Reductions in productivity due to land degradation in the drylands of the southwestern United States

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Abstract. Dryland degradation has long been recognized at regional, national, and global scales, yet there are no objective assessments of its location and severity. An assessment of reductions in net primary production (NPP) due to dryland degradation in the southwestern United States is reported. The local NPP scaling (LNS) approach was applied to map the extent and magnitude of degradation. LNS seeks to identify reference sites in which there is no degradation that can be used as a standard for comparison with other sites that share the same environment, except for degradation. Twelve years were analyzed (2000–2011), using Normalized Difference Vegetation Index (NDVI) data (250 m) from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite-borne multispectral sensor. The results indicated that the total NPP reductions in the study area were about 35.9 ± 4.7 Tg C/yr, which equates to 0.31 ± 0.04 Mg C ha⁻¹ yr⁻¹. The NPP reductions in grassland-savanna and livestock grazing areas were large and mostly consistent between years in spite of large variations in overall NPP caused by differences in land-use, interannual variations in rainfall, and other aspects of weather. In comparison with other cover types, forested land generally had higher NPP reduction per unit area. The maps also enable attribution of degradation from the finest management units to entire agencies, such as the Bureau of Land Management, which had 50% less production per unit area than the U.S. Forest Service. The degradation within Native American land was low with total NPP reduction of about 2.41 ± 0.24 Tg C/yr and unit area reduction of productivity of just 0.21 ± 0.02 Mg C ha⁻¹ yr⁻¹, yet the percent reduction from potential was in equivalence with other land management agencies.

Key words: degradation; drylands; ecosystem health; MODIS; NDVI; NPP; rangelands; reference conditions; southwestern United States.

Introduction

Drylands cover 41% of the global terrestrial surface (Safriel and Adeel 2005) and nearly 40% of land area in the United States (White and Nackoney 2003). While vegetation in drylands has low biomass and low carbon (C) sequestration per unit area, they still store approximately twice the amount of organic C stored in temperate forest ecosystems due to their large extent and to their high soil organic carbon (SOC) pool (Eswaran et al. 2000, Safriel and Adeel 2005). Lal (2004) and Eswaran et al. (2000) estimated that global drylands store about 15% (241 Pg) of the Earth’s total SOC. Waltman and Bliss (1997) estimated that about 5% (75–90 Pg C) of the global SOC pool is stored in U.S. soils, with 15.3–16.5 Pg alone in grazing lands. Thus, dryland ecosystems are potentially large sinks for atmospheric CO₂ and play an important role in the terrestrial C balance with feedbacks to climate change (Lal 2004, Wohlfahrt et al. 2008).

Degradation is considered to be one of the major environmental problems in drylands (UNCED 1992, Goetz et al. 1999, Reynolds et al. 2007; UNCCD 1994:27). It involves adverse changes in one or more aspects of the biota and their environment, loss of species diversity, including palatable species, soil erosion, and reduced biological productivity (Schlesinger et al. 1990, Milchunas and Lauenroth 1993). SOC is a key indicator of soil quality (Brady and Weil 2010), and reduction is often associated with degradation (Ardö and Olsson 2003, Lal 2004). Large portions of U.S. drylands are rangelands and management to reduce degradation has been...
estimated to be able to increase SOC by 0.1–0.6 Mg C ha⁻¹ yr⁻¹ (Schuman et al. 2002). When the vast areas of rangelands are considered, these rates translate into 43 million Mg C/yr (Schuman et al. 2002) addition to the total for the United States.

Despite its significance, the extent and severity of all forms of rangeland degradation are still unknown (Lund 2007), mainly due to the lack of objective, practical methods of measurement (Verstraete 1986, Prince 2002). The few, existing, global maps of desertification (dryland degradation) are based on coarse resolution soil maps (Middleton and Thomas 1997, Eswaran and Reich 2003) from which vulnerability is assessed, but not the actual occurrence of degradation. The absence of quantitative maps showing the degree of degradation of the world’s drylands is universally agreed to be a major hindrance to critical science questions, several associated with global change, and for mitigation and prevention of future degradation (Chasek et al. 2015).

Several measurable indicators have been proposed to monitor land degradation such as: accelerated soil erosion rates (Stroosnijder 2007), deteriorating soil fertility (Batterbury et al. 2002), and long-term and irreversible reductions in vegetation cover or production efficiency (Nicholson et al. 1998, Prince et al. 1998, Batterbury et al. 2002, Prince 2002). Changes in vegetation NPP, which are inherently linked to the major processes that lead to degradation (Prince 2002, Safriel 2007, Nicholson 2011), can be monitored using repeated satellite observations (e.g., Prince and Goward 1995, Myneni et al. 2002, Hansen et al. 2003, Running et al. 2004). The underlying challenge when using NPP to detect degradation lies in distinguishing human-induced degradation from the variability caused by the climate and other environmental factors, such as soils, climate, vegetation type, rainfall, temperature, and others (Prince 2015), all of which can also reduce NPP. Several studies have attempted to identify land degradation by long-term and persistent reductions in NPP below the potential set by the environmental conditions, in the absence of land degradation caused by humans (Prince et al. 1998, 2009, Prince 2002, Evans and Geerken 2004, Hirata et al. 2005, Wessels et al. 2007, Wylie et al. 2012, Reeves and Baggett 2014). In the present study, a reference NPP was estimated using the LNS method (Prince 2004, Prince et al. 2009).

Our objectives were to quantify and map the extent and severity of loss of production in the southwestern United States, having first normalized the effects of long- and short-term natural environmental factors. The basis of LNS is to stratify the land into homogeneous regions, called land capability classes (LCCs), within which, in the absence of degradation, productivity can be expected to be the same throughout. The potential NPP is estimated for each LCC using the maximum NPP, which is then compared with all other parts of the LCC. Any deficits of NPP are regarded as possible cases of anthropogenic degradation.

**Materials and Methods**

**Study area**

The study was conducted in the southwestern United States, based on the Southwest Regional Sequestration Partnership (SWRP) and the Regional Sequestration Partnership Program of the U.S Department of Energy.

![Fig. 1. (a) The study region and (b) the National Land Cover Database (2006) land cover types present in the region.](image-url)
(US-DOE 2003; Fig.1). It consisted of New Mexico (NM), Utah (UT), Colorado (CO), parts of Arizona (AZ), west Texas (TX), Oklahoma (OK), Kansas (KS), and Nebraska (NE). The vegetation is diverse, with desert in the west, changing successively to bush, grassland, savanna, and shortgrass prairie eastwards as summer rainfall increases. Land uses include extensive ranching on public land principally managed by the Bureau of Land Management and the U.S. Forest Service, large areas of Native American reserves, large preserves of various types, some irrigated and dryland farming, and small areas of exurban development.

**Data**

*Land cover.*—The National Land Cover Database (NLCD; Fry et al. 2011) was used to provide land cover information at 30-m resolution to identify areas belonging to the NLCD classes: evergreen forest, deciduous forest, mixed forest, shrubland, and herbaceous. Data for these classes was from the year 2006; ideally, yearly land cover data would be used, but these were not available. All other land cover classes, such as water, developed, barren, planted/cultivated, and wetlands, were excluded from the analyses.

*Soils.*—Eight interpretive soil capability classes from the U.S. Department of Agriculture (USDA) Natural Resources Conservation Services (NRCS) State Soil Geographic (STATSGO) soil database based on use limitation (e.g., soil depth, SOC, texture, erosion risk, slope, porosity, etc.) were used (data available online).¹

*Meteorology.*—Meteorological information of annualized precipitation totals, yearly average maximum and minimum temperatures, and the dew point at 4-km resolution were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al. 2002) data sets.

*Elevation.*—The United States Geological Survey (USGS) Shuttle Radar Topography Mission (SRTM; Farr et al. 2007) 90-m digital elevation model (DEM) was used to provide topographic information.

*Slope.*—The slope was calculated from the USGS SRTM 90-m DEM, and areas having slopes >15% were excluded to minimize the presence of natural erosion which is more common on steeper slopes.

*Aspect.*—Slope and azimuth were combined in “southness” (Franklin et al. 2000), in order to represent different exposure to the sun in one index.

*Riparian vegetation.*—Riparian land, although small compared to the typical LCC, is usually very different from the neighboring land. These were excluded using a stream map and a buffer, the width of which was adjusted to the flow accumulation of the waterway, as available in HydroSHEDS (Lehner et al. 2008). Pixels with >450 upstream-contributing pixels were buffered using an exponential basis relationship based on number of contributing streams. The width was varied from 200 m (at 450 contributing pixels) to 1500 m, maximum. In addition, the National Wetland Inventory (NWI; Cowardin et al. 1979, Cowardin and Golet 1995) data set was used to mask the wetlands and surface water bodies.

**Land use and land management.**—Croplands were masked using 2012 USDA National Agricultural Statistical Services (USDA-NASS) cultivated data layer (CDL; data available online).² To identify areas managed by the Bureau of Land Management (BLM), U.S. Forest Service (USFS), Native American Land (NAL), National Park Service (NPS), Department of Defense and Energy (DOD-DOE), and State Land Board (SLB) the Terrestrial Protected Areas of North America data set was used (data available online).³

*Roads.*—Roads and other paved areas were identified from the National Atlas data set and masked, together with one pixel on each side, to create a 750-m-wide buffer to exclude verges and disturbed land associated with roads (data available online).⁴

*NDVI.*—It is now generally accepted that light-use efficiency models (LUE) forced with multi-temporal NDVI data can be used to map terrestrial gross primary production (Tucker et al. 1985, Prince 1991, Rasmussen 1992, Running et al. 1999, 2004). However, in arid and semi-arid regions, annually or seasonally summed vegetation indices (e.g., NDVI; Enhanced Vegetation Index, EVI) themselves, without the added complexity of light-use efficiency, have also been found to be adequate, since they are linearly related to primary production (Fensholt et al. 2006, Sjöström et al. 2011). This simplification has the advantage of eliminating the additional errors in the variables needed for full LUE models. Thus, NDVI was used as a proxy for NPP (Prince and Justice 1991, Tucker et al. 1991, Nicholson et al. 1998). Yearly averages of MODIS NDVI (MOD13Q1), 250 m, 16-d data for 2000–2011 were used to calibrate the NDVI values in NPP units.

**Land capability classification**

Every data set used, including the annualized precipitation totals and the yearly averages of maximum and minimum temperature and dew point, were geographically registered to match the resolution and grid of the MOD13Q1, 250 × 250 m data.

The following steps were used to define the LCCs. First, potential errors caused by inadequate classification were minimized by removing small patches with extreme low or high NPP that were unrepresentative of their LCC; ² http://www.nass.usda.gov/research/Cropland/Release/index.htm
³ http://www.cec.org/naatlas
⁴ http://nationalmap.gov/small_scale/atlasftp.html?openChapters=chptrtrans#chptrtrans

¹ http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629
these included areas such as riparian strips, small wetlands, cropland, roads, and settlements. A very conservative approach was used, adding buffers around such features. The excluded areas were combined to a single mask and applied to all input data sets. Second, the digital elevation and meteorological data sets were normalized to zero mean and unit variance before unsupervised classification of the pixels using ISODATA clustering algorithm (Ball and Hall 1967). Unsupervised classes were derived with a stopping criterion of 100 iterations and a convergence factor of 0.975. The class numbers were chosen to be arbitrarily large to maintain spatial heterogeneity and also to constrain the influence of residual environmental factors on productivity. Third, the unsupervised classes were intersected with land cover, soil, and land management maps. The final number of classes after intersection was between 3000 and 5000. Fourth, for each year, two LCC maps were generated, one based on unsupervised classes, soil, and land cover (UMD) and the other (UMDLM) with the land management agency added (federal public lands only). Both LCC maps were different for each year because of the differences in annual meteorological variables, but the land cover, land management, and soil information were assumed to be the same for all years. Fifth, the LCCs were assessed by estimating the extent to which they reduced the correlation between the environmental factors that were used in their creation.

In addition to UMD and UMDLM maps, two existing land stratifications were analyzed and compared with the UMD LCCs: USDA Common Resource Area (USDA-CRA) and USGS Gap Analysis Program (USDA-GAP) National Land Cover data (USGS 2011), which shows both vegetation and land use (CRA and GAP data available online)\(^5\)\(^6\).

### Local NPP scaling

A reference or maximum NDVI of each LCC was estimated by finding the 85th percentile of the frequency distribution of yearly average NDVI (Fig. 2). The effect of unrepresentative, highly productive pixels was thus reduced (Prince et al. 2009). The 85th percentile was an arbitrary cutoff. Reductions were quantified by subtracting the actual NDVI from the reference value. The reduction in productivity, therefore, was relative to a reference or standard against which degradation within its LCC was assessed (Prince et al. 2009). The yearly LNS maps of the differences between actual and reference NDVI were expressed in terms of the reduction of NPP (in Mg C ha\(^{-1}\) yr\(^{-1}\)) compared with the reference. The reference NDVI identified using 85th percentile threshold within each LCC was matched with the yearly MODIS NPP product (MOD17A3; Running et al. 2004), resampled at 250-m resolution, to calibrate the NDVI data with NPP. The relative NPP reductions within a LCC were therefore in NPP units.

LNS maps were made for each year using the appropriate annual UMD and UMDLM LCC classifications and also from the USDA-CRA and USGS-GAP maps. Thus, there were 12 UMD LNS maps, taking account of weather differences between years; however the USDA-CRA and USGS-GAP LCC maps were the same for all years.

### Assessment of reference NDVI and LNS

It is important that the reference NDVI pixels are representative of the LCC for which they were selected. The extent to which this was achieved was determined by the following four criteria. (1) A visual comparison with Google Earth (GE; Google, Mountain View, California, USA), high-resolution (<\(4\) m), true color imagery was made. Although visual interpretation is subjective, the GE images were adequate to detect differences between the detailed land cover of the reference pixels and their LCC. One hundred reference locations were selected using a stratified random sampling in each NLCD land cover type, and a binary decision of good/bad reference was made. (2) Very low LNS values were checked with GE to eliminate land cover that was not typical of the LCC (e.g., unmasked wetland, unmapped settlements). (3) The relationships of reference NDVI and environmental variables used to

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\(^5\) http://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/survey/geo/

\(^6\) http://gapanalysis.usgs.gov/gaplandcover/
create the LCCs were analyzed in a one-way ANOVA to determine by how much the within LC variance had been reduced in the classification. (4) To determine the efficiency of classification to group separate classes, the variability in reference NDVI across the full range of LCCs was analyzed by calculating the increments of NDVI between pairs of LCCs ranked by NDVI.

The UMD, USDA-CRA, and USGS-GAP LNS maps were compared numerically. The comparison used a fuzzy numerical extension (Hagen-Zanker et al. 2006) of the simple, binary, pixel-by-pixel kappa ($\kappa$) test (Cohen 1960) by using continuous LNS data and weighted values for spatially close mismatches, which often arise in map comparisons. Kappa was calculated for both entire maps ($\bar{\kappa}$) and, in order to visualize the spatial distribution of differences, for individual pixels ($\kappa$).

## Results
### Land capability classification
UMD and UMDLM classifications were made for each year. Examples of one year are shown in Fig. 3a and b. The number of classes varied between years. In the UMD, the average was approximately 5000, and for UMDLM, 3000. The CRA and GAP maps (Fig. 3c and d) differed from the two UMD LCC maps in two respects: (1) CRA had 89 LCCs and GAP had 152 LCCs, many fewer than UMD classifications, and therefore, were less able to discriminate differences in land capability; and (2) the classifications were created without consideration of interannual changes. Few of the CRA or GAP LCCs coincided with either of the UMD classifications.

The majority of the UMD LCCs were in the NLCD shrubland, herbaceous, and evergreen forest vegetation classes, since these cover about 97% of the study region. The UMD LCCs were distributed across most of the elevation, precipitation, temperature, and dew point gradients. However, at higher elevations, some LCCs consisted of pixels with a wide range of “southness” values while, at lower elevation, about 10% were confined to narrower ranges of values. The frequency distributions of numbers of LCCs along the environmental variables used to derive the two UMD classifications all had strong central tendencies, varying degrees of skewness, and some slight irregularities in the numbers of LCCs in adjacent classes, reflecting unevenness of the occurrence of different environments in the study area.

### Local NPP scaling
Using the high resolution GE imagery, the assessment of the extent to which the reference pixels were the same as the rest of the pixels in its LCC showed that, of the 100 reference pixels examined in each land cover type, the agreement was >94% (95% confidence limits 82 and 95). The agreement in LCCs for three of the major land cover types (evergreen forest, shrubland, and herbaceous) was higher, >98% (95% confidence limits 96 and 100). Therefore, the reference pixels were judged, albeit visually, to be adequately representative of their respective LCCs.

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**Fig. 3.** The UMD (unsupervised classes, soil, and land cover), UMDLM (UMD with the land management agency added), CRA (USDA Common Resource Area), and GAP (USGS Gap Analysis Program) LCC maps. For UMD and UMDLM, there were 12 LCC maps, one each year. The 2010 maps are shown. Panel (a) shows UMD LCCs created from the intersection of unsupervised classes, soil, and land cover and panel (b) shows UMDLM, which added land management to the UMD classification. Panels (c) and (d) show USDA-CRA and USGS-GAP, respectively. The black areas are excluded land cover and land management types. Owing to the large number of classes in UMD and UMDLM, only a representative subset illustrating the spatial heterogeneity is presented. Colors were assigned arbitrarily and do not indicate the same classes across all four maps.
The reference NDVI values of UMD LCCs were positively correlated with precipitation \((r > 0.8)\) and dew point \((r < 0.4)\) across all LCCs. Correlations with precipitation were even higher \((r > 0.8)\) within individual land cover types than for all types together, except for deciduous \((r < 0.3)\). The correlations with dew point were higher in shrubland and herbaceous \((r > 0.7)\) than across all cover types \((r < 0.4)\). The one-way ANOVA found differences in reference NDVI and their environmental variables: the relationships of reference NDVI and the environmental variables were significantly different \((P < 0.001)\) between land cover types; surprisingly, the reference NDVI and the environment variables in the land managed by different agencies (BLM, USFS, NAL, NPS, DOD-DOE, and SLB) were also significantly different \((P < 0.0001)\). There were strong correlations between two groups of environmental variables: elevation with all three temperature variables and among the three temperature variables.

A LCC classification is successful if the classes have different potential NDVI values and is most efficient when the reference NDVI values are equally spread over the full range. For the two UMD classifications, the increments in reference NDVI across the entire range of values were almost equal except for the extreme low and high classes, but were highly variable in the CRA and GAP classifications. However, it should be recalled that the UMD LCCs were derived from a set of environmental variables that could be expected to be good predictors of potential NDVI, unlike the CRA and GAP classification.

The LNS maps derived from the UMD and UMDLM LCCs were nearly identical, but the USDA-CRA and USGS-GAP maps were noticeably different from both the UMD maps and each other. The average similarity for the entire UMD vs. USDA-CRA, UMD vs. USGS-GAP, and USDA-CRA vs. USGS-GAP map comparisons were low \((\kappa = 0.521, \ 0.495, \text{and} \ 0.484, \text{respectively})\). The maps of differences in individual pixels between each pair of classifications (UMD, USDA-CRA, and USGS-GAP LNS), measured by \(\kappa\) showed that the two UMD maps were similar, but both comparisons of UMD with USDA-CRA and USGS-GAP LNS maps were very different. Since the UMD LNS maps were different from USDA-CRA and USGS-GAP LNS maps, we used the UMD LNS maps to summarize the NPP reductions within the CRA and GAP classes (Tables 3 and 4).

The mean LNS and interannual variations differed between land cover types (Fig. 5). Comparisons of the 12-year average UMD LNS maps with high spatial resolution imagery showed many examples of correspondence of LNS with obvious ground conditions that can be expected to cause differences in LNS. Furthermore, the visual assessments showed that all the maps had some generally coherent groups of similar LNS values, mostly related to mountainous areas, rather than a speckle of pixels with different LNS.

The average LNS values in active and abandoned mining areas were very low (i.e., large deficits from reference; low \(-ve\) LNS values) and had low interannual variability (i.e., low coefficient of variation; CV) showing clear signs of permanent reduction. The interannual average LNS values of grassland and savanna were high (i.e., small negative deficits from reference), and their CVs was high (Fig. 5c2), indicating strong interannual variability in absolute LNS \((\text{g} \text{C ha}^{-1} \text{yr}^{-1})\), which is expected since precipitation plays an important role in these ecosystems (e.g., Fig. 5b3) and annual precipitation totals are highly variable. High variability in LNS was also observed around the watering points within the grazing allotments (Fig. 5c4), however, the average LNS values in these areas remained high (Fig. 5b4).

Reduction in net primary production in degraded areas

The 12-year (2000–2011) average reduction of productivity varied between cover types (Table 1). The total reduction of 35.88 \pm 4.72 Tg C/yr (11.80% below potential) and per unit area reduction of 0.31 \pm 0.04 Mg C ha\(^{-1}\) yr\(^{-1}\) among land cover types was largely due to reductions in shrubland and herbaceous cover types (17.20 \pm 2.02 and 10.02 \pm 1.88 Tg C/yr).

The results were also tabulated for the six agencies with the largest land holdings in the study area (Table 2). Each agency has a different mix of land cover types and size, so direct comparisons between them is only useful, for example, to inform policies and capacities for changes in C sequestration for an overall agency. The total reduction of productivity among land management types was 15.25 \pm 1.61 Tg C/yr, 12.53% below potential. Three agencies (BLM, USFS, and NAL) together occupy about 91% of the land which accounted for a reduction of 14.38 \pm 1.5 Tg C/yr. The USFS area (24.98%) contributed 6.69 Tg C/yr, much higher than BLM even though the land managed by BLM is approximately twice the USFS. The unit area reduction of productivity was highest for USFS \((0.56 \pm 0.07 \text{ Mg C ha}^{-1} \text{yr}^{-1})\) and lowest for DOD-DOE \((0.15 \pm 0.03 \text{ Mg C ha}^{-1} \text{yr}^{-1})\). NAL with similar land area (23.62%) as USFS accounted for just 2.41 Tg C/yr reductions, clearly indicating lower productive potential. Although, the reduction expressed as a percentage of the potential was similar to the other agency lands (Table 2).

Forested land had the highest NPP per unit area and hence capacity for reduction by degradation, so the high reference NDVI and the large area of USFS land explains its high total reduction. In comparison with USFS, BLM had 50% less production per unit area, probably because of the small forest component (13%) and the rest occupied by shrublands (87%), which had lower reference productivity. NAL had similar land cover as BLM but a slightly lower NPP reduction per unit area. The NPS and DOD-DOE lands had the lowest per unit area reduction.
Table 1. Average (2000–2011) NPP reductions in land cover types.

| Land cover type (NLCD) | NPP reduction per unit area (Mg C ha\(^{-1}\) yr\(^{-1}\)) | Land area (%) | Total NPP reduction (Tg C yr\(^{-1}\)) | Reduction from potential (%) |
|------------------------|--------------------------------------------------------|----------------|----------------------------------------|----------------------------|
| Shrublands             | 0.27 ± 0.03                                            | 54.96          | 17.20 ± 2.02                           | 12.30                      |
| Herbaceous             | 0.28 ± 0.05                                            | 30.46          | 10.02 ± 1.88                           | 9.93                       |
| Evergreen forest       | 0.51 ± 0.07                                            | 12.66          | 7.53 ± 0.99                            | 12.78                      |
| Deciduous forest       | 0.50 ± 0.08                                            | 1.7            | 0.98 ± 0.15                            | 11.01                      |
| Mixed forest           | 0.56 ± 0.10                                            | 0.22           | 0.14 ± 0.03                            | 13.00                      |
| Total                  | 0.31 ± 0.04                                            | 100            | 35.88 ± 4.72                           | 4.10                       |

Note: Reductions are the summed differences between each pixel and its reference, averaged across 12 years (mean ± SD).

Of the 89 CRAs in the study region, only 36 occupy more than 1% of land area (Table 3). Shrubland and herbaceous account for about 85%. Five CRAs (codes 35.60, 36.10, 39.10, 47.20, and 48A.1) were >50% forested and the rest were dominated by shrubland–herbaceous. The average annual reduction of NPP in the 36 CRAs was 30.68 ± 3.97 Tg C yr\(^{-1}\), the highest being in CRA code 48A.1 with a reduction of 3.75 ± 0.56 Tg C yr\(^{-1}\). The CRAs that are predominantly coniferous tree had the highest per unit area reduction of all the CRAs.

The Colorado Plateau CRAs occupied the largest land area (14.86%) in the study region. Although their combined NPP reduction was large (4.64 ± 0.54 Tg C/yr), the unit area reduction of productivity in each CRA was relatively small. The Chihuahuan Desert Shrubs (42.20) and Grassland (42.30) together accounted for the second largest area (10.73%). They also had small NPP reduction (about 0.21 ± 0.06 Mg C ha\(^{-1}\) yr\(^{-1}\)). Another small NPP reduction per unit area was in the Central Rolling Red Plains, eastern (78C.1) and western parts (78B.1), areas that have distinctive rangeland vegetation and are widely used for livestock grazing.

There are 152 GAP land cover types in the study region, of which only 26 occupy >1% land area (Table 4). The NPP reduction per unit area was generally smaller than for the CRA classification, except for a few coniferous woodland areas, but their differences in area made up for the difference. The largest area (13.37%) is occupied by Western Great Plains Shortgrass Prairie (code 7310) which had the highest total NPP reductions (4.10 ± 0.78 Tg C/yr), followed by the Colorado Plateau Pinyon–Juniper Woodland (code 4512) with a reduction of 3.28 ± 0.45 Tg C/yr. While this land cover type occupies nearly 40% less area than Western Great Plains Shortgrass Prairie (code 7310), it still had large NPP reductions. Furthermore, in comparison with Western Great Plains Shortgrass Prairie, the Colorado Plateau Pinyon–Juniper Woodland had higher NPP reductions per unit area (0.35 ± 0.05 Mg C ha\(^{-1}\) yr\(^{-1}\)), largely due to the dominance of pinyon–juniper woodlands. Similarly, the Ponderosa Pine Woodland and Pinyon-Juniper Woodland in the Southern Rocky Mountain range, mostly with coniferous vegetation, exhibited relatively high NPP reduction per unit area (0.40 ± 0.07 Tg C ha\(^{-1}\) yr\(^{-1}\)). Among the 26 GAP land cover types, the Inter-Mountain Basins Montane Sagebrush Steppe, had higher unit area reduction of productivity (0.72 ± 0.11 Mg C ha\(^{-1}\) yr\(^{-1}\)) than land cover types dominated by coniferous vegetation. Interestingly, the Sonoran Palo-verde-Mixed Cacti Desert Scrub had low NPP reduction per unit area (0.16 ± 0.05 Mg C ha\(^{-1}\) yr\(^{-1}\)).

**Discussion**

In general, the 12-year average UMD LNS map (Fig. 4) indicated widespread, large reductions in productivity compared with their reference conditions. NPP reductions also varied between different land cover and land management types. NPP reduction per unit area was high for all areas of forest cover, possibly due to insect damage, diseases, fire, and managed clearing (Floyd et al. 2009, Heath et al. 2011, Hicke et al. 2012, Anderegg et
In the shrubland and herbaceous NLCD vegetation classes, the NPP reduction per unit area was relatively low, but they occupy nearly 85% of the study region and therefore, in total, contribute large reduction of potential NPP.

Livestock grazing allotments showed similar patterns to grassland-savanna with large areas of small reductions below potential, but with high interannual variability. Overgrazing is often stated to be one of the key drivers of land degradation, associated with alterations in ecosystem structure (Asner et al. 2004) and soil erosion, both of which may lead to steep decline in forage production (Pellant et al. 2005). In addition, Holechek et al. (1995) and Ganskopp (2001) have demonstrated strong association between water availability and forage utilization. Higher utilization can be

| Common Resource Area (CRA) | CRA code | NPP reduction per unit area (Mg C ha\(^{-1}\) yr\(^{-1}\)) | Land area (%) | Total NPP reduction (Tg C/yr) |
|----------------------------|----------|--------------------------------------------------|---------------|-------------------------------|
| Irrigated cropland         | 35.10    | 0.32 ± 0.04                                     | 5.73          | 2.16 ± 0.28                   |
| Shrub–grasslands           | 35.20    | 0.22 ± 0.03                                     | 4.89          | 1.27 ± 0.15                   |
| Sagebrush–grasslands       | 35.30    | 0.24 ± 0.05                                     | 3.24          | 0.89 ± 0.20                   |
| Pinyon-Juniper–Sagebrush   | 35.60    | 0.27 ± 0.05                                     | 1.00          | 0.32 ± 0.06                   |
| Southwestern plateaus, mesas, and foothills | 36.10 | 0.51 ± 0.08                                     | 1.03          | 0.61 ± 0.09                   |
| Warm semi-arid mesas and plateaus | 36.20 | 0.38 ± 0.06                                     | 2.70          | 1.19 ± 0.18                   |
| Lower interior chaparral   | 38.10    | 0.17 ± 0.03                                     | 1.88          | 0.36 ± 0.06                   |
| Interior chaparral–woodlands | 38.20 | 0.28 ± 0.05                                     | 1.36          | 0.45 ± 0.08                   |
| Mogollon Plateau coniferous forests | 39.10 | 0.44 ± 0.08                                     | 2.33          | 1.19 ± 0.21                   |
| Sonoran Desert             |          |                                                  |               |                               |
| Upper                      | 40.10    | 0.17 ± 0.06                                     | 1.34          | 0.27 ± 0.09                   |
| Middle                     | 40.20    | 0.17 ± 0.05                                     | 1.20          | 0.23 ± 0.07                   |
| Chihuahuan                 | 41.30    | 0.20 ± 0.05                                     | 1.64          | 0.38 ± 0.10                   |
| Lower interior chaparral   | 38.10    | 0.17 ± 0.03                                     | 1.88          | 0.36 ± 0.06                   |
| Interior chaparral–woodlands | 38.20 | 0.28 ± 0.05                                     | 1.36          | 0.45 ± 0.08                   |
| Mogollon Plateau coniferous forests | 39.10 | 0.44 ± 0.08                                     | 2.33          | 1.19 ± 0.21                   |
| Sonoran Desert             |          |                                                  |               |                               |
| Sagebrush basins and slopes | 28A.1   | 0.26 ± 0.05                                     | 2.78          | 0.84 ± 0.15                   |
| Shadscale-dominated saline basins | 28A.3 | 0.24 ± 0.07                                     | 1.53          | 0.42 ± 0.13                   |
| Cool central desertic basins and plateaus | 34A.1   | 0.46 ± 0.06                                     | 1.12          | 0.60 ± 0.08                   |
| Warm central desertic basins and plateaus | 34B.1 | 0.35 ± 0.04                                     | 1.46          | 0.60 ± 0.06                   |
| Warm semi-arid mesas and plateaus | 34B.2 | 0.39 ± 0.06                                     | 1.07          | 0.49 ± 0.08                   |
| High mountains and foothills | 47.10   | 0.53 ± 0.09                                     | 1.13          | 0.69 ± 0.12                   |
| High mountains             | 47.20    | 0.74 ± 0.14                                     | 2.10          | 1.81 ± 0.34                   |
| Southern Rocky Mountain foothills | 49.10 | 0.38 ± 0.06                                     | 1.65          | 0.73 ± 0.11                   |
| Upper Arkansas Valley rolling plains | 69.10 | 0.30 ± 0.07                                     | 2.75          | 0.96 ± 0.21                   |
| Central high tableland     | 72.10    | 0.33 ± 0.10                                     | 2.38          | 0.90 ± 0.26                   |
| Great Salt Lake area       |          |                                                  |               |                               |
| Sagebrush basins and slopes | 28A.1   | 0.26 ± 0.05                                     | 2.78          | 0.84 ± 0.15                   |
| Shadscale-dominated saline basins | 28A.3 | 0.24 ± 0.07                                     | 1.53          | 0.42 ± 0.13                   |
| Cool central desertic basins and plateaus | 34A.1   | 0.46 ± 0.06                                     | 1.12          | 0.60 ± 0.08                   |
| Warm central desertic basins and plateaus | 34B.1 | 0.35 ± 0.04                                     | 1.46          | 0.60 ± 0.06                   |
| Warm semi-arid mesas and plateaus | 34B.2 | 0.39 ± 0.06                                     | 1.07          | 0.49 ± 0.08                   |
| Warm semi-arid mesas and plateaus | 34B.3 | 0.24 ± 0.07                                     | 1.53          | 0.42 ± 0.13                   |
| High mountains and foothills | 48A.1   | 0.68 ± 0.10                                     | 4.73          | 3.75 ± 0.56                   |
| Central Great Plains, southern part | 67B.1 | 0.29 ± 0.07                                     | 2.66          | 0.89 ± 0.20                   |
| Northern New Mexico highlands | 70A.1  | 0.26 ± 0.06                                     | 2.67          | 0.81 ± 0.19                   |
| Central Pecos valleys and plains | 70B.1 | 0.21 ± 0.05                                     | 2.38          | 0.59 ± 0.15                   |
| Central New Mexico highlands | 70C.1   | 0.25 ± 0.05                                     | 2.90          | 0.85 ± 0.16                   |
| High Plains                |          |                                                  |               |                               |
| Northern part              | 77A.1    | 0.25 ± 0.08                                     | 1.07          | 0.31 ± 0.10                   |
| Cotton Belt                | 77C.1    | 0.22 ± 0.09                                     | 1.07          | 0.28 ± 0.11                   |
| Southwestern part          | 77D.1    | 0.16 ± 0.05                                     | 1.70          | 0.32 ± 0.10                   |
| Northeastern part          | 77E.1    | 0.24 ± 0.08                                     | 2.21          | 0.61 ± 0.19                   |
| Rolling Red Plains         |          |                                                  |               |                               |
| Western part               | 78B.1    | 0.25 ± 0.08                                     | 3.31          | 0.96 ± 0.31                   |
| Eastern part               | 78C.1    | 0.29 ± 0.09                                     | 2.89          | 0.97 ± 0.29                   |
| Western Edwards Plateau    | 81A.1    | 0.23 ± 0.06                                     | 1.38          | 0.36 ± 0.10                   |

Notes: Thirty-six USDA-CRAs that occupy more than 1% of the study area are reported. Reductions (mean ± SD) were calculated using the UMD LNS, expressed in NPP units.
observed around the cattle drinking locations within the grazing allotments as noted elsewhere (Pickup et al. 1998, DelCurto et al. 2005), including utilization by livestock in riparian areas (Bear et al. 2012, Dalldorf et al. 2013) which are, however, generally masked in the LNS procedure. The high interannual variability in the LNS around the watering points may be indicative of deliberate management of livestock access to water.

The LNS maps have some sharp boundaries between degraded and less-degraded land associated with human activities (Fig. 5), especially at the edges of active and abandoned mining and oil extraction facilities, across fences between neighboring grazing allotments and at the edges of forest clearings. Such abrupt differences across boundaries are not surprising given the role of human management in degradation. While many LNS values were low each year, interannual variability in LNS could be caused by changes in land use, such as livestock grazing and fire, which were not used in the creation of LCCs.

The classification into LCCs with uniform environmental variables is a critical step since they are the basis for comparisons between degraded and non-degraded reference sites. Without such reference sites, any statement of degradation can simply be differences, for example, in rainfall, soil, or other irrelevant factors and therefore have little meaning. A good example is the Native American reserves in the Four Corners district, which are generally considered to be extreme cases of degradation, attributed to poor management. On the

Table 4. Average (2000–2011) NPP reductions in the USGS-GAP land cover classes.

| Land cover (USGS-GAP)                                      | Class code | NPP reduction per unit area (Mg C ha⁻¹ yr⁻¹) | Land area (%) | Total NPP reduction (Tg C yr⁻¹) |
|------------------------------------------------------------|------------|---------------------------------------------|---------------|--------------------------------|
| Western Great Plains Shortgrass Prairie                    | 7310       | 0.26 ± 0.05                                 | 13.37         | 4.10 ± 0.78                   |
| Western Great Plains Sandhill Steppe                       | 5301       | 0.25 ± 0.08                                 | 3.17          | 0.91 ± 0.28                   |
| Western Great Plains Mesquite Woodland and Shrubland       | 5810       | 0.26 ± 0.08                                 | 3.80          | 1.17 ± 0.35                   |
| Southern Rocky Mountain Ponderosa Pine Woodland            | 4530       | 0.40 ± 0.07                                 | 3.77          | 1.76 ± 0.31                   |
| Southern Rocky Mountain Pinyon–Juniper Woodland           | 4534       | 0.42 ± 0.07                                 | 1.28          | 0.62 ± 0.10                   |
| Southern Rocky Mountain Juniper Woodland and Savanna       | 5606       | 0.25 ± 0.05                                 | 1.08          | 0.31 ± 0.07                   |
| Sonoran Paloverde–Mixed Cacti Desert Scrub                 | 5213       | 0.16 ± 0.05                                 | 1.94          | 0.35 ± 0.10                   |
| Sonora–Mojave Creosotebush–White Bursage Desert Scrub     | 5207       | 0.22 ± 0.05                                 | 1.35          | 0.34 ± 0.08                   |
| Madrean Pinyon–Juniper Woodland                            | 4518       | 0.26 ± 0.04                                 | 1.61          | 0.49 ± 0.07                   |
| Introduced Upland Vegetation–Perennial Grassland and Forbland | 8407     | 0.22 ± 0.05                                 | 1.23          | 0.31 ± 0.08                   |
| Introduced Upland Vegetation–Annual Grassland             | 8404       | 0.22 ± 0.05                                 | 1.11          | 0.28 ± 0.06                   |
| Inter-Mountain Basins Semi-Desert Shrub Steppe             | 5309       | 0.33 ± 0.03                                 | 4.08          | 1.57 ± 0.14                   |
| Inter-Mountain Basins Semi-Desert Grassland               | 7305       | 0.31 ± 0.04                                 | 2.94          | 1.06 ± 0.13                   |
| Inter-Mountain Basins Montane Sagebrush Steppe             | 5308       | 0.72 ± 0.11                                 | 1.55          | 1.29 ± 0.19                   |
| Inter-Mountain Basins Mixed Salt Desert Scrub              | 5205       | 0.29 ± 0.04                                 | 2.69          | 0.91 ± 0.11                   |
| Inter-Mountain Basins Greasewood Flat                      | 9810       | 0.29 ± 0.03                                 | 1.12          | 0.37 ± 0.03                   |
| Inter-Mountain Basins Big Sagebrush Shrubland              | 5706       | 0.38 ± 0.04                                 | 3.86          | 1.71 ± 0.18                   |
| Great Basin Pinyon–Juniper Woodland                        | 4514       | 0.33 ± 0.11                                 | 1.05          | 0.40 ± 0.13                   |
| Colorado Plateau Pinyon–Juniper Woodland                  | 4512       | 0.35 ± 0.05                                 | 7.99          | 3.28 ± 0.45                   |
| Colorado Plateau Mixed Bedrock Canyon and Tableland        | 3218       | 0.28 ± 0.05                                 | 1.02          | 0.33 ± 0.05                   |
| Colorado Plateau Blackbrush–Mormon-tea Shrubland          | 5803       | 0.16 ± 0.04                                 | 1.12          | 0.21 ± 0.05                   |
| Chihuahuan Mixed Desert and Thorn Scrub                    | 5212       | 0.21 ± 0.06                                 | 2.15          | 0.53 ± 0.15                   |
| Chihuahuan Creosotebush, Mixed Desert and Thorn Scrub     | 5201       | 0.23 ± 0.05                                 | 4.27          | 1.16 ± 0.25                   |
| Central Mixedgrass Prairie                                 | 7302       | 0.26 ± 0.08                                 | 3.50          | 1.07 ± 0.34                   |
| Apacherian–Chihuahuan Semi-Desert Grassland and Steppe     | 5303       | 0.23 ± 0.05                                 | 4.89          | 1.32 ± 0.26                   |
| Apacherian–Chihuahuan Mesquite Upland Scrub                | 5211       | 0.18 ± 0.05                                 | 4.09          | 0.85 ± 0.22                   |

Notes: Twenty-six USGS-GAP land cover classes that occupy more than 1% of the study area are reported. Reductions (mean ± SD) were calculated using the UMD LNS, expressed in NPP units.
contrary, the LNS results reported here found that the reserves have a low reference potential and are therefore less degraded in the sense that it is used here.

There is a long history of conceptually similar land evaluation (FAO 1976, McRae and Burnham 1981), however, these are developed for specific purposes, such as evaluation of land for new forest plantations or suitability for the passage of heavy vehicles. In the case of LNS, the criterion for an LCC is an area in which productivity would be equal throughout, unless there is some other factor, such as degradation, present. The environmental variables used were selected to represent the chief controlling factors of NPP in the study region and that were available in maps with adequate spatial and temporal resolutions. Precipitation is the major environmental factor that controls productivity in the arid and semi-arid regions (Noy-Meir 1973, Graetz et al. 1988) but the effects of precipitation can be significantly more complex than the annual totals used here can specify. Changes in the frequency and seasonal distribution of precipitation may alter the vegetation response at critical times in the life cycle (Knapp et al. 2008) and could influence the vegetation more strongly than annual totals (Graetz et al. 1988, Ojima et al. 1993).

While more functional metrics could be included in the creation of the LCCs, the selection depends on having the necessary data. Naturally, the more variables relevant to NPP that are included in the creation of LCCs, the better their homogeneity. Process models that convolve the controlling factors in a more mechanistic representation of NPP than a statistical model, as used here, could yield better LCCs, but most process models need more data and parametrizations than were available at the scale of this study. Nevertheless, progress in LCC development using mechanistic NPP models is an obvious way forward.

There are various reasons why LNS may not indicate land degradation. For example, if important factors that affect the potential NPP are not included in the LCC step, differences in LNS may be a reflection of the differences in potential rather than degradation. Another is if any areas that are not representative of the LCC, such as wetlands and riparian areas, are inadvertently included. Yet another is if there are no pixels in an LCC at their potential production, the LNS values will indicate less degradation than is the case. However, in spite of these shortcomings, the only other methods available at present involve direct field measurement of NPP, which is impossible for areas larger than a few square kilometers, or a mechanistic productivity model. However, adequate parameterization and forcing data to resolve differences in NPP at a scale that is relevant to the typical areas of anthropogenic degradation is not possible. Given these circumstances, LNS is used here, in the knowledge of its limitations.

The reductions of the potential NPP that are revealed by LNS can have many causes in addition to degradation. These include any natural conditions (e.g., natural erosion) or management (e.g., application of fertilizers) that affect NPP but are not normalized in the classification into LCCs. Since these factors are difficult to normalize, the role of LNS is to identify, map, and assess

Fig. 4. LNS maps for (a) UMD and (b) UMDLM expressed as NDVI units. Blue areas (0) are at their reference condition and therefore interpreted as not degraded, while other colors show reductions below the reference condition. Black areas are masked land cover, land use types, roads, riparian buffers, and slope >15% that were excluded from the study. Note that panel (b) is for federal public lands only.
Fig. 5. Examples of LNS calculated using UMD LCCs representing different levels of degradation. Panels (a1–a5) show the high-spatial-resolution true-color image (ESRI 2014); (b1–b5) show the LNS map (average of 2000–2011); and (c1–c5) show the interannual coefficient of variation (12 years). Black pixels in LNS and coefficient of variation maps are areas excluded from the analyses.
the severity of reductions in LNS, but the causes require further interpretation. This may involve further remote sensing or field reconnaissance. Once sites that are affected by degradation are identified, then actions can be taken to better understand the causes and develop sustainable utilization avoiding irreversible degradation and to increase the capacity of land to sequester CO$_2$.

Identification of the causes of low LNS may not be possible if low values occur in the first year of study, which indicates degradation was caused prior to the study period.

Errors in LNS can be caused if reference pixels have different potential NPP owing to factors other than those accounted for in the classification: for example, small run-on patches can have a high NPP that is unrelated to the rest of the LCC. Similarly, overly conservative masking may eliminate some of the most degraded areas, such as livestock trampling near water. Even unrepresentative areas that are smaller than the pixel size used could bias the classification. Finer spatial resolution data, such as Landsat 30 m, would reduce this problem, but usually such finer spatial resolution data have low repeat frequency that reduces the accuracy of estimation of the total, seasonal NPP. Moreover, if data for environmental variables at this scale are not available, nothing would be gained.

In a recent study, Reeves and Baggett (2014) reported rangeland degradation relative toreference condition in the northern and southern Great Plains of the United States (Fig. 6c). Their method created reference areas using the NDVI of each individual pixel relative to the mean maximum NDVI of the ecological unit in which it occurred. There are three differences with LNS. (1) The ecological units were the same in each year, irrespective of any differences in interannual environmental variation such as rainfall. (2) The mean maximum was influenced by the NDVI of all the pixels in the unit, some of which may themselves be degraded, thus the measure of degradation could be biased in a heavily degraded ecological unit. (3) Since the pixel data were the mean of the maxima of NDVI across the entire study period (13 yr), any interannual variation could not be detected. Nevertheless, Reeves and Baggett’s (2014) results have some broad similarities to LNS, for example, in the areas of eastern New Mexico and Colorado and northwestern Texas. There were, however, large differences in the degree of degradation, even in some known areas of degradation.

The USDA NRCS-NRI rangeland degradation assessment maps (Fig. 6b; Herrick et al. 2010) differ from LNS to a much greater extent than Reeves and Baggett’s (2014). For example, the NRI map of biotic integrity shows intense degradation in areas where LNS has only moderate departure from the reference condition, such as in the region at the intersection of state lines of Utah, Colorado, New Mexico, and Arizona (four corners), and also western Texas and Oklahoma. Changes in species

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**Fig. 6.** Comparison of the (a) UMD LNS, (b) USDA-NRI (USDA Natural Resources Inventory) map of nonfederal rangelands, where biotic integrity shows at least moderate departure from reference condition (Herrick et al. 2010), and (c) overlapping parts of Reeves and Baggett (2014) map of degradation represented as $P$ values from $t$ tests between the mean response of each pixel and reference conditions. Both the UMD LNS and Reeves and Baggett (2014) maps of degradation were created using satellite-based imagery.
composition may reduce the rangeland health through reduction in biotic integrity and palatability, but, at the same time, may increase the NPP (Knapp et al. 2008). For example, several studies (Asner et al. 2003, Laliberte et al. 2004, Liu et al. 2013) have found woody encroachment into grassland-savanna ecosystem by honey mesquite (Prosopis glandulosa Torr.) in the southwestern United States (Goslee et al. 2003) that changes species composition and simultaneously increases NPP. Thus, there are some fundamental differences in LNS and NRI’s methods that contribute to the differences. However, NRI was based on non-federal lands alone, while LNS included federal lands, as well; also the NRI maps use ecosystem metrics such as “hydrologic function” and “soil and site stability,” in addition to biotic integrity, and not NPP. Aside from these legitimate differences, the NRI maps are an interpolation between data from field samples (sections) that were between 16 and 259 ha, giving a spatial sampling rate of between 0.063% and 1%, but without an explicit method to allow for variations between point samples, whereas LNS uses satellite data with complete coverage.

Conclusions

With growing population and increased human consumption of primary production (Rojstaczer et al. 2001, Haberl et al. 2007, Kraussmann et al. 2013), land degradation is increasing. While there are broad changes that increase the risks of degradation, such as anthropogenic climate change, pollution, and governmental policies, human-induced degradation is characterized by strong local spatial patterns caused by local differences in management. Thus, the complete coverage and high spatial resolution of satellite-based monitoring systems are needed, coupled with field interpretation (Herrick et al. 2010). The elaborated methodology and the reduction assessments reported here will not only help local sustainable management, but also influence policies intended to enhance U.S., as well as global, carbon sequestration. Currently, policies for carbon sequestration often use the findings of potential primary production models. However, such models do not take into account human modifications of land and its processes. The differences between potential and actual production can be very large, to the extent that potential models can be irrelevant.

This study provides an assessment of dryland degradation and estimates of reductions of productivity in the southwestern United States study area. It also identifies areas where remediation efforts would have the greatest effects on regional C sequestration if applied to areas with higher productive potential and vice versa. The total NPP reductions were 35.9 ± 4.7 Tg C/yr. The reductions were large and mostly consistent between years in spite of large variations in overall NPP caused by interannual differences in rainfall and other aspects of weather. The results indicate the overall difference between potential and actual NPP in the southwestern United States was 11.8%.

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