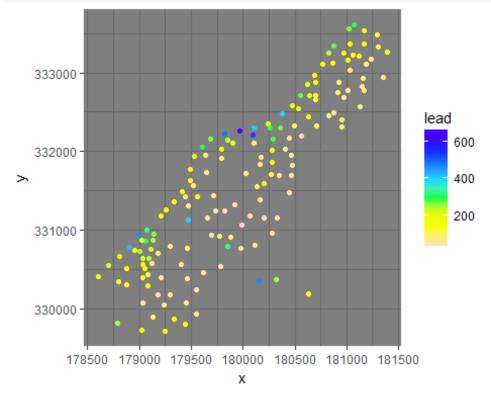
STAT 506 Homework 1

```
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January 24, 2018
4)
a)
soil <- read.table(file = "soil.txt", header = T)</pre>
head(soil)
##
                y lead zinc
## 1 181072 333611 299 1022
## 2 181025 333558
                   277 1141
## 3 181165 333537 199 640
## 4 181298 333484 116 257
## 5 181307 333330 117 269
## 6 181390 333260 137 281
#quick summary of the data
summary(soil)
##
                                          lead
                                                         zinc
                                                   Min. : 113.0
##
   Min.
          :178605
                    Min. :329714
                                     Min. : 37.0
   1st Qu.:179371
                    1st Qu.:330762
                                     1st Qu.: 72.5
                                                    1st Qu.: 198.0
##
## Median :179991
                    Median :331633
                                     Median :123.0
                                                    Median : 326.0
## Mean :180005
                                     Mean :153.4
                    Mean :331635
                                                   Mean : 469.7
## 3rd Qu.:180630
                    3rd Qu.:332463
                                     3rd Qu.:207.0
                                                     3rd Qu.: 674.5
## Max.
          :181390
                    Max.
                           :333611
                                     Max. :654.0 Max.
                                                           :1839.0
#plot of the geodata
g <- ggplot(data = soil, aes(x=x, y=y))</pre>
h <- g + geom_point(aes(colour = lead)) + scale_color_gradientn(colours =rev(topo.colors(8))) +
  theme dark()
h
```

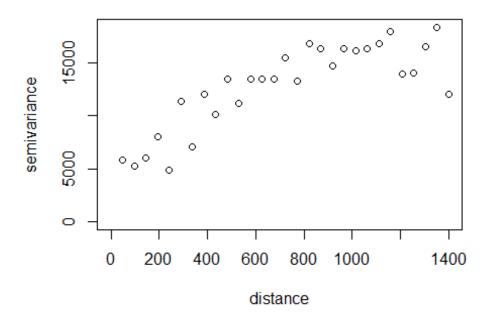


```
b)
```

```
#convert to geodata format
soilgeo <- as.geodata(soil, coords.col = 1:2, data.col = 3, covar.col = 4)
#compute empirical variogram and plot</pre>
```

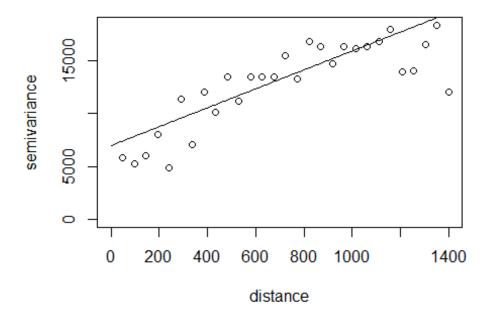
```
#visually, nugget is 5000, sill is 17500, range ~ 800, partial sill 17500-5000=12500
omndvar <- variog(soilgeo, option = "bin", uvec = seq(0, 1400, length = 30 ))
## variog: computing omnidirectional variogram
plot(omndvar, main = "Omnidirectional Variogram up to Lag Distance 1400")</pre>
```

Omnidirectional Variogram up to Lag Distance 140



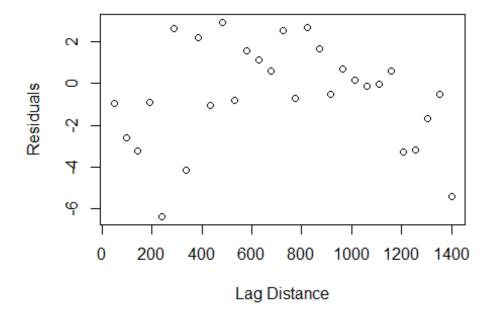
```
c)
##Triangular Model
#Compute variogram
#Need to use linear model with sigma^2/a instead of sigma^2,
#and then range becomes A/A = 1 using geoR's specification
vario.tri <- variofit(omndvar, ini.cov.pars = c(12500/800, 1), cov.model = "linear", weights =</pre>
"cressie")
## variofit: covariance model used is linear
## variofit: weights used: cressie
## variofit: minimisation function used: optim
## Warning in variofit(omndvar, ini.cov.pars = c(12500/800, 1), cov.model =
## "linear"
           ', : unreasonable initial value for sigmasq + nugget (too low)
vario.tri
## variofit: model parameters estimated by WLS (weighted least squares):
## covariance model is: linear
## parameter estimates:
##
       tausq
               sigmasq
                             phi
## 6992.4645
                8.9583
                          1.0000
## Practical Range with cor=0.05 for asymptotic range: Inf
## variofit: minimised weighted sum of squares = 175.2857
#Fit values and calculate residuals
fit.tri = vario.tri$nugget + vario.tri$cov.pars[1] * (omndvar$u/vario.tri$cov.pars[2])
res.tri = sqrt(omndvar$n) * ((omndvar$v - fit.tri)/fit.tri)
#plot of Empirical Variogram vs. Fitted Model
plot(omndvar, main = "Triangular Variogram Model vs. Empirical") + lines(vario.tri)
```

Triangular Variogram Model vs. Empirical



```
## integer(0)
#Plot of residuals
plot(y = res.tri, main = "Triangular Model Residuals", ylab = "Residuals", xlab= "Lag Distance",
x=omndvar$u)
```

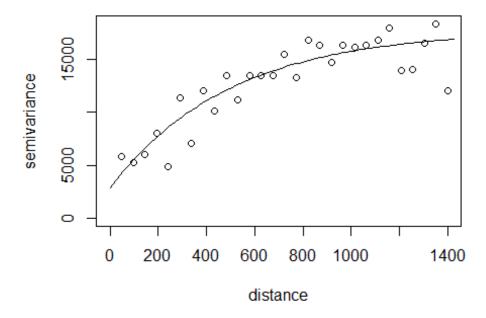
Triangular Model Residuals



```
##Exponential Model
#Compute Variogram
vario.exp <- variofit(omndvar, ini.cov.pars = c(12500, 800), cov.model = "exp", weights =
"cressie", nugget = 5000)
## variofit: covariance model used is exponential
## variofit: weights used: cressie
## variofit: minimisation function used: optim</pre>
```

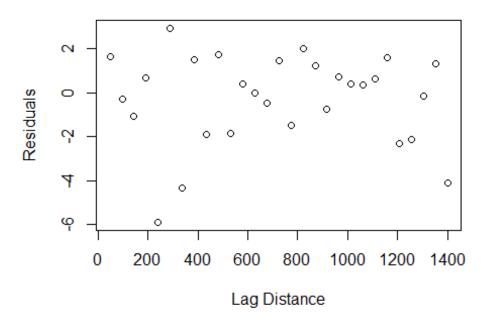
```
vario.exp
## variofit: model parameters estimated by WLS (weighted least squares):
## covariance model is: exponential
## parameter estimates:
##
        tausq
                 sigmasq
                                phi
##
   2837.1802 14957.5009
                           498.8027
## Practical Range with cor=0.05 for asymptotic range: 1494.279
## variofit: minimised weighted sum of squares = 121.38
#Fit Values and calculate residuals
fit.exp = vario.exp$nugget + vario.exp$cov.pars[1] * (1 - exp(-omndvar$u/vario.exp$cov.pars[2]))
res.exp = sqrt(omndvar$n) * ((omndvar$v - fit.exp)/fit.exp)
#plot of Empirical Variogram vs. Fitted Model
plot(omndvar, main = "Exponential Variogram Model vs. Empirical") +lines(vario.exp)
```

Exponential Variogram Model vs. Empirical



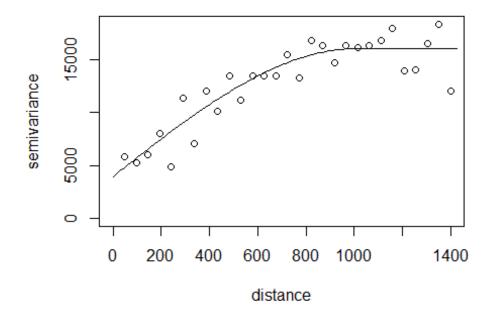
```
## integer(0)
#Plot of residuals
plot(y=res.exp, main = "Exponential Model Residuals", ylab = "Residuals", xlab= "Lag Distance",
x=omndvar$u)
```

Exponential Model Residuals



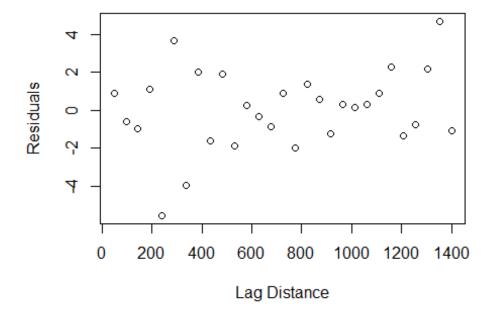
```
##Spherical Model
#Compute Variogram
vario.sph <- variofit(omndvar, ini.cov.pars = c(12500, 800), cov.model = "spherical", weights =</pre>
"cressie", nugget = 5000)
## variofit: covariance model used is spherical
## variofit: weights used: cressie
## variofit: minimisation function used: optim
vario.sph
## variofit: model parameters estimated by WLS (weighted least squares):
## covariance model is: spherical
## parameter estimates:
       tausq
               sigmasq
## 3959.946 12114.263 1010.333
## Practical Range with cor=0.05 for asymptotic range: 1010.333
## variofit: minimised weighted sum of squares = 114.6208
#Fit Values and calculate residuals
fit.sph = vario.sph$nugget + vario.sph$cov.pars[1] * (1.5*(omndvar$u/vario.sph$cov.pars[2])-
.5*(omndvar$u/vario.sph$cov.pars[2])^3)
res.sph = sqrt(omndvar$n) * ((omndvar$v - fit.sph)/fit.sph)
#plot of Empirical Variogram vs. Fitted Model
plot(omndvar, main = "Spherical Variogram Model vs. Empirical") + lines(vario.sph)
```

Spherical Variogram Model vs. Empirical



```
## integer(0)
#Plot of residuals
plot(y = res.sph, main = "Spherical Model Residuals", ylab = "Residuals", xlab= "Lag Distance",
x=omndvar$u)
```

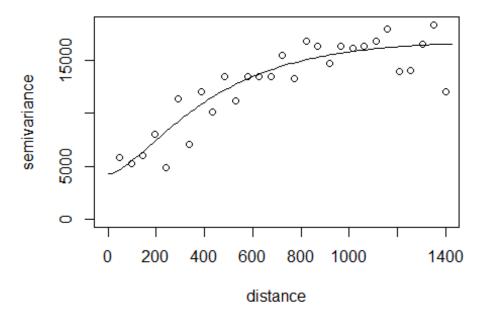
Spherical Model Residuals



```
##Matern Model
#Compute Variogram
vario.matern <- variofit(omndvar, ini.cov.pars = c(12500, 800), cov.model = "matern", weights =
"cressie", kappa = 1)</pre>
```

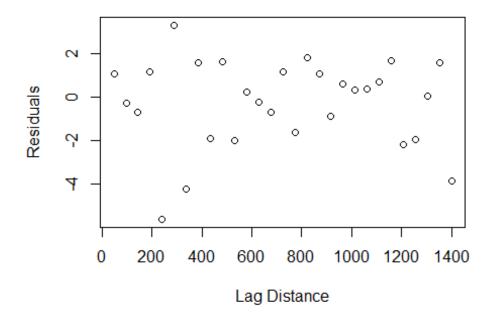
```
## variofit: covariance model used is matern
## variofit: weights used: cressie
## variofit: minimisation function used: optim
vario.matern
## variofit: model parameters estimated by WLS (weighted least squares):
## covariance model is: matern with fixed kappa = 1
  parameter estimates:
                 sigmasq
        tausq
  4261.6368 12630.1329
                           293.6961
##
## Practical Range with cor=0.05 for asymptotic range: 1174.35
##
## variofit: minimised weighted sum of squares = 116.6109
#Fit Values and calculate residuals
fit.mtr = vario.matern$nugget + vario.matern$cov.pars[1] * (1 - (1/gamma(1)) * (abs(omndvar$u) /
vario.matern$cov.pars[2]) * besselK((abs(omndvar$u) / vario.matern$cov.pars[2]), nu = 1))
res.mtr = sqrt(omndvar$n) * ((omndvar$v - fit.mtr)/fit.mtr)
#plot of Empirical Variogram vs. Fitted Model
plot(omndvar, main = "Matern Variogram Model vs. Empirical") + lines(vario.matern)
```

Matern Variogram Model vs. Empirical



```
## integer(0)
#Plot of residuals
plot(y = res.mtr, main = "Matern Model Residuals", ylab = "Residuals", xlab= "Lag Distance",
x=omndvar$u)
```

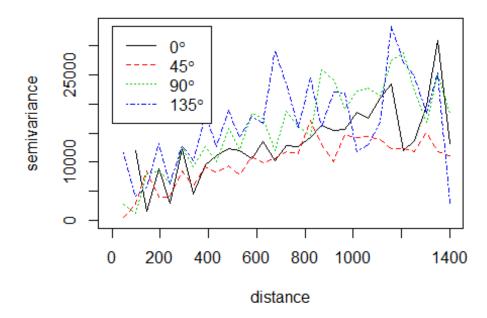
Matern Model Residuals



The triangular model is clearly a poor fit, but the others (Exponential, Spherical, Matern) all appear to be reasonable fits for the data based on the fitted model and residual plots. Spherical has the smallest weighted sum of squares and also the most reasonable looking residual plot, so by that primitive reasoning I would say spherical model is the best.

d)

```
#Compute Direction Variograms
var.direct <- variog4(soilgeo, uvec = seq(0, 1400, length = 30), direction =</pre>
c(0,pi/4,pi/2,3*pi/4))
## variog: computing variogram for direction = 0 degrees (0 radians)
##
           tolerance angle = 22.5 degrees (0.393 radians)
## variog: computing variogram for direction = 45 degrees (0.785 radians)
##
           tolerance angle = 22.5 degrees (0.393 radians)
## variog: computing variogram for direction = 90 degrees (1.571 radians)
           tolerance angle = 22.5 degrees (0.393 radians)
##
## variog: computing variogram for direction = 135 degrees (2.356 radians)
##
           tolerance angle = 22.5 degrees (0.393 radians)
## variog: computing omnidirectional variogram
#Plot Empirical Variograms
plot(var.direct)
```



There is no convincing visual evidence for anisotropy in any direction. All of the directional variograms appear to follow similar patterns, especially at short lag distances, which suggests that the variogram only depends on lag distance and not direction. Most of the difference is likely due to the nugget effect. IF there is anisotropy, it would likely be in the 3pi/4 direction as that one is visually the most different.