Description of the approach, data, and analytical methods used to estimate natural land loss in the western U.S.

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Approach

Here we provide metadata that describes the approaches, datasets, and spatial modeling techniques used to estimate the amount of natural land loss across the 11 western United States. We used established methods to map the degree of human modification (Theobald 2013) at a high spatial resolution (30 m) and to estimate the amount of natural land loss between two time periods: 2001-06 and 2006-11. These years were selected to coincide with the availability of a central dataset to our effort, the National Land Cover Dataset (v3). The work involved four important elements: (a) the framework to organize human activities and stressors; (b) the data sources used to represent each of the activities/stressors; (c) the measurements of intensity and extent; and (d) the method used to combine multiple stressors.

Framework

We organized our list of stressors (or threats to natural lands) based on the Human Activities Framework (Salafsky et al. 2008; http://cmp-openstandards.org/using-os/tools/threats-taxonomy/). Using this framework helps to move from a simple, unstructured “laundry list” of stressors to one that is organized, thereby minimizing redundancy, resulting in a comprehensive, but parsimonious list of stressors. At the top level, stressors are organized into five Level I classes: residential and commercial development, agriculture, energy production and mining, transportation and service corridors, and biological harvesting (Table 1). These are further broken into 1-3 specific activities, resulting in 11 Level II classes.

For each stressor, we identified and evaluated specific datasets on which to calculate a specific indicator(s), and to the maximum extent possible, selected those datasets that provided multiple observations between 2001 and 2011. In total, we examined nearly three dozen datasets, and retained 12 types of human activities built on nearly two dozen datasets (Table 1). Each of these datasets was based on readily and freely available spatial data that represented multiple time periods. These are described in detail below.

For each indicator, we calculated two factors at a given location (cell): intensity and footprint. Intensity (*I)* is the degree to which a human activity at a location generally modifies terrestrial and aquatic ecosystems, which is useful to differentiate effects of different types of land uses. For example, using a patch of land as pasture is likely to have a lower overall effect on the physical integrity of ecosystems than conversion to a parking lot. The intended use is more of a general, coarse-filter conservation approach, rather than a fine-filter, single species approach (see Tingley et al. 2015). The second is the footprint *(F)*, or the areal extent of a given human activity. In practice, the footprint is measured as the proportion of a 30-m raster cell that is occupied by a given land use. Thus, the overall degree of human modification (H) at a location is calculated as: $H = I \times F$, where a value of 0.0 has no human modification and a value of 1.0 has high modification. Estimates of I and F for each indicator were made from two different sources: expert opinion or empirical datasets. For the empirically-based stressors, we estimated I as a value from 0.0 to 1.0 based on the relative amount of energy required to maintain a particular land use type, obtained from Brown and Vivas (2005; Table 2). Thus, H accounts for a gradient of impact of human activities, has a direct physical interpretation, and the value remains a ratio data type so that differences within the range are meaningful (i.e., a value of 0.8 has twice the effect of 0.4), unlike most index-based approaches where values are converted to nominal or interval values. Note the *H* value was set to No Data (i.e., masked out) for locations that intersected lakes, reservoirs, or rivers (represented by the USGS National Hydrography Dataset as waterbodies and river area maps; http://nhd.usgs.gov/; accessed June 2015).

Table 1. A list of human activities that were included in the land loss maps, including their general stressor type and years for which datasets were available.

Human activities framework				*Dataset year*		
Level I	**Level II**	**Indicator**	**Primary Datasets**	**2001**	**2006**	**2011**
Residential and commercial development	Commercial and industrial	Commercial land use	NLCD	*2001*	*2006*	2011
	Housing and urban areas	Urban residential	NLUD/LUC	2000	2006*	2010
	Housing and urban areas	Low density residential	ICLUS/SERGoM	2000	2006*	2010
Agriculture	Croplands	Crop and pastureland	NLCD	2001	2006	2011
	Livestock ranching and grazing	Public grazing	Open range	2011	2011	2011
		Private lands livestock	Private lands FLAPS	2007	2007	2012
Energy production and mining	Oil and gas	Oil and gas wells	State O and G commissions	2001	2006	2011
	Mining and quarrying	Quarries mines	Mine footprints	2001	2006	2011
		Coal mines	Coal mines	2001	2006	2011
	Renewable	Concentrated and PV solar	Solar footprints	2001	2006	2011
		Wind farms	Wind farms	2001	2006	2011
Transportation and service corridors	Roads	Road footprint	TIGER	2000	2006*	2010
	Railroads	Railway footprint	TIGER	2000	2006*	2010
	Utility	Above-ground powerlines	Powerlines	2012	2012	2012
Biological harvesting	Logging/timber	Timber harvesting	NLCD differencing	2001	2006	2011

* Interpolated from 2000 and 2010 data

Table 2. Estimated intensity (*I*) values (0 to 1.0) for different land use types, developed by cross-walking National Land Cover Database (NLCD) classes to Brown and Vivas (2005) and Theobald (2013).

Land use type	Intensity	NLCD classes
Undeveloped	0.0	11, 12, 31, 41, 42, 43, 52, 71, 90, 95
Residential	0.7	23
Mixed-use developed	0.9	24
Agricultural cropland	0.5	82
Agricultural pastureland	0.4	81
Resource extraction	0.8	N/A
Industrial	1.0	24
Recreation	0.2	N/A
Transportation	1.0	NLUD
Unknown*	0.3	N/A

* But human modified—estimated to be 0.3 because it reflects clear signs of human modification but from miscellaneous and unknown types of activities.

Data sources and measurements

Commercial land use and urban residential

To map urban land use/cover, we used the National Land Cover Database v3 (NLCD) that provides a consistent methodology for 2001, 2006, and 2011 (Homer et al. 2015). We processed these data to remove what we considered artifacts that are caused by "burning in" roads from the US Census Bureau TIGER/Line files (v2001) when generating the impervious surface layer that forms the basis for the built-up classes (21, 22, 23, and 24; Pers. comm. J. Dewitt 2015). That is, we used the specific roads data layer where polylines that represented roads (even secondary, local and some driveways) were converted to raster cells, and these locations were "locked in" in NLCD to the identification of impervious surface (Figure 1). This results in an exaggeration in the extent of these land cover types, because most roads, even secondary and some primary roads, are less than 30-m wide (Theobald 2014). This step also reduces the amount of change observed in urban land covers over time because the road layer is static in NLCD (based on 2001 TIGER data). Consequently, we developed a routine to reduce these artifacts by reducing the width of interstate level roads to 2 cells wide (note that each part of a divided highway is represented as a line, so would be 4 cells total), and removing all other (smaller) roads, except in dense urban areas where built-up land cover was contiguous with other cells adjacent to the road cells.[1] Importantly, removing these artifacts results in a nearly *halving* of the estimated urban/built-up land (Table 3), and also removes undesirable artifacts such as built-up areas identified in a wilderness area (e.g., Washington state) because of a) an incorrect attribution of trails being burned in as roads, b) double-counting major roads or representing "ghost" roads caused by spatial mismatch (Las Vegas), and c) 90-120-m wide locations in remote 2-lane rural highways (e.g., Rocky Mountain National Park).

Table 3. Percentage of the conterminous US identified in urban/built-up land cover classes (21-24) in the National Land Cover Database (NLCD; v3) for three different years.

Dataset	2001	2006	2011
Raw NLCD	5.37%	5.53%	5.62%
NLCD w/roads filtered	3.37%	3.53%	3.63%

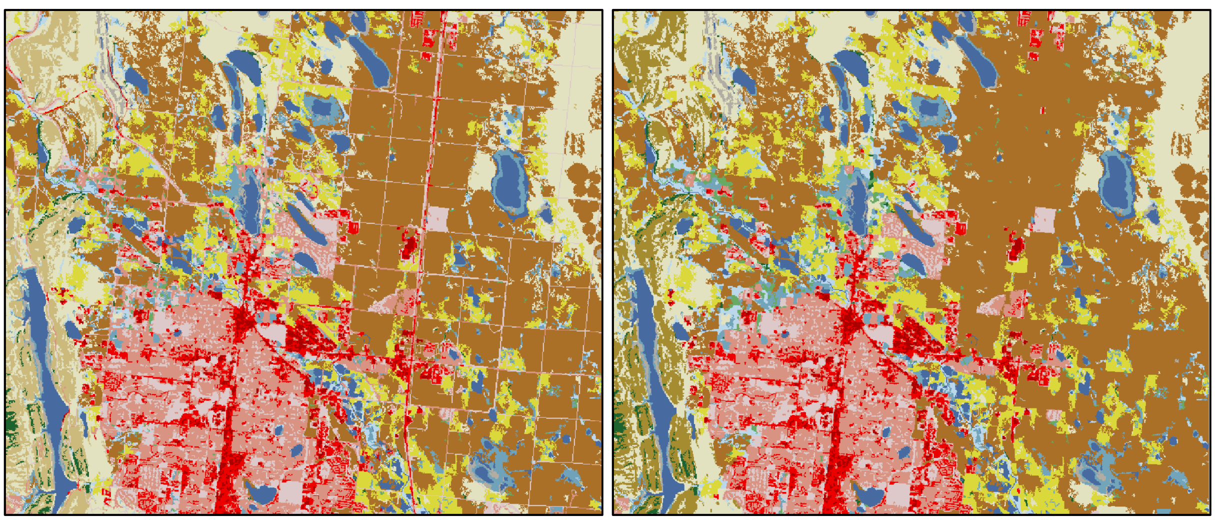

Figure 1. The raw National Land Cover Database (2011; v3) showing the city of Fort Collins, Colorado (left), with the roads filtered out (right).

[1] Processing steps: 1. Remove 1 cell on each side of interstate roads. 2. Remove cells identified as urban/built-up that intersected with secondary and local road. 3 replace them with the nearest non-urban/built-up land cover class.

Urban and low density residential

Based on Table 2, we assigned an intensity value *I* that was associated with each land cover type *c* in the NLCD. We were able to directly incorporate the effects of mis-classifications (the overall accuracy for NLCD 2006 was 78%; Wickham et al. 2013). To do this, we calculated a probability-weighted average intensity value, *I**. That is,

$$I^* = {\sum_c^n I_c P_c}\Big/{\sum_c^n P_c}$$

where P_c is the probability of correctly classifying class *c* of *n* classes. Rather than using the results reported for conterminous US or regional stratifications (10 regions), we calculated a confusion matrix using 5 classes that represent the rural-to-urban gradient. The 5 rural-to-urban classes were generated by using calculating a quintile classification of the brightness value of the Defense Meteorological Satellite Program night lights in 2006 (http://ngdc.noaa.gov/eog/dmsp.html), averaged across a 10-km radius moving window. Following the equation above, we calculated the probability-weighted intensity value for each class (Table 4).

Table 4. The probability-weighted intensity values for each land cover class, obtained from the 2006 accuracy assessment (provided in Wickham et al. 2013).

		Rural-to-urban gradient				
Class	**Intensity**	**1**	**2**	**3**	**4**	**5**
Water	0	0.011	0.060	0.020	0.027	0.017
Snow/ice	0	0	0	0	0	0
Built-up open	0.2	0.342	0.372	0.325	0.358	0.341
Built-up low	0.5	0.341	0.414	0.535	0.507	0.511
Built-up mod	0.7	0.366	0.571	0.712	0.638	0.638
Built-up high	0.9	0.42	0	0	0.711	0.731
Barren	0	0.008	0.072	0.055	0.138	0.223
Forest deciduous	0	0.085	0.115	0.082	0.084	0.143
Forest conifer	0	0.025	0.058	0.036	0.067	0.364
Forest mixed	0	0	0.088	0.136	0.063	0.130
Shrubland	0	0.042	0.090	0.115	0.139	0.217
Grassland	0	0.155	0.198	0.156	0.207	0.296
Ag - pasture	0.4	0.365	0.352	0.355	0.356	0.330
Ag - cropland	0.5	0.516	0.546	0.474	0.483	0.524
Wetland - woody	0	0.084	0.076	0.060	0.133	0.114
Wetland - herbaceous	0	0.132	0.168	0.154	0.121	0.084

Crop and pastureland

We used an intensity value of 0.5 for cropland and 0.4 for pastureland, following Theobald (2013). These values were used to calculate the probability-weighted intensity values (see Table 4).

Livestock and grazing

To map the distribution and intensity of livestock on private lands, we generated density surfaces from the Farm Location and Population Simulator (Burdett et al. 2015; http://flaps.biology.colostate.edu/). We generated 10 iterations of the simulated populations for chickens (layers and broilers), cows (dairy, beef, and feedlots), sheep and swine, and calculated the mean density value (applying a kernel density function with radius of 3 km). We then calculated a total overall density score by weighting animal types for cattle = 1.0, sheep = 0.2, hogs = 0.3, and chickens = 0.003 for 2007 and 2012 (following Brown and Froemke 2010). To convert the overall livestock density to intensity, we log-transformed, max-normalized and multiplied by 0.5, assuming maximum intensity value I was equal to 0.5.

To represent effects of grazing on federal lands, we obtained maps of grazing allotments directly from the US Forest Service (i.e., the National Range Data) and Bureau of Land Management (BLM Grazing Allotments). We joined permit information to active allotments and removed BLM allotments that were < 10 acres or had 0 animal unit months (AUMs), and removed allotments with > 3 AUM/acre (to remove artifacts such as sliver polygons). We weighted AUM density based on grazing availability by identifying natural cover types with forage (grasslands, shrublands, forestlands) and adjusted the AUM density to decrease with increased slope (s), derived from a 10-m USGS digital elevation model. Adjusted AUM density $S = ((100-s)/100)^2 * 100$. We max-normalized values and multiplied by 0.2, so the maximum intensity of grazing was 0.2. We examined adjusting the density of use as a function of distance from drinking water sources, but did not include this factor because of limited data on the location and timing of water availability from stock tanks and springs.

Oil and gas wells

To map the effects of oil and gas activities, we obtained well point location data from each of the 11 western states' Oil and Gas offices (accessed in June 2015). We selected only wells that were active at a given time period. We represented an average footprint for each well of 5.67 ha per well (McDonald et al. 2009; Allred et al. 2015) and a maximum intensity value of 0.5 using a kernel density with radius of 450 m.[2]

[2] To implement this in ArcGIS v10, we first found that setting the Kernel Density tool with a population of 3, radius of 450 m, and density in hectares using 90-m cells, resulted in a surface that summed close to 5.67 ha, with a maximum estimated intensity value at 0.18. Although the intensity at the location of a well or pad is likely much higher (perhaps approximating 1.0), we used the kernel density with 450-m radius to incorporate possible uncertainties in the spatial location. Where multiple wells were located within the same well pad, the intensity value from the kernel density could exceed 1.0. We capped the maximum intensity value at 0.5, however, as a conservative estimate of the effects.

Quarries and mines

To map the effects of extraction of mineral resources such as quarries and mines, we selected mines where there was evidence of production and that were classified as large production size surface mines from the USGS Mineral Resources Data System (http://mrdata.usgs.gov/mrds/; accessed November 2015; *n* = 800). We then hand-digitized the footprint visible with each mine at each epoch from high-resolution aerial photography in Google Earth. We assigned an intensity value of 1.0 to each mine footprint.

To map the effects of surface coal mines, we selected large coal mines in the western US from the US Energy Information Administration (2013; http://www.eia.gov/maps/layer_info-m.cfm; *n* = 50). We then hand-digitized the footprint visible for each mine at each epoch from high-resolution aerial photography in Google Earth. We assigned an intensity value of 1.0 to each mine footprint.

Concentrated and photovoltaic solar

To map the effects of concentrated and photovoltaic solar facilities, we identified all medium and large facilities (> 50 MW capacity, *n*=136) from the EIA power plant tabular database (Solar Energy Industries Association, https://www.seia.org/research-resources/major-solar-projects-list, accessed on July 2015) and spatially cross-referenced these using Argonne National Laboratory's Solar Mapper (http://bogi.evs.anl.gov/solmap/portal/). We then hand-digitized the footprint visible at each solar facility at each epoch from high-resolution aerial photography in Google Earth. We assigned an intensity value of 1.0 to each facility footprint.

Wind farms

To map the effects of wind turbines located in "wind farms," we obtained turbine point location data from the Federal Aviation Administration (http://www.fws.gov/southwest/es/Energy_Wind_FAA.html; accessed June 2015). We assumed a maximum intensity value of 0.25 with kernel density radius of 450 m (Theobald 2013).

Road footprint

Following Theobald (2013), we mapped the physical impacts of roads by estimating the typical width of roads of different types from the TIGER 2010 datasets. Because roads that were mapped in the past decades are often not aligned with 2010 and the spatial precision of the roads has greatly improved, we selected the roads in 2010 that were presumably the same road but not mapped as precisely (within 30 m), and then used the selected subset of roads from the 2010 dataset to represent roads that were likely present in the past decades. We assumed that interstates/highways were 30-m wide so the intensity value was 1.0 (note that divided roads are represented by a separate line for each direction of travel), secondary roads were assigned an intensity value of 0.5, local roads 0.2, and rural/4WD roads 0.1.

Above ground powerlines

We mapped the impact of powerlines using the density raster from Theobald (2013), which represented intensity as a maximum value of 0.125, using a kernel density of 0.5-km radius.[3] Note that we were unable to map the impact of above and below-ground pipelines because a high resolution, freely available dataset was not available.

Timber harvesting and clearing

Timber management and harvesting occurs on over 9.8-million acres per year in the US (USFS Forest Inventory and Analysis; http://www.fia.fs.fed.us/slides/major-trends.pdf), yet there are no spatially-explicit maps available for federal (e.g., forest service) or private lands. As a coarse proxy, we identified areas where timber harvesting or clearing occurred by comparing locations mapped as forest land cover types that occurred in the previous time step as forest but non-forest (and non-urban developed) in the current epoch. That is, if a pixel was classified as grassland in 2011 but forested in 2006, we assumed that pixel had timber removed (due to mechanical thinning). The intensity value of forest harvesting was estimated at 0.2 partially because this is a bit of a transitory effect, lasting likely 20 to 50 years depending on regrowth and successional rates. We did not include cells where forest loss was likely due to a large fire that occurred since 1992 (http://www.mtbs.gov/), nor if the location was within a wilderness area or national park (i.e., GAP status 1 or 2 lands; http://gapanalysis.usgs.gov/padus/data/).

Combining stressors (cumulative)

We used a method that minimizes bias associated with non-independence among several stressor/threats layers (Theobald 2013), and that assumes the contribution of a given threat decreases as values from other threats overlap. Locations with multiple threats will have a higher human modification value than locations with just a single threat (assuming the same value), but the cumulative human modification score converges to 1.0 as multiple human impact data layers are added. Individual factors were combined across multiple data layers using an "increasive" function (Theobald 2013), also referred to as a fuzzy sum (Bonham-Carter 1994).

Vetting process

We developed a 3-stage process to vet our work, for which we briefly report results of the internal and validation steps:

1. Internal team review
    a. Review maps at local, county, and state scales
    b. Generate basic descriptive statistics for each year, state/county
    c. Calculate change statistics between years
2. Internal comparison
    a. Ad hoc comparison to other maps and patterns

[3] To implement this in ArcGIS v10, we first found that setting the Kernel Density tool with a population of 1, radius of 500 m, and density in hectares using 90-m cells. We then simply found the maximum density value, which we used to then max normalize the intensity values, and then multiplied by 0.125.

    b. Calculate correlations with other existing datasets
    c. Develop a priori expectations of our estimates to other datasets
    d. Examine consistency of temporal changes (esp. Nightlights)
3. Validation
    a. Quantify/acknowledge uncertainty
    b. Compare detailed, random sample land use/cover dataset (GLUED)
4. Peer review
    a. Send out for initial independent peer reviews
    b. Prepare manuscript to submit to peer-reviewed scientific journal

Internal team review

During construction of the human modification model, we typically generated spatial maps and viewed these at multiple extents, including West-wide, state, county, and local levels. These were visually compared to aerial photos in an *ad hoc* manner. This revealed a number of issues that were subsequently corrected, including:

- incorrect extents that led to clipping of the overall map
- fine-tuning of estimates of impact and edge-effects
- incorrect attributes, such as playas attributed as water bodies

In conjunction with the visualization of preliminary products, we also calculated and examined basic descriptive statistics for each year, including:

- mean and standard deviation of *H* for the West, states, and counties
- minimum and maximum to ensure bounding of functions had occurred properly

To aid in understanding the basic differences between the new human modification dataset discussed here (*H*) and other existing datasets, we provide a comparison table (Table 5). We compared *H* for 2011 to other various existing datasets that were developed for similar purposes (Tables 6 and 7). We expected that there would be moderate overall correlation (~0.5-0.8), but that few or no other datasets would have strong correlation (> 0.8).

Table 5. A comparison of the types of human activities and stressors that are included (or not) in comparison datasets.

Human activities			*Datasets**							
Level I	**Level II**	**Stressor**	**H**	**NRI**	**NLCD**	**C of Ag**	**CDL**	**USGS LCT**	**LCM**	**HFL**
Res and commercial development	Comm. and industrial	Urban sprawl	A	p	A			s	A	A
	Housing and urban areas	Urban sprawl	A	p				s		
Agriculture	Croplands	Ag/logging	A		A	p	A		A	
	Livestock ranching	Ag/logging	A			p				
Energy production and mining	Oil and gas	Energy	A							
	Mining and quarrying	Energy	A					s		A
	Renewable	Energy	A							
Transportation and service corridors	Roads	Transportation	A	p				s	A	A
	Railroads	Transportation	A	p					A	A
	Utility	Transportation	A							A
Biological harvesting	Logging and timber	Ag/logging	A					s		

H = Human Modification (Theobald 2013); NRI = Natural Resource Conservation Service National Resource Inventory; NLCD v3 = National Land Cover Database v3; C of Ag = Census of Agriculture; CDL = Cropland Data Layer; USGS LCT = Land Cover Trends; LCM = Landscape Condition Model (Comer and Hak, 2014, personal communication); HFL = Human Footprint by Leu et al. (2008); A = all lands; p = non-federal, s = sampled.

Table 6. Correlation of *H* human modification map with other spatial datasets.

Source	Correlation
Landscape condition model (NatureServe) - raster	0.68
Human footprint (Sanderson et al. 2002) - raster	0.52
Human footprint (Leu et al. 2008) - raster	0.76
CDL 2011 Modified - developed and cropland/pasture	0.74
CDL 2011 Developed - developed but not ag/crop, state acreage	0.75

Table 7. The loss of natural land (in acres) for three datasets that can be used for monitoring change through time, with area adjusted by type of activity to match the degree of human modification (e.g., mining and urban = 1.0, cropland = 0.5). Note that the estimate of *H* is twice that of the other datasets, but that the NRI is only for non-federal lands, which is roughly half of the West. Moreover, *H* incorporates a much more comprehensive suite of human activities than do other datasets that are just land cover datasets (i.e., NLCD).

Dataset	2001	2011
NRI*	51,151,500	53,008,500
NLCD v3	49,295,915	50,154,678
H	102,636,407	105,401,678

* The Natural Resources Inventory (NRI) is for non-federal lands, which is roughly half of the West.

Validation

To validate the human modification metric, we compared values of H for 2011 (H2011) against an independently derived set of data on the degree of human modification, obtained from aerial-photo interpretation of high resolution imagery (acquired ~2011) at points drawn at random using the GLUED[4] sampling design and protocol (hereafter, gH2011). To obtain H2011, we extracted the mean predicted human modification within a 100-m buffer for each of the 2,604 GLUED sample points. We excluded points where a stressor could not be identified or if a

[4] Available through Google Group: https://groups.google.com/forum/?fromgroups#!forum/global-land-use-emergent-database

change in land use had occurred during or since 2011. To account for potential bias among different GLUED interpreters, the recorded human modification for a given point was averaged with the mean human modification score for the recorded stressor type to calculate the final value of gH2011. These values were then compared with the mean predicted human modification within the buffer for which a human modification score was assigned in the GLUED dataset. We found that the Pearson's correlation coefficient was 0.67 (n = 2,604, p < 0.0001; Figure 2). The differences between the observed GLUED human modification values and the predicted human modification values were most apparent in two specific stressor types: grazing and low- density residential development. These differences were due to inherent challenges in interpreting subtle activities on the ground. In general, the GLUED human modification scores were higher than the predicted values. This difference may be due to an interpreter's ability to identify specific human activities or modifications from aerial imagery that are not represented in the data used to develop the human modification layer (i.e., recreation and other forms of human intrusion). We are taking additional steps to quantify and resolve such uncertainties in future iterations of the human modification data and associated validation process.

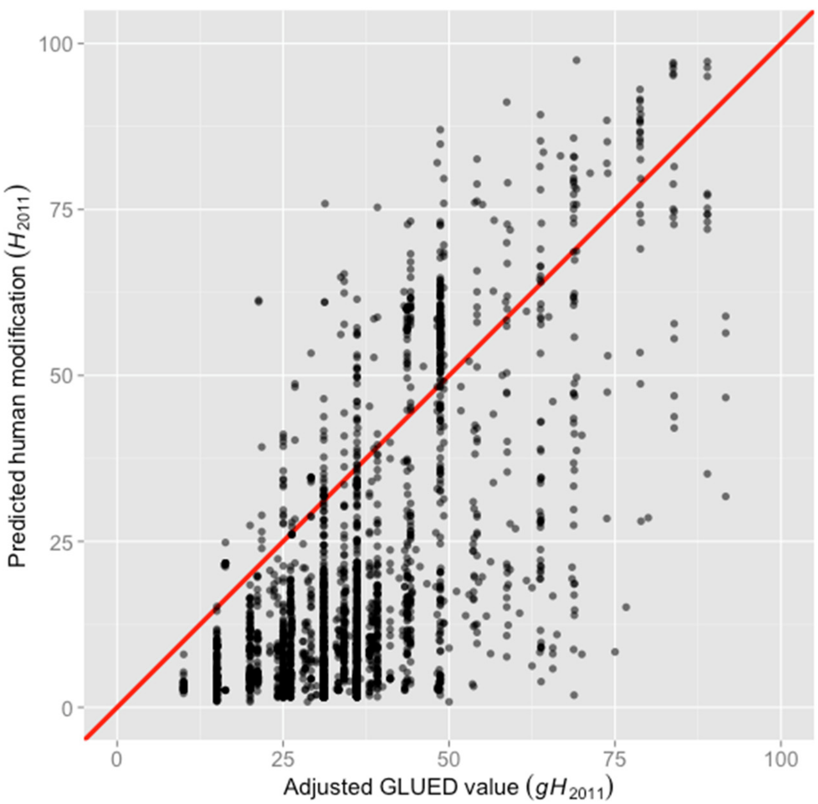

Figure 2. A scatterplot of 2,604 random locations showing the degree of human modification values H2011 (y-axis) against the estimated degree of human modification obtained from the GLUED aerial-photo interpreted database. The 1:1 line is shown in red.

Summary of results

Due to the expanding human footprint, open, natural lands in the Western U.S.[5] are steadily disappearing (Tables 8 and 9). Over a recent decade (2001-2011), the total amount of natural area (i.e., open lands, natural lands) lost to development was roughly equivalent to two Grand Canyon National Parks (~2.8 million acres). Each year, on average, we lost close to a Rocky Mountain National Park worth of natural area (276,527 acres), although the rate of loss slowed to 246,555 acres annually between 2006 and 2011.[6] We found that the dominant development stressor varied among states, although agricultural land uses resulted in the largest development footprint (Tables 10 and 11). We also found that about two-thirds of all modified acres consist of privately owned land. On public lands, Bureau of Land Management and US Forest Service lands were the most modified (Table 12). In addition to loss of natural area, patterns of human development have further fragmented the West, eroding natural lands an additional 0.3 miles, on average. That is, if you randomly were dropped out of a plane into a natural area, on average, you would be 3.5 miles from developed land in 2011, compared to 3.8 miles in 2001. The degree of change in natural area fragmentation (7.4% change from 2001 to 2011) was more than twice the degree of natural area loss (2.7%).

Table 8: Cumulative acres of human modification in each of the western states between 2001 and 2011.

State	2001	2006	2011
Arizona	7,399,000	7,541,000	7,636,000
California	19,108,000	19,404,000	19,610,000
Colorado	11,794,000	11,981,000	12,130,000
Idaho	7,194,000	7,241,000	7,290,000
Montana	15,030,000	15,119,000	15,213,000
Nevada	5,340,000	5,395,000	5,433,000
New Mexico	8,055,000	8,186,000	8,259,000
Oregon	7,956,000	8,093,000	8,219,000
Utah	5,279,000	5,402,000	5,520,000
Washington	8,840,000	8,963,000	9,132,000
Wyoming	6,642,000	6,846,000	6,959,000

[5] Defined as: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.

[6] The acreage statistics reported in this document are estimates based on models of human modification. We report loss down to the level of individual acres in the interest of being thorough, even if the actual level of precision is lower (perhaps 1000s of acres). Accordingly, we recommend rounding such numbers in public communications to reflect the actual level of precision (e.g., 246,555 acres becomes ~247,000 acres).

Table 9: Amount of natural area loss (in acres) in each of the western states during two periods spanning 2001-2011.

State	2001-2006	2006-2011
Arizona	143,000	95,000
California	296,000	206,000
Colorado	187,000	150,000
Idaho	47,000	50,000
Montana	89,000	94,000
Nevada	54,000	39,000
New Mexico	131,000	73,000
Oregon	137,000	126,000
Utah	123,000	118,000
Washington	123,000	169,000
Wyoming	204,000	113,000

Table 10: Cumulative acres of human modification in each of the western states between 2001 and 2011, based on land use activities grouped into four major stressor categories: agricultural (including timber harvest), energy (both conventional and renewable), residential (including commercial and other urban land uses), and transportation (including powerlines).

Stressor	State	2001	2006	2011
Energy	Arizona	65,000	73,000	80,000
	California	565,000	595,000	622,000
	Colorado	707,000	828,000	939,000
	Idaho	5,000	10,000	13,000
	Montana	373,000	414,000	440,000
	Nevada	72,000	80,000	92,000
	New Mexico	804,000	886,000	922,000
	Oregon	8,000	23,000	33,000
	Utah	261,000	305,000	364,000
	Washington	11,000	22,000	30,000
	Wyoming	826,000	1,032,000	1,140,000
Transportation	Arizona	1,086,000	1,126,000	1,153,000
	California	2,577,000	2,623,000	2,654,000
	Colorado	1,074,000	1,100,000	1,118,000
	Idaho	785,000	828,000	857,000
	Montana	1,105,000	1,128,000	1,143,000
	Nevada	789,000	801,000	810,000
	New Mexico	1,243,000	1,268,000	1,284,000
	Oregon	1,176,000	1,230,000	1,266,000
	Utah	750,000	808,000	847,000

	Washington	1,000,000	1,020,000	1,034,000
	Wyoming	915,000	925,000	932,000
Agriculture	Arizona	4,938,000	4,943,000	4,917,000
	California	11,044,000	11,037,000	11,002,000
	Colorado	8,324,000	8,361,000	8,357,000
	Idaho	5,348,000	5,364,000	5,348,000
	Montana	11,539,000	11,573,000	11,558,000
	Nevada	3,836,000	3,870,000	3,865,000
	New Mexico	4,776,000	4,826,000	4,822,000
	Oregon	5,282,000	5,339,000	5,344,000
	Utah	3,284,000	3,304,000	3,299,000
	Washington	5,907,000	5,888,000	5,928,000
	Wyoming	3,824,000	3,851,000	3,846,000
Residential	Arizona	768,000	906,000	1,003,000
	California	3,970,000	4,293,000	4,489,000
	Colorado	667,000	764,000	816,000
	Idaho	272,000	305,000	326,000
	Montana	234,000	252,000	265,000
	Nevada	335,000	387,000	409,000
	New Mexico	348,000	384,000	409,000
	Oregon	646,000	704,000	734,000
	Utah	426,000	485,000	519,000
	Washington	1,162,000	1,269,000	1,339,000
	Wyoming	125,000	133,000	143,000

Table 11: Amount of natural area loss (in acres) in each of the western states for two periods spanning 2001-2011, based on land use activities grouped into four major stressor categories: agricultural (including timber harvest), energy (both conventional and renewable), residential (including commercial and other urban land uses), and transportation (including powerlines). Note that negative values indicate a gain in natural lands, likely due to recovery from ag/logging to a more natural land cover class.

Stressor	State	2001-2006	2006-2011
Energy	Arizona	8,000	8,000
	California	30,000	27,000
	Colorado	121,000	111,000
	Idaho	5,000	3,000
	Montana	41,000	26,000
	Nevada	8,000	12,000
	New Mexico	83,000	36,000
	Oregon	15,000	10,000
	Utah	44,000	59,000

	Washington	12,000	8,000
	Wyoming	206,000	108,000
Transportation	Arizona	40,000	27,000
	California	46,000	31,000
	Colorado	26,000	17,000
	Idaho	43,000	29,000
	Montana	23,000	16,000
	Nevada	13,000	8,000
	New Mexico	25,000	16,000
	Oregon	54,000	36,000
	Utah	58,000	39,000
	Washington	20,000	13,000
	Wyoming	10,000	6,000
Agriculture	Arizona	5,000	-26,000
	California	-7,000	-35,000
	Colorado	37,000	-4,000
	Idaho	16,000	-16,000
	Montana	34,000	-15,000
	Nevada	34,000	-5,000
	New Mexico	49,000	-4,000
	Oregon	57,000	5,000
	Utah	20,000	-5,000
	Washington	-19,000	40,000
	Wyoming	27,000	-5,000
Residential	Arizona	138,000	97,000
	California	323,000	196,000
	Colorado	97,000	52,000
	Idaho	33,000	22,000
	Montana	18,000	13,000
	Nevada	53,000	21,000
	New Mexico	36,000	25,000
	Oregon	58,000	30,000
	Utah	60,000	34,000
	Washington	107,000	70,000
	Wyoming	8,000	11,000

Table 12: Cumulative human modification, and percent change in cumulative human modification, by ownership, in 2001 and 2011. About two-thirds of human modified acres in the West were on private lands. Among federal jurisdictions, Bureau of Land Management and US Forest Service lands had the most modified acres.

	Cumulative acres of human modification		*Percent change*
Ownership	**2001**	**2011**	**2001-2011**
Private	67,286,000	69,318,000	3.0
BLM	12,499,000	12,790,000	2.3
USFS	7,743,000	7,897,000	2.0
State	5,037,000	5,180,000	2.8
Federal, Other*	4,904,000	4,950,000	0.9
Non-Federal, Other**	4,227,000	4,320,000	2.2
NPS	942,000	948,000	0.7

* Including Bureau of Reclamation, Department of Energy, Bureau of Indian Affairs, USDA Natural Resources Conservation Service, and USDA Agricultural Research Service

** Including Native American Land, Local Government, Regional Agency Land, County Land, Regional Water District, The Nature Conservancy, Audubon Society, and Ducks Unlimited

Loss

To calculate the area of natural lands lost, we simply calculated the H-weighted area, where H refers to the degree of human modification at a given location. That is, if H at a given location (i.e., map pixel) was 1.0, then the loss of natural area would equal the area of the pixel (typically 900 m^2). If the H value was 0.3, then 0.3 x 900 or 270 m^2. In 2001, the mean degree of modification for the West (H') was 0.136 (H'_{2001}) and in 2011, H'_{2011} was 0.140.

Fragmentation

We calculated fragmentation as the mean distance away from areas that had a human modification (H) value greater than a given threshold, t. That is, Euclidean distance of locations was calculated away from locations (pixels) where $H \geq t$. The mean distance (in meters) was then calculated for those locations where $H < t$. The graph below (Figure 7) shows the proportion of the West where $H \geq t$ (y-axis), which declines exponentially from 1.0 at $t = 0$ to ~0.35 at $t = 0.1$ and so on. We chose to report our single measure of fragmentation at $t = 0.4$ because (1-t) matches the percolation theory critical threshold of ~0.6 (Szaro and Johnston 1996).

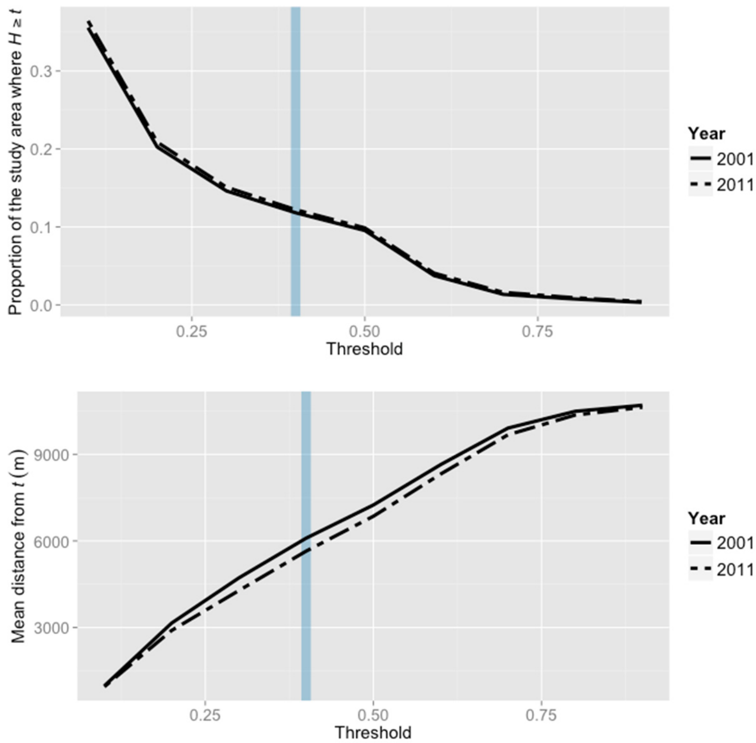

Figure 7. Graphs portraying the fragmentation of the West from developed areas, showing (upper panel) the proportion of the West with the degree of human modification (H) below a given threshold t (shown on x axis); and (lower panel) the mean distance away from locations with H values greater than the threshold for t.

Protected lands

To place our findings within the context of protected lands in the West, we also examined the proportion of lands under permanent protection to maintain a primarily natural state (Table 13). To calculate this, we selected GAP status 1 and 2 lands from the PADUS dataset version 1.3 (http://gapanalysis.usgs.gov/padus/). We updated these data with recent designated wilderness areas (obtained from Wilderness.net) as well as wilderness study areas.[7]

[7] This added the following wilderness and wilderness study areas (WSAs): Hermosa Creek (CO); White Clouds (ID); Jim McClure-Jerry Peak, Hemingway Boulders, Homestead WSA (NV); and Wovoka, Palisades WSA, and Shoal Creek WSA (WY). We included WSAs based on the assumption that most WSAs are being managed effectively as wilderness areas, so this is a conservative assumption.

Table 13: The percentage of lands with permenent protection in 2016 managed to maintain a primarily natural state.

State	Percentage
Arizona	11.40%
California	23.71%
Colorado	9.01%
Idaho	12.47%
Montana	6.85%
Nevada	14.71%
New Mexico	6.43%
Oregon	11.37%
Utah	12.72%
Washington	12.82%
Wyoming	10.67%
Westwide	13.96%

Intended uses and guidance

We intend these data to be used to inform discussion regarding patterns of natural land loss in the West, as well as rates of land loss between 2001-2011 and the two intermediate time periods, 2001-2006 and 2006-2011. Two approaches can be used that make different assumptions about land loss in these periods, and which will result in slightly different results for some areas. The first approach assumes that any negative loss in development (e.g., agricultural crops going out of rotation) is forced to zero, such that no loss is recorded for that time period. This approach accounts for the 'gross loss' and only allows for non-negative loss over the time period 2001-2011. This approach was taken in the interactive map to generate county summaries. The second approach accounts for the 'net loss' and allows for negative loss over the time period 2001-2011. In this approach, negative and positive loss is cumulative over the two intermediate time periods. This approach was taken in the tables shown on the microsite for the project. Further guidance regarding the derivation and interpretation of statistics presented in this document and elsewhere (on the microsite for the project, as well as in the interactive map) is provided in the appendix (Figure A1). We provide the data publicly at a resolution of 270 m and recommend that any analysis should consider a minimum mapping unit of roughly 810 m (cell size, roughly 160 acres). Note that perennial water features (i.e. lakes, reservoirs, rivers, etc.) were coded as NO DATA – that is, we estimated human modification of lands, not waters.

Next steps

We are currently developing a manuscript that builds on the work described in this document, and to be submitted to a peer-reviewed scientific journal. In the manuscript, we will provide greater detail on the scientific basis of our work, the procedures used, and the overall results. We also will investigate: adjusting the forest disturbance layer to better reflect changes in vegetation structure due to wildfire; our use of the USDA Cropland Data Layer as an additional source of information regarding cropland locations; a review and revision of the TIGER roads data layer (namely, the attributes of roads in rural/remote landscapes); and adjusting the wind turbine locations to better reflect the distinction between completed and approved project dates, so as to reduce a very small over-representation of wind farms in the current data. In addition, we are investigating including additional data layers on reservoirs, pipelines, communication towers, and general activities that are represented in “night lights” datasets (from NOAA Defense Military Satellite Program). Going forward, we anticipate using more recent datasets to reflect conditions in 2016, especially the NLCD (available 2017/2018) and oil and gas well locations. Finally, we will address several useful suggestions provided by independent reviewers, including: framing our work in the context of coarse-filter conservation targets; strengthening the discussion that this approach generally captures physical integrity of ecological systems, but does not directly account for other aspects, such as chemical integrity (e.g., acidification due to air pollution or application of fertilizer/pesticides); and examining the sensitivities of the results to key parameters and decision rules (e.g., the variance around the empirically-estimated intensity factors, in addition to the mean value).

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Appendix

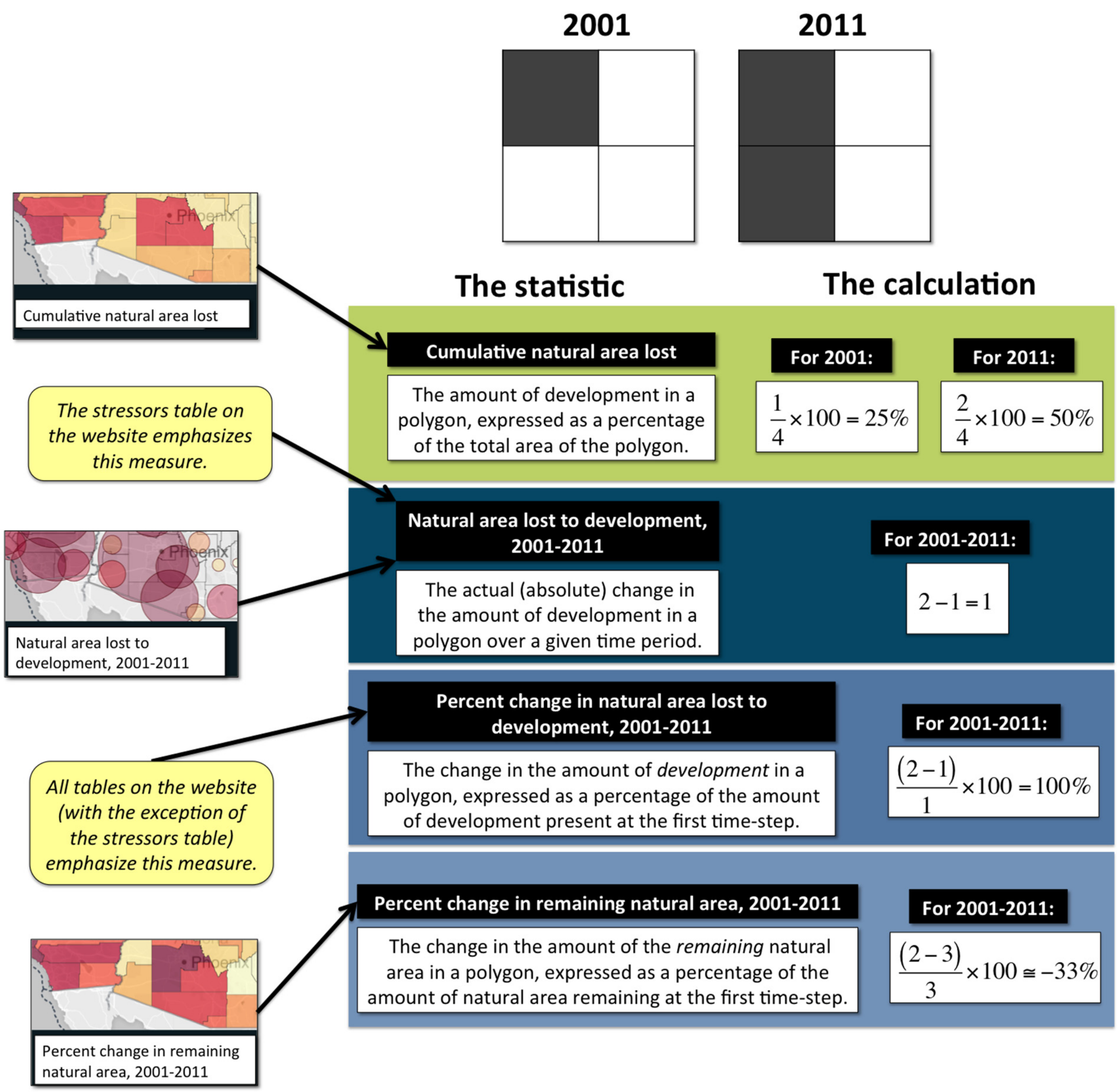

Figure A1: Overview of the various statistics reported in this document, on CAP's microsite for the project, and in the interactive map. Descriptions and example calculations are provided for each statistic assuming a hypothetical area in which development is represented by grey cells and natural areas by white cells. Note that some statistics pertain to individual years (i.e., cumulative natural area lost), while others involve a period of years (statistics highlighted in blue cells). Additionally, some are relative (involving percentages) while others are absolute measures (involving, e.g., acres).