\chapter{

%Modeling Animal space-usage with

%Detection Models based on Ecological Distance

%Ecological Distance Models in Spatial Capture-Recapture

Modeling Space Usage: Ecological Distance in Spatial Capture-Recapture Models

}

\markboth{Chapter XXX}{}

\label{chapt.ecoldist}

\vspace{.3in}

\begin{comment} % RBC commented this out as suggested by Rahel

%% this material is a general introduction for a manuscript

%Spatial capture-recapture models are a relatively new class of models

%for estimating animal density from capture-recapture data with

%auxiliary information about individual capture locations

%\citep{efford:2004,borchers\_efford:2008, royle\_young:2008, efford\_etal:2009ecol,

% royle\_etal:2009ecol}.

Spatial capture-recapture models

express encounter probability

as a function of the distance between an individual's activity center,

say ${\bf s}\_{i}$, and trap location, say ${\bf x}\_{j}$.

In these models ${\bf s}\_{i}$ is regarded as a latent variable and

conventional methods of statistical inference either based on marginal

likelihood \citep{borchers\_efford:2008} or Bayesian analysis by MCMC

\citep{royle\_young:2008}.

While the models are a relatively recent innovation, their use is

already becoming widespread \citep{efford\_etal:2009ecol,

gardner\_etal:2010jwm, gardner\_etal:2010ecol,kery\_etal:2010,

borchers:2011,gopalaswamy\_etal:2012, foster\_harmsen:2012} because they resolve

critical problems with using ordinary non-spatial capture-recapture

methods such as ill-defined area sampled, and heterogeneity in

encounter probability due to the juxtaposition of individuals with

traps, and they provide a framework for modeling of trap-specific

covariates. Furthermore, essentially all real capture-recapture

studies produce auxiliary spatial information and therefore SCR models

are directly relevant to standard data collected from such studies.

% Indeed, the use of ordinary

%capture-recapture models essentially admits a model misspecification

%(i.e. homogeneous encounter probability) by ignoring the explicit

%spatial information.

XXX MAYBE YOU COULD START THE CHAPTER AT THIS POINT; THE OTHER STUFF HAS BEEN COVERED BY THE PREVIOUS BOOK CHAPTERS XXXXX

\end{comment}

xxxAdd more relevant references at places like this. I mean, biological stuffxxxx

Every spatial capture-recapture model that we have considered so far

has expressed encounter probability as function of the Euclidean

distance between individual activity

centers $\bf s$ and trap locations $\bf x$. While these simple encounter

probability models will often

be sufficient for practical

purposes, especially in small data sets, sometimes developing more

complex models of the detection process as it relates to space usage

of individuals will be useful. Animals may not judge distance in

terms of Euclidean distance but, rather, according to quality of local

habitat, landscape connectivity, perceived mortality risk, and other

considerations affecting movement behavior.

\begin{comment}

As an example of the potential problem of parameterizing SCR models

using Euclidean distance, imagine a study area bisected by a large

semi-permeable barrier. In standard SCR models, the probability of

capturing an animal in a trap located on the opposite side of the

barrier would simply be a function of distance, whereas in reality it

should be a function of both distance and the permeability of the

barrier.

Such situations are extremely common in capture-recapture

studies where multiple habitats occur in the study area or when

animals use linear features such as trails, corridors, or rivers.

\end{comment}

Moreover, because encounter probability and the distance

metric upon which it is based represent outcomes of individual

movements about their home range, ecologists might have explicit

hypotheses about how environmental variables affect the distance

metric, and it is therefore desirable to incorporate these hypotheses

directly into SCR models so that they may be formally evaluated

statistically.

In this chapter we develop a framework for modeling animal space usage

in SCR models, by parameterizing models for encounter probability

based on ``ecological distance''. In particular, following

\citet{royle\_etal:2012ecol}, we adopt a cost-weighted distance metric

(the least-cost path) used widely in landscape ecology for modeling

connectivity, movement and gene flow

\citep{adriaensen\_etal:2003,manel\_etal:2003,mcrae\_etal:2008}. In the

context of SCR models we can use this as the basis for computing the

distance between traps and individuals activity centers. In this way

we can explicitly accommodate landscape structure and account for how

animals use space in SCR models. We develop a likelihood-based

inference framework for SCR model parameters using this new distance

metric when the ecological distance function is known. We show that

the MLEs are approximately unbiased in moderate sample sizes, as

expected, but also that the misspecified model based on Euclidean

distance can produce substantial bias in estimates of $N$ and hence

density. Further, we extend the model to allow for likelihood

estimation of parameters of the cost function.

Using this methodological extension of SCR models, it is possible to

make formal statistical inferences

about movement and connectivity from

capture-recapture studies that generate sparse individual encounter

history data without subjective prescription of resistance

or cost surfaces.

\section{Distance Models}

In the standard SCR model we model encounter probability as a function

of Euclidean distance. For example, using the binomial observation model

as an example (Chapt. \ref{chapt.scr0}), let

$y\_{ij}$ be individual- and trap specific binomial counts

with sample size $K$ and probabilities

$p\_{ij}$. The Gaussian or ``half-normal'' model is \footnote{Note the

parameter labeling is not consistent with the rest of the book} xxxxI would change that or else say why this is necessaryxxxxx

\[

log(p\_{ij})= \theta\_{0} + \theta\_{1} dist({\bf x}\_{j} - {\bf s}\_{i})^{2}

\]

or, equivalently,

\[

p\_{ij} = \lambda\_{0} exp(- dist({\bf x}\_{j} - {\bf s}\_{i})^{2}

/(2\sigma^{2}) )

\]

where $\theta\_{0} = log(\lambda\_{0})$ and $\theta\_{1} =

-1/(2\sigma^2)$.

%In all previous applications of SCR models in this book, as well as in

%the literature,

The main problem with the normal Euclidean distance metric, i.e.,

$dist({\bf x}\_{j} - {\bf s}\_{i}) = ||{\bf x}\_{j} - {\bf s}\_{i}||$,

%and

%the parameters $\theta\_0$ and $\theta\_1$ have been estimated using

%standard methods (likelihood or Bayesian). The main problem with this

%approach

is that it is unaffected by

habitat or landscape structure, and it implies that the space used by

individuals is stationary and symmetric which may be unreasonable

assumptions for some species. By stationary here we mean in the formal

sense of

invariance to translation. That is, the properties of an individual

home range centered at some point ${\bf s}$ are exactly the same as

any other point say ${\bf s}'$.

As an example, if the common detection model based on a bivariate

normal probability distribution function is used, then the implied

space usage by {\it all} individuals, no matter their location in

space or local habitat conditions, is symmetric with circular contours

of usage intensity (density contours of the pdf).

\citet{royle\_etal:2012ecol} extended this class of SCR models to

accommodate alternative distance metrics that explicitly incorporate

information about the landscape so that a unit of distance is variable

depending on identified covariates. Thus, where an individual

lives on the landscape, and the state of the surrounding landscape,

will determine the character of its usage of space. In particular, they

suggest distance metrics that imply irregular, asymmetric and

non-stationary home ranges of individuals. As an example,

Fig. \ref{fig.distort} shows a typical symmetric home range, and a

compressed home range resulting from the effect of an environmental

variable on an animal's movement behavior.

\begin{figure}[h]

\centering

\includegraphics[width=5in,height=1.3in]{Ch10/figs/distort}

\caption{A symmetric home range (left), a habitat variable (center),

and a non-symmetric home range (right) resulting from the cost imposed on

movement by the habitat variable.}

xxxxx$Say what this habitat variable does, what it stands for, how it transforms a HR like in the left panel into one in the panel on the rhs$xxxxxx

\label{fig.distort}

\end{figure}

\section{Cost-Weighted Distance}

We adopt a cost-weighted distance metric here which defines

the effective distance between points by accumulating pixel-specific costs

determined under a cost function defined by the user. The idea of

cost-weighted distance to characterize animal use of landscapes is

widely used in landscape ecology for modeling connectivity, movement

and gene flow \citep{beier\_etal:2008}. As is customary for reasons of

computational tractability we consider a discrete landscape

defined by

a raster of some prescribed resolution. The distance between any two

points ${\bf x}$ and ${\bf x}'$ can be represented by a sequence of

line segments connecting neighboring pixels, say ${\bf l}\_{1},{\bf

l}\_{2},\ldots,{\bf l}\_{m}$. Then the cost-weighted distance between

${\bf x}$ and ${\bf x}'$ is

\begin{equation}

d({\bf x},{\bf x}')

= \sum\_{i=1}^{m-1} cost({\bf l}\_{i},{\bf l}\_{i+1})||{\bf l}\_{i} - {\bf l}\_{i+1}||

\label{eq.costweighted}

\end{equation}

{\flushleft

where } $cost({\bf l}\_{i},{\bf l}\_{i+1})$ is the user-defined cost function

to move

from pixel ${\bf l}\_{i}$ to neighboring pixel ${\bf l}\_{i}$ in the sequence.

Given the ``cost'' of each pixel, it is a simple matter to compute the

cost-weighted distance between any two pixels, along {\it any} path,

simply by accumulating the incremental costs weighted by

distances.

In the context of

spatial capture-recapture models (and, more generally, landscape

connectivity) we are concerned with the {\it minimum} cost-weighted

distance, or the {\it least-cost path}, between any two points which

we will denote by $d\_{lcp}$, which is

the

sequence ${\bf l}\_{1},{\bf l}\_{2},\ldots,{\bf l}\_{m}$ that minimizes

the objective function defined by Eq. \ref{eq.costweighted}. That is,

\begin{equation}

d\_{lcp}({\bf x},{\bf x}')

= min\_{{\bf l}\_{1},\ldots,{\bf l}\_{m}} \sum\_{i=1}^{m-1} cost({\bf l}\_{i},{\bf l}\_{i+1})||{\bf l}\_{i} - {\bf l}\_{i+1}||

\label{eq.lcp}

\end{equation}

{\flushleft

Least-cost} path distance can be calculated in

many geographic information systems and other software packages,

including the {\bf R} package \mbox{\tt

gdistance} \citep{vanetten:2011}.

The key ecological aspect of least-cost path modeling is the

development

of models for pixel-specific cost.

In this paper we model cost as a function of one or more covariates

defined on every pixel of the according raster. For example, using a

single covariate $z(x)$ we define the cost of moving from some pixel

${\bf x}$ to neighboring pixel ${\bf x}'$ as

\begin{equation}

log(cost({\bf x},{\bf x}'))= \theta\_{2} \frac{z({\bf x})+z({\bf x}')}{2}

\label{ecoldist.eq.cost}

\end{equation}

Thus, if $\theta\_{2} = 0$ then substituting $cost({\bf x},{\bf x}')

=exp(0) = 1$ into

Eq. \ref{eq.lcp} will produce the ordinary Euclidean distance

between points. Here we assume the covariate $z$ is positive-valued

and constrain $\theta\_{2}\ge 0$ so as to avoid

negative costs. While not necessarily problematic from a mathematical

standpoint, negative costs are unrealistic biologically. %unless there's a people mover....

In practical applications, variables that influence the cost of moving

across the landscape include things like highways

\citep[e.g.,][]{epps\_etal:2005}, elevation \citep{cushman\_etal:2006},

ruggedness \citep{epps\_etal:2007}, snow cover

\citep{schwartz\_etal:2009}, distance to escape terrain

\citep{shirk\_etal:2010}, range limitations \citep{mcrae\_beier:2007},

or distance from urban areas, highways, human disturbance or other

factors that animals might avoid. Together multiple environmental

variables create a resistance surface, which forms the linchpin of all

connectivity planning \citep{spear\_etal:2010}. Often $\theta\_{2}$ is

fixed by the investigator. Although $\theta\_{2}$ is rarely known,

conservation biologists design linkages that require this resistance

value as input \citep[see][and articles cited

therein]{beier\_etal:2008}. Typically planners pick a value based on

expert opinion \citep{beier\_etal:2008}, although recently researchers

have begun to define costs based on resource selection functions,

animal movement \citep{tracy:2006, fortin\_etal:2005}, or genetic

distance data (e.g., \citet{gerlach\_musolf:2000};

\citet{epps\_etal:2007}; \citet{schwartz\_etal:2009}.

To formalize the use of cost-weighted distance in SCR models, we

substitute Eq. \ref{eq.lcp} in the expression for encounter

probability (Eq. \ref{eq.encounter}) and maximize the resulting

likelihood which we address below. This allows us to formally model

these factors that influence space usage, and test explicit hypotheses

about these things using only individual level encounter history data

from capture-recapture studies.

\subsection{Example of Computing Cost-weighted distance}

As an example of the cost-weighted distance calculation consider the

following landscape comprised of 16 pixels with unit spacing

identified as follows, along with the pixel-specific cost:

\begin{center}

\begin{verbatim}

pixel ID Cost

1 5 9 13 100 1 1 1

2 6 10 14 100 100 1 1

3 7 11 15 100 100 100 1

4 8 12 16 100 100 1 1

\end{verbatim}

\end{center}

This simple cost

raster is shown in Fig. \ref{ecoldist.fig.raster}. We assume the scale

is such that the distance between neighboring pixels in any cardinal

direction is 1 unit, and the distance between neighbors on a diagonal

is $\sqrt{2}$ units.

We assigned low cost of 1 to ``good habitat'' pixels (or pixels

we think of as ``highly connected'' by virtue of being in good

habitat) and, conversely, we assign high cost (100) to ``bad

habitat''. So the shortest cost-weighted distance between pixels 5 and

9 in this example is just 1 unit, the shortest cost-distance between

pixels 5 and 10 is $\sqrt{2}(1+1)/2 = 1.414214$ units, the shortest

distance between pixels 4 and 8 is 100 units, while the shortest

cost-distance between 4 and 12 is 150.5. A tough one is: what is the

shortest distance between 7 and 16? An individual at pixel 7 can move

diagonal (which has distance $\sqrt{2}$) and pay $sqrt(2)\*(100+1)/2 + 1 =72.41778$.

\begin{figure}

\begin{center}

\includegraphics[height=3.25in,width=3.25in]{Ch10/figs/raster\_2values}

\end{center}

\caption{A $4 \times 4$ raster with cost = 1 (white) or 100 (shaded) to represent ease of movement across a pixel.}

\label{ecoldist.fig.raster}

\end{figure}

Once the cost raster is created, the least-cost path distances are

computed with just a couple {\bf R} commands, and those can be

inserted directly into the likelihood construction for an ordinary

spatial capture-recapture model The {\bf R} package

\mbox{\tt gdistance} uses the implementation of Dijkstra's algorithm

\citep{dijkstra:1959} found in the \mbox{\tt igraph} package

\citep{csardi:2010}. Using \mbox{\tt gdistance}, we

define the incremental cost of moving from one pixel to another as the

distance-weighted {\it average} of the 2 pixel costs. We demonstrate

how to do this subsequently.

The {\bf R} commands for computing the least-cost distance between all pairs of pixels

are as follows:

\begin{verbatim}

r<-raster(nrows=4,ncols=4)

projection(r)<- "+proj=utm +zone=12 +datum=WGS84"

extent(r)<-c(.5,4.5,.5,4.5)

costs1<- c(100,100,100,100,1,100,100,100,1,1,100,1,1,1,1,1)

values(r)<-matrix(costs1,4,4,byrow=FALSE)

par(mfrow=c(1,1))

plot(r)

\end{verbatim}

Then we use the functions \mbox{\tt transition}, \mbox{\tt

geoCorrection} (which is only necessary if the data are not

projected or if cells are considered to have more than 4 neighbors)

and \mbox{\tt costDistance} to compute the distance

matrix. The transition function computes the cost of making a

transition between

any two pixels, and it operates on the inverse-scale (''conductance'')

and so the

\mbox{\tt transitionFunction} argument is given as $1/mean(x)$.

To compute the cost distance we prescribe a set of points, or we

can compute it between

two sets of points (which is handy when one of the sets is of trap

locations, and the other is of individual activity centers).

To compute the distances for pixels in a raster,

we use the center points of each raster. The {\bf R}

commands altogether are as follows:

{\small

\begin{verbatim}

tr1<-transition(r,transitionFunction=function(x) 1/mean(x),directions=8)

tr1CorrC<-geoCorrection(tr1,type="c",multpl=FALSE,scl=FALSE)

pts<-cbind( sort(rep(1:4,4)),rep(4:1,4))

costs1<-costDistance(tr1CorrC,pts)

outD<-as.matrix(costs1)

\end{verbatim}

}

Now we can look at the result and see if it makes sense to us. Here we

print the first 5 columns of this distance matrix to illustrate a

couple of examples of calculating the minimum cost-weighted distance

between points:

\begin{center}

{\small

\begin{verbatim}

> outD[1:5,1:5]

1 2 3 4 5

1 0.0000 100.00000 200.0000 205.2426 50.50000

2 100.0000 0.00000 100.0000 200.0000 71.41778

3 200.0000 100.00000 0.0000 100.0000 171.41778

4 205.2426 200.00000 100.0000 0.0000 154.74264

5 50.5000 71.41778 171.4178 154.7426 0.00000

\end{verbatim}

}

\end{center}

An interesting case is that between point 1 and 4. Note that simply

taking the shortest Euclidean distance, weighted by cost, produces a

cost-weighted distance of $100 \times 1$ to move from pixel 1 to pixel

2, and similarly from 2 to 3 and 3 to 4, producing a total

cost-weighted distance of $300$. However, the actual {\it least-cost

path} has cost-weighted distance $205.2426$.

The shortest path has an individual moving from pixel 1 to 5, then 5

to 10, 10 to 15, 15 to 12, 12 to 8 and 8 to 4 which should add up to

$205.2426$.

\section{Fitting Models of Space Usage by MLE}

\label{ecoldist.sec.mle}

Throughout much of this book we rely on Bayesian analysis by MCMC

mostly using

{\bf BUGS}, but sometimes (as in Chapt. \ref{chapt.mcmc}) developing

our own

implementations. However, occasionally we prefer to use likelihood

estimation, such as when

we can compare a set of models directly by likelihood either to do a

direct hypothesis test of a parameter, or to tabulate a bunch of AIC

values. It turns out, for this class

of models for space usage based on ecological distance, we actually

prefer likelihood methods

not because they have any conceptual or methodological benefit, but

simply because

they are more computationally efficient to implement

\citep{royle\_etal:2012ecol}.

So here we adopt our formulation of maximum likelihood estimation

\citep{borchers\_efford:2008}

from Chapt. \ref{chapt.mle}

for the class of models based on ecological distance. This is really

just a straightforward

adaptation.

We continue to work here with the binomial model:

\[

y\_{ij}| {\bf s}\_{i} \sim \mbox{Bin}(K, p\_{\theta}(d\_{lcp}({\bf x}\_{j},{\bf s}\_{i};\theta\_{2}); \theta\_{0}, \theta\_{1})

\]

where we have indicated the dependence of $p\_{ij}$ on the parameters

${\bm \theta}$, and also $d\_{lcp}$ which

itself depends on $\theta\_{2}$, and the latent variable ${\bf s}$.

%The parameters

%${\bm \theta}$ include whatever parameters are involved in the

%cost-weighted distance function, i.e., at least $\theta\_{2}$ from

%Eq. \ref{eq.cost}.

For the random effect we have ${\bf s}\_{i} \sim \mbox{Unif}({\cal

S})$. Recall that the state-space $\cal S$ is defined by the raster

data in this context.

The joint distribution of the data for individual $i$ is the product

of $J$ binomial terms, i.e., one contribution for each of $J$ traps:

\[

[{\bf y}\_{i} | {\bf s}\_{i} , \theta] =

\prod\_{j=1}^{J} \mbox{Bin}(K, p\_{\theta}({\bf x}\_{j},{\bf s}\_{i}) )

\]

{\flushleft This} assumes that encounter of individual $i$ in each

trap is independent of encounter in every other trap. Conditional on

${\bf s}\_{i}$ this is reasonable in most applications in our view.

The xxxxxxhere is an example of where I suggest you clean up the whole book and make things more consistent: given that you explained marginal = integrated likelihood in a chapter at the start, and have used it over an over again, you should not call it ‘so-called’. This implies that the reader probably does not know what it is. But s/he is really supposed by now to know what it isxxxxxxxmarginal likelihood is computed by removing

${\bf s}\_{i}$, by integration, from the conditional-on-${\bf s}$

likelihood and regarding the {\it marginal} distribution of the data

as the likelihood. That

is, we compute:

\[

[y|{\bm \theta}] =

\int\_{{\cal S}} [ {\bf y}\_{i} |{\bf s}\_{i},{\bm \theta}] g({\bf s}\_{i}) d{\bf s}\_{i}

\]

{\flushleft where}, under the uniformity assumption, we have

$g({\bf s}) = 1/||{\cal S}||$.

The joint likelihood for all $N$ individuals, assuming independence of

encounters among individuals, is the product of $N$ such terms:

\[

{\cal L}({\bm \theta} | {\bf y}\_{1},{\bf y}\_{2},\ldots, {\bf y}\_{N}) = \prod\_{i=1}^{N}

[{\bf y}\_{i}|{\bm \theta}]

\]

The key operation for computing the likelihood is solving the

2-dimensional integration problem to remove ${\bf s}$, which we

resolve as we did previously in Chapt. \ref{chapt.mle}, using the

rectangular rule for integration, and averaging the integrand over a

fine mesh of points.

Therefore,

the marginal pmf of ${\bf y}\_{i}$, is

approximated by

\begin{equation}

[{\bf y}\_{i}|\theta] = \frac{1}{nG} \sum\_{u=1}^{nG} [ {\bf

y}\_{i} |{\bf s}\_u, \theta]

\label{mle.eq.intlik}

\end{equation}

To deal with the fact that $N$ is unknown, there are two key issues

that need to be addressed. First is that we don't observe the

``all-zero'' encounter histories (i.e., $y\_{ij} = 0$ for all $j$)

corresponding to uncaptured individuals, so we have to make sure we

compute the probability for that all zero encounter history which we

do operationally by tacking a row of zeros onto the encounter history

matrix. We include the number of such all-zero encounter histories as

an unknown parameter of the model, which we label $n\_{0}$. In

addition, we have to be sure to include a combinatorial term to

account for the fact that of the $n$ observed individuals there are

${N \choose n}$ ways to realize a sample of size $n$. The

combinatorial term involves the unknown $n\_{0}$ and thus it must be

included in the likelihood.

We wrote an {\bf R} function to evaluate the likelihood which we optimize

using the {\bf R} function \mbox{\tt nlm}.

The likelihood is given in the {\tt scrbook} package as the function

\mbox{\tt intlik3ed}. The help file

provides an example of its usage and for simulating data.

To use this function the cost covariate $z(x)$ has to be of class

\mbox{\tt RasterLayer} which requires packages \mbox{\tt sp} and

\mbox{\tt raster} to manipulate.

The following is a stylized and more concise verstion of the actual

function, and we apply this in the following section.

{\small

\begin{verbatim} $I would try to make this as readable as possible by doing four things:

* add hashed-out comments
* put stuff in paragraphs
* add a few spaces before lines inside if statements and for loops
* clean up code as much as possible

$

intlik3ed<-function(start=NULL,y=y,K=NULL,X=traplocs,

distmet="ecol",covariate,theta2=NA){

nc<-covariate@ncols

nr<-covariate@nrows

Xl<-covariate@extent@xmin

Xu<-covariate@extent@xmax

Yl<-covariate@extent@ymin

Yu<-covariate@extent@ymax

### ASSUMES SQUARE RASTER -- NEED TO GENERALIZE THIS

delta<- (Xu-Xl)/nc

xg<-seq(Xl+delta/2,Xu-delta/2,delta)

yg<-seq(Yl+delta/2,Yu-delta/2,delta)

npix.x<-length(xg)

npix.y<-length(yg)

area<- (Xu-Xl)\*(Yu-Yl)/((npix.x)\*(npix.y))

G<-cbind(rep(xg,npix.y),sort(rep(yg,npix.x)))

nG<-nrow(G)

if(distmet=="euclid")

D<- e2dist(X,G)

if(distmet=="ecol"){

if(is.na(theta2))

theta2<-exp(start[4])

cost<- exp(theta2\*covariate)

tr1<-transition(cost,transitionFunction=function(x) 1/mean(x),directions=8)

tr1CorrC<-geoCorrection(tr1,type="c",multpl=FALSE,scl=FALSE)

D<-costDistance(tr1CorrC,X,G)

}

theta0<-start[1]; theta1<-start[2]; n0<-exp(start[3])

probcap<- (exp(theta0)/(1+exp(theta0)))\*exp(-theta1\*D\*D)

Pm<-matrix(NA,nrow=nrow(probcap),ncol=ncol(probcap))

ymat<-y ; ymat<-rbind(y,rep(0,ncol(y)))

lik.marg<-rep(NA,nrow(ymat))

for(i in 1:nrow(ymat)){

Pm[1:length(Pm)]<- (dbinom(rep(ymat[i,],nG),rep(K,nG),probcap[1:length(Pm)],log=TRUE))

lik.cond<- exp(colSums(Pm))

lik.marg[i]<- sum( lik.cond\*(1/nG) )

}

nv<-c(rep(1,length(lik.marg)-1),n0)

part1<- lgamma(nrow(y)+n0+1) - lgamma(n0+1)

part2<- sum(nv\*log(lik.marg))

out<- -1\*(part1+ part2)

out

}

\end{verbatim}

}

$ Do you want to show code without any example of its application ? I.e., without showing any results ? Perhaps refer specifically to the section in which you USE this likelihood function$

\subsection{Bayesian Analysis}

$ I find that the numbering here is not logical. I would prefer to see frequentist and Bayesian analysis on an equal footing, so e.g., have 10.3. Analysis of xxxx model

10.3.1. Analysis by maximum likelihood

10.3.3. Bayesian Analysis

While implementation of these ecological distance SCR models is reasonably straightforward, it is difficult to fit them using the {\bf BUGS} engines

because it is not possible, to the best of our knowledge, to compute

the least-cost path distance. It would be possible to fit the models

in {\bf BUGS} if the parameter $\theta\_{2}$ was fixed. In that case,

one could compute the distance matrix ahead of time and reference the

required elements for a given ${\bf s}$.

Alternatively, it would be possible to write a custom MCMC routine

using the methods we present in Chapt. \ref{chapt.mcmc}, although we

have not yet developed our own implementation.

\section{Example: SCR model based on ecological distance}

In this section we provide examples that we think are typical of how

cost-weighted distance models can be used in real capture-recapture

problems. We define a $20 \times 20$ pixel covariate raster with

extent = $[0.5, 4.5] \times [0.5, 4.5]$. We regard this, for the

purposes of our example, as a coarse landscape covariate, with pixels

having some arbitrary scaling say, a $2 \times 2$ km resolution. Thus,

the raster defines a landscape of $40 \times 40$ km and we suppose

that 16 camera traps are established at the integer coordinates

$(1,1), (1,2), \ldots, (4,4)$. We could think of this as a landscape

within which we're studying a population of ocelots, lynx or some

other cat.

For our analyses, cost is characterized by a single covariate raster

and we consider two specific cases. First is an increasing trend from

the NW to the SE (''systematic raster''), where $z(x)$ is defined as

$z(x) = r(x) + c(x)$ and $r(x)$ and $c(x)$ are just the row and

column, respectively, of the raster. This might define something

related to distance from an urban area or a gradient in habitat

quality due to land use, or environmental conditions such as

temperature or precipitation gradients. In the second case we make up

a covariate by generating a field of spatially correlated noise to

emulate a typical patchy habitat covariate (''patchy raster'') such as

tree or understory density. The two covariates are shown in

Fig. \ref{ecoldist.fig.raster100}, along with a sample realization of

$N=100$ individuals (left panel only). For both covariates we use a

cost function in which transitions from pixel ${\bf x}$ to ${\bf x}'$

is given by:

\[

log(cost({\bf x},{\bf x}'))= \theta\_2 \frac{z({\bf x}) + z({\bf x}')}{2}

\]

{\flushleft where} $\theta\_2 = 1$ for simulating the observed data.

Remember that with $\theta\_2=0$ the

model reduces to one in which the cost of moving across each pixel is

constant, and therefore Euclidean distance is operative.

\begin{figure}

\begin{tabular}{cc}

\includegraphics[height=3.25in,width=3.25in]{Ch10/figs/raster\_withN100}

\includegraphics[height=3.25in,width=3.25in]{Ch10/figs/raster\_krige} &

\end{tabular}

\caption{Two covariate rasters used for simulations. A hypothetical

realization of $N=100$ activity centers is superimposed on the left,

along with 16 trap locations. }

$more info: say that raster i1 20 by 20. Say what they are. BTW: I don’t see the traps$

\label{ecoldist.fig.raster100}

\end{figure}

\subsection{Non-stationarity of home range structure}

When distance is defined by the cost-weighted distance metric given

by Eq. \ref{eq.lcp} then individual space-usage varies

spatially in response to the landscape covariate(s) used in the

distance metric. As a consequence, home ranges contours are no longer

circular, as in SCR models based on Euclidean distance.

For example, using one of the covariates we use in

our simulation study below (Fig. \ref{ecoldist.fig.raster100}, right

panel) with a Gaussian pdf detection function but having distance

metric defined by Eq. \ref{eq.lcp}, produces home ranges such

as those shown in Fig. \ref{fig.homeranges}. Later we simulate data

under the model that produces these home ranges and fit spatial

capture-recapture models to evaluate the efficacy of likelihood

estimation under this model.

\begin{figure}

\begin{center}

\includegraphics[height=6in,width=3.75in]{Ch10/figs/home\_ranges}

\end{center}

\caption{

Typical home ranges for 6 individuals based on the cost surface shown in the right panel of

Fig. \ref{ecoldist.fig.raster100} with $\theta\_{2}=1$. The black dot indicates the home

range center and the pixels around each home range center are shaded

according to the probability of encounter, if a trap were located in

that pixel.

}

\label{fig.homeranges}

\end{figure}

\subsection{Simulation and Analysis}

We begin by simulating some data... we have to load the \mbox{\tt

scrbook} library, use the function \mbox{\tt make.EDcovariates} to generate

our raster covariates, process that into a least-cost path distance

matrix, and then simulate observed encounter data using standard methods

which we have used many times previously in this book. The complete set

of {\bf R} commands is:

{\small

\begin{verbatim}

$ make code as readable as possible by adding comments and layout it$

library("scrbook")

out<-make.EDcovariates()

covariate<-out$covariate.patchy

set.seed(2013)

N<-200

theta0<- -2

sigma<- .5

K<- 5

theta1<- 1/(2\*sigma\*sigma)

r<-raster(nrows=20,ncols=20)

projection(r)<- "+proj=utm +zone=12 +datum=WGS84"

extent(r)<-c(.5,4.5,.5,4.5)

theta2<-1

cost<- exp(theta2\*covariate)

tr1<-transition(cost,transitionFunction=function(x) 1/mean(x),directions=8)

tr1CorrC<-geoCorrection(tr1,type="c",multpl=FALSE,scl=FALSE)

# make up some trap locations

xg<-seq(1,4,1); yg<-4:1

pts<-cbind( sort(rep(xg,4)),rep(yg,4))

traplocs<-pts

points(traplocs,pch=20,col="red")

ntraps<-nrow(traplocs)

S<-cbind(runif(N,.5,4.5),runif(N,.5,4.5))

D<-costDistance(tr1CorrC,S,traplocs)

probcap<-plogis(theta0)\*exp(-theta1\*D\*D)

# now generate the encounters of every individual in every trap

Y<-matrix(NA,nrow=N,ncol=ntraps)

for(i in 1:nrow(Y)){

Y[i,]<-rbinom(ntraps,K,probcap[i,])

}

Y<-Y[apply(Y,1,sum)>0,]

\end{verbatim}

}

Now we use the {\bf R} function \mbox{\tt nlm} along with

our \mbox{\tt intlik3ed} function to evaluate the likelihood so that we can obtain the MLEs of the

model parameters. We'll do that for both the standard Euclidean distance

and then for the ecological distance based on the ``patchy'' covariate:

{\small

\begin{verbatim}

frog1<-nlm(intlik3ed,c(theta0,theta1,3)),hessian=TRUE,y=Y,K=K,X=traplocs,

distmet="euclid",covariate=covariate,theta2=1)

frog2<-nlm(intlik3ed,c(theta0,theta1,3,-.3),hessian=TRUE,y=Y,K=K,X=traplocs,

distmet="ecol",covariate=covariate,theta2=NA)

\end{verbatim}

}

Show nlm() output for each and comment .......................XXXX

\subsection{Simulation study} $This is really the same section as the next one ?$

\citet{royle\_etal:2012ecol}

carried-out a limited simulation study to evaluate the

general statistical performance of the density estimator under

this new model, the effect of mis-specifying the model with a

normal Euclidean distance metric and whether the parameter of the

cost function could be effectively estimated.

We recapitulate their results here.

For population sizes of 100 and 200 individuals with activity

centers randomly distributed on the $20 \times 20$ landscape, they

subjected individuals

to encounter by 16 traps arranged in a $4\times 4$ grid

using a Gaussian

encounter model with least-cost path distance metric:

\[

log(p\_{ij})= \theta\_{0} + \theta\_{1} d\_{lcp}({\bf x}\_{j},{\bf

s}\_{i}; \theta\_{2})^{2}

\]

where $\theta\_{0} = -2$ and $\theta\_{1} = 2$, the latter value

corresponding to $\sigma = 0.5$ of a stationary bivariate normal home

range model. Different numbers of replicate samples were considered,

$K=3,5,10$

(e.g., nights in a camera trapping study), in order

to produce varying sample

sizes.

Three different models were fitted

to each simulated data set: the

misspecified euclidean distance model; (ii) the true data-generating

model with the relative cost raster {\it known} and (iii) the true

data-generating model but estimating the relative cost parameter by

maximum likelihood. We used both the ``systematic'' and ``patchy''

covariates defined previously.

\subsection{Simulation Results}

For both landscapes and all simulation conditions (levels of $K$ and

$N$) the average sample sizes of individuals captured are given in

Tab. \ref{tab.samplesize}. The simulation results for estimating $N$

for the prescribed state-space are presented in Table

\ref{tab.results1}. For the ``patchy'' landscape we see extreme

bias in estimates of $N$ when the Euclidean distance is used. There is

moderate small sample bias of 3-5\% in the MLE of $N$ using the

least-cost distance which becomes negligible as $K$ increases. For

$N=200$ the bias is on the order of 2\% for the lowest sample size

case ($K=3$) but negligible otherwise. Interestingly, for the

landscape exhibiting systematic structure, there is a persistent bias

in the MLE of $N$ of 1-3\% even for the highest level of $K$.

We were

initially surprised by this but, in fact, it is due to the fact that

the state-space is small relative to the extent of the trap grid and

sensitivity to a state-space that is too small is expected because the

support of the integrand is truncated. In the particular case of the

systematic landscape, we find that, in the NW corner of the raster

where cost of movement is low, individuals use large areas of space,

and the fitted model is under-stating the apparent

heterogeneity in encounter probability for the prescribed raster. We

found that the issue is resolved when the traps are moved away from

the boundary (Tab. \ref{tab.results3}).

The performance of estimating the cost parameter $\theta\_{2}$ mirrors

the results for estimating $N$ for the prescribed state space. In the

patchy landscape where we don't expect a systematic gradient in space

usage around the edge of the state-space, we see

(Table \ref{tab.results2}) that $\theta\_{2}$ is estimated with

diminishing bias as the sample size increases, but with persistent

bias due to truncation of the likelihood under the systematic

landscape which, as with the MLE of $N$, is resolved by moving the

traps away from the edge of the raster. Equivalently, in practice,

this could be resolved by expanding the raster away from the trap

locations so that all regions used by animals exposed to capture are

included in the state-space.

\begin{table}[htp]

\centering

\caption{

Expected sample sizes of captured individuals under each configuration of

$N$ (population size for the prescribed state-space) and $K$ (number of replicate samples).

}

\begin{tabular}{l|rrrr}

& \multicolumn{2}{c}{Systematic} & \multicolumn{2}{c}{Patchy} \\

& N=100 & N=200 & N=100 & N=200 \\ \hline

K=3 & 38.69 & 78.17 & 37.30 & 74.93 \\

K=5 & 51.10 & 103.18 & 51.89 & 103.71 \\

K=10& 65.81 & 132.39 & 69.44 & 138.76 \\

\end{tabular}

\label{tab.samplesize}

\end{table}

\begin{table}[htp]

\label{tab.results1}

{\tiny

\caption{Simulation results for estimating population size $N$ for a prescribed state-space with

$N=100$ or $N=200$ and various levels of replication ($K$) chosen to affect the observed sample

size of individuals (Tab. \ref{tab.samplesize}). For each simulated data set, the SCR model was fitted with

standard Euclidean distance (``euclid''), least-cost path assuming the

cost parameter $\theta\_2$ is known (``lcp/known''), or allowing it to

be estimated by maximum likelihood (``lcp/est'').

The summary statistics of the

sampling distribution reported are the mean, standard deviation

(``SD'') and quantiles (0.025, 0.50, 0.975).

}

{\bf Systematic trend raster:} \\

\begin{tabular}{l|rrrrr|rrrrr}

& \multicolumn{5}{c}{N=100 } & \multicolumn{5}{c}{N=200 } \\

& mean & SD & 0.025 & 0.50 & 0.975 & mean & SD & 0.025 & 0.50 & 0.975 \\ \hline

K=3 & & & & & & & & & & \\

euclid & 63.65& 12.62& 44.77 & 61.17& 90.98 & 126.68& 17.05& 98.93& 124.49& 168.26 \\

lcp/known& 99.28& 20.80& 68.83 & 97.55& 152.59 & 196.47& 27.39& 152.03& 192.96& 259.78\\

lcp/est & 101.93& 21.68& 67.95 &101.56& 156.21 & 201.58& 28.14& 154.96& 200.15& 263.20\\

K=5 & & & & & & & & & & \\

euclid & 64.60 & 7.11 & 51.52 & 63.86& 77.33 & 130.02& 10.25& 113.48& 128.96& 151.32\\

lcp/known& 95.96 &11.64 & 74.21 & 96.16& 117.65 & 193.04& 17.13& 166.84& 191.88& 226.16\\

lcp/est & 98.94 &12.97 & 74.68 & 99.00& 123.88 & 198.80& 19.60& 166.87& 197.97& 239.46\\

K=10 & & & & & & & & & & \\

euclid & 69.24 & 4.83 & 59.37 & 69.47& 79.18 & 139.83& 7.62& 125.65& 139.65& 154.82\\

lcp/known& 94.46 & 7.04 & 81.45 & 94.04& 108.83 & 190.47& 11.55& 170.49& 189.74& 213.19\\

lcp/est & 97.53 & 8.18 & 82.02 & 97.62& 113.16 & 195.19& 13.28& 171.63& 194.58& 217.96\\ \hline

\end{tabular}

\\

{\bf Patchy "random" raster: } \\

\begin{tabular}{l|rrrrrrrrrr}

& \multicolumn{5}{c}{N=100 } & \multicolumn{5}{c}{N=200 } \\

& mean & SD & 0.025 & 0.50 & 0.975 & mean & SD & 0.025 & 0.50 & 0.975 \\ \hline

K=3 & & & & & & & & & & \\

euclid & 78.68 & 18.12& 49.40 & 76.34 & 125.47 & 154.34& 33.74& 107.00& 146.34& 221.43\\

lcp/known& 109.09 & 27.52& 69.50 &104.86 & 183.72 & 207.18& 46.53& 143.31& 198.42& 315.89\\

lcp/est & 110.96 & 28.65& 69.55 &106.98 & 181.84 & 208.77& 49.29& 141.68& 197.89& 325.77\\

K=5 & & & & & & & & & & \\

euclid & 77.85 & 11.55& 59.17 & 77.44 & 101.14 & 153.39& 15.57& 129.31& 149.54& 185.38\\

lcp/known& 103.57 & 15.83& 78.15 &100.58 & 137.48 & 201.57& 21.25& 165.94& 199.95& 243.26\\

lcp/est & 104.44 & 15.79& 78.38 &101.47 & 139.55 & 200.91& 20.78& 164.42& 200.47& 246.46\\

K=10 & & & & & & & & & & \\

euclid & 78.01 & 5.26 & 68.00 & 77.96 & 87.81 & 156.27& 8.51& 142.17& 156.05& 174.55\\

lcp/known& 99.84 & 7.09 & 86.86 & 99.84 & 114.11 & 198.64& 11.04& 181.43& 197.62& 220.45\\

lcp/est & 100.42 & 7.56 & 86.72 &100.34 & 115.47 & 198.45& 11.44& 180.06& 198.04& 219.52\\ \hline

\end{tabular}

}

\end{table}

\begin{table}[htp]

\centering

\caption{

Mean of sampling distribution of the cost function parameter

$\theta\_{2}$ for the different simulation

conditions.

}

\begin{tabular}{l|rrrr}

& \multicolumn{2}{c}{Patchy} & \multicolumn{2}{c}{Systematic} \\

& N=100 & N=200 & N=100 & N=200 \\ \hline

K=3 & 1.05& 1.03 & 1.17 & 1.14 \\

K=5 & 1.02& 1.01 & 1.12 &1.12 \\

K=10& 1.01& 1.00 & 1.10 &1.08 \\

\end{tabular}

\label{tab.results2}

\end{table}

\begin{table}[htp]

{\tiny

\caption{Simulation results for estimating population size $N$ for a prescribed state-space with

$N=100$ or $N=200$ and various levels of replication ($K$) chosen to affect the observed sample

size of individuals. These results correspond to those of the

systematic landscape in Table 2 except with the traps

moved 0.5 units in from the boundary of the raster.

Each grouping of 3 rows (for a given value of $K$) summarizes the

performance of $\hat{N}$ under 3 distance models: (1) A model in which

Euclidean distance was used (``euclid''); (2) A model in which the

least-cost path distance was used, with the coefficient of the cost

function fixed (``lcp known''); and (3) A model in which the

coefficient was estimated (``lcp est''). The summary statistics of the

sampling distribution reported are the mean, standard deviation

(``SD'') and quantiles (0.025, 0.50, 0.975).

}

{\bf Systematic trend raster:} \\

\begin{tabular}{l|rrrrr|rrrrr}

& \multicolumn{5}{c}{N=100 } & \multicolumn{5}{c}{N=200 } \\

& mean & SD & 0.025 & 0.50 & 0.975 & mean & SD & 0.025 & 0.50 & 0.975 \\ \hline

K=3 & & & & & & & & & & \\

euclid & 84.48& 20.42& 51.16 & 81.51& 140.62 &163.70 &24.55 &126.64 &157.67 &223.63 \\

lcp known& 104.14& 25.49& 65.67 &101.50& 173.19 &200.16 &29.27 &158.65 &191.04 &268.78\\

lcp est $etc$& 105.90& 26.19& 65.95 &103.40& 182.30 &201.34 &29.54 &161.88 &192.36 &268.98\\

K=5 & & & & & & & & & & \\

euclid & 81.21 &11.33 &61.35 &79.20 & 98.86 &163.27 &13.06 &140.21 &162.97 &185.94\\

lcp/known& 99.93 &12.86 &76.97 &99.75 &117.76 &199.80 &16.60 &170.25 &198.23 &227.66\\

lcp/est & 100.84 &13.15 &79.96 &99.51 &119.08 &200.25 &16.53 &168.88 &199.29 &227.39\\

K=10 & & & & & & & & & & \\

euclid & 80.10 & 7.81 &66.45 &79.14 &93.33 &158.40 & 9.25 &142.74 &157.86 &173.18\\

lcp/known& 100.07 & 9.50 &82.99 &100.33&114.81 &197.62 &12.58 &171.95 &199.21 &217.19\\

lcp/est & 100.10 & 9.88 &82.31 &100.91&116.27 &197.52 &13.03 &169.49 &200.68 &217.82\\ \hline

\end{tabular}

}

\label{tab.results3}

\end{table}

\section{Illustration: Example Good vs. Bad habitat}

We provide another illustration of how to employ ecological distance

calculations in SCR models. This example shows a more GIS-like analysis

for a situation where we have something like a hard habitat boundary

created to mimic a habitat corridor or park unit or some other block

of relatively homogeneous good-quality habitat for some species. This

particular system (shown in Fig. \ref{ecoldist.fig.corridor}) could

be habitat surrounded by a suburban wasteland of McDonalds and

Wal-Marts, much less hospital habitat for most species. For our

purposes, we suppose that individuals live within the buffered ``f''

shaped region, although we could also imagine the negative of the

situation in which individuals live outside of the region, so that the

polygon represents a barrier (a lake) or bad habitat (an urban area)

or similar. We describe the steps for creating this landscape

shortly, so that you can use a similar process to generate more

relevant landscapes for their own problems.

In this case we're not going to estimate any parameters of the cost

function (though we could) but instead we're going to use ecological

distance ideas only to constrain movement within (or to avoid)

landscape features. However, you are encouraged to adapt the

likelihood function given in the previous section for this specific

case, so that a parameter of the cost function can be estimated.

\subsection{Basic Geographic Analysis in R}

In practical applications our landscape will contain one more more

polygons which delineate good or bad habitat or other important

characterisetics of the landscape. These might exist as GIS

shapefiles or merely as a text file with coordinates defining polygon

boundaries. To work with polygons in the context of SCR models we need

to create a raster, overlay the polygon and assign values to each pixel

depending on whether pixels are in the polygon or not, or how far they

are from polygon boundaries. These operations are relatively easy to

do within a GIS system $way why we need to be able to do this$ but we need to be able to do them in ${\bf R}$

and we develop methods for this here. See also

secs. \ref{mle.sec.shapefile} and \ref{mcmc.sec.state-space}

for examples of reading in the shapefile and using them to affect

calculations in SCR models.

The first thing we do here is create a set of polygons by

buffering and joining some line segments.

In the {\bf R} library \mbox{\tt scrbook}, we provide

a function \mbox{\tt make.seg} which allows you to make such

lines segments given a

specific trap region. To involve \mbox{\tt make.seg} we first

create a plot region and then call \mbox{\tt make.seg} which has a

single argument being the number of points used to define the line

segment. In the following set of commands we generate two line

segments, \mbox{\tt l1} consisting of 9 points and \mbox{\tt l2}

consisting of 5 points, and these reside in a geographic region

enclosedd by $[0,10] \times [0,10]$:

{\small

\begin{verbatim}

library("scrbook")

library("sp")

plot(NULL,xlim=c(0,10),ylim=c(0,10))

l1<-make.seg(9)

plot(l1)

l2<-make.seg(5)

plot(l1)

lines(l2)

\end{verbatim}

}

We used this function to create a couple of line segments of class

\mbox{\tt SpatialLines} from the {\bf R} package \mbox{\tt sp}, which

can be loaded from \mbox{\tt scrbook} as follows

\begin{verbatim}

data("fakecorridor")

\end{verbatim}

This has 2 line files in it (\mbox{\tt l1} and \mbox{\tt l2}) and a

trap locations file (\mbox{\tt traps}).

We use some functions from the {\bf R} packages \mbox{\tt sp} and

\mbox{\tt rgeos} to join and

buffer (by 0.5 units) the two segments. The commands are as follows

and the result is shown in Fig. \ref{ecoldist.fig.corridor}.

{\small

\begin{verbatim}

data("fakecorridor")

library("sp")

library("rgeos")

buffer<- 0.5

par(mfrow=c(1,1))

aa<-gUnion(l1,l2)

plot(gBuffer(aa,width=buffer),xlim=c(0,10),ylim=c(0,10))

pg<-gBuffer(aa,width=buffer)

pg.coords<- pg@polygons[[1]]@Polygons[[1]]@coords

xg<-seq(0,10,,40)

yg<-seq(10,0,,40)

delta<-mean(diff(xg))

pts<- cbind(sort(rep(xg,40)),rep(yg,40))

points(pts,pch=20)

in.pts<-point.in.polygon(pts[,1],pts[,2],pg.coords[,1],pg.coords[,2])

points(pts[in.pts==1,],pch=20,col="red")

\end{verbatim}

}

\begin{figure}

\begin{center}

\includegraphics[height=3.25in,width=3.25in]{Ch10/figs/corridor}

\end{center}

\caption{A made-up corridor or reserve.}

\label{ecoldist.fig.corridor}

\end{figure}

We focus on devising a SCR model for this corridor system and we

imagine that animals will tend to severely avoid leaving the buffered

habitat zone. Therefore, we assign $\mbox{\tt cost}=1$ if a pixel

is within the buffer,

and $\mbox{\tt cost} = 10000$ if a pixel is outside of a

buffer. Therefore the cost to move to a neighboring pixel outside of

the buffered area is $5000.5$ compared to the cost of 1 to move to a

neighboring pixel inside the buffer.

In this example, we're not going to estimate parameters of the cost

function. Therefore, in that case, we can compute the ecological

distance matrix one time and modify our likelihood code to accept the

distance matrix as input. We give that likelihood in the library

\mbox{\tt scrbook} as the function \mbox{\tt intlik3edv2}.

We note also that it provides a vector of 0's and 1's that

define any potential state-space restrictions. i.e., 1 if the pixel is

an element of the state-space and 0 if it is not.

In the analysis of this

simulated data set, we define the state-space to be the buffered

corridor system. The help file for \mbox{\tt intlik3edv2} contains the

script that follows.

Here we simulate $N=200$ guys in the corridor system and so we

restrict our state-space accordingly for purposes of fitting the

model. However we encourage you to refit the model without the

state-space restriction (for fitting the model only) and then

compare the results. The code for doing all of this is as follows

{\small

\begin{verbatim}

$add as many comments as you possibly can without overloading the thing$

cost<-rep(NA,nrow(pts))

cost[in.pts==1]<-1 # low cost to move among pixels but not 0

cost[in.pts!=1]<-10000 # high cost

library("raster")

r<-raster(nrows=40,ncols=40)

projection(r)<- "+proj=utm +zone=12 +datum=WGS84"

extent(r)<-c(0-delta/2,10+delta/2,0-delta/2,10+delta/2)

values(r)<-matrix(cost,40,40,byrow=FALSE)

par(mfrow=c(1,1))

plot(r)

points(pts,pch=20,cex=.4)

library("gdistance")

tr1<-transition(r,transitionFunction=function(x) 1/mean(x),directions=8)

tr1CorrC<-geoCorrection(tr1,type="c",multpl=FALSE,scl=FALSE)

costs1<-costDistance(tr1CorrC,pts)

outD<-as.matrix(costs1)

plot(pts,pch=".")

points(pts[in.pts==1,],pch=20,col="red")

library(``scrbook'')

traplocs<-traps$loc

trap.id<-traps$locid

ntraps<-nrow(traplocs)

set.seed(2013)

N<-200

S.possible<- (1:nrow(pts))[in.pts==1]

S.id<-sample(S.possible,N,replace=TRUE)

S<- pts[S.id,]

D<- outD[S.id,trap.id]

eD<- e2dist(S,traplocs)

Dtraps<-outD[trap.id,]

alpha0<- -1.5

sigma<- 1.5

beta<- 1/(2\*sigma\*sigma)

K<-10

probcap<-plogis(alpha0)\*exp(-beta\*D\*D)

Y<-matrix(NA,nrow=N,ncol=ntraps)

for(i in 1:nrow(Y)){

Y[i,]<-rbinom(ntraps,K,probcap[i,])

}

Y<-Y[apply(Y,1,sum)>0,]

frog1<-nlm(intlik3edv2,c(-2.5,2,log(4)),hessian=TRUE,y=Y,K=K,X=traplocs,

S=pts,D=Dtraps,inpoly=in.pts)

frog2<-nlm(intlik3edv2,c(-2.5,2,log(4)),hessian=TRUE,y=Y,K=K,X=traplocs,

S=pts,D=Deuclid,inpoly=in.pts)

\end{verbatim}

}

In the example that we ran above we compared the result for using

distance-within-the-corridor to normal Euclidean distance and the

results do not differ too much in this single instance. One reason is

that the distance between individuals and traps that they are likely

to be captured in is well-approximated by normal Euclidean distance.

\section{A stream network}

Later we might add a 3rd prototype situation involving a stream network.

We could use ``distance from stream'' to model effects of habitat

and corridors or whatever

\section{Summary and Outlook}

All published applications of SCR models to date have been based on models for the

encounter probability that are functions of the standard Euclidean

distance between individuals and traps. The obvious limitations are

that it is unaffected by landscape or habitat structure and implies

stationary, isotropic and symmetrical home ranges. These are standard

criticisms of the basic SCR model as universally applied in

practice so far. However, it is not a relevant criticism of the basic

conceptual formulation of SCR models, because, as we have

demonstrated, one can modify the Euclidean distance metric to

accommodate more realistic space usage considerations. Following

\citet{royle\_etal:2012ecol},

we demonstrated how to use

minimum cost-weighted distance (i.e., ``least-cost

path'') between points, and where ``cost'' is characterized by one or

more spatially explicit covariates that are believed to influence

movement or space-usage of individuals.

How animals use space and therefore how distance to a trap is

perceived by individuals is not something that can ever be known. We

can only ever conjure up models to describe this phenomenon and fit

those models to limited data on a sample of individuals during a

limited amount of time. Here we have shown that there is hope to

estimate parameters, from capture-recapture data, that describe how

animals use space and thereby allow for irregular home range geometry

that is influenced by landscape structure.

Not surprisingly, our simulation study demonstrated

(Table 2) that the MLE of model parameters is

approximately unbiased in moderate sample sizes. Moreover, the effect

of ignoring ecological distance and using normal Euclidean distance in

the model for encounter probability, has the logical effect of causing

negative bias in estimates of $N$. We expect this because the effect

is similar to failing to model heterogeneity, i.e., if we mis-specify

``model $M\_h$'' \citep{otis\_etal:1978} with ``model $M\_0$''

\citep{otis\_etal:1978} then we will expect to under-estimate $N$. So

the effect of mis-specifying the ecological distance metric with a

standard homogeneous Euclidean distance has the same effect. As a

practical matter, it stands to reason that many previous applications

of SCR models based on homogeneous distance metrics have under-stated

density of the focal population.

In our view, this bias is not really the most important reason to

consider models of ecological distance. Rather, inference about the

structure of ecological distance is fundamental to many problems in

applied and theoretical ecology related to modeling landscape

connectivity, corridor and reserve design, population viability

analysis, gene flow, and other phenomena. Our new model allows

investigators to evaluate landscape factors that influence movement of

individuals over the landscape from non-invasively collected

capture-recapture data. Therefore SCR models based on ecological

distance metrics might aid in understanding

aspects of space usage and movement in animal populations and, ultimately, in addressing conservation-related problems such as corridor design.

We considered inference for ecological distance models based on

marginal likelihood \citep{borchers\_efford:2008}

(see Chapt. \ref{chapt.mle}).

In principle,

Bayesian analysis does not pose any unique challenges for this new

class of models, except that computing the cost-weighted distance is

computationally intensive. So, having to do this at each iteration of

an MCMC algorithm may be impractical using existing algorithms. A

related issue is that the size of the raster slows things down. For

very large rasters, even likelihood analysis can be computationally

challenging and methods for efficient calculation of the ecological

distance given the raster covariate(s) and parameters might be needed.