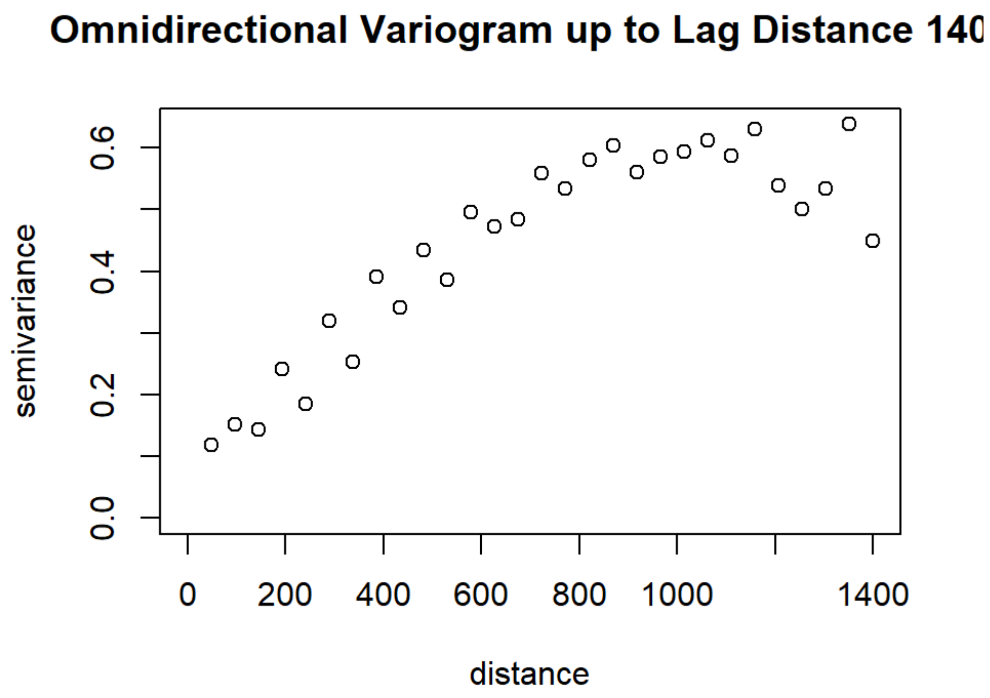
3)

a)

```
soil <- read.table(file = "soil.txt", header = T)
soil$lead <- log(soil$lead)
soilgeo <- as.geodata(soil, coords.col = 1:2, data.col = 3, covar.col =
4)

#####
#estimate the empirical variogram
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"
)
```




```
#exponential model
vario.exp <- variofit(omndvar, ini.cov.pars = c(.6, 1100), cov.model = "
exp", weights = "cressie", nugget = 0.1)
mle.exp = likfit(soilgeo,ini.cov.pars = vario.exp$cov.pars,nugget = vari
o.exp$nugget, cov.model = "exp")
```

```r
mle.exp
```

```
## likfit: estimated model parameters:
##         beta       tausq     sigmasq         phi 
## "   5.2014" "   0.0564" "   0.7655" "1099.9997" 
## Practical Range with cor=0.05 for asymptotic range: 3295.305
## 
## likfit: maximised log-likelihood = -96.97
```

```r
#spherical model
vario.sph <- variofit(omndvar, ini.cov.pars = c(.6, 1100), cov.model = "
spherical", weights = "cressie", nugget = 0.1)
mle.sph = likfit(soilgeo,ini.cov.pars = vario.sph$cov.pars,nugget = vari
o.sph$nugget, cov.model = "spherical")
```

```r
mle.sph
```

```
## likfit: estimated model parameters:
##         beta       tausq     sigmasq         phi 
## "   4.9809" "   0.0608" "   0.4928" "1184.3991" 
## Practical Range with cor=0.05 for asymptotic range: 1184.399
## 
## likfit: maximised log-likelihood = -95.22
```

```r
#matern model
vario.mtr <- variofit(omndvar, ini.cov.pars = c(.6, 1100), cov.model = "
matern", weights = "cressie", kappa = 1)
mle.mtr = likfit(soilgeo,ini.cov.pars = vario.mtr$cov.pars,nugget = vari
o.mtr$nugget, cov.model = "matern", kappa = 1, fix.kappa = T)
```

```r
mle.mtr
```

```
## likfit: estimated model parameters:
##         beta       tausq     sigmasq         phi 
## "   5.5393" "   0.1063" "   1.9395" "1099.9898" 
## Practical Range with cor=0.05 for asymptotic range: 4398.334
## 
## likfit: maximised log-likelihood = -96.63
```

```r
#compare BICs
c(mle.mtr$BIC, mle.exp$BIC, mle.sph$BIC)
```

```
## [1] 213.4313 214.1098 210.6073
```

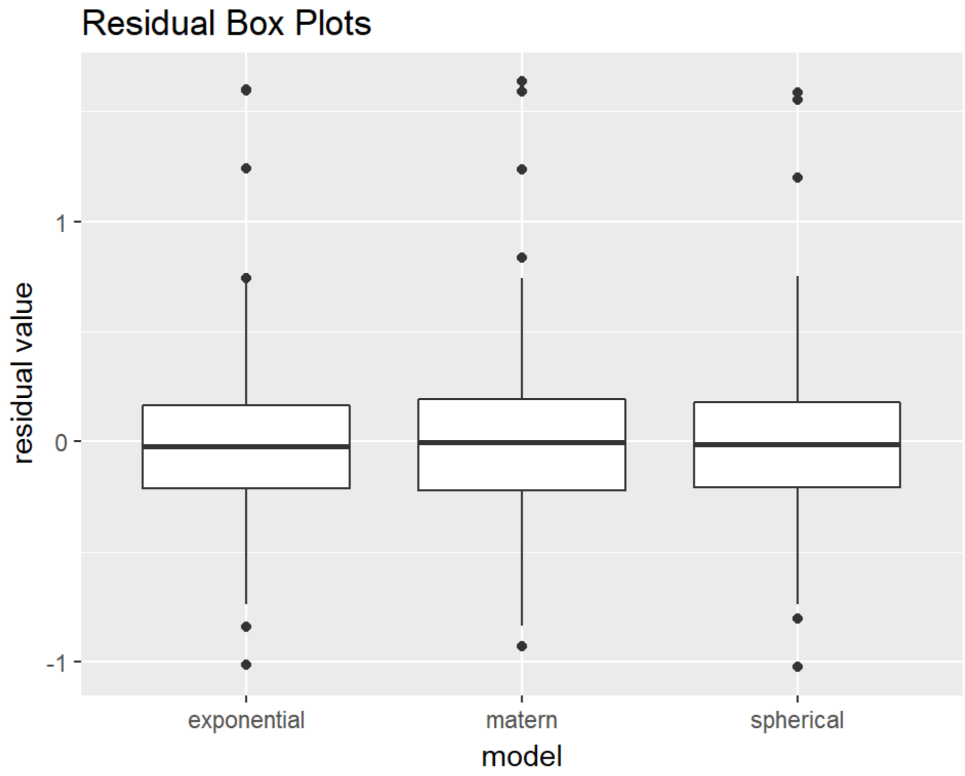
b)

```r
#exponential model cross validation
exp.xv <- xvalid(soilgeo, model = mle.exp, locations.xvalid = "all", ree
stimate = F)
exp.mspe <- (1/length(exp.xv$error))*sum((exp.xv$error)^2)

#spherical model cross validation
sph.xv <- xvalid(soilgeo, model = mle.sph, locations.xvalid = "all", ree
stimate = F)
sph.mspe <- (1/length(sph.xv$error))*sum((sph.xv$error)^2)

#matern model cross validation
mtr.xv <- xvalid(soilgeo, model = mle.mtr, locations.xvalid = "all", ree
stimate = F)
mtr.mspe <- (1/length(mtr.xv$error))*sum((mtr.xv$error)^2)
```

```r
#now let's take a look at the MSPE values
resids <- data.frame(cbind(exp.xv$error, sph.xv$error, mtr.xv$error))
names(resids) <- c("exponential", "spherical", "matern")
mspes <- rbind(c(names(resids)), c(exp.mspe,sph.mspe, mtr.mspe))
mspes
```

```
##      [,1]                 [,2]                 [,3]
## [1,] "exponential"        "spherical"          "matern"
## [2,] "0.156225452532669" "0.154837815713956" "0.156442241366865"
```

```r
#spherical has the lowest MSPE, just as it had smallest BIC. Conclude sp
herical is the best model

#get residuals from the xvalid() object to plot
#boxplots look very similar, just as the MSPEs were very close to each o
ther
resids1 <- gather(resids)
b <- ggplot(data = resids1, aes(x = key, y = value))
b+ geom_boxplot() + ylab("residual value") + xlab("model") + ggtitle("Re
sidual Box Plots")
```

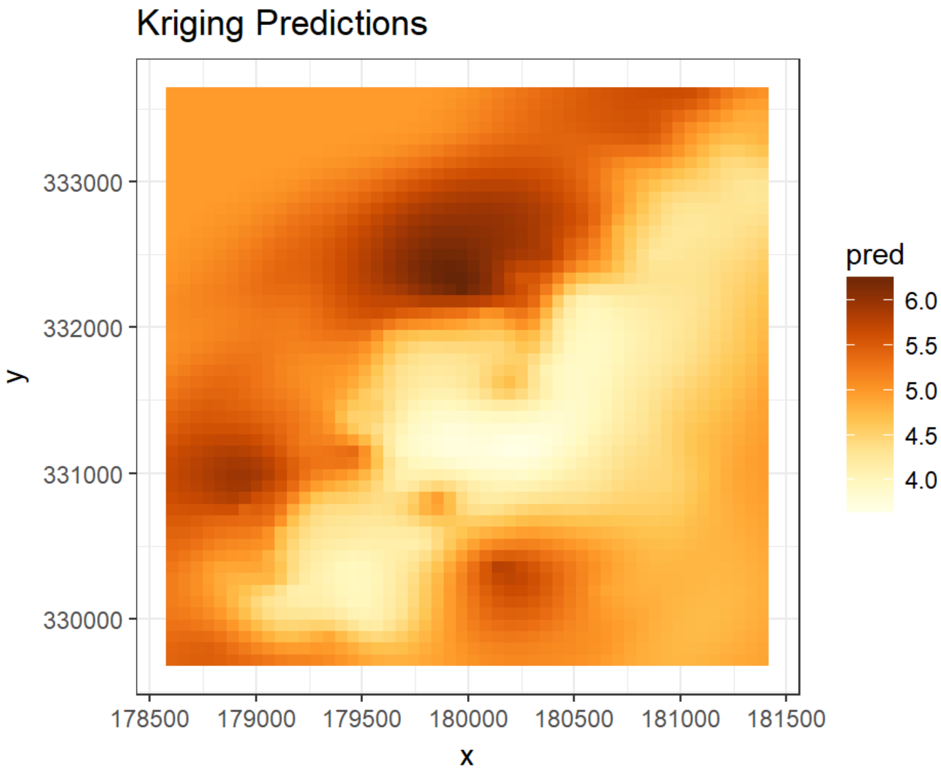


c)

```
#Create our grid to plot
xrange <- range(soil[,1])
yrange <- range(soil[,2])
grid <- expand.grid(x = seq(xrange[1],xrange[2],l=50),y=seq(yrange[1],yr
ange[2],l=50))

#Krige using our best model, which was the Spherical model
kc.sph <- krige.conv(geodata=soilgeo, locations= grid, krige=krige.contr
ol(type.krige="OK",obj.model = mle.sph))
```

```
## krige.conv: model with constant mean
## krige.conv: Kriging performed using global neighbourhood
```

```
#Plot our predictions using ggplot2
krigimage <- data.frame(x=grid$x,y = grid$y, pred=kc.sph$predict)
i <- ggplot(krigimage,mapping = aes(x = x, y = y))
h <- i + geom_tile(mapping = aes(fill = pred)) +  scale_fill_gradientn(c
olours = brewer.pal(n = 9, name = "YlOrBr"))+
    theme_bw() + xlab("x") + ylab("y")+ ggtitle("Kriging Predictions")
h
```




```r
#Now a plot of our kriging variances
variances.sph = data.frame(x=grid$x,y = grid$y,var=kc.sph$krige.var)
v <- ggplot(variances.sph,mapping = aes(x = x, y = y))
v + geom_tile(mapping= aes(fill = var)) + scale_fill_gradientn(colours =
brewer.pal(n = 9, name = "Purples")) +
  theme_bw() + xlab("x") + ylab("y") + ggtitle("Kriging Variances")
```