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Monitoring the Impact of Grazing on Rangeland Conservation Easements Using MODIS Vegetation Indices☆

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ABSTRACT

Monitoring the effects of grazing on rangelands is crucial for ensuring sustainable rangeland ecosystem function and maintaining its conservation values. Residual dry matter (RDM), the dry grass biomass left on the ground at the end of the grazing season, is a commonly used proxy for rangeland condition in Mediterranean climates. Moderate levels of RDM are correlated with soil stability, forage production, wildlife habitat, and diversity of native plants. Therefore RDM is widely monitored on rangeland conservation properties. Current ground-based methods for RDM monitoring are expensive, are labor intensive, and provide information in the fall, after the effects of grazing have already occurred. In this paper we present a cost-effective, rapid, and robust methodology to monitor and predict RDM using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data. We performed a time series analysis of three MODIS-based vegetation indices (VIs) measured over the period 2000–2012: Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Fraction of Photosynthetically Active Radiation (FPAR). We examined the correlation between the four VIs and fall RDM measured at The Nature Conservancy's Simon Newman Ranch in central California. We found strong and significant correlations between maximum VI values in late spring and RDM in the fall. Among the VIs, LAI values had the most significant correlation with fall RDM. MODIS-based multivariate models predicted up to 63% of fall RDM. Importantly, maximum and sum VIs values were significantly higher in management units with RDM levels in compliance with RDM conservation easement terms compared with units out of compliance. On the basis of these results, we propose a management model that uses time series analysis of MODIS VIs to predict forage quantities, manage stocking rates, and monitor rangeland easement compliance. This model can be used to improve monitoring of rangeland conservation by providing information on range conditions throughout the year.

Introduction

Rangelands provide important ecosystem services, including water filtration, soil stability, and wildlife habitat, and encompass great biodiversity (Cingolani et al., 2005; Ferranto et al., 2011). These ecosystems serve as a substantial carbon sequestration pool, accounting for 20% of the world's soil carbon (Follett and Reed, 2010). In addition, rangelands are often grazed by livestock and are a large component of the meat and dairy production in the western United States and across the world (Follett and Reed, 2010). Although overgrazing of rangelands has led to land degradation and in some cases to desertification (Dregne, 2002), moderate grazing that ensures regeneration processes and biodiversity protection can serve as an economically viable land use that helps to preserve rangelands from land transformation (Watkinson and Ormerod, 2001; McIntyre et al., 2003). Indeed, many conservation organizations maintain sustainable livestock grazing on their conservation easement and fee-owned properties (Reiner, 1999; Hacker et al., 2010). Therefore, monitoring the effects of grazing on rangeland conditions is essential for long-term management and stewardship. To decrease the extensive time, labor, and economic resources demanded by rangeland monitoring, many proxies for rangeland condition have been developed. One of the most widely applied proxies is residual dry matter (RDM), the dry grass material left on the ground in the fall, at the end of the grazing season (Bartolome et al., 2007). Currently, RDM levels are used as a key conservation easement compliance requirement (Reiner, 1999).

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Extensive literature shows the relationship between RDM levels and several aspects of rangeland productivity and conservation. For example, intermediate RDM promotes grass regeneration and supports higher forage production in the next growing season (Allen-Diaz and Jackson, 2000; Bartolome et al., 2007). RDM quantities are also correlated with soil stability, nutrient cycling, water infiltration, and grass community health (Bartolome, 2002; Bartolome et al., 2007). Moreover, RDM is related to numerous biodiversity values, including native species diversity, marsh vegetation cover, habitat for wildlife and endangered birds, butterfly diversity, and native forb diversity (Diaz et al., 1998; Jackson and Allen-Diaz, 2001; Allen-Diaz et al., 2004; Allen-Diaz and Jackson, 2005; Cingolani et al., 2005; Richmond et al., 2012).

In California, RDM is monitored annually at a considerable cost across hundreds of thousands of acres of conservation lands. Currently, all estimates of RDM are ground based and are performed in the fall, at the end of the grazing season (Guenther and Hayes, 2008). RDM is monitored by clipping grass at sample points across the landscape or by double sampling, which uses calibrated visual estimation or a photo point system (Harris et al., 2002; Guenther and Hayes, 2008). Although the visual estimation methods are faster than destructive sampling, RDM monitoring is still time consuming and costly, especially when performed over large landscapes. Moreover, the typical ground-based method suffers from several potential drawbacks. First, insufficient sampling across large spatial scales can yield overly coarse estimates, with relatively wide error intervals. Second, it is challenging to compare results across observers, who vary over properties and years, because of observer-dependent subjectivity (Coulloudon, 1999). Finally, the effectiveness of RDM monitoring is limited because these data can be implemented only in the year following their collection.

In contrast to observer-collected monitoring approaches, remote sensing provides information to support a synoptic and temporal view of the landscape. Advances over recent decades in the application of remote sensing for monitoring and assessing rangeland ecosystems include forecasting forage yields, measuring primary productivity and vegetation cover, and quantifying the effects of restoration practices on forage productivity (Todd et al., 1998; Washington-Allen et al., 2006; Malmstrom et al., 2009). For example, the effect of implementing best management grazing practices on prairie cordgrass establishment was monitored using aerial photographs and the Normalized Difference Vegetation Index (NDVI) (Kamp et al., 2013). Rangeland vegetation cover, net primary productivity, and fire occurrence in Cerrado Pastures, Brazil, were assessed using three Moderate Resolution Imaging Spectroradiometer (MODIS)-based products: Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), and land surface temperature (Ferreira et al., 2013). NDVI was used to estimate stocking rates across large areas (Hunt and Miyake, 2006) and to model ecosystem performance in sagebrush habitat (Wylie et al., 2012). Washington-Allen et al. (2006) used Landsat time series to monitor degradation on rangelands and measure productivity, composition, soil erosion, and soil quality. More recently, Li et al. (2012) have demonstrated a model based on MODIS EVI and NDVI to measure Net Primary Production and forage production in pastures with different grazing regimens in California. Despite both these advancements and landowner interest, remote-sensing tools are not widely applied in rangeland management (Butterfield and Malmstrom, 2006; Karl et al., 2012), and remote sensing is not used for monitoring RDM.

The use of remote sensing to directly measure dry grass biomass presents a challenge (Huete, 1988; Roberts et al., 1993). RDM is measured in the fall, when grasses are typically senescent and nongreen (Guenther and Hayes, 2008). Low chlorophyll content of senescent vegetation reduces the red-to-near infrared (NIR) spectral contrast, which hinders the ability to distinguish vegetation from the background soil (Huete, 1988; Butterfield and Malmstrom, 2009). Although the literature on the application of remote sensing for estimating dry vegetation biomass is substantial, the following examples are particularly relevant to this paper. Hand-held devices (Wang et al., 2013), hyperspectral sensors (Arsenault and Bonn, 2005), and Landsat and ASTER satellites (Serbin et al., 2009, 2013) have all been used to measure dry vegetation remotely. For example, Harris and Asner (2003) used hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) to detect photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and bare soil cover on a gradient of grazing pressures, while the Soil-Adjusted Total Vegetation Index (SATVI) has been used to measure both green and dry vegetation cover and biomass (Marsett et al., 2006). In a more recent case, ground data were combined with MODIS and Landsat satellite data to produce estimates of total and senescent vegetation cover (Hagen et al., 2012). Many recent developments in the application of remote sensing for assessing nongreen vegetation focus on the measurement of crop residue on agricultural land (Arsenault and Bonn, 2005; Zhao et al., 2012; Zheng et al., 2012). For example, the Normalized Difference Tillage Index (NDTI), the Shortwave Infrared Difference Residue Index (SINDRI), and the Cellulose Absorption Index (CAI) have been used to measure dry crop residue cover and to classify the effects of different tillage practices (Watts et al., 2011; de Paul, 2012). These methods often require extensive field work, are expensive, and need specialized training and preprocessing steps, which makes them impractical for extensive management application.

In contrast to the previously mentioned methods, in this paper we present a rapid, cost-effective, and near-real-time system to monitor annual rangeland forage production and to estimate RDM using freely available Terra-MODIS satellite imagery. Our overall objective is to examine the relationship between MODIS-derived vegetation indices and RDM in a variety of spatial and temporal resolutions and habitat types, in order to determine if there is a reliable protocol that can help rangeland managers to monitor RDM with freely available remote sensing data. Our specific objectives were to 1) determine which of three MODIS-driven vegetation indices (VIs): NDVI, LAI, and Fraction of Photosynthetically Active Radiation (FPAR), best predicts RDM; 2) identify which covariates improve RDM prediction; 3) assess whether vegetation indices can be used across habitats to identify management units in and out of RDM easement compliance; and, on the basis of the results of these three steps, 4) identify a model that uses MODIS data for improved RDM monitoring and management. This management model is a three-step approach that uses remotely sensed vegetation indices in three modes during the grazing year: *prediction* in early spring, *management* for the whole year, and *monitoring* RDM in the fall. To our knowledge, this is the first time remote sensing has been used in a direct easement compliance context to measure RDM.

Methods

Study Site

The Simon Newman Ranch is a 133 km^2 property located in Stanislaus and Merced Counties, California, United States (37°20′N, 121°10′W). It was selected as the study site because it is managed to achieve land conservation alongside a sustainable grazing regimen. The property has been owned by The Nature Conservancy (TNC) since 1998. TNC annually monitors the compliance of the ranch's land management activities against conservation easement terms developed for conservation objectives. The topography is hilly and rocky in the west and flat in the east. The climate is dry-Mediterranean, with average annual precipitation of 280 mm. yr^{-1}

and temperature ranging between 2–12°C (daily min–max) in the winter and 16–36°C in the summer. The prevalent vegetation types are annual grassland, chaparral, oak woodland, and riparian vegetation. The annual grasses are dominated by exotics that produce most of their yearly growth between February and June. The prevalent oak species are Blue Oak *(Quercus douglasii)* and Valley Oak *(Quercus lobata)*. The property is divided by fences into 56 pastures, or management units (Guenther, 2005).

Data Acquisition

RDM Data

We used RDM data, collected annually in the Simon Newman Ranch for the years 2000–2012 (Guenther, 2005), to ground truth our method of estimating RDM. These data were collected in early October each year, at the end of the grazing season, using photographed reference monitoring sites ("photo points"), as described by Guenther (Guenther and Hayes, 2008). Zones with similar RDM value were delineated visually around each reference site and varied in size between 0.1 and 8 km^2 (Guenther, 2012).

RDM Classification

TNC's conservation easement terms require quantitative fall RDM goals for each management unit. At the Simon Newman Ranch, management units dominated by grassland or riparian vegetation have an RDM goal of 750–1 000 lb · acre^{-1} (841–1 121 kg · ha^{-1}), while management units dominated by oak woodland or chaparral vegetation have an RDM goal of 1 000–1 500 lb · acre^{-1} (1 121–1 681 kg · ha^{-1}) (Guenther, 2012). Note, use of non-metric units is retained because these are the units currently used by TNC managers. Although RDM is a continuous value, RDM in the Simon Newman Ranch is measured and reported as a categorical value (Table 1).

GIS Data

Geographic information system (GIS) layers for the Simon Newman Ranch included the property boundary, boundaries of the management units, locations of the ground measurement reference points, and the vegetation type at each management unit. GIS data were available in Universal Transverse Mercator (UTM, 1983) NAD83/UTM Zone 10N (Snyder 1987) projection. For the analysis, we re-projected our GIS layers to the sinusoidal projection of MODIS satellite data.

Terra-MODIS Satellite Data Acquisition

We used Terra-MODIS satellite imagery as our source of data because it has many advantages for efficient conservation management implementation. MODIS satellite imagery is freely available through NASA's Reverb system (EODIS, 2013), in a preprocessed, geo-referenced, and atmospherically corrected form (Solano et al., 2010). In this paper we used three Terra-MODIS VIs: NDVI, LAI, and FPAR. These VIs' product algorithms are confirmed with extensive modeling and ground-based data (LP DAAC, 2000-2012; Solano et al., 2010). The MODIS sensor has daily earth coverage: daily data is averaged over 16 or 8 days, for NDVI or LAI/FPAR products, respectively. The 250 × 250 m (0.065 km^2) spatial resolution of MODIS-NDVI and 1 × 1 km resolution of MODIS-LAI and -FPAR are adequate for measurement of aboveground biomass on each management unit because the ground-based RDM was estimated for zones with an average size of 1.9 km^2 (Guenther, 2012). Because one MODIS scene covers most of California, it can be used to analyze multiple conservation properties. We acquired MODIS LAI and FPAR data for 2002–2012 (LP DAAC, 2002-2012) and NDVI data for 2000–2012 (LP DAAC, 2000-2012) (Table 2).

NDVI is calculated using the formula $NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$, where ρ_{red} and ρ_{NIR} are the reflectance measured by the satellite sensor in the red (centered at 645 nm) and near infrared (858 nm) wavelengths, respectively (Tucker et al., 1981). The relationship between NDVI and green aboveground biomass has been well established (Tucker, 1979; Gamon et al., 1995). Although we have predicted that NDVI would capture grass productivity well, we examined two additional VIs that we thought might improve quantification of dry biomass in the fall. MODIS-based LAI and FPAR use information on canopy structural attributes and spectral properties. Hence these indices might provide better prediction than NDVI of dry vegetation biomass (Knyazikhin et al., 1999). LAI is an important structural property of a plant canopy because it measures the number of equivalent layers of leaves in the vegetation, relative to a unit ground area (Knyazikhin et al., 1999; LP DAAC, 2002–2012). FPAR is a unitless fraction that measures the proportion of radiation that the canopy absorbs, out of the total available radiation in the photosynthetically active wavelengths of the spectrum, 400–700 nm. Research has demonstrated that both LAI and FPAR are more strongly correlated with senesced grass height and biomass than is NDVI (Butterfield and Malmstrom, 2009).

We compared which of the three VIs most accurately predicts RDM levels and RDM easement compliance. We removed null VI values and resampled FPAR and LAI data to 250 × 250 m pixel resolution, to match the resolution of NDVI data.

Climate Data

Detailed climate data for the Simon Newman Ranch were obtained from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) database (PRISM Climate Group, 2000–2012). We used monthly rainfall data for 2000–2010, at a resolution of 0.0416 decimal degrees (PRISM Climate Group, 2000–2012).

GIS Spatial Statistics

We extracted values of three MODIS VIs for the whole Simon Newman Ranch and for each of the 56 management units, using the

Table 1
Residual dry matter (RDM) classifications for the Simon Newman Ranch.

RDM categories for 2000–2007		RDM categories used after 2008		
Category	RDM class (kg·ha^{-1}) [1]	Class	RDM value for grassland/riparian vegetation (kg·ha^{-1})	RDM value for oak woodland/chaparral vegetation (kg·ha^{-1})
	–	Very low	<112	<112
1	336	Low	<336	<560
2	560	Below	336–841	560–1121
3	785	Meets	841–1121	1121–1681
4	1121	Exceeds	1121–1681	1681–2242
5	1681	High	1681–3363	2242–4483
6	3363 (added 2007)	Very high	>3363	>4483

[1] lb·acre^{-1} is the common unit used by rangeland managers in the Simon Newman Ranch and in RDM measurement reports. We have converted it to the scientific unit of kg·ha^{-1} in Table 1.

Table 2
Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation indices used in this research and the parameters of each index.

Vegetation index shortcut	Vegetation index name	MODIS product name	Temporal resolution	Spatial resolution	Boolean dates and years used	Data range	Scale factor
NDVI	Normalized Difference Vegetation Index	MOD13Q1	16 days	250 × 250 m	049.2000–275.2010	−2 000, 10 000 Fill value: −3000	0.0001
FPAR	Fraction of Photosynthetically Active Radiation	MCD15A2	8 days	1 × 1 km	185.2002–321.2010	0–100 Null values: 249–255	0.01
LAI	Leaf Area Index	MCD15A2	8 days	1 × 1 km	185.2002–321.2010	0–100 Null values: 249–255	0.1

Zonal Statistics ++ Auto function in Hawth's tools extension in ArcGIS 9.3 (Beyer, 2004). We extracted PRISM rainfall data for the property, using the same methodology.

Statistical Analysis

Time Series Analysis of VIs and RDM

We constructed a time series for each VI in order to characterize the vegetation productivity patterns over time and their responses to rainfall at the Simon Newman Ranch. In California's Mediterranean climate, the growing season starts with the onset of rains in the fall of the previous calendar year and concludes with grass senescence in the current calendar year (Allen-Diaz and Jackson, 2005). Therefore we consider a particular "growth year" to start from mid-October of the preceding year until mid-October of the current year; for example, data for year 2011 used data from 16 October 2010 to 15 October 2011. This approach synchronizes VI and rainfall time series with the timing of RDM data collection in October. All statistical analyses for each of the three VIs were performed separately for the whole property, as well as for each individual management unit. RDM values for the whole property were calculated as an area-weighted average of RDM values for all the management units.

We calculated the following summary statistics values for each growth year, for each VI: annual average, annual median, annual standard deviation, annual minimum, date of minimum occurrence, annual maximum, and date of maximum occurrence. Additionally, we calculated the annual sum of the VI values in a growth year, defined as $\sum_{i=1}^{n} \mathrm{VI}_i$, where i is each date the VI is calculated by MODIS (n is 23 or 46, for NDVI or for LAI/FPAR, respectively). We also calculated the length of the growing season, which we define as the number of days VI levels exceeded 50% of the difference between the minimum and the maximum VI value for that year.

Linear and Multivariate Regression

We performed regression between RDM and each VI at two spatial scales: the whole property and each management unit. Because one of the goals of our analysis is to identify which MODIS-based VI is the most useful as a management tool for RDM prediction, for all the statistical analyses that follow, we created separate models for each of the three VIs, NDVI, LAI, and FPAR, as elaborated more fully later. Additionally, in line with our goal to have models useful to management, we focused on keeping our methods as simple as possible. We started with the simplest statistical model—one with only one prediction variable—because this requires minimal data acquisition. Thus to identify the VI and summary statistic that best predicts RDM, we performed a univariate linear regression between RDM, as the predicted variable, and each of the summary statistics values for each VI (i.e., for NDVI, LAI, or FPAR).

Next, we identified the multivariate regression models that best predict fall RDM values for each management unit because at this finer spatial scale a univariate model did not provide adequate

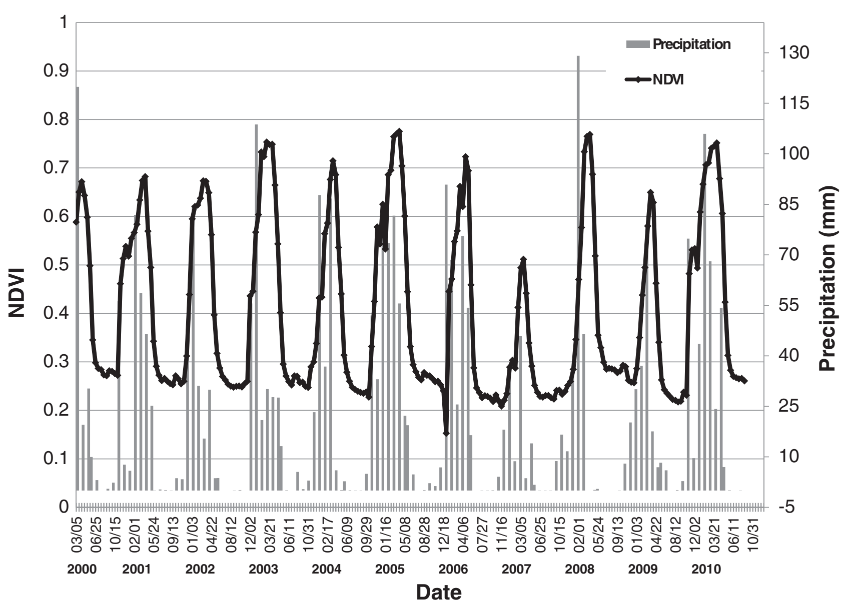

Fig. 1. Time series profile of Normalized Difference Vegetation Index (NDVI) and rainfall for the Simon Newman Ranch for 2000–2010. Each NDVI data point is a 16-day average extracted for the entire property. Bars represent monthly rainfall (in millimeters) for the ranch.

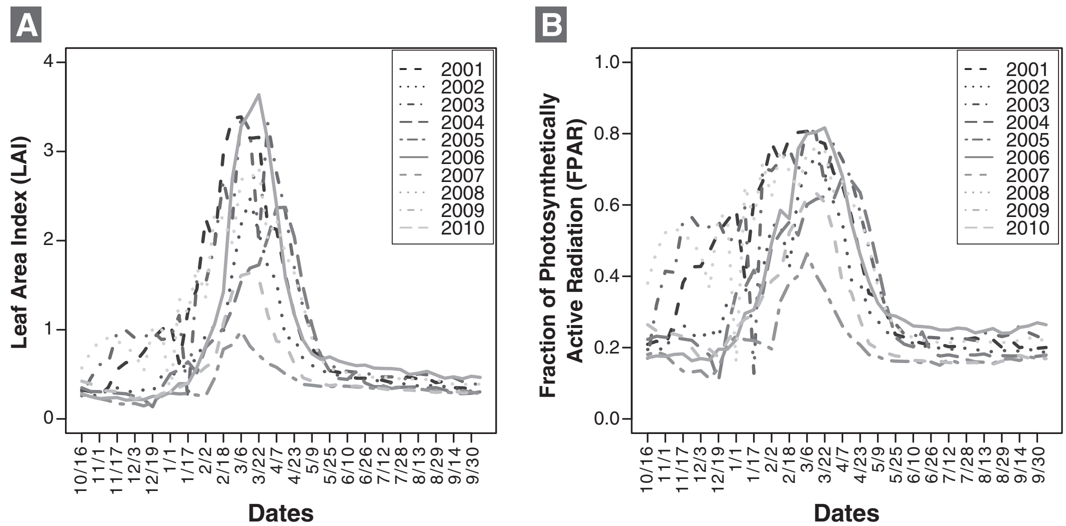

Fig. 2. Time series profile of vegetation indices (VIs) values for the Simon Newman Ranch. Each line represents one year from 2002–2010. **A,** Leaf Area Index (LAI). **B,** Fraction of Photosynthetically Active Radiation (FPAR).

predictive power. We included as covariates all the individual MODIS-measured VI values (23 or 46 values, for NDVI or LAI/FPAR, respectively) and their summary statistics (additional nine values). The year and vegetation type were included as categorical variables in the model. In order to optimize this model, to reduce the number of covariates used in the model, and to identify the most important parameters for RDM prediction, we performed an automated backward stepwise model selection procedure, which uses the Akaike Information Criterion (AIC) as the model selection criterion (Murtaugh, 2009).

Analysis of Variance (ANOVA)

To assess how well VI summary statistics measure RDM easement compliance, we performed ANOVA comparing VI values for management units in or out of compliance. The compliance threshold for each management unit was determined on the basis of its vegetation type, where RDM $\geq$ 750 lb $\cdot$ acre^{-1} (841 kg $\cdot$ ha^{-1}) is required for management units with grassland or riparian vegetation, and RDM $\geq$ 1 000 lb $\cdot$ acre^{-1} (1 121 kg $\cdot$ ha^{-1}) is required for management units with oak woodland or chaparral vegetation. We performed the analysis for NDVI, LAI, and FPAR, separately, and used the VI annual maximum, sum, and average values as predictors of compliance. To verify how well MODIS data predicted RDM in different habitats, we repeated the ANOVA including an interaction term for compliance and habitat type. We performed factorial ANOVA and then compared the averages of each combination pair, using Tukey Honest Significant Differences (HSD) to correct for multiple comparisons (Yandell, 1997).

Logistic Regression

We performed logistic regression to parameterize the relationship between RDM compliance and each VI. We calculated the log odds of management units in compliance compared with units out of compliance as a function of each of the three VI summary statistics using the glm function in R (family = binomial, link = logit) (R Development Core Team, 2007). We then repeated the analysis including the habitat type as a covariate in the regression, to measure how well MODIS predicted RDM in different habitats. We calculated the odds ratios and their 2.5% and 97.5% confidence intervals. We performed all statistical analysis using R 2.15.2 software (R Development Core Team, 2007).

Case Study: Monitoring 1-Year of Residual Dry Matter

After testing the process, we developed a standardized workflow in order to demonstrate a proof-of-concept monitoring framework that can be used by rangeland managers. In this section we describe how we applied this proposed management model with the Simon Newman Ranch data. In the “Management Application” section that follows, we further describe how this model can be applied by rangeland managers. Our workflow proceeds from imagery acquisition through multivariate analysis using LAI and is focused on the entire property, as well as individual management units.

We acquired LAI data for the entire Simon Newman Ranch and individual management units and analyzed them according to the methods described earlier. We then calculated baseline LAI values that coincide with RDM compliance for the whole property and for each habitat type. We used these baseline values in a three-step methodology during the grazing year: *prediction* of productivity in early spring, *management* for the whole year, and *monitoring* RDM in the fall:

Step 1: Prediction

We extracted LAI values in early spring (mid-March) of each year for the whole property and for each management unit. We compared these values to the MODIS-LAI time course (2002–2012), focusing on how current year LAI values compare with years when the property (or specific management units) were in versus out of compliance with RDM easement terms.

Step 2: Management

We mapped forage conditions as measured by spring LAI and RDM outcomes for each management unit. This evaluation of forage conditions can inform management early in the spring about appropriate stocking rates and cattle rotation.

Step 3: Monitoring

We extracted and plotted LAI values at the end of September of each year. We compared the annual LAI sum and average values for each year and at each management unit, to the threshold LAI value

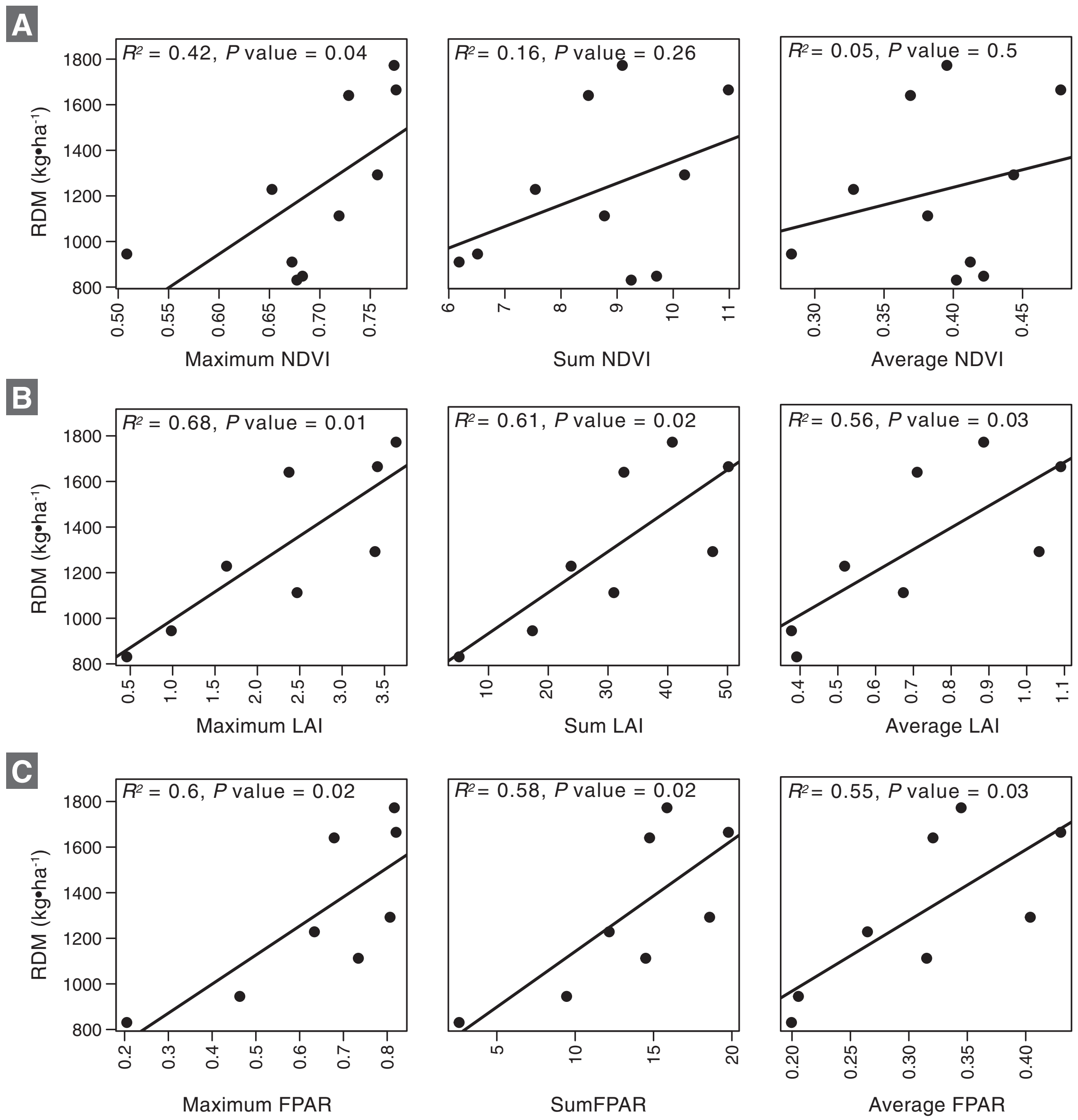

Fig. 3. Correlations between property-based residual dry matter (RDM) (kg ● ha^{-1}) levels and the annual maximum, sum, and average of MODIS-based data for Simon Newman Ranch. **A,** Normalized Difference Vegetation Index (NDVI). **B**, Leaf Area Index (LAI). **C,** Fraction of Photosynthetically Active Radiation (FPAR).

for RDM compliance. This comparison was then used to identify units out of compliance and to pinpoint potential problematic areas that should be further monitored.

Results

Relationship between Time Series of Vegetation Indices and Residual Dry Matter

NDVI time series over 11 years showed a distinct annual vegetation growth cycle that is highly repetitive throughout the decade (Fig. 1), with one peak of green vegetation growth per year that occurs around the same time every year. Maximum greenness occurred around March 6 in areas with riparian or grassland vegetation and around March 22 in oak woodland and chaparral areas. Minimum vegetation greenness appeared around mid-October. An analysis of these time series showed a close relationship between the amount of green vegetation and the amount of rainfall. For example, in 2007 precipitation was about half the average annual value for the decade; the NDVI values for that year were the lowest of the decade. Average annual precipitation was indeed highly correlated with average annual NDVI ($R^2 = 0.69$, $P = 0.001$). Similarly, the timing of vegetation growth followed rainfall closely, with a lag of about 2 weeks between the timing of rainfall and the resulting growth (Fig. 1). For example, a very low NDVI value for December 2005 likely can be ascribed to the late rainfall that year, which began January 2006. Likewise, we detected a significant correlation between the maximum monthly rainfall and the maximum NDVI values each year ($R^2 = 0.57$, $P = 0.007$) and a moderate correlation between RDM and the total annual rainfall ($R^2 = 0.39$; $P < 0.01$). Although NDVI is influenced by the timing of the rainfall, no significant correlation between the timing of the first and last rains of the year and RDM values was found.

Time series of LAI and FPAR showed similar patterns to NDVI, with one growing cycle each year (Fig. 2A–B). However, within the growing season, LAI and FPAR increased slower than NDVI and decreased

Table 3
Best models selected by stepwise regression for fall RDM prediction, for each VI.

Parameter	Coefficient Estimate	Standard error	*P*-value
Best model: Normalized Difference Vegetation Index (NDVI)			
Intercept	-3891.67	831.84	0.00
vegetation type	-501.38	139.60	0.00
year factor	5739.86	606.48	0.00
NDVI value January 17	-3149.73	780.88	0.00
NDVI value June 10	-13994.97	3734.04	0.00
NDVI value June 26	9302.11	4241.49	0.03
NDVI value August 29	13381.28	2835.08	0.00
NDVI value September 30	-4122.78	1219.15	0.00
Standard deviation	15364.13	2092.71	0.00
Minimum value	-2767.46	1552.50	0.08
Maximum value	5.45	2.41	0.02
Length of growth period (days)	-2.30	1.41	0.10
Best model: Leaf Area Index (LAI)			
Intercept	338.37	364.94	0.35
vegetation type	356.30	172.26	0.04
year factor	2911.67	348.16	0.00
LAI value October 16	-1047.06	467.49	0.03
LAI value December 03	-994.46	645.57	0.12
LAI value December 19	667.17	442.18	0.13
LAI value January 17	-353.34	167.43	0.04
LAI value February 2	-307.54	134.49	0.02
LAI value February 18	-181.83	87.59	0.04
LAI value March 22	155.88	85.38	0.07
LAI value April 7	-185.50	107.13	0.08
LAI value May 25	-1341.44	695.17	0.05
LAI value June 10	1817.68	909.46	0.05
LAI value June 26	-1490.39	821.95	0.07
Standard deviation	1504.09	535.99	0.01
Minimum value	1840.68	742.82	0.01
Length of growth period (days)	1.91	1.28	0.14
Best model: Fraction of Photosynthetically Active Radiation (FPAR)			
Intercept	675.02	517.54	0.19
vegetation type	-420.52	161.63	0.01
year factor	2314.46	685.56	0.00
FPAR value January 1	1280.30	648.38	0.05
FPAR value February 2	-1675.04	736.72	0.02
FPAR value March 6	2334.69	1081.21	0.03
FPAR value March 22	1332.20	769.08	0.08
FPAR value June 10	3177.46	2213.58	0.15
FPAR value August 29	7892.30	2429.07	0.00
FPAR value September 14	-2161.03	1482.60	0.15
FPAR value September 30	-4068.46	2341.71	0.08
Median	4842.42	1624.05	0.00
Sum	-412.26	99.20	0.00
Standard deviation	12600.19	3508.63	0.00

slightly faster. The FPAR temporal pattern had the highest interannual variability among the three vegetation indices (Fig. 2B).

There were significant correlations between RDM and the annual maximum, average, and sum of LAI and FPAR, as well as between RDM and maximum NDVI (Fig. 3A–C). Importantly, for all three VIs, the annual maximum value was the most significant predictor of RDM in the fall. LAI had the strongest correlation with RDM, explaining a large portion of the variability in fall RDM. Maximum annual values of LAI explained as much as 68% of RDM variability (Fig. 3B).

Prediction of RDM with Multivariate Regression

The multivariate model containing all NDVI covariates predicted RDM with $R^2 = 0.6$, $P < 0.001$; the LAI-based model with $R^2 = 0.56$, $P < 0.001$; and the FPAR-based model with $R^2 = 0.57$, $P < 0.001$. When we used the stepwise model selection with AIC criteria, all the selected RDM prediction models contained the vegetation type and the year as significant covariates (Table 3). The selected NDVI-based model (AIC = 7914.24) included as important covariates NDVI values from 4 months, the annual NDVI standard deviation, the minimum and the maximum annual values, and the length of the growing season (Table 3). This selected NDVI model predicted 63% of the variability in fall RDM ($R^2 = 0.63$, $P < 0.0001$). The selected LAI model (AIC = 6832.96) predicts RDM with $R^2 = 0.57$, $P < 0.0001$ and includes LAI values from 8 months, the annual LAI standard deviation, the minimum annual value, and the length of the growing season. The FPAR selected model (AIC = 6820.3) included as covariates values from 6 different months, the annual median, sum, and standard deviation values (Table 3). It predicted fall RDM with $R^2 = 0.58$, $P < 0.001$.

RDM Compliance Monitoring

Management units in compliance with RDM conservation easement terms had significantly higher annual maximum, sum, and average VIs than those out of compliance ($P < 0.01$) (Fig. 4A–C). Maximum LAI provided the most pronounced and significant difference between management units in and out of compliance (Fig. 4B).

When comparing RDM management units in and out of compliance separately in each habitat type (i.e., chaparral, grassland, oak woodland and riparian habitat), the overall resulting ANOVA was significantly different for units in and out of compliance within each habitat type, for all three VIs (NDVI sum and average: $P = 0.055$; LAI and FPAR: $P < 0.001$). However, when we compared each pair of habitat type separately using Tukey's Honest Significant Difference method, the difference was significant only for LAI and FPAR in the grassland and oak woodland habitats (Fig. 5A–C).

Logistic regression provided further parameterization of the difference in VI values in management units in or out of RDM compliance terms (Table 4). In grassland habitats, increase in one unit of NDVI annual sum significantly increased the odds ratio (OR) of RDM compliance versus noncompliance by 1.13. Increase in one unit in the annual NDVI average increased the OR of compliance by 17.1. Increase in one unit of LAI maximum, sum, and average increased the OR of compliance by 1.86, 1.06, and 17.8, respectively (Table 4). The increase in annual values of LAI and FPAR significantly increased the OR of compliance in all habitats (Table 4). Although the ORs of compliance versus noncompliance were highest in models using LAI or FPAR averages, the confidence intervals for these odds ratios were wide, especially in chaparral habitat (Table 4).

Three-Step Management Model and Application at the Simon Newman Ranch

Our results suggest the feasibility of an RDM monitoring framework that is based on MODIS NDVI, LAI, and/or FPAR satellite data. In this section we present such a framework and demonstrate an operational monitoring process using MODIS-LAI data acquired for the Simon Newman Ranch. On the basis of the analysis of the MODIS-LAI time courses and data on RDM compliance from 2002–2012, we determined that years when the RDM of the whole property was in compliance had an average annual maximum LAI value of 2.2. Management units in compliance with RDM terms had maximum LAI values of 1.7, 2.8, 2.1, and 2.3 for chaparral, grassland, oak woodland, and riparian habitat, respectively. We used these baseline values in a three-step methodology: *prediction, management*, and *monitoring* (see methods).

Step 1: Prediction

LAI values in early spring (mid-March) for the whole Simon Newman Ranch were above the compliance threshold in years when the property was in RDM compliance, and vice versa. For

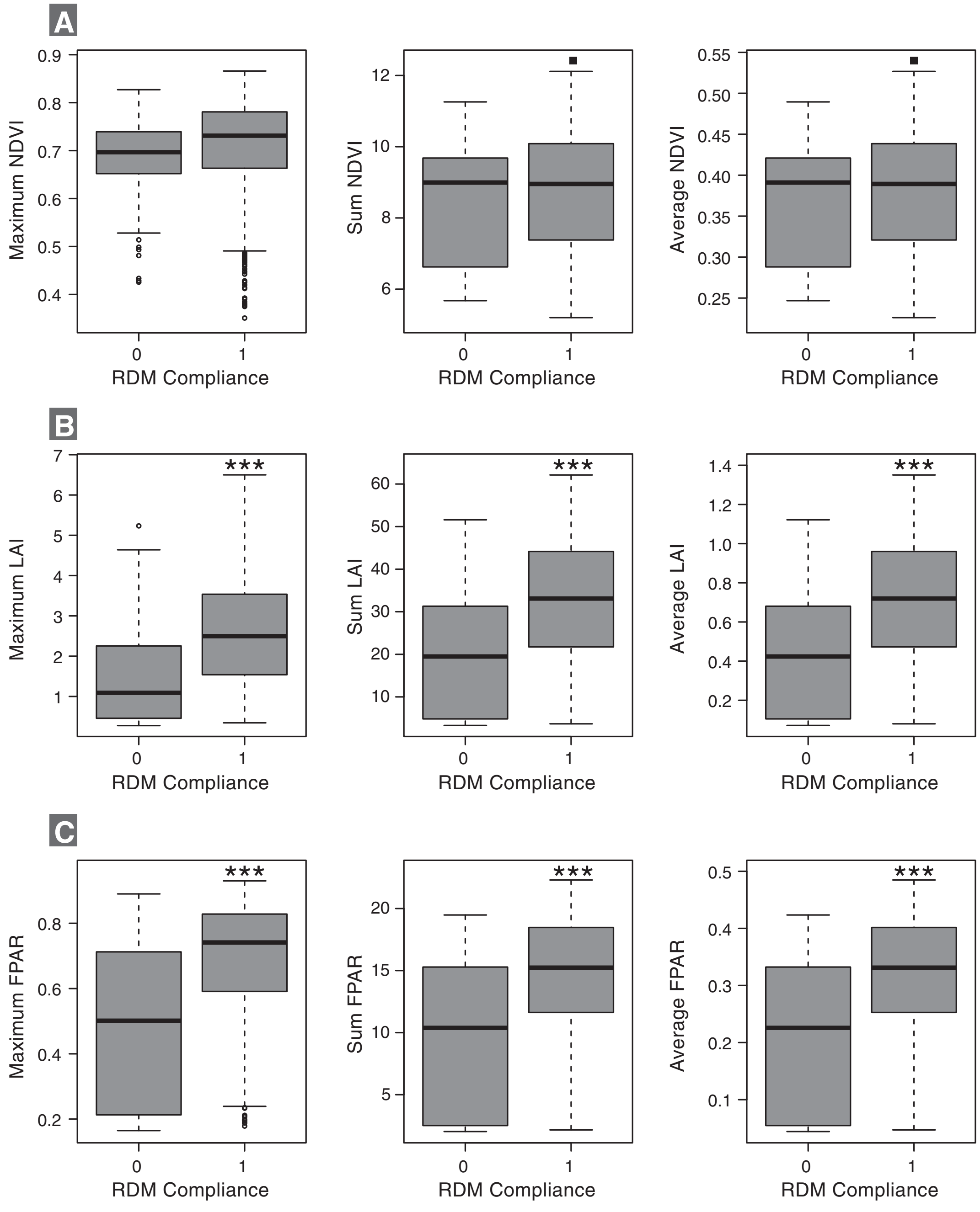

Fig. 4. Analysis of variance (ANOVA) of annual maximum, sum, and average of each VI in management units in compliance with RDM easement terms (symbolized with a "1") compared with management units out of RDM compliance (symbolized with a "0"). **A,** Normalized Difference Vegetation Index (NDVI). **B,** Leaf Area Index (LAI). **C,** Fraction of Photosynthetically Active Radiation (FPAR). Asterix above columns denote ANOVA statistical significance: ( ) $P < 1$; (·) $P < 0.1$; (*) $P < 0.05$; (**) $P < 0.01$; (***) $P < 0.001$.

example, in March 2007 the property-wide LAI average was 1.02, which was below the value for RDM compliance of 2.2 (Fig. 6). On the basis of this March LAI value, we would predict that property-wide fall RDM level would be lower than a minimum value of 952 kg · ha^{-1} required for easement compliance; indeed, the property-wide RDM average in 2007 was 944 kg · ha^{-1} (Fig. 6). In contrast, in March 2004 the property-wide LAI was 2.4, which was above the threshold for easement compliance. On the basis of this March LAI value, we would predict that fall RDM levels would be within easement compliance terms, and that is indeed what we saw; the property-wide RDM average in 2004 was 1 113 kg · ha^{-1} (Fig. 6).

Step 2: Management

By proactively comparing March LAI values to the established baseline values for compliance, we could identify potential problem areas and consider management adjustments of stocking rates or grazing rotations early in the season. Fig. 7A shows a map of RDM values for each management unit at the Simon Newman Ranch in fall 2008. Indeed, areas with higher RDM also had higher spring LAI

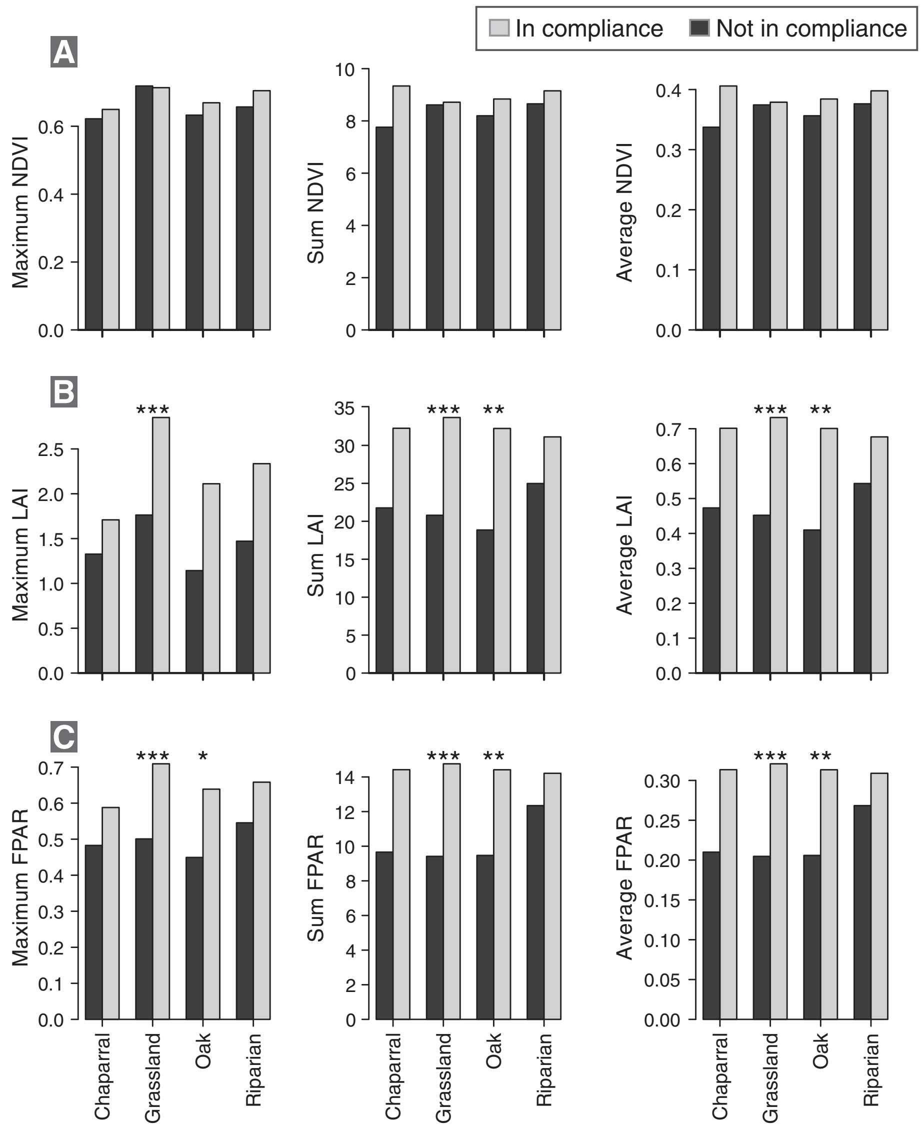

Fig. 5. Difference in the annual maximum, sum, and average values of each VI in management units in compliance with RDM easement terms compared with management units out of RDM compliance, depending on habitat type. **A,** Normalized Difference Vegetation Index (NDVI). **B,** Leaf Area Index (LAI). **C,** Fraction of Photosynthetically Active Radiation (FPAR). Asterix above columns denote Tukey Honest Significant Differences: ( ) $P < 1$; (·) $P < 0.1$; (*) $P < 0.05$; (**) $P < 0.01$; (***) $P < 0.001$.

(Fig. 7B) and, in the some cases, also higher LAI values in the fall (Fig. 7C).

Step 3: Monitoring

By the end of September, LAI data for the rest of the growth year should be extracted and plotted, as demonstrated in Fig. 6. The sum and average of LAI values for the year are calculated and compared with the established compliance values for each area. By this time in the growth year, LAI time course and all three statistics (annual maximum, sum, and average) can be used to identify which management units are likely to be out of compliance (Fig. 6). This can inform more targeted ground monitoring. For example, at the Simon Newman Ranch, management units with RDM compliance should have annual LAI sum ≥ 33 and LAI average ≥ 0.72. In 2008, the total LAI sum was 40.67, and LAI average $= 0.88$, above the threshold values for compliance. Indeed, in 2008 90% of the 56 management units were in compliance.

Discussion

Monitoring the effects of grazing on rangelands is essential to ensuring proper ecological functioning of the ecosystem and to protecting biodiversity on conservation easement properties. Field-based monitoring of vast rangeland easement areas demands considerable time and resources, making such monitoring difficult with increasingly limited funds available for conservation. In this paper, we developed a method that uses multitemporal MODIS data that is cost-effective and efficient at monitoring RDM on rangeland conservation easements. To our knowledge this is the first time that remote sensing has been applied to monitor RDM in the context of rangeland easement compliance.

Analyses of the three MODIS vegetation indices over time—NDVI, LAI, and FPAR—showed that a strongly repetitive pattern exists across California's rangelands (Figs. 1 and 2). This pattern matches the Mediterranean climate of California, where the growth cycle of annual grass-dominated rangelands has one clear peak, around March,

Table 4
Results of logistic regression of RDM compliance as a function of vegetation indices (VI) summary statistics. (CI = confidence intervals).

VI	Vegetation type	Log odds	Odds ratio	CI 2.5%	CI 97.5%	*P*-value
NDVI	Maximum					
NDVI	All	1.15	3.15	0.51	18.31	0.21
NDVI	Chaparral	1.41	4.09	0.35	53.22	0.27
NDVI	Grassland	1.17	3.22	0.51	19.11	0.20
NDVI	Oak woodland	1.09	2.98	0.39	21.84	0.29
NDVI	Riparian	0.71	2.04	0.26	15.07	0.49
NDVI	Sum					
NDVI	All	0.11	1.12	1.00	1.26	0.06
NDVI	Chaparral	0.14	1.15	0.99	1.36	0.08
NDVI	Grassland	0.12	1.13	1.01	1.27	0.04
NDVI	Oak woodland	0.11	1.12	0.99	1.27	0.08
NDVI	Riparian	0.08	1.08	0.95	1.23	0.23
NDVI	Average					
NDVI	All	2.60	13.45	0.93	195.74	0.06
NDVI	Chaparral	3.24	25.48	0.74	1279.92	0.08
NDVI	Grassland	2.83	17.01	1.12	263.05	0.04
NDVI	Oak woodland	2.54	12.73	0.73	228.75	0.08
NDVI	Riparian	1.78	5.93	0.32	114.73	0.23
LAI	Maximum					
LAI	All	0.62	1.86	1.50	2.35	0.00
LAI	Chaparral	0.93	2.54	1.21	7.36	0.03
LAI	Grassland	0.59	1.81	1.47	2.28	0.00
LAI	Oak woodland	0.90	2.47	1.65	3.99	0.00
LAI	Riparian	0.67	1.95	1.29	3.33	0.00
LAI	Sum					
LAI	All	0.06	1.06	1.04	1.09	0.00
LAI	Chaparral	0.06	1.07	1.02	1.14	0.01
LAI	Grassland	0.06	1.06	1.04	1.09	0.00
LAI	Oak woodland	0.07	1.07	1.04	1.10	0.00
LAI	Riparian	0.05	1.05	1.02	1.09	0.00
LAI	Average					
LAI	All	2.88	17.86	7.50	44.85	0.00
LAI	Chaparral	2.98	19.67	2.74	352.02	0.01
LAI	Grassland	2.89	18.02	7.25	48.34	0.00
LAI	Oak woodland	3.11	22.38	6.52	92.54	0.00
LAI	Riparian	2.43	11.33	2.94	57.55	0.00
FPAR	Maximum					
FPAR	All	3.84	46.40	15.37	145.34	0.00
FPAR	Chaparral	4.32	75.52	7.13	1790.81	0.00
FPAR	Grassland	3.82	45.62	14.92	146.40	0.00
FPAR	Oak woodland	4.17	64.93	14.94	324.97	0.00
FPAR	Riparian	3.52	33.86	7.12	201.93	0.00
FPAR	Sum					
FPAR	All	0.18	1.20	1.14	1.26	0.00
FPAR	Chaparral	0.19	1.20	1.09	1.39	0.00
FPAR	Grassland	0.18	1.20	1.14	1.27	0.00
FPAR	Oak woodland	0.18	1.20	1.13	1.29	0.00
FPAR	Riparian	0.15	1.16	1.09	1.26	0.00
FPAR	Average					
FPAR	All	8.25	3824.86	416.58	38732.44	0.00
FPAR	Chaparral	8.53	5076.45	49.71	3802139.30	0.00
FPAR	Grassland	8.46	4734.56	456.92	56161.66	0.00
FPAR	Oak woodland	8.38	4346.01	246.12	105234.23	0.00
FPAR	Riparian	6.91	998.62	44.64	35695.80	0.00

that drops to its minimum value during the early fall months, when vegetation is senescent (Mooney and Dunn, 1970; Jackson, 1985). The maximum value of each of the three VIs occurs at our study site at almost the same time every year, around mid-March (Figs. 1 and 2). This suggests that data can be extracted for an assessment of ranch conditions at the same time of spring every year, without the need to wait until the end of the season. We expect a similar phenological pattern across California's rangeland ecosystems, which are mostly dominated by annual grass species. For other areas, the exact timing of maximum NDVI, LAI, or FPAR would need to be assessed. The strong correlation we found between NDVI and the quantity and timing of rainfall is consistent with previous research across rangeland ecosystems (Garcia et al., 2010; Mao et al., 2012).

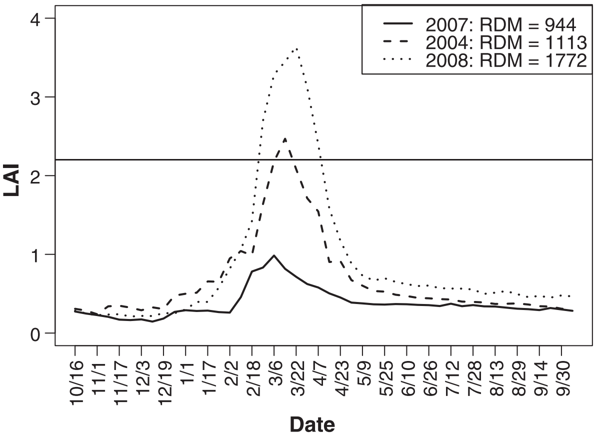

Fig. 6. Comparison of Leaf Area Index (LAI) time series for the Simon Newman Ranch property-wide average in years with low (2007), medium (2004), and high (2008) RDM ($kg \cdot ha^{-1}$) outcomes in the fall. Horizontal line marks LAI = 2.2, the threshold property-wide annual maximum LAI value for RDM in compliance.

Spring maximum values of all three VIs had the strongest correlation with fall RDM in our study area (Fig. 3). These results suggest that land managers and conservation practitioners can use MODIS-based estimates of maximum productivity, as measured by maximum NDVI, LAI, or FPAR, to make within season decisions about grazing practices, including those related to stocking rate and grazing timing that help ensure easement compliance, protect conservation values, and maximize the productivity and profitability of the grazing operation. This finding has important management implications, especially across lands with conservation easements where RDM is typically monitored in the fall, at the end of the grazing season, when the impacts of grazing, whether positive or negative, have already occurred (Harris et al., 2002).

We examined a range of univariate and multivariate models to determine whether we could accurately predict RDM levels using remote sensing data. We found that these models were highly significant and could successfully measure high proportion of RDM variability (Fig. 3, Table 3). The use of multiple VIs in this research improved our overall ability to monitor RDM; LAI provided the best RDM prediction in the univariate models (68%), while NDVI provided the best RDM prediction in the multivariate models (63%) (Table 3). All of the selected multivariate models included both fall and spring VI values, which suggests a possibility to develop models that use fall VIs to monitor RDM directly. The year factor had an important role in the models, which indicates the central effect climate variability has on RDM outcomes. The vegetation type also appeared as an important factor in all predictive models, emphasizing the importance of habitat type in the relationship between the VI and RDM.

LAI and FPAR had stronger correlated with RDM and were better predictors of RDM compliance across our study site than NDVI. There are few possible explanations for this result. First, while NDVI is a measure of vegetation greenness, LAI and FPAR measure structural and functional properties of vegetation, which are more relevant for measuring senesced vegetation (Knyazikhin et al., 1999; Myneni et al., 2002). LAI and FPAR have been shown to have a strong relationship with grassland biomass, both green and senescent, in variety of ecosystems (Asner et al., 1998), including California rangelands (Malmstrom et al., 2009; Butterfield and Malmstrom, 2009). LAI describes the canopy structure of the number of equivalent layers of leaves relative to a unit ground area (Knyazikhin et al., 1999), which may explain LAI's superiority at predicting RDM in the fall, since RDM is the cumulative outcome of year-round grass availability. FPAR measures the photosynthetic capacity of vegetation, a capacity

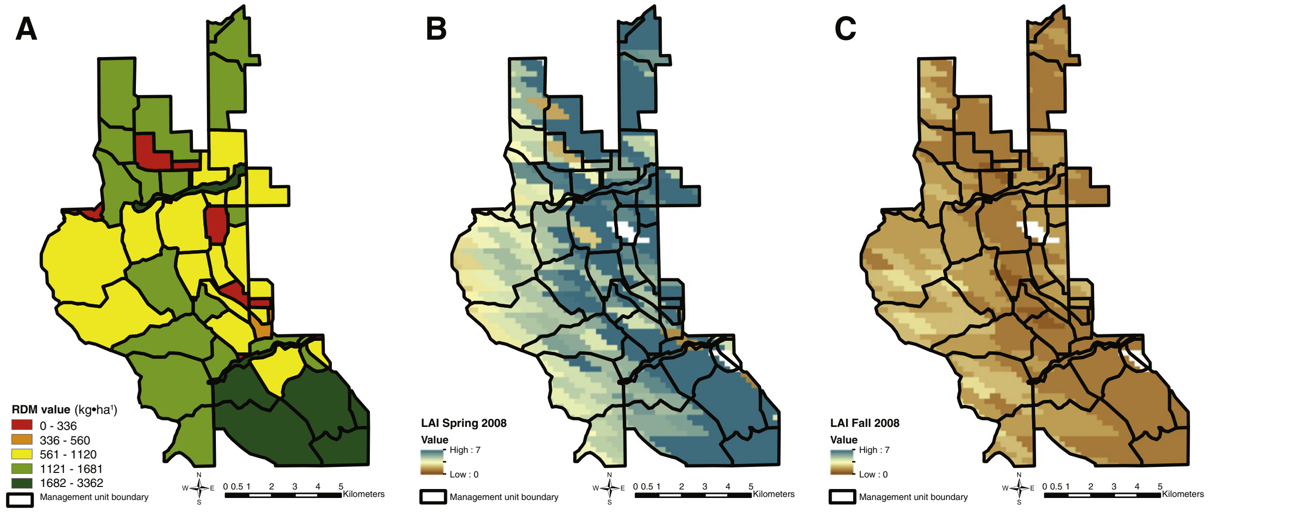

Fig. 7. Results from the three-step management model for Simon Newman Ranch. **A,** RDM ($kg \cdot ha^{-1}$) values in each management unit of the Simon Newman Ranch for fall 2008. **B,** Leaf Area Index (LAI) for March 2008. **C,** LAI for October 2008.

that continues, to some degree, in dry vegetation as well (Butterfield and Malmstrom, 2009). Second, MODIS-based LAI and FPAR data have higher temporal resolution (every 8 days) than NDVI (every 16 days), which potentially allows them to capture finer vegetation dynamics and hence be more sensitive to changes in biomass. Finally, the model that MODIS uses to calculate LAI and FPAR includes NDVI, as well as canopy reflectance data, sun-view geometry, a cover radiance transfer model specific for each land cover type, and extensive ground validation (Knyazikhin et al., 1999). These additional data sets may improve the correlation between LAI and FPAR and the ground-based measure of RDM.

We found a significant difference among the annual maximum, sum, and average values of NDVI, LAI, and FPAR within management units that were in compliance versus out of compliance with The Nature Conservancy's RDM easement terms; these findings were consistent when evaluated compliance within individual habitat types (Fig. 5, Table 4). Ability to evaluate compliance in all examined habitat types demonstrates the robustness of our approach to predict RDM easement compliance across the grazing season and within a variety of rangeland ecosystems.

Interestingly, we found excellent RDM compliance prediction capability in oak woodlands even though the satellite view of the grass layer in this habitat is partially obscured by woody vegetation. A possible explanation is that the tree cover in these regions is relatively sparse (Guenther, 2012). Another explanation may be that because the difference between RDM compliant and noncompliant units is more significant when measured by LAI or FPAR, and the algorithms calculating these indices take the vegetation type into consideration, these algorithms normalize the relative influence of tree canopy cover (Myneni et al., 2002). Finally, the correlation between VIs and RDM in woody vegetation may be explained by an indirect effect. Tree canopy enhances grass productivity by concentrating nutrients and providing shade (Belsky, 1994). Therefore, higher tree greenness may predict greater grass biomass. This hypothesis needs to be further examined using field data and satellite imagery with finer resolution.

Future improvements to our analysis may include more refined field RDM measurements. Because we used RDM data that were acquired for management purposes by using photo points, these data were relatively coarse both in spatial and in class resolution. Incorporating detailed topographic data and cattle stocking rates into the analysis should improve RDM predictions. In the future, if finer spectral and spatial resolution satellite data are made available to the public in a preprocessed form, it may further improve RDM prediction ability (Irons et al., 2012).

Management Implications

We propose a novel rangeland monitoring framework. Our data-driven rangeland monitoring and management approach uses MODIS-LAI and has three steps: "*Predict, Manage*, and *Monitor*." Our model uses analysis of multiyear time series to establish LAI baseline values for annual maximum, average, and sum, for a property that is in good conditions and is RDM compliant. In early spring, *prediction* of forage availability is performed by extracting LAI data for a site and comparing it with baseline LAI values for compliance. We suggest that land managers evaluate closely areas with LAI below the established spring LAI for easement compliance. Next, data-driven *management* entails choosing stocking rates according to forage availability, as indicated by the spring LAI, to assure moderate grazing pressure. Evaluating forage conditions and potential easement compliance in early spring allows land managers and conservation practitioners to adjust grazing practices to meet both the needs of the cattle operation and the terms of the conservation easement. For example, cattle may be rotated out of management units where potential problems exist and into units where additional forage may be available. In extreme conditions, like extended drought, managers can determine early in the season, before the largest economic impacts may occur, that cattle need to be moved out of an easement property where forage conditions are low and where threats to conservation values are greatest, and on to a property where more forage exists. Finally, RDM *monitoring* during October is improved by using LAI sum and average values to identify management units with low RDM and targeting potential problem areas for monitoring. We suggest this method as an augmentation, rather than a replacement of typical ground-based monitoring. Although remote sensing cannot replace the direct contact of land managers with the land, it can enhance monitoring efforts by directing them to the most needed areas.

Finally, our methodology is cost-effective, simple, and easily scalable, which ensures that it can be easily implemented by land managers and conservation practitioners. Great cost savings are realized because MODIS satellite data are free; have been around for 15 years, which allows retrospective analyses, as well as current and future ones to be undertaken; are preprocessed, and are easily manipulated using open-source software (e.g., GDAL, R). The low cost and technical simplicity of our methodology makes it especially viable for use across large rangeland properties. We demonstrated that MODIS data can be used to predict RDM levels and RDM easement compliance at a variety of habitats and spatial and temporal scales.

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