

## Integration of geospatial and cattle nutrition information to estimate paddock grazing capacity in Northern US prairie

Rebecca Phillips<sup>a,\*</sup>, Ofer Beeri<sup>b</sup>, Eric Scholljegerdes<sup>a</sup>, David Bjergaard<sup>c</sup>, John Hendrickson<sup>a</sup>

<sup>a</sup> USDA-ARS, Northern Great Plains Research Laboratory, Highway 6 South, P.O. Box 459, Mandan, ND 58554, United States

<sup>b</sup> University of North Dakota, Space Studies Department, P.O. Box 9008, Grand Forks, ND 58202, United States

<sup>c</sup> The Johns Hopkins University, Baltimore, MD, United States

### ARTICLE INFO

#### Article history:

Received 6 March 2008

Received in revised form 9 January 2009

Accepted 14 January 2009

Available online 13 February 2009

#### Keywords:

Landsat thematic mapper

Advanced spaceborne thermal emission and reflection radiometer

ASTER

Livestock

Grassland

Remote sensing

Grazing capacity

### ABSTRACT

Spatiotemporal variability in forage quantity and quality requires that regular assessment is needed of the capacity for grasslands to support livestock nutritional requirements. Current methods for estimating grazing capacity are typically production-based and lack the forage quality data necessary to match nutrients in forage with livestock requirements in real time. This paper describes a method for estimating short-term grazing capacity for small (1–20 ha) paddocks using cattle nutrition and high spatial resolution forage data in Geographic Information Systems (GIS) for mixed-grass prairie. We define grazing capacity as the number of days a specific paddock will support the nutritional requirements of beef cattle. We integrate previously published methods for estimating cattle nutritional requirements, forage quality (crude protein) and forage quantity (phytomass) to estimate grazing capacity based on current standing-crop. The model utilizes high-resolution (<30-m) satellite imagery or field data to estimate short-term grazing capacity for small paddocks. Three versions of the model were evaluated on one paddock under cattle use in 2007. One version was parameterized using data collected on June 22 from the Landsat Thematic Mapper (TM), one version was parameterized using data collected June 23 from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and one version was parameterized using data collected June 20 from field clippings. TM and ASTER versions underestimated grazing capacity by four days while the field version overestimated grazing capacity by one day. Results suggest integration of cattle nutrition and forage data in GIS could assist with stocking rate adjustments, but additional trials are needed.

Published by Elsevier Ltd.

### 1. Introduction

Producers need real-time estimates of grazing capacity for multiple paddocks because the capacity for Northern US prairie grasslands to meet livestock nutritional requirements changes seasonally and annually (Vallentine, 2001; Diaz-Solis et al., 2006; Grigera et al., 2007). Stocking rates should be dynamic to preserve the sustainable balance between livestock production and grassland health (Diaz-Solis et al., 2006). Livestock performance is directly influenced by the quantity and quality of forage, so these variables are typically used as indicators of grazing capacity. However, determination of forage quality and quantity in the field typically requires intensive surveys that are time-consuming and expensive, so managers often estimate grazing capacity based on historical land-use and visual inspections (Vallentine, 2001). Forage quantity and quality can be estimated remotely for North Dakota grasslands at multiple locations with <20% error (Phillips

et al., 2006; Beeri et al., 2007), so incorporation of forage data into existing livestock performance models is a logical next-step towards building decision support systems. Linking these dynamic forage data with cattle nutrition requirements in a Geographic Information Systems (GIS) framework would help optimize resource utilization by matching real-time forage availability to livestock nutritional needs (Moen, 1984; Hobbs et al., 1985) and support adaptive and sustainable grassland management (Hunt et al., 2003).

Landsat Thematic Mapper (TM) and Advanced Very High Resolution Radiometer (AVHRR) data have been applied toward monitoring grassland trend and condition in Western Australia (Bastin et al., 1998; Edirisinghe et al., 2000; Wallace et al., 2004), the Brazilian Amazon (Asner et al., 2004; Numata et al., 2007), the Southwestern, USA (Qi et al., 2000), and Western China (Zha et al., 2003). In many cases, the focus is on delineation of vegetation from bare soil or on qualitative differences in spectral vegetation index values (Pickup et al., 1993; Qi et al., 1994), which is practical for long-term monitoring. Some have used Moderate Resolution Imaging Spectroradiometer (MODIS) and AVHRR data in models of radiation

\* Corresponding author. Tel.: +701 667 3002; fax: +701 667 3054.

E-mail address: [rebecca.phillips@ars.usda.gov](mailto:rebecca.phillips@ars.usda.gov) (R. Phillips).

use efficiency to estimate pasture growth rates in sub-humid temperate (Grigera et al., 2007) and Mediterranean (Hill et al., 2004) climates, providing quantitative pasture data. The frequency of MODIS and AVHRR data is much greater than other satellite-based sensors, and they provide data at spatial resolutions well-suited for kilometer-scale pasture assessment. Previously developed, high-resolution (<30-m pixel) forage quality and quantity data could support grazing capacity inventories for small (1–20 ha) paddocks, given a model for interpreting these data in the context of livestock management (Wallace et al., 2004).

Determining the length of time a paddock might sustainably support a cattle herd without damaging the grassland resource requires current forage information. Typically, this is ocularly estimated, which is often based on current standing crop and historical resilience of the grassland to grazing. Current methods for assessing the capacity of grasslands to support a specific herd of cattle rarely include needed forage quality information (Vallentine, 2001), which influences animal intake, selection and performance (Ellis, 1978). Recent advances in satellite-based indicators of forage quality now make it possible to garner forage nutritional information on a mass basis to assist with stocking rate adjustments (Phillips et al., 2006), based on grassland capacity to support beef cattle.

We addressed the problem of matching livestock nutritional needs with crude protein available in forage at a paddock scale by employing previously published methods for estimating forage quality (Phillips et al., 2006), quantity (Beeri et al., 2007), and cattle nutritional needs (National Research Council, 2000) in a model designed to estimate the number of days a specific paddock might support a specific cattle herd. We evaluated three versions of this model on one 11.9 ha paddock (#1314). One version of the model was parameterized using TM data, one using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, and one using field data. We compared these grazing capacity estimates with forage used by cattle in a grazing trial. Following are the steps required to build and implement the model, including satellite data calibration, paddock mapping, model construction, and a cattle grazing trial. Our objective was to describe a method for estimating grazing capacity for small paddocks by matching livestock nutritional requirements with forage quality and quantity to support more timely land management decisions. We compare three model versions (each parameterized using different data sources) with forage utilization by cattle use in a short-term grazing trial.

## 2. Methods

### 2.1. Study area

The study area is located in Mandan, ND, USA (46°46'N, 100°54'W), which is located in the Northern Great Plains Ecoregion and the larger Northern mixed-grass prairie physiographic region (Omernik, 1987). Vegetation is comprised of historically native species, including blue grama [*Bouteloua gracilis* (HBK.) Lag. Ex Griffiths], Western wheatgrass [*Pascopyrum smithii* (Rydb) Löve], needle-and-thread [*Hesperostipa comata* Comata Trin. and Rupr.], green needle grass [*Nassella viridula* (Trin.) Barkworth] and carex (*Carex filifolia* Nutt. and *Carex heliophila* Mack.) (USDA, 2006). However, these native species have been displaced in recent decades by the invasion of smooth brome (*Bromus inermis* Leyss.) and Kentucky bluegrass (*Poa pratensis* L.), which together comprise ~60% of the basal area (J. Hendrickson, unpublished data). Predominant soils are Temvik–Wilton silt loams (FAO: Calcic Siltic Chernozems; USDA: fine-silty, mixed, superactive, frigid Typic and Pachic Haplustolls). Long-term weather station records (1913–2006) indi-

cate that average annual air temperature during the growing season (April–September) is 20 °C and annual precipitation is 412 mm (Mandan Experiment Station, 2007).

### 2.2. Satellite data processing

Image processing was performed with a June 22, 2007 Landsat TM image, a June 23, 2007 ASTER image, and field calibration data collected June 20, 2007. Images were pre-processed using ERDAS Imagine 8.7 software and geo-referenced to the same projection (UTM, 14 North, WGS 84 Datum) with less than one-half pixel error. Atmospheric corrections were performed using the empirical line method and spectra collected from field calibration sites (Moran et al., 2001; Clark et al., 2002) with less than 4% error for each spectral band used in this study.

Previously published methods for deriving canopy carbon/nitrogen ratio (C/N) and photosynthetically-active vegetation (PV) mass were used to estimate forage quality and quantity (Phillips et al., 2006; Phillips and Beeri, 2008), which utilize spectral reflectance data available from multispectral satellites in the red and short-wave infrared (SWIR) spectral regions (Beeri et al., 2007). The computation for C/N is similar for both TM and ASTER sensor data and does not require field calibration points (Phillips et al., 2006). The C/N ratio is converted to percentage crude protein (CP<sub>c</sub>) by assuming a 40% carbon content and the 6.25% multiplier for conversion of plant N to crude protein (Beeri et al., 2007):

$$CP_c = 6.25 \times \left( \frac{40}{C/N} \right). \quad (1)$$

The Modified Soil Adjusted Vegetation Index (MSAVI) can be derived from TM and ASTER data to estimate PV mass and is calculated as follows:

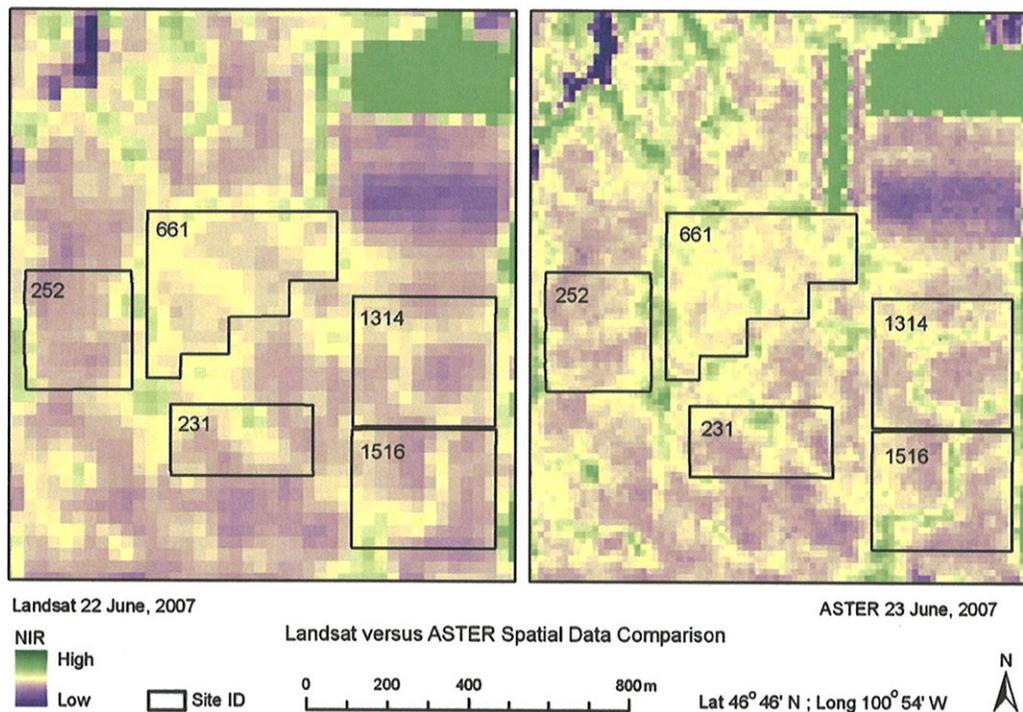
$$MSAVI = 0.5 \cdot ((2 \cdot \rho_{NIR} + 1) - \sqrt{((2 \cdot \rho_{NIR} + 1)^2 - 8 \cdot (\rho_{NIR} - \rho_{red}))}), \quad (2)$$

where  $\rho_{NIR}$  is reflectance for the wavelength ( $\lambda$ ) band in the near infra-red spectral region ( $\lambda_{777-904}$  for TM;  $\lambda_{756-876}$  for ASTER) and  $\rho_{red}$  is reflectance for the  $\lambda$  band in the red spectral region ( $\lambda_{627-693}$  for TM;  $\lambda_{629-689}$  for ASTER). MSAVI index values <0.50 are considered below the saturation threshold (Hill et al., 2004); however, we also collected MSAVI values at a standardized field site where spectral reflectance values were characteristically high to determine if grassland pixels were near saturation. The MSAVI, calculated for each pixel, was linearly regressed on the 25 field calibration points to derive equations for estimating PV mass. The mass of crude protein in PV (CP<sub>m,pv</sub>) for all TM and ASTER pixels was then calculated (Beeri et al., 2007):

$$CP_{m,pv} = \frac{CP_c}{100} \times (PV \text{ mass}). \quad (3)$$

### 2.3. Phytomass data

Data necessary for calibrating image data to field estimates of PV mass were collected within three days of satellite overpasses from five random points within each of five physiographically similar (plant species, soils, topography) paddocks located within the study area described above (Fig. 1). Only one paddock (#1314) was used in the cattle grazing trial. Since this model is intended for rancher application, we clipped aboveground vegetation in paddocks using the small frames recommended for estimation of grassland phytomass (Vallentine 2001). These data were used to convert spectral data from units of reflectance to kg phytomass ha<sup>-1</sup>. The 25 random points were generated in ERDAS Imagine software (Leica Geosystems GIS and Mapping LLC, Norcross, GA) and mapped in the field using a GPS with sub-meter resolution



**Fig. 1.** Illustration of the paddocks used for spectral data calibration and the paddock used for the cattle trial (#1314) overlaid on the two satellite data sources used to parameterize two versions of the model. The 30-m Landsat Thematic Mapper (Landsat TM) pixel data for the near infrared band ( $\rho_{\text{NIR}}$ ) is depicted on the left and the 15-m Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) pixel data for  $\rho_{\text{NIR}}$  is depicted on the right.

(Trimble Model). On June 20, 2007, we clipped one frame ( $0.25 \text{ m}^2$ ) at each of the 25 points (leaving 4 cm of stubble). Clippings were separated into photosynthetically active (PV) and non-photosynthetically active vegetation (NPV) pools in the laboratory, oven-dried for 48 h at  $60^\circ\text{C}$ , and ground using a 1 mm mesh screen. PV ( $\text{kg dry matter ha}^{-1}$ ) was used for TM and ASTER model calibration. The dried material was analyzed further for forage quality (methods to follow).

#### 2.4. Forage quality laboratory analyses

Forage quality was determined for dried, ground vegetation collected in the field at each of the 25 points on June 20, with separate analyses for PV and NPV. Samples were analyzed for C and N using a combustion analyzer (Carlo Erba Model NA 1500 Series 2 N/C/S analyzer, CE Elantech, Lakewood, NJ). Forage *in vitro* dry matter digestibility (IVDMD) was analyzed using a Daisy<sup>II</sup> incubator (Ankom Technology, Fairport, NY) as described by Vogel et al. (1999) and rumen fluid was collected from two ruminally cannulated beef heifers that were participating in the grazing trial. Weighted means were calculated for C/N, IVDMD and  $\text{CP}_c$  for each pasture, based on the laboratory data for PV and NPV and the proportion of PV and NPV comprising the canopy on a mass basis.

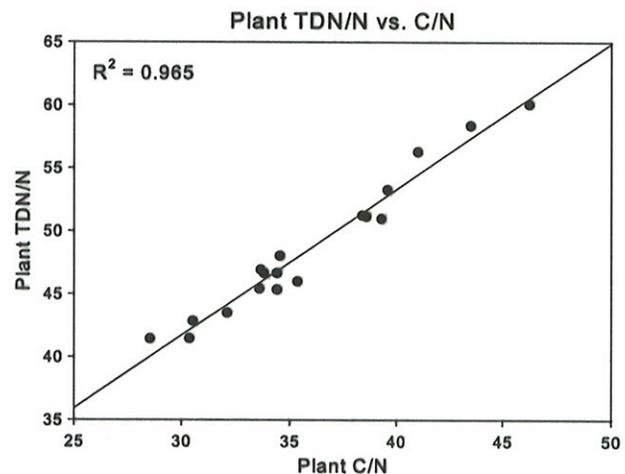
Total Digestible Nutrient (TDN) is an indicator of forage quality and therefore can be used to estimate the capacity of a pasture to support cattle nutritional requirements (National Research Council, 2000). Initially, we determined if plant C/N could be used to estimate TDN/N by performing repeated plant chemical analyses in the laboratory using plant material collected monthly (June–September 2007) from five points within each paddock as described previously. The mixture of both materials (as collected in the field) was processed and analyzed. Plant samples were analyzed for dry matter (AOAC, 1990), N and C (Carlo Erba Model NA 1500 Series 2 N/C/S analyzer, CE Elantech, Lakewood, NJ), and Acid

Detergent Fiber (ADF%) content using the procedures of Goering and Van Soest (1970) as modified by Vogel et al. (1999) with an Ankom 200 fiber analyzer (Ankom Technology, Fairport, NY). TDN was calculated from ADF (Linn and Martin, 1989):

$$\text{TDN (\%)} = 0.889 - (\text{ADF\%} \times 0.779). \quad (4)$$

Laboratory data collected for C/N were regressed on TDN/N data. The linear regression equation (Fig. 2) was used to estimate TDN in the nutrient-based grazing capacity model:

$$\text{TDN (\%)} = \text{C/N} \times 1.16 + 6.95 \times (40 \div \text{C/N}). \quad (5)$$



**Fig. 2.** Regression of plant total digestible nutrients/nitrogen (TDN/N) on plant carbon/nitrogen ratio measured in the laboratory from dried and ground field vegetation data.

2.5. Nutrient-based grazing capacity model

The grazing capacity model framework (Fig. 3) is similar when parameterized using TM, ASTER or field data. The goal of the model is to estimate the number of days geo-located pastures can support

a given herd of cattle based on body weight and stage of production. The model can be conceptually subdivided into three main tasks: (1) process image data (as described previously) to estimate PV mass, CP<sub>c</sub>, TDN (%), and CP<sub>m,PV</sub>; (2) apply satellite-based estimates of TDN and TDN recommendations for the herd of interest

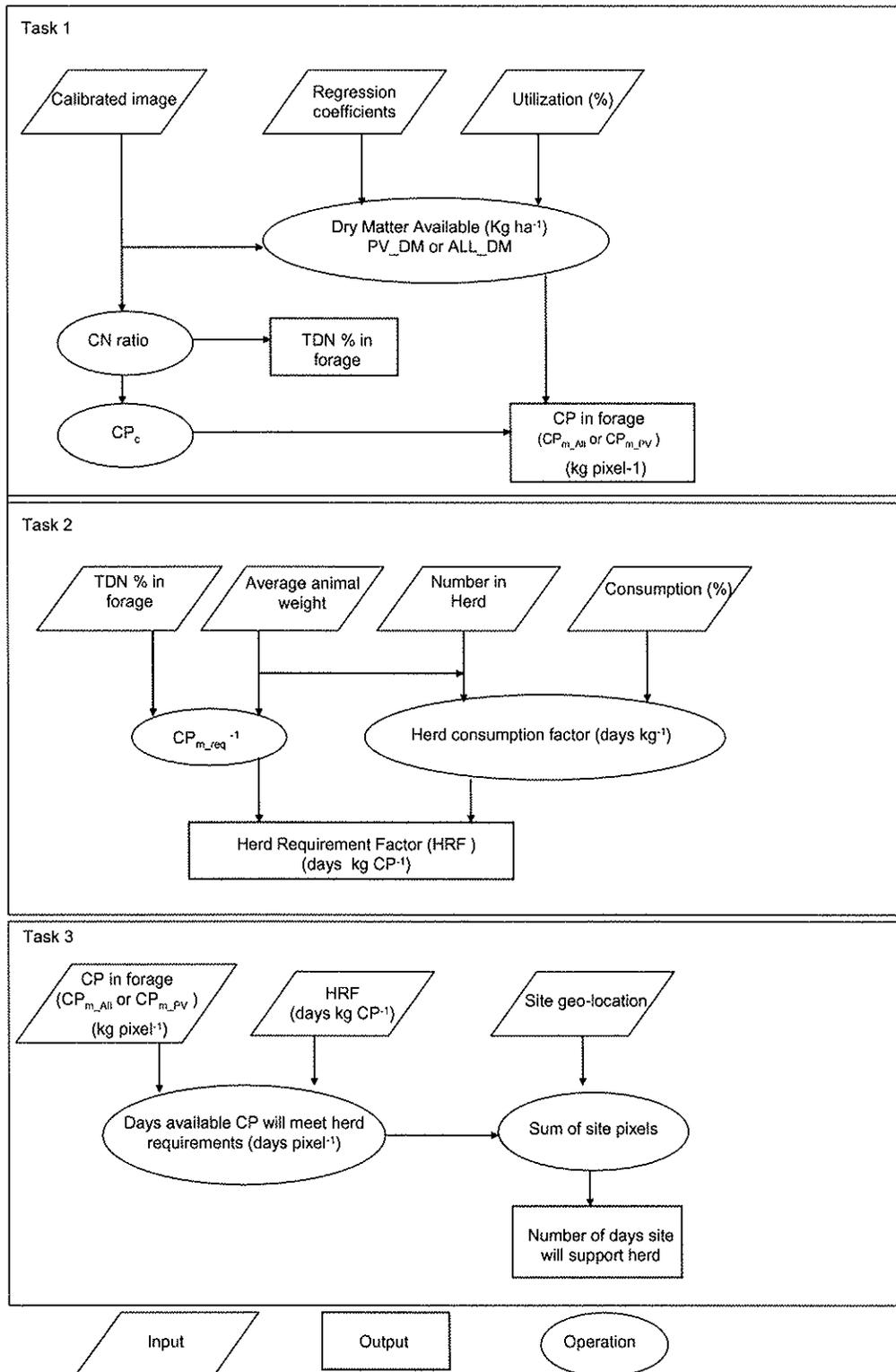


Fig. 3. Schematic representation of the grazing capacity model, divided into three main tasks.

based on the National Research Council (2000) to calculate a temporary Herd Requirement Factor (HRF); and (3) calculate the number of days current forage might support the herd for geo-located pastures, based on estimated available  $CP_{m,pv}$  and the HRF (Fig. 3).

Inputs required for Task 1 are: a calibrated image (with each band in units of reflectance); MSAVI regression coefficients for estimation of PV mass; and targeted forage utilization (%). Inputs required for Task 2 are: available TDN in forage (input from Task 1); the number of animal units (AU) expected to graze a specific area; average weight of each AU; and animal consumption as a percent of animal weight (National Research Council, 2000). Based on the National Research Council tabular data, we constructed a look-up table which used our calculated TDN and average animal weight to determine percentage of crude protein required ( $CP_{c,req}$ ). This is multiplied by the herd consumption factor (consumption as percentage of average animal weight multiplied by the number of head) to determine the HRF. The HRF does not specify the proportion of photosynthetically or non-photosynthetically active vegetation:

$$HRF (\text{Days kg } CP_{m,req}^{-1}) = [\text{Mass consumed/day} * \text{head}] - 1 * CP_{c,req} \quad (6)$$

In Task 3, forage  $CP_{m,pv}$  (input from Task 1) is multiplied by the HRF (input from Task 2) to find the number of days  $CP_{m,pv}$  will meet herd nutritional requirements. Pixel data are then layered onto the geo-located paddock to determine the number of days for which forage will be available to support the cattle herd. For evaluation purposes, we output three versions of the model: one based on forage estimates derived from TM data (30-m pixels), one based on forage estimates derived from ASTER data (15-m pixels), and one based on forage estimates derived from field clippings (paddock average). Satellite-based indices typically delineate PV (either as mass, leaf area, or cover), rather than NPV, because spectral response in the visible and short-wave infrared is largely due to absorption and reflectance by photosynthetically active pigments in the leaf. Depending upon sward structure, stocking rate, feed availability, etc., cattle may also consume NPV. Therefore, we considered all three versions, since each could underestimate actual grazing capacity because the model does not include estimation of NPV mass (due to TM and ASTER spectral limitations). The sensitivity of the model to phytomass error was evaluated by determining how a percent change in PV mass affects the estimated number of grazing days. We performed a similar analysis to evaluate the sensitivity of the model to error in  $CP_c$ .

### 2.6. Cattle grazing trial

We evaluated actual cattle use on one paddock (#1314) in a grazing trial. The geographic border of 1314 was surveyed with a corrected, real-time differential Global Position System (GPS) Beacon receiver with an external antenna (Trimble Model GeoXT). ASTER and TM pixel sizes are not equal (Fig. 1), yet model version comparisons required that both sensors represent areas of equal size to be valid. Therefore, we overlaid ASTER and TM data and corrected the paddock boundaries so that only full pixels of both

ASTER and TM data were included. Four 15-m ASTER pixels were aligned within each 30-m TM pixel, so the ASTER data contained four times as many data points as the TM data set (Fig. 1).

The cattle grazing trial was initiated on paddock 1314 after image acquisitions for the purpose of comparing actual cattle utilization with the satellite data-driven models. The 28-day trial was initiated on July 16, 2007 with 30 AUs, consisting of 24 Angus cow/calf pairs and six 2-year old heifers (average initial body weight per AU =  $514 \pm 69.8$  kg). Cattle were weighed at the beginning and end of the trial to determine average daily weight gain. Forage utilization was estimated by clipping and drying total phytomass (as described previously) just prior to cattle turn out and just after cattle removal at eight points for paddock 1314 and for eight points excluded from grazing. The average difference in total phytomass before and after the 28-day trial was calculated to determine the proportion of phytomass removed by cattle.

### 2.7. Data analysis

Average ( $\pm$ standard deviation) values for  $CP_c$  and PV mass ( $\text{kg ha}^{-1}$ ) on paddock 1314 were calculated for TM, ASTER and field estimates. We also calculated the margin-of-error associated with collecting PV mass calibration data on 25 sample points, based on a 95% confidence interval. A t-test was used on enclosure data before and after the 28-day trial to determine if there was an increase in phytomass during the trial. We correlated ASTER estimates for  $CP_{m,pv}$  against TM estimates for  $CP_{m,pv}$  at the same geographic location using the average of the four ASTER pixels nested within each TM pixel to determine how  $CP_{m,pv}$  varied with data source.

## 3. Results

Satellite estimates of PV mass required field calibration data, and the field average ( $\pm$ standard deviation) for all points was  $1790 \pm 360 \text{ kg ha}^{-1}$ . The percentage of PV versus NPV for the canopy was, on average, 76%. The margin-of-error associated with clipping 25 points to estimate PV mass was 9%. Average PV mass derived from the TM and ASTER sensors for these 25 points (following calibration with field data) was  $1906 \pm 61 \text{ kg ha}^{-1}$  and  $1886 \pm 96 \text{ kg ha}^{-1}$ , respectively. MSAVI spectral index values for our standardized field site ranged from 0.65 to 0.75, while MSAVI for pixels in our study area ranged from 0.25 to 0.45. This spectral response for both TM and ASTER images and low MSAVI values for our study area indicate that spectral index saturation was not an issue. Laboratory analyses performed on clippings at the 25 sample points were, on average,  $8.4 \pm 0.74\%$  for  $CP_c$  and  $67 \pm 2.4\%$  for IVDMD.

Based on the cattle-use trial, the TM and ASTER versions underestimated grazing capacity by 4 days while the field version overestimated grazing capacity by 1 day. This was calculated according to the number of days needed to achieve our targeted 50% utilization and our actual usage by cattle of 43% over 28 days. Models parameterized using TM, ASTER and field data indicated we would meet our targeted utilization in 28, 28 and 33 days, respectively (Table 1). The pre and post-trial grazing enclosure data indicated

**Table 1**  
Grazing capacity model inputs and outputs.

Paddock	Area (ha)	AU	Average cattle mass (kg)	Target utilization (%)	Grazing days field clipping June 20	Grazing days ASTER June 23	Grazing days TM June 22	Actual utilization (%)	Actual grazing days	Actual weight gain ( $\text{kg d}^{-1}$ )	Actual consumption ( $\text{kg ha}^{-1} \text{d}^{-1}$ )
1314	11.9	30	514	50	33	28	28	43	28	0.6	41

Model inputs for grazing capacity estimates and model outputs for each version of the model (one using field data, one using ASTER data and using TM data) compared with actual cattle utilization and performance.

**Table 2**  
Phytomass estimates.

Paddock	Field clipping June 20 PV mass (kg ha <sup>-1</sup> ) Average ± standard deviation	ASTER June 23 PV mass (kg ha <sup>-1</sup> ) Average ± standard deviation	TM June 22 PV mass (kg ha <sup>-1</sup> ) Average ± standard deviation
1314	2003 ± 98	1898 ± 52	1892 ± 62

Average (±standard deviation) for live phytomass (PV mass), based on the field clippings, ASTER, and Landsat-based data for paddock 1314.

**Table 3**  
Forage quality estimates.

Paddock	Field clipping June 20 IVDMD (%) Average ± standard deviation	Field clipping June 20 CP <sub>c</sub> (%) Average ± standard deviation	ASTER June 23 CP <sub>c</sub> (%) Average ± standard deviation	TM June 22 CP <sub>c</sub> (%) Average ± standard deviation
1314	68.7 ± 2.0	8.1 ± 1.2	6.9 ± 0.2	7.0 ± 0.2

Average (±standard deviation) for forage quality variables (crude protein and *in vitro* dry matter digestibility) based on field clippings, ASTER, and TM data for paddock 1314.

phytomass did not increase during the trial, so our estimated percentage utilization was based on paddock 1314 pre and post-trial clippings only. If cattle were allowed to continue grazing at the same rate, they would have reached our targeted utilization of 50% in 32 days.

Average PV mass estimated from field data for the cattle grazing trial in paddock 1314 was 2003 ± 200 kg ha<sup>-1</sup>, while TM and ASTER-based PV mass estimates for paddock 1314 were 1898 ± 52 kg ha<sup>-1</sup> and 1892 ± 62 kg ha<sup>-1</sup>, respectively (Table 2). Average CP<sub>c</sub> estimated from field data for paddock 1314 was 8.1 ± 1.2%, while paddock 1314 TM and ASTER-based averages were 7.0 ± 0.2 and 6.9 ± 0.2, respectively (Table 3). Both TM and ASTER-based estimates for PV mass and CP<sub>c</sub> fell below field-based estimates by approximately 100 kg PV ha<sup>-1</sup> and by approximately 1% CP<sub>c</sub>. The correlation between ASTER and TM for CP<sub>m,PV</sub> on a pixel-by-pixel basis was positive ( $R = 0.49$ ;  $P < 0.0001$ ), with the absolute difference between sensor data averaging 2.4 kg CP<sub>m,PV</sub> ha<sup>-1</sup> (Fig. 4).

A 1% error in estimating PV mass would lower or raise the number of grazing days by 0.3 days/ or 0.025 days ha<sup>-1</sup>. The paddock averages for PV mass for both TM and ASTER versions were 5% less than the field-based average (Table 1). A 5% error in PV mass would result in underestimating grazing capacity by 1.5 days. Similarly, a 1% error in CP<sub>c</sub> would lower or raise the number of grazing days by

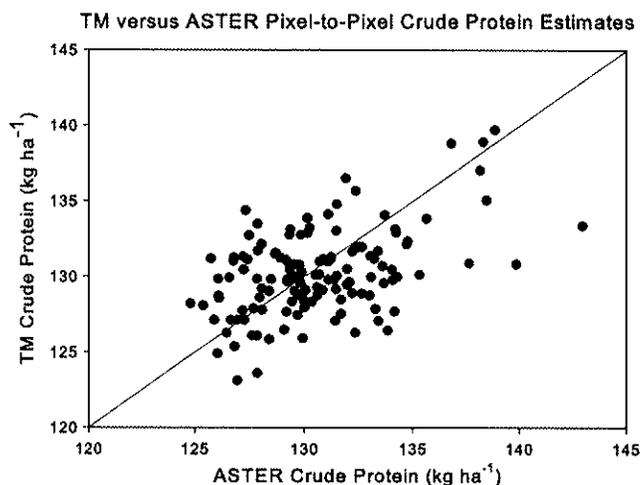
0.32 days or 0.027 days ha<sup>-1</sup>. The paddock average CP<sub>c</sub> for both TM and ASTER versions was 14% less than the field-based average (Table 3). A 14% error in CP<sub>c</sub> would result in an underestimation of grazing capacity by 4.5 days. Accordingly, the combined PV mass and CP<sub>c</sub> errors would have resulted in underestimating paddock grazing capacity by 6 days. This 6-day approximation of model sensitivity to both PV mass and CP<sub>c</sub> in paddock 1314 is greater than the 4 days observed here. The six-day approximation, however, is based on comparison with paddock averages from field and laboratory data, which are not error-free.

#### 4. Discussion

TM, ASTER and field data collected within 3 days of each other made it possible to compare model outputs using alternate data sources for parameterizing a cattle nutrition model in GIS. Cattle data as well as all three methods for estimating forage quality and quantity (TM, ASTER, and field) have been published but have not been integrated previously to determine small-paddock grazing capacity. Other geospatial grassland assessment programs support land managers by mapping estimates of pasture growth rate (<http://www.regional.org.au/au/gia/19/620donald.htm?print=1>), forage production (Grigera et al., 2007), and plant greenness (<http://rangeview.arizona.edu/index.html>) for larger areas at coarser spatial resolutions and with more frequent satellite overpasses. Here, we complement these programs with an option for estimating grazing capacity for smaller paddocks (<20 ha) that includes forage quality as well as quantity.

The field-based version of the model estimated grazing capacity within 1 day (3%) of actual use in the cattle trial, compared to 4 days (12.5%) for the TM and ASTER-based versions (Table 1). The sensitivity analysis suggests this was largely due to the underestimation of forage quality and quantity by TM and ASTER, as compared to field clipping estimates. TM and ASTER-based forage quality estimates approximated laboratory analyses of forage quality, but they both underestimated CP<sub>c</sub> by 1% (Table 3). A 1% difference falls within the previously determined detection limit (Beeri et al., 2007; Phillips et al., 2008), but a 1% difference can nonetheless be substantial with respect to cattle nutrition. Narrowing the range of error in CP<sub>c</sub> estimates may be achieved with additional hyperspectral sensor research (Starks et al., 2006; Beeri et al., 2007).

This grazing capacity model uses a single inventory and does not account for changes in forage quantity and quality during the cattle-use time period. For season-long grazing, additional imagery and model runs are necessary to confirm or readjust capacity based on updated conditions (Grigera et al., 2007). This method may be well-suited to rest rotation and high intensity-low frequency



**Fig. 4.** Scattergram of crude protein mass for photosynthetically active vegetation (CP<sub>m,PV</sub>) derived from Landsat Thematic Mapper (Landsat TM) and from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images. Data are the average of four ASTER pixels within one Landsat TM pixel for paddock 1314.

grazing systems. In these systems, utilization and grazing days are important management factors (Heitschmidt and Taylor, 1991). In these cases, the compatibility of pixel size and cell size would need to be considered. For example, 0.5 ha cells may accommodate the smaller ASTER pixels, whereas TM pixels may require cells >1 ha in area. Upon completion of grazing for one set of cells, a new model run would be needed to estimate grazing capacities for additional, ungrazed cells.

Finally, forage utilization (%) is a model input that must be adjusted according to expert knowledge or historical data for a specific pasture (Vallentine, 2001). For areas where precipitation limits production, 50% utilization may not always reflect proper utilization in dry years (Hacker and Smith, 2007). While 50% forage utilization should result in 50% of the forage mass remaining at the end of the grazing period, actual pasture utilization should nonetheless be monitored to ensure pasture-specific issues are not affecting actual usage. For example, this model assumes all forage is usable and therefore would over-predict grazing days if a pasture was infested with a noxious weed, requiring adjustment of forage utilization or removing these areas from the pasture map. Inclusion of forage quality as well as quantity in our pasture-scale determination of grazing capacity provides an overview of how well available forage will meet livestock nutritional requirements. Ideally, historical data would be available, so that results for the same geographic area could be evaluated across multiple years. Continued comparison of model results with actual forage intake is needed prior to large-scale application to livestock production systems.

## 5. Conclusions

The worldwide need for optimum grassland resource utilization points toward development of models that synoptically integrate real-time forage quality data with livestock performance requirements. The nutrient status of multiple pastures is difficult to estimate and is not typically measured in production-based estimates of grazing capacity. Here, we describe a method for estimating grazing capacity for small paddocks by matching livestock nutritional requirements with forage quality and quantity to support more timely land management decisions. The model parameterized with field data most closely tracked animal use (within 3%), while model versions parameterized with TM and ASTER underestimated grazing capacity by 12.5%.

This paper describes how we used published cattle nutritional requirement data and satellite data-based methods to build a model in GIS to estimate grazing capacity. The model itself is not spatially linked to a specific location but can be applied to any grassland of interest, given field and/or satellite-based data. Differences between model versions parameterized with field versus satellite-based data were associated with errors in satellite-based estimates of forage quality and quantity. Since actual cattle use was only tracked for one paddock, different results would be expected with a greater number of validation sites.

This model is designed for short-term, multiple-paddock grazing systems and is not a substitute for the land manager. Instead, it provides an indication of the capacity of specific paddocks to support livestock nutritional requirements. By representing grazing capacity for several paddocks at one time, managers have the opportunity to select those paddocks that might better meet livestock nutritional requirements. Additional model testing is needed to determine model accuracy at multiple locations and the potential management benefits derived from parameterizing a cattle nutrition model using satellite-based, versus field-based, forage data.

## Acknowledgements

This work was supported by the USDA Rangeland and Livestock Resource Management Program 5445-21310-001-000 and by Cooperative Agreement 58-5445-3-314. The authors gratefully acknowledge technical support provided by Scott Bylin, Gordon Jensen, Clay Erickson, and Faye Kroh, and Bruce Smith, Dean of the John D. Odegard School of Aerospace Sciences at the University of North Dakota.

## References

- Association of Official Analytical Chemists, 1990. Official methods of analysis. 15th ed., Arlington, Virginia.
- Asner, G.P., Townsend, A.R., Bustamantes, M.M.C., Nardoto, G.B., Olander, L.P., 2004. Pasture degradation in the central Amazon: linking changes in carbon and nutrient cycling with remote sensing. *Global Change Biology* 10, 844–852.
- Bastin, G.N., Tynan, R.W., Chewings, V.H., 1998. Implementing satellite-based grazing gradient methods for rangeland assessment in South Australia. *The Rangeland Journal* 20, 61–76.
- Beeri, O., Phillips, R., Hendrickson, J., Frank, A.B., Kronberg, S., 2007. Estimating forage quantity and quality using aerial hyperspectral imagery for Northern mixed-grass prairie. *Remote Sensing of Environment* 110, 216–225.
- Clark, R.N., Swayze, G.A., Livo, K.E., Kokaly, R.F., King, T.V.V., Dalton, J.B., Vance, J.S., Rockwell, B.W., Hoefen, T., McDougal, R.R., 2002. Surface reflectance calibration of terrestrial imaging spectroscopy data: a tutorial using AVIRIS. In: AVIRIS Airborne Geoscience Workshop Proceedings, Pasadena, California.
- Diaz-Solis, H., Kothmann, M.M., Grant, W.E., De Luna-Villarreal, R., 2006. Application of a simple ecological sustainability simulator (SESS) as a management tool in the semi-arid rangelands of Northeastern Mexico. *Agricultural Systems* 88, 514–527.
- Edirisinghe, A., Hill, M.J., Donald, G.E., 2000. Estimating feed-on-offer and pasture growth rate using remote sensing. In: Proceedings of the 10th Australasian remote sensing and photogrammetry conference, Adelaide, August, 2000.
- Ellis, W.C., 1978. Determinants of grazed forage intake and digestibility. *Journal of Dairy Science* 61, 1828–1840.
- Goering, H.K., Van Soest, P.J., 1970. Forage Fiber Analyses (Apparatus, Reagents, Procedures, and Some Applications). USDA Agricultural Research Service, Washington, DC.
- Grigera, G., Oesterheld, M., Pacin, F., 2007. Monitoring forage production for farmers' decision making. *Agricultural Systems* 94, 637–648.
- Hacker, R.B., Smith, W.J., 2007. An evaluation of the DDH/100N mm stocking rate index and an alternative approach to stocking rate estimation. *The Rangeland Journal* 29, 139–148.
- Heitschmidt, R.K., Taylor Jr., C.A., 1991. In: Heitschmidt, R.K., Stuth, J.W. (Eds.), *Grazing Management: An Ecological Perspective*. Timber Press, Portland, pp. 161–177.
- Hill, M.J., Donald, G.E., Hyder, M.W., Smith, R.C.G., 2004. Estimation of pasture growth rate in the south west of Western Australia from AVHRR NDMI and climate data. *Remote Sensing of Environment* 93, 528–545.
- Hobbs, N.T., Thompson, M.T., Swift, D.M., 1985. Estimates of habitat carrying capacity incorporating explicit nutritional constraints. *Journal of Wildlife Management* 49, 814–822.
- Hunt Jr., R.E., Everitt, J.H., Ritchie, J.C., Moran, M.S., Booth, D.T., Anderson, G.L., Clark, P.E., Seyfried, M.S., 2003. Applications and research using remote sensing for rangeland management. *Photogrammetric Engineering and Remote Sensing* 69, 675–693.
- Linn, J.G., Martin, N.P., 1989. Forage Quality Tests and Interpretation. University of Minnesota Extension Service, St. Paul.
- Mandan Experiment Station, 2007. High Plains Regional Climate Center. National Oceanographic and Atmospheric Administration, May 10, 2007. <[http://hprcc1.unl.edu/cgi-bin/cli\\_perl\\_lib/cliMAIN.pl?nd5479](http://hprcc1.unl.edu/cgi-bin/cli_perl_lib/cliMAIN.pl?nd5479)>.
- Moen, A.N., 1984. Ecological efficiencies and forage intake of free-ranging animals. In: Science, National Research Council/National Academy of Science (Eds.), *Developing Strategies for Rangeland Management*. Westview Press, Boulder, pp. 215–273.
- Moran, M.S., Bryant, R., Thome, K., Ni, W., Nouvellon, Y., Gonzalez-Dugo, M.P., Qi, J., Clarke, T.R., 2001. A refined empirical line approach for reflectance factor retrieval from Landsat-5 TM and Landsat-7 ETM+. *Remote Sensing of Environment* 78, 71–82.
- National Research Council, 2000. *Nutrient Requirements of Beef Cattle*. 7th revised ed., National Academic Press, Washington, DC.
- Numata, I., Roberts, D.A., Chadwick, O.A., Schimel, J., Sampaio, F.R., Leonidas, F.C., Soares, J.V., 2007. Characterization of pasture biophysical properties and the impact of grazing intensity using remotely sensed data. *Remote Sensing of Environment* 109, 314–327.
- Omernik, J.M., 1987. Ecoregions of the conterminous United States. *Annals of the Association of American Geographers* 77, 118–125.
- Phillips, R.L., Beeri, O., 2008. Scaling up Knowledge of growing season net ecosystem exchange for long term assessment of North Dakota grasslands under the Conservation Reserve Program. *Global Change Biology* 14, 1008–1017.

- Phillips, R.L., Beeri, O., Liebig, M., 2006. Landscape estimation of canopy C:N ratios under variable drought stress in Northern Great Plains rangelands. *Journal of Geophysical Research* 111, G02015.
- Pickup, G., Chewings, V.H., Nelson, D.J., 1993. Estimating changes in vegetation cover over time in arid rangelands using Landsat MSS data. *Remote Sensing of Environment* 43, 243–263.
- Qi, J., Chehbouni, A., Huete, A., Kerr, Y.H., Sorooshian, S., 1994. A modified soil adjusted vegetation index. *Remote Sensing of Environment* 48, 119–126.
- Qi, J., Marsett, R.C., Moran, M.S., Goodrich, D.C., Heilman, P., Kerr, Y.H., Dedieu, G., Chehbouni, A., Zhang, X.X., 2000. Spatial and temporal dynamic of vegetation in the San Pedro River basin area. *Agriculture and Forest Meteorology* 105, 55–68.
- Starks, P.J., Zhao, D., Phillips, W.A., Coleman, S.W., 2006. Development of canopy reflectance algorithms for real-time prediction of Bermudagrass pasture biomass and nutritive values. *Crop Science* 46, 927–934.
- USDA, N.R.C.S., 2006. The PLANT Database. National Plant Data Center, Baton Rouge, LA. <<http://plants.usda.gov>>.
- Vallentine, J.R., 2001. *Grazing Management*, second edition. Academic Press, San Diego.
- Vogel, K.P., Pedersen, J.F., Masterson, S.D., Toy, J.J., 1999. Evaluation of a filter bag system for NDF, ADF, and IVDMD forage analysis. *Crop Science* 39, 276–279.
- Wallace, J.F., Caccetta, P.A., Kiiveri, H.T., 2004. Recent developments in analysis of spatial and temporal data for landscape qualities and monitoring. *Australian Ecology* 29, 100–107.
- Zha, Y., Gao, J., Niu, S., Liuc, Y., Jianga, J., Weia, Y., 2003. A spectral reflectance-based approach to quantification of grassland cover from Landsat TM imagery. *Remote Sensing Environment* 87, 371–375.