

# Case Study 2, Part 2

*Peter Claussen*

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```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.3.2
```

```
library(rsm)
```

```
library(ncf)
```

```
library(ape)
```

```
## Warning: package 'ape' was built under R version 3.3.2
```

```
##
```

```
## Attaching package: 'ape'
```

```
## The following object is masked from 'package:ncf':
```

```
##
```

```
##      mantel.test
```

```
cbPalette <- c("#999999", "#E69F00", "#56B4E9", "#009E73", "#0072B2", "#D55E00", "#F0E442", "#CC79A7", "#
```

## East Quarter

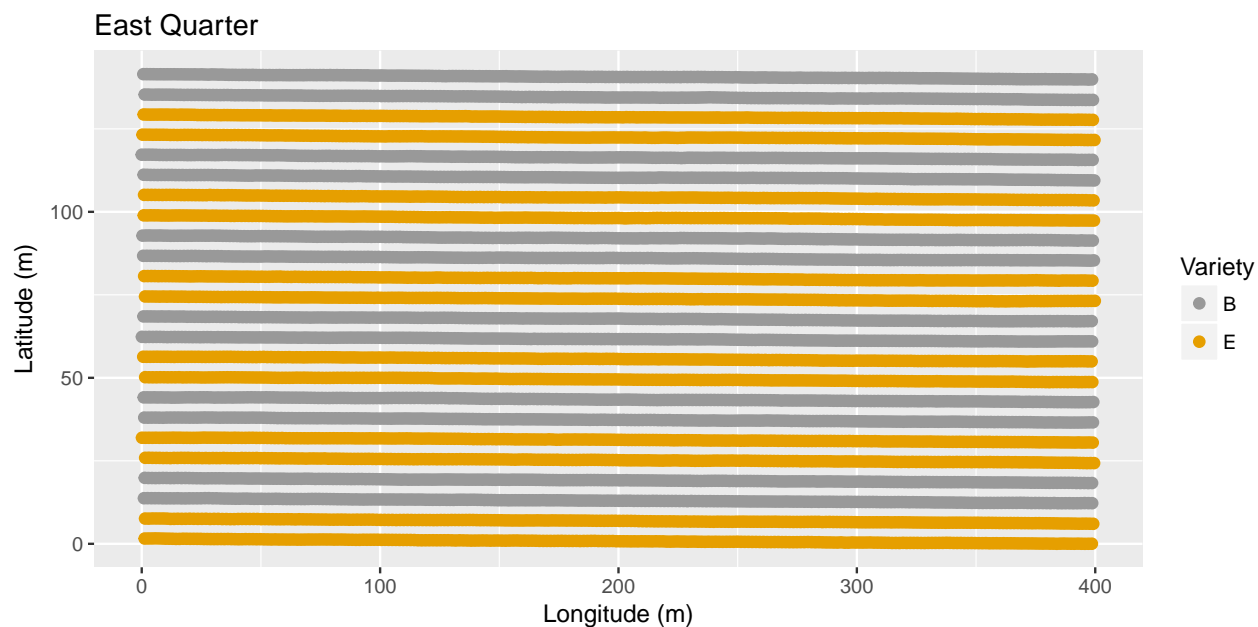
```
load(file="Strips.Rda")
```

```
ggplot(EastQuarter.dat, aes(Easting,Northing)) +
```

```
geom_point(aes(colour = Product),size=2) +
```

```
scale_colour_manual(values=cbPalette) +
```

```
labs(colour = "Variety", x="Longitude (m)", y="Latitude (m)", title = "East Quarter")
```



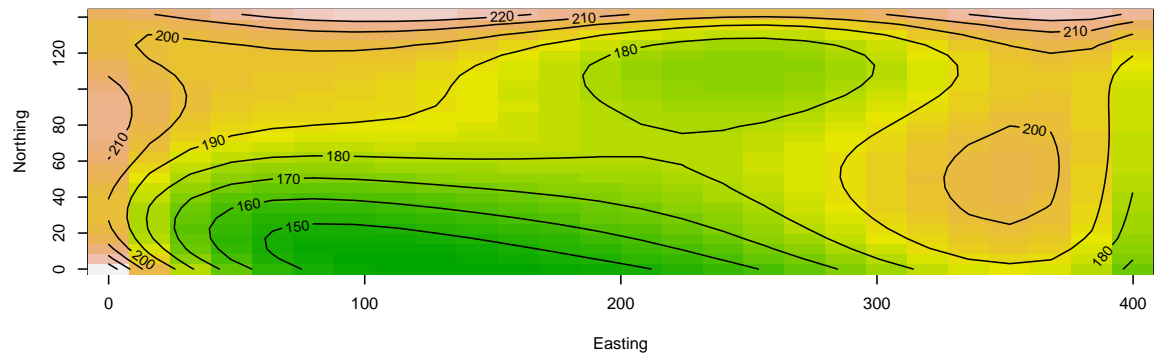
We'll want to look at measures of spatial correlation, but first let's try to determine a trend model for each. We aren't too interested in kriging, since we won't be trying to map yields to a uniform set of points.

## Trend Surface

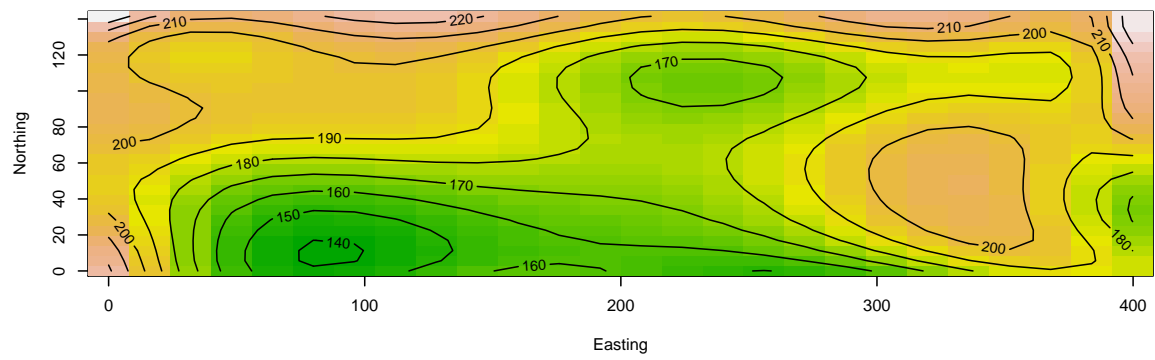
```
Yield5.lm <- lm(Yield ~ poly(Easting, Northing, degree=5), data=EastQuarter.dat)
Yield7.lm <- lm(Yield ~ poly(Easting, Northing, degree=7), data=EastQuarter.dat)
Yield9.lm <- lm(Yield ~ poly(Easting, Northing, degree=9), data=EastQuarter.dat)
Yield11.lm <- lm(Yield ~ poly(Easting, Northing, degree=11), data=EastQuarter.dat)

par(mfrow=c(4,1))
contour(Yield5.lm, Northing ~ Easting, image = TRUE, main="Poly 5")
contour(Yield7.lm, Northing ~ Easting, image = TRUE, main="Poly 7")
contour(Yield9.lm, Northing ~ Easting, image = TRUE, main="Poly 9")
contour(Yield11.lm, Northing ~ Easting, image = TRUE, main="Poly 11")
```

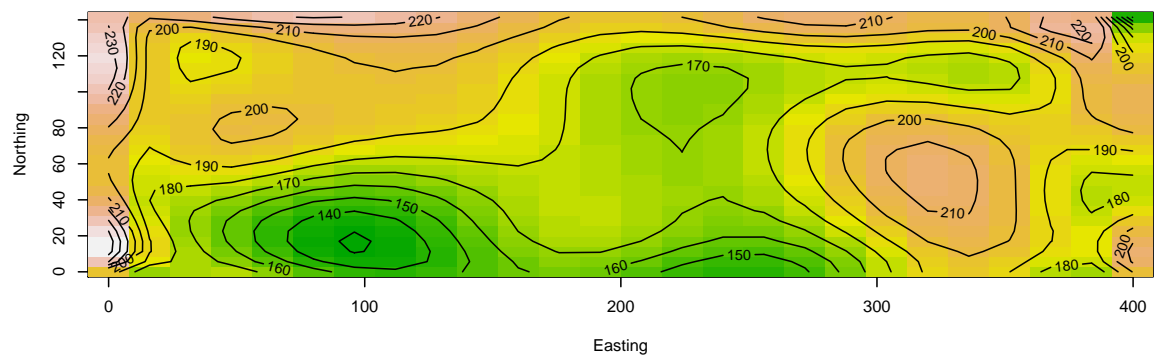
**Poly 5**



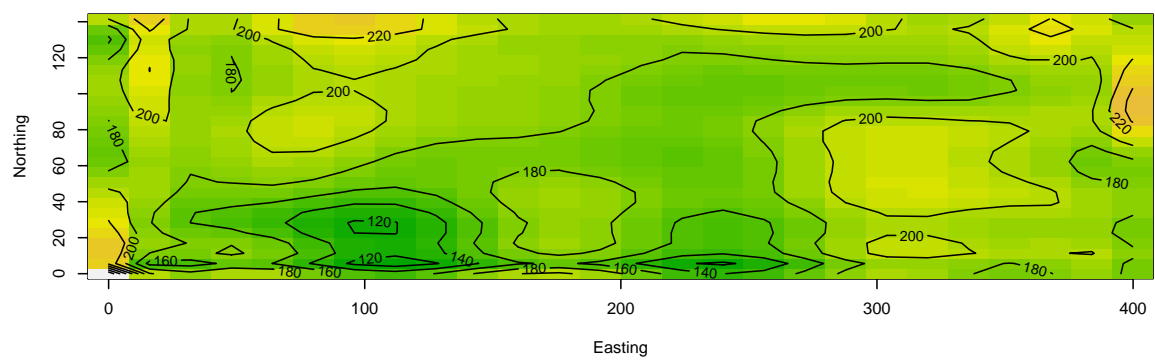
**Poly 7**



**Poly 9**



**Poly 11**



```
par(mfrow=c(1,1))
```

I'm concerned that Poly 11 might be overfitting in the lower left corner, so we'll choose Poly 9 (note - we could continue with diagnostics of Local I to check that assertion).

```
EastQuarter.dat$Yield9.resid <- Yield9.lm$residuals
```

## Check for white noise

```
Distance.mat <- as.matrix(dist(cbind(EastQuarter.dat$Easting, EastQuarter.dat$Northing)))
Distance.mat <- 1/Distance.mat
diag(Distance.mat) <- 0
```

```
print(Moran9Yield <- Moran.I(EastQuarter.dat$Yield, Distance.mat))
```

```
## $observed
## [1] 0.1223093
##
## $expected
## [1] -0.0001570352
##
## $sd
## [1] 0.0003680123
##
## $p.value
## [1] 0
```

```
print(Moran9Resid <- Moran.I(EastQuarter.dat$Yield9.resid, Distance.mat))
```

```
## $observed
## [1] 0.03937349
##
## $expected
## [1] -0.0001570352
##
## $sd
## [1] 0.0003680108
##
## $p.value
## [1] 0
```

## Local Correlation

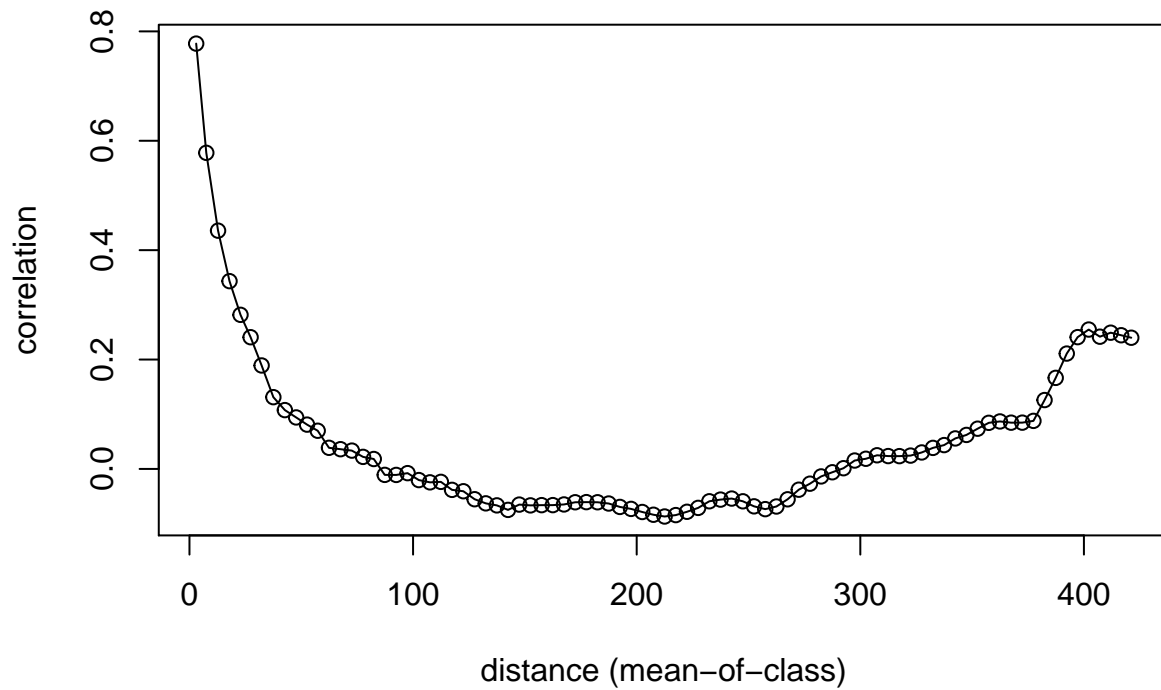
Resampling can take a very long time, so I'll use a flag to control whether we resample or simply plot local measures. Resampling is needed for p-values; I'm not concerned about p-values for the points in the correlogram.

```
resample = 100
```

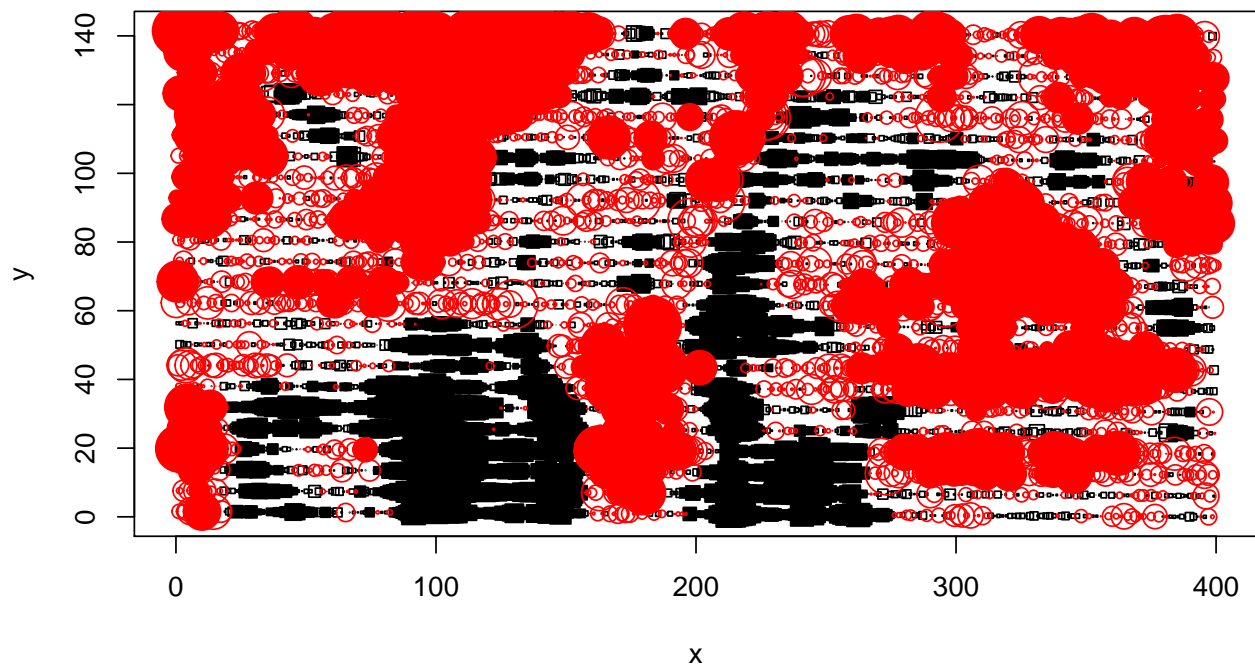
## Correlation in Yield

```
Yield.clg <- correlog(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Yield,  
                      increment=5, resamp=0, quiet=TRUE)  
plot(Yield.clg)
```

**Correlogram**



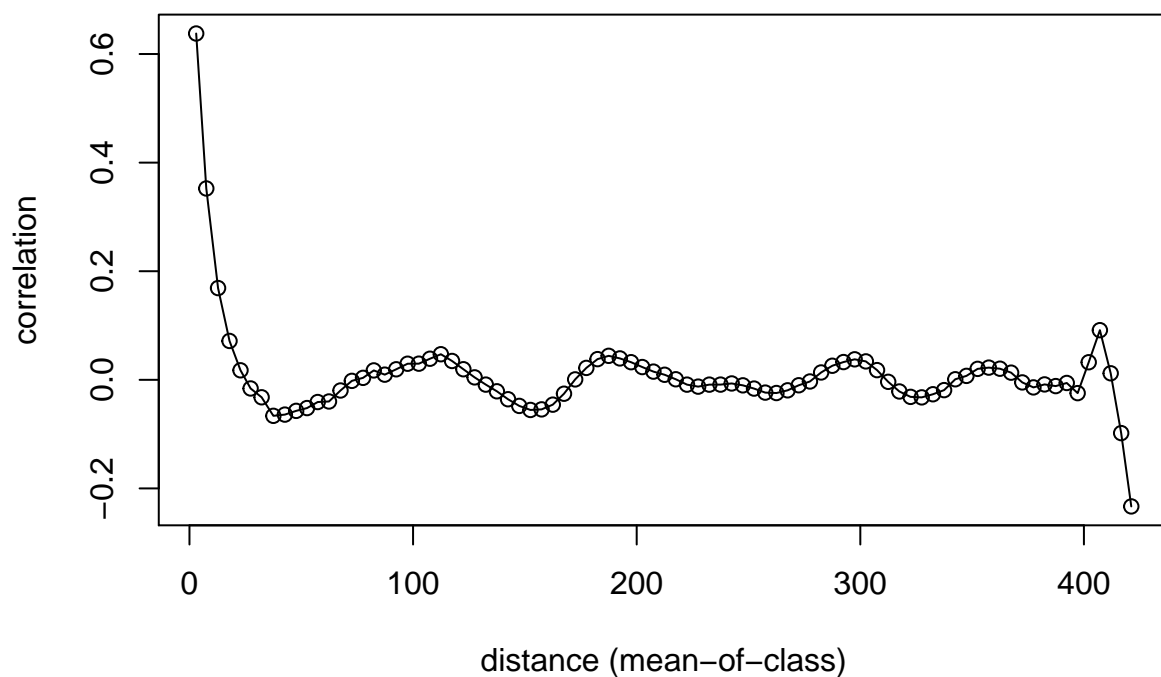
```
Yield9.lisa <- lisa(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Yield,  
                   neigh=10, resamp=resample, quiet=TRUE)  
plot.lisa(Yield9.lisa, negh.mean=FALSE)
```



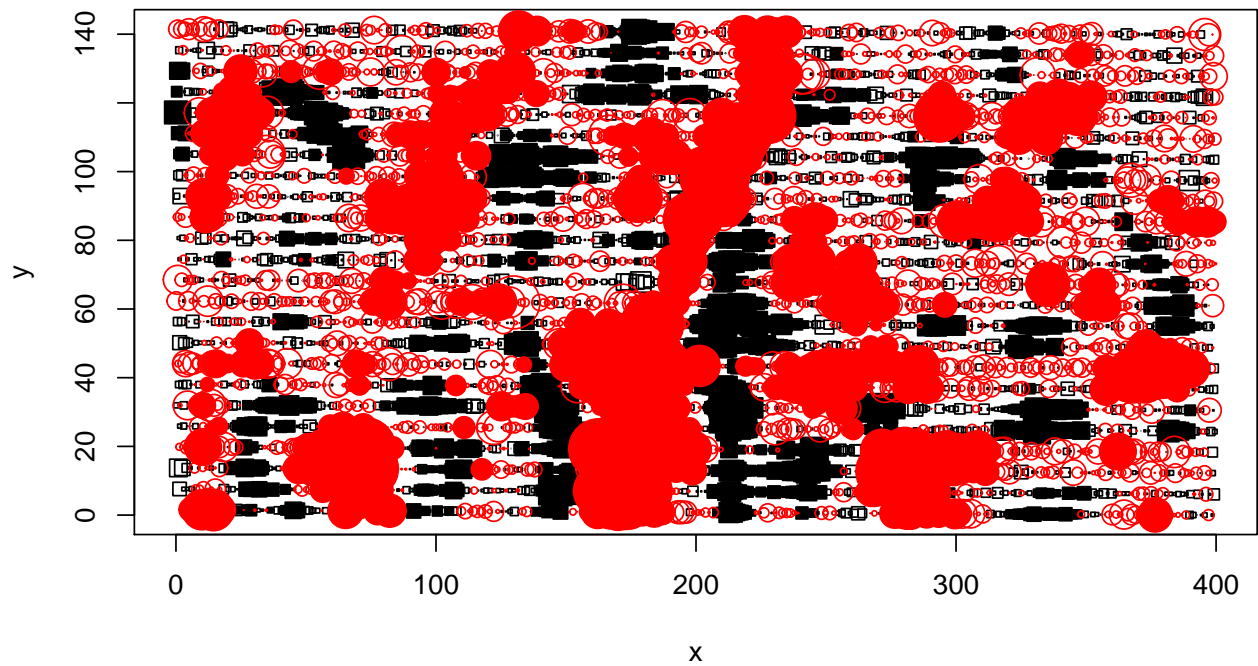
### Correlation in Yield Residuals

```
Yield9.resid.clg <- correlog(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Yield9,
                             increment=5, resamp=0, quiet=TRUE)
plot(Yield9.resid.clg)
```

### Correlogram

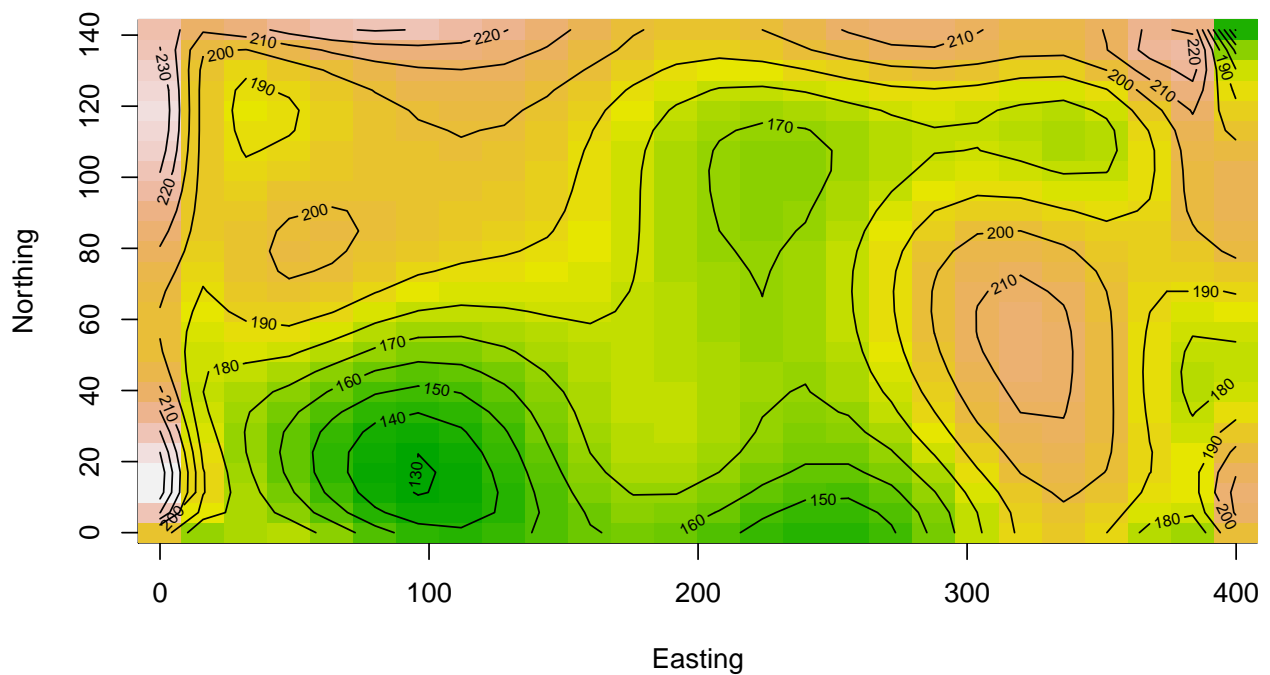


```
Yield9.resid.lisa <- lisa(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Yield9.resid,
                        neigh=10, resamp=resample, quiet=TRUE)
plot.lisa(Yield9.resid.lisa, neigh.mean=FALSE)
```



```
contour(Yield9.lm, Northing ~ Easting, image = TRUE, main="Poly 9")
```

**Poly 9**

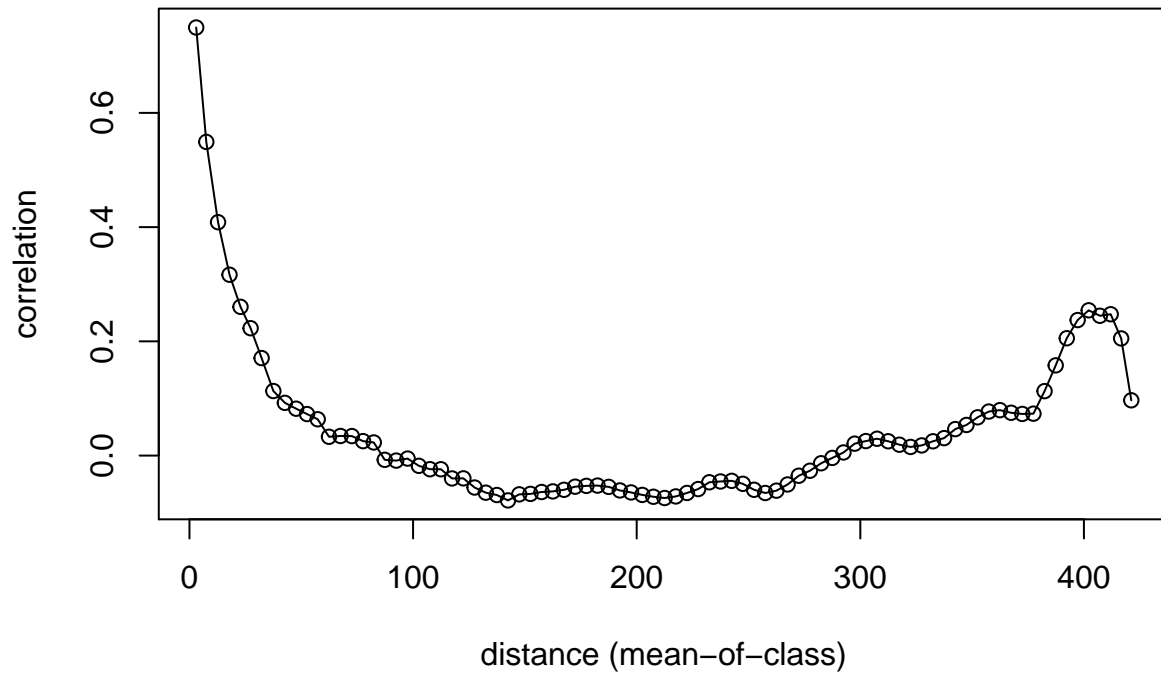


## Correlation in Quantiles

```
Quantile9.lm <- lm(Quantile ~ poly(Easting, Northing, degree=9), data=EastQuarter.dat)  
EastQuarter.dat$Quantile9.resid <- Quantile9.lm$residuals
```

```
Quantile.clg <- correlog(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Quantile,  
                          increment=5, resamp=0, quiet=TRUE)  
plot(Quantile.clg)
```

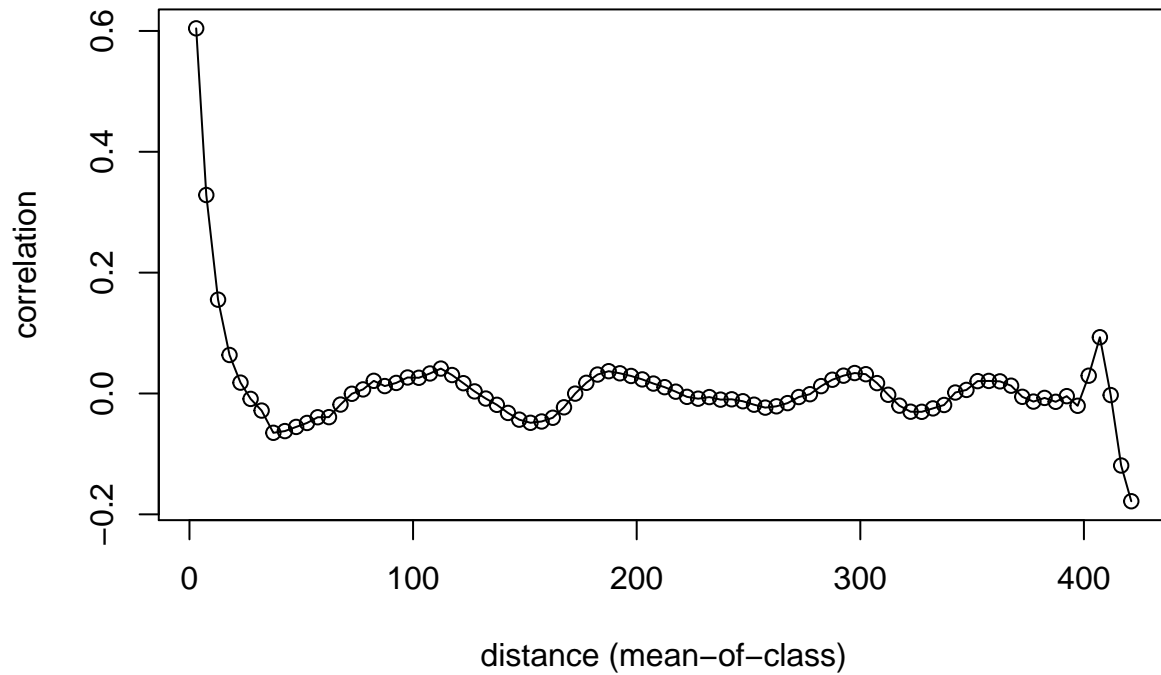
### Correlogram



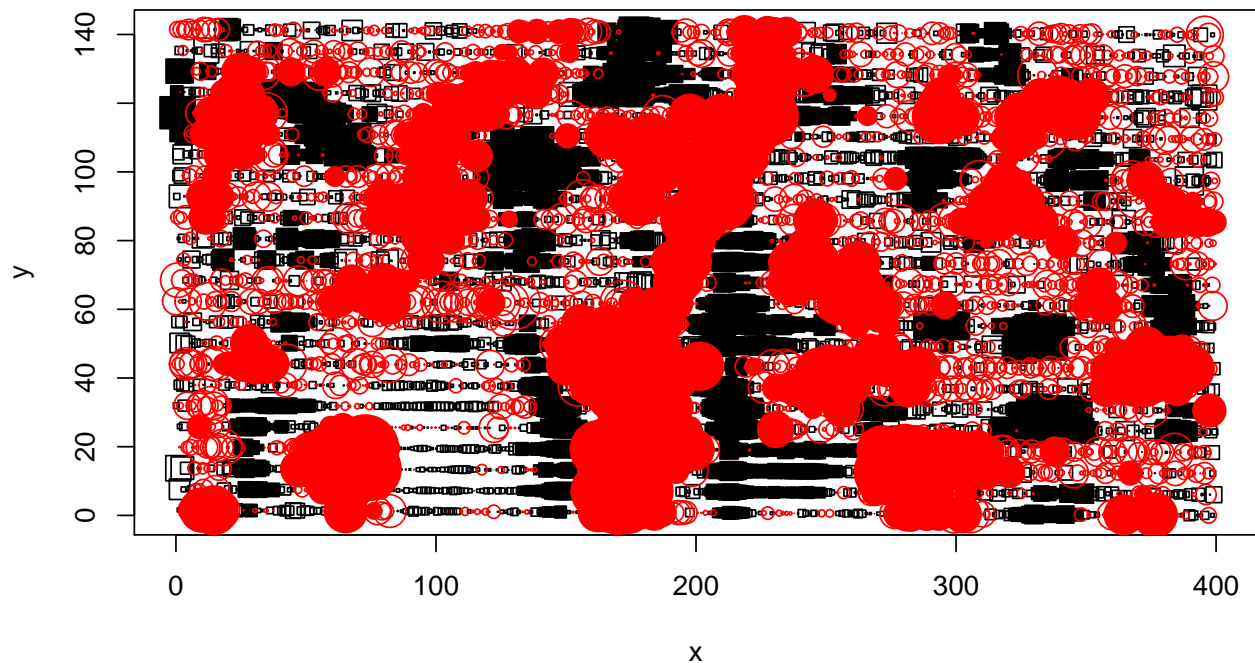
```
Quantile.resid.clg <- correlog(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Quantile9.resid,  
                               increment=5, resamp=0, quiet=TRUE)  
plot(Quantile.resid.clg)
```



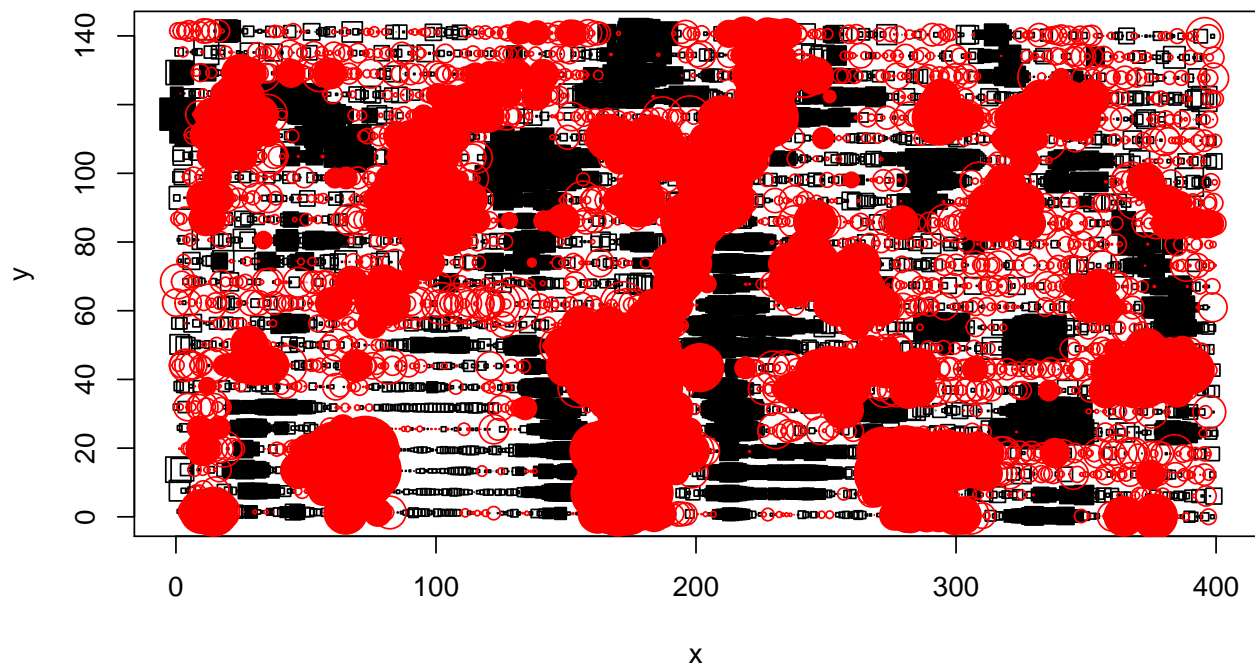
## Correlogram



```
Quantile.lisa <- lisa(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Quantile9,
                     neigh=10, resamp=resample, quiet=TRUE)
plot.lisa(Quantile.lisa, neigh.mean=FALSE)
```



```
Quantile.resid.lisa <- lisa(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$Quantile9,
                           neigh=10, resamp=resample, quiet=TRUE)
plot.lisa(Quantile.resid.lisa, neigh.mean=FALSE)
```



## Trend + Variety AOV

Does including variety (Product) in the model improve spatial correlation?

```
YieldVariety5.lm <- lm(Yield ~ poly(Easting, Northing, degree=5) + Product, data=EastQuarter.dat)
summary(aov(YieldVariety5.lm))
```

```
##                                Df  Sum Sq Mean Sq F value Pr(>F)
## poly(Easting, Northing, degree = 5)  20 1790930    89547   144.6 <2e-16
## Product                               1   208996   208996   337.6 <2e-16
## Residuals                           6347 3929539     619
##
## poly(Easting, Northing, degree = 5) ***
## Product                               ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
YieldVariety9.lm <- lm(Yield ~ poly(Easting, Northing, degree=9) + Product, data=EastQuarter.dat)
summary(aov(YieldVariety9.lm))
```

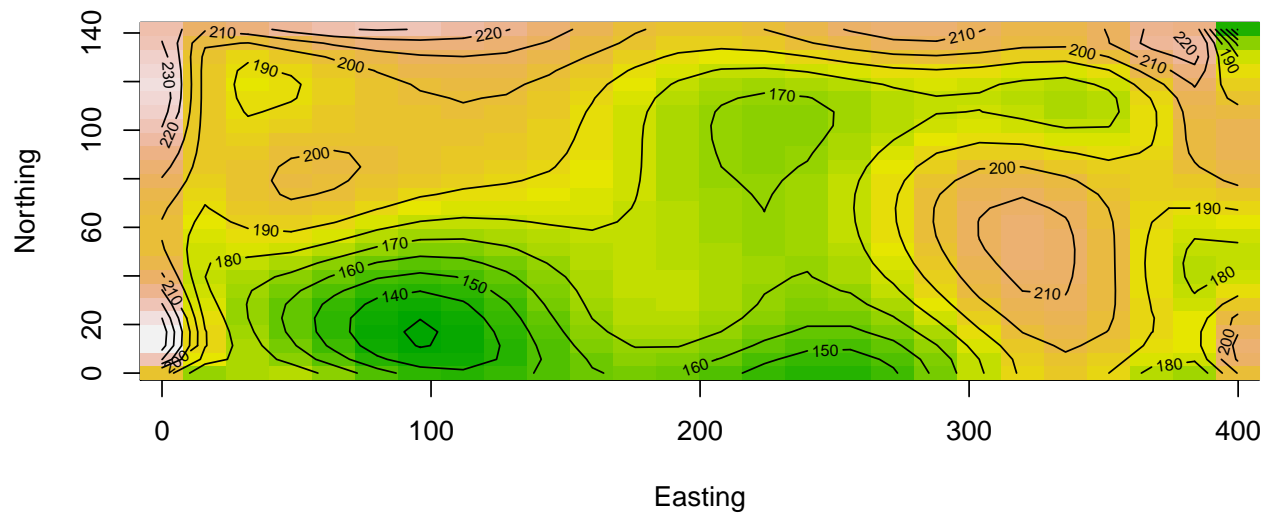
```
##                                Df  Sum Sq Mean Sq F value Pr(>F)
## poly(Easting, Northing, degree = 9)  54 2284150    42299   78.09 <2e-16
## Product                               1   225691   225691  416.65 <2e-16
## Residuals                           6313 3419624     542
##
## poly(Easting, Northing, degree = 9) ***
## Product                               ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
YieldVariety11.lm <- lm(Yield ~ poly(Easting, Northing, degree=11) + Product, data=EastQuarter.dat)
summary(aov(YieldVariety11.lm))
```

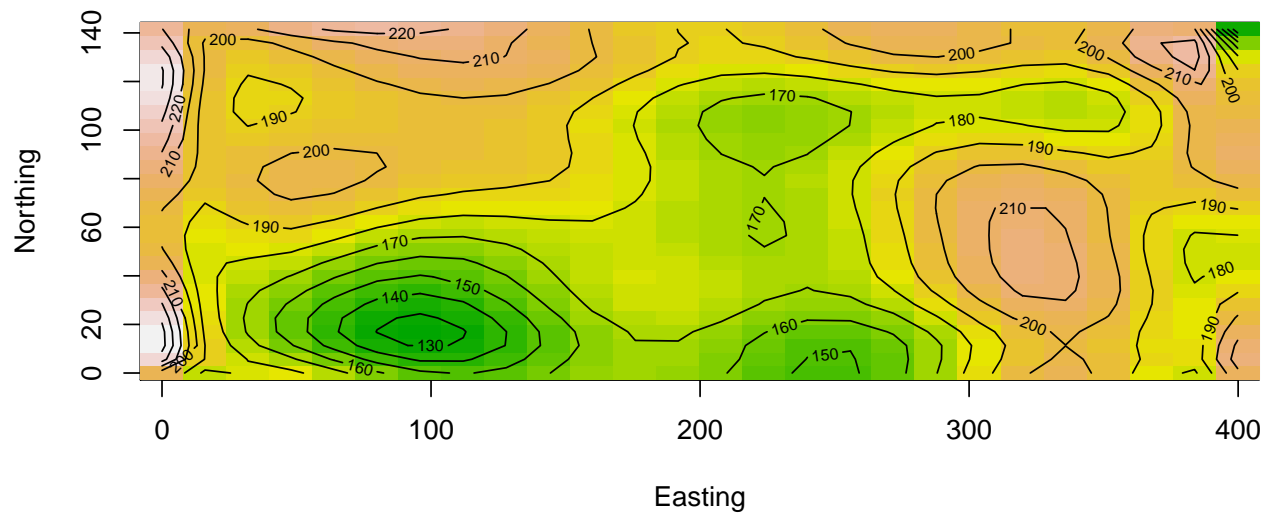
```
##                                Df  Sum Sq Mean Sq F value Pr(>F)
## poly(Easting, Northing, degree = 11)    77 2765104    35910    75.84 <2e-16
## Product                                1  185973    185973   392.75 <2e-16
## Residuals                             6290 2978388      474
##
## poly(Easting, Northing, degree = 11) ***
## Product                                ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow=c(2,1))
contour(Yield9.lm, Northing ~ Easting, image = TRUE, main="Poly 9")
contour(YieldVariety9.lm, Northing ~ Easting, image = TRUE, main="Poly 9 + Product")
```

### Poly 9



### Poly 9 + Product



```
par(mfrow=c(1,1))

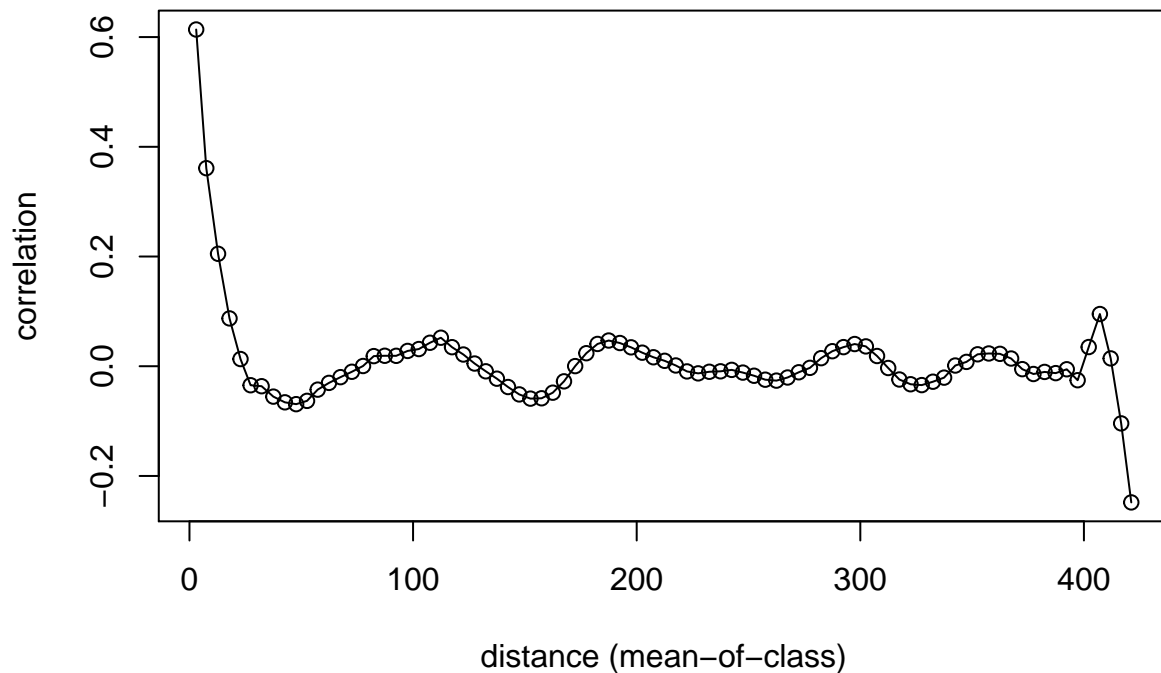
EastQuarter.dat$YieldVariety9.resid <- YieldVariety9.lm$residuals
print(Moran9Variety <- Moran.I(EastQuarter.dat$YieldVariety9.resid, Distance.mat))

## $observed
## [1] 0.04017208
##
## $expected
## [1] -0.0001570352
##
## $sd
## [1] 0.0003680105
##
## $p.value
```

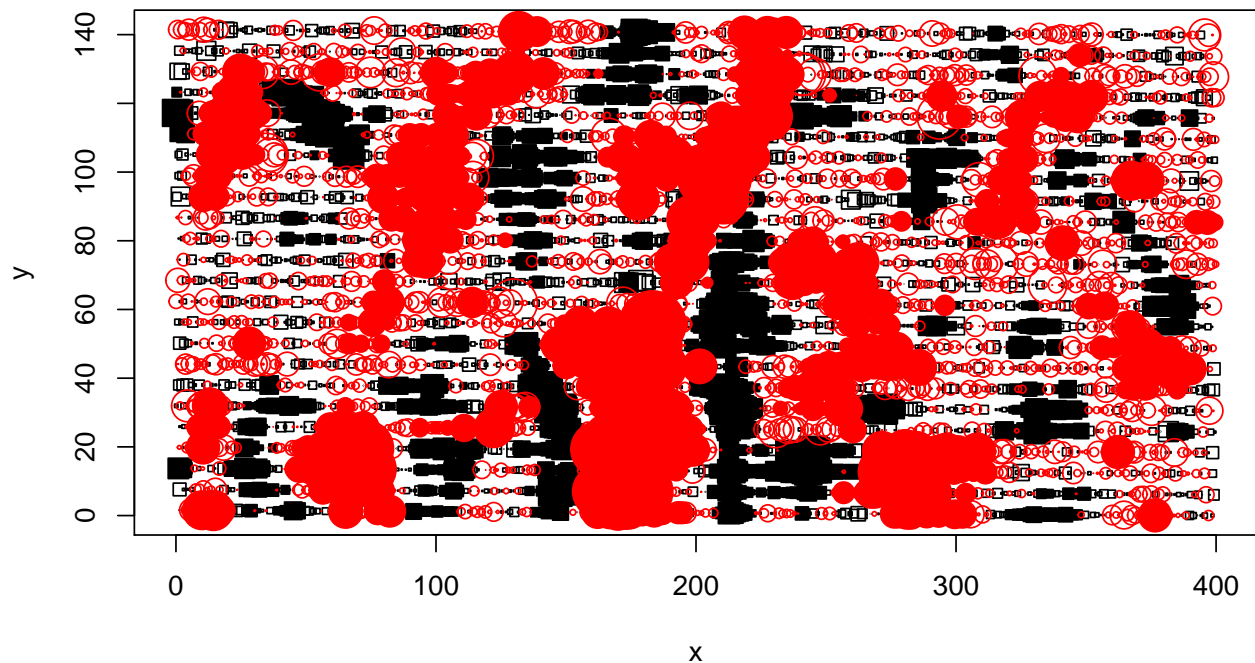
```
## [1] 0
```

```
YieldVariety9.resid.clg <- correlog(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$YieldVariety9,
                                     increment=5, resamp=0, quiet=TRUE)
plot(YieldVariety9.resid.clg)
```

**Correlogram**



```
YieldVariety9.resid.lisa <- lisa(EastQuarter.dat$Easting, EastQuarter.dat$Northing, EastQuarter.dat$YieldVariety9,
                                 neigh=10, resamp=resample, quiet=TRUE)
plot.lisa(YieldVariety9.resid.lisa, neigh.mean=FALSE)
```



```

library(lsmeans)

## Warning: package 'lsmeans' was built under R version 3.3.2
## Loading required package: estimability
## Warning: package 'estimability' was built under R version 3.3.2
Yield.lm <- lm(Yield ~ Product, data=EastQuarter.dat)
lsmeans(Yield.lm, cld ~ Product)

##   Product    lsmean      SE    df lower.CL upper.CL .group
##   E         177.0918 0.5237125 6367 176.0652 178.1185    1
##   B         192.3915 0.5233015 6367 191.3657 193.4174    2
##
## Confidence level used: 0.95
## significance level used: alpha = 0.05
lsmeans(YieldVariety5.lm, cld ~ Product)

##   Product    lsmean      SE    df lower.CL upper.CL .group
##   E         174.8325 0.9233101 6347 173.0225 176.6425    1
##   B         187.0460 0.9233202 6347 185.2360 188.8560    2
##
## Confidence level used: 0.95
## significance level used: alpha = 0.05
lsmeans(YieldVariety9.lm, cld ~ Product)

##   Product    lsmean      SE    df lower.CL upper.CL .group
##   E         166.7770 1.371456 6313 164.0885 169.4655    1
##   B         179.7785 1.375834 6313 177.0814 182.4756    2
##
## Confidence level used: 0.95
## significance level used: alpha = 0.05
lsmeans(YieldVariety11.lm, cld ~ Product)

##   Product    lsmean      SE    df lower.CL upper.CL .group
##   E         160.8354 1.542851 6290 157.8109 163.8599    1
##   B         174.4552 1.538617 6290 171.4390 177.4714    2
##
## Confidence level used: 0.95
## significance level used: alpha = 0.05

```