1. Terrestrial Intactness

Overview

Intactness is an estimate of naturalness. It's based on the level of human disturbance for an area, quantified by available spatial data. Terrestrial intactness is high in places where anthropogenic impacts such as urban development and natural resource extraction are low and native vegetation fragmentation is low.

Intactness is an estimate of naturalness, based on the level of human impacts and quantified by available spatial data.

The term "terrestrial intactness", which is used as a quantifiable state descriptor, has been largely applied to forested landscapes (Lee et al. 2002, Heilman et al. 2002, Strittholt et al. 2006, Potapov et al. 2008), but many of the same principles apply to any natural landscape, including desert ecosystems. The state (or condition) of the natural ecosystem may be viewed and quantified as the ecological stage upon which the actors (species) and the play itself (ecological processes) are carried out over time. Intactness considers an assemblage of spatially explicit indicators that helps define the condition of the natural landscape. Different species may possess different tolerances to these conditions, but natural assemblages of species and natural patterns and processes are increasingly compromised as human influences intensify. For this study, a terrestrial intactness model was created at the 1km^2 level (Figure 1-1) to use as a foundation against which the ecological condition of species' habitats and areas planned for development can be quantitatively evaluated.

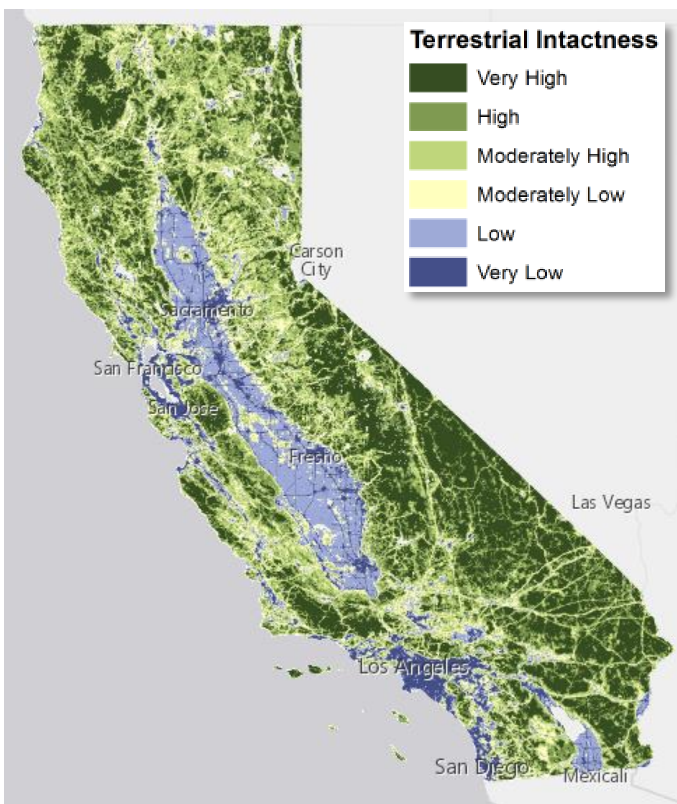


Figure 1-1. Terrestrial intactness (v30) in six classes from Very High (relatively undisturbed in dark green) to Very Low (highly disturbed from urbanization, agriculture, or resource development in dark blue) depicted within 1 km X 1 km reporting units.

Logic Models

EEMS is a tree-based, fuzzy logic modeling system developed by the Conservation Biology Institute.

Terrestrial intactness values were generated using a logic model constructed within the EEMS (Environmental Evaluation Modeling System) framework using ArcGIS Model Builder and custom Python Scripts. A *logic model* is a cognitive map (Jensen et al. 2009) that presents networks of various spatial data components and their logical relationships to evaluate a complex topic such as terrestrial intactness (Figure 1-5, Figure 1-6). EEMS is a tree-based, fuzzy logic modeling system developed by the Conservation Biology Institute as an open source alternative to the EMDS (Ecosystem Management Decision Support) software package (Sheehan and Gough 2016, Reynolds 1999, Reynolds 2001). With the EEMS system, data from different sources and different numerical domains can be combined to answer complex questions concerning a landscape's ecological condition, its conservation values, or its vulnerability to climate change (Sheehan and Gough 2016).

Logic models rely solely on spatial data layers that are arranged in a hierarchical fashion to answer a primary question that is located at the top of the diagram (Figure 1-5, Figure 1-6). In this case, what is the level of terrestrial landscape intactness within each 1km X 1km reporting unit in the study area? Data and analysis flows from the bottom up.

Unlike conventional GIS applications that use Boolean logic (1s and 0s) or scored input layers, logic models rely on fuzzy logic. Simply put, fuzzy logic allows the user to assign shades of gray to thoughts and ideas rather than being restricted to black (false) and white (true) determinations. All data inputs (regardless of the type—ordinal, nominal, or continuous) are assigned relative values between -1 (false) and +1 (true) up to six decimal places. There are many advantages of this modeling approach: (1) it is highly interactive and flexible; (2) it is easy to visualize thought processes; (3) the logic components are modular making it easy to include or exclude pieces of the logic design; (4) the logic can be managed using a number of different mechanisms; and (5) numerous, diverse topics can be included into a single integrated analysis. Raw spatial data source inputs (gold boxes) are populated by one or more GIS data layers (indicated by the stack of gray files). Moving up the diagram, these data are arranged and analyzed to form intermediate map products (purple boxes), which are then arranged and analyzed to generate the final results (green box). One way the user controls the logic of the information is the arrangement of the various data inputs and intermediate products—the higher up in the diagram, the greater the influence on the final result.

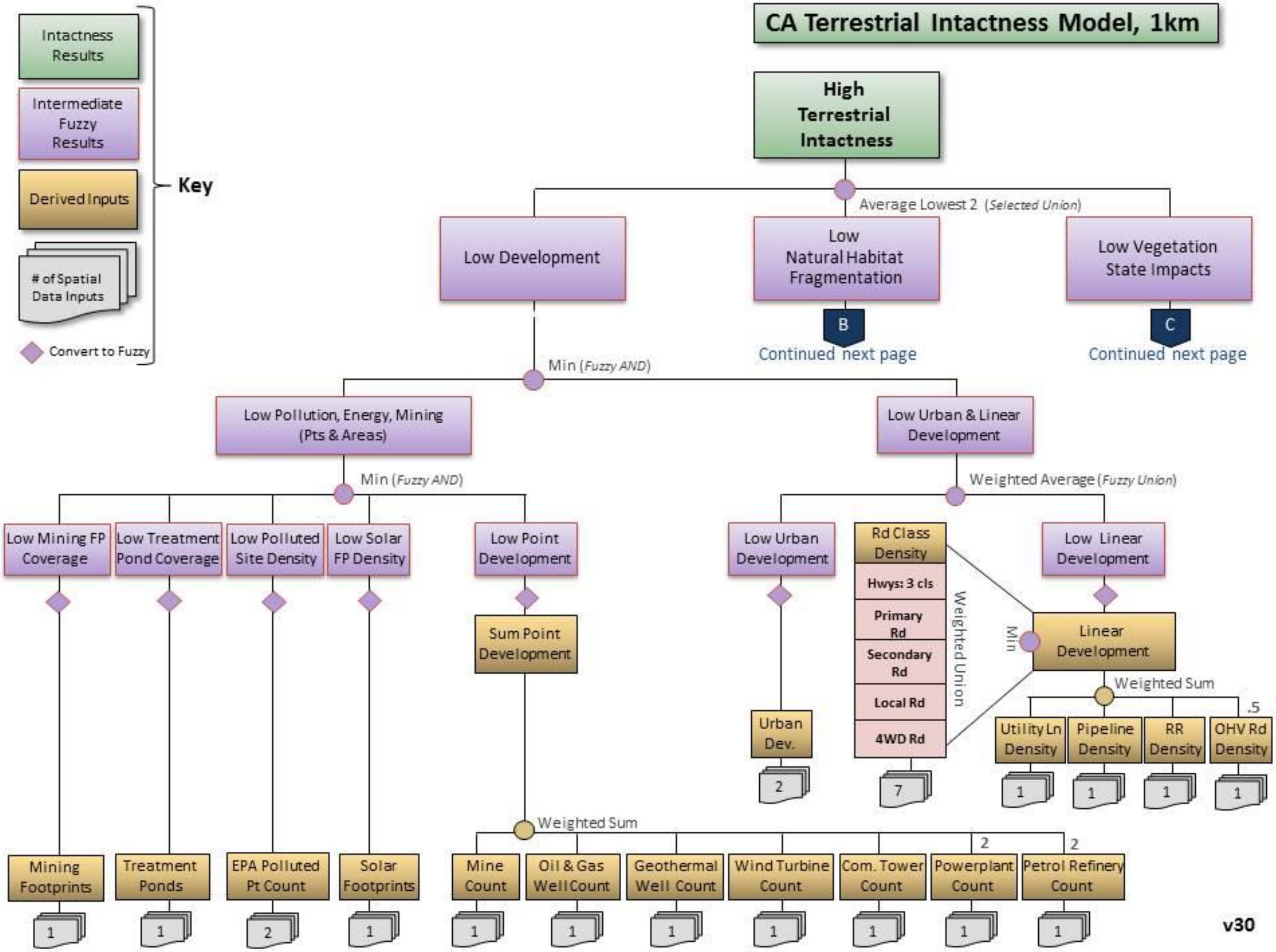


Figure 1-5. Logic model for terrestrial landscape intactness (v30) for the California study area (Page 1 of 2)

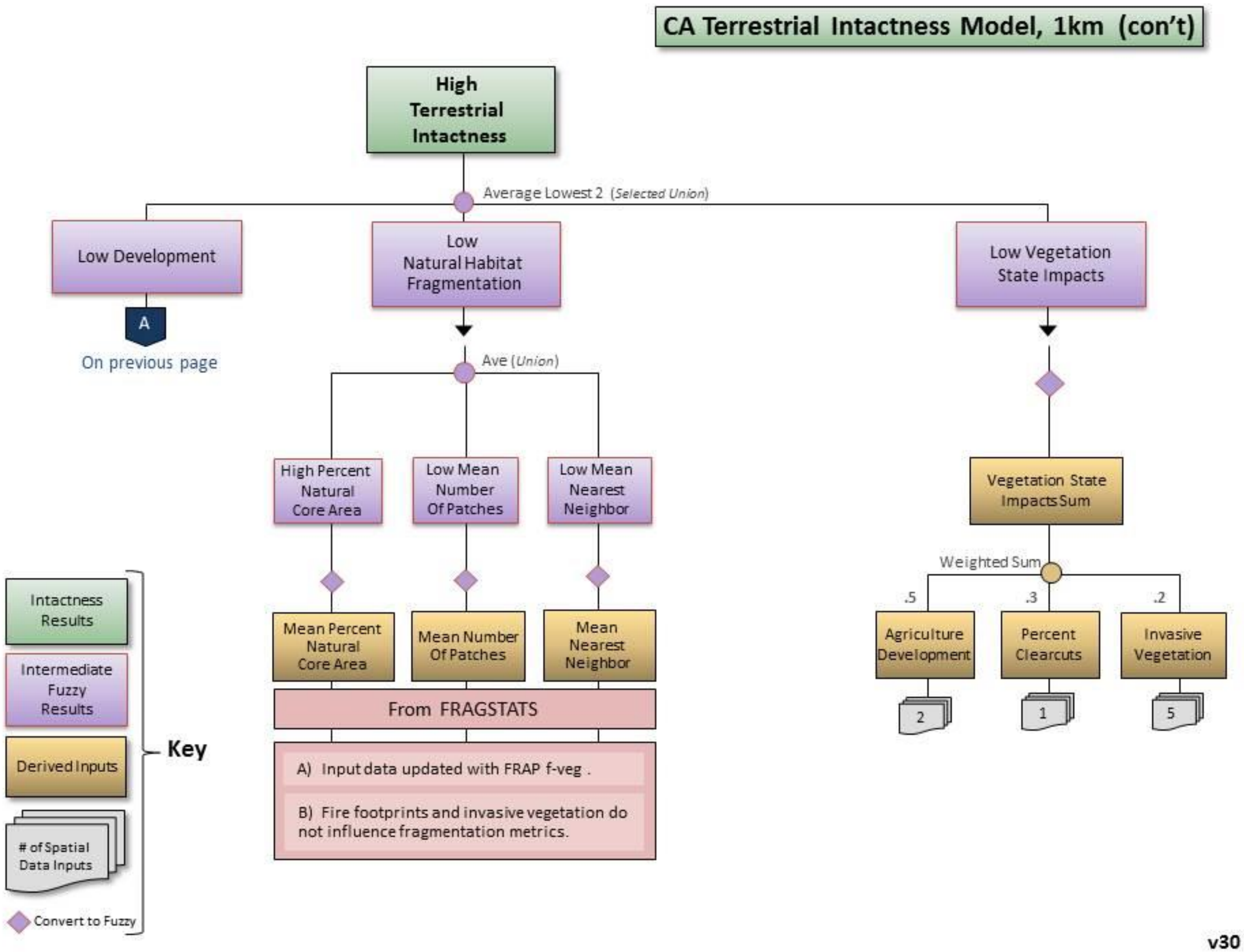


Figure 1-6. Logic model for terrestrial landscape intactness (v30) for the California study area (Page 2 of 2).

Using fuzzy logic as the core modeling principle, logic model performance is achieved in several ways. For every spatial data input, the user determines how to assign the range of values along a truth continuum. For example, when trying to determine and map the most suitable habitat from the standpoint of road density for wildlife—the greater the road density, the greater is the risk to wildlife through habitat degradation and direct mortality. In our example, road density ranges from 0 km/km^2 to 24.5 km/km^2. To assign a fuzzy logic continuum for this range of values, one could assign a -1 to the high value (this value is totally harmful for wildlife or false) and a +1 to the lowest value (this value is totally beneficial for wildlife, or true, red line in Figure 1-7). However, mountain lion research has shown that mountain lion populations have a low probability of persistence in areas with road densities > 0.6 km/km^2 (Van Dyke et al. 1986). A more meaningful alternative then for setting fuzzy thresholds for this parameter would be that a road density of > 0.6 km/km^2 is totally false (-1) and 0 remains totally true (+1, green line in Figure 1-7). Of course, not all wildlife species have the same sensitivity to roads, but this example illustrates how the logic in the model can be altered for known thresholds.

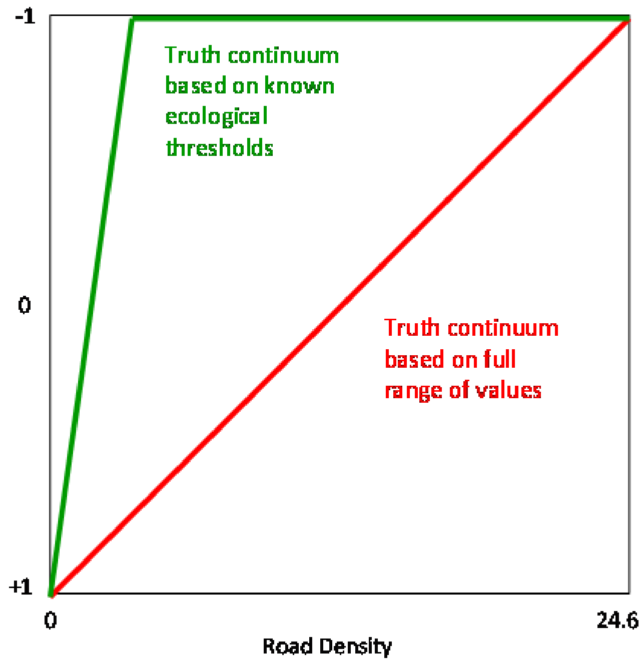


Figure 1-7. Diagram of two treatments of road density in fuzzy logic modeling illustrating important model control options, one based on a full range of values (red line) and the other based on a known threshold for road density (> 0.60 km/km^2 is totally false [-1], green line).

Individual thresholds used for each component in the terrestrial landscape intactness logic are provided in Table 1-1. Note, some input components were created by summing several input values together before applying fuzzy thresholds.

Table 1-1. List of fuzzy logic data inputs for the California terrestrial landscape intactness model (v30), showing data type, range of values, and true and false modeling thresholds for each item at 1 km^2 resolution.

Input	Range	Mean	Standard Deviation	Data Type	1km True Threshold	1km False Threshold
Urban Development	0 - 100	10.5	21.0	Percent Cover	0	20[2]
***Linear Road Class Development (km/km^2)**	0 – 724.0	4.5	10.1	Density	0	10[3,2]
***Other (non-Rd Class) Linear Development (km/km^2)**	0 - 42.4	0.3	0.7	Density	0	4[3,2]
Energy & Mining Point Development (pts/km^2)	0 - 1062	0.6	8.8	Count	0	12[2]
Polluted Sites (pts/km^2)	0 - 72	0.004	0.2	Count	0	2[2]
Treatment Pond Polygons	0 - 100	0.04	1.7	Percent Cover	0	80[2]
Large Mine Footprints	0 - 100	0.06	2.0	Percent Cover	0	70[2]
Large Solar Footprints	0 - 100	0.05	1.6	Percent Cover	0	70[2]
Number of Patches	1 - 416	20.7	29.3	Count	0	50[2]
Mean Nearest Neighbor (m)	60 – 3,903	82.6	116.0	Distance	59	90[2]
Percent Natural Core Area	0 – 90	47.8	28.8	Percent Cover	90	0[2]
Vegetation State Impacts	0 – 70	7.6	14.8	Percent Cover	0	70[1]

1. Used full range or full range with outliers ignored; 2. Expert opinion/ Heuristics, guided by statistical distribution of the data; 3. Taken from the literature

Spatial data are integrated together using one of several logic 'operators'. The operators used in the terrestrial intactness model for California include <u>Weighted Sum, Weighted Average (or *Fuzzy Union*), Average Lowest (or *Selected Union*), and Minimum (or *Fuzzy And*)</u>. The Sum operator simply combines similar data into a single file before assigning fuzzy thresholds. For example, Linear Development could be calculated using the fuzzy expression of three linear feature densities—ground transportation, utility lines, and pipelines. Weighted Sum multiplies each input value by the specified weight and then sums the resulting values. Weighted Average (or *Fuzzy Union*) multiplies each input value by the specified weight, sums the resulting values, and then divides by the sum of the weights. (Weights are shown in figures 1-5 and 1-6.) Average Lowest 2 (or *Selected Union*) finds the mean value of the lowest (*Falsest*) 2 inputs. Minimum (or *Fuzzy And*) causes the lowest value to dominate in the resultant map between two or more inputs. For example, in producing the Low Pollution, Energy, Mining Development intermediate file, cells that are the lowest in any input are reflected in the resulting map. Table 1-2 describes the full range of logic operators available in the EEMS software package and the type of data (fuzzy or raw) the operator expects as input.

Table 1-2. Logic operators available in the EEMS software package.

EEMS TOOL	INPUT DATA	DESCRIPTION
AND	Fuzzy	Finds the AND value of the inputs (minimum value). (previously OrNEG in EEMS version 1.0)
CONVERT TO FUZZY	Raw	Converts a field's values into fuzzy values.
CONVERT TO FUZZY CATEGORY	Raw	Converts a field's values into fuzzy values by using the user defined category values and matching fuzzy values. Input values that are not in the user defined categories are assigned the user-defined default fuzzy value.
DIFFERENCE	Raw	Computes the difference sum for each row of the inputs.
EEMS EMDS AND	Fuzzy	Fuzzy logic operator for EEMS (Environmental Evaluation Modeling System). Finds the EMDS AND value of the inputs. The formula is min + [(mean - min) * (min + 1) / 2]
MAX	Raw	Finds the maximum for each row of the input fields.
MEAN	Raw	Finds the mean for each row of the input fields.
MIN	Raw	Finds the minimum for each row of the input fields.
NOT	Fuzzy	Logical NOT for fuzzy modeling. Reverses the sign of values of the input field.
OR	Fuzzy	Finds the truest value of the inputs (maximum value).
SELECTED UNION	Fuzzy	Finds the union value (mean) of the specified number of TRUEest or FALSEest inputs.
SUM	Raw	Computes the sum of the inputs.
UNION	Fuzzy	Finds the union value of the inputs (mean value).
WEIGHTED EMDS AND	Fuzzy	Finds the weighted EMDS AND value of the inputs. The formula is min + [(mean - min) * (min + 1) / 2] where the mean is weighted.
WEIGHTED MEAN	Raw	Finds the weighted mean for each row of the input fields.
WEIGHTED SUM	Raw	Finds the weighted sum for each row of the input fields. Multiplies each field by its weight before adding. Like a weighted mean without the division.
WEIGHTED UNION	Fuzzy	Finds the weighted union (mean) for each row of the input fields.
XOR	Fuzzy	Finds the fuzzy EXCLUSIVE OR value of the inputs by comparing the two truest values. If both are fully true or fully false, false is returned. Otherwise, applies the formula: (truest value - second truest value) / (full true - full false)

All intermediate and final map results in a logic model are rendered as fuzzy outputs, which range from -1.000000 (totally false) to +1.000000 (totally true). Interpretation of the range of values for a given map can be organized and interpreted in many ways using standard GIS binning such as Natural Breaks or Equal Area. For the terrestrial landscape intactness results, where an estimate of ecologically meaningful results was attempted using a careful selection of operators, thresholds, and input data, a modified EMDS classification was used to characterize intactness and assigned six classification descriptions—Very Low, Low, Moderately Low, Moderately High, High, and Very High (Table 1-3). This way, the degree of intactness could be evaluated against multiple conservation values and easily compared to potential future conditions based on updated raw inputs (e.g. new urban development projections) using the same scale.

Table 1-3. Intactness value ranges and legend descriptions. Fuzzy output map results range from -1.000000 (totally false) to +1.000000 (totally true) in six intactness classes from Very Low to Very High intactness.

Intactness Value	Legend
-1.000 to -0.750	Very Low
-0.750 to -0.500	Low
-0.500 to 0.000	Moderately Low
0.000 to 0.500	Moderately High
0.500 to 0.750	High
0.750 to 1.000	Very High

Source Data

Data used as input to the terrestrial intactness model were acquired from multiple sources. Data were either downloaded directly from the source, acquired from partner agencies, or created by analysts at CBI. Table 1-4 lists all of the input data used in the analysis as well as data type and originator.

It was often necessary to compare several datasets for a particular theme to determine those that were most appropriate for the modeling effort. Consequently, many more datasets were pre-screened and evaluated than were actually used in modeling. Several datasets were provided without metadata, or limited amounts of metadata. In these cases, the data were either not used or efforts were made to contact the data originators in order to obtain information about the data. In total, over 30 data layers were used to generate the final results.

The input data used to create this version range in currency from 2011-2015; the majority of data portray the more recent condition of the landscape.

This model integrates agriculture development (from FRAP Vegetation FVEG and CDL Cropscape), urban development (from LANDFIRE EVT and NLCD Impervious Surfaces), polluted areas (from NHD treatment ponds and EPA Superfund and Brownfield sites), linear development (OHV routes from owlsheadgps.com, roads from TIGER (broken down by type), utility lines, railroads, and pipelines from various state and BLM sources), point development (communication towers from the FCC), energy and mining development (from the state's Office of Mine Reclamation mine dataset, larger mine footprints, state geothermal wells, USGS wind turbines, solar footprints, renewable projects in development, oil refineries and state oil/gas wells), clear cuts from Statewide Timber Harvest Plans, invasive vegetation (compiled from multiple sources including LANDFIRE EVT, NatureServe Landcover, and NISIMS BLM database), and measures of natural vegetation fragmentation calculated using FRAGSTATS analysis of FRAP Vegetation FVEG and built features described above (percent natural core area, number of patches, and nearest neighbor). Overall intactness results are dependent on the quality of available input data for a given area.

This most recent version of this model (v30) addresses over-estimation of fragmentation impacts seen in previous versions, which stemmed from invasive vegetation and fire effects in FRAGSTATS calculations. New fragmentation metrics shift focus to anthropogenic development. Invasive vegetation is now compartmentalized within the logic model and influences the overall condition score to a lesser extent.

The input data, intermediate layers, and final results of this analysis can be explored via the EEMS Explorer of Data Basin (http://databasin.org/), where they are accessible as online interactive maps showing the signature of human impact across the landscape:
https://databasin.org/datasets/e3ee00e8d94a4de58082fdbc91248a65

Table 1-4. Source Data (Inputs to the Terrestrial Intactness model).

Input	**Data Type**	**Originator**
Cropland Data Layer (CDL), Cropscape 2014	Raster	USDA National Agricultural Statistics Service
FRAP Vegetation (FVEG), 2015	Raster	CAL FIRE
Impervious Surfaces, National Landcover Dataset (NLDC) 2011	Raster	U.S. Geological Survey (USGS)
LANDFIRE Existing Vegetation Type (EVT) v1.3	Raster	LANDFIRE
LANDFIRE Vegetation Departure (VDEP) v1.3	Raster	LANDFIRE
LANDFIRE Succession Class (SCLASS) v1.2	Raster	LANDFIRE
NatureServe Landcover (Terrestrial Ecological Systems) v3	Raster	NatureServe
Forest Practice GIS Timber Harvest Plan Clearcuts, 2000-2016	Polygon	California Department of Forestry and Fire Protection (CAL FIRE)
Modeled Tamarisk Coverage	Raster	Catherine Jarnevich et al.
Modeled Sahara Mustard Coverage	Raster	Conservation Biology Institute (CBI)
Tamarisk Lines	Line	TMAP, C. Jarnevich

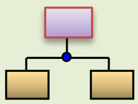
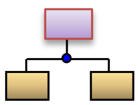
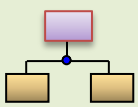
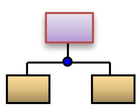
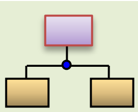
Input	Data Type	Originator
Off-Highway Vehicle (OHV) Routes, 2015	Line	Owlshead GPS
CA Solar Facility Footprints, 2015	Polygon	Digitized from solar project maps and best available imagery by CBI
2015 Tiger Roads[1]	Line	U.S. Census Bureau TIGER database
CA Electric Transmission Lines, 110-500 kV	Line	CEC, Scott Flint
CA Power Plants	Point	U.S. Energy Information Administration
California Rail Network	Line	CalTrans
CA Large Mine Footprints, 2015	Polygon	Digitized from best available imagery by CBI
CA Mine Sites	Point	CA Office of Mine Reclamation
California Natural Gas Pipelines	Line	CEC, Scott Flint
CA Petroleum Refineries	Point	U.S. Energy Information Administration
California Oil and Gas Wells, 2016	Point	CA Department of Conservation, Division of Oil, Gas and Geothermal Resources
FCC Communication Towers	Point	Federal Communications Commission, WFDSS
Onshore Industrial Wind Turbines, 2014	Point	USGS
CA Geothermal Resources	Table	CA DOC, Division of Oil, Gas and Geothermal Resources
EPA, Brownfield Sites	Point	Environmental Protection Agency (EPA),Facility Registry System (FRS)
EPA, Superfund Sites	Point	Environmental Protection Agency (EPA),Facility Registry System (FRS)
National Hydrography Dataset, Treatment & Tailing Ponds	Polygon	USGS, High Res. National Hydrography Dataset (NHD)

1. The TIGER roads dataset was created by merging multiple county level datasets.

The Modeling Process

There were five phases to the terrestrial intactness modeling process (*Preprocessing Data, Preparing Inputs (Invasives), Preparing Inputs (Fragstats), Calculating Densities,* and *Logic (EEMS) Model Execution*)**.** These phases were carried out using a set of models developed in ArcGIS Model Builder in conjunction with custom Python scripts. Table 1-5 provides an overview of the functions that each model performed.

Table 1-5. Models used in the terrestrial intactness modeling process.

Model	Model Diagram[1]	Model Overview
1. Preprocess Data		Clips all the input datasets to the study area and projects all input datasets to CA Teale-Albers NAD83; performs preliminary aggregation of datasets.
2. Prepare Inputs (Invasives)		Prepares (combines) input data for the invasive species component of the Terrestrial Intactness model. Extracts the location of invasive species from multiple sources. Extracted data is binary (0=absence, 1=presence). Combines all binary rasters using Boolean OR logic. That is, if ANY of the input datasets report the presence of invasives (i.e., the cell value=1), a cell value of 1 is retained in the final output.
3. Prepare Inputs (Fragstats)[2]		Prepares (combines) input data for the Fragstats component of the Terrestrial Intactness model. Extracts the location of features that fragment the landscape (e.g., roads, power lines, impervious surfaces), as well as the location of native vegetation. Extracted data is binary (native veg=1, other=0). Output from this model is used as input to Fragstats.
4. Calculate Densities		Prepares input data for all additional components of the Terrestrial Intactness model. In addition, this model calculates a density value for all components of the Terrestrial Intactness model. It then combines those density values into separate fields in a single feature class. This feature class is then used as input to the EEMS model (phase 5).
5. Logic (EEMS) Model Execution		Applys fuzzy logic within the EEMS model framework. Calculates a Terrestrial Intactness value for each 1km x 1km polygon in the reporting units feature class based on input data, operators used, thresholds, and weightings applied.

Habitat Fragmentation Modeling

The three inputs to the Natural Fragmentation component of the terrestrial landscape intactness logic model (percent natural core area, number of patches, and average mean nearest neighbor) were generated using FRAGSTATS (McGarigal and Marks 1995). FRAGSTATS produces a series of metrics that are focused at the individual patch, class, and landscape levels. All three fragmentation indicators chosen were class-level metrics. Prior to running FRAGSTATS, the entire landscape was mapped into two classes—natural vegetation and "other" (including developed, agriculture, and water). For this exercise, spatial details on fragmentation of different natural communities were not of primary interest, meaning that differentiating various vegetation communities (e.g. desert scrub from woodlands) was not needed.

The layers output from FRAGSTATS, depicting the average level of fragmentation on the landscape for each 1km reporting unit (Percent Natural Core Area, Number of Natural Patches, and Average Mean Nearest Neighbor) were combined using an Average (or *Fuzzy Union*) to generate the final Low Natural Habitat Fragmentation component in the model (Figure 1-8).

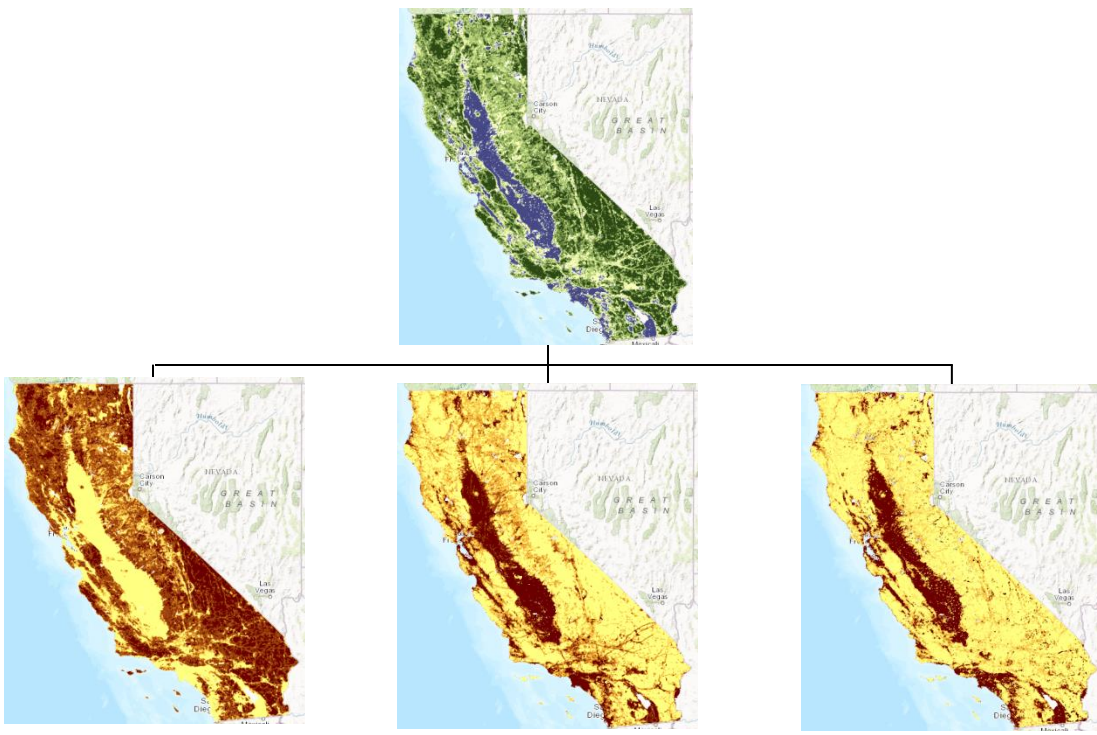


Figure 1-8. FRAGSTATS-based fragmentation metrics used in the terrestrial landscape intactness model (Percent Natural Core Area, Number of Natural Patches, and Average Mean Nearest Neighbor) and resulting final Low Natural Habitat Fragmentation component in the model. Note: High core area indicates better landscape condition, whereas low number of patches and nearest neighbor indicate more intact areas.

References Cited

Jensen, M., K. Reynolds, U. Langner, and M. Hart. 2009. Application of logic and decision models in sustainable ecosystem management. 2009. Proceedings of the 42nd Hawaii International Conference on Systems Sciences. Waikoloa, Hawaii. 5-8 January 2009.

Lee, P., D. Aksenov, L. Laestadius, R. Nogueron, and W. Smith. 2002. Canada's large intact forest landscapes. Global Forest Watch Canada, Edmonton, Canada. http://www.globalforestwatch.org/english/canada/pdf/Canada_LIFL-Text_Section.pdf

McGarigal, K., and B.J. Marks. 1995. FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. U.S. Forest Service, General Technical Report PNW-GTR-351, U.S. Forest Service, Pacific Northwest Research Station, Portland, Oregon. 122pp.

Potapov P., A. Yaroshenko, S. Turubanova, M. Dubinin, L. Laestadius, C. Thies, D. Aksenov, A. Egorov, Y. Yesipova, L. Glushkov, M. Karpachevskiy, A. Kostikova, A. Manisha, E. Tsybikova, and I. Zhuravleva. 2008. Mapping the world's intact forest landscapes by remote sensing. *Ecology and Society*, 13(2): http://www.ecologyandsociety.org/vol13/iss2/art51/

Reynolds, K.M. 1999. NetWeaver for EMDS version 2.0 user guide: A knowledge base development system. U.S. Forest Service, General Technical Report PNW-GTR-471, U.S. Forest Service, Pacific Northwest Research Station, Portland, Oregon.

Reynolds, K.M. 2001. EMDS: Using a logic framework to assess forest ecosystem sustainability. *Journal of Forestry* 99(6): 26–30.

Sheehan, T. and M. Gough. 2016. A platform-independent fuzzy logic modeling framework for evironmental decision support. *Ecological Informatics* 34(1): 92-101.

Strittholt, J.R., R. Nogueron, M. Alvarez, and J. Bergquist. 2006. Mapping undisturbed landscapes in Alaska. World Resources Institute, Washington, DC. http://www.globalforestwatch.org/english/us/pdf/GFW-Alaska_report_final.pdf.

Van Dyke, F.G., R.H. Brocke, H.G. Shaw, B.B. Ackerman, T.P. Hemker, and F.G. Lindzey. 1986. Reactions of mountain lions to logging and human activity. *The Journal of Wildlife Management* 50(1): 95–102.