

ml-HFI

The machine-learning-based human footprint index (ml-HFI) is an index of human pressure on the landscape based on remotely sensed surface imagery.

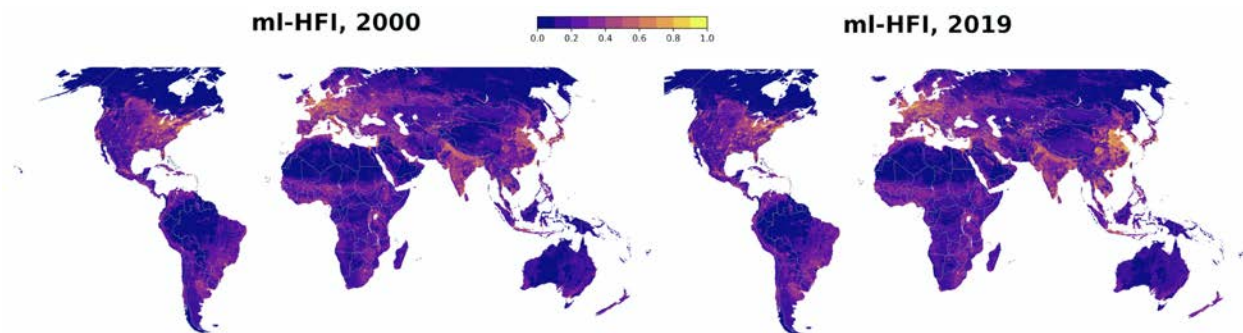
Motivation

Governments worldwide have poured massive capital into strategies for conserving biodiversity while also meeting the resource needs of their populations. However, the pace and scale of human development has exceeded our ability to monitor human influence on Earth's surface, creating a major challenge to sustainable development. The ml-HFI addresses this problem directly as a near-real-time index that quantifies human pressure on the landscape globally based only on freely available Landsat imagery. Specifically, the ml-HFI is computed via an interpretable convolutional neural network which converts global, remote sensing imagery into a metric of the human footprint on the landscape.

Version status

This is version v1.0 of the ml-HFI. Future updates to this data will be released at the GitHub repository: <https://github.com/eabarnes1010/ml-hfi>

Get the data



The ml-HFI is a continuous value between 0. and 1., ranging from no human impact to high human impact. ml-HFI v1.0 contains a global map of the ml-HFI for the year 2000 and the year 2019 on a 0.00989 deg latitude x 0.00989 deg longitude grid running from 70S-70N. Data for each year can be accessed below via netcdf (.nc) files. Each file is 3.6GB in size.

- ml-HFI 2000: ml_hfi_v1_2000.nc
- ml-HFI 2019: ml_hfi_v1_2019.nc

Algorithm

We train a convolutional neural network (architecture shown in the image) to ingest three channels of Landsat imagery and predict the human footprint index for that location.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 120, 120, 3)]	0
conv2d (Conv2D)	(None, 120, 120, 64)	1792
max_pooling2d (MaxPooling2D)	(None, 60, 60, 64)	0
conv2d_1 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_2 (Conv2D)	(None, 30, 30, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 15, 15, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
conv2d_4 (Conv2D)	(None, 7, 7, 128)	147584
max_pooling2d_4 (MaxPooling2D)	(None, 3, 3, 128)	0
dropout (Dropout)	(None, 3, 3, 128)	0
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 32)	36896
dense_1 (Dense)	(None, 1)	33
Total params: 555,329		
Trainable params: 555,329		
Non-trainable params: 0		

For training, we utilize the gridded HFI product computed by Williams et al. (2020) for the year 2000. The Williams et al. (2020) HFI is comprised of eight different sub indices representing different aspects of human pressures to the terrestrial surface of the Earth, including 1) extent of the built environment, 2) population density, 3) electric infrastructure, 4) agricultural lands, 5) pasture lands, 6) roadways, 7) railways, and 8) navigable waterways. Continental regions were trained separately and then the final predictions for each continental region were combined to create a final, single ml-HFI product.

The grid resolution of the Williams et al. (2020) training data and the ml-HFI product is 0.00989 deg latitude x 0.00989 deg longitude, and the ml-HFI is computed from 70S-70N. The ml-HFI algorithm was coded with python 3.6 and run on the Walter Scott College of Engineering HPC "Asha". A detailed description of the ml-HFI and its computation is provided in Keys et al. (2021).

Credits

The ml-HFI was conceived and created as a collaborative effort between [Dr. Elizabeth A. Barnes](#), [Dr. Patrick W. Keys](#) and [Dr. Neil Carter](#).

Recommended data citation

Keys, P. W., Barnes, E. A., & Carter, N. Dataset associated with "A machine-learning approach to human footprint index estimation with applications to sustainable development." Colorado State University. Libraries. <http://dx.doi.org/10.25675/10217/216207>

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References

- Williams, B. A., and Coauthors, 2020: Change in terrestrial human footprint drives continued loss of intact ecosystems. 2020.05.04.077818, <https://doi.org/10.1101/2020.05.04.077818>
- Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science* 342 (15 November): 850–53. Data available on-line from: <http://earthenginepartners.appspot.com/science-2013-global-forest>.
- Keys, Patrick, Elizabeth A. Barnes and Neil Carter: A machine-learning approach to human footprint index estimation with applications to sustainable development. *Environmental Research Letters*, DOI: 10.1088/1748-9326/abe00a.

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