Designing Sustainable Landscapes: Traffic settings variable

A project of the Landscape Ecology Lab, Department of Environmental Conservation, University of Massachusetts, Amherst

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UMass Amherst

Reference:

McGarigal K, Compton BW, Plunkett EB, DeLuca WV, and Grand J. 2020. Designing sustainable landscapes products, including technical documentation and data products. http://umassdsl.org/.

General description

Traffic is one of several ecological settings variables that collectively characterize the biophysical setting of each 30 m cell at a given point in time (McGarigal et al 2017). Traffic measures the estimated probability of an animal crossing the road being hit by a vehicle given the mean traffic rate (**Fig. 1**), an important determinant of landscape connectivity for mobile terrestrial organisms. It is based on an empirical model of mean vehicles per day, using point counts of traffic, and a transformation to estimate the mortality rate for road crossings. Traffic is a dynamic settings variable, increasing in future timesteps with urban growth.

Use and interpretation of this layer

Traffic is one of the most important ecological settings variables, used for the traffic, similarity, and connectedness metrics (see technical document on integrity, McGarigal et al 2017). For the connectedness metric, it strongly influences connectivity across the landscape. It is also used in a number of species models. In the landscape design models, it has a major influence on the boundaries of terrestrial cores and the paths of connectors between cores.

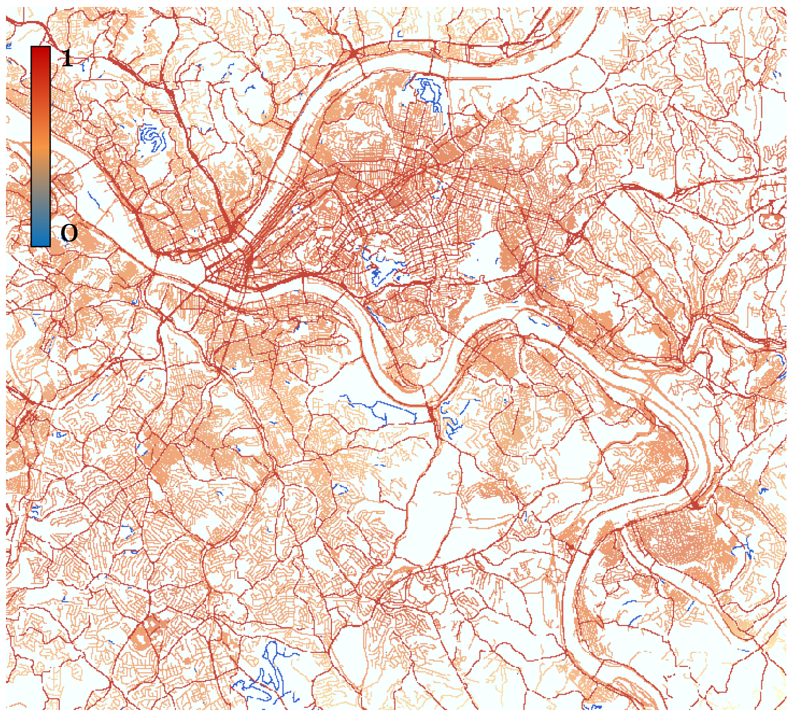

Figure 1. The traffic settings variable, in the Pittsburgh area. Blue areas (very low traffic) are in parks and other protected land, while expressways show the highest traffic. Note that depicted values are the probability of an animal being killed while crossing the road, not raw traffic rates.

Traffic contains a value between zero and one for each road cell, representing the probability that an animal will be killed crossing the road. Since species vary greatly in their road-crossing behavior, this probability must be interpreted in a general sense. In general, extremely low-traffic roads (e.g., gated roads through protected areas) will have near-zero mortality for most species, while extremely high-traffic roads such as expressways pose very high mortality risks for all terrestrial species (or conversely, will represent a barrier for species that are able to assess the danger and thus avoid crossing).

Measured traffic rates are not available for most roads across the region, so we built an empirical model that interpolates point data from TrafficMetrix (MPSI) for expressways, and a two-phase regression model that estimates traffic rates for other road classes by road class from the amount of development in the region, using the TrafficMetrix points as the dependent variable. The models that estimate raw traffic rates carry a number of assumptions:

- Open Street Map (OSM) correctly maps roads, and road classes are properly assigned. In general, linework from OSM appears to be excellent, but road class assignment is imperfect. In particular, the local roads class is extremely broad, encompassing both urban streets and little-used roads in extremely rural areas (though note that we differentiate by the intensity of development in the vicinity when assigning traffic rates).
- Measured point traffic rates from TrafficMetrix are correct and unbiased. There is a clear bias against measuring traffic on low-traffic roads, which we attempted to correct for in the second stage of the regression (see Algorithm, below).
- Traffic rates for motorways (expressways) are adequately represented in the TrafficMetrix point data, and interpolation is adequate to represent traffic rates. This is probably generally true.
- Traffic rates for roads other than motorways are dependent upon road class and the amount of development in the vicinity. This implies that nearby roads of the same class will have similar traffic rates, which is obviously not true.
- Local roads through protected open space (i.e., with mapped secured land on both sides) are gated, closed, or otherwise receive very little traffic. Although this is clearly not always the case, we believe this is more often correct than the opposite assumption, that protected land status does not affect road traffic rates.

Raw traffic rates were transformed to an estimated probability of an animal being killed while crossing the road. This model carries several simplifying assumptions:

- The crossing mortality model assumes an animal 1 m long is crossing the road perpendicularly at a constant rate of 5 m/min, and further assumes that neither vehicles nor animals attempt to avoid each other. While generalized and unrealistic, these assumptions provide a reasonable index of traffic mortality.
- For animals that are able to assess the danger posed by road crossing, and thereby avoid crossing when danger is high, the traffic variable estimates the probability that animals will not attempt to cross roads—still an important component of landscape connectivity. Note that behavioral avoidance by animals is dependent on both species and on vehicle speed, which are omitted from this model.
- We assume that traffic mortality rates on active railroad lines are equivalent to 500 vehicles/day on highways. Rail traffic rates obviously vary widely, and it is unclear how to relate mortality from trains to that from cars.

In summary, given the unavailability of measured road traffic rates throughout the Northeast, our approach to modeling road traffic seems to provide a reasonable, though far from perfect approximation of the likely effect of road traffic on terrestrial animal movement and mortality.

Derivation of this layer

Data sources

- Open Street Map (OSM). We used this open-source global map of roads (http://www.openstreetmap.org) as our source of linework for roads and railroads. Data were downloaded in November 2018. We aggregated OSM roads and railroads into the following classes:
  - **Motorway** - A restricted access major divided highway, normally with 2 or more running lanes plus emergency hard shoulder; U.S. usage is usually "Freeway" or "Expressway." OSM class motorway.
  - **Primary road** – A major highway, often linking towns. OSM classes primary, trunk, trunk_link, primary_link, motorway_link, and access_ramp.
  - **Secondary road** – Minor highways. OSM classes secondary and secondary_link.
  - **Tertiary road** – Minor connecting roads. OSM classes tertiary and tertiary_link.
  - **Local road** – Minor roads, often residential, but includes a wide variety of roads, including those of unknown class. OSM classes road, living_street, mini_roundabout, minor, residential, unclassified, service, turning_loop, turning_circle, and x-residential.
  - **Active train** – Active railroads. OSM classes light_rail, narrow_guage, rail, spur, preserved, and active.
  - **Abandoned train** – Abandoned railways, with or without rails. OSM classes disused and abandoned.
- TrafficMetrix (MPSI). Traffic counts at approximately 220,000 measured points throughout the northeast. Compiled from state and local data by MPSI, Inc. We used AADT, average annual daily traffic.
- MassDOT road traffic. Interpolated traffic rates for Massachusetts, based on an empirical modeling driven by measured traffic rates. This data source has not been updated, and is no longer available.
- Secured land. Permanently-protected conservation land, compiled by The Nature Conservancy.

Algorithm

Motorways. Expressways (aka motorways): We used kriging from TrafficMetrix point data to estimate traffic rates for expressways. This approach did not work well for other road classes, as the sampling data were relatively sparse, especially for smaller roads, so we used a two-stage regression dependent upon development density (described below). Expressways were well-sampled in the TrafficMetrix data, and traffic rates on expressways are somewhat less dependent upon local population density, so an interpolation approach made sense.

We used Euclidian-distance based kriging. Network and Euclidean-based kriging of traffic point data has been shown to perform almost identically (Selby and Kockelman 2011); therefore, we used Euclidean distance which requires significantly less processing time as well as readily available software. Other important covariates as discussed in Selby and Kockelman (2011), such as speed and number of lanes, were not available; however, Wang and Kockelman (2009) indicate that kriging with limited information performed far better than other methods such as assigning AADT on the basis of a site's nearest sampling location.

We excluded all TraffixMetrix points collected prior to 1995 and points that had more than 50% change between the two most recent sampling dates (on the assumption that one of these represents an error). We used the ArcGIS Geostatistical Wizard to create a kirged traffic grid from point data for expressways.

Other road classes. We decided that the TrafficMetrix data were too unreliable and sparse for kriging to work well for any of the classes except motorways. For the other road classes, we adopted a two step regression approach as described below.

For the dependent variable, we selected a stratified random sample of TraffixMetrix points for each road class. We cleaned these by excluding points sampled prior to 2006, points with more than 50% difference between first and second Average Daily Traffic (ADT) counts, points more than 10 m from road line, motorway points with ADT < 1000, points on primary highways where ADT < 100, points on local roads where ADT > 20,000, and points sampled by a number of methods deemed unreliable (AWET, AWDT, ADT Peak Hour Intersection, ADT intersection, ADWDT, AADT intersection, peak hour, SADT, and all codes indicating one-way counts). Because very few 2006 or later points were located in low/no development areas, we merged in points from 2000-2005 that otherwise met the above criteria and were > 20 km from previously sampled points.

For each road class, we stratified points across ten quantiles of a 50 km development kernel to ensure that we represented the range of the predictor. We selected a subset of points that were separated by at least 1 km.

To create predictor variables, we used development kernels at two scales (1.6 km and 12.8 km), based on the same weights we used for urban growth modeling (1:2:3 for low:medium:high density development). These grids were upscaled to 90 m.

We fit quantile regressions (using medians, to reduce the influence of outliers) to our sampled traffic rates in each road class with qr in the quantreg package in R. Predictor variables were the development kernels at two scales, plus an interaction. We used tile.predict in the gridio package in R to create continuous predicted grids for each road class, which we then assigned to all road cells (except motorways).

The TrafficMetrix data are biased, because sampling tends to focus on higher-traffic roads. We attempted to mitigate this bias with a second regression, calibrating results of our quantile regressions to MassDOT interpolated traffic rates, which we believe do not exhibit the same upward bias. We sampled the predicted grids from the quantile regression at random points in Massachusetts where the OSM and MassDOT roads overlapped, enforcing a 1 km network separation distance between points. We eliminated all points from this sample that were within 1 cell of a different traffic rate, to eliminate errors from sampling the wrong road at or near intersections.

Because the MassDOT data contained values of 0 and 100 as placeholders for low traffic roads that were not sampled, we converted all 0 and 100 values to 10, which was a more reasonable traffic value for these roads. In the few cases where 0 values occurred in the larger road classes, they were set to 100.

Using the MassDOT traffic values as the response variable, and the traffic values from the quantile regression predictions as the predictor variable, we fit a simple linear regression for each road class. We then created continuous predicted grids for each road class, which we then assigned to all road cells, taking care to lap higher traffic rates over lower ones at intersections.

Adjustment for protected land. Roads passing through protected land such as national and state parks are often gated, with little or no traffic. Data on gated roads are unavailable, so we couldn't correct this directly. Although high-traffic roads sometimes have protected land on either side, the more common situation (we think) is for roads through protected land to be closed. Additionally, the effects of such errors in our ecological integrity and species modeling were worse for incorrectly predicting high traffic in protected land (resulting in artificially low IEI for state and national forests and parks, for instance) than the reverse (artificially raising IEI for stretches of protected land on both sides of roads). Accordingly, we set traffic rates to 10 vehicles/day for local roads that had secured land (from TNC data) on both sides. We did not apply this adjustment to road classes other than local.

Railroads. Since data were unavailable on railroad traffic rates, and we have no estimate of mortality from trains, we arbitrarily set traffic rates on all active railways to 500.

Road mortality. Our goal for this settings variable was to estimate mortality from traffic, rather than raw traffic rates. This is impossible to do in a generic sense for many species, as road-crossing behavior varies widely among taxa, so we used a single-species approach (most suited to amphibians, turtles, and small mammals), with the assumption that this would provide a reasonable index to road mortality for terrestrial species in general. We used a model that has been applied to amphibians (Hels and Buchwald 2001), turtles (Gibbs and Shriver 2002), and small mammals (van Langevelde and Jaarsma 2004). This model assumes that cars arrive following a Poisson distribution (this is likely a good assumption at low to moderate traffic rates), that animals cross perpendicularly to roads, that animals move at a constant rate, and that drivers do not react to animals.

$$P(killed) = 1 - e^{\frac{-traffic \cdot (2 \cdot tires + 2 \cdot length)}{velocity}}$$

where *tires* (combined width of tires) = 25 cm, *length* (length of animal) = 1 m, and *velocity* (animal's constant velocity) = 5 m/min. Traffic rates were reduced by 20% to correspond to daytime traffic (Festin 1996, cited in Gibbs and Shriver 2002). Under this model, mortality stays near zero for low traffic rates (up to 100 or so vehicles/day), then rises rapidly, reaching 1.0 at around 10,000 vehicles/day (**Fig. 2**).

Bridges and culverts. Bridges and some large culverts often provide passage for terrestrial animals, allowing them to avoid crossing roads. We used a model to estimate the passability of bridges and culverts (see terrestrial barriers document, McGarigal et al 2017). For the connectedness metric, we treated the passability as a probability that an animal would safely cross under the road, and reduced road mortality accordingly. On high-traffic roads, this has the effect of funneling connectivity in the vicinity of highly passable bridges and culverts under the road, thereby increasing connectivity. We also used this approach for cores and connectors in the landscape conservation design.

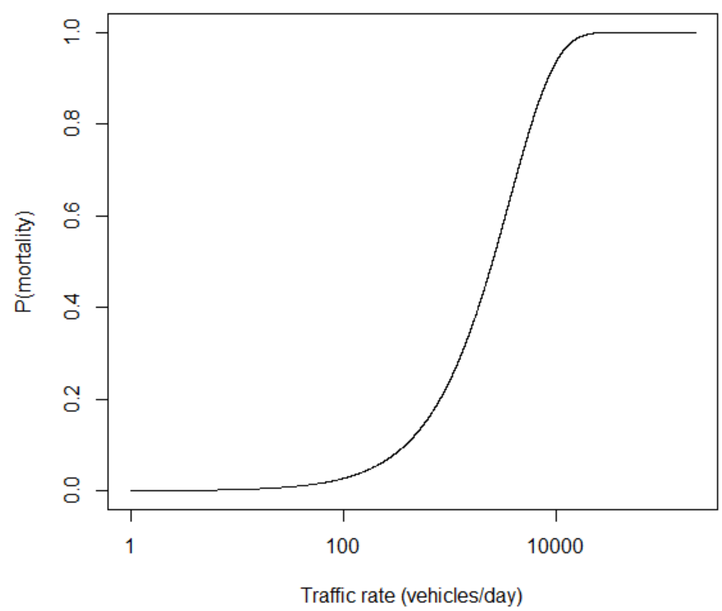

Figure 2. Relationship between raw traffic rate and probability of mortality for an animal crossing the road.

Future timesteps. Traffic rates for future timesteps were estimated using the following procedure. First, we used a kernel estimator with a 10 km bandwidth to smooth the probability of development (see technical document on urban growth, McGarigal et al 2017) for that timestep. This smoothed development probability surface was rescaled to range from 1 to x, with a mean equal to the mean development rate (future total development / initial total development) for the entire region from the RPA assessment. Traffic rates for the 2010 timestep were multiplied by this surface to yield an estimate of future traffic rates. We applied the Gibbs transformation to these raw rates, yielding an estimated probability of mortality.

GIS metadata

This data product is distributed as a geoTIFF raster (30 m cells). The cell value ranges from 0 to 1, representing the estimated probability of an animal being killed while crossing a road or railroad at each point. Cells not on roads or railroads have a value of zero. This data product can be found at McGarigal et al (2017).

Literature cited

Gibbs, J. P. and W. G. Shriver. 2002. Estimating the effects of road mortality on turtle populations. Conservation Biology 16:1647-1652.

Hels, T. and E. Buchwald. 2001. The effect of road kills on amphibian populations. Biological Conservation 99:331–340.

McGarigal K, Compton BW, Plunkett EB, DeLuca WV, and Grand J. 2020. Designing sustainable landscapes products, including technical documentation and data products. http://umassdsl.org/.

Selby B. and K. Kockelman. 2011. Spatial prediction of AADT in unmeasured locations by universal kriging. Presented at the 90th Annual Meeting of the Transportation Research Board, Washington, D.C.

van Langevelde, F., and C. F. Jaarsma. 2004. Using traffic flow theory to model traffic mortality in mammals. Landscape Ecology 19:895-907.

Wang, X. and K. Kockelman. 2009. Forecasting network data: spatial interpolation of traffic counts using Texas data. Transportation Research Record 2105:100-108.