

hw10.R

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Mon Nov 10 09:59:42 2014

```
#####  
# Attach packages  
#####  
library(gdata)
```

```
## gdata: read.xls support for 'XLS' (Excel 97-2004) files ENABLED.  
##  
## gdata: read.xls support for 'XLSX' (Excel 2007+) files ENABLED.  
##  
## Attaching package: 'gdata'  
##  
## The following object is masked from 'package:stats':  
##  
##     nobs  
##  
## The following object is masked from 'package:utils':  
##  
##     object.size
```

```
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'  
##  
## The following object is masked from 'package:stats':  
##  
##     filter  
##  
## The following objects are masked from 'package:base':  
##  
##     intersect, setdiff, setequal, union
```

```
library(maptools)
```

```
## Loading required package: sp  
## Checking rgeos availability: TRUE
```

```
library(rgdal)
```

```
## rgdal: version: 0.9-1, (SVN revision 518)  
## Geospatial Data Abstraction Library extensions to R successfully loaded  
## Loaded GDAL runtime: GDAL 1.10.1, released 2013/08/26  
## Path to GDAL shared files: /usr/share/gdal/1.10  
## Loaded PROJ.4 runtime: Rel. 4.8.0, 6 March 2012, [PJ_VERSION: 480]  
## Path to PROJ.4 shared files: (autodetected)
```

```
library(spatstat)
```

```
##  
## spatstat 1.38-1      (nickname: 'Le Hardi')  
## For an introduction to spatstat, type 'beginner'
```

```
#####  
# Set working directory to the haiti directories on local machine  
#####  
if(Sys.info()["sysname"] == "Windows"){  
  wd <- 'C:/Users/BrewJR/Documents/uf/phc6194/hw10'  
} else {  
  wd <- '/home/joebrew/Documents/uf/phc6194/hw10'  
}  
setwd(wd)  
  
#####  
# DIRECTIONS  
#####  
# For this assignment you will investigate clustering of P. falciparum parasite  
# rates in an African country. Data and appropriate shapefiles are provided  
# through Sakai. Please perform the following tasks and include all requested  
# outputs and answers in a separate Word file numbered according to step:  
  
#####  
# 1. Choose a country to investigate, there are four options: Brazil,  
# Ghana, Kenya, and Tanzania. State your choice in your word file.  
#####  
  
# I choose.... Ghana!  
  
#####  
# 2. Import the World and country shapefile of choice into ArcGIS.  
# Import the country's data.  
#####  
ghana_map <- readOGR("Ghana", "Ghana")
```

```
## OGR data source with driver: ESRI Shapefile  
## Source: "Ghana", layer: "Ghana"  
## with 3 features and 8 fields  
## Feature type: wkbPolygon with 2 dimensions
```

```
ghana_data <- read.csv("Ghana/Ghana_MAP_CSV.csv")  
  
#####  
# 3. Perform a global autocorrelation on the parasite rate  
# variable with either ArcGIS or GeoDa. If using GeoDa, right  
# click on plot and select "Display Statistics". Copy html  
# output if using ArcGIS or the Moran's I plot if using GeoDa.  
# Interpret these statistics.  
#####
```

```

# Basically, see if the points I have are significantly different from
# random points

# Create point pattern dataset
coords.ppp <- ppp(x = ghana_data$longitude,
                 y = ghana_data$latitude,
                 xrange = range(ghana_data$longitude),
                 yrange = range(ghana_data$latitude))

# Define number of points
n <- coords.ppp$n

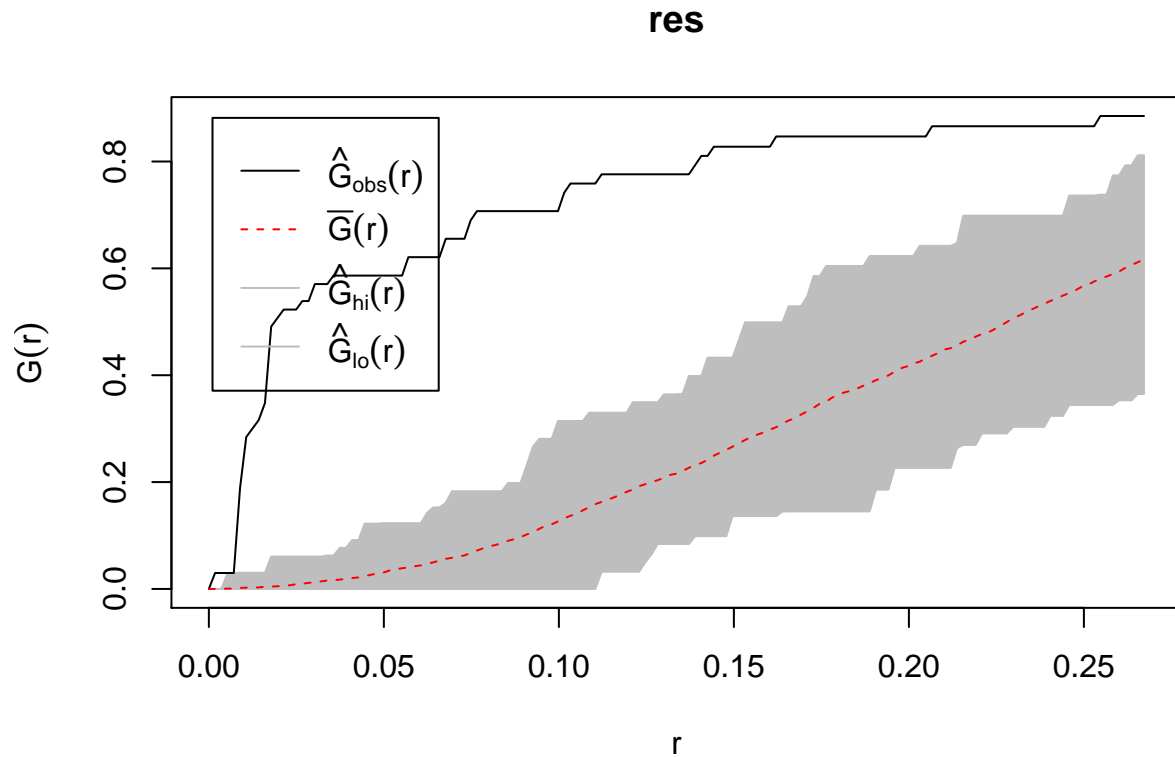
# Generate random points to compare with observed
ex <- expression(runifpoint(n, win = owin(c(range(ghana_data$longitude)),
                                           c(range(ghana_data$latitude))))))

# Set a seed to make reproducible
set.seed(130920)

# Use Gest to compute nearest neighbor distance function (g(r))
res <- envelope(coords.ppp,
               Gest,
               nsim = 99,
               simulate = ex,
               verbose = FALSE,
               savefuncs = TRUE)

# Plot
plot(res)

```



```
##      lty col  key      label
## obs      1  1  obs hat(G)[obs](r)
## mmean    2  2 mmean      bar(G)(r)
## hi       1  8  hi  hat(G)[hi](r)
## lo       1  8  lo  hat(G)[lo](r)
##
##                                     meaning
## obs                observed value of G(r) for data pattern
## mmean              sample mean of G(r) from simulations
## hi    upper pointwise envelope of G(r) from simulations
## lo    lower pointwise envelope of G(r) from simulations
```

```
# In the above plot, the fact that the black line (observed)
# does not remain in the grey confidence area means
# that THERE IS SPATIAL AUTOCORRELATION.

# But the above demonstrates correlation between the points,
# not between the data values (PR)

# Moran's I (http://www.ats.ucla.edu/stat/r/faq/morans\_i.htm)
library(ape)
```

```
##
## Attaching package: 'ape'
##
## The following objects are masked from 'package:spatstat':
##
##      edges, rotate
```

```

# First generate a matrix of inverse distance weights
ghana_dists <- as.matrix(dist(cbind(ghana_data$longitude, ghana_data$latitude)))
ghana_dists_inv <- 1/ghana_dists
diag(ghana_dists_inv) <- 0

# Now, having created a matrix where each off-diagonal entry (i,j)
# in the matrix equals 1 / distance between points i and j,
# we can calculate Moran's I.
x <- Moran.I(ghana_data$PR, ghana_dists_inv)
x

```

```

## $observed
## [1] 0.4769296
##
## $expected
## [1] -0.01515152
##
## $sd
## [1] 0.04395428
##
## $p.value
## [1] 0

```

```

# We can reject the null hypothesis that there is no
# spatial autocorrelation. In other words, PARASITE RATE
# IS SPATIALLY AUTOCORRELATED.

#####
# 4. Perform a local autocorrelation to show clusters
# using either ArcGIS (either local Moran's I or Getis-Ord Gi)
# or GeoDa. Add any outputted maps to your Word file. Include
# legends and titles as appropriate.
#####

# Hotspots
library(hotspots)

```

```

## Loading required package: lattice
##
## Attaching package: 'lattice'
##
## The following object is masked from 'package:spatstat':
##
##     panel.histogram
##
## Loading required package: ineq

```

```

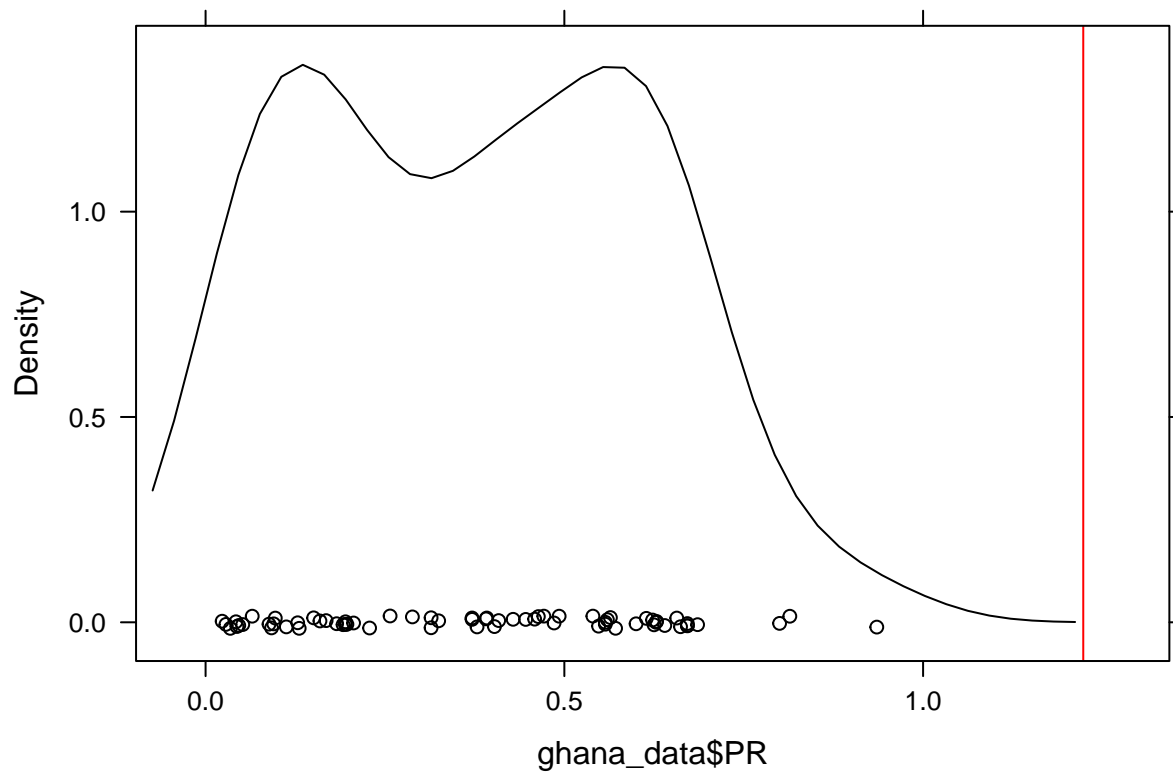
# Calculate a cutoff for t-distribution
x <- hotspots(ghana_data$PR, p = 0.95, tail = "positive")

# summarize
summary(x)

```

```
##
## Source data: ghana_data$PR
## Distribution and probability: t, 0.95
## Tail: positive hot spots only
## Mean:          0.37669
## Median:         0.39093
## Min:           0.02312
## Max:           0.93548
## mad:           0.30996
## CV (mad/median): 0.79287
##
## n = 67
##
## positive hot spots:
##   Cutoff  number positive hot spots  % positive hot spots  % sum
##   1.223                0                0                0
```

```
# plot
plot(x)
```



```
# Mantel test (http://www.ats.ucla.edu/stat/r/faq/mantel\_test.htm)
library(ade4)
```

```
##
## Attaching package: 'ade4'
##
## The following object is masked from 'package:spatstat':
##
##   disc
```

```
ghana_dists <- dist(cbind(ghana_data$longitude, ghana_data$latitude))
pr_dists <- dist(ghana_data$PR)
x <- mantel.rtest(pr_dists, ghana_dists, nrepet = 9999)
```

```
## Warning in is.euclid(m1): Zero distance(s)
```

```
## Warning in is.euclid(distmat): Zero distance(s)
```

```
x
```

```
## Monte-Carlo test
## Observation: 0.3128844
## Call: mantel.rtest(m1 = pr_dists, m2 = ghana_dists, nrepet = 9999)
## Based on 9999 replicates
## Simulated p-value: 1e-04
```

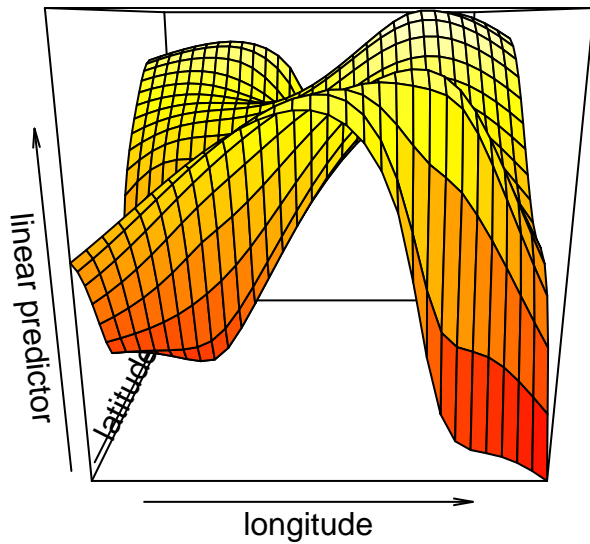
```
# Using both Moran's I and Mantel (Monte Carlo simulations), we get
# very small P-values. There is definitely spatial autocorrelation.
```

```
# GAM
library(mgcv)
```

```
## Loading required package: nlme
##
## Attaching package: 'nlme'
##
## The following object is masked from 'package:dplyr':
##
## collapse
##
## This is mgcv 1.8-3. For overview type 'help("mgcv-package")'.
```

```
my_gam <- gam(PR ~ s(longitude, latitude),
              data = ghana_data)
```

```
# Visualize GAM
vis.gam(my_gam)
```



```
vis.gam(my_gam,
  ticktype = "detailed",
  n.grid = 100,
  plot.type = "contour",
  too.far = 20,
  contour.col = adjustcolor("black", alpha.f=0.4))
```

```
## Warning in plot.window(...): "ticktype" is not a graphical parameter
```

```
## Warning in plot.xy(xy, type, ...): "ticktype" is not a graphical parameter
```

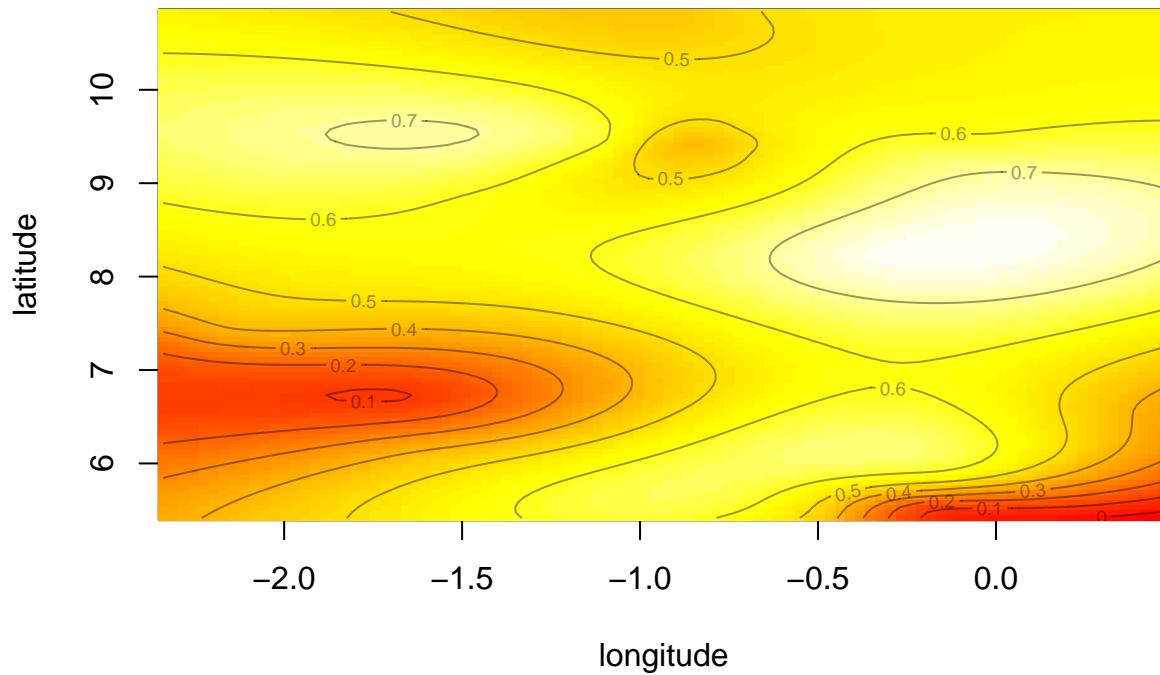
```
## Warning in axis(side = side, at = at, labels = labels, ...): "ticktype" is
## not a graphical parameter
```

```
## Warning in axis(side = side, at = at, labels = labels, ...): "ticktype" is
## not a graphical parameter
```

```
## Warning in box(...): "ticktype" is not a graphical parameter
```

```
## Warning in title(...): "ticktype" is not a graphical parameter
```


linear predictor



```
# More visualizations: KRIGING
library(gstat)
```

```
##
## Attaching package: 'gstat'
##
## The following object is masked from 'package:spatstat':
##
##     idw
```

```
library(geoR)
```

```
## Loading required package: MASS
##
## Attaching package: 'MASS'
##
## The following object is masked from 'package:dplyr':
##
##     select
##
## -----
## Analysis of geostatistical data
## For an Introduction to geoR go to http://www.leg.ufpr.br/geoR
## geoR version 1.7-4.1 (built on 2012-06-29) is now loaded
## -----
```

```

library(rgdal)
library(RColorBrewer)
# Define color vector
my_colors <- colorRampPalette(c("blue", "white", "darkred"))(100)

SurfaceFun <- function(var = "PR",
                        boundary_shape = ghana_map){

  # getting coordinates of alachua boundary
  boundary_points <- boundary_shape@polygons[[1]]@Polygons
  boundary_points <- boundary_points[[1]]@coords

  # Get trap locations and data values
  a <- data.frame("x" = ghana_data$longitude,
                  "y" = ghana_data$latitude,
                  "z" = ghana_data[,var])
  # Make into a geodata object
  b <- as.geodata(a)

  # Predict multiple points in Alachua County's boundary
  x <- seq(min(boundary_points[,1]), max(boundary_points[,1]), length = 100)
  y <- seq(min(boundary_points[,2]), max(boundary_points[,2]), length = 100)

  # Make a grid of those points
  pred.grid <- expand.grid(x,y)

  # kriging calculations
  kc <- krige.conv(geodata = b, coords = b$coords, data = b$data,
                  locations = pred.grid,
                  borders = boundary_points,
                  #borders = boundary@polygons,
                  # borders = ALACHUA BORDERS!,
                  krige = krige.control(type.krige = "ok",
                                         cov.pars = c(10, 3.33)))

  # Plot!
  # displaying predicted values
  image(kc, loc = pred.grid,
        col = my_colors,
        xlab=NA, ylab=NA,
        xaxt = "n",
        yaxt = "n",
        xpd = NA,
        bty = "n")

  # Define percentiles for legend
  legtemp <- round(quantile(kc$predict, probs = seq(0,1,, length = 10)),
                  digits = 3)

  legend(x="topright",

```

```

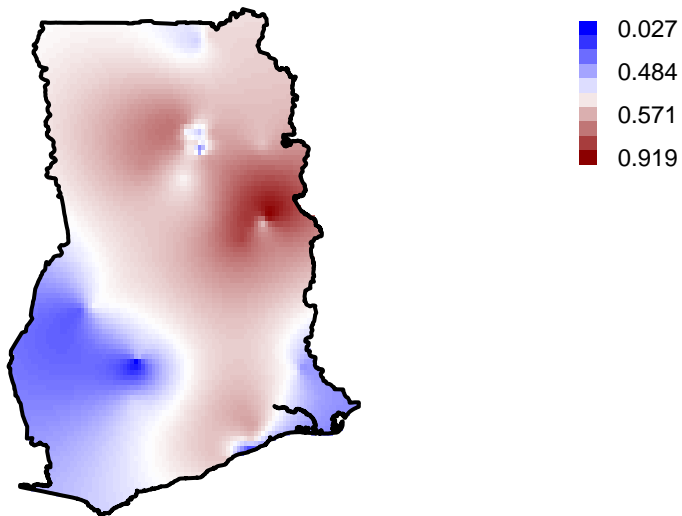
    fill = my_colors[c(1,11,22,33,44,55,66,77,88,100)],
    legend = c(legtemp[1], NA, NA, legtemp[4], NA, NA, legtemp[7], NA, NA, legtemp[10]),
    border = NA,
    bty = "n",
    ncol = 1,
    y.intersp = 0.5,
    #title = "Interpolation",
    cex = 0.75)
}
SurfaceFun()

```

```

## krige.conv: results will be returned only for prediction locations inside the borders
## krige.conv: model with constant mean
## krige.conv: Kriging performed using global neighbourhood

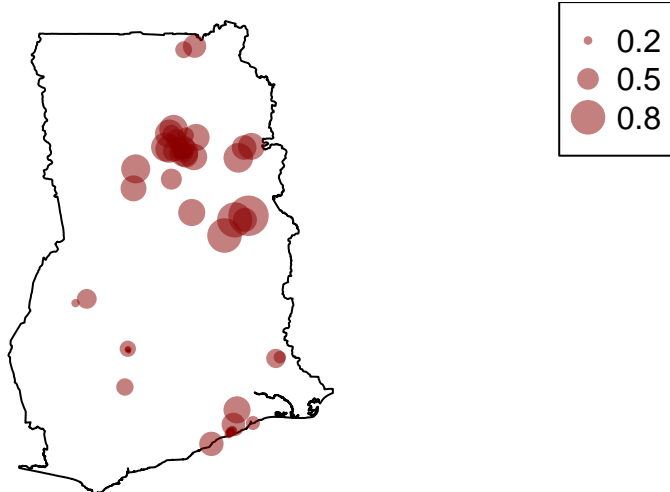
```



```

# SIMPLE POINT MAP
plot(ghana_map)
points(ghana_data$longitude,
       ghana_data$latitude,
       pch = 16,
       col = adjustcolor("darkred", alpha.f = 0.5),
       cex = ghana_data$PR * 3)
legend(x = "topright",
       pch = 16,
       col = adjustcolor("darkred", alpha.f = 0.5),
       pt.cex = c(0.2, 0.5, 0.8) * 3,
       legend = c(0.2, 0.5, 0.8) )

```



```
#####
# 5. Describe you what you see in your maps in a few sentences.
#####
# In all methods, there appears to be a cluster of high parasite rates
# in the eastern part of the country, at the northern age of lake Volta,
# along the Oti River, near the border with Togo. Specifically, this
# parasite "hotspot" appears to be located in a triangle near
# Domanko, Nakpayili and Kpandai.

library(maps)
map("world", c("ghana", "togo", "burkina faso", "ivory coast",
              "nigeria", "benin"),
    fill = TRUE, col = sample(colorRampPalette(c("white", "black"))(100),6))
map("world", "ghana", fill = TRUE, col = "red", add = TRUE)
title(main = "West Africa")
legend("topleft",
      fill = "red",
      legend = "Ghana")
```

West Africa

