



EXECUTIVE SUMMARY

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For the project entitled:

Loss and fragmentation of natural lands in the conterminous U.S. from 2001 to 2017

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Goal

The goal of this executive summary is to briefly describe our approach to estimating the rate and degree of natural land area loss across the conterminous United States between 2001 and 2017, as well as the degree of land fragmentation by 2017. This document describes the relationship of this new work to the Disappearing West project outputs, details the principal methods and results, and offers a number of recommended uses, as well as caveats associated with the approach and outputs.

Approach and Methods

We leveraged and extended established methods from the Disappearing West (DW) project (www.disappearingwest.org; Theobald et al. 2016) to map the degree of human modification (H) with values that range from 0.0 to 1.0 (after Theobald 2013) and estimate natural land loss across the conterminous US. This required two major extensions of our earlier DW work. First, we extended our approach for DW to be inclusive of the lower 48 states. Second, we extended our analyses to provide more recent conditions, estimating the amount of natural land for 2001 and 2017 and loss between 2001 and 2017. Similar to DW, our approach has four key 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. We grouped the individual stressors into agricultural, energy, transportation, and urban classes, although some stressors could be placed into multiple classes.¹

To estimate the loss of natural lands in the US, we first calculated the human modified area (H_a) across all 900-m² pixels (A), adjusted by H (i.e. weighted), or $H \times A$. That is, if H at pixel was 0.5, then the area of that pixel would be: $0.5 \times 900 \text{ m}^2 = 450 \text{ m}^2$. We then accounted for edge effects (Figure A1), which includes the spatial context of adjacent land uses/stressors. Edge effects present a well-documented source and range of impacts in ecological systems (Sisk et al. 1997), and the negative effects of an edge at a given location can originate at an adjacent or nearby source, from such processes as noise, light, pollution, change in evapotranspiration, increased predation from domestic animals, etc. For our analyses, the edge effect (H_e) is calculated as a function of the local intensity value (e.g., 1.0 for urban) and decays with distance using a ‘halving distance’ of 500 m. Note that accounting for the edge effect is a refinement over the previous Disappearing West approach and results.

To estimate the rate of loss of natural lands, we calculated the difference in human modification between 2001 to 2017 (i.e., $H_{a,2017} - H_{a,2001}$). We assumed that once a human-caused modification was present in an area, the ecological impact associated with the modification would remain, even if later our estimate of human modification has declined. Although we recognize that this does not address areas that may have been restored, we argue that it is unlikely that significant recovery can occur over the short duration that we are examining changes (16 years).

¹ Because of the timeline for this analysis, as well as the limited and relatively static footprint associated with some activities or stressors (e.g., pipelines, rail lines, transmission lines), our new approach did not consider these features in estimates of human modification and natural land loss.

Agricultural stressors

Although cropland and pastureland agriculture occupy roughly 50% of the US, we were unable to adequately map the change in cropland and pastureland because we did not have data available for conditions after 2011. Our previous work on the DW indicated that cropland and pastureland agriculture land uses were changed minimally between 2001-2011 time period, with very little expansion into natural lands. Our more recent work with the American Farmland Trust further suggests little change between 2011-2017, finding that agricultural lands in many parts of the US are readily being converted to urban areas (i.e., from one human modified type to another), and that the area of restoration, while important, is very limited in extent. We do recognize there was some conversion to cropland and pasture, particularly in the northern Great Plains (Lark et al. 2015).

In addition to croplands, we considered extraction of timber products in forested areas as part of the “agriculture” stressor. We were able to use a recently available dataset to map timber harvesting on US Forest Service lands, namely commercial thinning, patch clearcut, single-tree selection cut, and stand clearcut ([FS Topo Geodata Clearinghouse](#), accessed September 2018). Note that we did not map timber harvesting activities on non-USFS lands (including private land), as no consistent spatial data are available. The intensity value of forest harvesting was estimated at 0.5 partially because that activity has a transitory effect, and we calculated a linear decrease assuming the recency of the cut, out to a maximum of 60 years, to account for regrowth and succession rates. That is, the more recent the activity, the higher the modification, up to a maximum of 0.5.

Energy stressors

To map the effects of oil and gas extraction activities, we expanded and updated data on well point location from oil and gas offices for oil-producing states: Alabama, Arizona, Arkansas, California, Colorado, Illinois, Kansas, Kentucky, Louisiana, Michigan, Missouri, Montana, Nebraska, Nevada, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, South Dakota, Tennessee, Texas, Virginia, Washington, and West Virginia.² We selected only wells that were producing at a given epoch (i.e., 2001, 2017). We also included wells that had produced but were no longer active (i.e., dormant or capped), under the logic that the disturbance associated with constructing and operating wells has long-lasting effects (e.g., grading/leveling for roads and pads and associated invasive plant species). 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 declining linearly within a radius of 450 m.³ For surface coal mines, we selected large coal mine locations in the 11 western states (from the US Energy Information Administration (2013; http://www.eia.gov/maps/layer_info-m.cfm; $n = 50$), and hand-digitized the footprint visible for each mine at each epoch using high-resolution aerial photography from 2000-2017 in Google Earth. For the eastern US, we obtained footprints estimated from remotely sensed data

² We attempted to acquire data from all 48 states, but found appropriate data for only those we listed.

³ Although the intensity at the location of a well or pad is likely much higher (perhaps approximating 1.0), we used a kernel density estimate with 450-m radius to incorporate possible uncertainties in the spatial location.

through time, particularly focused on mountaintop coal mining in the Appalachian region (Pericak et al. 2018). We assigned an intensity value of 1.0 to each mine footprint.

To map 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](#), accessed August 2018) and spatially cross-referenced these using Argonne National Laboratory's Solar Mapper (<http://bogi.evs.anl.gov/solmap/portal/>). We mapped wind energy sites by year by obtaining turbine point-of-location data from the USGS (<https://eerscmap.usgs.gov/uswtdb/> accessed September 2018). For each wind turbine, we assumed a maximum intensity value of 0.25 with linear distance decline using a radius of 450 m (Theobald 2013).

Transportation stressors

We mapped the physical impacts of roads by estimating the typical width of roads of different types from the US Census Bureau's [TIGER](#) datasets (Theobald 2013). We discovered and removed road segments that were found to overlap wilderness areas (<https://www.wilderness.net>, accessed November 1, 2018). Because roads that were mapped in previous decades (i.e., 2000, 2010) are often not aligned with 2017 data, and the spatial precision of the roads has greatly improved with more recent data, we selected the roads from the 2017 data that were mapped in previous years (within 30-100 m). We then used the selected subset of roads from the 2000 and 2010 datasets to represent roads at 30-m pixels that were likely present for a given epoch (e.g., 2000 and 2010). 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), while other secondary, local, and rural roads were assigned a value of 0.1. We originally attempted to differentiate effects of different road types but found inconsistencies between states, and through time, which yielded numerous artifacts.

Urban stressors

Because this effort focused on the conterminous US and estimates of change between 2001 and 2017, and due to limitations in data availability, we made three major adjustments to the methods we used to map urban areas in the DW project. First, and most importantly, the most current year of the National Land Cover Dataset (NLCD) is 2011 (note that NLCD v4 for 2016 is expected in spring 2019); therefore NLCD was not available to our analysis (unlike with DW). Second, and to ensure proper calculation of change between 2001 and 2017, we used road networks derived from US Census TIGER datasets for 2000, 2010, and 2017 -- data that reflect a specific year and are developed in a consistent, standardized manner over time. We then estimated the urban land use intensity values based on the presence of roads at multiple spatial scales (i.e., using a circle with the area of 2.5, 5.0, 10, 20, 40, 160, 640 acres). We counted the number of scales within which a road was present, resulting in seven urban classes. To ensure consistency with DW, we calculated the mean intensity weighting for urban development (based on an NLCD 2011 classification and weightings) for each of the 0-7 urban classes, and then assigned the NLCD-derived intensity values to each urban class.

Third, to map the effect of miscellaneous human activities, including industrial, commercial, airports, oil and gas fields, and remote processing and mining facilities, we used data on 'stable nightlights' obtained from the

USAF Defense Meteorological Satellite Program (DMSP/OLS; NOAA 2018). We inter-calibrated multiple images for a given year to account for different satellite characteristics (Pandey et al. 2017), and manually aligned composite images for 2001 and 2013 (the latest available). Because the spatial resolution of DMSP is 1-3 km, we square-root transformed the max-normalized values and used an intensity factor of 0.5, accounting for the effects of over-glow (light extending beyond the origin of that light). Nightlights are known to have artifacts of very-low light level (due to “overglow” in urban areas and adjacent to large bodies of water and “northern lights” effects). To reduce these artifacts, typical pre-processing guidance suggests removing data (i.e., light density at a given cell) values less than 5 (Imhoff et al. 1997; values range from 0 to 63). Because we suspected that results might be sensitive to this threshold, we conducted a sensitivity analysis to vary this threshold. To identify appropriate thresholds to test, we calculated the cumulative distribution of the nightlights for the US (not globally, as the prior assumption is based), and found that 70% had values ≤ 3.12 , 75% had values ≤ 4.87 , 80% had ≤ 5.86 , and 90% had ≤ 9.37 . To test the degree to which our overall estimate of human modification was sensitive to this threshold, we calculated H using each threshold in turn. We decided to use results from a logical threshold at the 75th percentile.

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 $H < t$. 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). We removed isolated areas (“patches”) smaller than ~ 2 acres before calculating distances from developed areas.

Major Results

Due to the expansion and intensification of human land uses that lead to modification, natural areas in the conterminous US were steadily lost between 2001 and 2017. **Over this 16-year period, the total amount of natural area lost to development was over 24-million acres⁴**, roughly equivalent to nearly nine Grand Canyon National Parks (~ 2.8 million acres) or 49 Great Smoky Mountain National Parks ($\sim 520,000$ acres). This equates to more than **1.5-million acres lost annually** (Tables 1 and 2). Notably, and in terms of acres as a percent of change, the most rapid rate of loss from 2001 to 2017 occurred in: North Dakota (5.3%), Oklahoma (2.9%), and Pennsylvania (2.4%). Least changed states included: Nevada (0.2%), Maine (0.2%), and Connecticut (0.3%).

⁴ Here we report results based on the recommended nightlights data threshold of 5 -- because we believe the upper range reflects a more likely condition, and because we are quantifying only those stressors for which we have data; we are not explicitly capturing a range of additional stressors such as invasive species, hard-rock and aggregate mining, timber harvesting on private lands, etc.

Table 1: Acres of natural areas lost annually, and the minutes it took to lose a football field from 2001 to 2011, 2011 to 2017, and 2001 to 2017 to human modification in the western (11 western-most states), eastern, and conterminous US (CONUS).

Region	2001-2017	
	Acres lost annually	Minutes per football field
Western	420,000	1.65
Eastern	1,113,000	0.62
CONUS	1,533,000	0.45

Table 2: Acres of human modification in the conterminous US between 2001 and 2017, based on four major land use stressor categories: agriculture (i.e., timber harvest), energy (both conventional and renewable), transportation (highways and other roads), and urban (residential, commercial, industrial, etc.). Because there are interactions between stressors when aggregating, the sum of the individual stressors will not equal the overall values.

Major stressor	Acres modified
Agriculture	1,441,000
Energy	6,188,000
Transportation	2,580,000
Urban	13,809,000

In addition to loss of natural area, patterns of human development have further fragmented the US, eroding natural lands an additional 0.02 miles, on average, between 2001 and 2017. In other words, if you jumped out

of a plane into a random, undeveloped area, on average,⁵ you would be 0.79 miles from significant human development in 2001, decreasing to 0.46 miles in 2017. In the 11 western US states, you would be 1.75 miles from significant human development in 2001, decreasing to 1.43 miles in 2017.

Uses and Caveats

We intend these data and results to be used to inform discussion regarding patterns of natural land loss in the US, as well as rates of land loss between 2001-2017 and the two intermediate time periods, 2001-2011 and 2011-2017.

The human modification map presented here is a product of the best-available open-source, publically available data. That is, to meet the scientific standard of ensuring reproducibility of our work (Sandve et al. 2013), we used only open-source data -- no commercial data or data with restricted access were used. We prioritized collection and production of data to estimate natural area change through time, so data were generated with consistent, standardized methods and were tagged with specific image dates. For example, we elected not to incorporate the NLCD because it was only available for 2001 to 2011. Instead, our new approach to estimating urbanization uses a combination of road density and nightlight data. Using road density is advantageous because it delineates lower-density land uses at and beyond the urban fringe that are absent from approaches using only the NLCD datasets and US census blocks. The approach also removes spurious mapping of urban land uses that, while infrequent, can cause particularly serious errors in remote areas, like designated wilderness areas. We also used nightlights data to complement road density, particularly to represent commercial and industrial areas that have low-road density, yet have high intensity land use. Furthermore, nightlights uniquely provide data about land uses in remote locations, such as power plants, miscellaneous mining operations (e.g., potash), and oil and gas activities (for states where we were unable to collect locations). An important caveat with the nightlights data: there are artifacts caused by overflow near cities, moonlight and northern lights. We reduced these artifacts by applying a square-root transform to further dampen the values at low levels (slight overestimation can occur because of the large extent of these regions). We reiterate, however, that our calculations of trend or rates of loss are NOT affected by these artifacts because of our assumption of no decline in human modification.

For a number of stressors, we were limited to a restricted period for which usable data were available (e.g., DMSP/OLS “nightlights” is available only until 2013). Therefore, our estimate of change in human modification over time is limited to the stressors for which data was available for the epochs 2001, 2011, and 2017.

We assumed for our analysis that the degree of human modification only increases over time (except for the natural regeneration of timber-harvested areas). The rationale for this assumption is two-fold. First, the changes that we are most concerned with, and the easiest to measure and document, are those that have a substantial change that is detectable on the ground, even though the specific activity might no longer be

⁵ Calculated as the median.

occurring. For example, although a hard rock mine may no longer be “producing” (in operation), the remnants of that operation have long-term and substantial impact -- from changing/removing parts of hillsides or mountain tops and altering surface hydrology to leaving concentrated tailings to altering vegetation in the surrounding landscape. Similarly, although an oil/gas well may no longer be producing, or may even be plugged, the significant land alteration to establish the well and access it initially causes substantial changes, such as to vegetation (especially proliferation of invasive weeds) and compaction of soil (e.g., from service roads). Second, if change back to a less intensive land use has occurred, the period of our analysis (16 years) is too short for any meaningful ecological improvements to accrue. Note that, while ongoing activities and human presence have been shown to cause additional stress to natural systems beyond the changes in composition and structure in natural systems, our ability to map these activities, especially remote and dispersed activities, is limited.

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Appendix

Conceptual diagram of human modification (H) w/edge effect

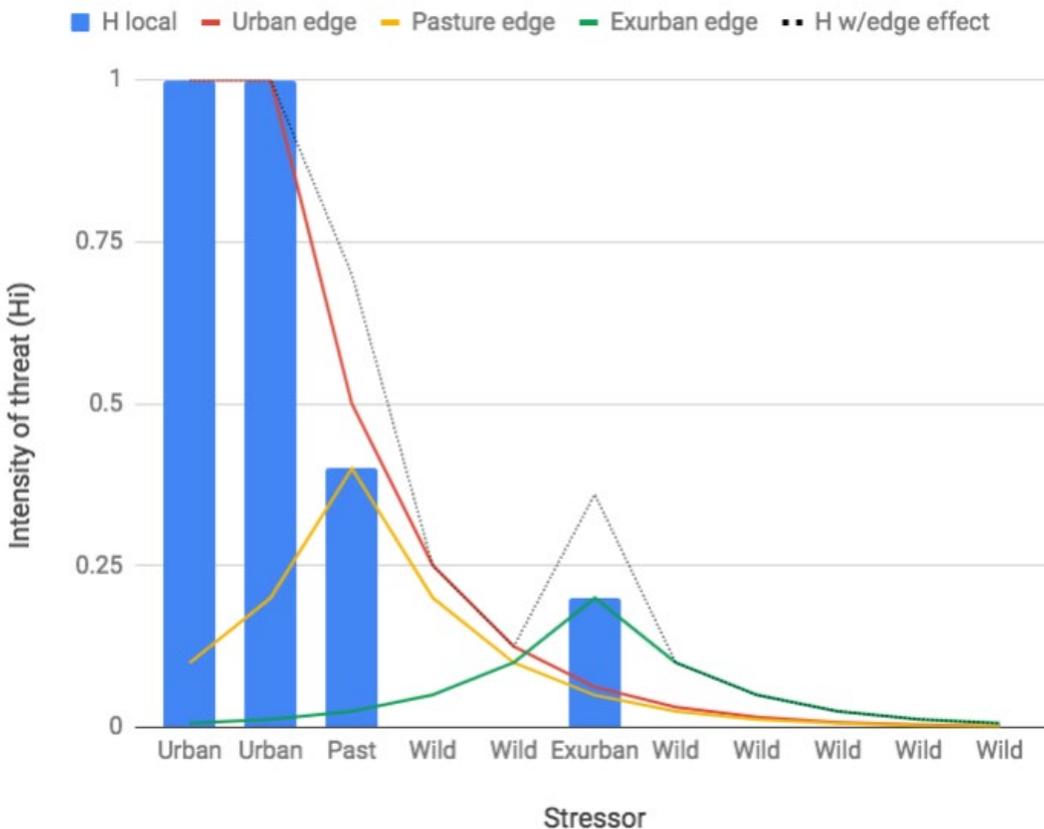


Figure A1. Human modification, designated as H_i , is calculated on a per-pixel basis (i.e. “locally”), shown by blue columns. These are arrayed across a hypothetical gradient from urban (left) to “wild” (right). To include the spatial context of adjacent land uses/stressors, we also calculated what is known as the “edge effect”. Here, the edge effect H_e , is calculated as a function of the local intensity value (e.g., 1.0 for urban) and decays with distance using a halving distance of 500 m. These are shown by the red, yellow, and green lines. We combined the effects of local and nearby stressors, called H_{ie} , using: $H_{ie} = 1 - ((1 - H_i) * (1 - H_e))$, following Theobald (2013). Edge effects are a well-documented source of impacts in ecological systems (Sisk et al. 1997), and the negative effects at a given location that originate at an adjacent or nearby source, from such processes as noise, light, pollution, change in evapotranspiration, increased predation from domestic animals, etc. For practical reasons, we chose to model edge effects using the overall H value (i.e. not differentiated for individual stressors). Also note that we chose not to include effects due to ecological processes related to broader-and longer-scale movements, typically considered through fragmentation/connectivity measures.