

Project 4

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April 19, 2017

PART A

Note: The dataset has some error in area, and I have fixed this problem.

*ACC: AlleghenyCounty_Council; ACM: AlleghenyCounty_Municipal

| Shapefile | Method | Adjacency | I/C value | Expectation | Variance | Standard Deviate | p-value |
|-----------|--------|-----------|-------------------|-------------------|--------------|------------------|----------|
| ACC | Moran | Rook | 0.31108273 | - 0.08333333 | 0.02560847 | 2.4647 | 0.006857 |
| ACC | Moran | Queen | 0.31108273 | - 0.08333333 | 0.02560847 | 2.4647 | 0.006857 |
| ACC | Geary | Rook | 0.6409275 | 1.0000000 | 0.0250958 | 2.2666 | 0.01171 |
| ACC | Geary | Queen | 0.6409275 | 1.0000000 | 0.0250958 | 2.2666 | 0.01171 |
| ACM | Moran | Rook | - 0.002915556 | - 0.007751938 | 0.003500366 | 0.081745 | 0.4674 |
| ACM | Moran | Queen | - 0.0001232697 | - 0.0077519380 | 0.0033378781 | 0.13204 | 0.4475 |
| ACM | Geary | Rook | 2.134989922 | 1.000000000 | 0.006785615 | -13.778 | 1 |
| ACM | Geary | Queen | 2.09170840 | 1.000000000 | 0.00645514 | -13.588 | 1 |

Interpretation:

For Allegheny County Council shapefile, no matter what method I use, the rook's result is always the same as queen's result. Rook's adjacency is sharing the same edge. Queen's adjacency is sharing same corner. When the results are same, it means there is no neighbor at the corner. When using Moran's method, the $I > 0.3$, which means a strong positive autocorrelation, and the $p\text{-value} < 0.05$ which means the result is strong trustable. When using Geary's method, the $0 < C < 1$ indicates a positive autocorrelation, and the p-value tells me this result is trustable, too.

For Allegheny County Municipal shapefile, the results for rook's and queen's are different, which means there are some neighbors at the corner. When using Moran's method, although it is negative, it is so close to 0 and the p-value is > 0.05 , which means, there is a very very very weak negative autocorrelation, it is even can be treat as no autocorrelation in it, and this result is very weak to trust. When using Geary's method, the p-value is even equals to 1, which means we don't need to see the result, it's totally untrustable.

PART B

Global G Statistic Result:

| Global G Statistic | Expectation | Variance | Standard Deviate | P-value |
|--------------------|--------------|--------------|------------------|----------|
| 2.974714e-02 | 1.515152e-02 | 1.600546e-05 | 3.6483 | 0.000132 |

Interpretion: $2.973714e-02 > 1.515152e-02$, when global G statistics is greater than expected value, which means high values clustered together, and it's a kind of "hot pots" potentially. The p-value makes us trust this result.

Geographically Weighted Regression (GWR):

| Summary of GWR coefficient estimates at data points | | | | | | |
|---|--------------------|---------------------|--------------------|---------------------|--------------------|-----------|
| | Min. | 1 st Qu. | Median | 3 rd Qu. | Max. | Global |
| X.Intercept | 1.070e+0 1 | 2.533e+0 2 | 4.138e+0 2 | 5.149e+0 2 | 7.124e+0 2 | 427.8579 |
| POP_CRI01 | 3.778e-02 | 4.646e-02 | 5.528e-02 | 5.780e-02 | 5.972e-02 | 0.0575 |
| AG_CRI01 | - 4.415e+0 2 | - 3.710e+0 2 | - 3.038e+0 2 | - 1.634e+0 2 | - 5.376e+0 1 | -333.0392 |

| | | | | | | |
|-------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Area | - 5.774e+0 3 | - 4.211e+0 3 | - 3.389e+0 3 | - 2.002e+0 3 | - 5.955e+0 2 | - 3255.564 2 |
|-------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|

The equation:

$$\widehat{Index01} = (10.1 \text{ to } 712.4) + \\ (0.03778 \text{ to } 0.05972)POP_{CRI01} + \\ (-441.5 \text{ to } -537.6)AG_{CRI01} + \\ (-5774 \text{ to } -595.5)Area$$

Global equation:

$$\widehat{Index01} = 427.8579 + 0.0575 * POP_CRI01 - 333.0392 * AG_CRI01 - 3255.5642 * Area$$

The original value of Index01 for Mifflin county is: 215

The prediction result of Mifflin county is: 105.36254

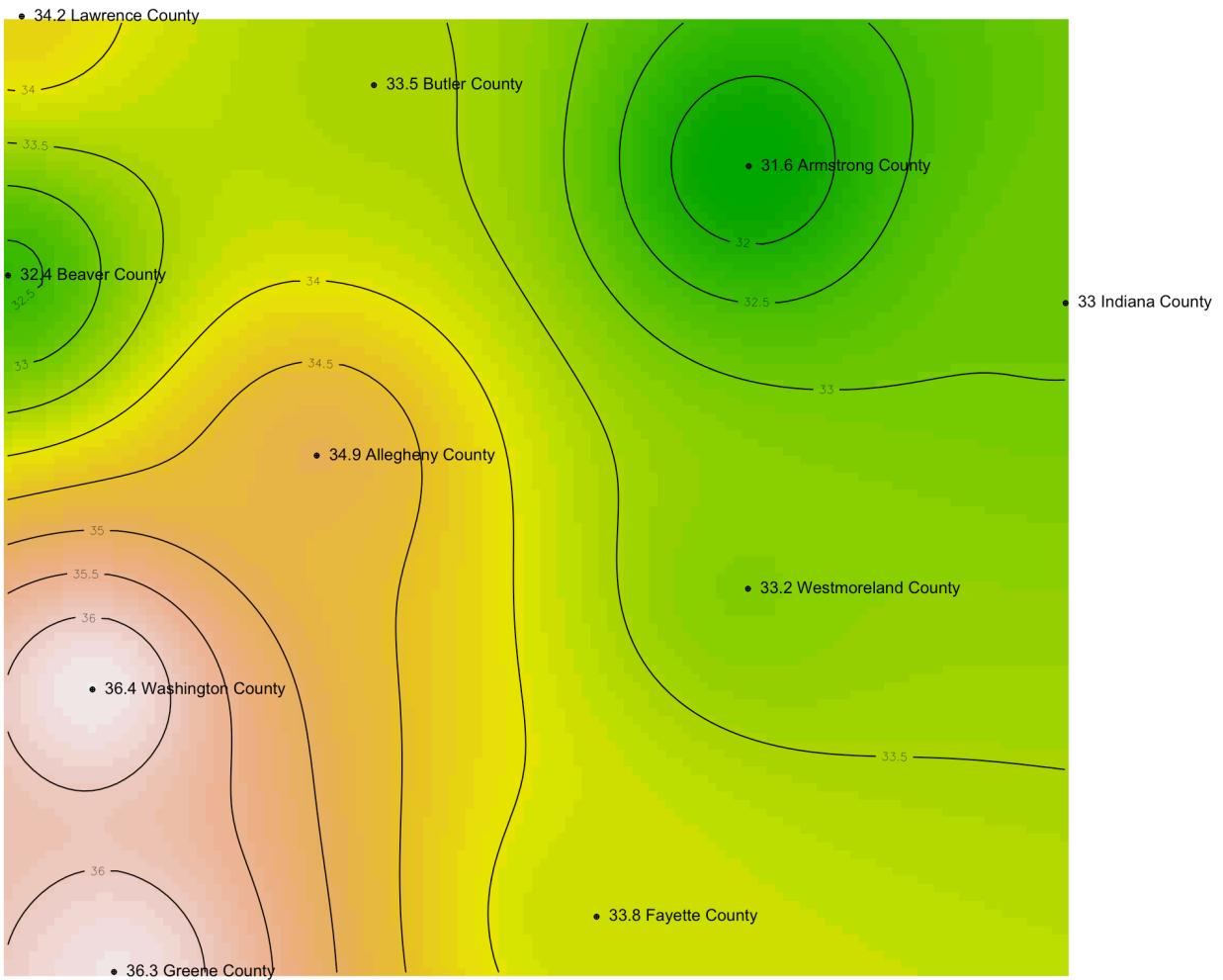
PART C

Using IDW technique:

| IDW interpolated results | | | |
|--------------------------|-----------|----------|------------------------|
| County | x | y | z (Interpolated value) |
| Butler | -79.91287 | 40.91113 | 33.53768 |
| Armstrong | -79.46588 | 40.81461 | 31.62437 |
| Indiana | -79.08792 | 40.65152 | 32.97690 |
| Lawrence | -80.33295 | 40.99304 | 34.24218 |
| Beaver | -80.34930 | 40.68440 | 32.39437 |
| Westmoreland | -79.46670 | 40.31117 | 33.16840 |
| Allegheny | -79.98108 | 40.46988 | 34.85891 |

| | | | |
|-------------------|-----------|----------|----------|
| Washington | -80.24858 | 40.19130 | 36.40584 |
| Fayette | -79.64728 | 39.92059 | 33.78217 |
| Greene | -80.22289 | 39.85479 | 36.32539 |

The Map using IDW:

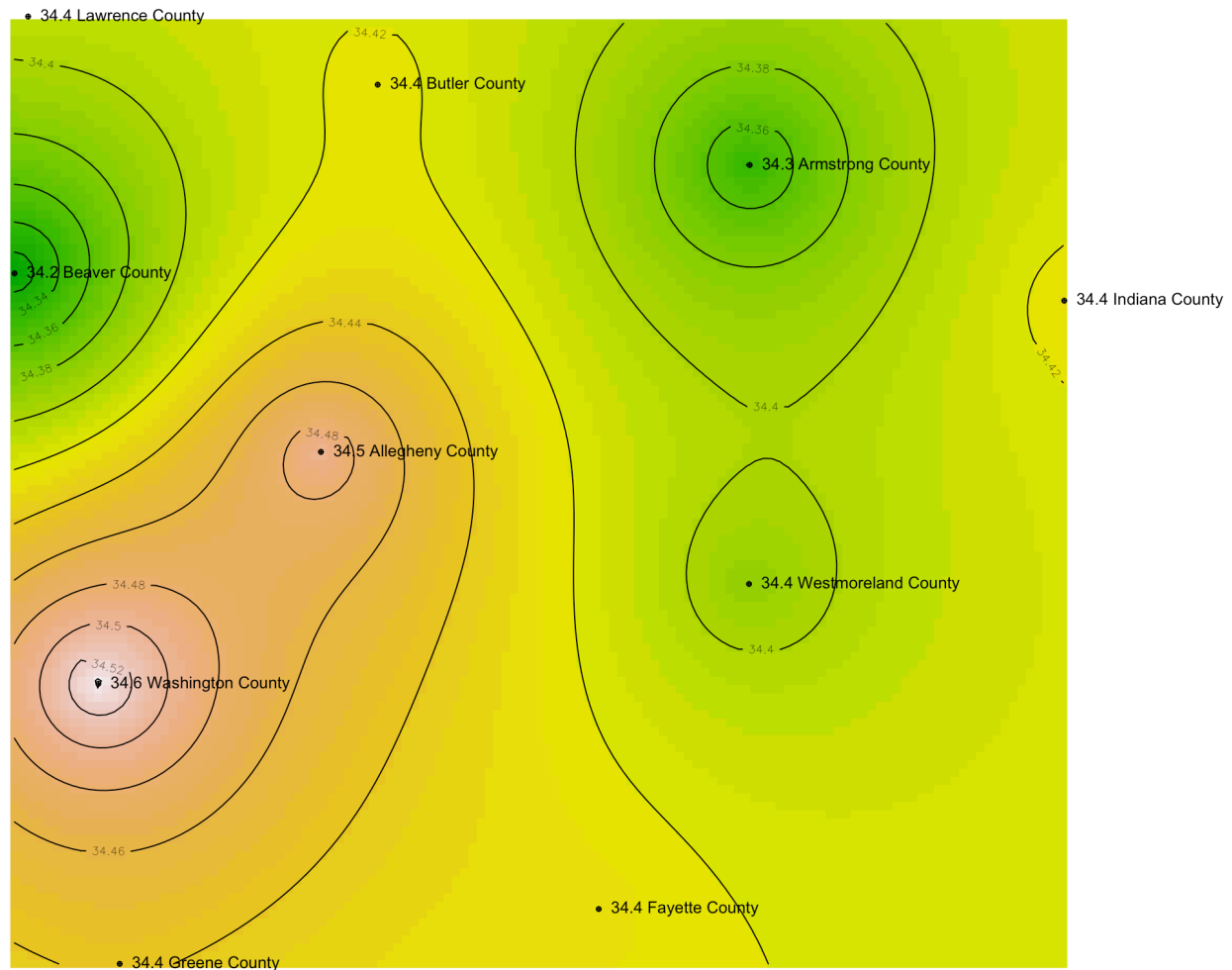


Using OK technique:

| OK interpolated results | | | |
|-------------------------|-----------|----------|------------------------|
| County | x | y | z (Interpolated value) |
| Butler | -79.91287 | 40.91113 | 34.42886 |

| | | | |
|---------------------|-----------|----------|----------|
| Armstrong | -79.46588 | 40.81461 | 34.29668 |
| Indiana | -79.08792 | 40.65152 | 34.43313 |
| Lawrence | -80.33295 | 40.99304 | 34.41276 |
| Beaver | -80.34930 | 40.68440 | 34.23777 |
| Westmoreland | -79.46670 | 40.31117 | 34.36798 |
| Allegheny | -79.98108 | 40.46988 | 34.53589 |
| Washington | -80.24858 | 40.19130 | 34.60604 |
| Fayette | -79.64728 | 39.92059 | 34.43163 |
| Greene | -80.22289 | 39.85479 | 34.44560 |

The Map Using OK:



The differences between two techniques:

For IDW, nearer locations are given more prominence in calculating the local mean. It used known z values and weights determined as a function of distances between the unknown and known points. IDW differs from Kriging because there is no statistical models used in it. There is no determination of spatial autocorrelation taken into consideration. IDW has the advantage that it is easy to define and understand the results. Kriging is most appropriate when you know there is a spatially correlated distance or directional bias in the data. Kriging is a statistical method that makes use of a variogram to calculate the spatial autocorrelation. The weights in Kriging are helped determined by the semivariogram.

The differences between two maps:

The OK map looks more detailed, smooth, and “natural” than IDW map.

Code

```
##### Load Libraries #####
library(rgdal)
library(UScensus2010)
library(spdep)
library(GWmodel)
library(spgwr)
library(dplyr)
library(fields)
library(gstat)
library(automap)

##### PART A #####
#Import files
AlleghenyCountyCouncil <- readOGR(".", "AlleghenyCounty_Council") # import A
llegghenyCounty_Council shapefile
AlleghenyCountyMunicipal <- readOGR(".", "AlleghenyCounty_Municipal") # impo
rt AlleghenyCounty_Municipal shapefile

# ACC is the abbr of AlleghenyCountyCouncil; ACM is the abbr of
# AlleghenyCountyMunicipal
ACC.area = areaPoly(AlleghenyCountyCouncil) # calculate the area of each pol
ygon in ACC
ACM.area = areaPoly(AlleghenyCountyMunicipal) # calculate the area of each p
olygon in ACM

## construct neighbours list from polygon
ACC.queen <- poly2nb(AlleghenyCountyCouncil, queen = TRUE)
ACC.rook <- poly2nb(AlleghenyCountyCouncil, queen = FALSE)
ACM.queen <- poly2nb(AlleghenyCountyMunicipal, queen = TRUE)
ACM.rook <- poly2nb(AlleghenyCountyMunicipal, queen = FALSE)

# change neighbour list to listw (get the spatial weights for neighbours
# lists)
ACC.nb2listw.queen <- nb2listw(ACC.queen)
ACC.nb2listw.rook <- nb2listw(ACC.rook)
ACM.nb2listw.queen <- nb2listw(ACM.queen)
ACM.nb2listw.rook <- nb2listw(ACM.rook)

# calculate moran's and geary's
moran.test(ACC.area, ACC.nb2listw.queen, randomisation = FALSE) # ACC moran
queen: 0.31108273, Expectation = -0.08333333
moran.test(ACC.area, ACC.nb2listw.rook, randomisation = FALSE) # ACC moran r
ook: 0.31108273, Expectation = -0.08333333
geary.test(ACC.area, ACC.nb2listw.queen, randomisation = FALSE) # ACC geary
queen: 0.6409275, Expectation = 1;
geary.test(ACC.area, ACC.nb2listw.rook, randomisation = FALSE) # ACC geary r
ook: 0.6409275, Expectation = 1;
moran.test(ACM.area, ACM.nb2listw.queen, randomisation = FALSE) # ACM moran
```

```

queen: -0.0001232697, Expectation = -0.007751938;
moran.test(ACM.area, ACM.nb2listw.rook, randomisation = FALSE) # ACM moran r
ook: -0.002915556, Expectation = -0.007751938
geary.test(ACM.area, ACM.nb2listw.queen, randomisation = FALSE) # ACM geary
queen: 2.09170840, Expectation = 1;
geary.test(ACM.area, ACM.nb2listw.rook, randomisation = FALSE) # ACM geary r
ook: 2.134989922, Expectation = 1;

##### PART B #####
# Import dataset Crime_PA2002 shapefile
Crime_PA2002 <- readOGR(".", "Crime_PA2002")

# Construct neighbours list from polygon list
Crime_PA2002.rook <- poly2nb(Crime_PA2002, queen = FALSE) # rook

# Spatial Weights for neighbours lists
Crime_PA2002.rook.nb2listw <- nb2listw(Crime_PA2002.rook)

##### Global G statistics
globalG.test(Crime_PA2002$BURG01, Crime_PA2002.rook.nb2listw) # Global G sta
tistic: 2.974714e-02 ; Expectation: 1.515152e-02; Variance: 1.600546e-05

# GWR
DistanceMatrix <- gw.dist(dp.locat = coordinates(Crime_PA2002)) # the euclid
ian distance matrix
DistanceMatrixMifflin <- DistanceMatrix[61, ]
DistanceMatrixMifflin <- DistanceMatrixMifflin[-61]
weight <- 1/DistanceMatrixMifflin
weight

# spgwr package gwr
bw <- gwr.sel(INDEX01 ~ POP_CRI01 + AG_CRI01 + Area, data = Crime_PA2002[Crim
e_PA2002$COUNTY != "Mifflin County", ])
gwr.model <- gwr(INDEX01 ~ POP_CRI01 + AG_CRI01 + Area, data = Crime_PA2002[C
rime_PA2002$COUNTY != "Mifflin County", ], bandwidth = bw, hatmatrix = TRUE,
se.fit = TRUE, weights = weight)
gwr.model
x <- gwr(INDEX01~POP_CRI01+AG_CRI01+Area, data = Crime_PA2002, bandwidth = bw
, predict = TRUE, se.fit = TRUE, fittedGWRObject = gwr.model)
x$SDF$pred[61] # the predict result

##### PART C #####
PA_County_Select <- readOGR(".", "PA_County_Select")
Ozone_Value <- read.delim("Ozone_Value.dat", header = FALSE, sep = "|")
Ozone_Sensor_Locs <- readOGR(".", "Ozone_Sensor_Locs")
PA_County_Select@data$COUNTY <- as.character(PA_County_Select@data$COUNTY)
names(Ozone_Value)[3] <- "id"

## Inverse Distance Weighting (IDW)

```



```

centroids <- as.data.frame(coordinates(PA_County_Select)) # get the centroid
s for each county
names(centroids) <- c("centroidX", "centroidY") # rename the column name
rownames(centroids) <- seq(1:length(centroids$centroidX)) # rename the row i
ndex
ControlPoints <- cbind.data.frame(Ozone_Sensor_Locs$id, Ozone_Sensor_Locs$lon
g, Ozone_Sensor_Locs$lat) # get all the points Long and Lat that would be th
e control points
names(ControlPoints) <- c("id", "controlX", "controlY") # rename the column
names
Sub_Ozone_Value <- Ozone_Value[Ozone_Value$id %in% ControlPoints$id, c(3, 6,
8)] # get the ozone value with the same id in the control points
# Create the IDW calculation table in loop and record the results
Sub_Ozone_Value <- Sub_Ozone_Value[Sub_Ozone_Value$V6 == "OZONE", -2] # get
the ozone value
ControlPoints$id <- as.character(ControlPoints$id) # change id to char
Sub_Ozone_Value$id <- as.character(Sub_Ozone_Value$id) # change id to char
ControlPoints <- inner_join(ControlPoints, Sub_Ozone_Value) # Join to get th
e ozone value for each sensor station
names(ControlPoints)[4] <- "ozone_value"
ResultTable <- as.data.frame(PA_County_Select@data$COUNTY) # This Table will
record the results
ResultTable$x <- centroids$centroidX # Long of centroid for each polygon
ResultTable$y <- centroids$centroidY # Lat of centroid for each polygon
ResultTable$z <- NA # interpolated ozone value
# using for loop to interpolate for each polygon
for (i in 1:length(centroids$centroidX)) {
  centroidX <- ResultTable$x[i]
  centroidY <- ResultTable$y[i]
  IDWtable <- ControlPoints
  IDWtable$Distance <- sqrt((IDWtable$controlX - centroidX)^2 + (IDWtable$c
ontrolY - centroidY)^2)
  IDWtable <- IDWtable[order(IDWtable$Distance), ]
  rownames(IDWtable) <- seq(1:length(IDWtable$id))
  IDWtable <- IDWtable[1:5, ] # keep only 5 nearest
  IDWtable$InverseDistance <- 1/IDWtable$Distance
  IDWtable$Weight <- IDWtable$InverseDistance/sum(IDWtable$InverseDistance)
  IDWtable$WeightedValue <- IDWtable$Weight * IDWtable$ozone_value
  ResultTable$z[i] <- sum(IDWtable$WeightedValue)
}
ResultTable <- ResultTable[, -1]
ResultTable

# Create the IDW Map
IDW.map <- as.data.frame(ResultTable)
coordinates(IDW.map) = ~x + y
xRange <- as.numeric(bbox(IDW.map)[1, ])
yRange <- as.numeric(bbox(IDW.map)[2, ])
grid <- expand.grid(x = seq(from = xRange[1], to = xRange[2], by = 0.01), y =
seq(from = yRange[1], to = yRange[2], by = 0.01))

```

```

coordinates(grid) <- ~x + y
gridded(grid) <- TRUE
IDW.data <- gstat::idw(ResultTable$z ~ 1, locations = IDW.map, newdata = grid
)
OzonePlot <- par(mar = c(0, 0, 0, 0))
image(IDW.data, "var1.pred", col = terrain.colors(50))
contour(IDW.data, "var1.pred", add = TRUE, nlevels = 10)
plot(IDW.map, add = TRUE, pch = 10, cex = 0.5)
text(coordinates(PA_County_Select), paste(as.character(round(ResultTable$z, 1
)), as.character(PA_County_Select$COUNTY)), pos = 4, cex = 0.8, col = "black"
)
map.axes(cex.axis = 0.8)
par(OzonePlot)

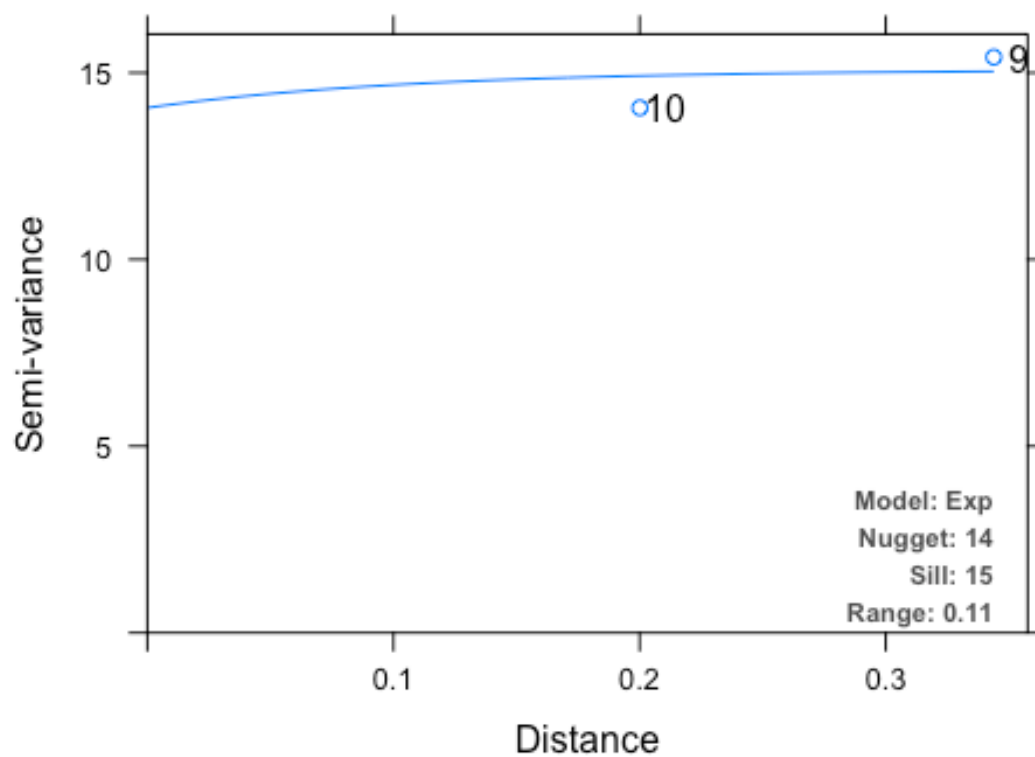
## Ordinary Kriging (OK)
Ozone_Value <- Ozone_Value[Ozone_Value$V6 == "OZONE", ] # get all the ozone
value
Ozone_Sensor_Locs_data <- Ozone_Sensor_Locs@data
Ozone_Sensor_Locs_data$id <- as.character(Ozone_Sensor_Locs_data$id)
Ozone_Value$id <- as.character(Ozone_Value$id)
Ozone_Sensor_Value <- inner_join(x = Ozone_Sensor_Locs_data, y = Ozone_Value)
Sensor.num <- nrow(Ozone_Sensor_Value) # there are 11 sensors has value
Ozone_Sensor_Value <- subset.data.frame(Ozone_Sensor_Value, select = c(long,
lat, V8))
names(Ozone_Sensor_Value) <- c("x", "y", "z")
centroids$z <- NA # create the new column z to store the ozone value
names(centroids) <- c("x", "y", "z")
dataset <- rbind.data.frame(Ozone_Sensor_Value, centroids)

# Create matrix D of distance between control points
D <- as.data.frame(matrix(data = NA, nrow = Sensor.num, ncol = Sensor.num))
names(D) <- c(1:nrow(D))
for (i in 1:nrow(D)) {
  for (j in 1:nrow(D)) {
    D[i, j] = sqrt((Ozone_Sensor_Value$x[i] - Ozone_Sensor_Value$x[j])^2+
(Ozone_Sensor_Value$y[i] - Ozone_Sensor_Value$y[j])^2)
  }
}

# exponential semivariogram model
variogram = Ozone_Sensor_Value
coordinates(variogram) = ~x + y
variogram <- autofitVariogram(z ~ x + y, variogram, model = "Exp") # exponen
tial
plot(variogram) # sill is 15, range is 0.11, nugget is 14

```

Experimental variogram and fitted variogram model



```
a <- 0.11 # range
c <- 15 # sill
n <- 14
gamma <- function(d) {
  g <- n + (c - n) * (1 - exp(-d/a))
  return(g)
}

# get Matrix A
A <- gamma(D)
A <- rbind.data.frame(A, 1)
A <- cbind.data.frame(A, 1)
diag(A) <- 0
names(A) <- c(seq(1:12))
A.inverse <- solve(A)

for (i in 1:10) {
  # for each centroid get vector d, d
  d <- c()
  for (j in 1:11) {
    # for each control point
    distance <- sqrt((centroids$x[i] - Ozone_Sensor_Value$x[j])^2 + (centroids$y[i] - Ozone_Sensor_Value$y[j])^2)
```

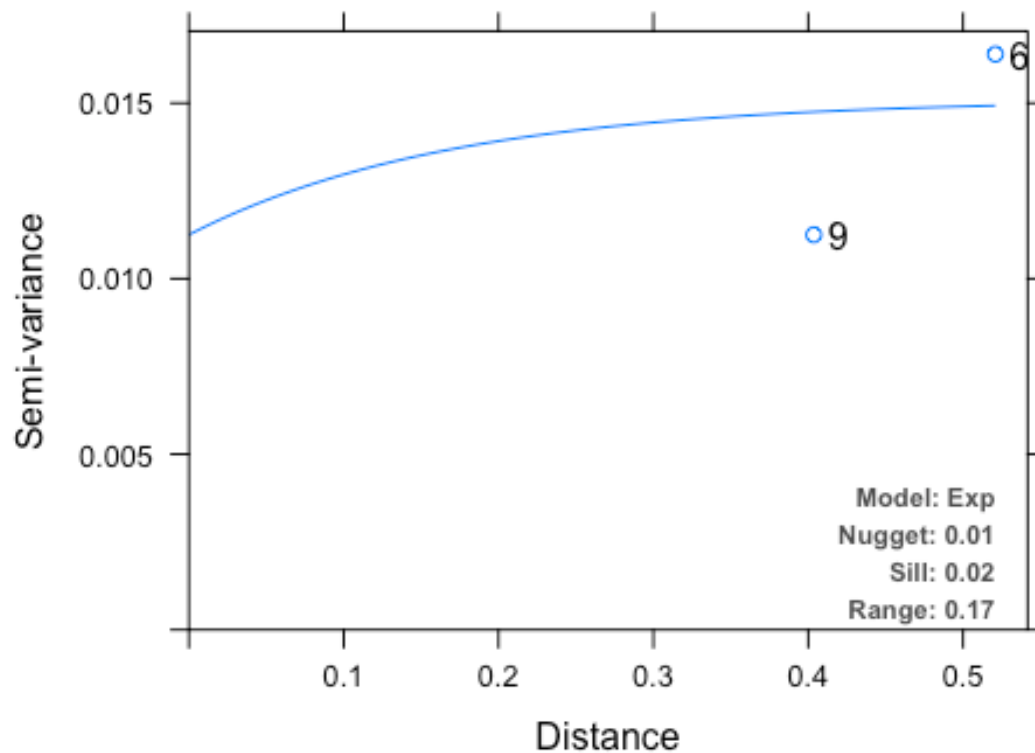
```

    d <- c(d, distance)
  }
  # get vector b
  b <- c(gamma(d), 1)
  # get the weight w
  w = A.inverse %%% b
  z.estimate <- sum(ControlPoints$ozone_value * w[1:11])
  centroids$z[i] = z.estimate
}
centroids

# create the OK map // parameters
OK.result <- as.data.frame(centroids)
coordinates(OK.result) = ~x + y
variogram <- autofitVariogram(z ~ x + y, OK.result, model = "Exp")
variogram
plot(variogram)

```

Experimental variogram and fitted variogram model



```

nugget = 0.01
sill = 0.02
range = 0.17
model <- vgm(psill = sill, model = "Exp", range = range, nugget = nugget)
krige <- krige(OK.result$z ~ 1, OK.result, grid, model = model) # using ordi

```

nary kriging

```
OzonePlot2 <- par(mar = c(0, 0, 0, 0))
image(krige, "var1.pred", col = terrain.colors(50))
contour(krige, "var1.pred", add = TRUE, nlevels = 10)
plot(OK.result, add = TRUE, pch = 10, cex = 0.5)
text(coordinates(OK.result), paste(as.character(round(OK.result$z, 1)), as.ch
aracter(PA_County_Select$COUNTY)), pos = 4, cex = 0.8, col = "black")
map.axes(cex.axis = 0.8)
par(OzonePlot2)
```