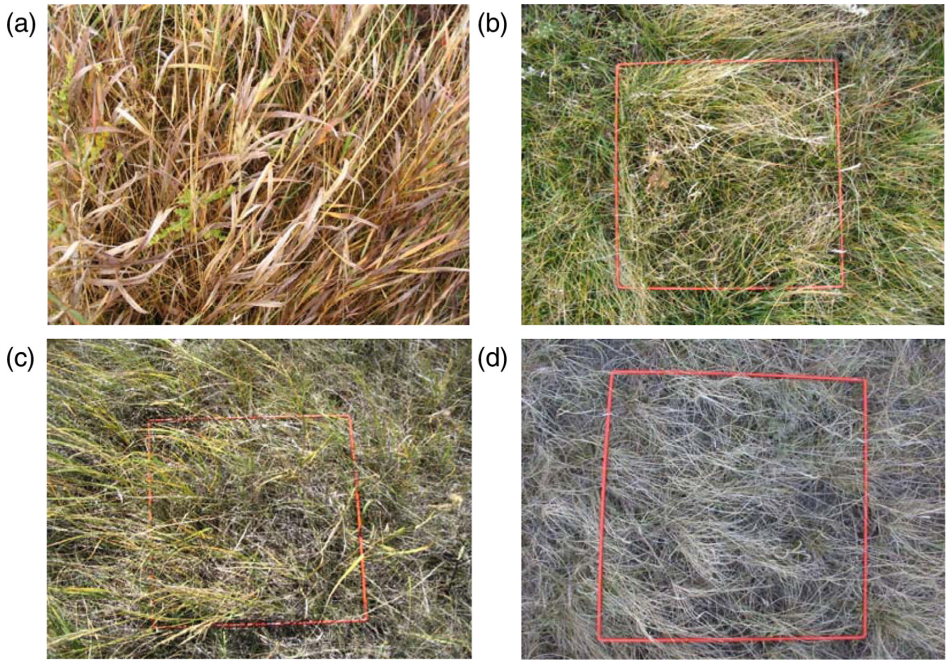

Figure 2. Typical vegetation cover at the four study areas: (a) Nanton, (b) Granum, (c) Barnwell, and (d) Onefour. Biomass was collected within square quadrats (0.25 m^2 red metal frames, shown in (b–d).

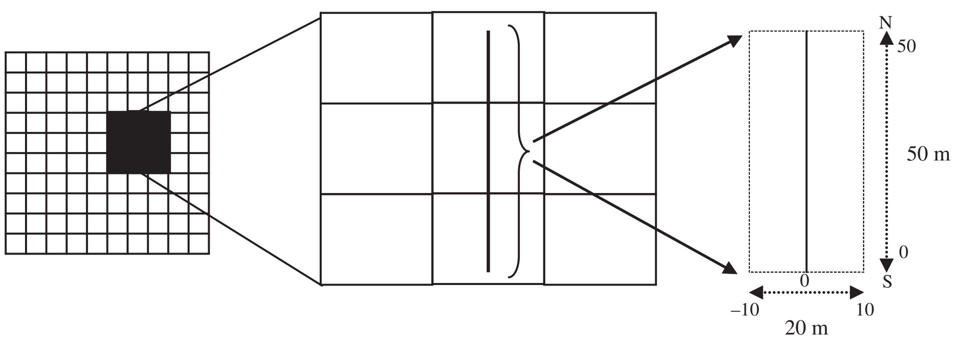

Figure 3. Layout of transect used for biomass sample collections on each pasture site within each study area. Biomass was estimated along 50 m transects. The total extent of each transect required three image pixels to ensure proper coverage (extracted from a 3 × 3 window of pixels centered on each transect midpoint).

for a minimum of 72 hours), and weighed. After clipping, NPV carryover was determined by sorting and separating green biomass (current-year growth) from NPV in a controlled environment for each biomass sample. As shown in **Table 1**, for the Foothills Fescue study areas green biomass ranged from 648 kg/ha to 3905 kg/ha, while total biomass ranged from 843 to 3905 kg/ha. The Dry Mixedgrass study areas had lower biomass (green, 163–1815 kg/ha; total biomass, 426–2728 kg/ha).

Satellite imagery

Obtaining information over larger areas for dynamic seasonal vegetation such as rangeland, grasslands, and crops requires higher temporal resolution that is often available only from coarser spatial resolution imagery (e.g., 1 km AVHRR, MODIS). However, this spatial resolution has been found to be less appropriate for northern mixed grass prairie ecosystems where pixel sizes in the 20–30 m range are required to adequately characterise the inherent heterogeneity (Guo et al., 2004; He et al., 2006). The twice monthly revisit period of Landsat and other satellites is insufficient (even with ideal weather). The programmable off-nadir capability of SPOT imagery significantly increases revisit periods (2–3 days) for 20 m (or less) spatial resolution imagery. The fact that SPOT imagery offered both appropriate spatial and temporal resolution was the basis for its use in this work.

SPOT 2005 imagery

SPOT High Resolution Visible (HRV) and HRV and Infrared (HRVIR) imagery were acquired throughout the 2005 growing season. Images with less than 25% cloud cover were deemed acceptable, except for instances where the specific study area within a scene was obscured. A total of 21 SPOT images were selected for the four study areas and different dates throughout the season (**Table 2**). The difference between date of image acquisition and date of field measurement ranged from 0 to 10 days (most were within a week) for 20 of the 21 SPOT scenes. The lone exception was the image for sample 5 at Onefour, which was acquired one month after biomass field sampling. This represented a small number of sample dates (2 pasture dates out of 13) at Onefour (one pasture site not sampled on 26 July, see **Table 2**), and further, this fifth sampling date was the last in the growing season, by which time most vegetation growth had ceased at this site (this was the hottest and the driest of the four sites, see **Table 1**). Therefore, while not ideal, this site was deemed appropriate to include and is also consistent with the operational realities of this type of study. The off-nadir imaging capability of SPOT sensors that provided significantly increased revisit timing (several days vs. weeks) was critical to acquiring time-sensitive imagery. Of course, this introduced a range of view zenith angles and possible bidirectional effects. However, owing to the larger number of images and the goal to minimise excessive preprocessing for an operational context, no angular image corrections were performed in this study. The ability to acquire this number of satellite images close to field dates for different study areas and for dates throughout the growing season represents a significant capability of interest for operational monitoring programs.

Radiometric and geometric correction

To properly assess vegetation biomass using satellite imagery, a radiometric correction was first applied. Image-based radiometric corrections such as dark object subtraction (DOS) and pseudo-invariant targets were considered but it was found that, as a result of the field study locations, there were no invariant targets (such as deep lakes or other suitably sized targets) captured in the imagery that were adequate for either method. Atmospheric correction using radiative transfer codes was also considered but rejected because these require in situ data collection of atmospheric properties and these data were not available. Instead, the image-based radiometric correction by Chavez (1996) was used. This is a variation of the DOS method and incorporates a multiplicative correction for transmittance to reduce the effects of haze due to scattering in the atmosphere that often attenuates the ground-level reflected radiance signal from vegetation.

Following radiometric correction, all images were geometrically corrected using the orthoengine module of PCI Geomatica Suite 9.0 (PCI, 2004). This correction required ground control points (GCPs) to co-register the raw imagery. Where possible, the GCPs used a vector set of Alberta roads (projection: Alberta 10TM, earth model: GRS 80). The Nanton, Granum, and Barnwell study areas were in locations with sufficient primary and secondary roads to allow use of this vector set. As the final step of image preparation, a 3 $\times$ 3 window of pixels was extracted around each sampling site to ensure that the entire sample collection at all field sites was covered with the imagery. Only pixels corresponding to the transect area were analyzed.

Table 2. Biomass sample collection dates and image acquisition dates for each of the four study areas from May until August 2005.

Nanton (area 1)						
Pasture sites 1, 2, and 3	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	
Biomass collection date, 2005	June 15	June 29	July 13	July 27	August 9	
Image acquisition date, 2005	June 22	July 4	July 11	July 23	August 19 August 13 (ps2)	
Granum (area 2)						
Pasture site 1	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Biomass collection date, 2005	May 24	June 16	June 30	July 12	July 25	August 8
Image acquisition date, 2005	May 18	June 22	June 29	July 11	July 23	August13
Barnwell (area 3)						
Pasture sites 1 and 2	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	
Biomass collection date, 2005	June 14	June 30	July 12	July 25	August 8	
Image acquisition date, 2005	June 14	July 3	July 10	July 24	July 29	
Onefour (area 4)						
Pasture sites 1, 2, and 3	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	
Biomass collection date, 2005	May 25 n/a (ps3)	June 13	June 27	July 11	July 26 n/a (ps1)	
Image acquisition date, 2005	May 27 n/a (ps3)	June 14	June 24	July 15	August 26 n/a (ps1)	

Note: ps1, ps2, or ps3 refer to pasture site 1, 2, or 3; n/a means for the pasture site indicated there was no biomass sample or image acquired on the specified date.

VIs and biomass prediction

Eight VIs were evaluated in this research (**Table 3**). They were selected from an extensive list of indices developed to suit different vegetative applications as reviewed in Bannari et al. (1995) and Chen (1996). The physiological basis of VIs that use red (R) and NIR reflectance is that as the amount of photosynthetically active biomass increases, R reflectance decreases and NIR reflectance increases. Nonphotosynthetic vegetation (carryover) as well as the timing of senescence may negatively impact the utility of VIs in this regard. The multitemporal nature of satellite imagery throughout (and in some cases after) the growing season enabled assessment of this. Several indices were excluded from consideration due to unavailable data such as VIs that use a blue band (not acquired by SPOT HRV and HRVIR) or that required additional field or spectral information such as soil measurements or correction factors (Chen, 1996) such as soil adjusted vegetation index (SAVI) (Huete et al., 1988) and SAVI-1 (Qi et al., 1994), the latter of which requires explicit soil spectral measurements (e.g., from a field spectroradiometer) that were not available in this study. Six of the VIs evaluated were based on R and NIR spectral bands. The other two were the Normalized Difference Greenness Index (NDGI) and the Redness Index (RI) and were based on ratios between the R and green (G) spectral bands to include those available SPOT bands and their potential information content. **Table 3** gives the abbreviations, equations and features of the eight VIs used.

Each index was derived from the SPOT imagery using the band math function in ENVI software (RTI, 2009). The field transects were then superimposed on the imagery as a vector layer using the same projection file as the imagery. The pixels representing each transect were identified and the indices for each pixel were recorded for each of the 20 biomass samples.

Statistical analyses of VIs

The satellite image VIs and transformations were tested for their ability to predict both green and total biomass at different dates throughout the growing season using multiple pasture sites at each study area. Regression models were used to predict biomass from the VIs. Analysis of Variance (ANOVA) and Tukey tests were used to compare data among fields, sample dates, and field by sample date (Davidson and Csillag, 2003). The nine pasture sites were grouped by area and assigned numbers as follows: Granum (1); Nanton (2, 3, 4); Barnwell (5, 6); and Onefour (7, 8, 9). The sample dates were labelled 1–6, with the first sample collection being the first date that biomass samples were collected during the 2005 growing season (**Table 2**).

The relationship between VIs and biophysical attributes can be nonlinear and in those cases can be more effectively described using mathematical transformations (e.g., Sellers, 1987; Gamon et al., 1995). Both green and total biomass were each compared against each of the indices using

Table 3. Eight vegetation indices used in this study.

Vegetation index	Reference	Equation	Adjustments
Simple ratio (SR)	Birth and McVey (1968)	$\frac{\mathrm{NIR}}{R}$	Ratio
Normalised Difference Vegetation Index (NDVI)	Rouse (1972)	$\frac{\mathrm{NIR}-R}{\mathrm{NIR}+R}$	Normalised difference
Transformed Vegetation Index (TVI)	Perry and Lautenschlager (1984)	$\frac{\mathrm{NDVI}+0.5}{\mathrm{NDVI}+0.5} * \sqrt{\lvert\mathrm{NDVI}+0.5\rvert}$	Avoid negative NDVI
Difference Vegetation Index (DVI)	Cleavers (1986)	$(\mathrm{NIR}-R)$	Difference
Renormalized Difference Vegetation Index (RDVI)	Roujean and Breon (1995)	$\frac{\mathrm{NIR}-R}{\sqrt{\mathrm{NIR}+R}}$	Combines DVI and NDVI
Modified Simple Ratio(MSR)	Chen (1996)	$\frac{\frac{\mathrm{NIR}}{R}-1}{\sqrt{\frac{\mathrm{NIR}}{R}+1}}$	Increase linear relationship from RDVI
Normalized Difference Greenness Index (NDGI)	Chamard et al. (1991)	$\frac{G-R}{G+R}$	Incorporates green band
Redness Index (RI)	Escadafal and Huete (1991)	$\frac{R-G}{R+G}$	Incorporates green band

regression models involving linear, logarithmic, exponential, and power equations. Two indices, NDGI and RI, were not log-transformed in any model as the outputs of these two ratios may include negative values. This resulted in six outcomes for all equations containing the natural log of the VI variables, compared with eight outcomes from the rest of the equations. The biomass data were also transformed and tested. Analyses of green and total biomass were performed for both the log-transformed and untransformed cases.

Results

Vegetation indices and biomass production

The satellite images that were acquired close to the field data collection dates and with acceptable cloud cover were analysed to assess how accurately biomass could be predicted on the rangeland fields. The statistical predictions based on the VIs derived from the imagery did not always coincide with field collection results. The green and total biomass increased over the growing season however the seasonal dynamic in terms of rate of growth varied in terms of predictive capability, particularly when NPV (carryover component of total biomass) was included.

Regression model results

Assessments across all study areas

Regression analysis was used to determine to what extent the dependant variable (above-ground vegetation biomass) can be predicted by the independent variable (VIs considered individually for each of the transformation models). The results for each VI using linear, log, exponential, and power models are shown in **Table 4** with standard errors provided in **Table 5**. The power regression model provided the best fit in most cases. Two of the VIs, NDGI and RI, were not assessed using log or power models as a result of the negative values these indices produced. **Table 4** shows that there were minimal differences in r^2 among most of the first six indices for green and total biomass. For green biomass, RDVI had the highest r^2 value (0.68) from the power model (shape of relationship shown in **Figure 4**), with the same r^2 also obtained for NDVI and TVI (exponential model). All six VIs had similar results using the power model ($r^2 = 0.65-0.68$), with a greater range ($r^2 = 0.56-0.68$) found from the exponential models. The linear and log transformations had lower r^2 values. When carryover was included (total biomass), the same VIs and models were preferred but had lower r^2 values (ranging to 0.51). For both green and total biomass, the two VIs that used the green band (NDGI and RI) instead of NIR had considerably lower r^2 values in all cases and substantially higher errors.

Mid-season assessment of individual subregions

As a further, more specific assessment, representative common-date samples from the two subregions were compared. **Tables 6–9** show the independently fitted regressions for each index by subregion, for both green and total biomass in each case. Results from the same sampling period (27–30 June) in the middle of the growing season field sampling period were assessed for both subregions. These were sample 3 from the Onefour study area in the Dry Mixedgrass subregion and sample 3 from the Granum study area in the Foothills Fescue subregion ($n = 100$ and 60,

Table 4. The coefficient of determination (r^2) for regression models that included the log-transformed and untransformed vegetation biomass (y) and remote sensing vegetation indices (x).

	Linear ($y = a + bx$)	Log ($y = a + b\ln(x)$)	Exponential ($\ln(y) = a + bx$)	Power ($\ln(y) = a + b\ln(x)$)
Green biomass (y)				
SR	0.56	0.61	0.56	0.65
NDVI	0.60	0.54	0.68	0.65
TVI	0.59	0.57	0.68	0.67
MSR	0.60	0.59	0.61	0.67
DVI	0.60	0.56	0.64	0.66
RDVI	0.62	0.58	0.67	0.68
NDGI	0.33	–	0.21	–
RI	0.33	–	0.21	–
Total biomass (y)				
SR	0.39	0.45	0.41	0.49
NDVI	0.45	0.42	0.51	0.50
TVI	0.45	0.44	0.51	0.51
MSR	0.43	0.45	0.46	0.51
DVI	0.42	0.39	0.44	0.42
RDVI	0.44	0.42	0.47	0.47
NDGI	0.25	–	0.23	–
RI	0.25	–	0.24	–

Note: In the NDGI and RI rows, the r^2 value is represented by a dash (–) due to possible negative numbers before applying the log transformations.

Table 5. The standard error (SE) of predicted values for regression models that included the log-transformed and untransformed vegetation biomass (y) and remote sensing vegetation indices (x).

	Linear ($y = a + bx$)	Log ($y = a + b\ln(x)$)	Exponential ($\ln(y) = a + bx$)	Power ($\ln(y) = a + b\ln(x)$)
Green biomass (y)				
SR	0.19	1.06	0.01	0.03
NDVI	3.84	2.30	0.11	0.07
TVI	8.13	8.56	0.23	0.24
MSR	0.92	1.12	0.03	0.03
DVI	0.04	1.50	0.01	0.04
RDVI	0.36	1.79	0.01	0.05
NDGI	12.60	–	0.45	–
RI	12.60	–	0.45	–
Total biomass (y)				
SR	0.23	1.23	0.01	0.03
NDVI	4.37	2.51	0.11	0.60
TVI	9.15	9.54	0.22	0.23
MSR	1.07	1.27	0.30	0.03
DVI	0.04	1.71	0.01	0.40
RDVI	0.42	2.05	0.10	0.50
NDGI	12.98	–	0.34	–
RI	12.98	–	0.34	–

Note: In the NDGI and RI rows, the r^2 value is represented by a dash (–) due to possible negative numbers before applying the log transformations.

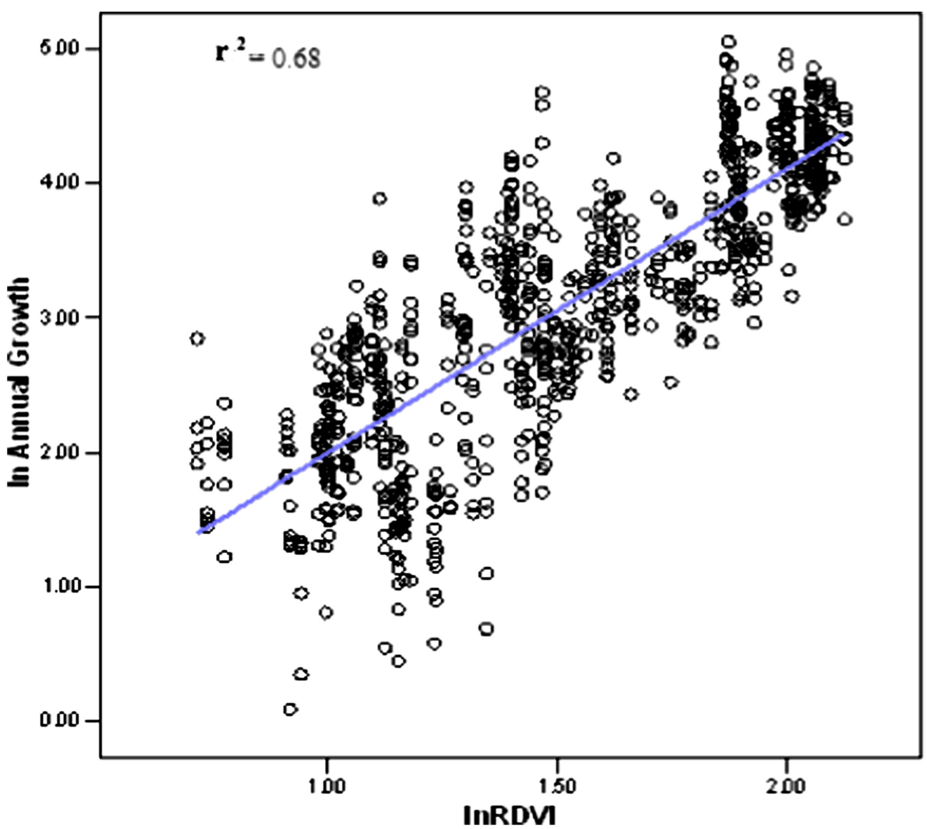

Figure 4. Shape of the relationship between log-transformed vegetation green biomass (y) and the best overall VI predictor (RDVI, power model: $\ln(y) = a + \text{bin}(x)$).

Table 6. Independently fitted regressions ($n = 60$) for each index for the mid-season Foothills Fescue subregion for green biomass on sample date 3 (27–30 June).

Variable	r^2	Label	DF	Estimate	Error	t value	Pr > |t|
lnSR	0.72	Intercept	1	1.39	0.20	6.87	<.0001
		Slope	1	1.27	0.10	12.34	<.0001
lnNDVI	0.73	Intercept	1	5.05	0.10	48.80	<.0001
		Slope	1	3.89	0.31	12.52	<.0001
lnTVI	0.73	Intercept	1	2.45	0.12	21.01	<.0001
		Slope	1	13.24	1.06	12.53	<.0001
lnMSR	0.72	Intercept	1	3.12	0.07	45.86	<.0001
		Slope	1	1.53	0.12	12.47	<.0001
lnDVI	0.68	Intercept	1	−5.28	0.81	−6.55	<.0001
		Slope	1	2.45	0.20	11.32	<.0001
lnRDVI	0.72	Intercept	1	−1.59	0.45	−3.53	0.0008
		Slope	1	2.90	0.24	12.09	<.0001
NDGI	0.67	Intercept	1	3.74	0.04	92.03	<.0001
		Slope	1	7.48	0.68	10.95	<.0001
RI	0.67	Intercept	1	3.74	0.04	92.03	<.0001
		Slope	1	−7.48	0.68	−10.95	<.0001

Table 7. Independently fitted regressions ($n = 60$) for each index for the mid-season Foothills Fescue subregion for total biomass on sample date 3 (27–30 June).

Variable	r^2	Label	DF	Estimate	Error	t value	Pr > |t|
lnSR	0.64	Intercept	1	1.82	0.20	8.96	<.0001
		Slope	1	1.07	0.10	10.34	<.0001
lnNDVI	0.64	Intercept	1	4.91	0.11	46.49	<.0001
		Slope	1	3.26	0.32	10.31	<.0001
lnTVI	0.64	Intercept	1	2.72	0.12	22.93	<.0001
		Slope	1	11.12	1.08	10.33	<.0001
lnMSR	0.64	Intercept	1	3.29	0.07	47.70	<.0001
		Slope	1	1.29	0.12	10.38	<.0001
lnDVI	0.63	Intercept	1	−3.89	0.79	−4.95	<.0001
		Slope	1	1.92	0.19	9.91	<.0001
lnRDVI	0.64	Intercept	1	−0.71	0.45	−1.58	0.119
		Slope	1	2.45	0.24	10.30	<.0001
NDGI	0.58	Intercept	1	3.81	0.04	92.96	<.0001
		Slope	1	6.21	0.69	9.02	<.0001
RI	0.58	Intercept	1	3.81	0.04	92.96	<.0001
		Slope	1	−6.21	0.69	−9.02	<.0001

respectively, from 20 biomass samples per field, with replicates; see also **Table 2**). Observed r^2 were higher in the Foothills Fescue subregion ranging from 0.58 to 0.72 (**Tables 6** and **7**) compared with the observed r^2 ranging from 0.34 to 0.61 for the Dry Mixedgrass subregion (**Tables 8** and **9**) for green and total biomass for both subregions. In all cases, the six VIs that used R and NIR bands produced better results compared with NDGI and RI that used the green band. As with the full analysis (**Tables 4** and **5**), the predictive capability was stronger for green biomass compared with total biomass for both subregions. For Foothills Fescue, the r^2 values for the six VIs that used R and NIR bands were consistently near 0.72 (**Table 6**) and 0.64 (**Table 7**) for green and total biomass, respectively. For Dry Mixedgrass, the Simple Ratio (SR) provided the highest r^2 values for both green biomass ($r^2 = 0.61$, **Table 8**) and total biomass ($r^2 = 0.43$, **Table 9**). The lower r^2 values with Dry Mixedgrass may be due to the greater heterogeneity in these grasses compared with Foothills Fescue.

Comparisons by subregion and growing season date

ANOVA and Tukey tests were used to compare the differences in biomass production among all dates, field sites, and the interactions using the best VI found from the full sample (**Table 4**) for green and total biomass. When using the entire data set (837 observations, i.e., number of biomass samples per pasture site, per study area, overall dates), the results showed a significant difference among the fields, sample dates, and the field by sample date interaction. **Table 10** illustrates the significant difference in biomass production obtained between the Foothills Fescue ($n = 378$)

Table 8. Independently fitted regressions ($n = 100$) for each index for the mid-season Dry Mixedgrass subregion for green biomass on sample date 3 (27–30 June).

Variable	r^2	Label	DF	Estimate	Error	t value	Pr > |t|
lnSR	0.61	Intercept	1	1.16	0.12	10.00	<.0001
		Slope	1	1.36	0.11	12.51	<.0001
lnNDVI	0.53	Intercept	1	3.62	0.11	32.57	<.0001
		Slope	1	1.28	0.12	10.66	<.0001
lnTVI	0.57	Intercept	1	2.71	0.44	61.26	<.0001
		Slope	1	6.09	0.53	11.46	<.0001
lnMSR	0.57	Intercept	1	3.00	0.05	51.15	<.0001
		Slope	1	0.94	0.08	11.40	<.0001
lnDVI	0.47	Intercept	1	–2.44	0.53	–4.64	<.0001
		Slope	1	1.55	0.16	9.47	<.0001
lnRDVI	0.54	Intercept	1	0.54	0.19	2.84	0.005
		Slope	1	1.74	0.16	10.75	<.0001
NDGI	0.00	Intercept	1	2.46	0.15	16.10	<.0001
		Slope	1	–1.04	2.45	–0.43	0.32
RI	0.00	Intercept	1	2.47	0.15	16.10	<.0001
				1.04	2.45	0.43	0.32

Table 9. Independently fitted regressions ($n = 100$) for each index for the mid-season Dry Mixedgrass subregion for total biomass on sample date 3 (27–30 June).

Variable	r^2	Label	DF	Estimate	Error	t value	Pr > |t|
lnSR	0.43	Intercept	1	1.98	0.14	14.09	<.0001
		Slope	1	1.14	0.13	8.60	<.0001
lnNDVI	0.39	Intercept	1	4.05	0.13	31.85	<.0001
		Slope	1	1.08	0.14	7.92	<.0001
lnTVI	0.40	Intercept	1	3.28	0.05	63.13	<.0001
		Slope	1	5.14	0.62	8.24	<.0001
lnMSR	0.40	Intercept	1	3.52	0.07	51.30	<.0001
		Slope	1	0.79	0.09	8.23	<.0001
lnDVI	0.25	Intercept	1	–0.53	0.63	–0.85	0.398
		Slope	1	1.14	0.19	5.86	<.0001
lnRDVI	0.34	Intercept	1	1.53	0.23	6.78	<.0001
		Slope	1	1.40	0.19	7.26	<.0001
NDGI	0.00	Intercept	1	2.98	0.15	19.60	<.0001
		Slope	1	–2.43	2.43	–1.00	0.32
RI	0.00	Intercept	1	2.98	0.15	19.6	<.0001
		Slope	1	2.43	2.43	1.00	0.32

Table 10. The predicted biomass for Foothills Fescue and Dry Mixedgrass natural subregions differ significantly for both green and total biomass, as indicated by ANOVA and by the Tukey grouping.

	Total biomass			Green biomass		
Natural subregion	n	Mean	Tukey grouping	n	Mean	Tukey grouping
Foothills Fescue	378	58.17	**A**	378	55.56	**A**
Dry Mixedgrass	459	29.39	**B**	459	16.32	**B**

Note: Means with the same letter are not significantly different at the $\alpha = 0.01$ level.

and the Dry Mixedgrass ($n = 459$) natural subregions for both green and total biomass.

Table 11 shows a comparison of biomass obtained between sample dates (number of biomass samples per date shown in Table; total $n = 837$). For total biomass there were significant differences when samples were collected in different months but not between consecutive samples taken within a month, with the exception that the late June and early July sample periods were also not significantly different. This exception may be due to a mid-season change in vegetation growth in terms of the rate of biomass production, possibly related to the timing of meteorological

Table 11. Tukey's multiple comparison of the biomass predictions for all study areas at each of the sampling dates during the growing season, for green and total biomass.

	Total biomass							Green biomass						
Sample date	*n*	Mean	Tukey grouping					*n*	Mean	Tukey grouping				
8–9 August	117	65.96	**A**					117	60.15	**A**				
25–27 July	160	47.84		**B**				160	43.08		**B**			
11–13 July	160	41.04		**B**	**C**			160	32.99			**C**		
27–30 June	160	37.56			**C**	**D**		160	29.30			**C**		
14–16 June	180	33.54				**D**		180	22.24				**D**	
24–25 May	60	24.93					**E**	60	9.88					**E**

Note: Means with the same letter are not significantly different at the $\alpha = 0.01$ level.

influences and the overall hotter and drier conditions in the Dry Mixedgrass compared with Foothills Fescue sites (**Table 1**). When green biomass was considered alone (without carryover), most of the sample dates were significantly different – the only exception again being the mid-season late June to early July period, again perhaps due to a change in the rate of biomass production with respect to the growing season peak and meteorological factors. The presence of carryover in the analysis may serve to regulate the results to some extent in terms of the overall multitemporal dynamic observed.

Discussion and conclusions

This analysis validated a methodology for multitemporal image analysis for biomass estimation, with field validation protocols. Biomass production varied significantly between the Foothills Fescue and the Dry Mixedgrass natural subregions. The RDVI and TVI as well as MSR and NDVI indices provided the overall highest r^2 results for predicting rangeland biomass production for this study. For these and most other indices, a power function best described the form of the relationship for predicting rangeland biomass.

Many of the VIs had similar levels of prediction (r^2) for biomass, and these typically did not differ greatly from the top-ranked index. Additionally, there was no particular VI that was clearly preferred across all tests (i.e., different tests often had a different top-ranked VI, with others having r^2 values that were close to the highest r^2 value). This is likely due to the functional equivalence of different VIs (Perry and Lautenschlager, 1984; Peddle et al., 2001). As another example, Gamon et al. (1995) assessed three vegetation types (including grasslands) and commented on the functional similarity of these mathematically interchangeable VIs (referring to NDVI and log-transformed SR for predicting biomass and other parameters) and concluded that the choice of VIs appeared to be arbitrary and not based on a difference in theoretical limitations of either index. Given the similar performances of a variety of indices tested in our study, the actual selection of VI may be less critical, similar to the conclusion of Davidson and Csillag (2001). Thus, from this study, there is no definitive conclusion that for landscapes of southern Alberta (or possibly elsewhere) that RDVI and TVI would be preferred, even though they yielded marginally better results here. Therefore, it may be necessary to test a variety of VIs for a given study to determine which VI (and transformations) may work best. The only clear VI result amongst the eight VIs assessed was that the VIs based on R and NIR bands outperformed those that used the green bands. Therefore, use of the green band cannot be recommended, at least for those tested here. For other studies elsewhere, the selection of which VIs to test should also be made with reference to their particular purpose, the wavelength bands used, the type of vegetation, and the theoretical properties and limitations of the VIs (e.g., Sellers, 1987; Chen, 1996; Hall et al., 1992; Peddle et al., 2001; Price et al., 2002; He et al., 2006) as well as to practical considerations such as feasibility, validation, and operational constraints, if any.

In terms of transformations, the power function was useful for most VIs. Similar to other studies (e.g., Sellers, 1987; Gamon et al., 1995), linearity in relationships between remote sensing products and biophysical parameters provides a strong analytical context, and transformations represent a way to help achieve that. It is therefore recommended that, for other studies, comparative tests be considered to assess a variety of VIs and transformations to maximize information extraction. In terms of operational monitoring programs, this is not prohibitive as these indices and transformations are easily derived and can be compared against field data that typically exist as standard field monitoring protocols.

Regarding overall information content, the highest r^2 values obtained (0.68 overall, 0.73 per site) suggest that consideration of other image processing methods may be warranted. This study was rather comprehensive in several respects, such as regional-scale landscape variability (two major subregions, four study areas, different pasture sites per area), multitemporal dynamics (field and image data throughout the growing season) and the VIs and processing methods considered, thus there is a reasonable basis for drawing conclusions. It is recognized that given the plethora of VIs, not all were considered in this study, and it was not feasible to assess all statistical methods; however, given the scope of the study areas and VIs considered, the results are considered as a good indicator of VI capabilities. Follow-on research in this context could consider additional VIs that adjust for characteristics such as soil (Huete, 1988; Major et al., 1990; Qi et al., 1994) and atmosphere (Kaufman and Tanre, 1992). It may also be warranted to test other image analysis methods such as SMA and modeling. Additional image preprocessing may also be warranted, for example more sophisticated atmospheric correction and the consideration of radiometric corrections for angular effects (Peddle et al., 2003). In this study, the use of off-nadir SPOT imagery was essential for appropriate multitemporal image acquisition (2–3 day revisit period); however, it did introduce additional variability in terms of different angular radiometric factors both per-scene and across the full set of images. The objectives, scope, and context of the study would need to be considered – in this work, our experimental design was driven by operational considerations in terms of larger-area, regional monitoring programs with a requirement for minimal data processing and analysis requirements.

It was also found that carryover (NPV) is an important factor to consider in studies of this nature. In terms of the VIs and transformations tested, the results were consistently lower when NPV was included (reduction in r^2 values by 0.15–0.20). Most VIs (including all but two used in this study) are based on green vegetation and thus would be expected to be more suited for green biomass than total biomass (Gamon et al., 1995), as there is considerably less contrast between the R and NIR reflectance for NPV (reduced chlorophyll and in some cases altered cell structure). Increased scatter in the VI relationship for predicting biophysical parameters has thus in part been attributed to the presence of dead (NPV) canopy material (e.g., Gamon et al., 1995; Vescovo and Damiano, 2006), and our results are consistent with this. Accordingly, although NPV is an important part of the overall biomass dynamic, it was not as well discerned using VIs. The presence of woody vegetation may have been an additional, albeit minor, source of error in this study, but for other studies this or related NPV may be more significant. For example, Gamon et al. (1995) found that although indices such as NDVI and SR were poor indicators of biomass due to the abundance of NPV, they were good indicators of green biomass across a variety of grassland types and times (i.e., seasonality). As a result, they performed a correction based on percent greenness on a dry mass basis to adjust for NPV and found higher correlations from using NDVI. VIs that incorporate other wavebands such as short-wave infrared could also be considered as these can be useful for dry biomass. As above, other VIs that consider background reflectance should also be tested; however, given the poorer performance (highest $r^2 = 0.45$) when NPV was included, it is quite possible that other methods such as SMA that explicitly account for subpixel scale components may be required. For example, Roberts et al. (1993) separated green vegetation from NPV explicitly using SMA. More comprehensive tests of different VIs and SMA such as that conducted by Peddle et al. (2001) involving ten VIs including three soil-adjusted indices versus SMA in a boreal forest application would be warranted for the grassland setting to determine if SMA results are superior to VIs as they were in that forest study. Attention to operational considerations should also be made in any such comparison in terms of broader viability. For SMA, the main issue is endmember spectral inputs, imaging scale, and surface heterogeneity. A variety of methods exist to derive these automatically and (or) from image data instead of relying on site-specific field spectra and corrections at those scales. For example, multiple endmember spectral mixture analysis (Roberts et al., 1998) reduces the reliance on individual endmember spectra and instead can utilize spectral libraries and determine optimal inputs for SMA that may be more appropriate for operational settings. However, these would need to be assessed in the particular rangeland–grassland domain of interest and with attention to the greater change in vegetation dynamics throughout a growing season (e.g., compared with forests). It is likely that scene-specific image endmember spectra would be required, which should be as feasible as a single-image based approach particularly given the increased availability of complementary spectral libraries.

Another important, broader conclusion from this study was the excellent availability of optical satellite imagery throughout the field season (**Table 2**) that was facilitated by the programmable, off-nadir capabilities of the SPOT sensor that enabled image acquisition windows every 2–3 days. Although off-nadir imagery introduces potentially variable atmospheric and bidirectional angular effects, we concluded that these were clearly acceptable given the much greater acquisition opportunities. Further, angular and atmospheric correction methods exist that were not explored in this study, which may improve on the biomass results obtained here. In rangeland areas such as southern Alberta that are characterized by clear sunny conditions, it was feasible to consider a large number of images at different locations throughout the growing season to provide a much more comprehensive study of biomass dynamics. This may also be important for other areas and applications such as agricultural zones throughout the region, as well as other areas that are not as sunny as southern Alberta.

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