Title
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Abstract: Intensity of human use (*IHU*) is a conceptual geographic characteristic that describes an area's rank on the continuum from high use (e.g., urban area or active strip mine) to low use (roadless wilderness). Customary measures of *IHU*, such as human population density or road density, lose their utility at the low-use end of the spectrum — and it is here that human activities may have their greatest ecological effect on some ecological resources, such as wildlife habitat. Conceptually, we suggest that *IHU* is determined by four factors:

$$IHU = P \times D \times A / C,$$

where *A* is human accessibility, *P* is the population of potential visitors, *D* is attraction to a destination, and *C* is the dilution effect of alternate destinations.

In our vehicle-centric culture, roads are essential determinants of human accessibility. Each time a road is built or opened, some area surrounding the opened road becomes more accessible, and each time a road is closed or reclaimed some area becomes less accessible.

Our modeling efforts have focused on small enough areas that factors *P*, *D*, and *C* are essentially constant. Our geographic information system (GIS) model of *A* expresses inaccessibility (roughly the reciprocal of *A*) as minimum travel time $T(x, y)$ from a paved road. The model depends on three digital geographic descriptors: elevation, land cover, and transportation. Calculations derive from estimates of vehicular speed on unpaved roads and walking speeds off-road. At present, our model ignores alternate off-road transportation modes, such as horse, motorized dirt bike, or all-terrain vehicle (ATV), although these can be easily incorporated under the basic model structure.

Introduction

Human Presence and Ecological Effects in the Backcountry

The last entry in Forman and others' (2003) figure of the lateral extent of road effects (their figure 11.6) is "human access, resulting in impacts on species and ecosystems," with an indication that these effects extend laterally more than one kilometer. How far do these human-generated, off road effects extend? Are some parts of the landscape matrix particularly prone to human presence and disturbance while other parts are relatively immune? How might the spatial pattern of human presence and disturbance change if a new road is built, or an old road closed? Is it possible to provide protection for sensitive ecological resources (e.g., threatened and endangered species) through seasonal closures that are synchronized with the resource's seasonal spatial distribution?

A distant goal is to answer the following three questions: (1) what is the probability or frequency of human presence in the neighborhood of any point on the backcountry landscape (by season, time of day, and day of week, for example); (2) what is the probability of various human behaviors and activities if a human is present (e.g., gunfire from practice shooting primarily near roads prior to hunting season, then gunfire farther from roads during hunting season); and (3) what is the ecological footprint of the activity? The composite of the probabilities, activities, and footprints expresses the density or likelihood of human disturbance. When each of these questions can be answered in the form of a model, then we will be able to estimate the specific backcountry ecological influence of a new road, or of the closure or removal of an old road.

Human presence and disturbance are spatially and temporally intermittent in the backcountry, so answers to the foregoing questions may be stated most appropriately as probabilities. For example, a wildlife species may respond behaviorally to campfire smoke, and it may be useful to know the probability by day, week, or season of camper presence in a valley that contains that species' habitat.

Is there evidence of a connection between human presence and wildlife response? It is our working hypothesis that the evidence has been published, but has been interpreted tangentially. An example occurs in models of grizzly bear habitat preference. Mace and others (1999), for example, documented negative correlations of grizzly bear locations in Montana with low-, moderate-, and high-use road densities during all seasons. Our hypothesis is that bears avoid human activities that associate with roads, and not roads and on-road activities themselves. Testing of this hypothesis requires that estimates of human activities associated with roads be brought together with animal location data to see whether human-activity estimators are better predictors than factors derived solely from the spatial arrangement of roads.

Different human activities in the backcountry have different spatial extents or *footprints*. The most extensive effect is likely to be accidental ignition of wildfire, but other activities also have potential large footprints — for example, the introduction of exotic species seeds from livestock feed or from hikers' clothing. Gunshots, or smoke from a campfire or from a remote cabin, may invoke behavioral responses in some wildlife species; these responses may extend roughly to the scale of small valleys (soundsheds or windsheds). In short, there are many mechanisms of ecological effect in the backcountry, and the footprints of various mechanisms are neither well documented nor readily estimated *a priori*; indeed, they may vary according to independent conditions, such as weather. Nevertheless, the most fundamental of footprints is simply the presence of humans, and it is here that we begin.

Relationship to Earlier Work

Watson and others (2000) reviewed methods for estimating wilderness recreation use. They emphasized counting of wilderness users for management purposes, rather than predicting the likelihood of visitation at any particular place on the landscape. Their work is an important reference point for our models, however, because nearly all backcountry users arrive at access points using motor vehicles. If sufficient monitoring information were available—along access roads, in parking lots, or on trails just beyond trailheads—then our intensity of human use model might be built directly on this observational foundation. Unfortunately, such a foundation is rarely obtainable; we have, therefore, based our model directly on populations that contribute to traffic at the trailhead (or other point of departure from the road network). Population and trailhead accessibility information are, at least in principle, readily available.

Lesslie and Maslen (1995) utilized a suite of four indicators to make a composite wilderness metric. The four indicators are: remoteness from settlements, remoteness from access, freedom from human construction, and biophysical naturalness (Fritz and Carver 2000). The Lesslie and Maslen analysis did not, however, consider the difficulty of off-road human transit. Fritz and Carver (2000) did the first GIS-based estimates of access times, which reflected quite directly the difficulty of human travel.

In this paper we extend earlier work in two ways: (1) we simplify the Fritz and Carver (2000) accessibility model, and (2) we treat accessibility as one component of a larger model of intensity of human use.

Summary of this Paper

Frequency of human use can and should be expressed quantitatively. We are not currently able to make numerical estimates, so we use the term *intensity of human use* (*IHU*) to express the general notion of relative spatial and temporal variation of human presence. We introduce a conceptual model for *IHU*, then focus on the factor in the model that relates directly to roads: human accessibility. We develop one quantitative measure of accessibility—the travel time to reach any point on the landscape—and illustrate a preliminary model for its calculation. We demonstrate changes in accessibility with simulated closure of roads, treating closed roads as trails.

Modeling Intensity of Human Use

We postulate that four factors determine the intensity of human use (*IHU*) of any area of the backcountry: (1) a source population of humans (factor *P*); (2) a desire among some of the human population to be in a particular place (factor *D*); accessibility (factor *A*); and competition with other places (factor *C*). Conceptually, therefore,

$$IHU = P \times D \times A / C\ .$$

There are salient geographic examples that illustrate the appropriateness of this conceptual model. Yosemite Valley, for example, is a few hours drive from the densely populated San Francisco Bay Area (high factors *A* and *P*), and it has spectacular scenery unmatched in the region (high factor *D* and low factor *C*). There are, of course, many layers of additional complexity; high *IHU* itself deters those among the population who seek simultaneous scenery and solitude, effectively reducing factor *P* and increasing factor *C*. Such secondary and feedback effects are beyond the scope of our preliminary work, but should be kept in mind when interpreting results from simple models.

Our work has not progressed to a point where we are able to calculate and present an actual *IHU* model. We present the discussion of this section to provide strategic context for our initial work on factor *A*.

Factor *P*: Human Population
Two places may be comparable in accessibility and desirability, but if one is close to a large population center and the other close to a small population center, then the former is more likely to receive frequent visitation. Among the residents—either permanent or itinerant—of any population center, however, there are those who are both equipped and inclined to visit the backcountry, and the remainder have little effect on *IHU*. Thus, factor *P* should count only the fraction of the population that is interested and equipped. While estimates of total population are readily available from censuses, it is considerably more difficult to estimate fractional populations. Surrogate measures (counts of bicycle shops or snowmobile sales, for example) may be useful, but evaluations of surrogate measures are beyond the scope of our work.

An interesting example of seasonal variation of factor *P* occurs in the Taylor Fork study area that we describe below. Temporary hunting camps are established to serve scores of hunters. Some of the camps are located at the very ends of roads accessible to full-size vehicles. The temporary populations served by these camps have significantly reduced access times.

Factor *D*: Desirability of Destination
Two major categories of human activity elevate factor *D*: resource extraction and recreation. Economically valuable extraction sites over time promote the enhancement of accessibility through additional road (or railroad) building. If this positive feedback process continues long enough, then an area becomes more industrial than backcountry in character, and our conceptual model is inappropriate.

The purpose of our investigation is to evaluate off-road ecological effects, and only a tiny fraction of mining, logging, and other resource extraction is done without direct road access. Thus, the primary desirability factors that should be considered in our conceptual model of *IHU* relate to recreation, not to extractive industry. Roads in the area of interest, however, may have been built in support of extractive activities—this is probably the case for the majority of backcountry roads— and consequences of the nature and timing of those activities (the stage of forest regrowth in a clear-cut area, for example) may influence factors *D* and *A*. Thus, resource extraction is relevant to the *IHU* model in many indirect ways.

Factor *D* encapsulates temporal information in two ways. First, the popularity of an activity varies by season, day of week, and time of day. *D* can be made a time-dependent variable proportional to these temporal changes.

Factor *A*: Accessibility
We evaluate accessibility every day; the measure we most often use is time. Strictly speaking, time of access is a measure of *in*accessibility, so at least as a concept, we can think of accessibility as the reciprocal of access time, or $A = 1 / T$. Much of the work presented in this paper relates to the estimation of *T*, spatial patterns of *T*, and influences of the road network over spatial patterns of *T*.

Travel time *T* does not express all dimensions of the influence of accessibility on *IHU*. For example, experience suggests that a place that requires an hour of automobile travel over dirt roads is considered by most people to be more accessible than a place that requires an hour of hiking on good trail. Fortunately, some of these differences can be captured in factor *P*; here, the discrimination is between people “interested and equipped to hike” versus those “interested and equipped to drive.” Thus, in a full numerical calculation of *IHU*—a level of model integration that we have not yet undertaken—judicious summation of activities by populations of “interested and equipped” people would resolve the ambiguities in factor *T*. Unfortunately, the populations do not separate cleanly into “drivers” and “hikers,” suggesting that population characterization itself deserves conceptual modeling and quantitative research. Also, the astute reader will note that this commentary on populations occurs within a discussion of accessibility—an indication of how tightly these aspects of human presence on the landscape are interwoven.

Factor *C*: Competition with Alternate Destinations
Within the area of a single model, factor *C* can be eliminated (set to 1). The purpose of *C* is normalization between or among somewhat independent areas, particularly when one population uses multiple areas.

Integration of the *IHU* model
The integrated analysis of intensity of human use must take into account the following factors:

- Multiple activities, both extractive and recreational
- Traffic that the activities generate, both on- and off-road

Here we express some of the notions in a more mathematical way in order to clarify the proper construction of an *IHU* model. Non-modelers can safely skip over this section.

The total intensity of human use is the sum of intensities for different activities. We use the summation index *i* to indicate one activity. As discussed above, there are different populations—although probably overlapping populations—that are interested and equipped to participate in each activity. The population for activity *i* is P_i. Similarly, the competition with other opportunities for this activity outside of the area of the model, which in effect splits P_i, is C_i. In a first-order treatment factors P_i and C_i are constant over the modeled area, i.e., they are not functions of position (x,y).

Factors *A* and *D*, on the other hand, are both position dependent. The desirability of a location depends on both location and activity, so $D = D_i(x,y)$. If different activities imply different modes of travel, then accessibility *A* depends on activity and location, so $A = A_i(x,y)$; in a simpler situation, when all activities involve the same mode of travel, then $A = A(x,y)$.

In a fully constructed *IHU* model, we need to consider visitation-in-transit at points along efficient routes to visitors' ultimate destinations. We will call this the traffic factor *T*, and it depends on activity and is spatially explicit; thus, $T = T_i(x,y)$. We will show below that *T* is a derived factor dependent on *D* and *A*.

It is helpful both conceptually and computationally to think of *T* in analogy to surface water flow in a watershed. In a cell-based watershed model, any cell that is not on a ridge or a summit has an associated assemblage of cells that are upstream, which drain through the cell in question. In the *IHU* model, "upstream" cells are the ones whose most efficient route of access traverses the cell in question. If a geographic information system (GIS) is used to calculate optimum travel times (optimum accessibilities *A*), then the GIS typically will generate simultaneously a travel-direction grid. Hydrologic functions can be used to weight and sum values from every upstream cell in the routing network—traffic routing rather than water routing in our case—and assign the result to the route cell in question. We are interested in the sum of upstream use that is generated by our enumerated activities on the landscape. Thus,

$$T_i(x,y) = T_0 \sum_{U(x,y)} D_i(x',y') A_i(x',y')$$

where T_0 is a scaling constant, $U(x,y)$ is the area upstream of (x,y), and (x',y') is a point within $U(x,y)$.
The full spatial model for *IHU* is

$$IHU(x,y) = \sum_i \frac{P_i}{C_i} \left[D_i(x,y) A_i(x,y) + T_i(x,y) \right].$$

The first term inside the square brackets, the *DA* product, represents human presence for activities at location (x,y); the second term, *T*, is human presence caused by travel to other "upstream" sites. Each factor in the model can vary with time. If an analysis requires averaging or totaling over time, then the appropriate way to handle the averaging is to calculate *IHU* for the shortest possible time interval and then to average or total the *IHU*. It is not appropriate to calculate *IHU* based on temporal averages or sums of its terms.

Modeling Accessibility
In a small area, factors *P* and *C* of the *IHU* model do not vary. Factor *D* consists of three parts: (1) intended backcountry activities, which are difficult to inventory without extensive interaction with users; (2) quantification of the number of participants in each activity; and (3) locations of intended participation. Lacking this information, we defer consideration of *D* and begin the exploration of the *IHU* model by calculating only the accessibility factor *A*. We refer to this sub-model as the human accessibility/remoteness model, or *hARM*.

Importance of the Transportation Network
If access time is a determinant of levels of human use, then the features of the landscape that most significantly influence access time also significantly influence use levels. Because roads offer rapid mechanized access, they are a core feature of an accessibility model.

Consider that an average walking speed on a level trail is about 3.2km/h (van Wagtendonk and Benedict 1980). A paved road makes speeds possible that are about 30 times greater, and a graded dirt road from 5 to 15 times greater. In an accessibility model, this has the effect of propagating a zone of near-zero access times along the parts of the road network that are accessible from the starting point (or starting zone).

Low accessibility, or high remoteness, occurs under two circumstances: (1) when the remote place is physically far from a road, or (2) when a difficult feature must be crossed. Although we do not illustrate such situations in this paper, the reader can imagine a road in the bottom of a deep canyon. Such a canyon road offers rapid access only to the bottomlands, while the canyon rim and lands beyond are shielded from access by the near-zero travel speed involved in scaling vertical walls. Similarly, a road on a canyon rim reduces accessibility on that rim but not on the canyon bottom or on the rim opposite. These spatial considerations illustrate the importance of basing model calculations on accurately located roads and topography.

Changes in the transportation network, including such changes as gate openings and closings, make far-reaching changes in accessibility. We imagine that a key application of *hARM* is the quantitative analysis of the area affected by these road-management adjustments. For wildlife species that are sensitive either to vehicular traffic or disseminated human presence, the opening and closing of a gate can alter habitat quality over a large area.

Off-Road Travel-Time Calculations

Fritz and Carver (2000) introduced GIS-based off-road accessibility modeling with an application of a walking-speed model known as "Naismith's rule." The original rule was developed in Scotland in the 19^{th} century; Fritz and Carver used a modification attributed to Langmuir (1995). It specifies a walking speed of 5km/h for level ground, with a time addition of 1 hour per 600m of climbing, a time subtraction of 20 minutes per 600m of descent for slopes between 5 and 12 degrees (grades of 9% to 21%), and a time addition of 20 minutes per 600m of descent for steeper slopes. Shortcomings of this model are apparent, such as its insensitivity to altitude and land cover.

Van Wagtendonk and Benedict (1980) timed trail hikers in Yosemite National Park and from their observations developed two equations of identical form for uphill and downhill travel. These are $v = v_0 e^{-ks}$, with k = 4.6 for uphill travel, k = 1.5 for downhill travel, v_0 = 3.2km/h = 0.89m/min, and slope s expressed as a gradient in m/m. We used van Wagtendonk and Benedict's rule with a further simplification; we used a single, mean value of k = 3.0. As explained below, our computational method was not sensitive to direction of travel and was thus unable to differentiate between uphill, downhill, or cross-slope travel. Our travel-time estimates are, therefore, biased downward for places reached with mostly uphill travel, upward for places reached with mostly downhill travel, and more strongly upward for places reached with mostly cross-slope travel. Roads and trails in hilly and mountainous landscapes—which are preferentially selected as elements of all time-efficient routes—occur mostly in valley bottoms. Most off-road travel is uphill, making the bias of downhill and cross-slope travel secondary in importance when assessing landscapes; these biases may, however, be quite important for specific, ill-conditioned routes.

Several approaches are available for doing the computations. The simplest of these breaks the modeled area into square or rectangular cells, then assigns travel times to the links that connect cells. Links can be in cardinal or diagonal directions; it is the job of the solution algorithm to select the most efficient link everywhere in the grid.

Fritz and Carver (2000) used an iterative method that assigned different crossing times to links depending on the direction of travel. Theirs is the more accurate way to do the calculations, but it involves iterative examination of travel direction and selection of corresponding link times. The iteration demands careful programming and considerably increases computation time. We chose a simpler approach that assigns a single time "cost" to traversing a cell, with no differentiation between crossing directions—except for appropriate distance weighting of diagonal versus cardinal links. This approach is computable in a single minimum-cost-distance GIS operation, although internally the GIS function also performs iterative analysis as it finds the optimum path. We speculate, but have not demonstrated, that the errors introduced by our direction-insensitive method are no greater than the errors inherent in estimating walking speeds from available data. Working out of the error budget of these models requires detailed hiking-speed data in various terrain and land-cover conditions, which can now be obtained without difficulty using global positioning system (GPS) receivers.

Study Area

Our study area is the valley of Taylor Fork of the Gallatin River in Gallatin County, Montana. Elevations in the valley range from 1350 to 3436m. A shaded relief image (fig. 1) demonstrates that the floors of the Gallatin River and Taylor Fork valleys (the former is in the northeast corner of figure 1, the latter branches west through the center of the image) are relatively flat; all other parts of the mountainous landscape have considerable slopes, which significantly influence access.

Calculating Celocity

We begin with a flat-ground (trail) walking speed of 3.2 km/h and then apply a series of adjustments, as described and illustrated below. Throughout this process our objective is to assign a speed to each cell in our grid, with the speed depending on local slope, land cover, and presence or absence of a road or a trail.

Slope-Dependent Walking Speed

We described our simplified approach to making speed adjustments for slope in the preceding section. Figure 2 shows bare-ground, no-land-cover walking speed calculated from slopes alone.

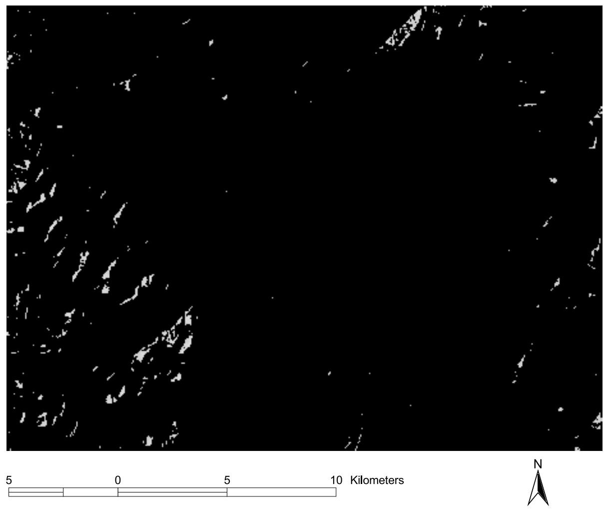

Fig. 1. Shaded-relief image of the valley of Taylor Fork of the Gallatin River in Gallatin County, Montana

Land Cover and Trails

We used the National Land Cover Dataset (NLCD) (Vogelman et al. 2001) to apply speed penalties (dividing factors) to various land cover types, as indicated in table 1. Cells that contained portions of trails were converted to the bare rock/soil class and thus had no speed penalty except for the slope penalty previously applied. Trail-imprinted land cover is shown in figure 3.

Our estimates of speed penalties are based on personal field experience; we have not assembled and rigorously analyzed walking-speed data in the various land-cover types. Our efforts to find cover-dependent walking-speed models in the research literature were fruitless. The speed penalties that we have specified are inappropriate during winter, when snow depth is the dominant factor. Speed factors in summer and fall may actually be time dependent, even though we have specified them as static. For example, stream crossings may be virtually impossible on foot during snowmelt season, but in late summer and fall may be little different from walking on bare ground.

Table 1.
Speed penalty factors by land-cover type

Bare rock/soil	1
Coniferous forest	2
Deciduous forest	1.5
Emergent wetland	3
Grass/herbaceous	1
Ice/snow	2
Mixed forest	2
Pasture	1
Shrubland	2.5
Transitional	1.5
Water	2
Woody wetland	3

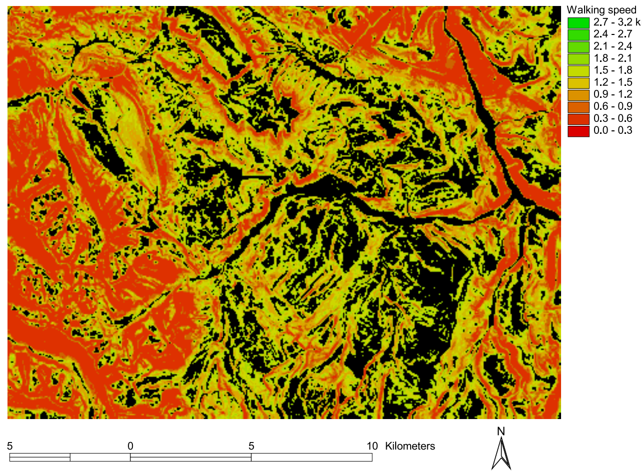

Fig. 2. Slope-dependent walking speed under bare-ground conditions.

Thus, the land-cover penalty portion of our model is uncalibrated but generally reflects comparative ease or difficulty of moving across the landscape. The lack of calibration means that travel-time numbers in the model are unreliable, but spatial patterns of relative travel times are generally reliable. It is likely that slope and land cover interact in determining walking speeds. Development of a multi-parameter, possibly nonlinear model is possible with time-stamped global positioning system (GPS) tracks obtained by hikers crossing a variety of terrains, but such a model is also likely to vary from region to region.

Gross-categorical data sets, such as NLCD, because they do not reliably reflect understory vegetation may be insufficient for development of reliable models in some regions. One important shortcoming of NLCD-based speed penalization in the Yellowstone area is NLCD's lack of discrimination between virgin and post-logging regrowth forest. Virgin forest often has numerous fallen logs in various states of decomposition, making walking speeds much slower than in regrowth forest.

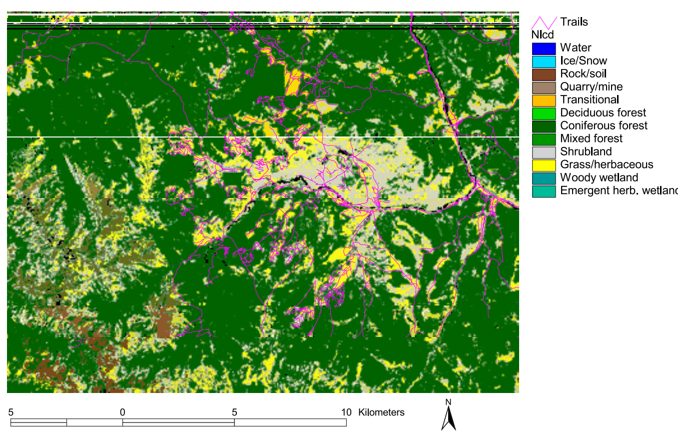

Fig. 3. National Land Cover Dataset (NLCD) categories, with trails superimposed.

Roads

We commented in an earlier section about the importance of the roads because of their high associated speeds. In the study area depicted in this paper, we mapped roads first by interpretation from air photos and later by field checking. Thus, we have reliable estimates of road speeds, although these inevitably vary according to antecedent and current weather conditions. We also documented where gates may be opened or closed and the state that we found them in during our fieldwork.

Roads are handled in the *hARM* model by assigning the driving speed on a road to each cell that the road crosses. In effect, the road speeds are "stamped" over all earlier speed estimates and adjustments; they therefore override speeds determined by slope and land cover. Figure 4 shows the complete speed model that accounts for slope, land cover, trails (as barren ground), and roads.

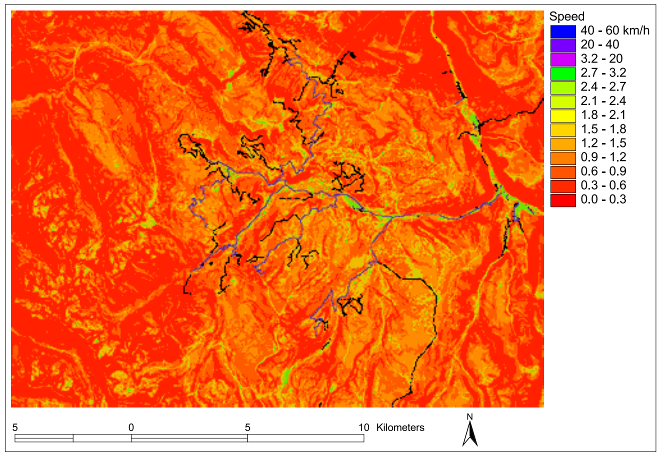

Fig. 4. Composite speed model taking into account slope, land cover, trails (treated as bare ground), and dirt roads.

The Locus of Zero Time

The modeler must decide where times are to be measured from. Many GIS implementations allow least-cost-distance modeling to establish a zero-time (zero-cost) origin over an arbitrary set of cells. This can be a single cell—at an intersection, for example— or a set of cells that represents one paved road, all paved roads, or a town. Speeds within the origin features are irrelevant; all points in the origin set are reached in zero time. For our illustrated model, paved roads were time zero. Paved roads occur only along the Gallatin River in the northeast quadrant of the model area, and are readily identified by their zero travel-time values in the results of the *hARM* model. At the scale of the model illustrated here, a different zero-time specification on the paved road—at a single point, for example, rather than along the entire paved road length—makes little difference because travel times along the high-speed paved road are so small.

hARM Model Results

Figure 5 shows the results of the minimum-cost (minimum travel-time) calculation.

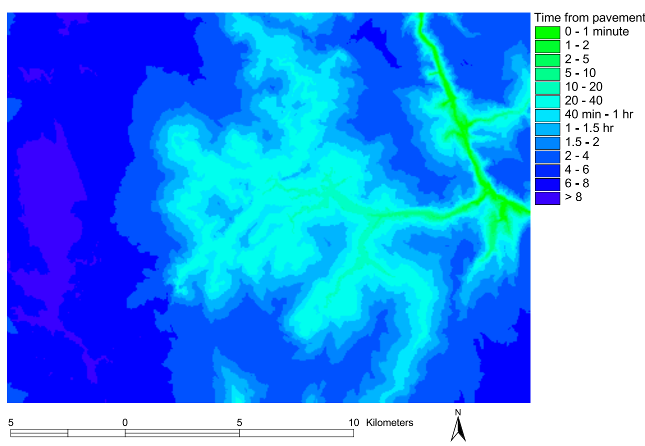

Fig. 5. Results of *hARM* model: travel time from paved road in the Taylor Fork valley.

Discussion

Interpretation of *hARM* Accessibility Maps

The Taylor Fork valley can be penetrated significantly—roughly 10km—in less than 20 minutes, but the area that is accessible in such a short time is quite small, a result of the generally steep-sided valley walls. A more complete picture of the accessibility of the whole landscape is obtained by plotting the fraction of the landscape that can be reached within a given travel time (fig. 6).

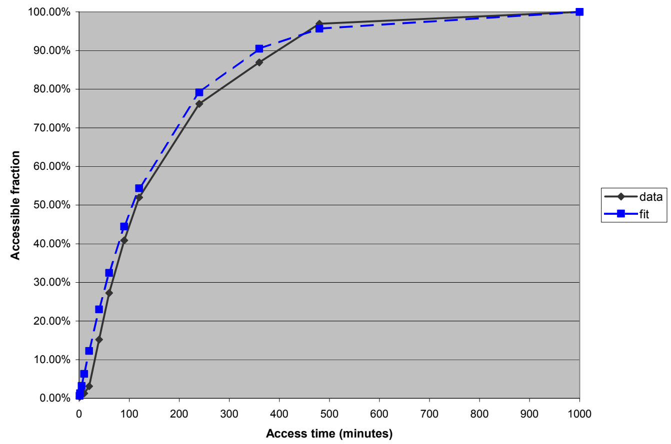

Fig. 6. Cumulative fraction of landscape that can be reached as a function of travel time from a paved road.

Figures 5 and 6 illustrate that travel on the highest-speed backcountry roads provides direct access to a small fraction of the landscape. This preliminary access, however, leads to rapidly expanding access with additional time investment on the part of the backcountry user. If t is travel time from pavement and a is the fraction of the landscape accessible with travel time $\leq t$, then $\ln(1 - a)$ is well approximated by the linear expression $-\alpha t$ with $\alpha = 0.00654$; the R^2 of this fit is 0.98. Solving this formula for a gives $a = 1 - \exp(-\alpha t)$, which is plotted in figure 6 together with the accessible-area versus time curve derived directly from figure 5. This result is specific to the roads, topography, and land-cover of the Taylor Fork valley as well as to the input assumptions of this run of the *hARM* model. The additional fraction of landscape that is accessible per minute of travel is given by $\Delta a = \alpha \exp(-\alpha t)$, an apparent exponentially diminishing return on time investment. One person can, however, go to only one place at a time, so what these formulas reveal is that—at least for this landscape—the longer the duration of a trip that one desires to make into the backcountry, the fewer the potential destinations.

More important than the specific quantitative results are the analysis possibilities. For example, any point that takes longer than four hours (240 minutes) to reach is almost certain to require either backpacking or livestock packing because of the duration—greater than eight hours—of the round trip. One can readily see that about 20 percent of the landscape lies at travel times greater than four hours, so in effect this 20 percent is managed exclusively for backpacking or other multi-day access.

Table 2
Color interpretations for Figure 7

Green	Low and accessible
Blue	Low and remote
Yellow	High and accessible
Magenta	High and remote

Spatial pattern and relationship among spatial variables may matter as much as summary statistics. Figure 7 shows access time and elevation together. Both variables were transformed to percentile ranks (an equal-area classification). Access time is rendered from green (accessible) to blue (remote); elevation is rendered from black (low) to red (high). These representations are then superimposed in a red-green-blue (RGB) display. Resulting color combinations are shown in table 2. Figure 7 illustrates that high and remote (magenta) conditions are significantly more prevalent than low and remote (blue). If a wildlife species requires both low-elevation resources and isolation from people (i.e., blue areas), then there is little space available. Two inaccessible low-elevation areas occur near the top of figure 7, one just right of center and the other in the northwest corner. A yellow-green band of intermediate-elevation accessible land separates the two blue areas.

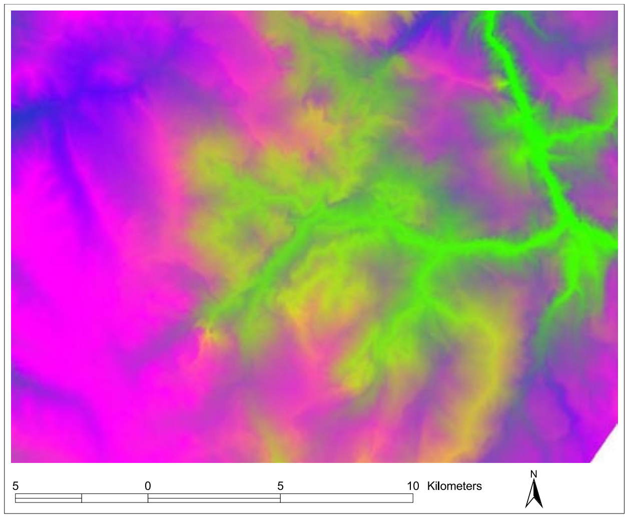

Fig. 7. Color composite of elevation and travel time from pavement. See Table 2 for interpretation of colors.

Thus, there is a management option of improving landscape connectivity for our hypothetical species by closing the roads that make the land between the two blue patches accessible. The *hARM* model can be used to evaluate such options. Figure 8 illustrates the changes in accessibility that would occur if gates were closed on several roads that branch from the main Taylor Fork road (roads inaccessible to motor vehicles are treated as trails). One result of this road closure is that the two blue patches along the top of the figure are now separated by a ridge that is inaccessible to humans rather than by an accessible ridge. Another effect is that the overall area of remote, low-elevation (blue) habitat is substantially increased, which would be advantageous to our hypothetical species.

Factors Affecting Model Accuracy

Transportation Mode

The great increase in thenumber of ATVs significantly blurs the distinction between road and trail, and the speeds achievable on these vehicles produce significant changes in estimates of access time. Recalling our earlier discussion about stratifying the *IHU* model by activity and by the population of those "able and equipped," we recommend that distinct models be used according to conveyance type.

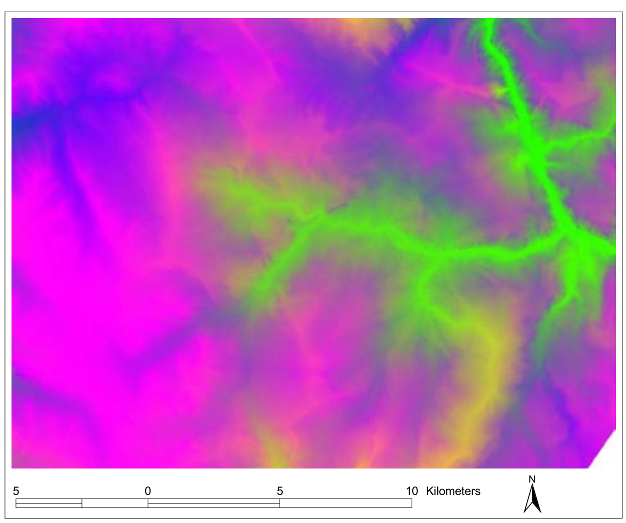

Fig. 8. Access times and elevation color-coded as in figure 7, with simulated closures of side roads.

Documentation of routes and travel speeds for ATVs, mountain bikes, motorized dirt bikes, horses, or llamas, is a non-trivial undertaking.

Some transportation modes are disallowed in some areas. Part of our study is in a formal wilderness area, where motorized travel is excluded. Other parts of our study area are on private land, where general access may be barred but where landowners can use any means of transportation that they desire. These are difficult issues to resolve in a systematic way without extensive, site-specific investigation.

Road and Trail Maps (GIS Data)

The differences between figures 7 and 8 illustrate the importance of accurate representation of the road network. The opening and closing of roads has a substantial impact on the spatial and statistical patterns of accessibility. To misrepresent road status in the model generates significant errors in interpretation of landscape accessibility.

We warn potential modelers about the risks inherent in using readily available GIS data and maps. These oftentimes are out of date; they omit accessible routes, show routes that are closed, and generally wreak modeling havoc. Our field studies have found areas where less than 50 percent of accessible roads are represented in available data sets. By the same token, we have found our own photo interpretations in some areas to over-represent open roads by as much as 100 percent because gates, berms, and other closure structures cannot be discerned in the photos. Apart from those areas where the transportation network is quite stable—in the United States this is likely limited to Wilderness Areas, National Parks, and some private land—validation of transportation data seems essential.

Speed Estimation and Travel-Time Calculation

We estimated speed penalties for various land cover types without robust data. Multiple regression formulas are needed that estimate travel speed based on slope, direction of travel, land cover, and elevation. Land cover characterization is particularly important and particularly difficult because it determines trafficability and speed for all transport modes—foot, horse, llama, ATV, and dirt bike. Important land-cover characteristics in this context are tree density, downed timber density, understory vegetation type and density, and ground roughness. The last of these, ground roughness, is also an important speed determinant on trails.

We used an algorithm that assigns speed without regard to direction of travel. The best algorithms that account for direction of travel appear to be *fast marching* algorithms (Sethian 1999); their application would allow for analysis of optimized travel in any direction, not limiting travel to a cardinal-and-diagonal, eight-direction set of node links.

Conclusions

Backcountry roads, including ATV and dirt bike trails, are the outposts of mechanized civilization. Wilderness—however one chooses to define it—does not occur when one steps off the road. Rather, this is the first step into a diffuse zone that leads to the most remote places. Our efforts are aimed at developing metrics to describe the degree of remoteness or wildness.

The multitude of customary pattern metrics used in landscape ecology (e.g., McGarigal and Marks 1995) do not discriminate the important ecological differences between a forest patch reachable by a short walk from a maintained road and a similar forest patch reachable only after a two-day hike. Some of these differences may be sufficiently described in terms of accessibility (*hARM* results) alone; others may require estimation of the frequency of human visitation and human activities (*IHU* results, when such a model is implemented). These landscape metrics may support improved models of ecological conditions, including improved measures of the quality of wildlife habitat.

Biographical Sketches: Ray Watts is a geographer at the U.S. Geological Survey. He was trained in physics (B.A., Pomona College), applied mathematics, and geophysics (MIT; Ph.D., U. of Toronto). He worked in NASA's Apollo program (1970-1974), developed and applied low-frequency radar instruments for measuring thickness of glacier ice (1974-1980), and similar instruments for mapping fractures in rocks (1980-1984). He served as deputy assistant director for research at USGS headquarters (1984-1989), where he participated in development of the U.S. Global Change Research Program. Since returning to research in 1989, he has applied mathematics and computer models to studies of river basin structure and sediment transport in New Mexico and to analysis of roads and their ecological effects in the Greater Yellowstone Area. He is currently leading a USGS effort to develop a downloadable, national distance-to-road data set.

Roger Compton is a geographer specializing in the documentation and interpretation of the human imprint on regional landscapes, particularly in backcountry areas of the western United States. He uses images, aerial photography, and GPS-supported field methods to develop GIS data sets that describe backcountry access and use. He holds a B.A. in geography, a B.F.A. in sculpture, and has completed graduate course work in geography and related fields, such as urban/regional planning and economics. Roger has extensive backcountry experience as an outdoorsman and artist.

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