



APPENDIX AVAILABLE ON THE HEI WEB SITE

Research Report 167

Assessment and Statistical Modeling of the Relationship Between Remotely Sensed Aerosol Optical Depth and PM_{2.5} in the Eastern United States

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Appendix E. R Code for Flexible Buffer Modeling

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E. R Code for Flexible Buffer Modeling

```
# this function creates the Z matrix for fitting the distance effect
# using random effects, essentially tricking the lme part of gamm()
# to do the smoothing for us
makeZmatrix=function(sourceLocations,maxDistance=500,numKnots=30,
  sourceStrength=NULL,receptorLocations,gridLocations=NULL,
  maxNumSources=1000){
  # sourceLocations should be a 2-column matrix of source locations
  # maxDistance is maximum distance in meters at which we model
  # any effect of a source on a receptor
  # numKnots is number of knots to use in penalized spline
  # sourceStrength is source strength, or NULL if all sources are
  # treated equally
  # receptorLocations is 2-column matrix receptor locations in same
  # coordinate system as sourceLocations
  # gridLocations is 2-column matrix defining a fine grid across the
  # study area for plotting purposes
  # maxNumSources is max number of sources within maxDistance of a
  # receptor - need this constrained for allocating space
  if(is.null(sourceStrength)){
    sourceStrength=rep(1,nrow(sourceLocations))
  }

  n=nrow(dataLocations)
  m=nrow(gridLocations)
  pointDistsReceptor=matrix(0,nr=n,maxNumSegments)
  pointDistsGrid=matrix(0,nr=nrow(gridLocations),maxNumSegments)
  pointEmitsReceptor=matrix(0,nr=n,maxNumSegments)
  pointEmitsGrid=matrix(0,nr=nrow(gridLocations),maxNumSegments)

  receptorLocations=data.frame(receptorLocations)

  # calculate distances to sources and strengths of those sources
  # for each receptor location
  for(i in 1:n){
    tmp=rdist(receptorLocations[i,],sourceLocations)
    ll=length(tmp[tmp<maxDistance])
    if(ll){
      pointDistsReceptor[i,1:ll]=(tmp[tmp<maxDistance])
      pointEmitsReceptor[i,1:ll]=sourceStrength[tmp<maxDistance]
    }
    if(i%%1000==0){print(i)}
  }
  # calculate distances to sources and strengths of those sources
  # for each grid location
  for(i in 1:m){
    tmp=rdist(gridLocations[i,],sourceLocations)
    ll=length(tmp[tmp<maxDistance])
    if(ll){
      pointDistsGrid[i,1:ll]=(tmp[tmp<maxDistance])
      pointEmitsGrid[i,1:ll]=sourceStrength[tmp<maxDistance]
    }
    if(i%%1000==0){print(i)}
  }
}
```

```

# create fixed effect vectors
U=rowSums(pointDistsReceptor*pointEmitsReceptor)
Ugrid=rowSums(pointDistsGrid*pointEmitsGrid)

knots=seq(0,maxDistance,len=numKnots)
k=length(knots)

omega=abs((outer(knots,knots,"-"))^3)
diag(omega)=0
omega.svd=try(svd(omega))
if(is.null(attr(omega.svd,"class"))){
  sqrt.omega=omega.svd$v%%diag(sqrt(1/omega.svd$d))%%t(omega.svd$u)
} else{
  stop("Error: error in SVD; rounded value was numerically p.d.")
}
# create random effects matrices for receptor locations
Z=matrix(0,nr=n,nc=k)
for(i in 1:maxNumSources){
  Ztmp=abs((outer(pointDistsReceptor[,i],knots,"-"))^3)
  Z=Z+(Ztmp%%sqrt.omega)*pointEmitsReceptor[,i]
}
# create random effects matrices for grid locations
Zgrid=matrix(0,nr=m,nc=k)
for(i in 1:maxNumSources){
  Ztmp=abs((outer(pointDistsGrid[,i],knots,"-"))^3)
  Zgrid=Zgrid+(Ztmp%%sqrt.omega)*pointEmitsGrid[,i]
}

# preparatory calculations to ensure zero contribution at exactly
#   maxDistance
Zmax=matrix(0,nr=n,nc=k)
Ztmp=matrix(abs((maxDistance-knots)^3),nr=n,nc=k,byrow=T)
Ztmp=Ztmp%%sqrt.omega
for(i in 1:maxNumSources){
  Zmax=Zmax+Ztmp*pointEmitsReceptor[,i]
}

Ztmp=matrix(abs((maxDistance-knots)^3),nr=m,nc=k,byrow=T)
Ztmp=Ztmp%%sqrt.omega
ZgridMax=matrix(0,nr=m,nc=k)
for(i in 1:maxNumSourceLocations){
  ZgridMax=ZgridMax+Ztmp*pointEmitsGrid[,i]
}

# ensure zero contribution exactly at maxDistance
U=U-maxDistance*rowSums(pointEmitsReceptor)
Ugrid=Ugrid-maxDistance*rowSums(pointEmitsGrid)
Z=Z-Zmax
Zgrid=Zgrid-ZgridMax

# set up fixed effects vector and random effects matrix for a
#   grid of distance values (0,maxDistance) for plotting
#   effect of a unit source with distance
Upoint=Ugridded=seq(0,maxDistance,len=200)
Ztmp=abs((outer(Upoint,knots,"-"))^3)
omega=abs((outer(knots,knots,"-"))^3)
diag(omega)=0
omega.svd=try(svd(omega))

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if(is.null(attr(omega.svd,"class"))){
  sqrt.omega=omega.svd$v**diag(sqrt(1/omega.svd$d))**t(omega.svd$u)
} else{
  stop("Error: error in SVD; rounded value was numerically p.d.")
}
Zpoint=Ztmp**sqrt.omega
Ztmp=matrix(abs((maxDistance-knots)^3),nr=nrow(Zpoint),nc=k,byrow=T)
Zpoint=Zpoint-Ztmp**sqrt.omega
Upoint=Upoint-maxDistance

return(list(U=U,Ugrid=Ugrid,Z=Z,Zgrid=Zgrid,Upoint=Upoint,
           Zpoint=Zpoint,Ugridded=Ugridded))
} # end of makeZmatrix()

Zlist=makeZmatrix(sourceLocations=sourceLocations,maxDistance=500,
  numKnots=numKnots,sourceStrength=sourceStrength,
  receptorLocations=receptorLocations,gridLocations=gridLocations)
# assume that necessary data objects already exist to be called as
# arguments to makeZmatrix

# assume dataset 'dat' exists with outcome and explanatory vars

dat$dummy=as.factor(rep(1,nrow(dat)))
# needed to trick lme() by having only one group

Z=Zlist$Z # for some reason gamm can't use Zlist$Z directly, so
# need to assign to new matrix
Zgrid=Zlist$Zgrid
U=Zlist$U
Ugrid=Zlist$Ugrid
Zpoint=Zlist$Zpoint
Ugridded=Zlist$Ugridded
Upoint=Zlist$Upoint

# assume that y output vector and Xmat design matrix exists;
# X can be replaced with the usual right hand side of a gam()
# model formula
mod=gamm(y~Xmat,random=list(dummy=pdIdent(~-1+Z)),data=dat)

beta.hat <- mod$lme$coef$fixed['XU']
b.hat <- unlist(mod$lme$coef$random$dummy)

meanFun=Upoint*beta.hat+c(Zpoint**t(b.hat))
# this plots an estimate of the contribution of one unit of
# traffic on a grid of distances over (0,maxDistance)
plot(Ugridded,Upoint*beta.hat+c(Zpoint**t(b.hat)),xlab='distance')

# code here is for uncertainty calculation; we need to manipulate
# the gamm() output to calculate the expression in (D3) in
# Section D.2.3)
# note that the Vp output of mod$gam is (in latex):
#  $\sigma^2 (X^T(\frac{Z^T G Z}{\sigma^2}+I)^{-1}X+S)^{-1}$  and we
# need S, which is the block of  $\hat{B}$  (8.3) that corresponds
# to the penalized components of any smooth terms in the mean
# model
# also, presumably for numerical reasons, the blocks of the resulting
# estimate of S corresponding to unpenalized mean parameters are

```

```

# not zero, so we need to enforce this manually

k=0 # need to specify how many design matrix columns there are
# for the smooth terms in the gamm() call mean representation,
# e.g. 299 if specify k=300 for a spatial smooth in mean
# function
pX=length(mod$gam$coef) # number of mean model coefficients
p=pX+numKnots # total number of coefficients in model
X=predict(mod$gam,type='lpmatrix') # design matrix for mean model
C=cbind(X,Z) # full design matrix
Bhat=matrix(0,nr=ncol(C),nc=ncol(C)) # Bhat in (8.3)
last=pX # index of end of smooth term design matrix columns for
# __penalized__ coefficients; BE CAREFUL HERE: some
# of the last columns may correspond to unpenalized
# coefficients, in which case these columns should
# not be included here, so that the Bhat block
# corresponding to these coefficients forced to be
# zero; if you have multiple smooth terms in the mean,
# you may need to deal with such columns interspersed
# in X and zero out the corresponding blocks in Bhat
first=pX-k+1 # index of start of smooth term design matrix columns
ind=first:last
tau2=exp(attr(mod$lme$apVar,'Pars')[1])^2
# the random effects variance
varY=Z%*%t(Z)*tau2/mod$gam$sig2 # (Z^T G Z)/sig2 in the notation
# of Ruppert, Wand and Carroll (RWC)
diag(varY)=diag(varY)+1 # (Z^T G Z + R)/sig2 in RWC notation;
# W^-1 in the notation of Wood (variance of Y divided by
# sig2 since Vp is sig2 * everything else
S=solve(mod$gam$Vp/mod$gam$sig2)-t(X)%*%solve(varY,X)
# extract implicit smoothing matrix of the fitted model
# from the Vp output of gam()
Bhat[ind,ind]=S[ind,ind] # block corresponding to smooth
# terms in mean model (the penalized coefficients); note that
# upper left block corresponding to fixed effects is forced to
# be all zeroes, as should be any block for unpenalized
# coefficients of the smooth terms
Bhat[(pX+1):p,(pX+1):p]=diag(rep(1/tau2,numKnots))
# block corresponding to random effects should be
# (1/tau2) times the identity
LtInv=chol((t(C)%*%C+Bhat)/mod$gam$sig2)
# Cholesky of precision matrix of fixed and random effects
Uposition=which(names(mod$gam$coef)=='U')
T=1000 # number of samples of decay function to
# draw from approximate Bayesian posterior
smp=backsolve(LtInv,matrix(rnorm(p*T),nr=p,nc=T))
betaSamples=beta.hat+smp[Uposition,]
# pick off random sample of decay function fixed effect
bSamples=c(b.hat)+smp[(pX+1):p,]
# pick off random samples of decay function random effects
smp=matrix(Upoint,nc=1)%*%matrix(betaSamples,nr=1)+Zpoint%*%bSamples
qu=apply(smp,1,quantile,c(.025,.975)) # pointwise 95% confidence
# (credible, really) interval for decay function

```