Measuring the Human Footprint in Protected Areas in the United States

Examining human disturbance and its proxies: road density and nighttime lights

Hannah Dempsey & Henry Hannon
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Executive Summary

The following map of the US highlights the HUCs with the most at-risk protected areas.

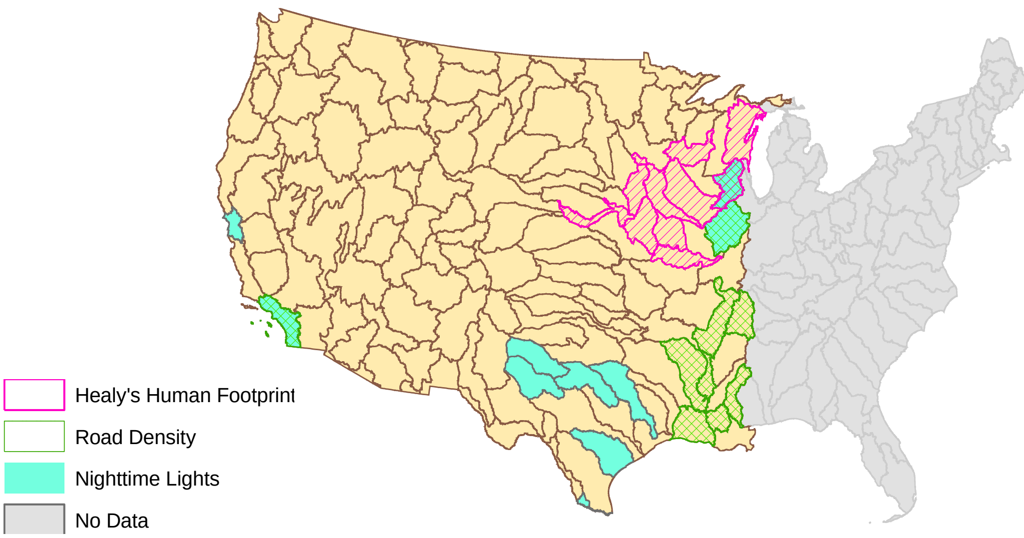

Figure 1. At-risk HUCs

Specifically, and with great confidence, HUC 0709 was listed as the single most at-risk HUC from NatureServe's robust human disturbance dataset, as well as for the indicator road density, and was included in the top 10 for nighttime lights. Both nighttime lights and road density serve as proxies for human development and disturbance, and as such are limited in how positively they can identify disturbed protected areas. The subsequent HUCs vary in confidence—with the exception of NatureServe's expansive dataset—but offer direction in terms of research and specific policy recommendations.

The researchers recommend that the HUCs highlighted in pink—based on Dr. Healy Hamilton's work—offer the protected areas with the greatest amount of disturbance and therefore the greatest benefit of restoration. A biodiversity impact study would be well served in this area, and more specific policies aimed to reduce the human footprint are dire.

The HUCs highlighted in blue (disturbed by nighttime lights) and green (disturbed by roads) offer locations that would likely benefit from a public education program in the reduction of light pollution, and a program geared towards the reduction of road effects. This could include habitat corridor rehabilitation, runoff reduction, or roadkill prevention, depending on the needs of the protected areas.

Purpose and Objectives

This project determines the most disturbed protected areas on average per HUC 4 in the Western United States, compares indicators and proxies for disturbance, and makes specific recommendations based on the indicator status.

Human development and disturbance of the environment is the greatest driver of habitat degradation, climate change, and extinction. NatureServe, a wildlife conservation non-profit, has turned their attention to the impact of humans on the environment. The effects of human influence on surrounding ecosystems is evident and efforts have been made in order to reduce these effects and increase biodiversity again in these disturbed areas, which is vital for community health, resilience to invasive species, and numerous other ecological and economics reasons.[1] The need for a map to quantify and easily present areas that are most at-risk to human disturbance in an effective and easily interpretable way is vital to make policy recommendations. Maps that show the worst of the human footprint throughout the western United States provides valuable information on what areas were most disturbed and influenced by human activity, and therefore where more research should be done, would be a valuable addition to the science literature[2].

In particular, NatureServe is interested in the human footprint in protected areas, and whether or not these protected areas are effective in preserving biodiversity. NatureServe's researchers provided a comprehensive dataset of human disturbance that compiled indicators—transportation, infrastructure, and land use/land change—into a raster that had values ranging from the least to most disturbed areas in the US. The addition of the proxy indicators (1) road density and (2) nighttime lights allow for an exploratory comparison of the indicators, as well as the opportunity for explicit policy recommendations regarding light pollution.

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[1] Pimentel et al. 1997. Economic and environmental benefits of biodiversity. *Bioscience* 47 (11): 747-57.

[2] Sanderson et al. 2002. The Human Footprint and the Last of the Wild. *Bioscience* 52(10): 891-904.

Background

The impact of humans on the environment has been obvious due to the increasing awareness of harmful effects from carbon emissions, urbanization, and deforestation. A need to measure and quantify this impact has spurred many to create a human footprint index[3]. Projects on creating this human footprint have approached the problem in different ways; their attempts ranging in area covered, indexes used, and their stance on protected areas.

In a project where the human influence was measured mainly focusing on the coastal and open-ocean regions of the United States, the effects of increased carbon emissions were seen to play a major role on U.S. biodiversity. The increased carbon emissions have led to many different negative effects on these coastal regions, including increased acidification of precipitation, coastal eutrophication, and increased climate. This project, although more focused on the biogeochemistry aspect of the environment highlighted the negative effects building up from increased carbon dioxide emissions[4].

The environment is also being affected by factors directly contributed by humans and also effects that can be traced back to human made utilities[5]. Constructing a highway is a direct cause of deforestation but the carbon emissions from the increased car density can be considered to be an indirect driving force on the loss of biodiversity. This creates a wide range of indexes to look at because there are so many direct causes for the human footprint but there are many indirect causes that can be overlooked. This creates a problem when indexes need to be chosen to when creating a map of the human footprint.

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[3] Sanderson et al. 2002. The Human Footprint and the Last of the Wild. *Bioscience* 52(10): 891-904

[4] Doney, Scott C 2010. The Growing Human Footprint on Coastal and Open-Ocean Biogeochemistry. *Science* 328(5985).

[5] Mora and Sale PF. 2011. Ongoing global biodiversity loss and the need to move beyond Protected areas: a review of the technical and practical shortcomings of protected areas on land and sea. *Marine Ecology Progress Series* 434: 251-266

Other teams have made maps that visually represent the human footprint, like Eric Sanderson (2002) and Matthias Leu (2008). The maps each have their differences; Sanderson's map covers a global scale while Liu's map is only of the western United States. Each map also differs greatly in what data was used to construct each[6][7].

In regards to protected areas, a study done on their effectiveness was done and the results came out to be negative. Most protected areas were proven to not make a difference in protecting the biodiversity of the area[8]. This makes research on protected areas and their ability to reduce the human footprint very important.

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[6] Sanderson et al. 2002. The Human Footprint and the Last of the Wild. *Bioscience* 52(10): 891-904

[7] Mora and Sale PF. 2011. Ongoing global biodiversity loss and the need to move beyond Protected areas: a review of the technical and practical shortcomings of protected areas on land and sea. *Marine Ecology Progress Series* 434: 251-266.

[8] Leu, Matthias, Steven E. Hanser, and Steven T. Knick 2008. *THE HUMAN FOOTPRINT IN THE WEST: A LARGE-SCALE ANALYSIS OF ANTHROPOGENIC IMPACTS*. *Ecological Applications* 18:1119–1139.

Definitions & Frame of Analysis

Human disturbance: The way human disturbance is defined is through human interactions with the environment. The interactions are negative and directly take away from the environment. Building roads and cutting down trees are examples of direct human disturbance to the environment[9].

Human footprint: Similar to human disturbance, the human footprint is the compilation of all kinds of human disturbance into one metric.

Protected Areas: The protected areas spatial data came from the USGS dataset available on their website. The spatial data was made using IUCN's definition of protected areas. A protected area is defined as a "clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values"[10].

Road Density: A proxy used for human disturbance, in this study road density includes US Census primary and secondary roads only.

Nighttime Lights: A proxy used for human disturbance with more light pollution correlated with negative environmental impacts, collected by satellite imagery.

Data Collection and Integration

Data Name	Data Type	Sources
LCM	Raster	Dr. Healy Hamilton and NatureServe
Road Density	Shapefile (line)	US Census TIGER Shapefiles (2015)
Nighttime Lights	Raster	NOAA's DMSP (2013)
Protected Areas (PAD)	Shapefile (polygon)	USGS
HUC 4	Shapefile (polygon)	USGS

[9] Sanderson et al. 2002. The Human Footprint and the Last of the Wild. *Bioscience* 52(10): 891-904

[10] USGS 2013.National Gap Analysis Program, Protected Areas Data Portal. *gapanalysis.usgs*. USGS.

The data which this research was largely based on—the LCM dataset—is comprehensive and the result of a robust analysis by Jon C. Hak and Patrick Comer of NatureServe. Their paper, "Modeling Landscape Condition for Biodiversity Assessment – Applied to Temperate North America," is currently in the process of being published and thus an incomplete dataset was provided. The data was compiled into 20 categories under three branches: transportation, urban and industrial development, and managed and modified land cover.

The road density data were downloaded through the US Census's TIGER shapefile system. The most recent (2015) line shapefiles were downloaded for each state in the interest area separately—approx. 30 states—and were merged using the tool "merge" on ArcGIS.

Both protected areas (PAD) and the HUC 4 shapefiles were downloaded from the USGS website. The PAD data had to be downloaded for each region (California, Southwest, South Central, Northwest, MidWest) due to issues with downloading all PADs for the country. These regions covered the area of interest perfectly. The HUC shapefiles were downloaded for the US as a whole, and were clipped to approximately two-thirds of the Western US because of the scale limitations in the LCM data.

The nighttime lights data were downloaded from NOAA's Defense Meteorological Satellite Program (DMSP) in a .tar file, unzipped using 7-zip portable. This was then clipped to the area of interest using the "mask" tool in ArcGIS.

The three main components of data (LCM, roads, nighttime lights) were not integrated in order to compare where their top 10 HUCs differed, and considering that the LCM already included factors like roads and infrastructure development—indeed there would have been so much overlap it wouldn't have been appropriate to integrate these data whatsoever. However, the scale of analysis was on the HUC 4 level, so the 3 areas of analysis were clipped first to the PAD shapefile, and then zonal statistics were applied to display the average amount of disturbance per HUC *only* in protected areas.

The inclusion of data that appears to overlap is intentional. For exploratory reasons it was interesting to see where the robust LCM dataset differed from two very simple human disturbance proxies (road development shows human development and nighttime lights gives a snapshot of development). In addition, while NatureServe's dataset is likely a more accurate depiction of where the most disturbance is happening—and therefore where park services or government authorities should focus their energy into researching or restoring—road density and nighttime lights are in and of themselves interesting factors that have explicit solutions. Roads, for example, can disrupt habitat corridors, produce noise pollution, runoff, and generally destroy habitat in their establishment. Nighttime lights show human development, and while saturation might be an issue to take into account for cities, when just looking at protected areas that shouldn't be as much of a problem (i.e., there really shouldn't be enough nighttime light to saturate an area that is protected—there are no cities in protected areas), and the also contribute to bird death by attracting birds to fly into lit windows at night. The HUCs that display disruptions based on these two indicators can investigate improving habitat corridors and decrease both noise and light pollution.

Data Analysis

The steps for the analysis were as follows:

1. Clip data of interest—human footprint, road density, nighttime lights—to USGS protected areas.

This had to be done separately for each region of USGS PAD given that the data were downloaded separately. This allows for the close analysis of human disturbance—in whatever proxy—explicitly for what the US government defines as protected areas.

2. Take the zonal statistics of the clipped data of interest → get the average for protected areas in each HUC.

The PAD polygons were small, and taking the average value of disturbance and displaying it on the scale of HUC 4 allows for easier visual interpretation. This also allows for an understanding of how each HUC's protected areas are faring, and could result in further research in these localized areas.

3. Convert to raster.
4. Subtract road density or nighttime lights raster from Healy's human footprint raster → find discrepancies in the data.

This answers the ultimate question: where does the LCM vary from the proxies of road density and nighttime lights? This allows for researchers to evaluate the use of these indicators as stand-alone proxies and to compare the use of roads versus lights as well.

5. Open the attribute table, display each variable in an ascending or descending order—roads and nighttime lights descending, LCM ascending—select the top 10 HUCs based on each variable.

We want to understand where the greatest human impact is occurring regardless of variable. This allows us to highlight the most at-risk HUCs for each indicator—which could spur further research and/or a policy recommendation—and allows for further comparison between metrics. For the roads and nighttime lights the larger the value the more at-risk the HUC, whereas for the LCM data the lower the value the more at-risk the HUC.

6. Overlay the top 10 HUCs.

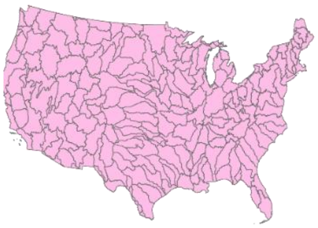
Where do the HUCs overlap and why? Understanding where the single most at-risk HUC is located is the first step, and the why prompts further research.

For the variables of road density and nighttime lights, a certain amount of uncertainty should be taken into consideration—particularly when policy recommendations are made—in order to make the most information decision possible. The authors were unsure of the exact amount of uncertainty, and therefore used up to 100% uncertainty in the final Monte-Carlo calculations. To included uncertainty, the values for both variables were multiplied by a number between 0 and 1 (e.g., RAND()), and then ranked from lowest to highest. 500 Monte-Carlo iterations were run for each HUC—the maximum possible for the researcher's computer to run in an appropriate time frame.

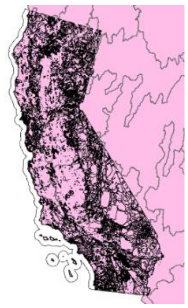
Results

The Data:

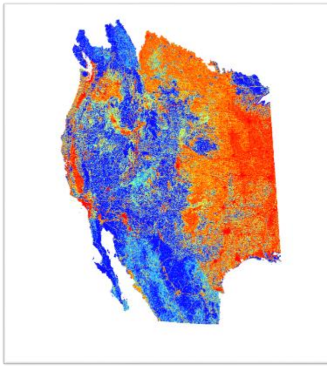
USGS-delineated HUC4



USGS-delineated protected areas (in CA)

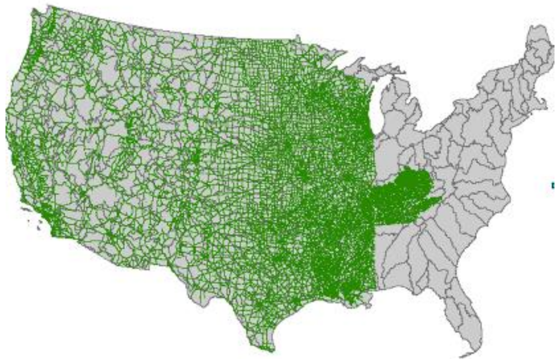


LCM Raster

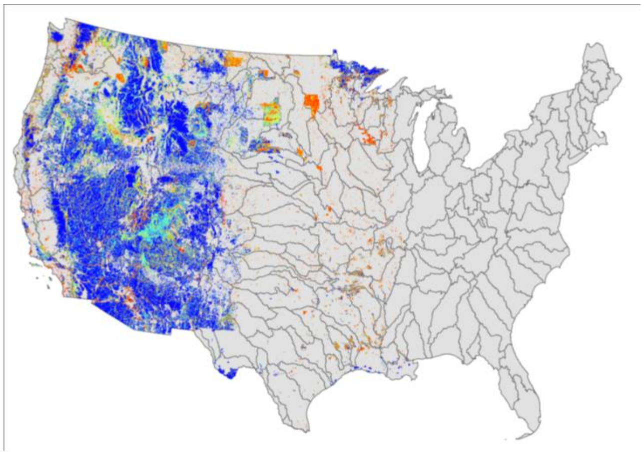


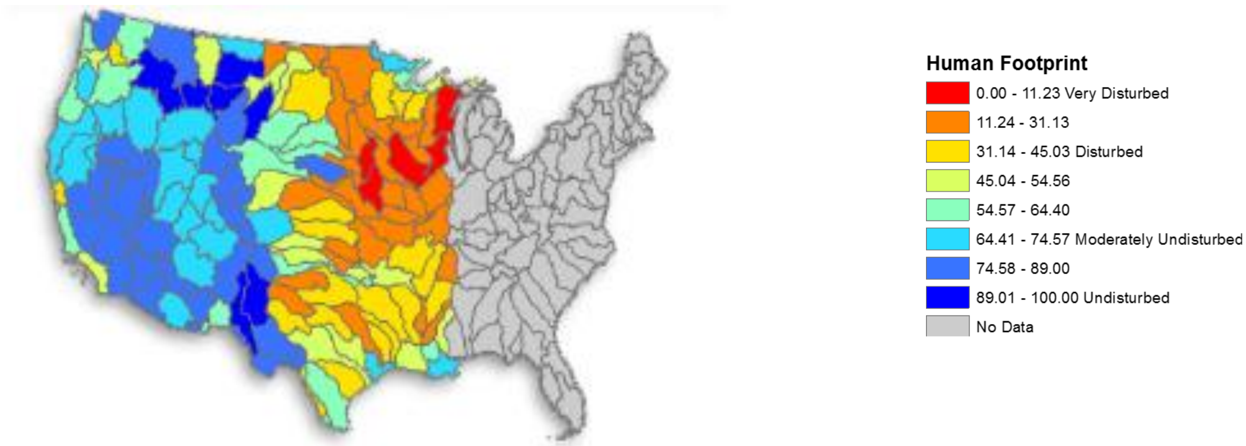
Nighttime Lights raster 2013

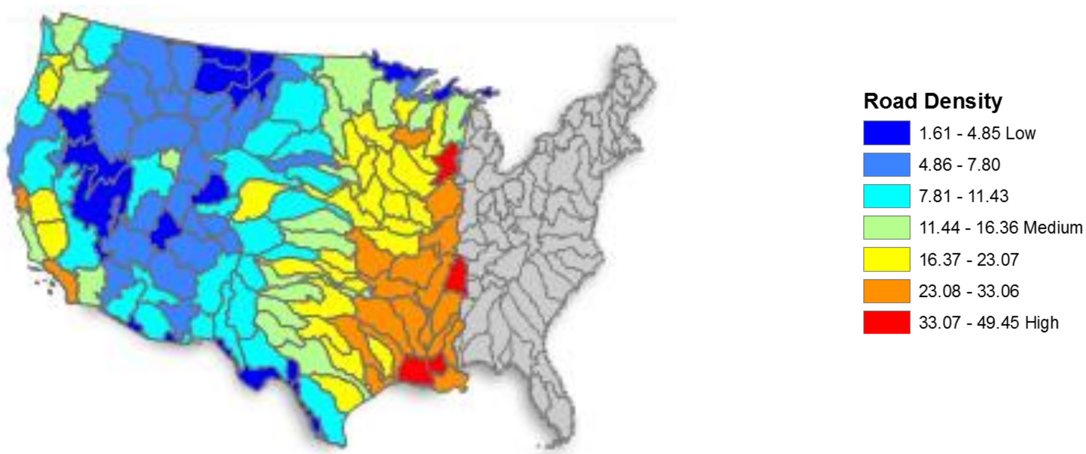
US Census primary & secondary roads

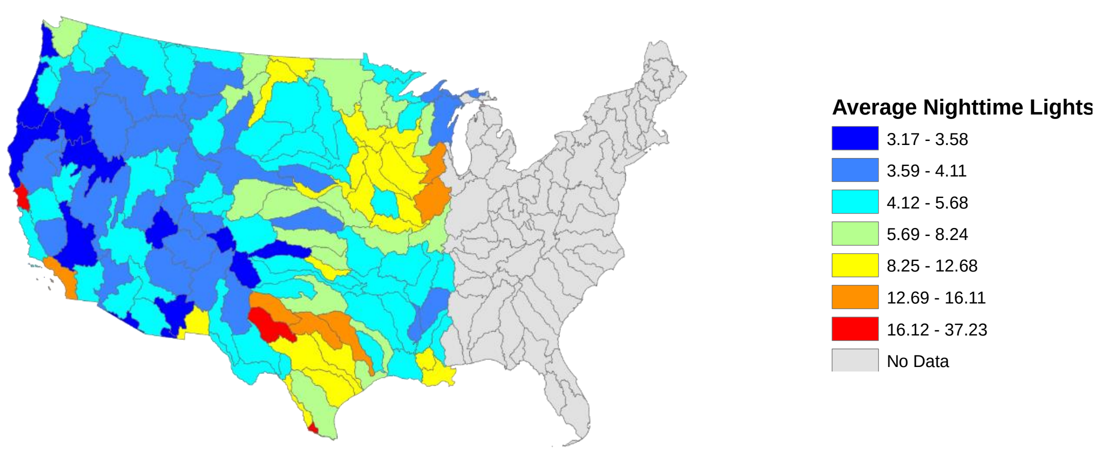


LCM raster clipped to protected areas



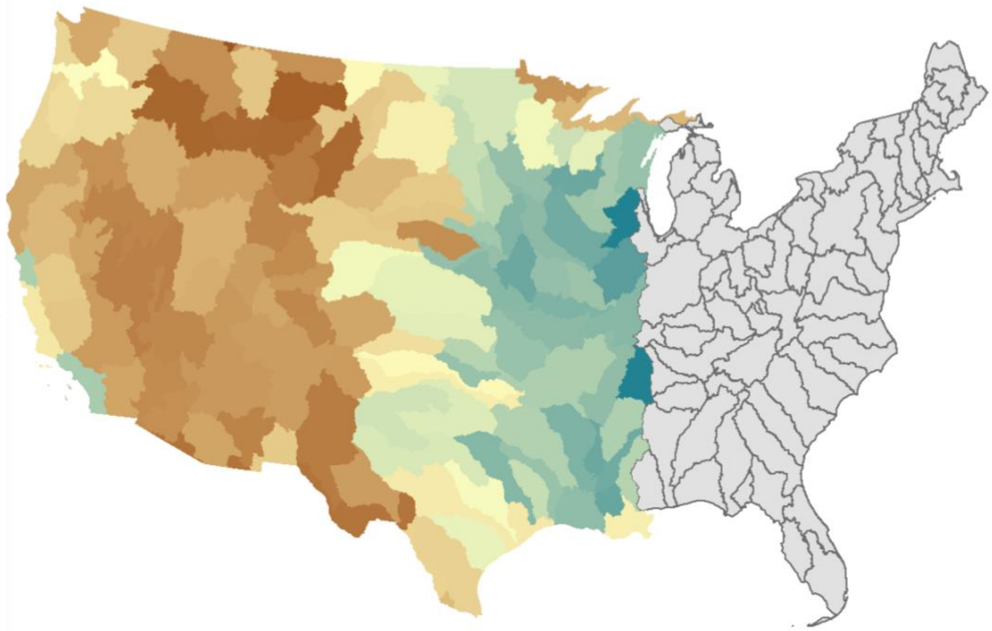

Human Footprint
0.00 - 11.23 Very Disturbed
11.24 - 31.13
31.14 - 45.03 Disturbed
45.04 - 54.56
54.57 - 64.40
64.41 - 74.57 Moderately Undisturbed
74.58 - 89.00
89.01 - 100.00 Undisturbed
No Data


Road Density
1.61 - 4.85 Low
4.86 - 7.80
7.81 - 11.43
11.44 - 16.36 Medium
16.37 - 23.07
23.08 - 33.06
33.07 - 49.45 High


Average Nighttime Lights
3.17 - 3.58
3.59 - 4.11
4.12 - 5.68
5.69 - 8.24
8.25 - 12.68
12.69 - 16.11
16.12 - 37.23
No Data

Comparing the Results:

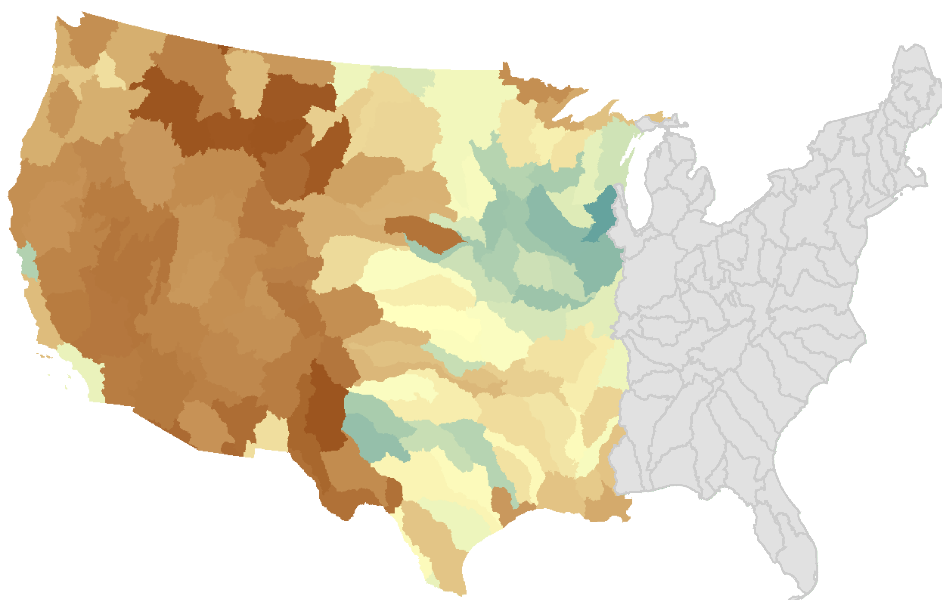
LCM subtracted from road density



subtraction
100.513: Agree Disturbed
Disagree
-89.0794 Agree Undisturbed

No Data

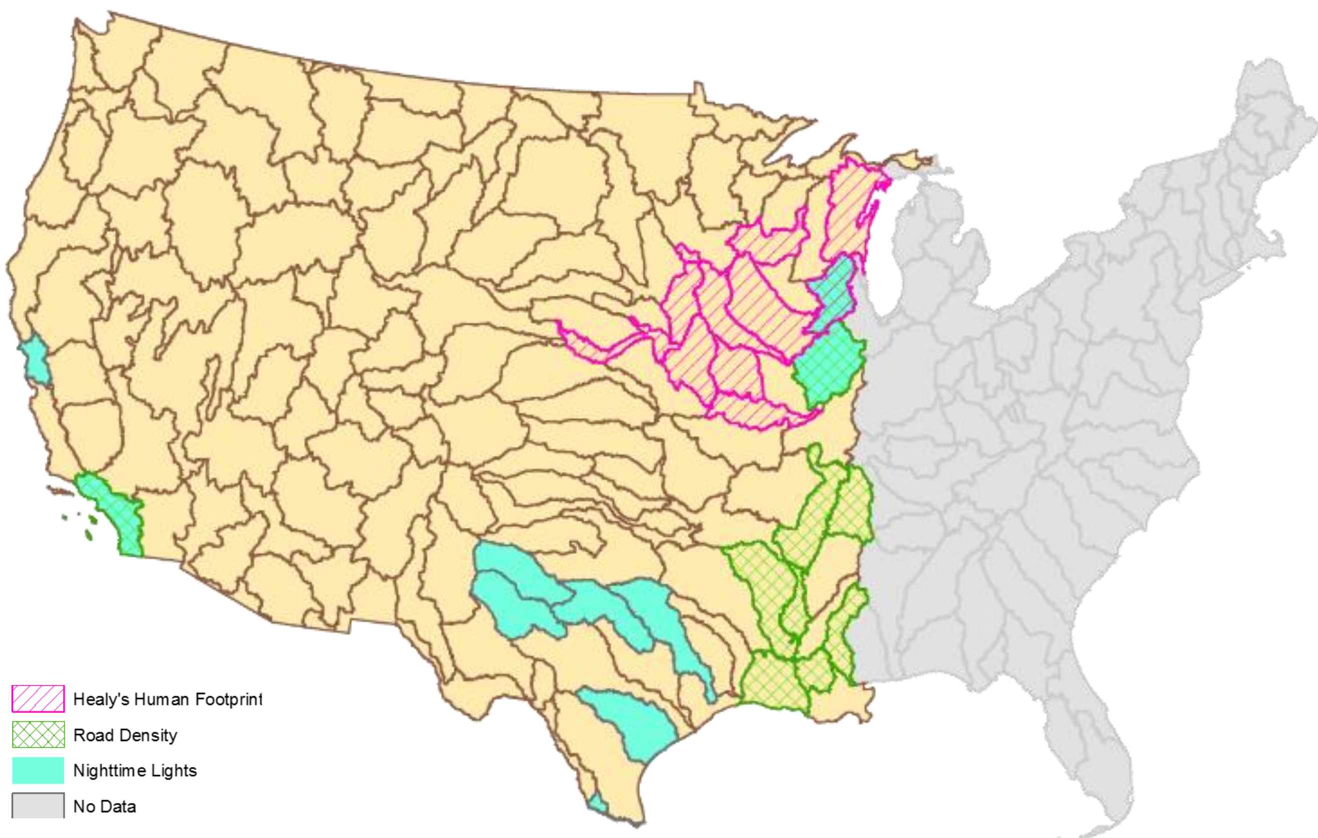
LCM subtracted from nighttime lights



Areas of Agreement
High : 91.28 Agree disturbed
disagree
Low : -96.78 Agree undisturbed

No Data

Top 10 most at-risk HUCs for each variable



Most Vulnerable HUCs

Most vulnerable HUCs: LCM

Rank	HUC
1	0709
2	0403
3	1024
4	0708
5	1023
6	0704
7	1028
8	0710
9	1030
10	1020

Table 1. LCM without uncertainty

Including Uncertainty:

Top 10 most vulnerable HUCs: Road Density

Rank	HUC	Median	Standard Deviation	HUCs w/o Uncertainty
1	0709	3	27.0	0709*
2	0711	10	27.1	1807*
3	1807	6	27.1	1805*
4	1022	14	27.4	0711*
5	0703	13	26.6	0708*
6	0708	12	27.8	0704*
7	1805	11	26.8	1101*
8	1101	13	26.6	1024
9	0704	15	29.6	1022*
10	0703	15	29.0	0706

Table 2. Road Density

Top 10 most vulnerable HUCs: Nighttime Lights

Rank	HUC	Median	Standard Deviation	HUCs w/o Uncertainty
1	1208	5	34.2	1208*
2	1805	7	35.2	1309
3	0709	10	38.5	1805*
4	0713	12	38.6	0709*
5	1204	10	36.1	1807*
6	1203	11	36.9	0713*
7	1808	11	36.8	1205*
8	1205	11	38.7	1206
9	0713	11	38.8	1203
10	1807	12	38.5	1210

Table 3. Nighttime Lights

Discussion & Conclusion

The final recommendation depends on which indicator the policymaker wishes to focus on. The robust LCM dataset indicates that there is a concentration of at-risk HUCs that covers the majority of Iowa and extends into Nebraska, Wisconsin, and Illinois (HUCs 0709, 0403, 1024, 0708, 1023, 0704, 1028, 0710, 1030, and 1020 in order of most at-risk to least). The road density indicates that disturbance is more widespread, although centered on Louisiana, Arkansas, Mississippi, and a swathe in Illinois and the Los Angeles area in California (HUCs 0709, 1807, 1805, 0711, 0708, 0704, 1101, 1022, and 0706 in order from most at-risk to least). Nighttime lights is mostly found in Texas, but also in California and Illinois (HUCs 1208, 1309, 1805, 0709, 1807, 0713, 1205, 1206, 1203, 1210 in order from most at-risk to least).

Interestingly, there was only 1 HUC that had overlap with all three indicators, number 0709 located in Illinois and Wisconsin, which was also placed at the single-most at-risk HUC for both road density and the LCM data. Therefore, the first priority to reduce human disturbance would be in that HUC.

The factors that likely made the largest difference in this analysis is the inclusion of land use and land change in the LCM data—especially considering the LCM HUCs are located exclusively in the mid-West “breadbasket.” The extensive agriculture in that area would not be captured by roads or nightlight density. However, these indicators still offer valuable information. The LCM data would point policymakers in the right direction in terms of further research and reducing the greatest amount of human disturbance, but roads and nighttime lights offer the most concrete options. HUCs that experience high amounts of road disturbance in their protected areas could likely use time and money towards building habitat corridors—something that roads strongly disrupt—especially in parts of the country that experience animal migratory patterns. HUCs that experience a high concentration of nighttime lights in their protected areas are likely disturbing nocturnal animals with light pollution, and could be contributing to bird death.

The least surprising observable pattern is that of the nighttime lights. The majority of troubled HUCs in this area are found around major cities, San Francisco, L.A., San Diego, Dallas and San Antonio. What is interesting—and could be confirmed by NatureServe—is that even though the LCM dataset comprises at least very similar data to the nighttime lights and road density, that the resulting HUCs were so different. A possible conclusion to draw is the relative weight and/or importance of land use and land change, particularly of agricultural lands.

Including uncertainty in the road density and nighttime light variables allowed for up to 100% error in the data. Even with this much error, both indicators showed similar results for the majority of their indicators (*Table 2.* and *3.),* although the large standard deviations make it difficult to make a certain policy recommendation solely of off the HUCs that include uncertainty.

Ultimately, the most powerful recommendation that could be made would also include indicators such as sensitivity, biodiversity value, or related metrics. We have been able to demarcate which HUCs contain the most disturbed protected areas, but these areas might not offer the most ecological value when compared to other protected areas. The combination of these variables could produce a powerful and persuasive map that should be taken very seriously by policymakers.

Works Cited

Doney, Scott C 2010. The Growing Human Footprint on Coastal and Open-Ocean Biogeochemistry. *Science* 328(5985).

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