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Abstract. Modern biogeographers recognize that humans are seen as constituents of ecosystems, drivers of significant change, and perhaps, the most invasive species on earth. We found it instructive to model humans as invasive organisms with the same environmental factors. We present a preliminary model of the spread of modern humans in the conterminous United States between 1992 and 2001 based on a subset of National Land Cover Data (NLCD), a time series LANDSAT product. We relied on the commonly used Maxent model, a species-environmental matching model, to map urbanization. Results: Urban areas represented 5.1% of the lower 48 states in 2001, an increase of 7.5% (18,112 km^2) in the nine year period. At this rate, an area the size of Massachusetts is converted to urban land use every ten years. We used accepted models commonly used for mapping plant and animal distributions and found that climatic and environmental factors can strongly predict our spread (i.e., the conversion of forests, shrub/grass, and wetland areas into urban areas), with a 92.5% success rate (Area Under the Curve). Adding a roads layer in the model improved predictions to a 95.5% success rate. 8.8% of the 1-km^2 cells in the conterminous U.S. now have a major road in them. In 2001, 0.8% of 1-km^2 cells in the U.S. had an urbanness value of > 800, (>89% of a 1-km^2 cell is urban), while we predict that 24.5% of 1-km^2 cells in the conterminous U.S. will be > 800 eventually. Main conclusion: Humans have a highly predictable pattern of urbanization based on climatic and topographic variables. Conservation strategies may benefit from that predictability.

Keywords: land use change, spatial models, species-environment matching models, Maxent

1 INTRODUCTION

Land use change, climate change, and invasive species are increasingly acknowledged as drivers of ecosystems. With the barrage of recent papers on continental-scale environments [1, 2], it is becoming increasingly difficult to dance around the number one element of recent change, us. Invasive species are defined as "alien species whose introduction does or is likely to cause economic or environmental harm or harm to human health" (Executive Order 13112; http://www.invasivespecies.org/resources/DefineIS.html). Modern humans may fit this definition, given that humans have substantial direct and indirect effects on habitat loss [3], habitat degradation [4], and extirpation and extinction [5, but see 6]. For example, direct conversions of wetlands to urban and agriculture uses have been associated with declines in the abundance of many wildlife species [7]. Urban sprawl has been directly linked to loss of bird species in grassland and shrubland habitats [8, 9]. Direct habitat loss due to roads, houses, and associated human services are well documented, but the literature cautions us we have much more to learn about the consequences of urbanization [10, 11], especially when we continue to "pave paradise, and put up a parking lot," as Joni Mitchell sang.

The indirect effects of the modern spread of humans have received much attention. Examples include the effects of air pollution and acid rain on aquatic species [12] and the introduction of other non-native species (e.g., horticultural plants, plant pathogens, feral pets)[13]. Meanwhile, remote sensing time series data have proven essential at quantifying forest biomass accumulation rates [14], urban forest changes [15], mapping urban and peri-urban agriculture changes [16], land use change [17] and mapping invading plant species [18]. Without a value judgment of any kind, we thought it would be instructive to map and model the recent continued spread of modern humans using a remote sensing time series with an ecological niche modeling perspective.

Species-environment matching models link the distribution of an organism to environmental factors such as climate factors or surrogates for primary productivity. A novel modeling method called maximum entropy distribution or Maxent, uses presence-only data and environmental variables to model species distributions [19, 20]. Maxent performs best among many different modeling methods [21]. Maxent has been successfully used to predict the habitat suitability for invasive American bullfrogs in Brazil [22], and diatoms and zebra mussels in the U.S. [23, 24]. Why not turn the model on ourselves?

A remote sensing time series has made such an analysis possible for the first time at continental scales. The Multi-Resolution Land Characteristics Consortium (MRLC; http://www.epa.gov/mrlc/) carefully resolved LANDSAT data from 1992 and 2001 to evaluate land use change and the conversion of natural vegetation types to urban cells (30 m x 30 m cells) across the United States [25, 26]. Details are provided below.

The objectives of this study were to: (1) use a remote sensing time series of recent changes in land use in the continental United States, combined with species-environmental matching models, to model modern humans as an invasive species; and (2) identify possible environmental drivers associated with those patterns.

2 METHODS

2.1 Quantifying Land Cover Change

We evaluated land cover change data in the conterminous United States between 1992 and 2001 based on a subset of National Land Cover Data (NLCD). The original NLCD for 1992 identified 21 different land cover classes at 30-m resolution from Landsat Thematic Mapper data [25]. NLCD 2001 added impervious surface and canopy density layers, and used improved classification algorithms [26]. We excluded land cover data for Alaska, Hawaii, and Puerto Rico. Additional information on the accuracy of the NLCD products can be found at http://www.epa.gov/mrlc/nlcd-2001.html.

However, a direct pixel-to-pixel comparison of NLCD 1992 and NLCD 2001 land cover is not recommended because of different classification algorithms, terrain corrections, differences in the numbers of classes in each time step, later increases in resolution for roads, and corrections for atmospheric effects (http://www.epa.gov/mrlc/change.html). To greatly minimize these problems, we followed the strict guidelines of the Multi-Resolution Land Characteristics Consortium (MRLC; http://www.epa.gov/mrlc/) including re-classifying NLCD 1992 era imagery, using the NLCD 2001, and reducing the classes to the more generalized Anderson Level I classification scheme (e.g., water, urban, barren, forest, shrub/grass, agriculture, and wetland).

Our analysis further simplified land use change by focusing on cells that changed from forest, shrub/grass, or wetland to the urban class, reducing the effect of errors in misclassification among the MRLC vegetation classes. Then, we rescaled the data from the original 30-m^2 resolution to 1-km^2 resolution. We did this to match the resolution of our predictor variables. We calculated the values for the coarser resolution by counting the number of 30-m^2 urban classified cells that completely fell within a 1-km^2 grid cell. Because each 1-km^2 grid cell contained 900 30-m^2 grid cells, the new values ranged between zero and 900. To create a model of urban suitability, we selected all 1km^2 cells from the 1992 dataset with a value of at least 800 (cells containing at least 800 30-m^2 urban cells). These cells depicted urban presence locations as the predictor variable in our model. After examining the distribution of values, we set the threshold to 800 cells. This ensured an adequate sample size of 40,000+ grid points for modeling.

2.2 Environmental variables

We considered 25 environmental variables as potential predictors of the "conversion to urban" patterns at the 1-km^2 scale, including 19 bioclimatic variables [27], which are biologically more meaningful than just annual means in modeling plant or animal distributions. We also included elevation, slope, and aspect because of biological relevance [24]. In addition, we included the distance to major roads: interstate routes, U.S. routes, state routes, and other large roads, as a predictor variable in a second model.

2.3 Modeling procedure

We used Maxent [20] to model potential suitable habitats for urban areas - the spread of modern humans. Maxent is an entropy-based machine learning program that estimates the probability distribution for a species' occurrence based on environmental constraints. It requires only species presence data (not absence). In this case, the 1-km^2 grid of areas with <800 urban 30-m^2 cells in 1992 were viewed as "presence" locations.

We used the latest version of freely available Maxent software, version 3.2.19 (http://www.cs.princeton.edu/~schapire/maxent/). Maxent logistic output generates a probability of habitat suitability for a species that varies from 0 to 1, where 0 is the lowest and 1 the highest probability.

We validated the model using the 2001 NLCD layer. "Conversion to urban" locations for validation included 1-km^2 cells with a value <800 in 1992 but >799 in 2001. Thus, if a 1-km^2 grid cell increased to 90% urban (based on conversions of 30-m^2 cells), it was considered a "conversion to urban" grid cell. We randomly selected an equal number of 1-km^2 cells that had a value of zero in both 1992 and 2001 to use with the "conversion to urban" cells as absence locations for validation. We calculated the validation statistics using the freely available program ROC_AUC version 1.3 available at http://brandenburg.geoecology.uni-potsdam.de/users/schroeder/download.html.

Urban areas represented 5.1% of the lower 48 states in 2001, an increase of 7.5% (18,112 km^2) in the nine year period. At this rate, an area the size of Massachusetts is converted to urban land use every ten years. The pattern of urbanization was highly predictable. 8.8% of the 1-km^2 cells in the conterminous U.S. now have a major road in them. In 2001, 0.8% of 1-km^2 cells in the U.S. had an urbanness value of > 800, (>89% of a 1-km^2 cell is urban), while we predict that 24.5% of 1-km^2 cells in the conterminous U.S. will be > 800 eventually.

3 RESULTS AND DISCUSSIONS

3.1 Predictability of modern human land use change

The raw data, consisting of 30 m x 30 m cells which were converted from forest, shrub/grass, or wetland, to the urban class, showed a clustered distribution (Fig. 1). Obvious "hotspots" of land conversion included areas around Atlanta, Chicago, Phoenix, Orlando and Florida coasts, Detroit, Las Vegas, Dallas-Fort Worth, Oklahoma City, Kansas City, the Front Range of Colorado, and the foothills areas in California. With the exception of Florida, growth appears concentrated in inland areas.

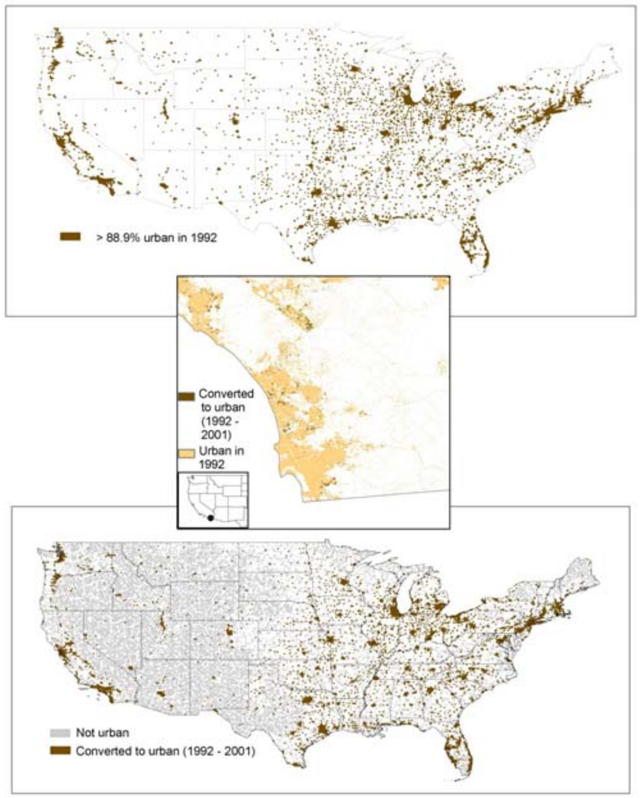

Fig. 1. Top. Urban 1-km^2 grid cells in 1992, defined as any cell containing at least 800 30-m^2 grid cells classified as urban by the NLCD data. Middle. Sample "conversion to urban" map in the San Diego, California area (the map for the entire US is impossible to see at this scale). Bottom: Locations used to validate the model including some conversion to urban locations (i.e., 1-km^2 cells with a value <800 in 1992 but >799 in 2001) and "non-urban" grid cells (i.e., 1-km^2 cells with a value of zero in both 1992 and 2001).

Humans urbanized agricultural lands and forests the most, with rates of 0.44% and 0.42% over the nine-year period (Table 1). The wetland cover class contributed twice that of barren lands to urbanization.

Table 1. Land cover class area in 1992, area converted to urban land cover, and percent of change from 1992 to 2001.

Class (NLCD1992-30m)	Area (ha)	Converted to urban class in NLCD2001(ha)	Percentage(%)
Barren	9257699	10716	0.115
Forest	213527204	905543	0.424
Grass/shrub	284195691	416603	0.147
Agriculture	182456109	803736	0.441
Wetlands	37392477	89750	0.240

Without roads included, the Maxent model predicted potential suitable habitats for the spread of modern humans between 1992 and 2001 with a 92.5% success rates (Fig. 2). The AUC was 0.925, sensitivity was 0.870, specificity was 0.866, the correct classification rate was 0.868, and kappa was 0.736. The areas of high suitability for future urbanization included broad areas around the hotspots listed above. The environmental factors associated with accurate "conversion to urban" predictions included growing degree days (35.4%), elevation (23.9%), humidity (10.7%), geology (7.3%), and slope (6.0%), primarily factors associates with warm-wet, flat, low-elevation places to live (Table 2). Urban conversion hotspots also tended to have ample precipitation and were near a water body or river.

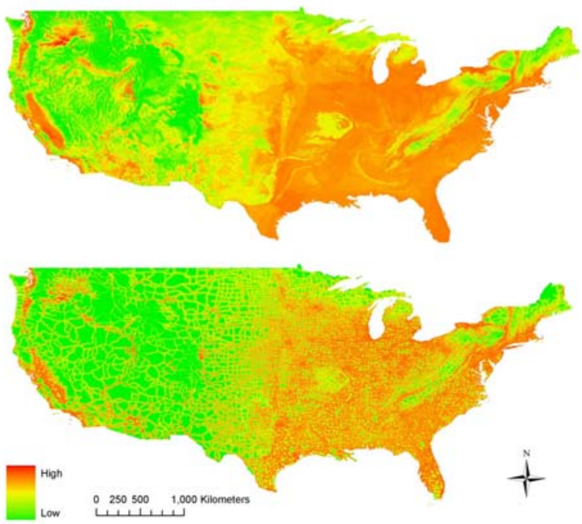

Fig. 2. Habit suitability for urban locations in the United States based on locations classified as urban in 1992. Top: Habitat suitability based on Maxent model without roads. Bottom: Habitat suitability based on Maxent model including roads as a predictor.

Table 2. Maxent model without roads: environmental factors contributing more than 1% explanatory power to the model.

Variable	Percent contribution
Growing degree days	35.4
Elevation	23.9
Humidity	10.7
Geology	7.3
Slope	6.0
Precipitation event size	3.8
Precip. coldest quarter	1.9
Frequency of precip.	1.82
Min. temp. coldest quarter	1.8
Diurnal temp. range	1.7
Precip. wettest month	1.2
Precip. wettest quarter	1.0

Several factors showed non-linear responses in the model (Fig. 3). For example, there were obvious threshold effects for growing degree days, whereby the spread of modern humans seems to require >3800 growing degree days per year on average. Below this threshold (in colder areas), far less land is converted to urban use. High elevation, low humidity, and high slope areas had lower probabilities for land conversion.

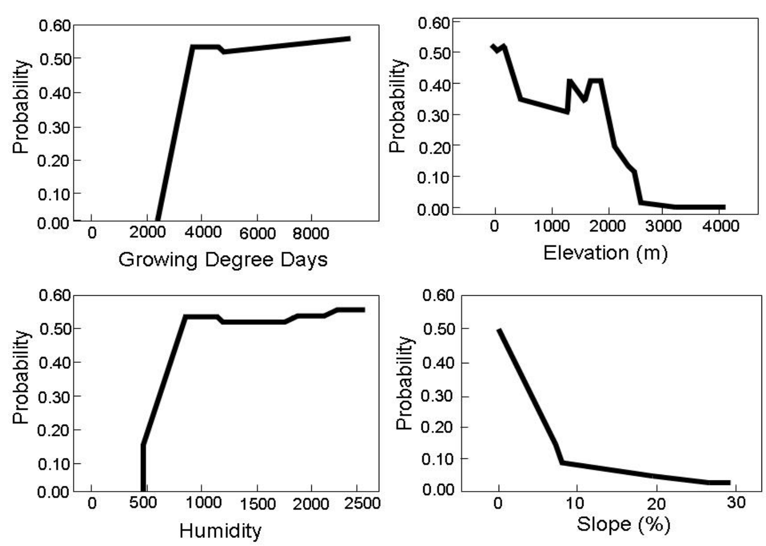

Fig. 3. Correlative relationship between the dominant environmental factors and habitat suitability for urban locations as defined by Maxent. The dominant environmental factors associated with conversion to urban habitats (roads not included).

3.2 Coincidence with roads

When we ran the model with the roads layer, distance to the nearest major road dominated the prediction, with a 72.2 % effect (Table 3). Most urban land conversion occurred less than 0.2 km from a road (Fig. 4). Growing degree days, elevation, and slope played similar roles (Fig. 3), as did geology. Geology was a categorical variable in the both models, relating primarily to lowland sedimentary formations. The model was improved with an AUC value of 0.955, a sensitivity of 0.907, a specificity of 0.906, a correct classification rate of 0.906, and a kappa value of 0.812.

Table 3. Roads included: environmental factors contributing more than 1% explanatory power to the model.

Variable	Percent contribution
Distance to major road	72.2
Growing degree days	11.4
Elevation	7.1
Geology	2.6
Slope	1.0

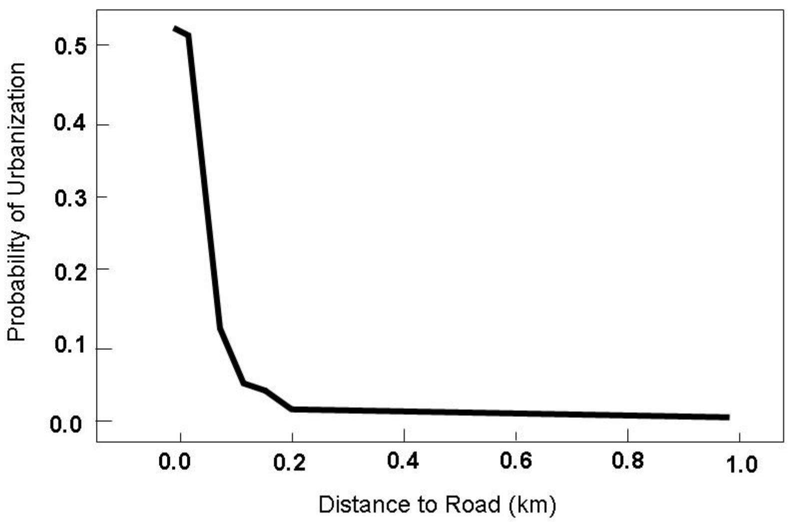

Fig. 4. Correlative relationship between the distance to major roads and habitat suitability for urban locations as defined by Maxent. The graphs for growing degree days, elevation, and slope are identical to those in Fig. 3.

The similarity in the mapped probabilities of urbanization with and without the roads layer underscores the strong role of environmental correlates to urban land use conversion (Figs. 2a,b). The environmental factors replaced by the roads layer included precipitation and temperature variables related to high plant productivity, where agriculture and forests prevail (Table 1). Roads are constructed in the path of least resistance (low elevations, low slopes) in and between areas of high productivity in a very predictable pattern (95.5% success rate).

3.3 Caveats

Statistically speaking, there are several caveats to studies such as this one ranging from the accuracy of the original data, selection of modeling techniques, and interpretation of results where no real cause-effect relationships can be determined. Land use data are limited by the resolution of the original remote imagery (30m cells and a limited number of classes in this case) and the accuracy of the classification algorithm used. Not all portions of each 30 m x 30 m cell might have been converted to buildings and impervious surfaces. Conversion to a coarser resolution required by computer processing constraints and resolution of available predictor variables may also introduce uncertainty. Likewise, some wildlife habitat exists in the 1-km^2 grids after 89% of cells within them are classified as urban, and grid cells with <89% urban cells may contain substantial human development. It is also difficult to determine the extent to which conversion to the urban class may have improved wildlife habitat for some native species in some areas that coexist well with human habitations.

Ecologically speaking, wildlife refugia may exist at scales smaller than measured here (i.e., backyards), due to conservation easements, or in greenbelts, parks, and conservation areas. More could be done to estimate ecosystem services gained or lost by habitat conversion [2, 11]. The human footprint on the landscape, due to rates of urbanization and road-building cannot be ignored [28]. Roads may be viewed as a response to favorable human habitat, and as a driver of ecological change.

3.4 Applications

Research programs such as NEON, the National Ecological Observatory Network, in partnership with the US Geological Survey's science centers, will be ideally suited to help monitor the effects of land use change on habitat loss, biodiversity, and indirect effects, along with the other drivers of change (climate change, land use change, invasive species, and contaminants; www.NEONInc.org). Since the most important predictor variables in our model were climate-related, climate change may facilitate the expansion of humans into warming areas. Poor economic times may slow our spread. Economic factors may be important predictors, but our models performed reasonably well without them in this case.

4 CONCLUSIONS

This study would have been impossible without careful interpretation of time series remote sensing data. Our study hopes to promote local, regional, and national studies of urbanization effects by providing spatial models of the potential for direct habitat loss, fragmentation, and loss in habitat quality (like many of the studies we cited). Modeling the distribution of modern humans allows ecologists to evaluate our potential direct and indirect effects on many native plants and animals. Once humans invade new territory through urbanization, they often landscape with invasive plant species [29], and further spread many devastating species. Indirect effects such as promotion of species invasions, contaminants, and resource consumption may follow our changing human footprint. Conservation strategies may benefit from that predictability.

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