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Mapping Total Vegetation Cover Across Western Rangelands With Moderate-Resolution Imaging Spectroradiometer Data

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Abstract

Remotely sensed observations of rangelands provide a synoptic view of vegetation condition unavailable from other means. Multiple satellite platforms in operation today (e.g. Landsat, moderate-resolution imaging spectroradiometer [MODIS]) offer opportunities for regional monitoring of rangelands. However, the spatial and temporal variability of rangelands pose challenges to consistent and accurate mapping of vegetation condition. For instance, soil properties can have a large impact on the reflectance registered at the satellite sensor. Additionally, senescent vegetation, which is often abundant on rangeland, is dynamic and its physical and photochemical properties can change rapidly along with moisture availability. Remote sensing has been successfully used to map local rangeland conditions. However, regional and frequently updated maps of vegetation cover in rangelands are not currently available. In this research, we compare ground measurements of total vegetation cover, including both green and senescent cover, to reflectance observed by the satellite and develop a robust method for estimating total vegetation canopy cover over diverse regions of the western United States. We test the effects of scaling from ground observations up to the Landsat 30-m scale, then to the MODIS 500-m scale, and quantify sources of noise. The soil-adjusted total vegetation index (SATVI) captures 55% of the variability in ground measured total vegetation cover from diverse sites in New Mexico, Arizona, Wyoming, and Nevada. Scaling from the Landsat to MODIS scale introduces noise and loss of spatial detail, but offers inexpensive and frequent observations and the ability to track trends in cover over large regions.

Resumen

Observaciones de pastizales con sensores remotos proporcionan una vista sinóptica de la condición de la vegetación que no está disponible usando otros medios. Múltiples plataformas satelitales en operación hoy en día (e.g. Landsat, MODIS) proporcionan oportunidades para un monitoreo regional de los pastizales. Sin embargo, la variabilidad espacial y temporal de los pastizales posee retos relacionados con el mapeo de la condición de la vegetación. Por ejemplo, las propiedades del suelo pueden tener gran impacto en la reflectancia registrada por el sensor del satélite. Adicionalmente, la vegetación senescente, la cual es a menudo abundante en los pastizales, es dinámica y sus propiedades físicas y fotoquímicas pueden cambiar rápidamente debido al contenido de humedad disponible. Los sensores remotos han sido utilizados con éxito para mapear las condiciones locales de los pastizales. Sin embargo, mapas regionales y frecuentemente actualizados de la cobertura de la vegetación en pastizales no están disponibles en la actualidad. En esta investigación, se compararon medidas del suelo del total de la cobertura, incluyendo ambas coberturas la verde y la senescente, contra la observada por el satélite para desarrollar un método robusto con la finalidad de estimar el total de la cobertura de la copa de la vegetación sobre la diversa región del Oeste de estado Unidos. Se evaluaron los efectos de escala desde observaciones al ras de suelo hasta aquellas usando Landsat a una escala de 30 m, entonces a la escala de 500 m en MODIS y se cuantificaron las fuentes de variación. El índice ajustado total de vegetación (SATV) captura 55% de la variabilidad en la estimación del total de la cobertura vegetal de diversos sitios en Nuevo México, Arizona, Wyoming, y Nevada. La conversión de escala de Landsat a MODIS introduce cierto margen de error y pérdida de detalle espacial, pero ofrece observaciones baratas y frecuentes así como la capacidad de rastrear las tendencias en cobertura sobre extensas regiones.

Key Words: multiresolution, rangeland management, remote sensing, SATVI, scaling

INTRODUCTION

Rangelands in the lower 48 states contain over 276 million hectares of grasslands and shrublands, or about 36% of the total land area in the contiguous United States (John Heinz III Center for Science, Economics and the Environment 2002). Van Tassell et al. (2001) note that the Bureau of Land Management (BLM) and US Forest Service (USFS) are the largest land managers in the 11 western states with 42% of the land, that 85% of federal lands are grazed by domestic

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livestock, and that more than half of the beef cattle operations in those western states hold grazing permits from the BLM and USFS. Other federal and state agencies also manage large areas of rangeland, and the Natural Resources Conservation Service (NRCS) provides technical support and conservation funding on private land, so there is a strong public interest in rangeland management across the West. Unfortunately, resources for agency rangeland vegetation monitoring efforts are inadequate. Fernandez-Gimenez et al. (2005) state:

> . . . [R]angeland monitoring simply does not happen as often or as well as it must to meet stewardship aspirations... Shortfalls in agency monitoring are, in large measure, the result of insufficient human and financial resources. In other words, rangeland monitoring is an unfunded mandate. (p. 345)

In the years since that comment was written, agency funding has declined further. At a time of inadequate and shrinking budgets, new ways to meet existing obligations at lower cost need to be explored. One long-recognized and potentially lower-cost option for rangeland monitoring is remote sensing. Rangeland conditions across a very large area can be monitored, often with frequent repeat observations; this breadth of coverage is not possible from a strictly ground-based monitoring approach. Improvements in the ability to manage large data sets and to access free raw imagery increase the feasibility of applying remotely sensed imagery for rangeland monitoring across areas as large as states and countries. Landsat Thematic Mapper (TM) scenes are available back to 1984. Products from the moderate-resolution imaging spectroradiometer (MODIS), with lower spatial resolution than Landsat, permit continuous analysis of large regions extending back to the year 2000.

Several recent studies have used Landsat-scale imagery to identify spatial or temporal patterns in rangeland vegetation using innovative techniques (e.g. Blanco et al. 2009; Karl 2010; Paudel and Andersen 2010; Brinkmann et al. 2011; Munyati et al. 2011) that show the ability of remote sensing to characterize the landscape. At the regional scale, time series of the National Oceanic and Atmospheric Administration's advanced very high resolution radiometer (AVHRR) and MODIS observations have been used to examine rangeland vegetation phenology and issues associated with degradation (e.g., Stellmes et al. 2010). A standard MODIS vegetation cover product has been produced under the name vegetation continuous fields (VCF; Hansen et al. 2003), and while the tree cover products are produced annually, the herbaceous cover products are available for a single year only (2001). These studies and products highlight the potential of remote sensing as a tool to assist rangeland management.

Quantitative comparisons of satellite-derived estimates of cover in rangelands have been infrequent. Baugh and Groeneveld (2006) compared 14 Landsat-derived vegetation indices over a sparsely vegetated region in Colorado and determined that derivatives of the normalized difference vegetation index (NDVI) performed the best. Amiri and Tabatabaie (2009) compared more than 25 indices derived from the advanced spaceborne thermal emission and reflection radiometer (ASTER) in a semiarid region of Iran and found NDVI to perform the best. These studies focus on regions of limited size and require calibration within these limited regions. Additionally, these approaches are limited by NDVI's lack of sensitivity to senescent vegetation, which plays an important role in rangelands.

As of 2012, there remains a large gap between the potential and actual application of remotely sensed data on rangelands. While there have been numerous limited-scale applications of remote sensing to rangeland management, remote sensing has not yet become a widely used operational tool. As Hunt et al. (2003) ask:

> So why isn't remote sensing currently applied for rangeland management? Since the beginning of remote sensing as a discipline, scientists have been studying potential applications [. . .T]here is a mismatch between the information wanted by range managers and the information provided by remote sensing. [. . .]The challenge remains to define cost-effective indicators and methods for rangeland assessment and monitoring. (p. 676–677)

Products typically derived from optical remote sensing data, such as NDVI, fractional photosynthetically active radiation (FPAR), and leaf area index (LAI), while conveying useful information about land cover and vegetation, do not correspond directly to any of the monitoring metrics normally collected in the field by rangeland managers, such as total vegetation fractional cover (TVFC). Additionally, the operational adoption of remote sensing tools is limited because remote sensing studies to date overwhelmingly offer methods and products that are calibrated to small regions.

In this study, we address one priority metric, total (green and senescent) vegetation cover, often collected on rangelands, though not in all monitoring protocols. Herrick et al. (2009) recommend the line point intercept procedure, which can be used to calculate the total vegetation cover, as a core long-term rangeland monitoring method. Booth and Tueller (2003) highlight the importance of cover for soil conservation and stability and recommend the application of remotely sensed estimates of cover to address soil conservation as the first priority ecological concern. Vegetation cover protects the soil by reducing erosion and thereby sustaining productivity over time and reducing sediment delivered to rivers and streams. Both green and senescent vegetation provide forage for cattle, though green feed offers higher nutritional and caloric content. In areas with seasonal precipitation, monitoring changes in senescent vegetation can be useful for understanding grazing distribution. By monitoring total green and senescent vegetation cover, one can capture the state of rangeland vegetation over time.

We present a robust method for scaling ground observations of TVFC (i.e., canopy cover of green and senescent vegetation) to the 30-m resolution of Landsat observations, and then up to the 500-m MODIS surface reflectance scale. By using information from across the western United States together with satellite observations from dozens of overpasses, we ensure that our approach is robust and applicable across seasons and ecosystems. By scaling to MODIS, this approach allows us to produce total vegetation cover estimates over regional to continental scales every 8 days. By using the 30-m data

Table 1. Summary of data sets used in this research.

Data set[1]	Category	Use
USGS vegetation cover	Field-based cover measurements	Model calibration
USGS spectral library reflectances	Field-based spectral measurements	Scaling and uncertainty estimation
Marsett vegetation cover	Field-based cover measurements	Model calibration
SWReGAP vegetation cover	Field-based cover ocular estimate	Validation
Landsat reflectances (TM & ETM+)	Remote sensing	30-m scale maps
MODIS reflectances (MCD43A4)	Remote sensing	500-m scale maps
MODIS VCF cover product	Remote sensing	Comparison
Arizona ownership polygons	polygon/vector	Scaling and uncertainty estimation
TNC grasslands map	polygon/vector	Scaling and uncertainty estimation
SRTM elevation data	raster elevation data	Scaling and uncertainty estimation
SRER cattle grazing tables	polygon/vector	Validation

[1]USGS indicates US Geological Survey; SWReGAP, Southwest Regional Gap Analysis Project; TM, Thematic Mapper; ETM+, Enhanced Thematic Mapper Plus; MODIS, moderate-resolution imaging spectroradiometer; VCF, vegetation continuous fields; TNC, The Nature Conservancy; SRTM, Shuttle Radar Topography Mission; SRER, Santa Rita Experimental Range.

(approximately one-tenth of a hectare per pixel), we can relate ground scale measurements, typically acquired for transects and plots representing less than 2 ha, to the MODIS scale (25-ha pixel size). Without the intermediate 30-m Landsat data, it would be difficult to make the leap in scales from 1 ha to 25 ha. Landsat and MODIS sensors acquire imagery of the Earth's surface in similar regions of the electromagnetic spectrum (i.e., spectral bands), and therefore are a natural pair for conducting regional to global scaling. Here we use field-based estimates of vegetation cover to compare with common vegetation indices and identify the most useful index for monitoring rangeland vegetation. We then present an independent validation of our approach to estimating total vegetation cover over wide regions and within the context of an analysis of cattle grazing.

METHODS

Data

The analysis conducted here combines information from 11 data sets that are categorized as field-based measurements, remotely sensed observations, and other (Table 1).

Field-Based Measurements. Ground measurements of total vegetation cover used for identifying and calibrating an optimal model came from two sources, the US Geological Survey (USGS) Digital Spectral Library 06 (Clark et al. 2007) and data collected by Robert Marsett (Marsett et al. 2006). These data were acquired across a range of seasons, conditions, and vegetation communities in four different western US states (Fig. 1). An additional ground-based data set of ocular estimates of cover from the Southwest Regional Gap Analysis Project (SWReGAP) in Arizona was used for independent validation.

USGS Digital Spectral Library and Ground Observations of Cover. As part of the USGS Joint Fire Sciences Program, Clark et al. (2007) assembled a digital reflectance spectral library of a wide range of minerals, soils, plants, and vegetation communities. In addition to ground-measured reflectance spectra, this data set provides a thorough characterization of each sample. For the current study, we extracted 90 samples measured in the rangelands near Left Hand Creek, Wyoming (lat 43°57.6′N, long 108°48.6′W) and Catnip Mountain, Nevada (lat 41°51.6′N, long 119°22.8′W). The rangeland observations were collected on circular plots 15.2 m in diameter. According to Clark et al. (2007):

> Within these plots, four subplots of 0.5 meter diameter were established 5 meters from the center at the four cardinal directions (north, east, south and west). Within these subplots, grass and forb species were identified and associated percent cover of each were visually estimated. Litter cover and the percent area of bare ground were also visually estimated. For each shrub in the larger plot, the species was identified, the lateral dimensions were measured, and the height was measured. The cover of trees, shrubs, grasses, forbs, litter and bare ground were calculated from the full plot and subplot measurements.

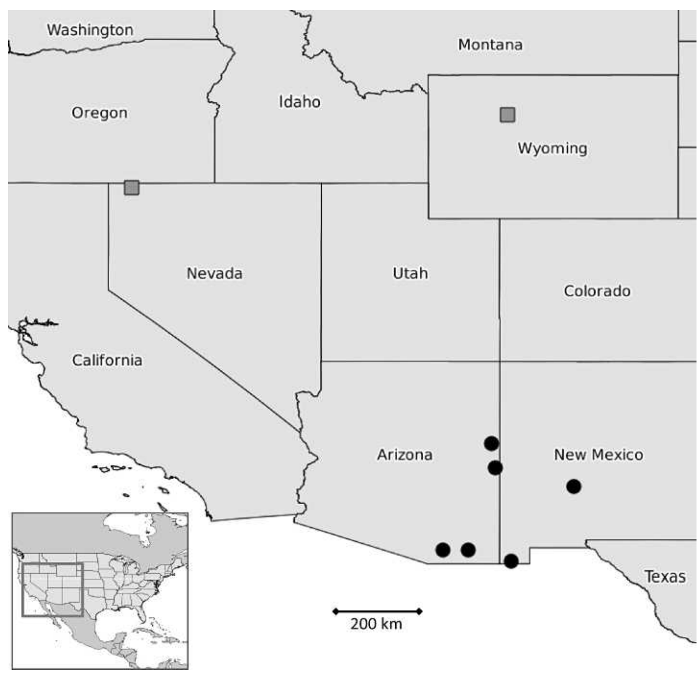

Figure 1. The field observations of total vegetation cover come from two sources: the US Geological Survey Joint Fire Sciences program with field campaigns conducted in Nevada and Wyoming (grey squares) and Robin Marsett, with field campaigns conducted in Arizona and New Mexico (black circles).

We use the ground measurements of vegetation cover, in combination with the Marsett measurements, to relate ground observations of cover to satellite measurements, while we use the ground measured reflectance spectra as part of our study on scaling between satellite platforms.

Marsett Ground Observations of Cover. As part of National Aeronautics and Space Administration (NASA)–funded research projects, ground measurements of total vegetation cover were taken in Arizona and New Mexico. About half of the field study sites were delineated as 90×150 m rectangles to accommodate 15 30-m Landsat pixels. This assured at least three pixels were uncorrupted by edge effects. Sites were chosen to maximize within-site homogeneity and to represent between-site heterogeneity in both vegetation and land use. The other field study sites were collected along 150-m transects. Identical measurement techniques were used in the plots and transects. The ground sites, located in eastern Arizona and western New Mexico, consist of 71 unique sites and a total of 92 observations, with some plots revisited two or three times over the course of 10 yr. These sites were chosen to represent a mix of biotic communities across western North America including semiarid desert grasslands, mixed grass grassland, subalpine parks, shortgrass prairie, open park woodlands, and Madrean woodland. Study sites included plots that were grazed and ungrazed, and contained native and nonnative vegetation, as well as riparian sites dominated by Sacaton (*Sporobolus wrightii* Munro ex Scribn). No ground-level reflectance spectra were collected at these sites.

SWReGAP Ground Observations of Cover. The SWReGAP (USGS National Gap Analysis Program, 2004; Lowry et al. 2007) involved the mapping and assessment of biodiversity and was coordinated by the USGS. As part of this effort, collaborators observed and reported ocular estimates of vegetation cover. These observations were collected in the SWReGAP training site database. Here, we used the training site database for the state of Arizona and select only the sites marked as representing greater than 25 ha ($n = 141$).

Remotely Sensed Observations. We used remote sensing data from three sources.

Landsat Data. We acquired and processed all available Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images that were free of cloud/cloud shadow near the field sites and were imaged less than 50 d before or after the field visit (Table 2; 46 total images). The images were downloaded from the USGS Earth Resources Observation and Science Center and were provided as terrain-corrected digital numbers (L1T). We converted the digital numbers to radiance using gains and offsets obtained from the metadata for each image and subsequently to reflectance at the top of the atmosphere using mean exoatmospheric solar irradiance values for each band from Chander et al. (2009). For Landsat ETM+ data acquired after May 2003 when the scan line corrector failed, we used the data for a site only if more than 80% of the site's pixels were not missing. For comparisons to MODIS observations, we reprojected the Landsat imagery to the sinusoidal projection.

MODIS Reflectance Data. Nadir-corrected surface reflectance observations from Aqua and Terra (MCD43A4) were downloaded from the NASA data pool. Images from two tiles (h08v05 and h09v05) were acquired to coincide with a subset

Table 2. Summary of the field campaigns and Landsat data used in scaling from ground measurements of vegetation cover to the Landsat scale. The table lists field data source, field visit year, field visit dates in ordinal day of year, number of field sites associated with the field visit, Landsat path row covering the location of the field visit, and number of minimal cloud Landsat scenes available within the ± 50-d window for the field campaign. A total of 43 Landsat scenes were used in this analysis.

Field data				Landsat	
Source	Visit year	Visit DOY[1]	No. of sites	Path/row	No. of scenes
Marsett	2000	101–117	8	035/038	4
Marsett	2000	254–257	7	035/038	4
Marsett	2001	129–157	8	035/038	1
Marsett	2001	247–270	5	035/038	2
Marsett	2002	204	3	035/038	2
Marsett	2002	259–269	3	035/038	2
Marsett	2007	272	6	035/038	3
Marsett	2010	308	4	035/038	1
Marsett	2010	297–299	15	036/036	2
Marsett	2008	114	9	035/036	1
Marsett	2010	154	16	033/037	3
Marsett	2001	283–284	2	033/037	3
Marsett	2002	257–258	3	033/037	2
Marsett	2001	282	1	034/038	3
Marsett	2002	255–256	2	034/038	2
USGS	2003	167–173	20	043/031	2
USGS	2004	165–169	8	043/031	1
USGS	2002	185–192	11	037/029	3
USGS	2004	182–183	1	037/029	2

[1]DOY indicates ordinal day of year; USGS, US Geological Survey.

of Landsat overpasses for use in the scaling analysis. Additionally, images from the same two tiles were processed for Arizona as part of the independent validation. These data were screened for cloud, cloud shadow, and sensor anomalies and used in the original sinusoidal projection.

MODIS Vegetation Continuous Fields Data. The Global Land Cover Facility processed MODIS surface reflectance observations to produce a VCF product (MOD44B) that is available via an ftp server (ftp://ftp.glcf.umd.edu; Hansen et al. 2003). The data used in this study were extracted from the North America 2001 product and include estimates of tree, herbaceous, and bare ground cover at a spatial resolution of 500 m.

Other Data Products. We used four additional products to preprocess and subset the above data sets for analysis.

Arizona Ownership Polygons. Ranchers and land managers require information on rangelands at the pasture or ranch scale. We utilized parcel boundary vectors (i.e., polygons) for grazed lands overseen by the USFS, by tribes, and by the State of Arizona. The polygons used were from the Arizona State Land Department, USFS, BLM, NRCS, and Arizona Geographic Information Council. Overlapping polygons were checked for spatial consistency and each polygon was reviewed against aerial photography for parcel accuracy. We used grazing district boundaries to subdivide very large land units with no internal ranch boundaries, or where not available, we used eight-digit Hydrologic Unit Code watersheds. All information used here is publicly available. There are 2 885 ownership allotments across Arizona that range in size from 4 ha to 604 275 ha; 90% of these are between 120 ha and 33 000 ha, with a median size of 2 872 ha.

The Nature Conservancy Grasslands Map. In 2003, The Nature Conservancy published a map that identified six primary grassland condition types in Arizona (Gori and Enquist 2003). The purpose of the study was to characterize the extent of the vegetation changes to grasslands and to identify the remaining native grasslands and restorable grasslands for conservation planning. We used this map to isolate grassland for use in our scaling analysis.

Shuttle Radar Topography Mission (SRTM) Elevation Data. The SRTM digital elevation data are publically available through the USGS (USGS 2004). Using a topography model, we estimated slope at the MODIS scale (500 m) and selected only those pixels with low slope (i.e., less than 8°) for use in our scaling analysis to minimize the influence of shadows from the landscape on our results.

Santa Rita Experimental Range (SRER) Cattle Grazing Data. The SRER is a research ranch administered by the University of Arizona's College of Agriculture. Pasture boundaries and a table containing livestock grazing schedule are available online (http://ag.arizona.edu/srer/). In this study, these data were used to examine the sensitivity of satellite-based estimates of cover to the effects of grazing.

Analytical Approach

Our objective is to identify a simple and robust combination of reflectance bands that is both sensitive to green and senescent vegetation and scalable to MODIS, and therefore useful for monitoring fractional total vegetation cover in rangelands across large regions. We recognize that the strength of the relationship between ground-measured cover and remotely sensed observations will be reduced as more diverse regions of grassland and rangeland are incorporated into a simple analysis. This effect is expected for several reasons. Most importantly, residual atmospheric contamination in imagery acquired from different times is expected, the spectral properties of plant communities vary between regions, and ground estimates of cover have inherent inaccuracies that are not always consistent. However, by identifying a relationship between the satellite observations and the ground measurements of cover across a variety of seasons and ecosystem types, we increase our chances of establishing a robust, operational approach to monitoring rangelands.

Scaling From Ground Measurements to Landsat. We combined field observations of total vegetation cover from two collections, the USGS Digital Spectral Library and the Marsett data set, with our Landsat observations. Depending on the size and shape, field plots were represented in the Landsat data by between 2 and 14 30-m pixels. The mean, standard deviation, and coefficient of variation (cv) of each spectral band was calculated for every field site for each date. The cv was used to identify potential problems in the reflectance data or the geometric registration, as each field site was selected to be relatively homogeneous. To reduce residual noise from remote sensing artifacts in the data (e.g., geometric registration uncertainties, residual effects of sun-sensor geometry changes from scene to scene, etc.), we averaged the mean plot reflectance from all relevant dates for the sites with corresponding Landsat imagery from multiple dates within the temporal window. The USGS plots are less than one-quarter the size of a Landsat pixel and are occasionally situated in areas with considerable topographical heterogeneity. We selected a subset of sites from the USGS database for use in our study based on the similarity between ground-measured reflectance and Landsat-measured reflectance. After this screening process, our data set consisted of 40 observations from the USGS Digital Spectral Library and 92 observations from the Marsett database for a total 132 observations of field-measured total cover and associated Landsat reflectance data.

We examined the relationship between field-measured total vegetation cover and 37 Landsat-derived spectral bands, simple band ratios, and indices. These included seven original spectral bands (i.e., blue, green, red, near-infrared, the two shortwave-infrared bands, and a thermal band), the simple ratio between each of the original spectral bands, and nine vegetation indices (Table 3). The nine vegetation indices tested here come from a wide range of applications. NDVI and the enhanced vegetation index have been applied and tested for sensitivity to green vegetation cover (Tucker 1979; Huete et al. 2002). The other seven indices have been used to map land surface properties such as crop residue cover and senescent vegetation. The soil-adjusted total vegetation index (SATVI) was developed and tested more recently for grassland applications (Qi et al. 2002; Marsett et al. 2006; Lebed et al. 2008). We also tested four indices developed and typically applied in the monitoring of tillage practice, because crop residue cover and senescent vegetation found in rangelands share common properties. Daughtry et al. (2006) tested the normalized difference tillage index (NDTI) and the normalized difference senescent vegeta-

Table 3. Formulas for the vegetation indices used in this analysis and the source for these formulas.[1]

Index	Formula	Source
NDVI	(NIR − RED)//(NIR + RED)	Tucker 1979
EVI	2.5 · (NIR − RED)/(NIR + 6.0 · RED − 7.5 · BLU + 1.0)	Huete et al. 2002
SATVI	1.1 · (SWIR1 − RED)/(SWIR1 + RED + 0.1) − SWIR2/2.0	Marsett et al. 2006
SATVIp	1.1 · (SWIR1 − RED)/(SWIR1 + RED + 0.1)	Qi et al. 2002
NDSVI	(SWIR1 − RED)/(SWIR1 + RED)	Daughtrey et al. 2006
NDTI	(SWIR1 − SWIR2)/(SWIR1 + SWIR2)	Daughtrey et al. 2006
CRC	(SWIR1 − BLU)/(SWIR1 + BLU)	Sullivan et al. 2008
CRCm	(SWIR1 − GRN)/(SWIR1 + GRN)	Sullivan et al. 2008
STI	SWIR1/SWIR2	Sullivan et al. 2008

[1]NDVI indicates normalized difference vegetation index; NIR, near infrared; RED, red; EVI, enhanced vegetation index; BLU, blue; SATVI, soil-adjusted total vegetation index prime; SWIR, shortwave infrared; SATVIp; NDSVI, normalized difference senescent vegetation index; NDTI, normalized difference tillage index; CRC, crop residue cover index; CRCm, modified crop residue cover index; GRN, green; STI, simple tillage index.

tion index (NDSVI) for sensitivity to residue cover. Sullivan et al. (2008) applied three indices: the crop residue cover index (CRC), a modified CRC index, and the simple tillage index (STI) to map crop residue cover. SATVI, STI, and NDTI include the second shortwave infrared (SWIR) band that is onboard the Landsat and MODIS platforms, but is not available on other often-used satellites such as the Advanced Wide Field Sensor (AWiFS) or Système Pour l'Observation de la Terre (SPOT). Also, we included the Landsat thermal bands in the analysis but recognize that many commonly used sensors don't have a thermal band.

Scaling to MODIS. Ultimately, we are interested in identifying an effective method of estimating fractional cover of vegetation over large spatial regions at frequent time intervals. With currently available technology, this is likely best accomplished using observations of reflectance from MODIS. A great deal of information is available in the high temporal frequency of MODIS observations. At the same time, however, information is lost when scaling from ground observations to Landsat, and then to MODIS. When scaling from Landsat to MODIS, noise can be introduced in several ways. We categorized these sources of noise into three groups: bandwidth discrepancies, spatial resolution differences, and other differences in the platform sensor and processing systems. We estimated the magnitude of these sources of noise with three separate exercises.

Bandwidth Discrepancies. Using the USGS database of ground-measured reflectance spectra, which are measured at a fine spectral resolution, we explored the effects of differences in Landsat and MODIS spectral band windows. Although Landsat and MODIS acquire imagery in the same general bands, the spectral window of the bands is not identical. Using the USGS ground-measured spectral reflectance data gathered over rangelands, we simulated Landsat TM, Landsat ETM+, and MODIS observations by aggregating the relatively narrow ground-measured spectral reflectance into the broader satellite-based spectral bands. By comparing these simulated reflectance estimates from each instrument, we estimated the potential noise introduced when scaling from Landsat to MODIS and established a translation function to be used in the scaling process.

Effect of Sensor Spatial Resolution on Cover Estimates at the Ranch Scale. The rangeland conservationists at NRCS in Arizona typically assess range conditions at the ranch or pasture scale. Ranches in Arizona range in size from a few hectares to thousands of hectares. To examine the effect of image resolution on the quality of vegetation cover estimates in Arizona, we used a ranch ownership boundary layer for the state and two Landsat scenes (path 35 row 38 and path 36 row 39) resampled to simulate sensors with different spatial resolutions. Using the vegetation index with the best correspondence to ground observations, we resampled the Landsat scenes to three additional spatial resolutions: 60 m, 240 m, and 480 m, meant to approximate AWiFS, MODIS 250-m, and MODIS 500-m data. We then examined how the estimated cover at the ranch scale changes as a function of image resolution.

Residual Sensor Discrepancies. MODIS 500-m surface reflectance data (product MOD43A4) were extracted to correspond with nine of the Landsat scenes from Arizona. We focused on areas identified as grasslands by The Nature Conservancy with limited terrain variation as calculated from the SRTM data. The MODIS observations (n=634 361) were compared to the aggregated Landsat data acquired over the same time period. A translation function derived from the bandwidth discrepancies analysis was first applied to the Landsat observations to minimize other sources of quantifiable noise.

Error Propagation. Relationships between measured ground cover and Landsat reflectance, and between Landsat and MODIS reflectance were defined using linear regression models. The standard errors in the linear regression coefficients from both models were then used as two sources of error estimates to account for uncertainty from the ground measurements up through the MODIS scale. We used a non-parametric resampling approach called "bagging," which is based on the statistical theory of Efron and Tibshirani (1986), to estimate prediction intervals in cover estimates at the MODIS scale. In this bagging procedure, we generated replicates of the original data by randomly drawing, with replacement, residual values from each of the two regressions. A model was fit to each replicate data set and then used to predict cover values. This process was repeated 10 000 times and the distribution of predictions generated are used to estimate the 90% prediction intervals. With the bootstrap algorithm, there is no underlying assumption about the statistical distribution of the data.

Table 4. The Santa Rita pasture grazing schedule and the corresponding moderate-resolution imaging spectroradiometer (MODIS) imagery used in the analysis. The table lists the pasture name (corresponds with Fig. 7), size of the herd turned out on the pasture, date of cattle turn-out to and removal from pasture, date of MODIS composite used to represent pre- and postcattle conditions, and number of MODIS pixels covering the pasture.

		Cattle turn-out dates		MODIS composite, first day[1]		
Pasture name	Herd size	Start	End	Before	After	Pixels
6A	460	25 August 2010	3 September 2010	5 August 2010	6 September 2010	52
6E	420	5 November 2010	18 November 2010	24 October 2010	25 November 2010	17
2N	402	19 November 2010	5 January 2011	1 November 2010	9 January 2011	86
2S	396	6 January 2011	26 January 2011	19 December 2010	25 January 2011	25
3	441	27 January 2011	3 March 2011	1 January 2011	6 March 2011	79
5S	440	4 March 2011	14 April 2011	18 February 2011	23 April 2011	76

[1]The MCD43A4 surface reflectance composites used here are created from observations over a 16-d window. The date given here is the first day of the 16-d window.

Additionally, the approach allows us to quantify and account for the heteroskedastisity, or non-constant variance, within the prediction intervals (Hagen et al. 2006).

Comparison of Cover Estimates With Independent Sources. Direct comparisons between remotely sensed and ground-based measurements of cover at the MODIS scale (approximately 25 ha) are not feasible due to the costly and time-consuming logistics associated with direct measurement of such a large area. Therefore, validation of cover estimates at the 500-m MODIS scale relies on visual estimates and indirect observations.

Using the SWReGAP database (USGS National Gap Analysis Program 2004), we extracted ground cover estimates for the largest sites (greater than 25 ha) in Arizona and compared them with our MODIS-based cover estimates, providing an independent evaluation of our approach. We further tested our approach against the current, best available product, the MODIS VCF cover estimates. Although the same source sensor was used, our cover products differ from the VCF cover estimates in that our estimates are produced every 8 d between 2000 and today, whereas the VCF products are available only as an annual average for 2001. To perform this test, we compared the same ground-observed cover estimates from SWReGAP product to the MODIS VCF herbaceous-plus-tree cover estimates. Results from this comparison gave a measure of the level of improvement our products provide, if any, over the current, existing product.

Pasture maps and grazing plans from the SRER were used together with satellite-based estimates of cover from MODIS to evaluate whether grazing effects are detectible in satellite observations (Table 4). According the SRER records, one large herd (approximately 400 animal units) of cattle were moved as a group between seven pastures starting on 25 August 2010 and concluding 14 April 2011. We examined six of those pastures for evidence of grazing (the seventh pasture was occupied between 4 September 2010 and 4 November 2010, but boundary information is not available via the SRER website). To do this, we subtracted the MODIS-based cover after grazing from the MODIS-based cover before the cattle were turned out and compared this difference to the difference calculated over the same time period on ungrazed pastures. The pastures range in size from 25 ha to 300 ha and are represented by a minimum of 20 MODIS pixels. Because grazing and the associated effects are not uniform over the entire pasture, we analyzed the distribution of cover within these pastures in the form of density plots. To minimize changes in cover associated with seasonal weather, we normalized these density plots by subtracting the mean change in the MODIS-based cover in ungrazed pastures from the measured changes in all pastures during that time period. We then compared each grazed pasture to the simultaneously ungrazed pastures using a Student's *t*-test.

RESULTS

Scaling From Ground Measurements to Landsat

The data from USGS and Marsett are from very different locations and ecosystem types and have a different distribution of vegetation cover (Fig. 2). These data sets were selected in part because a model that fits data from a wide range of vegetation communities is more likely to be widely applicable across the Western rangelands.

Our full examination of Landsat bands, band ratios, and indices and the relationship of each with ground-measured cover identified three combinations that are better than all others, all with R^2 values over 0.5. SATVI has the highest R^2 (0.55) and lowest root mean square error ($RMSE$=11.1; Fig. 3). NDSVI and the simple ratio of SWIR (SWIR1) to red reflectance perform nearly as well (R^2=0.52 and 0.50 and $RMSE$=11.5 and 11.7, respectively) and don't require the

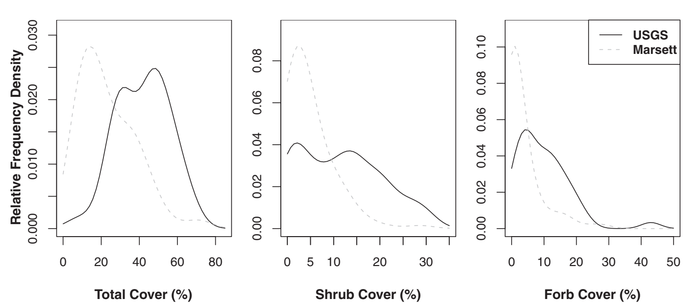

Figure 2. The two sources of field-measured cover come from areas with appreciably different cover distributions. The field sites measured by the US Geological Survey (USGS) in Nevada and Wyoming (solid line) have higher total vegetation cover than the plots measured by Marsett (dashed line) in Arizona and New Mexico. The USGS field sites have higher forb and shrub cover, as well.

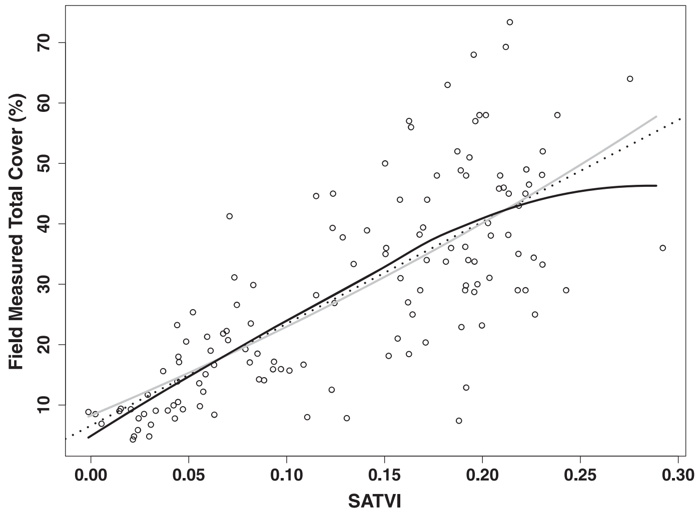

Figure 3. After the soil-adjusted total vegetation index (SATVI) was identified as the best candidate, three model frameworks were tested to find the best fit between SATVI and ground-measured total cover (%). The Akaike Information Criterion indicated that simple linear regression (dotted) was the best model. The loess regression (solid black) and the exponential regression (solid grey) were not as good fits to the data. Each of these three models behaves differently at high SATVI levels, indicating lower certainty at high levels.

second SWIR band that is available on Landsat, making these measurements appropriate for use with data from AWiFS and SPOT. The red and SWIR1 spectral bands are the only bands that appear in each of the top three performing indices and ratios, suggesting these bands are the most sensitive to total vegetation cover in rangelands.

We fit three types of models to identify the optimal relationship between SATVI and TVFC: linear, locally estimated smoothing (loess; Cleveland, 1979), and exponential (Fig. 3). These types of models and the associated goodness-of-fit to the data are evaluated using the Akaike Information Criteria (AIC; Akaike 1973). The AIC is useful for model intercomparison and penalizes model complexity (i.e., additional parameters). Low AIC indicates better model fit and the AIC is lowest for the linear fit, indicating a 58% likelihood that it is the best choice to fit these data. The best model likelihood for loess based on the AIC is 33%, suggesting it is also an appropriate model choice. The optimal exponential fit is a distant third best fit. Vegetation indices are recognized to saturate and become nonlinear at higher leaf area index levels (Gamon et al. 1995), which we do not see here, most likely because rangeland areas, in general, and the sites included in this study, specifically, have low leaf area index levels relative to most vegetated regions.

Due to the AIC score, as well as its simplicity and the ease of use for prediction, the linear model is selected as the best fit. For Landsat data, the optimal SATVI to TVFC linear relationship is:

$$TVFC = 6.60 + 168.65 \cdot SATVI_{Landsat} \qquad [\mathbf{1}]$$

Scaling to MODIS

Bandwidth Discrepancies. There are small but significant differences in the spectral bands measured by the Landsat (TM and ETM+) and MODIS sensors. These differences can be minimized by applying a linear translation function (Table 5) to correct for any biases caused by the difference in sensor bandwidth. Using our SATVI to TVFC relationship (Equation 1) and the reflectance spectra available at the USGS rangeland sites, we examined the effect of changing from the Landsat to MODIS sensor on our cover estimates. If these translation functions are not applied, one could expect systematic overestimation of cover by approximately 0.25% at the low end (SATVI=0.0) and 1.8% on the high end (SATVI=0.3). Based on these results, correcting for bandwidth discrepancies between Landsat and MODIS is not a critical step in this scaling application.

Effect of Sensor Spatial Resolution on Cover Estimates at the Ranch Scale. By degrading Landsat reflectance data from 30 m to 60 m, 240 m, and 480 m and examining mean SATVI for each ranch, we isolated the effect of sensor spatial resolution on cover estimates. Our results show that imaging the region at 60 m, 240 m, and 480 m typically introduces errors to SATVI of 0.0005 (less than 1% of average SATVI), 0.002 (1%), and 0.005 (3%), respectively. In other words, our areas of interest

Table 5. Linear translation functions and the effect of spectral bandwidth differences across rangeland sites in the US Geological Survey database.

Response	Predictor	Band	*RMSE*[1]	R^2	Intercept	Slope
TM	MODIS	RED	0.0007	0.9994	−0.0008	1.0289
TM	MODIS	SWIR1	0.0021	0.9977	0.0046	0.9978
TM	MODIS	SWIR2	0.0022	0.9973	0.0081	0.9322
ETM+	MODIS	RED	0.0008	0.9992	−0.0011	1.0339
ETM+	MODIS	SWIR1	0.0021	0.9977	−0.0055	0.9953
ETM+	MODIS	SWIR2	0.0018	0.9982	0.0060	0.9449
TM	ETM+	RED	0.0001	1.0000	−0.0003	1.0049
TM	ETM+	SWIR1	0.0004	0.9999	−0.0010	0.9974
TM	ETM+	SWIR2	0.0005	0.9999	−0.0021	1.0131
TM	MODIS	SATVI	0.0029	0.9967	−0.0017	0.9649
ETM+	MODIS	SATVI	0.0027	0.9973	−0.0064	0.9686
TM	ETM+	SATVI	0.0007	0.9998	0.0046	0.9963

[1]RMSE indicates root mean square error; TM, Landsat Thematic Mapper; MODIS, moderate-resolution imaging spectroradiometer; RED, red; SWIR, shortwave infrared; ETM+, Landsat Enhanced Thematic Mapper Plus; SATVI, soil-adjusted total vegetation index.

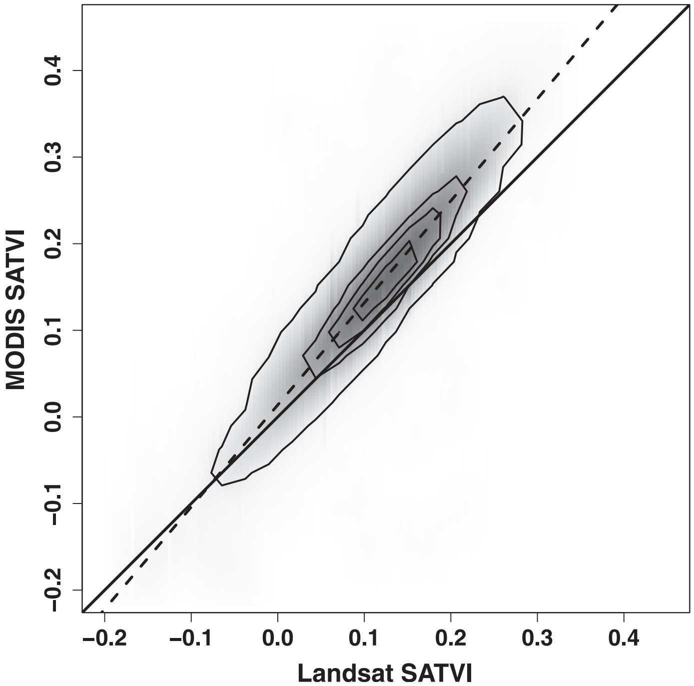

Figure 4. A density scatter plot of more than 600 000 soil-adjusted total vegetation index observations measured at two separate satellite platforms, moderate-resolution imaging spectroradiometer (MODIS) and Landsat, across nine Landsat scenes in Arizona shows high correlation (r=0.95; contours show density quartiles with the least dense region representing the 0.1 percentile through the 25th percentile). There is also a significant gain (0.76) that needs to be applied when scaling from Landsat to MODIS (dashed line is best fit; solid line is one-to-one line).

(i.e., ranches) are typically large enough and landscape variance is low enough that moving from 30 m to 60 m, 240 m, and 480 m introduces only modest additional error when estimating TVFC with remote observations. In areas with more landscape heterogeneity and smaller ranches, these scaling errors will be larger.

Residual Sensor Discrepancies. A linear comparison between MODIS- and Landsat-derived SATVI at the MODIS scale (500 m) shows high correlation (R^2=0.90) and a significant slope (Fig. 4). The 634 361 pixels from the nine Landsat scenes in Arizona show this relationship:

$$\mathrm{SATVI}_{\mathrm{Landsat}} = 0.0021 + 0.7605 \cdot \mathrm{SATVI}_{\mathrm{MODIS}} \qquad [2]$$

Although the bandwidth and scale differences between the sensors are the source of a small amount of error (less than 5%), residual sensor differences are the source of considerable noise. The high level of correlation indicates these differences are consistent across the domain studied here and, therefore, an additional linear translation function can be applied. The significant slope identified in the relationship between Landsat and MODIS SATVI is likely driven by fundamental differences in the MODIS and Landsat sensors, as well as differences in early stage data processing techniques applied at the data-providing agencies. Using the translation functions derived to account for bandwidth discrepancies (Table 5) combined with this scaling equation (Equation 2), we can produce a relationship between TVFC

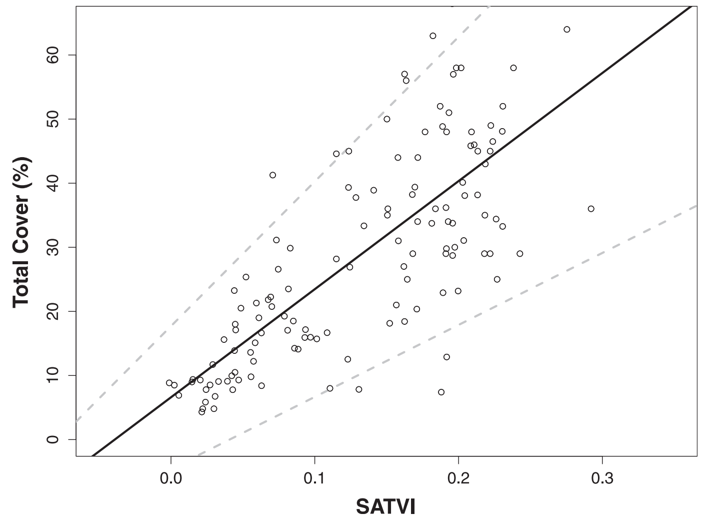

Figure 5. Using a bootstrapping approach to account for the heteroskedasticity, we estimate the uncertainty in the form of 90% prediction limits (dashed lines) for the linear relationship between soil-adjusted total vegetation index and total cover (%; solid line).

and MODIS-observed SATVI:

$$\mathrm{TVFC} = 6.65 + 123.76 \cdot \mathrm{SATVI}_{\mathrm{MODIS}} \qquad [3]$$

Error Propagation

The residuals from the best fit model are heteroskedastic, showing an increased variance as SATVI (and TVFC) increase. For this reason, we used a bagging approach to estimate the prediction intervals on MODIS-based estimates of TVFC. The 90% confidence limits derived from our bagging approach reflect the heteroskedasticity found in the relationship between the ground measurements of cover and the remotely sensed vegetation index (Fig. 5). At low SATVI levels, the 90% prediction limits around cover are typically

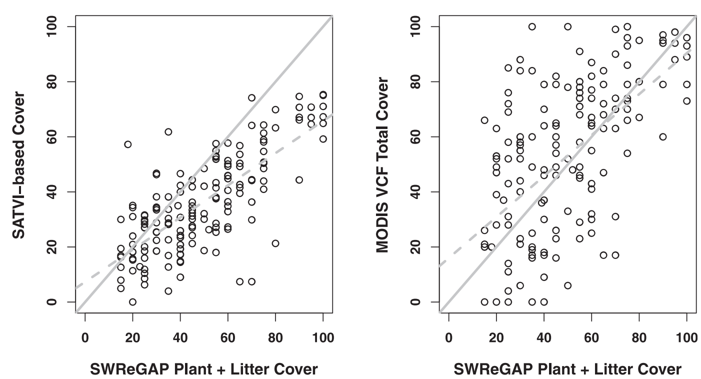

Figure 6. Comparison between the independent Southwest Regional Gap Analysis Project ground measurements of cover and moderate-resolution imaging spectroradiometer (MODIS)-based predictions of total cover (using the soil-adjusted total vegetation index [SATVI] relationship) and MODIS vegetation continuous fields (VCF) tree and herbaceous cover. The approach presented here using SATVI has a better relationship to ground observations of cover than the MODIS VCF cover product, which is the only other wide-area cover product available for comparison.

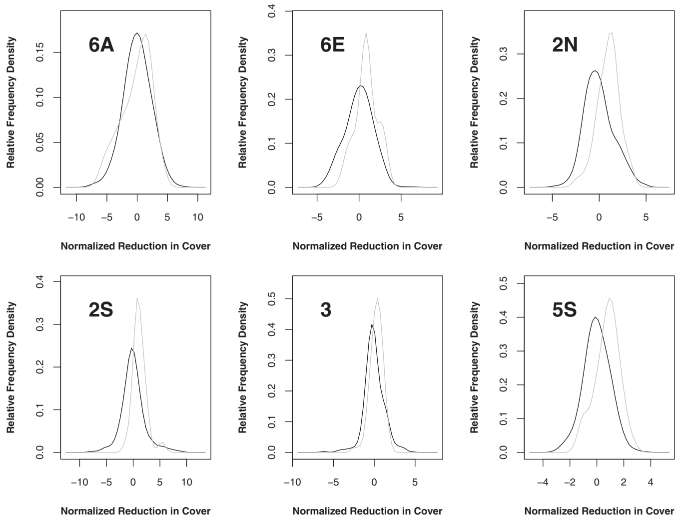

Figure 7. Moderate-resolution imaging spectroradiometer (MODIS) pixels in grazed pastures (grey) at the Santa Rita Experimental Range show a reduction in soil-adjusted total vegetation index–based total cover when compared with pixels from ungrazed pastures (black) in all six grazing periods, suggesting that MODIS provides useful information for rangeland management. The identification on each plot indicates the grazed pastures (from Table 4). The data have been normalized to minimize the effects of natural changes in cover due to phenology.

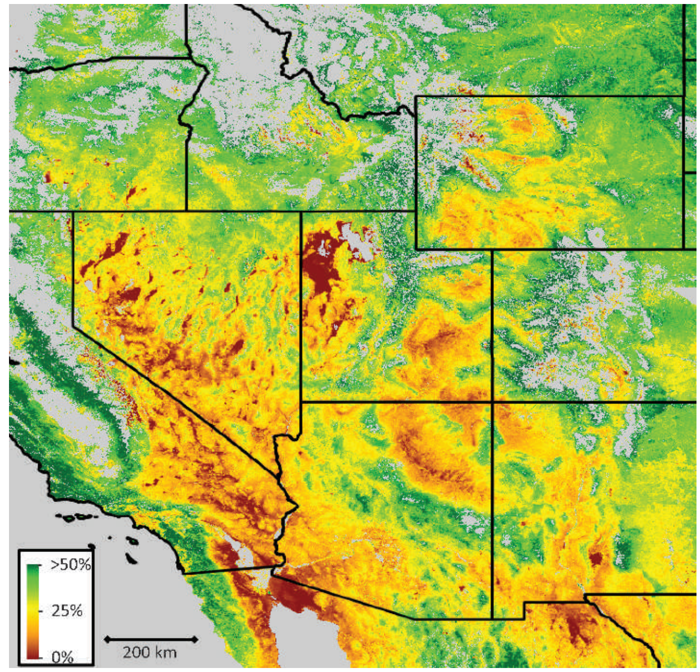

Figure 8. Eight-day moderate-resolution imaging spectroradiometer (MODIS) soil-adjusted total vegetation index (SATVI) measurements can be used to estimate the long-term average (2000–2010) total vegetation cover in western rangelands.

$\pm$10% cover. At high SATVI levels, our 90% prediction limits increase to $\pm$25% cover.

Comparison With Other MODIS Products and Publicly Available Ground Cover Estimates

A comparison of our estimates of TVFC in rangelands to independent ground estimates of cover collected as part of the SWReGAP project shows a high correlation ($r=0.75$; Fig. 6a), but also reveals a large intercept and slope ($TVFC_{SWReGAP}=14.72+0.95 \cdot TVFC_{MODIS}$). In other words, the remote sensing–based estimates of cover are consistently lower than the ground estimates of cover in the SWReGAP data set. Given the independent nature of these observations, as well as the mismatch in scale, this correlation is promising. Additionally, the standard MODIS VCF product is less correlated with the ground observations ($r=0.59$; Fig. 6b). These results indicate that the approach presented here is an improvement over existing methods of estimating fractional cover of vegetation in rangelands over large areas.

The density plots comparing grazed and ungrazed pastures show a greater reduction (or smaller increase) in MODIS-estimated cover within the grazed pastures during all six time periods examined (Fig. 7). Additionally, when combined into a single, normalized group, the mean changes in MODIS cover observed in grazed pastures are significantly greater than the mean changes measured from ungrazed pastures ($t=7.3$; $P<0.0001$). This analysis provides additional evidence that the MODIS-scale SATVI is sensitive to changes in rangeland total vegetation cover, and also to changes in vegetation as affected by grazing at the pasture scale.

DISCUSSION

We detail a robust method of mapping total vegetation cover in rangelands through time that can be applied to a very large area, such as the western United States. The approach outlined here can be used in an operational context and accounts for uncertainties in the scaling process, allowing users to test for statistical significance when comparing vegetation changes and trends. Discussion with rangeland managers in the field indicates variability in estimates of cover depending on the monitoring methods used. Consequently, some calibration of the remotely sensed estimates to field estimates may be needed for consistency with existing field-monitoring cover estimates. Nonrangelands (e.g., forests, deserts) and areas with significant topography were excluded from this analysis, so the operational application of the outlined methods does not apply to these areas.

This study confirms the findings of other studies that indicate the two SWIR bands and the red band provide the most sensitivity to differences in fractional cover of total vegetation in rangelands. While the focus here is on SATVI because of its superior fit to the field data, other combinations of the SWIR and red spectral bands can be used to achieve effective results. This is important to note, because many commonly used remote sensing platforms do not have a second SWIR band. Additionally, new satellite missions are being planned, such as the Joint Polar Satellite System, that will have spectral bands similar but not identical to those of current sensors. The approach identified here, while tuned to Landsat and MODIS observations, can be applied to data from a variety of sources. This research also makes several advances toward operational monitoring of public rangelands in the western United States (Fig. 8). Total vegetation cover products can provide rangeland managers with long-term annual or seasonal spatially detailed information (from Landsat), and temporally detailed information on vegetation dynamics, even in dry seasons (from MODIS). Even with those products in hand however, additional steps will be required for the operational application of that information on public lands. Rangeland managers will have to define acceptable error, realistically assess their institutional capability for monitoring based exclusively on field data, change official policies and procedures, and fund the processing of satellite imagery. Perhaps more importantly, rangeland managers and the remote sensing community together will have to develop and implement a hybrid monitoring and assessment approach to build on the complementary strengths of field observations, remote sensing, and potentially large scale aerial photography.

There are several applications and additions to the approach outlined here that would add valuable information needed by rangeland managers. Additional remotely sensed products that correspond to field-monitored variables, particularly related to plant composition, would speed the operational application of remotely sensed products. By combining this approach of estimating total vegetation cover with the more commonly applied green vegetation indices such as NDVI, the potential exist to examine the timing patterns of senescent and green vegetation cover (phenology), potentially yielding important information about species, including brush encroachment and invasive grasses. Total cover estimates derived from satellite information over a decade can be used to compare the relative effectiveness of rangeland management techniques and programs on a scale not previously possible. This type of comparison can help management agencies make better decisions about protecting and conserving rangeland.

IMPLICATIONS

The remotely sensed total canopy cover estimates provided through this approach can be used to assist public and private rangeland management. For public rangeland managers, the application of remotely sensed information on canopy cover is useful to the core functions of inventory (describing the current status of rangeland resources), monitoring (detecting change in rangeland resources, particularly in response to management and in relation to management objectives), and assessment (the interpretation of monitoring results in relation to management objectives and the resulting revision of the management plan). Operational application of remotely sensed information can strengthen the adaptive management of the large areas under public management, as well as the private rangelands getting technical advice from the NRCS. A particular strength of landscape-scale remote sensing over field-based methods is the ability to compare across ownership units with a consistent observation method that considers all rangeland management units, including ungrazed areas. Remote sensing–based products are ideal for use in tandem with ground measurements, where the remote sensing–based products allow for more efficient use of expensive ground-based measurements. Using remote sensing–based measurements, land managers can prioritize rangeland areas in need of further attention with the more expensive field visits by managers. Remote sensing–based products can also be used to premap allotments before site visits, providing information on trends in cover and saving the land manager time.

Because public rangeland managers are technically trained and legally responsible to manage very large areas, they are likely to be the initial adopters of new remotely sensed monitoring tools. Professional range conservationists should be the initial target audience for this type of tool as they are responsible for a much larger area than individual ranchers, they will only be able to personally visit a small fraction of the land to be managed in any given year, and any required training across an area the size of a state would be limited to dozens of individual conservationists, rather than hundreds or potentially thousands of ranchers. While ranchers could also benefit, their need is not as great: an observant rancher will be able to see, if not easily document, changes across a ranch-sized area due to weather, grazing, fire, and invasive species. An additional advantage of large-area monitoring of rangelands is the potential to observe processes that occur at continental scales. Often rangeland regulation is focused at the site or ranch level and leaves patterns in rangeland condition at the continental scale largely unexplored. Having large-area monitoring tools will enable improved assessment of exogenous processes, such as shifts in phenological timing or fire fuel load resulting from changing climate patterns. Further, the ability to gauge rangeland condition over continental scales allows for better quantification of potential changes or loss in ecosystem services provided by rangeland ecosystems.

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