

# Case Study 1, Part 3

*Peter Claussen*

*10/3/2017*

```
library(gstat)
```

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

```
library(ape)
```

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

```
library(ggplot2)
```

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

```
library(rsm)
```

```
library(ncf)
```

```
##
```

```
## Attaching package: 'ncf'
```

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

```
##
```

```
##      mantel.test
```

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

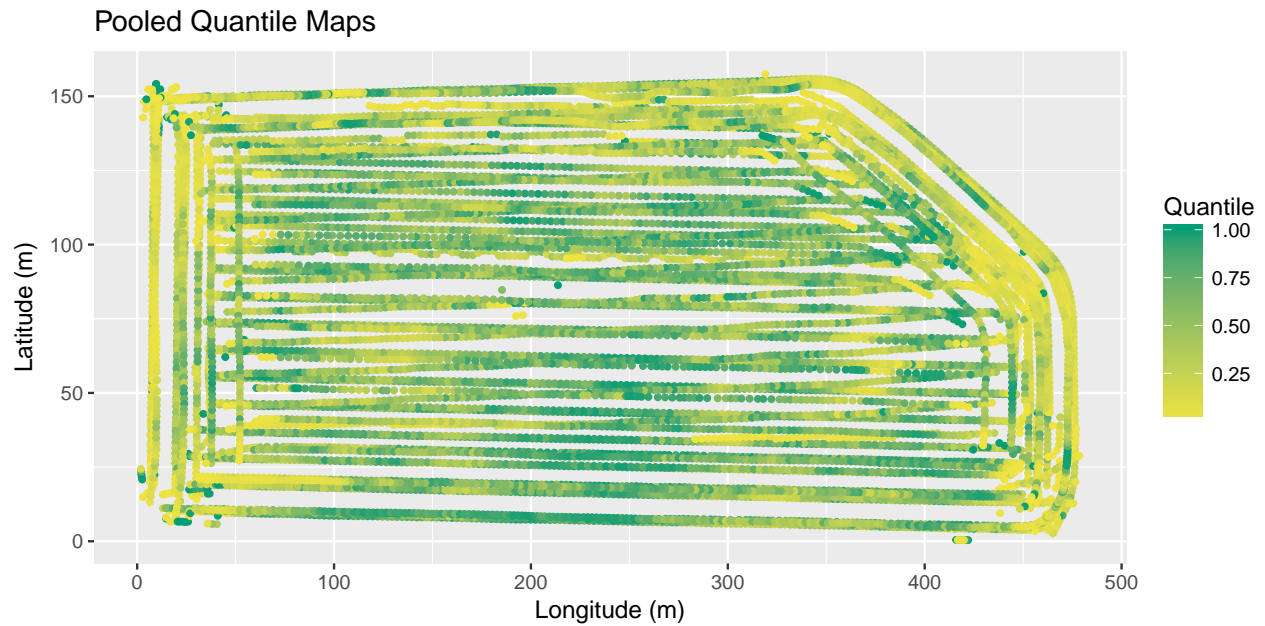
Now we consider trend analysis. First, using the pooled data, what is an appropriate polynomial?

## Load Data

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

```
Pooled.dat <- rbind(Corn2013.dat, Corn2015.dat, Soybean2014.dat, Soybean2016.dat)
```

```
ggplot(Pooled.dat, aes(Easting, Northing)) +  
  geom_point(aes(colour = Quantile), size=1) +  
  scale_colour_gradient(low=cbPalette[7], high=cbPalette[4]) +  
  labs(colour = "Quantile", x="Longitude (m)", y="Latitude (m)", title = "Pooled Quantile Maps")
```

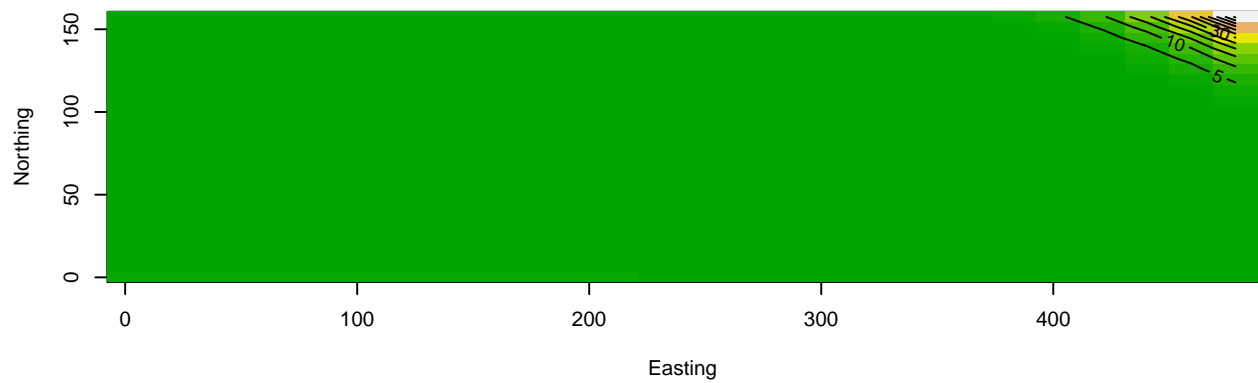
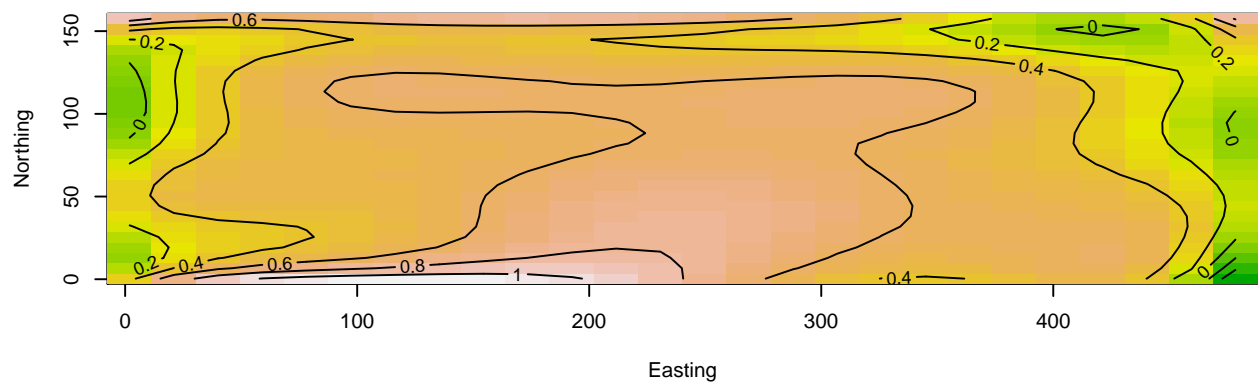
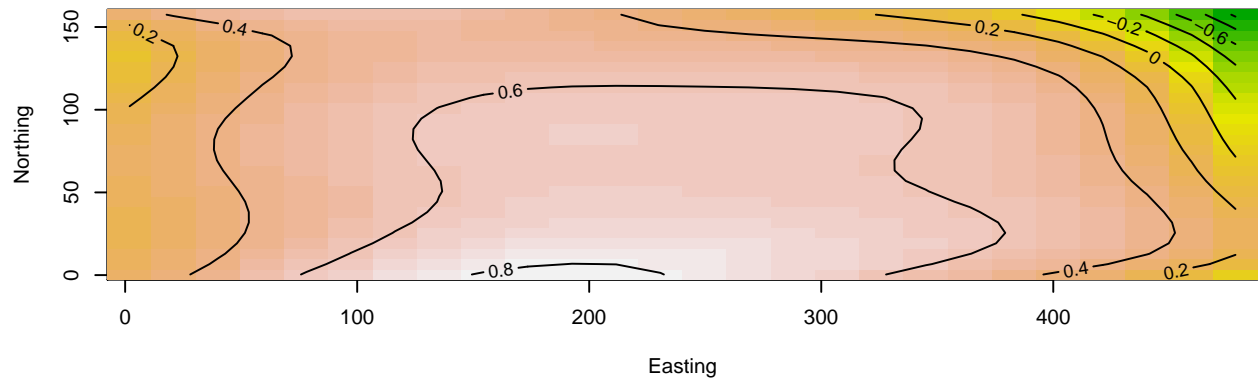


## Fit polynomial models

```
Quantile5.lm <- lm(Quantile ~ poly(Easting, Northing, degree=5), data=Pooled.dat)
Quantile6.lm <- lm(Quantile ~ poly(Easting, Northing, degree=6), data=Pooled.dat)
Quantile7.lm <- lm(Quantile ~ poly(Easting, Northing, degree=7), data=Pooled.dat)
Quantile8.lm <- lm(Quantile ~ poly(Easting, Northing, degree=8), data=Pooled.dat)
Quantile9.lm <- lm(Quantile ~ poly(Easting, Northing, degree=9), data=Pooled.dat)
```

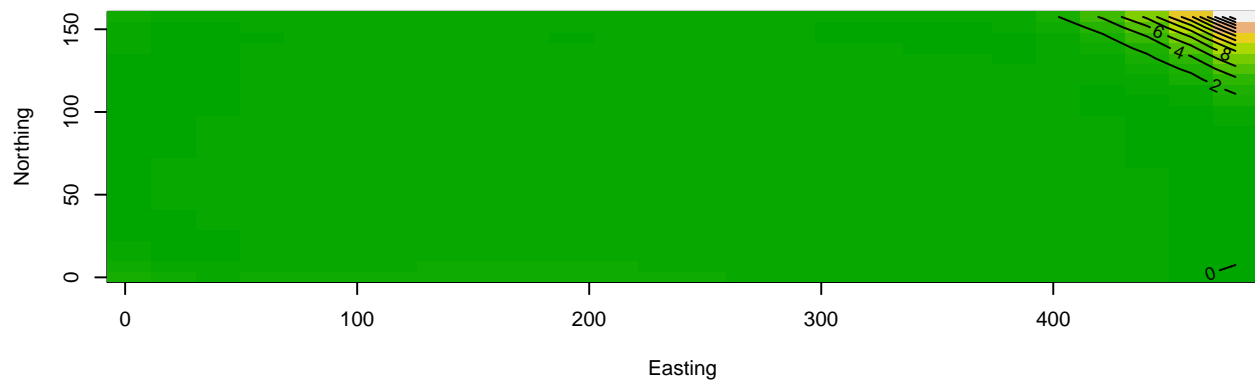
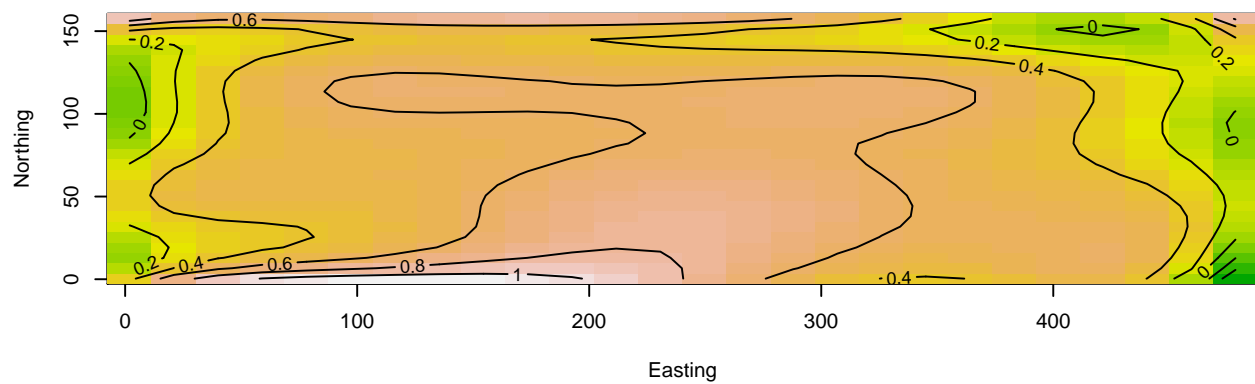
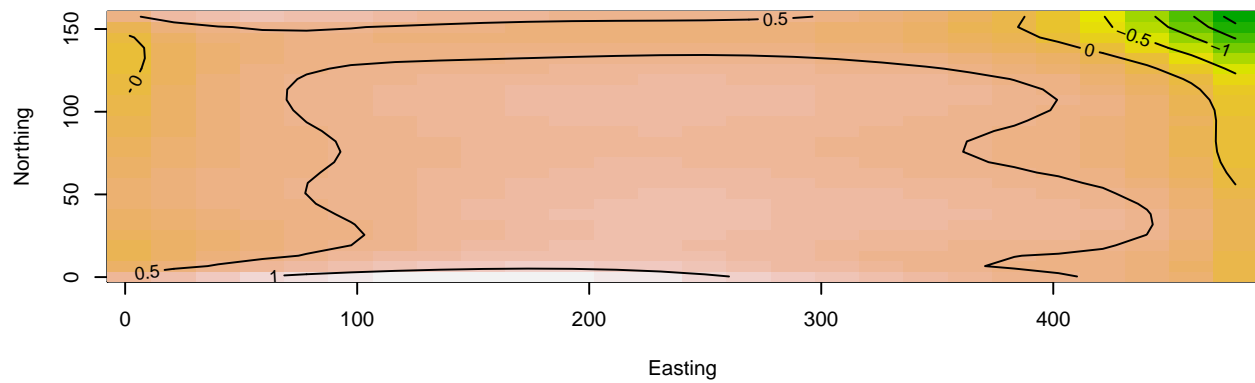
Here we see one limitation of trend analysis - it doesn't work well if we don't have a rectangular shape. The missing corner in our field tends to induce a bias in the models.

```
par(mfrow=c(3,1))
contour(Quantile5.lm, Northing ~ Easting, image = TRUE)
contour(Quantile7.lm, Northing ~ Easting, image = TRUE)
contour(Quantile9.lm, Northing ~ Easting, image = TRUE)
```



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

```
par(mfrow=c(3,1))
contour(Quantile6.1m, Northing ~ Easting, image = TRUE)
contour(Quantile7.1m, Northing ~ Easting, image = TRUE)
contour(Quantile8.1m, Northing ~ Easting, image = TRUE)
```



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

## Extract residuals

```
Pooled.dat$Quantile5.resid <- Quantile5.lm$residuals
Pooled.dat$Quantile6.resid <- Quantile6.lm$residuals
Pooled.dat$Quantile7.resid <- Quantile7.lm$residuals
Pooled.dat$Quantile8.resid <- Quantile8.lm$residuals
```

```
Pooled.dat$Quantile9.resid <- Quantile9.lm$residuals
```

## Check for white noise

The paired distance matrix is very large (1Gb) so we should save between analyses.

```
if(!file.exists("Distance.Rda")) {  
  Distance.mat <- as.matrix(dist(cbind(Pooled.dat$Easting, Pooled.dat$Northing)))  
  Distance.mat <- 1/Distance.mat  
  diag(Distance.mat) <- 0  
  save(Distance.mat, file="Distance.Rda")  
} else {  
  load(file="Distance.Rda")  
}
```

```
if(!file.exists("TrendI.Rda")) {  
  Moran5 <- Moran.I(Pooled.dat$Quantile5.resid, Distance.mat)  
  Moran6 <- Moran.I(Pooled.dat$Quantile6.resid, Distance.mat)  
  Moran7 <- Moran.I(Pooled.dat$Quantile7.resid, Distance.mat)  
  Moran8 <- Moran.I(Pooled.dat$Quantile8.resid, Distance.mat)  
  Moran9 <- Moran.I(Pooled.dat$Quantile9.resid, Distance.mat)  
  save(Moran5, Moran6, Moran7, Moran8, Moran9, file="TrendI.Rda")  
} else {  
  load(file="TrendI.Rda")  
}  
print(Moran5)
```

```
## $observed  
## [1] 0.02766664  
##  
## $expected  
## [1] -8.516437e-05  
##  
## $sd  
## [1] 0.0003870306  
##  
## $p.value  
## [1] 0
```

```
print(Moran6)
```

```
## $observed  
## [1] 0.02350059  
##  
## $expected  
## [1] -8.516437e-05  
##  
## $sd  
## [1] 0.0003870292  
##  
## $p.value  
## [1] 0
```

```
print(Moran7)
```

```
## $observed
## [1] 0.0192301
##
## $expected
## [1] -8.516437e-05
##
## $sd
## [1] 0.0003870274
##
## $p.value
## [1] 0
```

```
print(Moran8)
```

```
## $observed
## [1] 0.01445761
##
## $expected
## [1] -8.516437e-05
##
## $sd
## [1] 0.0003870244
##
## $p.value
## [1] 0
```

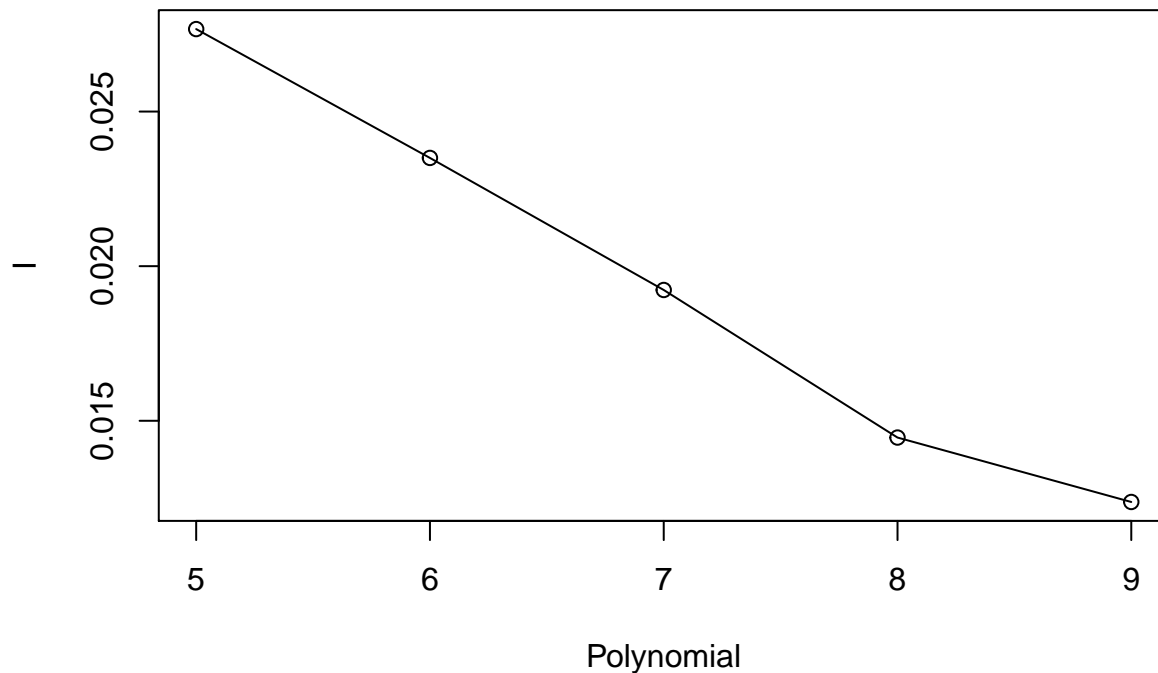
```
print(Moran9)
```

```
## $observed
## [1] 0.01237497
##
## $expected
## [1] -8.516437e-05
##
## $sd
## [1] 0.0003870239
##
## $p.value
## [1] 0
```

## Plot *I*

```
fit.dat <- data.frame(
  Polynomial = seq(5,9),
  I = c(Moran5$observed,
        Moran6$observed,
        Moran7$observed,
        Moran8$observed,
        Moran9$observed
  )
)
```

```
plot(I ~ Polynomial, data=fit.dat)
lines(I ~ Polynomial, data=fit.dat)
```



We can also reasonably use nested AOV to compare.

```
anova(Quantile5.lm, Quantile6.lm, Quantile7.lm, Quantile8.lm, Quantile9.lm)
```

```
## Analysis of Variance Table
##
## Model 1: Quantile ~ poly(Easting, Northing, degree = 5)
## Model 2: Quantile ~ poly(Easting, Northing, degree = 6)
## Model 3: Quantile ~ poly(Easting, Northing, degree = 7)
## Model 4: Quantile ~ poly(Easting, Northing, degree = 8)
## Model 5: Quantile ~ poly(Easting, Northing, degree = 9)
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1  11722 720.71
## 2  11715 696.55  7    24.164 63.548 < 2.2e-16 ***
## 3  11707 673.25  8    23.302 53.621 < 2.2e-16 ***
## 4  11698 645.61  9    27.638 56.533 < 2.2e-16 ***
## 5  11688 634.89 10    10.716 19.728 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

ANOVA suggests 8, since there is relatively little improvement at between 8 and 9 ( $\Delta SS \sim 10$ ).

We've fit a mean trend for four maps, but we also want to capture some of the year to year variability. To do this, we can extend our trend to include an interaction term:

```
Pooled.dat$Crop <- "Corn"
Pooled.dat$Crop[Pooled.dat$Year==2014] <- "Soybean"
Pooled.dat$Crop[Pooled.dat$Year==2016] <- "Soybean"
Pooled.dat$Crop <- as.factor(Pooled.dat$Crop)
Pooled.dat$Year <- as.factor(Pooled.dat$Year)
```

```
Quantile7Interaction.lm <- lm(Quantile ~ poly(Easting, Northing, degree=7) + Crop:poly(Easting, Northing, degree=7), data=Pooled.dat)
summary(aov(Quantile7Interaction.lm))
```

```
##                                Df Sum Sq Mean Sq F value
## poly(Easting, Northing, degree = 7)          35  305.3    8.724   170.84
## poly(Easting, Northing, degree = 7):Crop       35   34.4    0.983    19.25
## poly(Easting, Northing, degree = 7):Crop:Year  70   46.4    0.663    12.98
## Residuals                                11602  592.5    0.051
##                                Pr(>F)
## poly(Easting, Northing, degree = 7)          <2e-16 ***
## poly(Easting, Northing, degree = 7):Crop       <2e-16 ***
## poly(Easting, Northing, degree = 7):Crop:Year  <2e-16 ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Does this improve the residuals?

```
Pooled.dat$Quantile7Interaction.resid <- Quantile7Interaction.lm$residuals
if(!file.exists("Moran7InteractionI.dat")) {
  Moran7InteractionI <- Moran.I(Pooled.dat$Quantile7Interaction.resid, Distance.mat)
  save(Moran7InteractionI, file="Moran7InteractionI.dat")
} else {
  load(file="Moran7InteractionI.dat")
}
print(Moran7InteractionI)
```

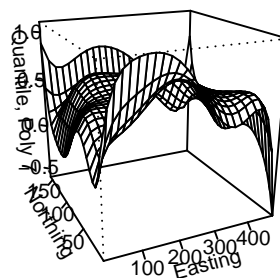
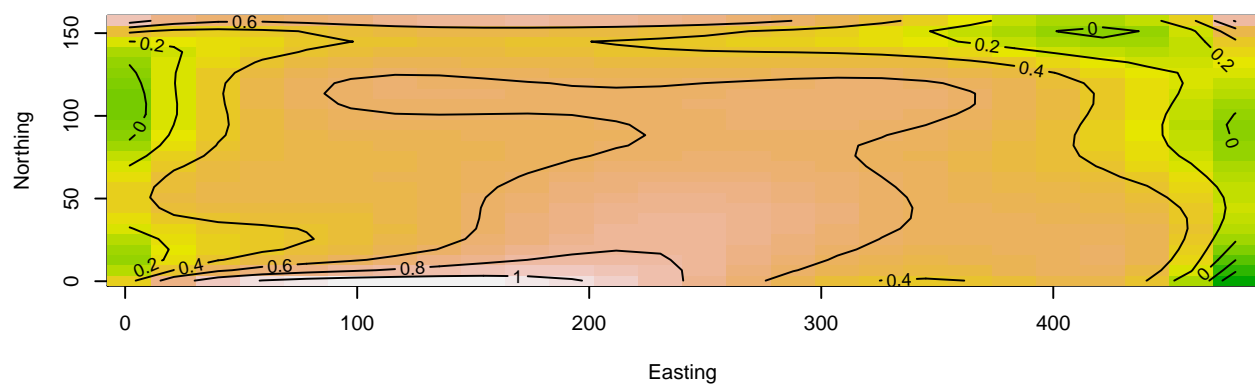
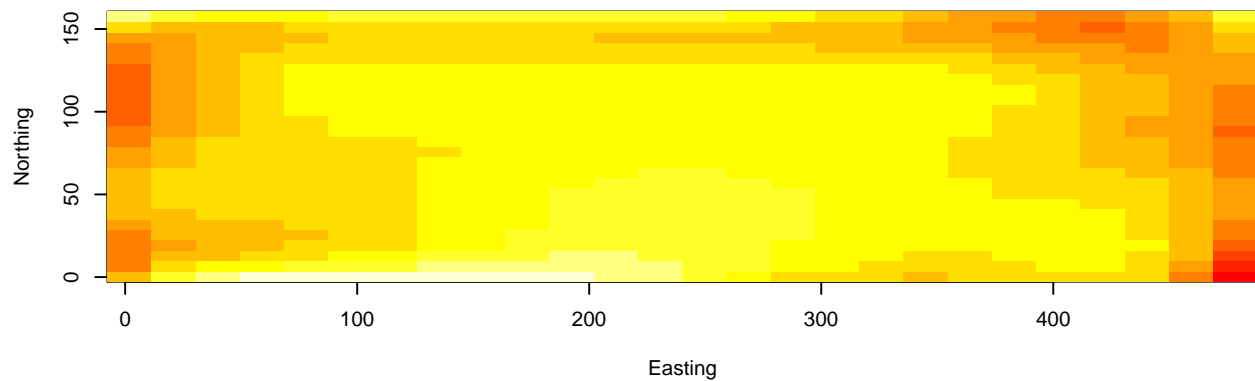
```
## $observed
## [1] 0.02055166
##
## $expected
## [1] -8.516437e-05
##
## $sd
## [1] 0.0003870245
##
## $p.value
## [1] 0
```

```
#reclaim some memory
Distance.mat <- NULL
```

## Surface Plots

```
par(mfrow=c(3,1))
image(Quantile7.lm, Northing ~ Easting)
contour(Quantile7.lm, Northing ~ Easting, image = TRUE)
persp(Quantile7.lm, Northing ~ Easting, zlab = "Quantile, Poly 7")
```





```
par(mfrow=c(3,1))
image(Quantile7Interaction.lm, Northing ~ Easting)

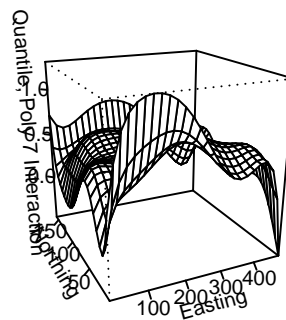
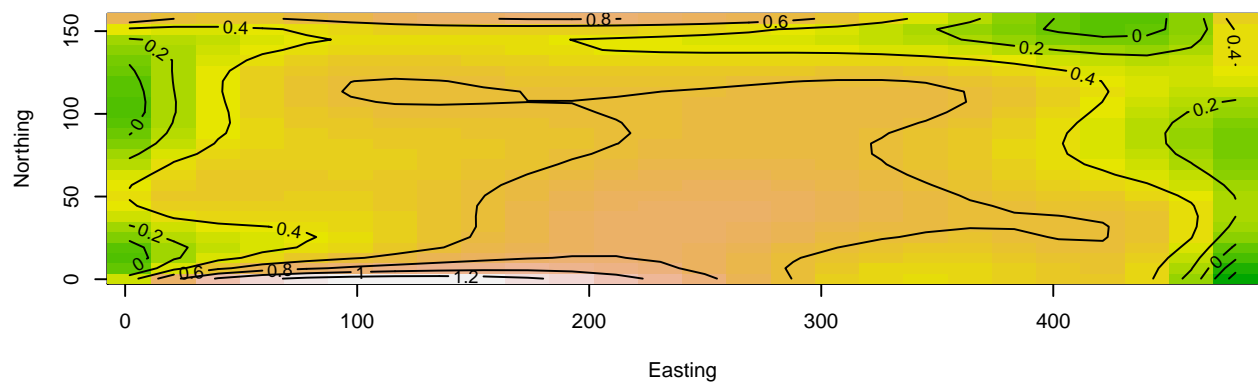
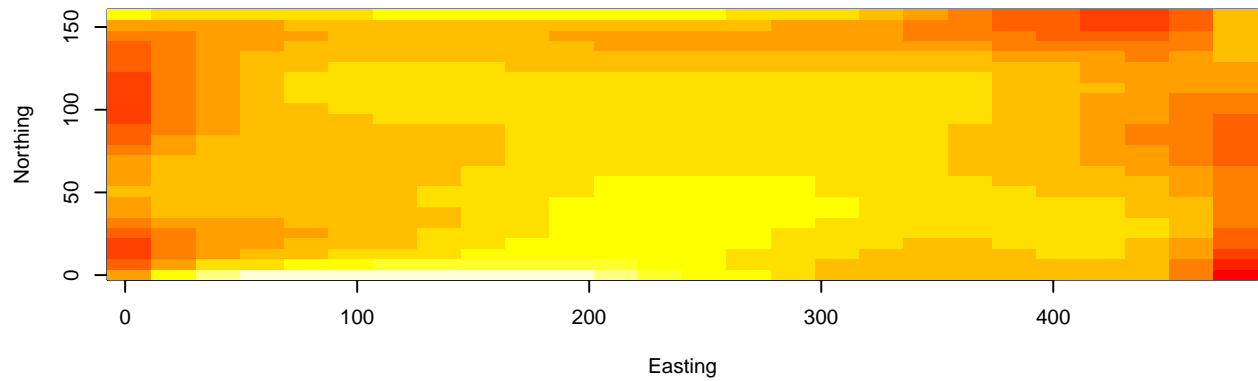
## Warning in predict.lm(lmobj, newdata = newdata): prediction from a rank-
## deficient fit may be misleading

contour(Quantile7Interaction.lm, Northing ~ Easting, image = TRUE)

## Warning in predict.lm(lmobj, newdata = newdata): prediction from a rank-
## deficient fit may be misleading

persp(Quantile7Interaction.lm, Northing ~ Easting, zlab = "Quantile, Poly 7 Interaction")

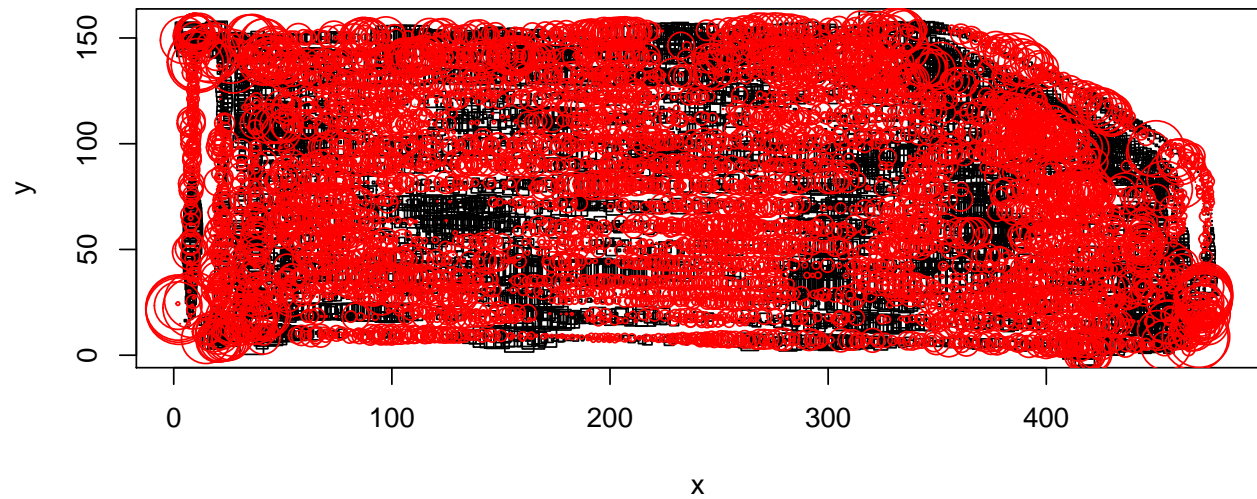
## Warning in predict.lm(lmobj, newdata = newdata): prediction from a rank-
## deficient fit may be misleading
```



## Residual Plots

```
if(!file.exists("TrendsLISA.Rda")) {
  Quantile7.resid.lisa <- lisa(Pooled.dat$Easting, Pooled.dat$Northing, Pooled.dat$Quantile7.resid,
                             neigh=30, resamp=10, quiet=TRUE)
  Quantile7Interaction.resid.lisa <- lisa(Pooled.dat$Easting, Pooled.dat$Northing, Pooled.dat$Quantile7Interaction.resid,
                                          neigh=30, resamp=10, quiet=TRUE)
  save(fit.dat, Quantile7.resid.lisa, Quantile7Interaction.resid.lisa, file="TrendsLISA.Rda")
} else {
  load(file="TrendsLISA.Rda")
}
```

```
plot.lisa(Quantile7.resid.lisa, negh.mean=FALSE)
```



```
plot.lisa(Quantile7Interaction.resid.lisa, negh.mean=FALSE)
```

