

Modelos para datos temporales y espaciales.

Trabajo Tema 5. Modelos espaciales.

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29 de agosto de 2017

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1 Formulación

Opción 2. Aplicar técnicas de krigeado a una de las variables logaritmo de la concentración de cadmio, cobre o plomo del conjunto de datos “meuse”, realizando la predicción sobre el conjunto pixelado “meuse.grid”. En concreto, realizar los pasos:

- Descripción de la variable (resumen y representaciones gráficas)
- CONSTRUCCIÓN DEL VARIOGRAMA MUESTRAL Y AJUSTE A UN MODELO TEÓRICO de la variable objetivo
- KRIGING ORDINARIO PARA LA VARIABLE OBJETIVO
- KRIGING UNIVERSAL PARA LA VARIABLE OBJETIVO y comparar con los resultados obtenidos en el paso anterior.
- KRIGING DERIVA EXTERNA PARA LA VARIABLE OBJETIVO CON PREDICTOR DISTANCIA AL RIO y comparar con los resultados obtenidos pasos anteriores.
- KRIGING RESIDUAL DIRECTO PARA LA VARIABLE OBJETIVO CON PREDICTOR DISTANCIA AL RIO y comparar con los resultados obtenidos pasos anteriores.

2 Carga de librerías

```
library(sp)
library(lattice)
library(xts)

## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric
library(gstat)
```

3 Lectura de datos

```
data(meuse)
class(meuse)

## [1] "data.frame"
dim(meuse)

## [1] 155 14
names(meuse)

## [1] "x"      "y"      "cadmium" "copper" "lead"    "zinc"    "elev"
## [8] "dist"   "om"     "ffreq"   "soil"    "lime"    "landuse" "dist.m"
head(meuse)

##      x      y cadmium copper lead zinc elev      dist      om ffreq soil
## 1 181072 333611    11.7     85  299 1022  7.909 0.00135803 13.6      1      1
```

```
## 2 181025 333558      8.6      81 277 1141 6.983 0.01222430 14.0      1      1
## 3 181165 333537      6.5      68 199 640 7.800 0.10302900 13.0      1      1
## 4 181298 333484      2.6      81 116 257 7.655 0.19009400 8.0      1      2
## 5 181307 333330      2.8      48 117 269 7.480 0.27709000 8.7      1      2
## 6 181390 333260      3.0      61 137 281 7.791 0.36406700 7.8      1      2
##   lime landuse dist.m
## 1    1      Ah     50
## 2    1      Ah     30
## 3    1      Ah    150
## 4    0      Ga    270
## 5    0      Ah    380
## 6    0      Ga    470
```

4 Conversión a objeto espacial

```
coordinates(meuse) = ~x+y
class(meuse)
```

```
## [1] "SpatialPointsDataFrame"
## attr(,"package")
## [1] "sp"
```

```
names(meuse)
```

```
## [1] "cadmium" "copper" "lead" "zinc" "elev" "dist" "om"
## [8] "ffreq" "soil" "lime" "landuse" "dist.m"
```

5 Resumen

```
summary(meuse)
```

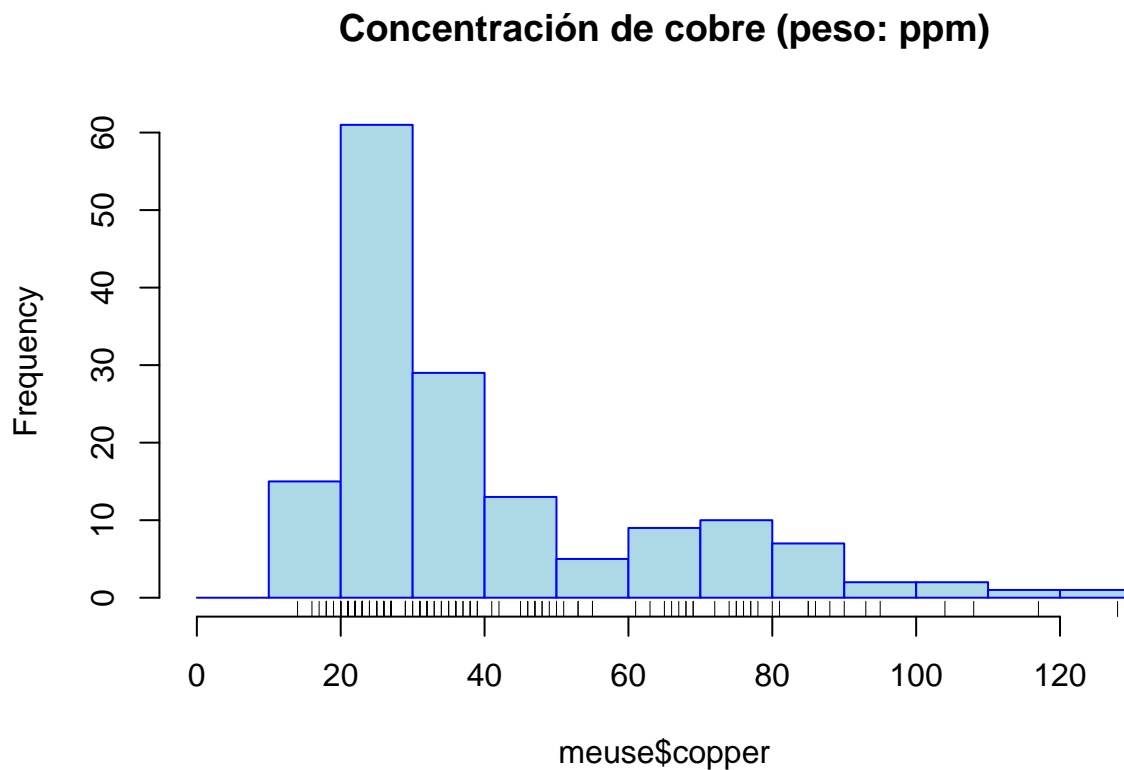
```
## Object of class SpatialPointsDataFrame
## Coordinates:
##      min      max
## x 178605 181390
## y 329714 333611
## Is projected: NA
## proj4string : [NA]
## Number of points: 155
## Data attributes:
##      cadmium      copper      lead      zinc
## Min.   : 0.200   Min.   : 14.00   Min.   : 37.0   Min.   : 113.0
## 1st Qu.: 0.800   1st Qu.: 23.00   1st Qu.: 72.5   1st Qu.: 198.0
## Median : 2.100   Median : 31.00   Median :123.0   Median : 326.0
## Mean   : 3.246   Mean   : 40.32   Mean   :153.4   Mean   : 469.7
## 3rd Qu.: 3.850   3rd Qu.: 49.50   3rd Qu.:207.0   3rd Qu.: 674.5
## Max.   :18.100   Max.   :128.00   Max.   :654.0   Max.   :1839.0
##
##      elev      dist      om      ffreq  soil  lime
## Min.   : 5.180   Min.   :0.00000   Min.   : 1.000   1:84  1:97  0:111
## 1st Qu.: 7.546   1st Qu.:0.07569   1st Qu.: 5.300   2:48  2:46  1: 44
```

```
## Median : 8.180   Median :0.21184   Median : 6.900   3:23   3:12
## Mean   : 8.165   Mean   :0.24002   Mean   : 7.478
## 3rd Qu.: 8.955   3rd Qu.:0.36407   3rd Qu.: 9.000
## Max.   :10.520   Max.   :0.88039   Max.   :17.000
##                                     NA's    :2
##      landuse      dist.m
## W       :50   Min.    : 10.0
## Ah      :39   1st Qu.: 80.0
## Am      :22   Median : 270.0
## Fw      :10   Mean    : 290.3
## Ab       : 8   3rd Qu.: 450.0
## (Other) :25   Max.    :1000.0
## NA's    : 1
```

Se centra el estudio en la variable concentración de Cobre (copper), con transformación logarítmica de la variable original.

6 Representaciones gráficas

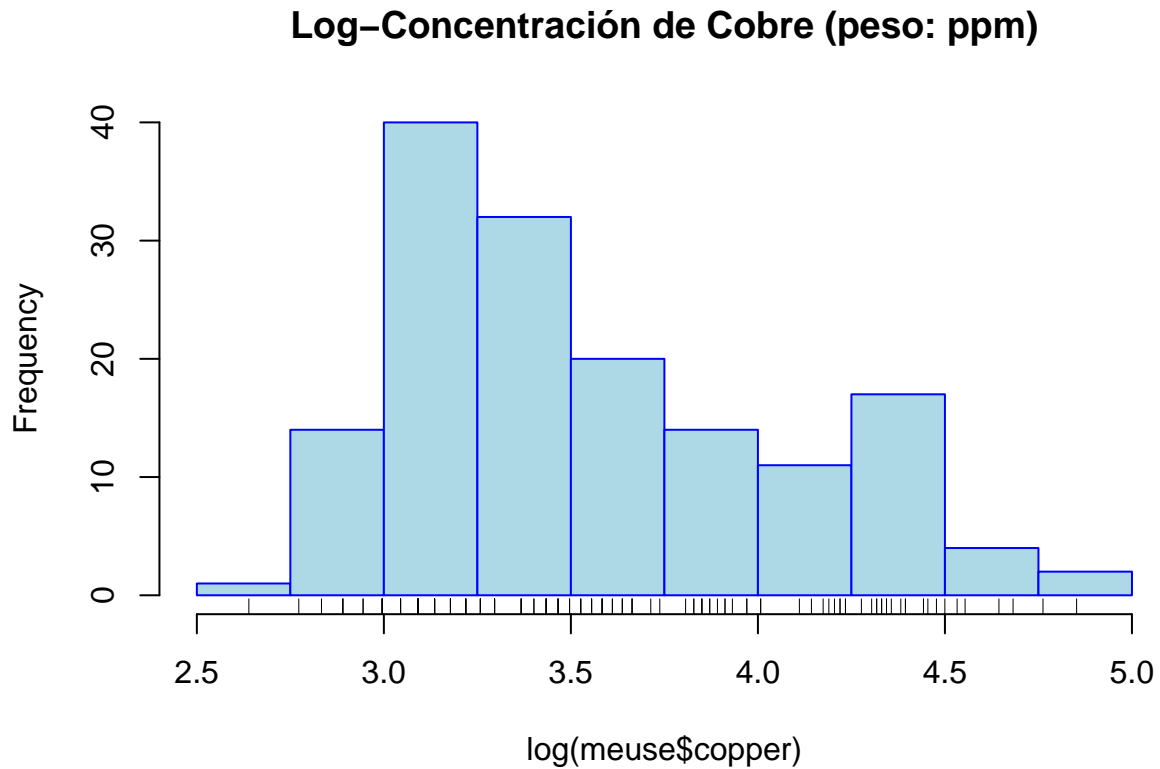
```
hist(meuse$copper, breaks = seq(0, 130, by = 10), col = "lightblue",
     border = "blue", main = "Concentración de cobre (peso: ppm)")
rug(meuse$copper)
```



```
summary(log(meuse$copper))
```

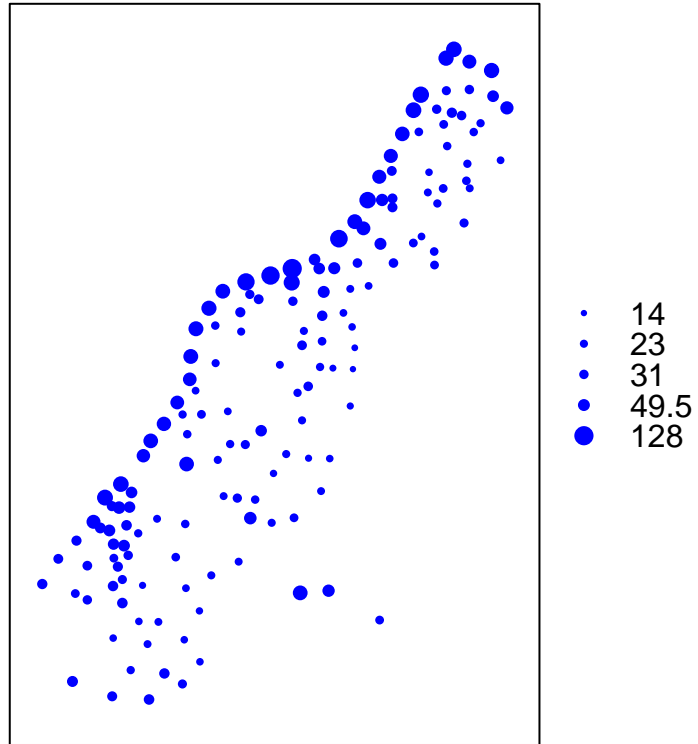
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      2.639   3.135   3.434   3.557   3.902   4.852
```

```
hist(log(meuse$copper), breaks = seq(2.5, 5, by = 0.25), col = "lightblue",
     border = "blue", main = "Log-Concentración de Cobre (peso: ppm)")
rug(log(meuse$copper))
```



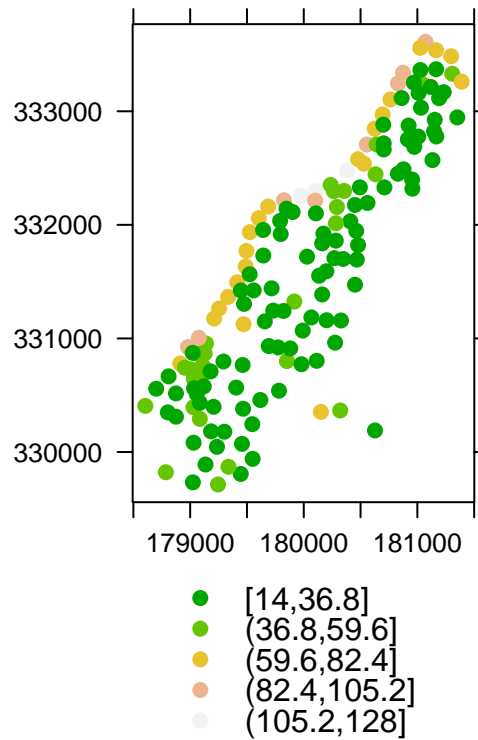
```
bubble(meuse, c("copper"),maxsize = 1.2, col = c("red","blue"), do.sqrt = TRUE,
      main = "Concentración de Cobre (ppm)")
```

Concentración de Cobre (ppm)



```
spplot(meuse["copper"],main="Concentración de Cobre (ppm)",  
       scales=list(draw=TRUE),col.regions=terrain.colors(10))
```

Concentración de Cobre (ppm)



7 Variables en rejilla

```
data(meuse.grid)
coordinates(meuse.grid) = ~x+y
gridded(meuse.grid) = TRUE
class(meuse.grid)
```

```
## [1] "SpatialPixelsDataFrame"
## attr(,"package")
## [1] "sp"
```

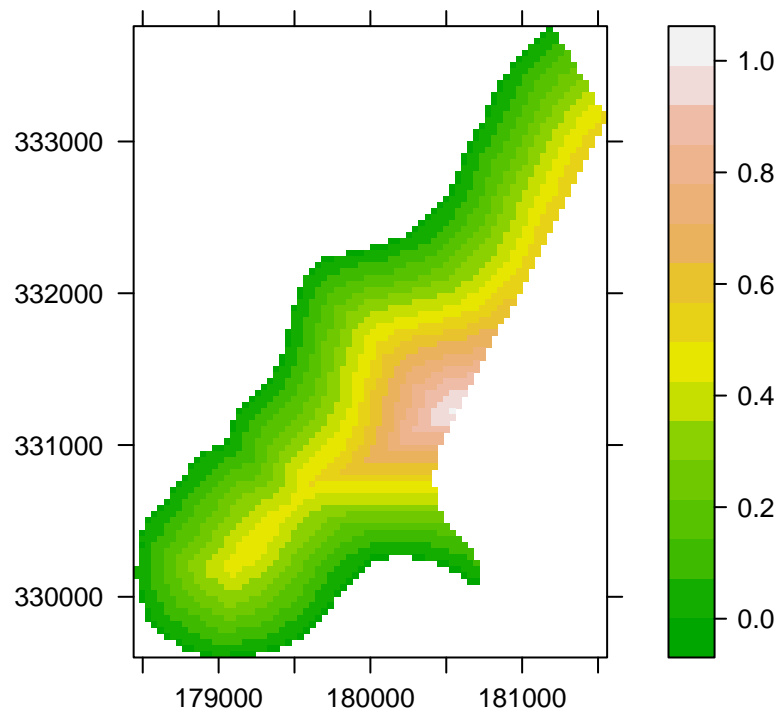
```
names(meuse.grid)
```

```
## [1] "part.a" "part.b" "dist"   "soil"   "ffreq"
```

```
meuse.grid$soil=factor(meuse.grid$soil,
  labels = c('calcáreo','arcilla pesada','arcilla limosa'))
meuse.grid$ffreq=factor(meuse.grid$ffreq,
  labels = c('cada 2 años',
             'cada 10 años',
             'cada 50 años'))
```

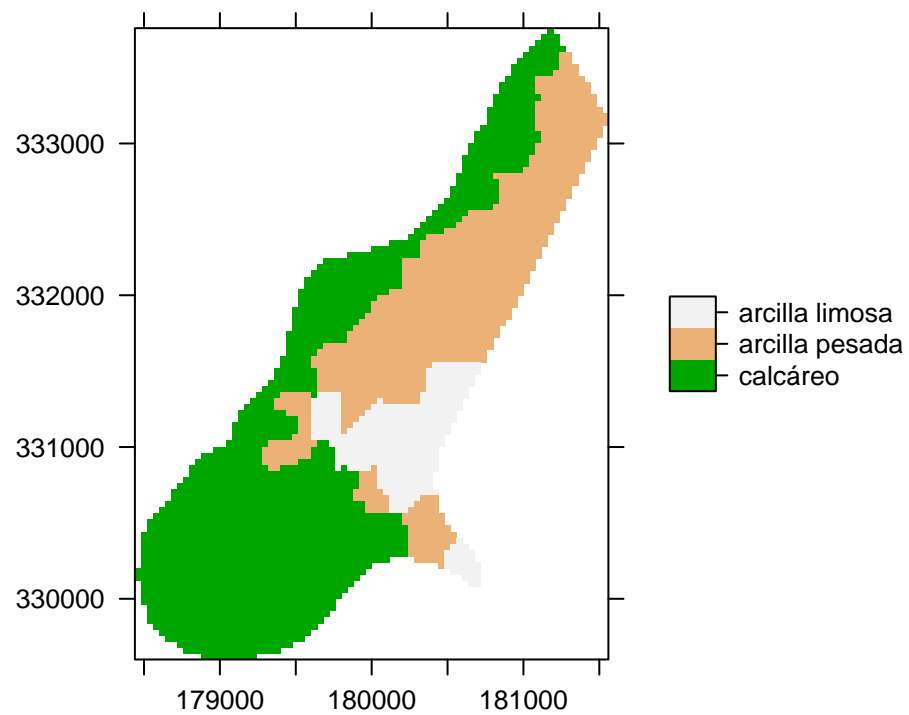
```
splot(meuse.grid, c("dist"), col.regions=terrain.colors(20),
  main="Distancia al río", scales=list(draw=TRUE), cex=0.5)
```


Distancia al río



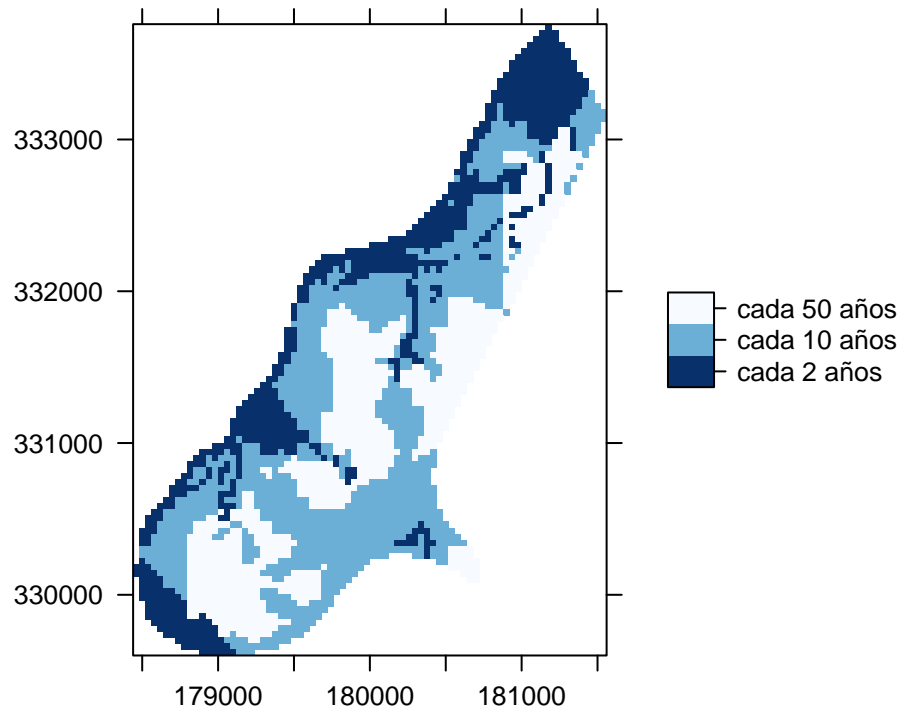
```
spplot(meuse.grid, c("soil"), col.regions=terrain.colors(3),  
       main="Tipo de Suelo", scales=list(draw=TRUE), cex=0.5)
```

Tipo de Suelo



```
spplot(meuse.grid, c("ffreq"), col.regions=rev(blues9),
       main="Frecuencia de inundación", scales=list(draw=TRUE), cex=0.5)
```

Frecuencia de inundación



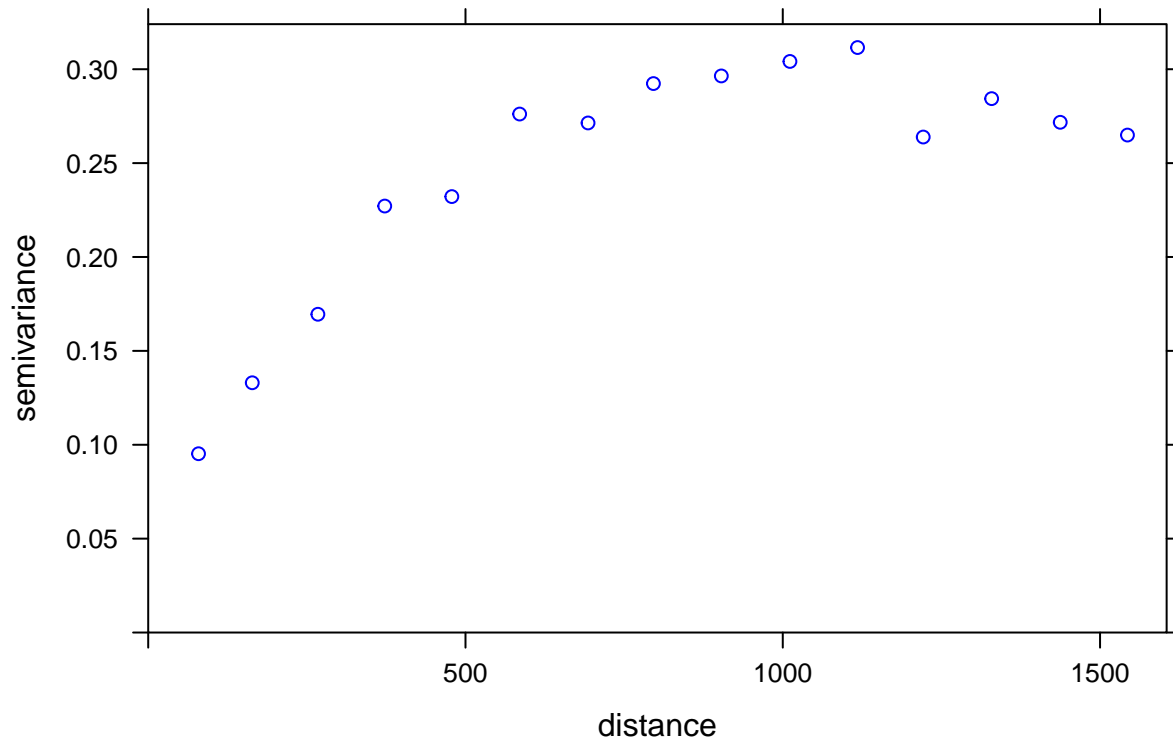
8 Variograma muestral

```
(lCu.vgm = variogram(log(copper)~1, meuse))
```

##	np	dist	gamma	dir.hor	dir.ver	id
## 1	57	79.29244	0.09522828	0	0	var1
## 2	299	163.97367	0.13301890	0	0	var1
## 3	419	267.36483	0.16949808	0	0	var1
## 4	457	372.73542	0.22712857	0	0	var1
## 5	547	478.47670	0.23217426	0	0	var1
## 6	533	585.34058	0.27613309	0	0	var1
## 7	574	693.14526	0.27139217	0	0	var1
## 8	564	796.18365	0.29236481	0	0	var1
## 9	589	903.14650	0.29642987	0	0	var1
## 10	543	1011.29177	0.30415935	0	0	var1
## 11	500	1117.86235	0.31154663	0	0	var1
## 12	477	1221.32810	0.26389361	0	0	var1
## 13	452	1329.16407	0.28434482	0	0	var1
## 14	457	1437.25620	0.27174256	0	0	var1
## 15	415	1543.20248	0.26493408	0	0	var1

```
plot(lCu.vgm, col="blue",main="Semivariograma experimental Log(Cobre)")
```

Semivariograma experimental Log(Cobre)



9 Ajuste de modelos teóricos

```
modelos = vgm()
modelos = data.frame(modelos, 'SSErr'=NA)
for (i in c(2:15,17,18)) { # Se han excluido manualmente los que han dado error
  modelos$SSErr[i] = attributes(fit.variogram(
    lCu.vgm, model=vgm(0.25, modelos$short[i], 900, 0.05)))$SSErr
}
```

```
## Warning in fit.variogram(object, model, fit.sills = fit.sills, fit.ranges =
## fit.ranges, : singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.vgm, model = vgm(0.25, modelos$short[i],
## 900, : No convergence after 200 iterations: try different initial values?
```

```
## Warning in fit.variogram(lCu.vgm, model = vgm(0.25, modelos$short[i],
## 900, : singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.vgm, model = vgm(0.25, modelos$short[i],
## 900, : singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.vgm, model = vgm(0.25, modelos$short[i],
## 900, : singular model in variogram fit
```

```
modelos
```

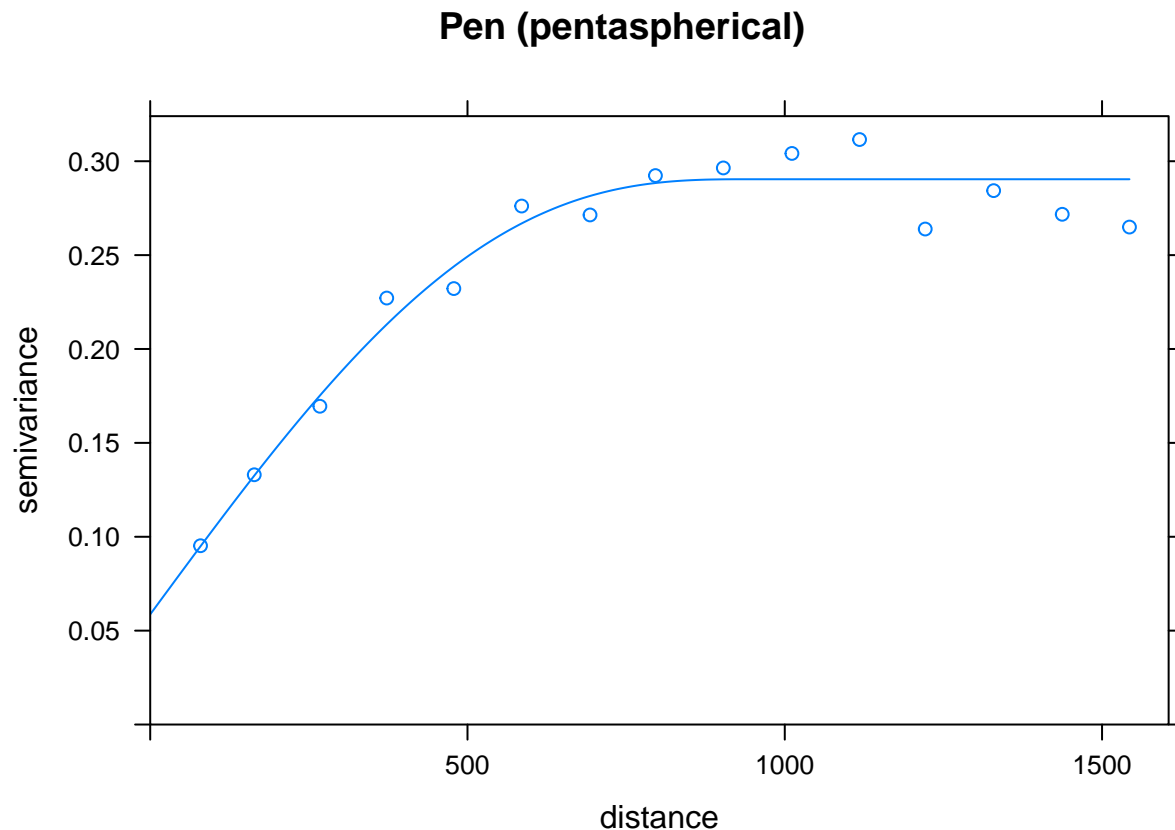
##	short	long	SSErr
## 1	Nug	Nug (nugget)	NA
## 2	Exp	Exp (exponential)	3.709119e-06
## 3	Sph	Sph (spherical)	2.266095e-06
## 4	Gau	Gau (gaussian)	2.951113e-06
## 5	Exc	Exclass (Exponential class/stable)	9.800221e-06
## 6	Mat	Mat (Matern)	3.709119e-06
## 7	Ste Mat	(Matern, M. Stein's parameterization)	3.709119e-06
## 8	Cir	Cir (circular)	2.436197e-06
## 9	Lin	Lin (linear)	3.102196e-06
## 10	Bes	Bes (bessel)	2.645632e-06
## 11	Pen	Pen (pentaspherical)	2.171773e-06
## 12	Per	Per (periodic)	1.953203e-04
## 13	Wav	Wav (wave)	4.001240e-05
## 14	Hol	Hol (hole)	5.420405e-04
## 15	Log	Log (logarithmic)	8.887894e-02
## 16	Pow	Pow (power)	NA
## 17	Spl	Spl (spline)	2.707089e+09
## 18	Leg	Leg (Legendre)	1.532755e-02
## 19	Err	Err (Measurement error)	NA
## 20	Int	Int (Intercept)	NA

10 Mejor modelo

```
(mejor.modelo = modelos[which.min(modelos$SSErr),])
```

```
##      short      long      SSErr
## 11  Pen Pen (pentaspherical) 2.171773e-06

lCu.fit = fit.variogram(lCu.vgm,
  model = vgm(0.25, mejor.modelo$short, 900, 0.05))
plot(lCu.vgm, lCu.fit, main=as.character(mejor.modelo$long))
```



11 Kriging Ordinario

```
lCu.kriged = krige(log(copper)~1, meuse, meuse.grid, model = lCu.fit)
```

```
## [using ordinary kriging]
```

```
summary(lCu.kriged)
```

```
## Object of class SpatialPixelsDataFrame
## Coordinates:
##      min      max
## x 178460 181540
## y 329620 333740
## Is projected: NA
## proj4string : [NA]
## Number of points: 3103
## Grid attributes:
##   cellcentre.offset cellsize cells.dim
## x           178460      40         78
## y           329620      40        104
## Data attributes:
##   var1.pred      var1.var
## Min.      :2.775   Min.      :0.08361
## 1st Qu.:3.191   1st Qu.:0.10879
## Median :3.367   Median :0.12083
```

```
## Mean :3.447 Mean :0.13192
## 3rd Qu.:3.637 3rd Qu.:0.14536
## Max. :4.625 Max. :0.26575
```

```
names(lCu.kriged)
```

```
## [1] "var1.pred" "var1.var"
```

```
dim(lCu.kriged)
```

```
## [1] 3103 2
```

```
lCu.kriged$var1.pred[1:5] # Predicción en los cinco primeros casos
```

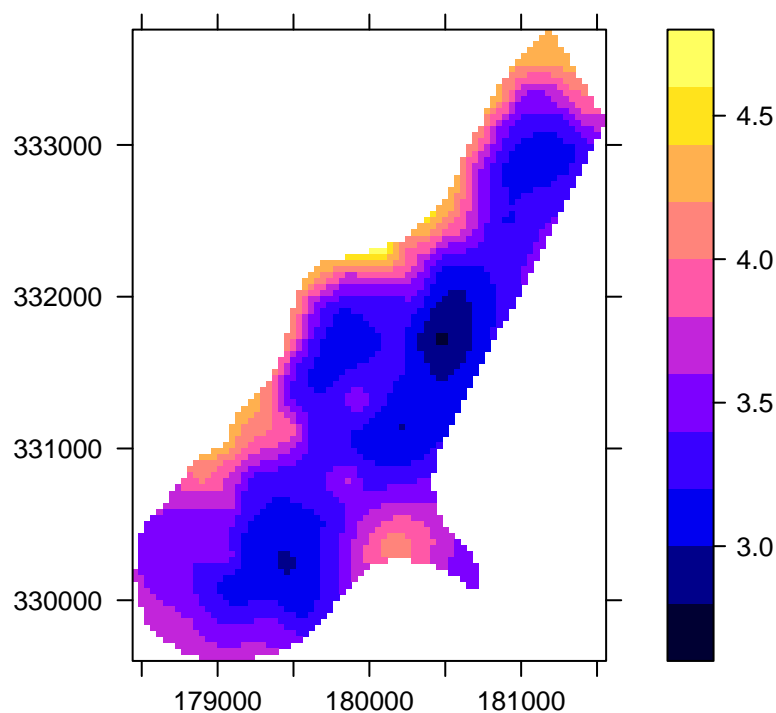
```
## [1] 4.200836 4.254413 4.238081 4.220696 4.303937
```

```
lCu.kriged$var1.var[1:5] # Varianza de la Predicción en los cinco primeros casos
```

```
## [1] 0.1907213 0.1619264 0.1707465 0.1804112 0.1300948
```

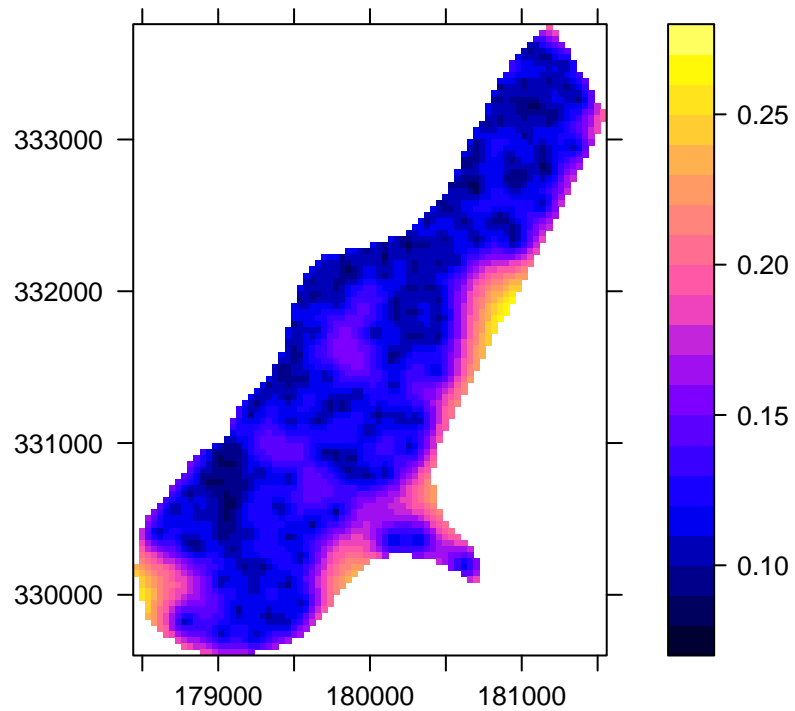
```
spplot(lCu.kriged["var1.pred"], pretty=T, col.regions=bpy.colors(64),
main="Predicción. Log(Cobre).",
scales=list(draw=T))
```

Predicción. Log(Cobre).



```
spplot(lCu.kriged["var1.var"], pretty=T, col.regions=bpy.colors(64),
main="Varianza de Predicción. Log(Cobre).",
scales=list(draw=T))
```

Varianza de Predicción. Log(Cobre).

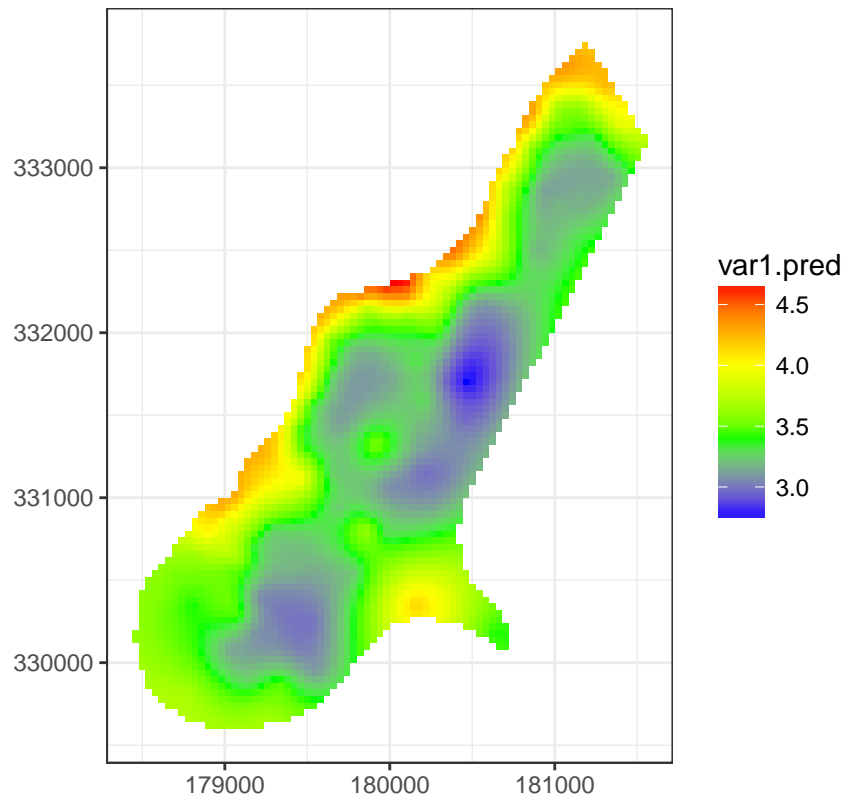


```
library(ggplot2)
df.lCu.kriged = as.data.frame(lCu.kriged)
head(df.lCu.kriged)
```

```
##           x           y var1.pred var1.var
## 1 181180 333740 4.200836 0.1907213
## 2 181140 333700 4.254413 0.1619264
## 3 181180 333700 4.238081 0.1707465
## 4 181220 333700 4.220696 0.1804112
## 5 181100 333660 4.303937 0.1300948
## 6 181140 333660 4.283831 0.1399075
```

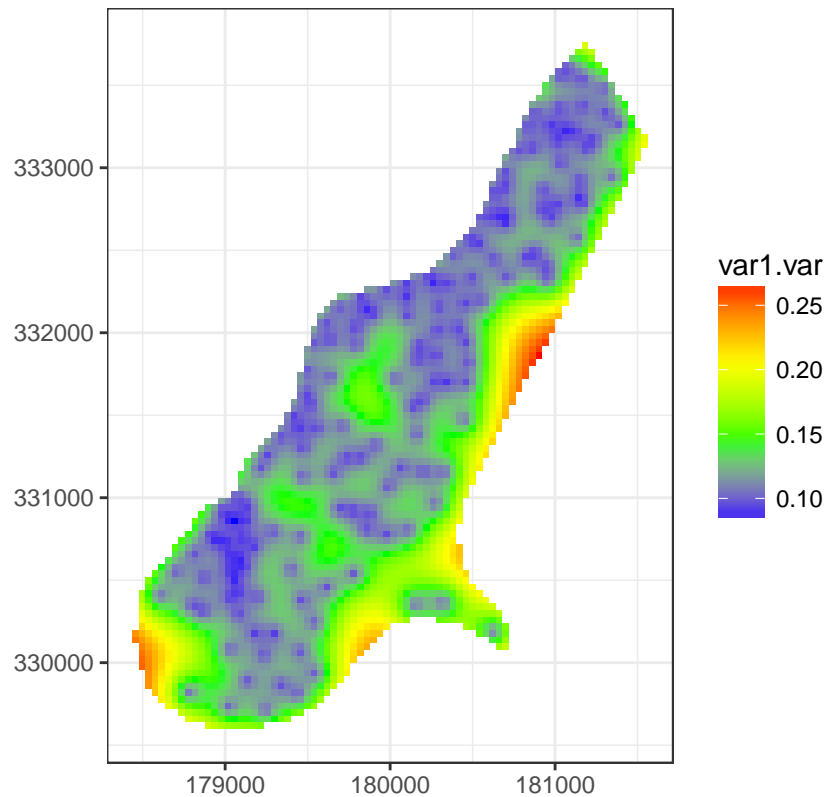
```
ggplot(df.lCu.kriged, aes(x,y,fill=var1.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Predicción. Log(Cobre).')
```


Predicción. Log(Cobre).



```
ggplot(df.lCu.kriged, aes(x,y,fill=var1.var)) +  
  geom_raster() + coord_equal() + theme_bw() +  
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +  
  labs(x=NULL,y=NULL,  
       title='Varianza de Predicción. Log(Cobre).')
```

Varianza de Predicción. Log(Cobre).



12 Kriging Universal

12.1 Ajuste lineal sobre coordenadas y sus residuos

```
# Sin transformación
summary(lm(formula=copper ~ coordinates(meuse), data=meuse))

##
## Call:
## lm(formula = copper ~ coordinates(meuse), data = meuse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -31.565 -15.170  -5.975  10.384  75.887
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -2.508e+03  5.379e+02  -4.663 6.78e-06 ***
## coordinates(meuse)x -2.571e-02  4.351e-03  -5.909 2.18e-08 ***
## coordinates(meuse)y  2.164e-02  3.098e-03   6.984 8.38e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.74 on 152 degrees of freedom
```

```
## Multiple R-squared:  0.243, Adjusted R-squared:  0.2331
## F-statistic: 24.4 on 2 and 152 DF, p-value: 6.456e-10

# Log
lCu<-log(meuse$copper)
summary(lm(formula=lCu ~ coordinates(meuse), data=meuse))

##
## Call:
## lm(formula = lCu ~ coordinates(meuse), data = meuse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7666 -0.3232 -0.1065  0.3308  1.4834
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -4.927e+01  1.138e+01  -4.331 2.68e-05 ***
## coordinates(meuse)x -5.998e-04  9.203e-05  -6.518 9.92e-10 ***
## coordinates(meuse)y  4.849e-04  6.553e-05   7.399 8.67e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4386 on 152 degrees of freedom
## Multiple R-squared:  0.2652, Adjusted R-squared:  0.2555
## F-statistic: 27.43 on 2 and 152 DF, p-value: 6.732e-11
```

12.2 Variograma de residuos y comparación

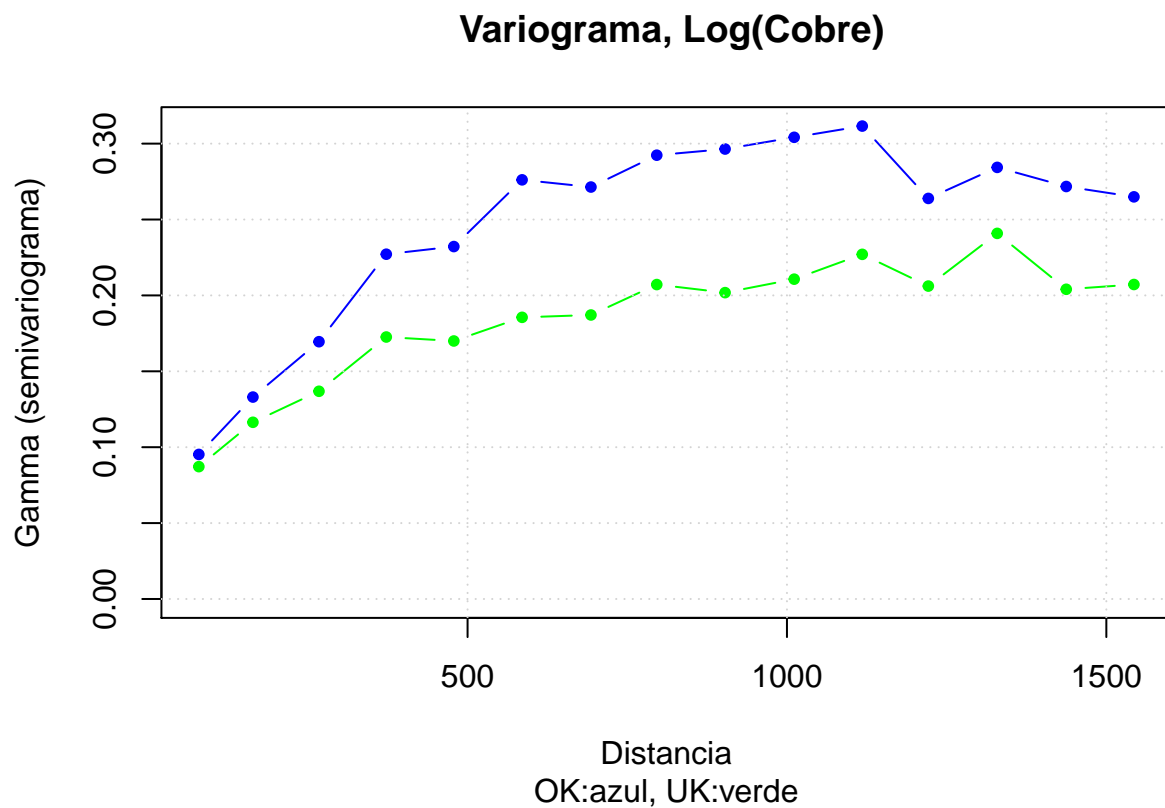
```
(lCu.res.vgm = variogram(log(copper)~x+y, meuse))

##      np      dist      gamma dir.hor dir.ver   id
## 1    57   79.29244 0.08719362      0      0 var1
## 2   299  163.97367 0.11641112      0      0 var1
## 3   419  267.36483 0.13683373      0      0 var1
## 4   457  372.73542 0.17257971      0      0 var1
## 5   547  478.47670 0.16997099      0      0 var1
## 6   533  585.34058 0.18554479      0      0 var1
## 7   574  693.14526 0.18709522      0      0 var1
## 8   564  796.18365 0.20714739      0      0 var1
## 9   589  903.14650 0.20182487      0      0 var1
## 10  543 1011.29177 0.21069077      0      0 var1
## 11  500 1117.86235 0.22705462      0      0 var1
## 12  477 1221.32810 0.20614711      0      0 var1
## 13  452 1329.16407 0.24085510      0      0 var1
## 14  457 1437.25620 0.20403254      0      0 var1
## 15  415 1543.20248 0.20717259      0      0 var1

(lCu.all.vgm <- data.frame(np = lCu.vgm$np,
                           dist = lCu.vgm$dist,
                           gamma.ok=lCu.vgm$gamma,
                           gamma.uk=lCu.res.vgm$gamma,
                           gamma.dif = lCu.vgm$gamma - lCu.res.vgm$gamma ))
```

##	np	dist	gamma.ok	gamma.uk	gamma.dif
## 1	57	79.29244	0.09522828	0.08719362	0.008034657
## 2	299	163.97367	0.13301890	0.11641112	0.016607784
## 3	419	267.36483	0.16949808	0.13683373	0.032664342
## 4	457	372.73542	0.22712857	0.17257971	0.054548855
## 5	547	478.47670	0.23217426	0.16997099	0.062203271
## 6	533	585.34058	0.27613309	0.18554479	0.090588300
## 7	574	693.14526	0.27139217	0.18709522	0.084296955
## 8	564	796.18365	0.29236481	0.20714739	0.085217422
## 9	589	903.14650	0.29642987	0.20182487	0.094604992
## 10	543	1011.29177	0.30415935	0.21069077	0.093468577
## 11	500	1117.86235	0.31154663	0.22705462	0.084492012
## 12	477	1221.32810	0.26389361	0.20614711	0.057746499
## 13	452	1329.16407	0.28434482	0.24085510	0.043489719
## 14	457	1437.25620	0.27174256	0.20403254	0.067710018
## 15	415	1543.20248	0.26493408	0.20717259	0.057761485

```
plot(lCu.all.vgm$gamma.ok ~ lCu.all.vgm$dist, pch=20, col="blue",
     type="b", xlab="Distancia", ylab="Gamma (semivariograma)",
     ylim=c(0,max(lCu.all.vgm$gamma.ok, lCu.all.vgm$gamma.uk)),
     main = " Variograma, Log(Cobre)", sub="OK:azul, UK:verde")
points(lCu.all.vgm$gamma.uk ~ lCu.all.vgm$dist, pch=20, col="green",
       type="b")
grid()
```



12.3 Ajuste de modelos teóricos

```
modelos = data.frame(modelos, 'SSErr_res'=NA)
for (i in c(2:15,17,18)) { # Se han excluido manualmente los que han dado error
  modelos$SSErr_res[i] = attributes(fit.variogram(
    lCu.res.vgm, model=vgm(0.20, modelos$short[i], 900, 0.05)))$SSErr
}
```

```
## Warning in fit.variogram(object, model, fit.sills = fit.sills, fit.ranges =
## fit.ranges, : singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.res.vgm, model = vgm(0.2, modelos$short[i], :
## No convergence after 200 iterations: try different initial values?
```

```
## Warning in fit.variogram(lCu.res.vgm, model = vgm(0.2, modelos$short[i], :
## singular model in variogram fit
```

```
## Warning in fit.variogram(object, model, fit.sills = fit.sills, fit.ranges
## = fit.ranges, : No convergence after 200 iterations: try different initial
## values?
```

```
## Warning in fit.variogram(lCu.res.vgm, model = vgm(0.2, modelos$short[i], :
## singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.res.vgm, model = vgm(0.2, modelos$short[i], :
## singular model in variogram fit
```

```
modelos
```

##	short	long	SSErr
## 1	Nug	Nug (nugget)	NA
## 2	Exp	Exp (exponential)	3.709119e-06
## 3	Sph	Sph (spherical)	2.266095e-06
## 4	Gau	Gau (gaussian)	2.951113e-06
## 5	Exc	Exclass (Exponential class/stable)	9.800221e-06
## 6	Mat	Mat (Matern)	3.709119e-06
## 7	Ste Mat	(Matern, M. Stein's parameterization)	3.709119e-06
## 8	Cir	Cir (circular)	2.436197e-06
## 9	Lin	Lin (linear)	3.102196e-06
## 10	Bes	Bes (bessel)	2.645632e-06
## 11	Pen	Pen (pentaspherical)	2.171773e-06
## 12	Per	Per (periodic)	1.953203e-04
## 13	Wav	Wav (wave)	4.001240e-05
## 14	Hol	Hol (hole)	5.420405e-04
## 15	Log	Log (logarithmic)	8.887894e-02
## 16	Pow	Pow (power)	NA
## 17	Spl	Spl (spline)	2.707089e+09
## 18	Leg	Leg (Legendre)	1.532755e-02
## 19	Err	Err (Measurement error)	NA
## 20	Int	Int (Intercept)	NA
##	SSErr_res		
## 1	NA		
## 2	1.107682e-06		
## 3	1.976535e-06		
## 4	2.626598e-06		
## 5	1.369745e-06		
## 6	1.107682e-06		

```
## 7 1.107682e-06
## 8 2.252892e-06
## 9 3.068402e-06
## 10 1.287015e-06
## 11 1.724752e-06
## 12 6.934794e-05
## 13 1.357247e-05
## 14 8.708338e-05
## 15 6.431726e-04
## 16 NA
## 17 1.732537e+09
## 18 1.016827e-02
## 19 NA
## 20 NA
```

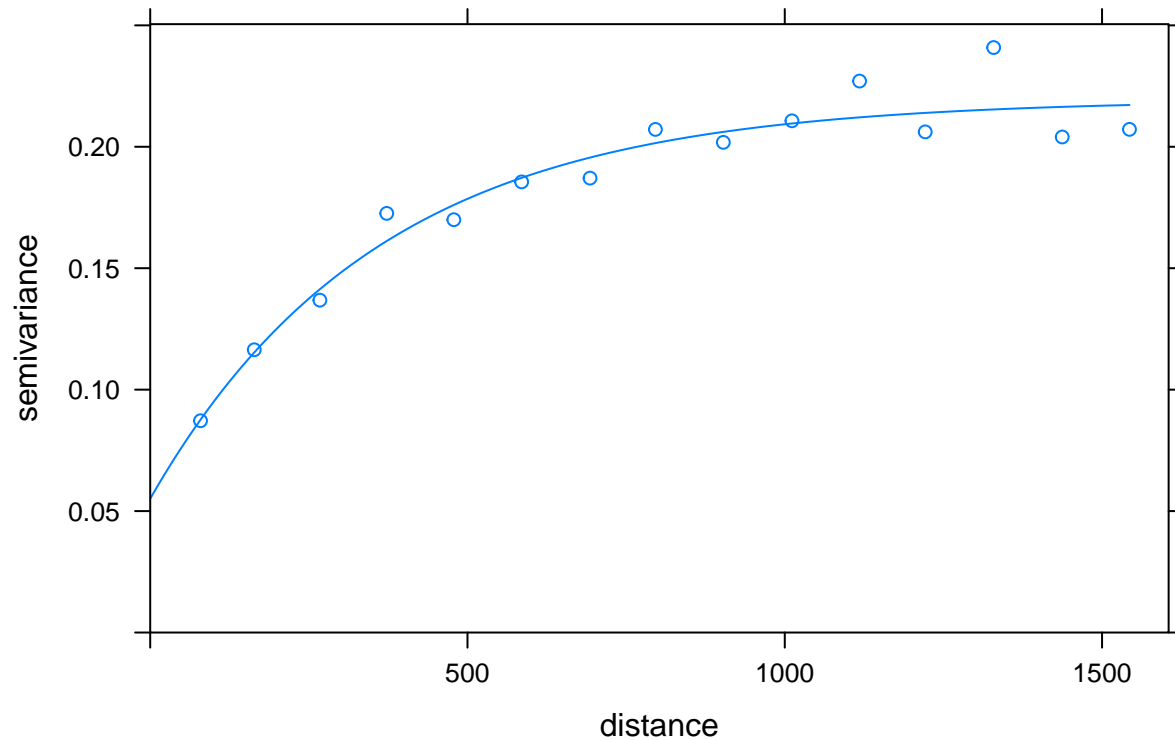
12.4 Mejor modelo

```
(mejor.modelo = modelos[which.min(modelos$SSErr_res),])

##      short                                long      SSErr
## 7 Ste Mat (Matern, M. Stein's parameterization) 3.709119e-06
##      SSErr_res
## 7 1.107682e-06

lCu.res.fit = fit.variogram(lCu.res.vgm,
                           model = vgm(0.20, mejor.modelo$short, 900, 0.05))
plot(lCu.res.vgm, lCu.res.fit, main=as.character(mejor.modelo$long))
```

Mat (Matern, M. Stein's parameterization)



12.5 Predicciones

```
lCu.Ukriged = krige(log(copper)~x+y,  
                    meuse, meuse.grid, model = lCu.res.fit)
```

```
## [using universal kriging]
```

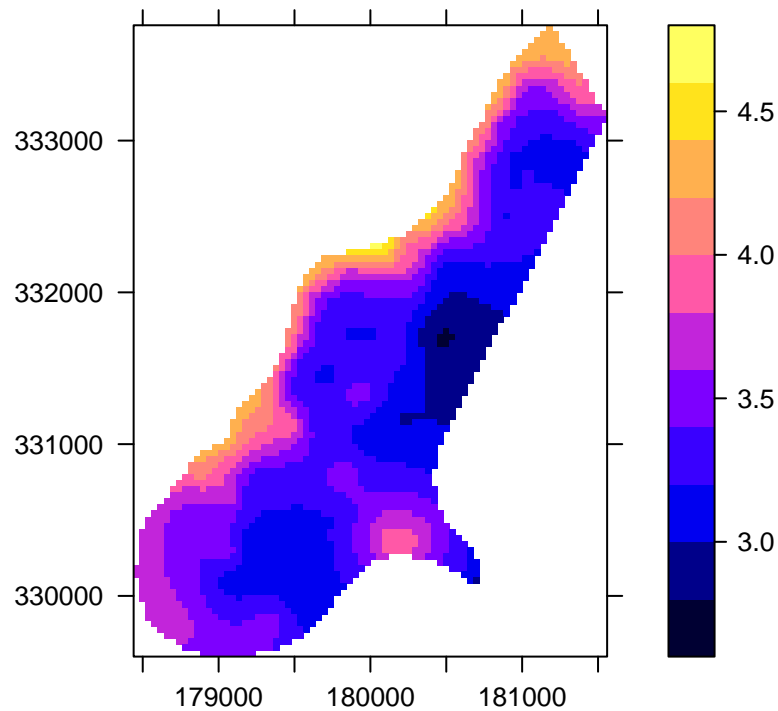
```
summary(lCu.Ukriged)
```

```
## Object of class SpatialPixelsDataFrame  
## Coordinates:  
##      min      max  
## x 178460 181540  
## y 329620 333740  
## Is projected: NA  
## proj4string : [NA]  
## Number of points: 3103  
## Grid attributes:  
##   cellcentre.offset cellsize cells.dim  
## x           178460      40         78  
## y           329620      40        104  
## Data attributes:  
##   var1.pred      var1.var  
## Min.      :2.772   Min.      :0.07894  
## 1st Qu.:3.191   1st Qu.:0.10212
```

```
## Median :3.335   Median :0.11256
## Mean   :3.424   Mean   :0.11955
## 3rd Qu.:3.610   3rd Qu.:0.13166
## Max.   :4.614   Max.   :0.20703
```

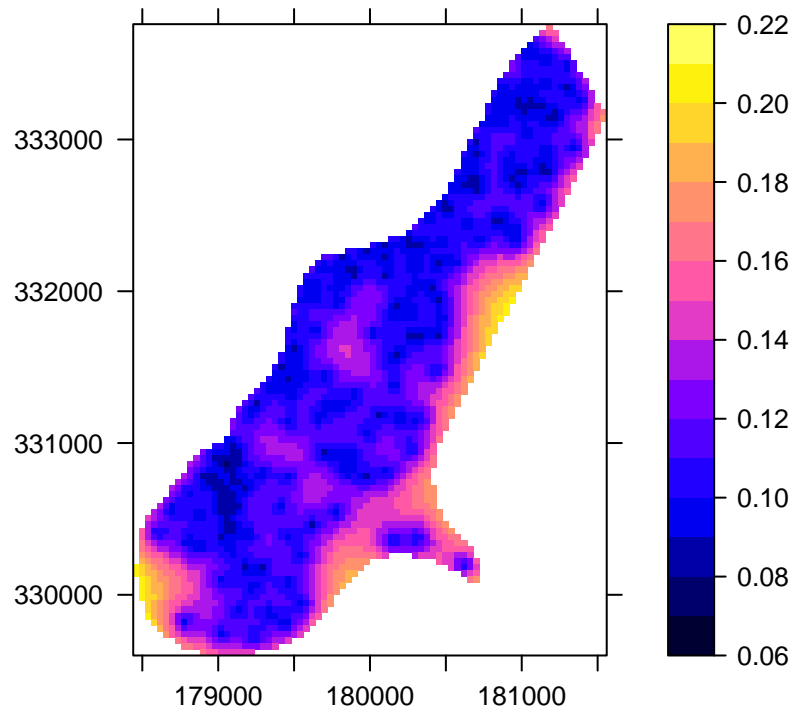
```
spplot(lCu.Ukriged["var1.pred"], pretty=T, col.regions=bpy.colors(64),
       main="Predicción UK. Log(Cobre).",
       scales=list(draw=T))
```

Predicción UK. Log(Cobre).



```
spplot(lCu.Ukriged["var1.var"], pretty=T, col.regions=bpy.colors(64),
       main="Varianza de Predicción UK. Log(Cobre).",
       scales=list(draw=T))
```


Varianza de Predicción UK. Log(Cobre).

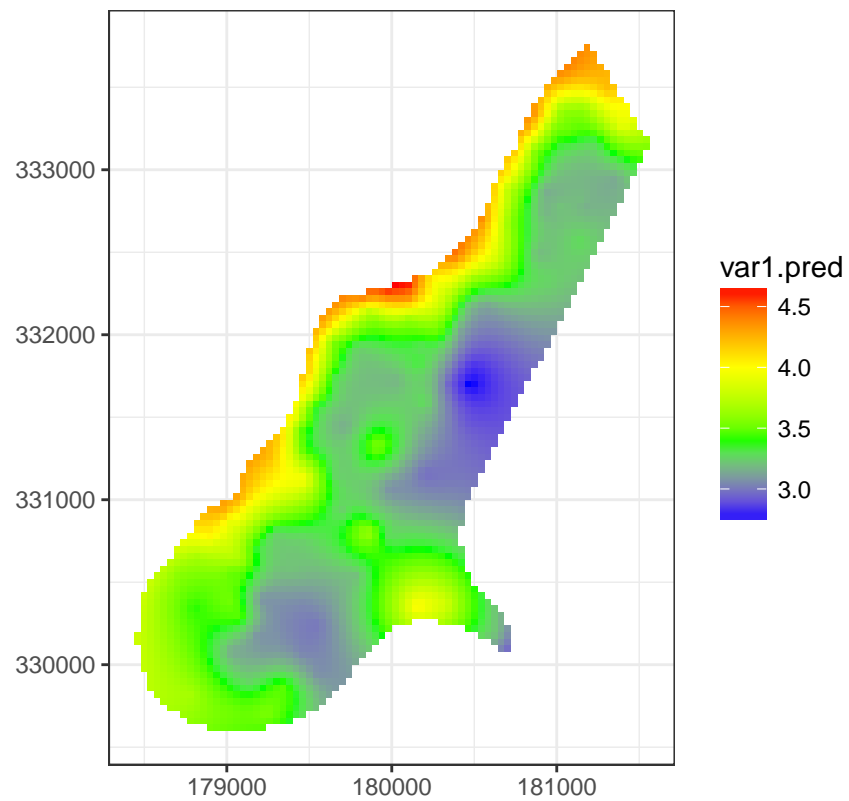


```
df.lCu.Ukriged = as.data.frame(lCu.Ukriged)
head(df.lCu.Ukriged)
```

```
##      x      y var1.pred var1.var
## 1 181180 333740 4.353439 0.1674917
## 2 181140 333700 4.370373 0.1455395
## 3 181180 333700 4.344553 0.1521081
## 4 181220 333700 4.319174 0.1591605
## 5 181100 333660 4.383838 0.1197542
## 6 181140 333660 4.355609 0.1278914
```

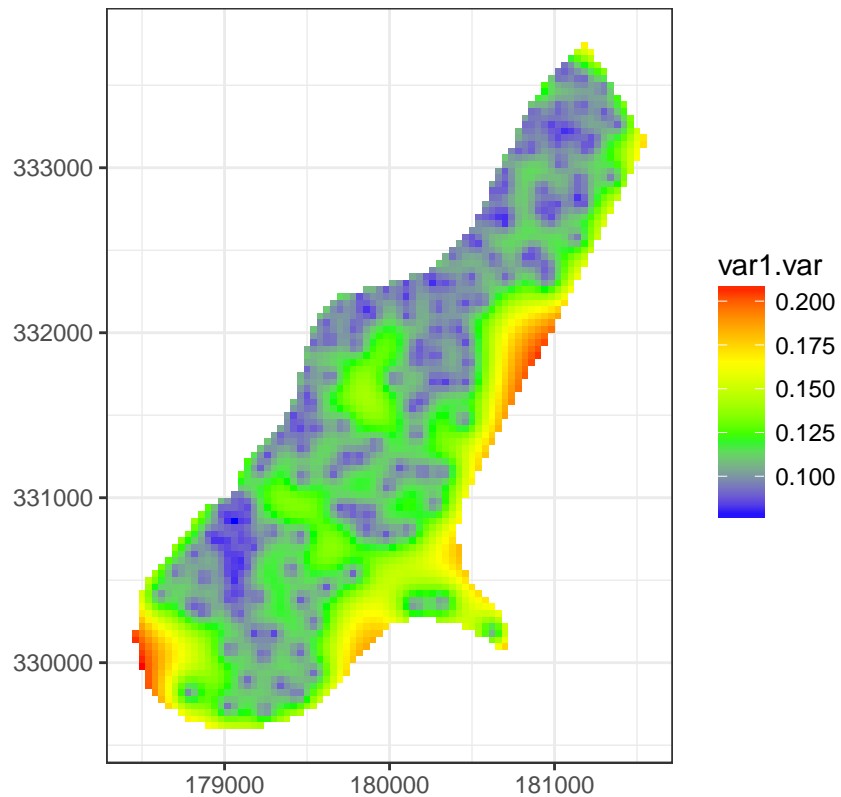
```
ggplot(df.lCu.Ukriged, aes(x,y,fill=var1.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Predicción UK. Log(Cobre).')
```

Predicción UK. Log(Cobre).



```
ggplot(df.lCu.Ukriged, aes(x,y,fill=var1.var)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Varianza de Predicción UK. Log(Cobre).')
```

Varianza de Predicción UK. Log(Cobre).



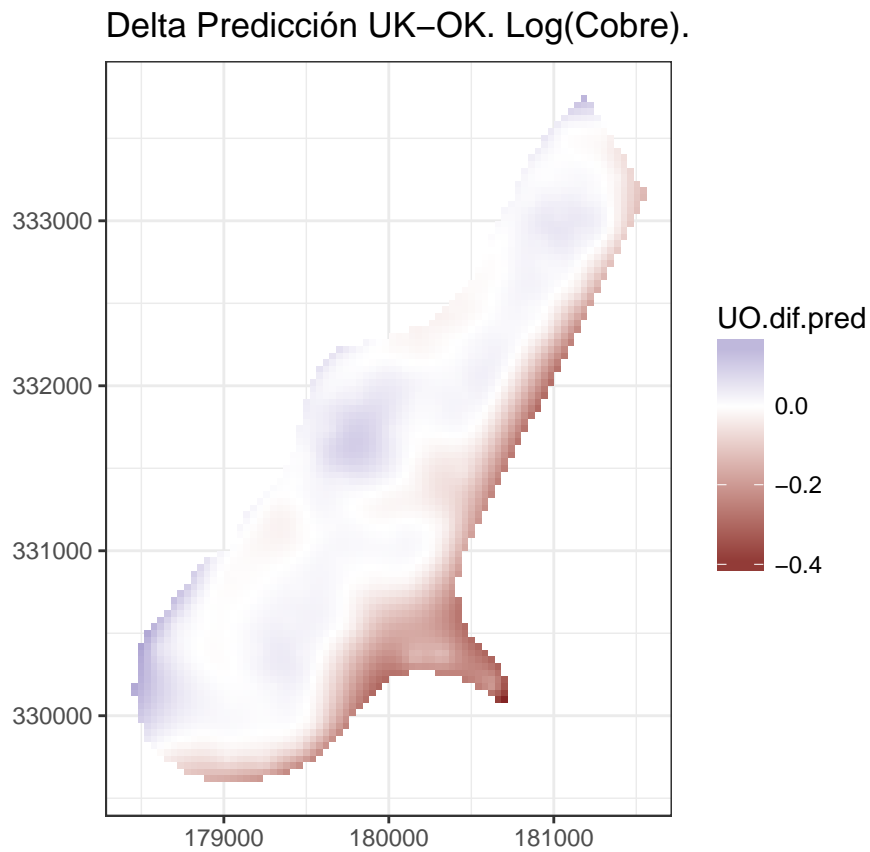
12.6 Comparativa

```
df.lCu.preds = data.frame(
  df.lCu.kriged,
  U.pred = lCu.Ukriged$var1.pred, U.var = lCu.Ukriged$var1.var,
  U0.dif.pred = lCu.Ukriged$var1.pred - lCu.kriged$var1.pred,
  U0.dif.var = lCu.Ukriged$var1.var - lCu.kriged$var1.var
)
```

```
summary(df.lCu.preds)
```

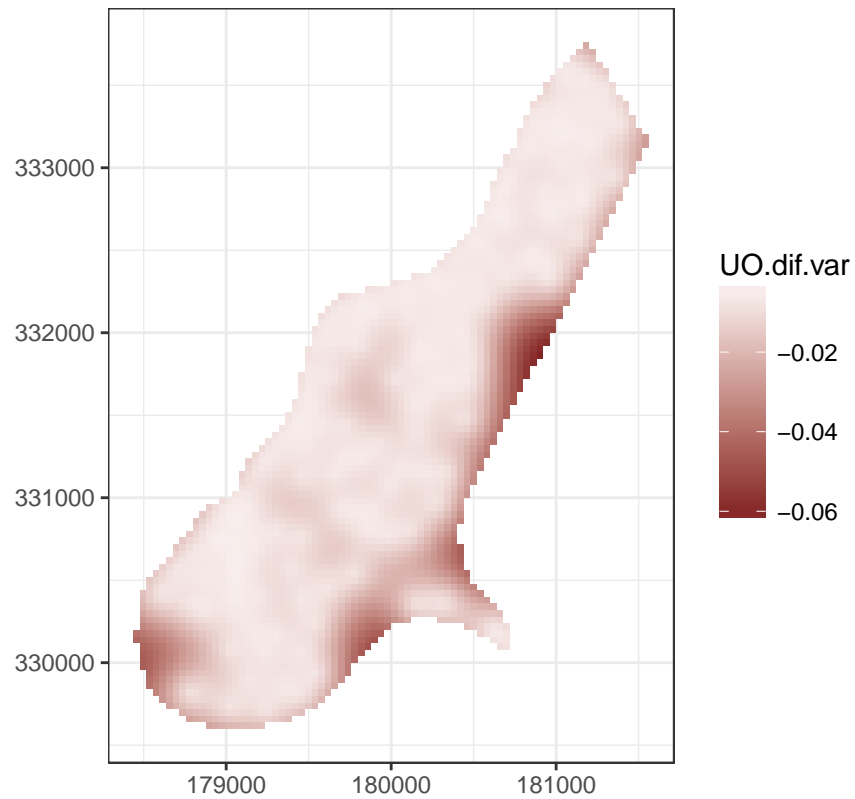
##	x	y	var1.pred	var1.var
##	Min. :178460	Min. :329620	Min. :2.775	Min. :0.08361
##	1st Qu.:179420	1st Qu.:330460	1st Qu.:3.191	1st Qu.:0.10879
##	Median :179980	Median :331220	Median :3.367	Median :0.12083
##	Mean :179985	Mean :331348	Mean :3.447	Mean :0.13192
##	3rd Qu.:180580	3rd Qu.:332140	3rd Qu.:3.637	3rd Qu.:0.14536
##	Max. :181540	Max. :333740	Max. :4.625	Max. :0.26575
##	U.pred	U.var	U0.dif.pred	U0.dif.var
##	Min. :2.772	Min. :0.07894	Min. :-0.444217	Min. :-0.061627
##	1st Qu.:3.191	1st Qu.:0.10212	1st Qu.: -0.034734	1st Qu.: -0.013732
##	Median :3.335	Median :0.11256	Median : 0.003102	Median :-0.008372
##	Mean :3.424	Mean :0.11955	Mean :-0.023218	Mean :-0.012369
##	3rd Qu.:3.610	3rd Qu.:0.13166	3rd Qu.: 0.019132	3rd Qu.: -0.006629
##	Max. :4.614	Max. :0.20703	Max. : 0.193378	Max. :-0.004670

```
ggplot(df.lCu.preds, aes(x,y,fill=UO.dif.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Predicción UK-OK. Log(Cobre).')
```



```
ggplot(df.lCu.preds, aes(x,y,fill=UO.dif.var)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Varianza de Predicción UK-OK. Log(Cobre).')
```

Delta Varianza de Predicción UK-OK. Log(Cobre).

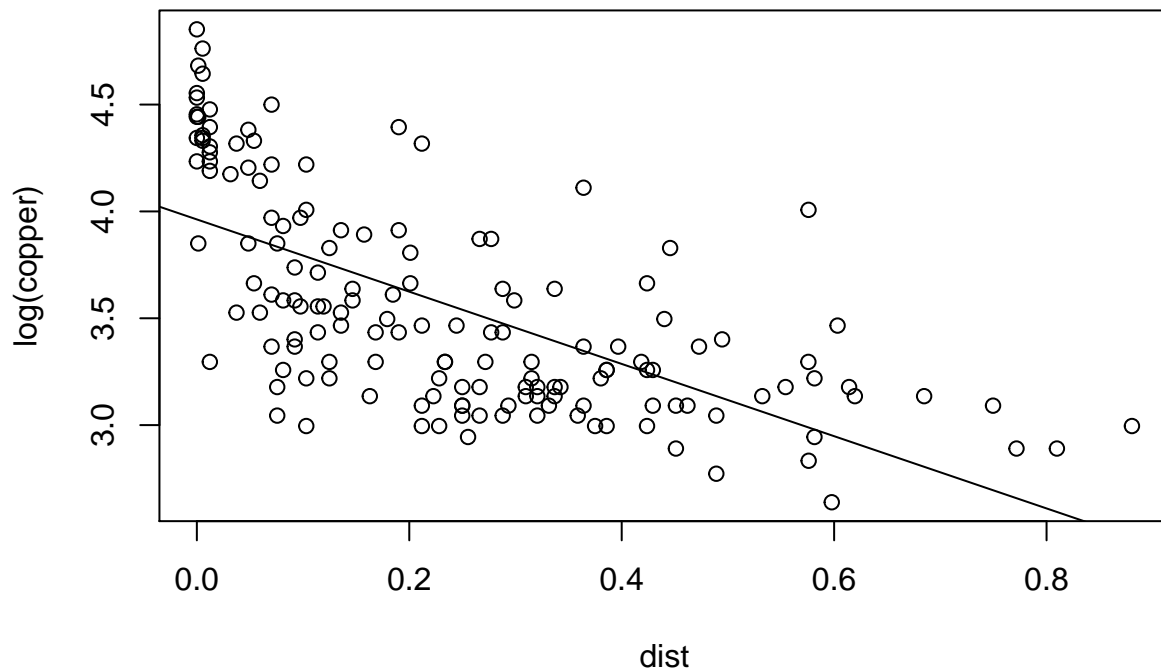


Conclusión: No existen grandes diferencias pero Universal Kriging es preferible a Kriging Ordinario en este caso por mostrar menor varianza de las predicciones.

13 Kriging Deriva Externa

13.1 Ajuste lineal

```
plot(log(copper)~ dist, meuse)
abline(lm(formula=log(copper) ~ dist, data=meuse))
```



```
summary(lm(formula=log(copper) ~ dist, data=meuse))
```

```
##
## Call:
## lm(formula = log(copper) ~ dist, data = meuse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.79260 -0.29425 -0.05632  0.28662  1.01837
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.96251    0.04864   81.47  <2e-16 ***
## dist         -1.69055    0.15662  -10.79  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3843 on 153 degrees of freedom
## Multiple R-squared:  0.4323, Adjusted R-squared:  0.4286
## F-statistic: 116.5 on 1 and 153 DF, p-value: < 2.2e-16
```

```
# summary(lm(formula=log(copper) ~ coordinates(meuse)+dist, data=meuse))
```

13.2 Variograma de residuos

```
(lCu.rdist.vgm = variogram(log(copper)~dist, meuse))
```

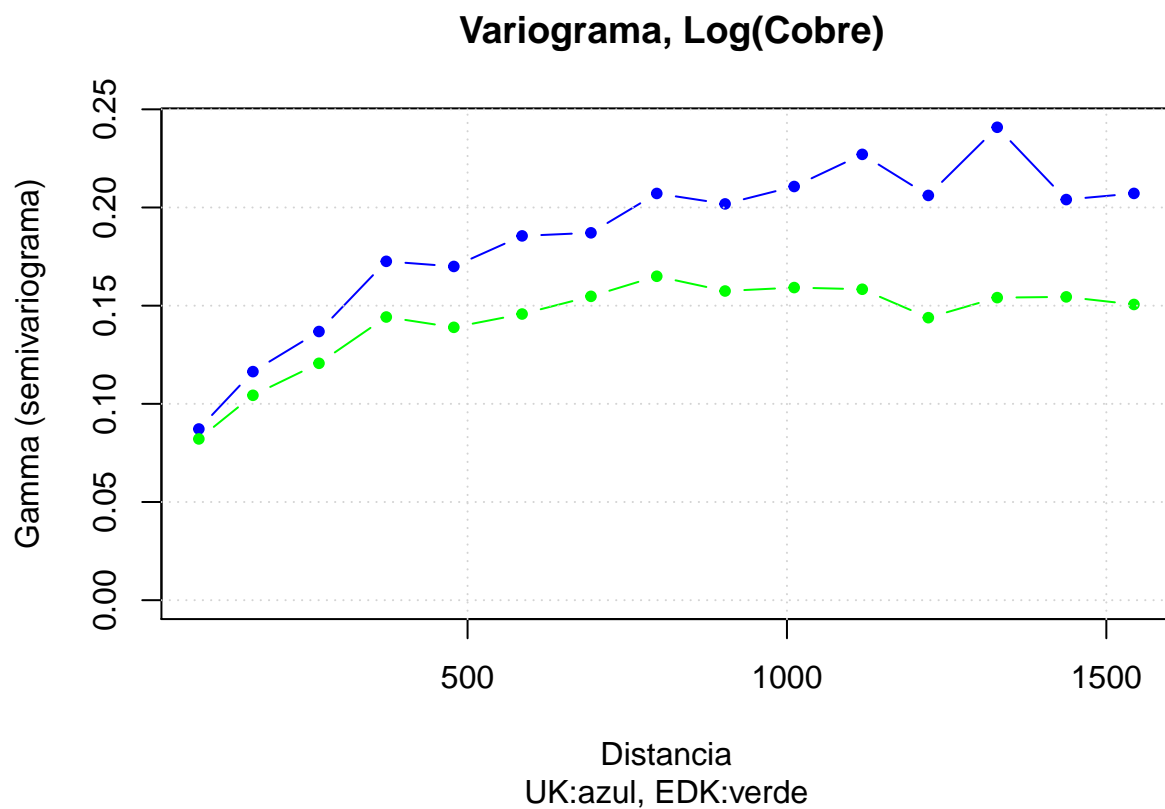
```
##      np      dist      gamma dir.hor dir.ver   id
## 1    57   79.29244 0.08212415      0      0 var1
## 2   299  163.97367 0.10434468      0      0 var1
## 3   419  267.36483 0.12064817      0      0 var1
## 4   457  372.73542 0.14421991      0      0 var1
## 5   547  478.47670 0.13896273      0      0 var1
## 6   533  585.34058 0.14574394      0      0 var1
## 7   574  693.14526 0.15474880      0      0 var1
## 8   564  796.18365 0.16497612      0      0 var1
## 9   589  903.14650 0.15746204      0      0 var1
## 10  543 1011.29177 0.15921954      0      0 var1
## 11  500 1117.86235 0.15836408      0      0 var1
## 12  477 1221.32810 0.14388508      0      0 var1
## 13  452 1329.16407 0.15409336      0      0 var1
## 14  457 1437.25620 0.15447101      0      0 var1
## 15  415 1543.20248 0.15061042      0      0 var1
```

```
(lCu.all.vgm = data.frame(
  lCu.all.vgm,
  gamma.edk = lCu.rdist.vgm$gamma,
  gamma.dif.edk = lCu.res.vgm$gamma - lCu.rdist.vgm$gamma
)
```

```
##      np      dist  gamma.ok  gamma.uk  gamma.dif  gamma.edk
## 1    57   79.29244 0.09522828 0.08719362 0.008034657 0.08212415
## 2   299  163.97367 0.13301890 0.11641112 0.016607784 0.10434468
## 3   419  267.36483 0.16949808 0.13683373 0.032664342 0.12064817
## 4   457  372.73542 0.22712857 0.17257971 0.054548855 0.14421991
## 5   547  478.47670 0.23217426 0.16997099 0.062203271 0.13896273
## 6   533  585.34058 0.27613309 0.18554479 0.090588300 0.14574394
## 7   574  693.14526 0.27139217 0.18709522 0.084296955 0.15474880
## 8   564  796.18365 0.29236481 0.20714739 0.085217422 0.16497612
## 9   589  903.14650 0.29642987 0.20182487 0.094604992 0.15746204
## 10  543 1011.29177 0.30415935 0.21069077 0.093468577 0.15921954
## 11  500 1117.86235 0.31154663 0.22705462 0.084492012 0.15836408
## 12  477 1221.32810 0.26389361 0.20614711 0.057746499 0.14388508
## 13  452 1329.16407 0.28434482 0.24085510 0.043489719 0.15409336
## 14  457 1437.25620 0.27174256 0.20403254 0.067710018 0.15447101
## 15  415 1543.20248 0.26493408 0.20717259 0.057761485 0.15061042
##      gamma.dif.edk
## 1    0.005069476
## 2    0.012066431
## 3    0.016185560
## 4    0.028359796
## 5    0.031008252
## 6    0.039800849
## 7    0.032346422
## 8    0.042171271
## 9    0.044362830
```

```
## 10 0.051471236
## 11 0.068690543
## 12 0.062262031
## 13 0.086761747
## 14 0.049561535
## 15 0.056562173
```

```
plot(lCu.all.vgm$gamma.uk ~ lCu.all.vgm$dist, pch=20, col="blue",
     type="b", xlab="Distancia", ylab="Gamma (semivariograma)",
     ylim=c(0,max(lCu.all.vgm$gamma.uk, lCu.all.vgm$gamma.edk)),
     main = " Variograma, Log(Cobre)", sub="UK:azul, EDK:verde")
points(lCu.all.vgm$gamma.edk ~ lCu.all.vgm$dist, pch=20, col="green",
       type="b")
grid()
```



13.3 Ajuste de modelos teóricos

```
modelos = data.frame(modelos, 'SSErr_rdist'=NA)
for (i in c(2:15,17,18)) { # Se han excluido manualmente los que han dado error
  modelos$SSErr_rdist[i] = attributes(fit.variogram(
    lCu.rdist.vgm, model=vgm(0.15, modelos$short[i], 500, 0.05)))$SSErr
}
```

```
## Warning in fit.variogram(object, model, fit.sills = fit.sills, fit.ranges =
## fit.ranges, : singular model in variogram fit
```



```
## Warning in fit.variogram(lCu.rdist.vgm, model = vgm(0.15, modelos
## $short[i], : No convergence after 200 iterations: try different initial
## values?

## Warning in fit.variogram(lCu.rdist.vgm, model = vgm(0.15, modelos
## $short[i], : singular model in variogram fit

## Warning in fit.variogram(lCu.rdist.vgm, model = vgm(0.15, modelos
## $short[i], : singular model in variogram fit

## Warning in fit.variogram(lCu.rdist.vgm, model = vgm(0.15, modelos
## $short[i], : singular model in variogram fit
```

```
modelos
```

##	short	long	SSErr
## 1	Nug	Nug (nugget)	NA
## 2	Exp	Exp (exponential)	3.709119e-06
## 3	Sph	Sph (spherical)	2.266095e-06
## 4	Gau	Gau (gaussian)	2.951113e-06
## 5	Exc	Exclass (Exponential class/stable)	9.800221e-06
## 6	Mat	Mat (Matern)	3.709119e-06
## 7	Ste Mat	Matern, M. Stein's parameterization)	3.709119e-06
## 8	Cir	Cir (circular)	2.436197e-06
## 9	Lin	Lin (linear)	3.102196e-06
## 10	Bes	Bes (bessel)	2.645632e-06
## 11	Pen	Pen (pentaspherical)	2.171773e-06
## 12	Per	Per (periodic)	1.953203e-04
## 13	Wav	Wav (wave)	4.001240e-05
## 14	Hol	Hol (hole)	5.420405e-04
## 15	Log	Log (logarithmic)	8.887894e-02
## 16	Pow	Pow (power)	NA
## 17	Spl	Spl (spline)	2.707089e+09
## 18	Leg	Leg (Legendre)	1.532755e-02
## 19	Err	Err (Measurement error)	NA
## 20	Int	Int (Intercept)	NA
##	SSErr_res	SSErr_rdist	
## 1	NA	NA	
## 2	1.107682e-06	5.383024e-07	
## 3	1.976535e-06	7.447525e-07	
## 4	2.626598e-06	8.346376e-07	
## 5	1.369745e-06	8.529689e-07	
## 6	1.107682e-06	5.383024e-07	
## 7	1.107682e-06	5.383024e-07	
## 8	2.252892e-06	8.145562e-07	
## 9	3.068402e-06	1.376126e-06	
## 10	1.287015e-06	5.253159e-07	
## 11	1.724752e-06	6.628005e-07	
## 12	6.934794e-05	2.919926e-05	
## 13	1.357247e-05	2.727819e-06	
## 14	8.708338e-05	3.624011e-05	
## 15	6.431726e-04	1.141330e-04	
## 16	NA	NA	
## 17	1.732537e+09	1.832742e+08	
## 18	1.016827e-02	5.662254e-03	

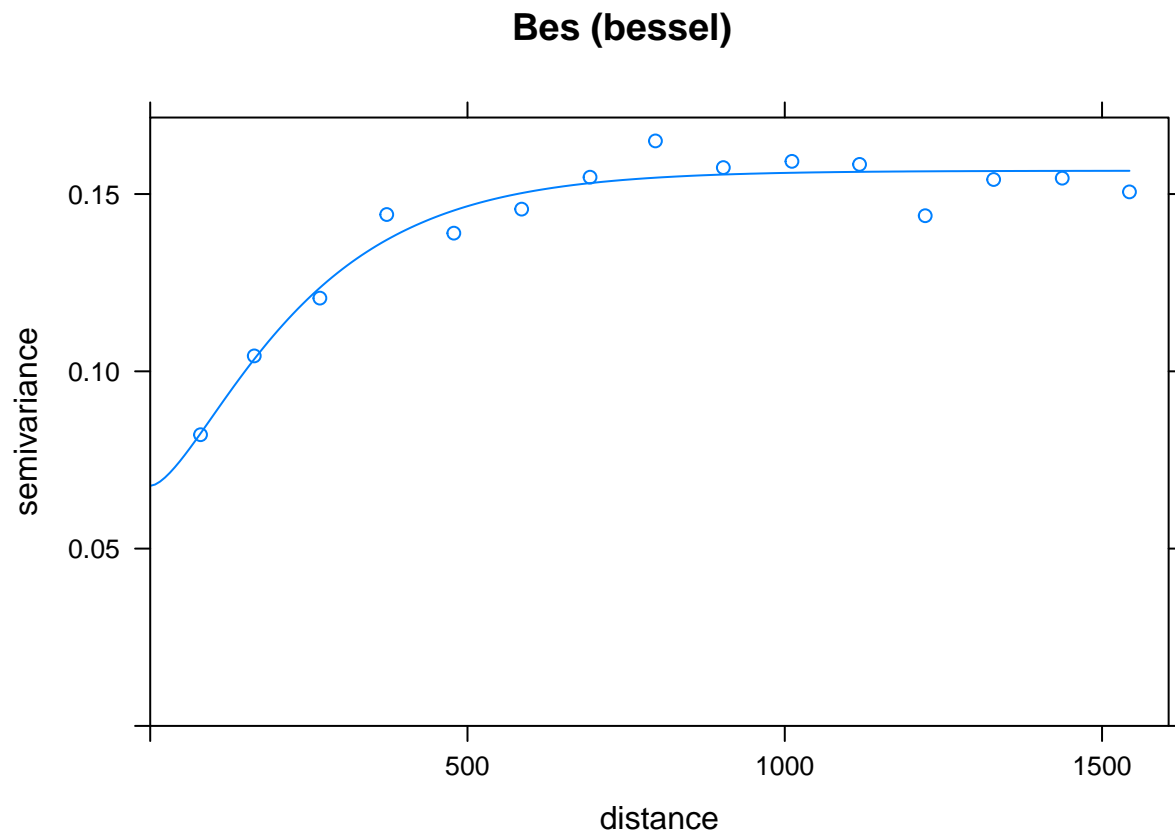
```
## 19      NA      NA
## 20      NA      NA
```

13.4 Mejor modelo

```
(mejor.modelo = modelos[which.min(modelos$SSErr_rdist),])

##      short      long      SSErr  SSErr_res  SSErr_rdist
## 10  Bes Bes (bessel) 2.645632e-06 1.287015e-06 5.253159e-07

lCu.rdist.fit = fit.variogram(lCu.rdist.vgm,
                             model = vgm(0.15, mejor.modelo$short, 500, 0.05))
plot(lCu.rdist.vgm, lCu.rdist.fit, main=as.character(mejor.modelo$long))
```



13.5 Predicciones

```
lCu.EDkriged = krige(log(copper)~dist,meuse,
                    meuse.grid, model = lCu.rdist.fit)
```

```
## [using universal kriging]
```

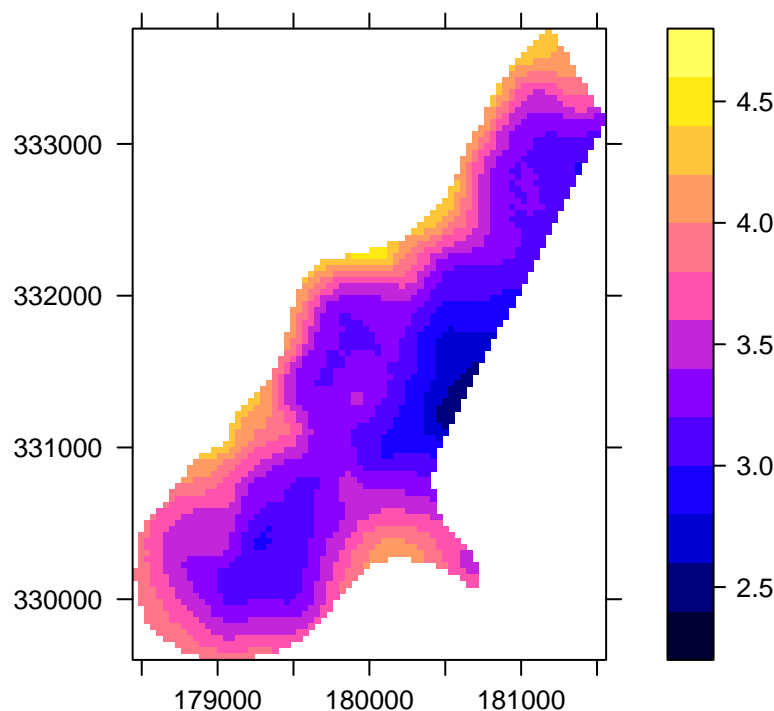
```
summary(lCu.EDkriged)
```

```
## Object of class SpatialPixelsDataFrame
## Coordinates:
```

```
##      min      max
## x 178460 181540
## y 329620 333740
## Is projected: NA
## proj4string : [NA]
## Number of points: 3103
## Grid attributes:
##   cellcentre.offset cellsize cells.dim
## x           178460      40      78
## y           329620      40     104
## Data attributes:
##   var1.pred      var1.var
## Min.   :2.434   Min.   :0.08370
## 1st Qu.:3.181   1st Qu.:0.09752
## Median :3.362   Median :0.10458
## Mean   :3.434   Mean   :0.10975
## 3rd Qu.:3.699   3rd Qu.:0.11863
## Max.   :4.545   Max.   :0.16252
```

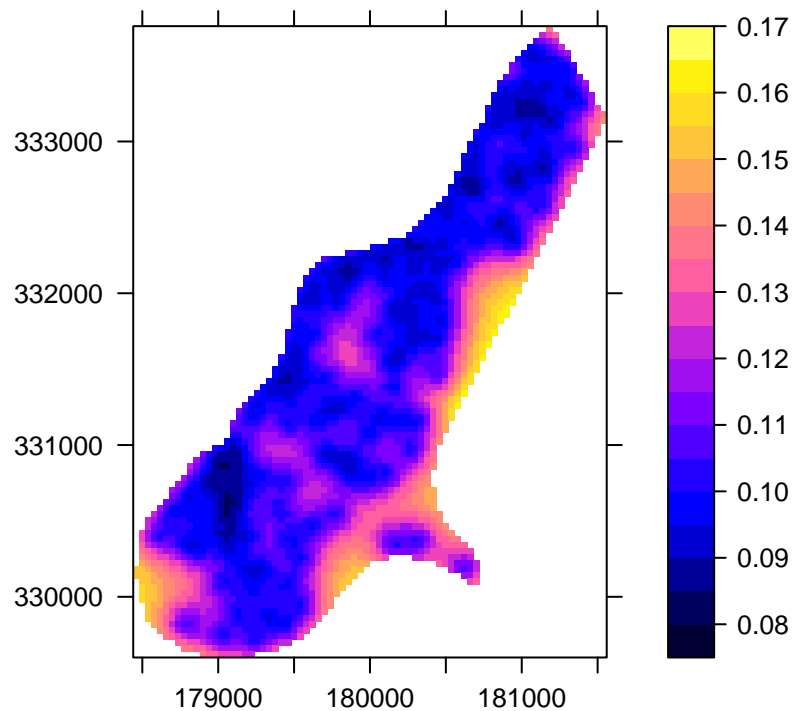
```
spplot(lCu.EDkriged["var1.pred"], pretty=T, col.regions=bpy.colors(64),
       main="Predicción EDK (Distancia al Río). Log(Cobre).",
       scales=list(draw=T))
```

Predicción EDK (Distancia al Río). Log(Cobre).



```
spplot(lCu.EDkriged["var1.var"], pretty=T, col.regions=bpy.colors(64),
       main="Varianza de Predicción EDK (Distancia al Río). Log(Cobre).",
       scales=list(draw=T))
```

Varianza de Predicción EDK (Distancia al Río). Log(Cobre).

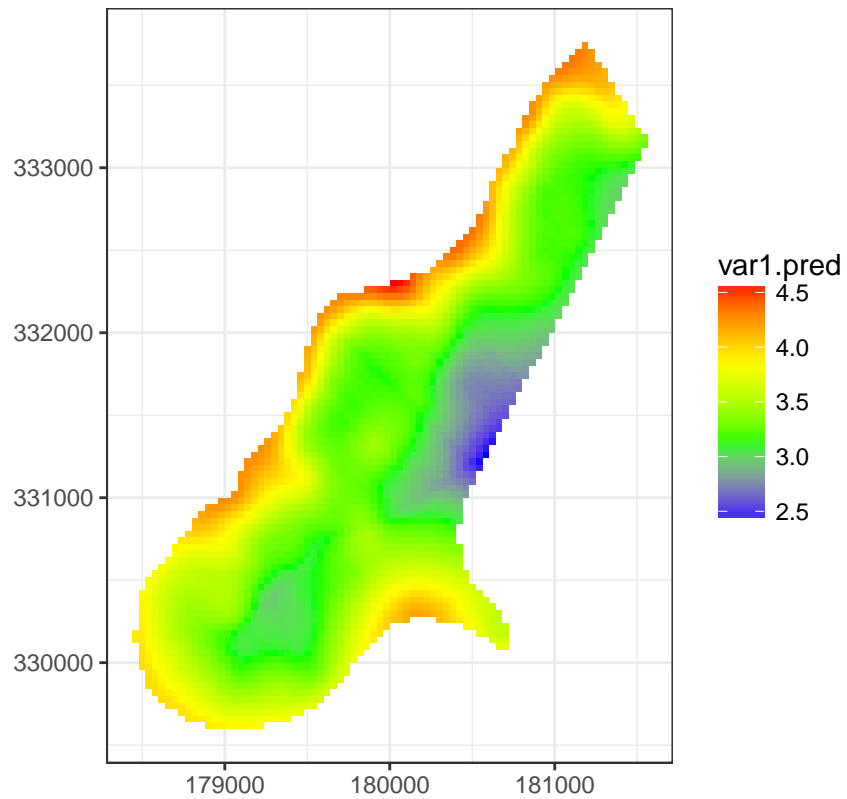


```
df.lCu.EDkriged = as.data.frame(lCu.EDkriged)
head(df.lCu.EDkriged)
```

```
##      x      y var1.pred var1.var
## 1 181180 333740 4.271363 0.1363428
## 2 181140 333700 4.305936 0.1237270
## 3 181180 333700 4.284158 0.1278679
## 4 181220 333700 4.225923 0.1318495
## 5 181100 333660 4.332084 0.1085873
## 6 181140 333660 4.313877 0.1131608
```

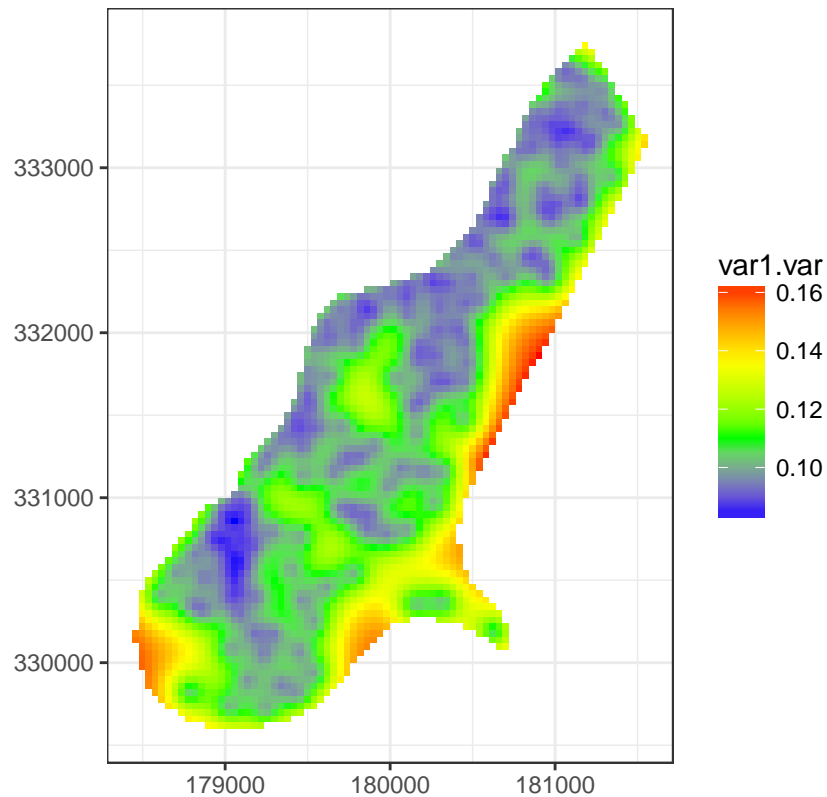
```
ggplot(df.lCu.EDkriged, aes(x,y,fill=var1.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Predicción EDK (Distancia al Río). Log(Cobre).')
```

Predicción EDK (Distancia al Río). Log(Cobre).



```
ggplot(df.lCu.EDkriged, aes(x,y,fill=var1.var)) +  
  geom_raster() + coord_equal() + theme_bw() +  
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +  
  labs(x=NULL,y=NULL,  
       title='Varianza de Predicción EDK (Distancia al Río). Log(Cobre).')
```

Varianza de Predicción EDK (Distancia al Río). Log(Cobre).



13.6 Comparativa

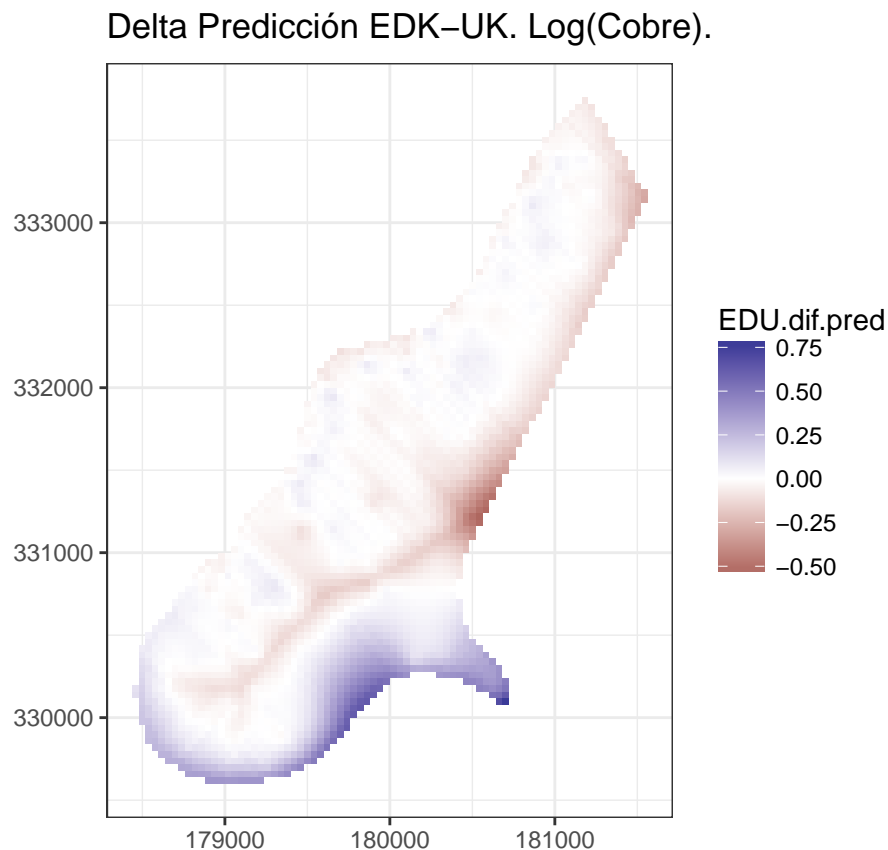
```
df.lCu.preds = data.frame(df.lCu.kriged,
  U.pred = lCu.Ukriged$var1.pred, U.var = lCu.Ukriged$var1.var,
  U0.dif.pred = lCu.Ukriged$var1.pred - lCu.kriged$var1.pred,
  U0.dif.var = lCu.Ukriged$var1.var - lCu.kriged$var1.var,
  ED.pred = lCu.EDkriged$var1.pred, ED.var = lCu.EDkriged$var1.var,
  EDU.dif.pred = lCu.EDkriged$var1.pred - lCu.Ukriged$var1.pred,
  EDU.dif.var = lCu.EDkriged$var1.var - lCu.Ukriged$var1.var
)
```

```
summary(df.lCu.preds)
```

##	x	y	var1.pred	var1.var
##	Min. :178460	Min. :329620	Min. :2.775	Min. :0.08361
##	1st Qu.:179420	1st Qu.:330460	1st Qu.:3.191	1st Qu.:0.10879
##	Median :179980	Median :331220	Median :3.367	Median :0.12083
##	Mean :179985	Mean :331348	Mean :3.447	Mean :0.13192
##	3rd Qu.:180580	3rd Qu.:332140	3rd Qu.:3.637	3rd Qu.:0.14536
##	Max. :181540	Max. :333740	Max. :4.625	Max. :0.26575
##	U.pred	U.var	U0.dif.pred	U0.dif.var
##	Min. :2.772	Min. :0.07894	Min. :-0.444217	Min. :-0.061627
##	1st Qu.:3.191	1st Qu.:0.10212	1st Qu.: -0.034734	1st Qu.: -0.013732
##	Median :3.335	Median :0.11256	Median : 0.003102	Median : -0.008372
##	Mean :3.424	Mean :0.11955	Mean : -0.023218	Mean : -0.012369

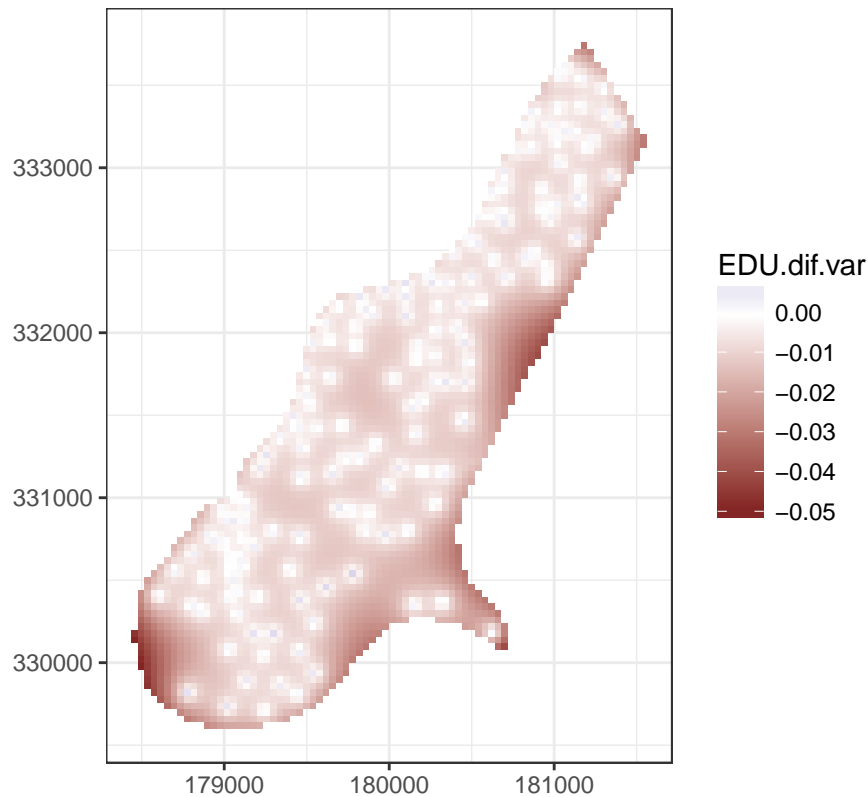
```
## 3rd Qu.:3.610 3rd Qu.:0.13166 3rd Qu.: 0.019132 3rd Qu.: -0.006629
## Max. :4.614 Max. :0.20703 Max. : 0.193378 Max. : -0.004670
## ED.pred ED.var EDU.dif.pred EDU.dif.var
## Min. :2.434 Min. :0.08370 Min. : -0.527312 Min. : -0.050320
## 1st Qu.:3.181 1st Qu.:0.09752 1st Qu.: -0.042246 1st Qu.: -0.012627
## Median :3.362 Median :0.10458 Median : -0.005182 Median : -0.008097
## Mean :3.434 Mean :0.10975 Mean : 0.009642 Mean : -0.009799
## 3rd Qu.:3.699 3rd Qu.:0.11863 3rd Qu.: 0.026527 3rd Qu.: -0.004845
## Max. :4.545 Max. :0.16252 Max. : 0.757908 Max. : 0.009885
```

```
ggplot(df.lCu.preds, aes(x,y,fill=EDU.dif.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Predicción EDK-UK. Log(Cobre).')
```



```
ggplot(df.lCu.preds, aes(x,y,fill=EDU.dif.var)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Varianza de Predicción EDK-UK. Log(Cobre).')
```

Delta Varianza de Predicción EDK–UK. Log(Cobre).



Conclusión: No existen grandes diferencias pero Kriging con Deriva Externa sobre la variable Distancia al Río es preferible a Universal Kriging por mostrar menor varianza de las predicciones. Por tanto, el orden de preferencia actual sería: EDK (Distancia al Río) > UK > OK

14 Kriging Residual Directo

14.1 Ajuste lineal y cálculo de residuos

```
lCu.lm.dist = lm(formula=log(copper) ~ dist, meuse)
summary(lCu.lm.dist)

##
## Call:
## lm(formula = log(copper) ~ dist, data = meuse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.79260 -0.29425 -0.05632  0.28662  1.01837
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.96251    0.04864   81.47  <2e-16 ***
## dist         -1.69055    0.15662  -10.79  <2e-16 ***
## ---
```



```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3843 on 153 degrees of freedom
## Multiple R-squared:  0.4323, Adjusted R-squared:  0.4286
## F-statistic: 116.5 on 1 and 153 DF,  p-value: < 2.2e-16

res = residuals(lCu.lm.dist)
```

14.2 Inclusión de residuos en datos originales

```
meuse1 = data.frame(as.data.frame(meuse), 'R0'=res)
head(meuse1)

##          x          y cadmium copper lead zinc  elev      dist    om ffreq soil
## 1 181072 333611    11.7     85  299 1022  7.909 0.00135803 13.6     1     1
## 2 181025 333558     8.6     81  277 1141  6.983 0.01222430 14.0     1     1
## 3 181165 333537     6.5     68  199  640  7.800 0.10302900 13.0     1     1
## 4 181298 333484     2.6     81  116  257  7.655 0.19009400  8.0     1     2
## 5 181307 333330     2.8     48  117  269  7.480 0.27709000  8.7     1     2
## 6 181390 333260     3.0     61  137  281  7.791 0.36406700  7.8     1     2
##    lime landuse dist.m      R0
## 1     1      Ah     50 0.4824349
## 2     1      Ah     30 0.4526028
## 3     1      Ah    150 0.4311715
## 4     0      Ga    270 0.7533010
## 5     0      Ah    380 0.3771242
## 6     0      Ga    470 0.7638363

coordinates(meuse1) = ~x+y
```

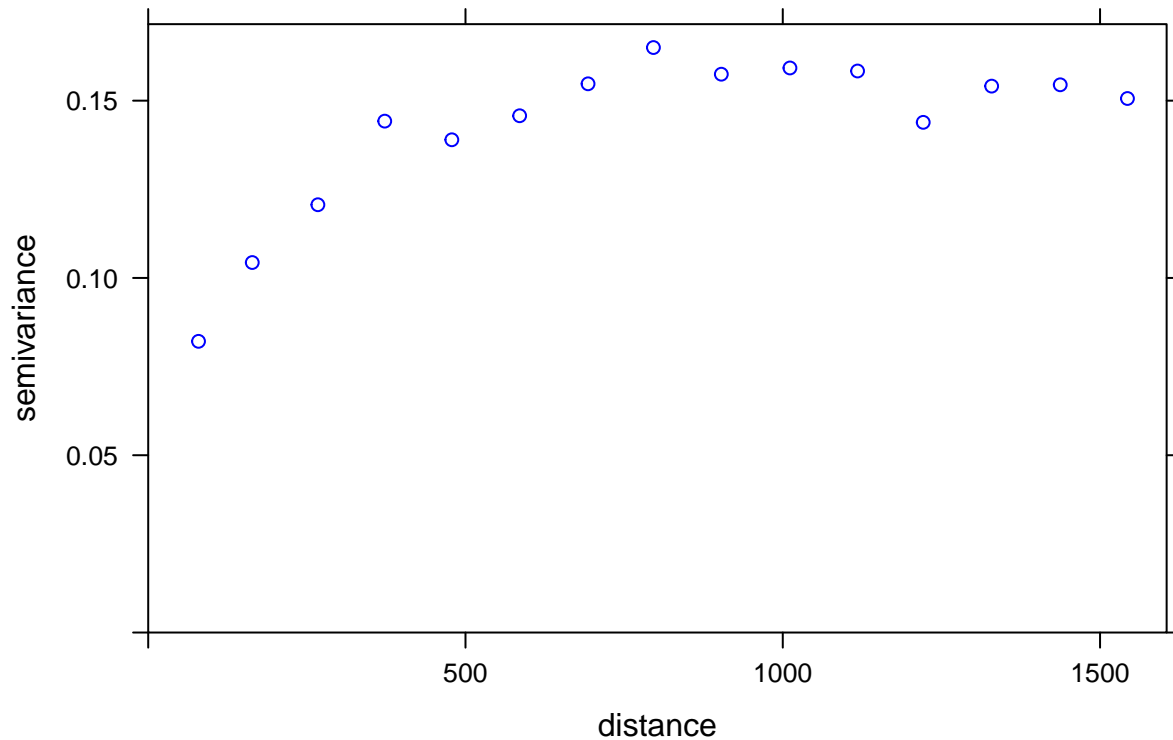
14.3 Variograma de residuos

```
(lCu.R0.vgm = variogram(R0~1,meuse1))

##      np      dist      gamma dir.hor dir.ver  id
## 1    57   79.29244 0.08212415      0      0 var1
## 2   299  163.97367 0.10434468      0      0 var1
## 3   419  267.36483 0.12064817      0      0 var1
## 4   457  372.73542 0.14421991      0      0 var1
## 5   547  478.47670 0.13896273      0      0 var1
## 6   533  585.34058 0.14574394      0      0 var1
## 7   574  693.14526 0.15474880      0      0 var1
## 8   564  796.18365 0.16497612      0      0 var1
## 9   589  903.14650 0.15746204      0      0 var1
## 10  543 1011.29177 0.15921954      0      0 var1
## 11  500 1117.86235 0.15836408      0      0 var1
## 12  477 1221.32810 0.14388508      0      0 var1
## 13  452 1329.16407 0.15409336      0      0 var1
## 14  457 1437.25620 0.15447101      0      0 var1
## 15  415 1543.20248 0.15061042      0      0 var1

plot(lCu.R0.vgm, col="blue",main="Variograma Resíduos: Log(Cobre)~Dist")
```

Variograma Resíduos: Log(Cobre)~Dist



14.4 Ajuste de modelos teóricos

```
modelos = data.frame(modelos, 'SSErr_R0'=NA)
for (i in c(2:15,17,18)) { # Se han excluido manualmente los que han dado error
  modelos$SSErr_R0[i] = attributes(fit.variogram(
    lCu.R0.vgm, model=vgm(0.15, modelos$short[i], 900, 0.05)))$SSErr
}
```

```
## Warning in fit.variogram(object, model, fit.sills = fit.sills, fit.ranges =
## fit.ranges, : singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.R0.vgm, model = vgm(0.15, modelos$short[i], :
## No convergence after 200 iterations: try different initial values?
```

```
## Warning in fit.variogram(lCu.R0.vgm, model = vgm(0.15, modelos$short[i], :
## singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.R0.vgm, model = vgm(0.15, modelos$short[i], :
## singular model in variogram fit
```

```
## Warning in fit.variogram(lCu.R0.vgm, model = vgm(0.15, modelos$short[i], :
## singular model in variogram fit
```

```
modelos
```

```
##      short                long      SSErr
## 1      Nug              Nug (nugget)      NA
```

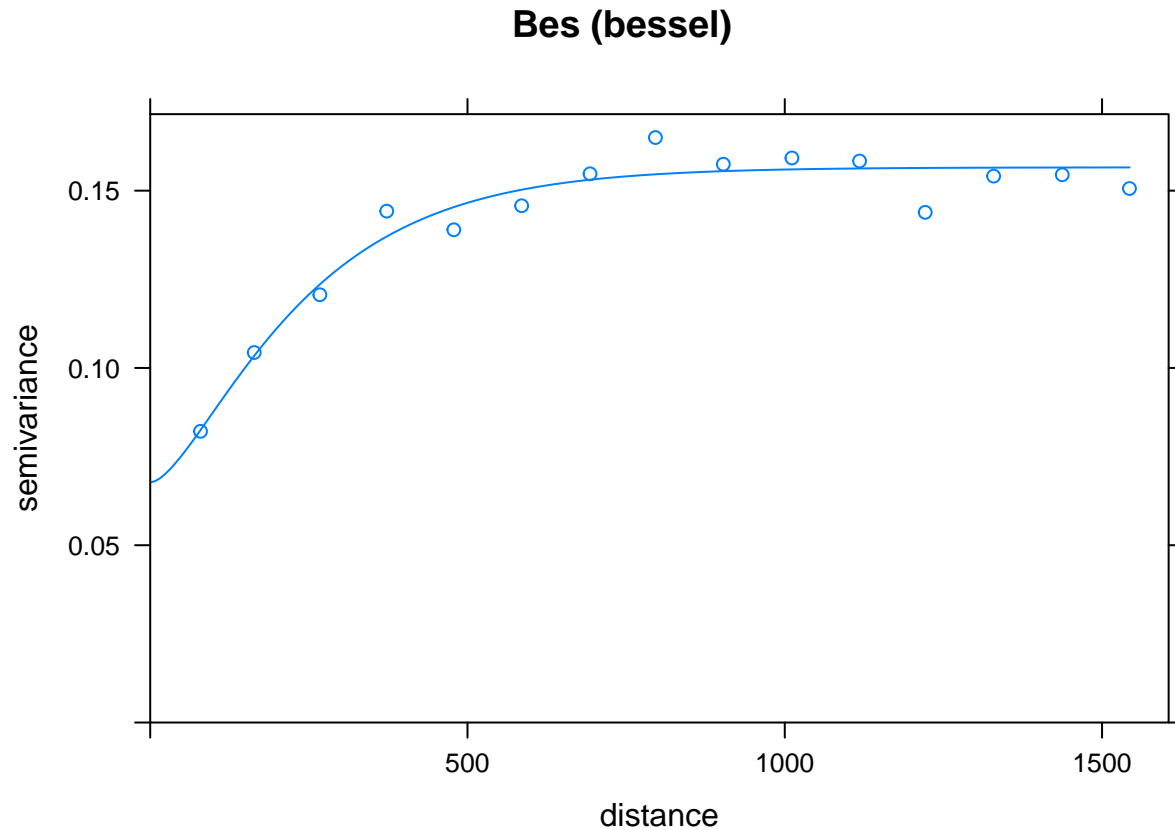
```
## 2      Exp                      Exp (exponential) 3.709119e-06
## 3      Sph                      Sph (spherical) 2.266095e-06
## 4      Gau                      Gau (gaussian) 2.951113e-06
## 5      Exc      Exclass (Exponential class/stable) 9.800221e-06
## 6      Mat                      Mat (Matern) 3.709119e-06
## 7      Ste Mat (Matern, M. Stein's parameterization) 3.709119e-06
## 8      Cir                      Cir (circular) 2.436197e-06
## 9      Lin                      Lin (linear) 3.102196e-06
## 10     Bes                      Bes (bessel) 2.645632e-06
## 11     Pen                      Pen (pentaspherical) 2.171773e-06
## 12     Per                      Per (periodic) 1.953203e-04
## 13     Wav                      Wav (wave) 4.001240e-05
## 14     Hol                      Hol (hole) 5.420405e-04
## 15     Log                      Log (logarithmic) 8.887894e-02
## 16     Pow                      Pow (power) NA
## 17     Spl                      Spl (spline) 2.707089e+09
## 18     Leg                      Leg (Legendre) 1.532755e-02
## 19     Err                      Err (Measurement error) NA
## 20     Int                      Int (Intercept) NA
##      SSError_res SSError_rdist SSError_R0
## 1      NA      NA      NA
## 2 1.107682e-06 5.383024e-07 5.383024e-07
## 3 1.976535e-06 7.447525e-07 7.447523e-07
## 4 2.626598e-06 8.346376e-07 8.346381e-07
## 5 1.369745e-06 8.529689e-07 8.529689e-07
## 6 1.107682e-06 5.383024e-07 5.383024e-07
## 7 1.107682e-06 5.383024e-07 5.383024e-07
## 8 2.252892e-06 8.145562e-07 8.145562e-07
## 9 3.068402e-06 1.376126e-06 1.376126e-06
## 10 1.287015e-06 5.253159e-07 5.253159e-07
## 11 1.724752e-06 6.628005e-07 6.628008e-07
## 12 6.934794e-05 2.919926e-05 2.919926e-05
## 13 1.357247e-05 2.727819e-06 9.265158e-06
## 14 8.708338e-05 3.624011e-05 3.612345e-05
## 15 6.431726e-04 1.141330e-04 1.141328e-04
## 16      NA      NA      NA
## 17 1.732537e+09 1.832742e+08 9.745523e+08
## 18 1.016827e-02 5.662254e-03 5.654429e-03
## 19      NA      NA      NA
## 20      NA      NA      NA
```

14.5 Mejor modelo

```
(mejor.modelo = modelos[which.min(modelos$SSError_R0),])
```

```
##      short      long      SSError SSError_res SSError_rdist SSError_R0
## 10     Bes Bes (bessel) 2.645632e-06 1.287015e-06 5.253159e-07 5.253159e-07

lCu.R0.fit = fit.variogram(lCu.R0.vgm,
                          model = vgm(0.15, mejor.modelo$short, 900, 0.05))
plot(lCu.R0.vgm, lCu.R0.fit, main=as.character(mejor.modelo$long))
```



14.6 Predicciones

```
lCu.R0kriged = krige(R0~1,meuse1,
                    meuse.grid, model = lCu.R0.fit)
```

```
## [using ordinary kriging]
```

```
summary(lCu.R0kriged)
```

```
## Object of class SpatialPixelsDataFrame
## Coordinates:
##      min    max
## x 178460 181540
## y 329620 333740
## Is projected: NA
## proj4string : [NA]
## Number of points: 3103
## Grid attributes:
##   cellcentre.offset cellsize cells.dim
## x              178460      40        78
## y              329620      40       104
## Data attributes:
##   var1.pred      var1.var
## Min.      :-0.52791   Min.      :0.08370
## 1st Qu.: -0.17737   1st Qu.: 0.09747
```

```
## Median :-0.04672   Median :0.10448
## Mean  :-0.02500   Mean   :0.10920
## 3rd Qu.: 0.14008   3rd Qu.:0.11812
## Max.   : 0.57773   Max.    :0.15576

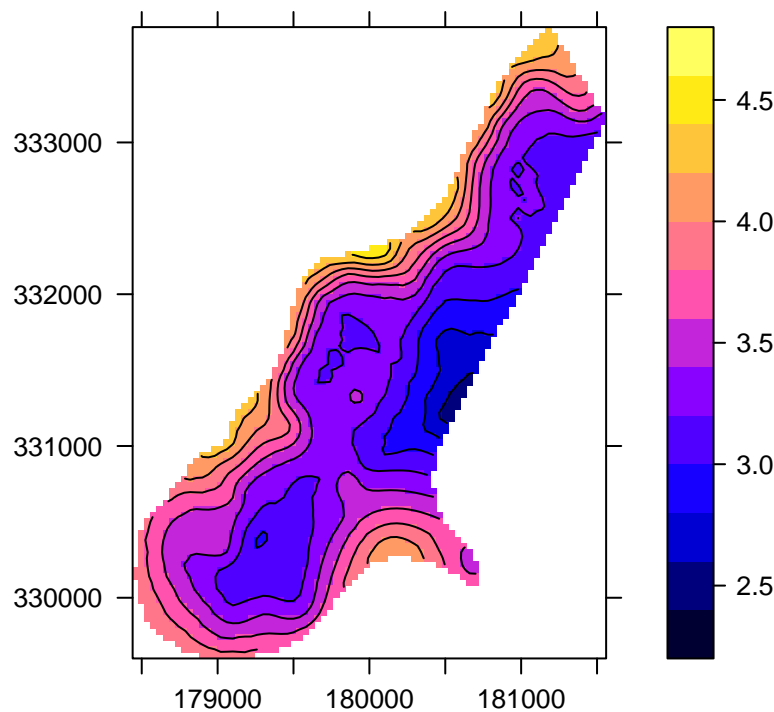
lCu.lm.dist.pred = predict(lCu.lm.dist, meuse.grid) # Predicción Deriva
lCu.R0kriged.pred = lCu.R0kriged@data$var1.pred     # Predicción Residuos
lCu.dR0.pred = lCu.lm.dist.pred + lCu.R0kriged.pred # Predicción Conjunta

lCu.lm.dist.var = predict(lCu.lm.dist, meuse.grid, se.fit = TRUE)$se.fit
lCu.R0kriged.var = lCu.R0kriged@data$var1.var
lCu.dR0.var = lCu.lm.dist.var + lCu.R0kriged.var

meuse1.grid=meuse.grid
meuse1.grid@data=cbind(meuse1.grid@data,lCu.dR0.pred,lCu.dR0.var)

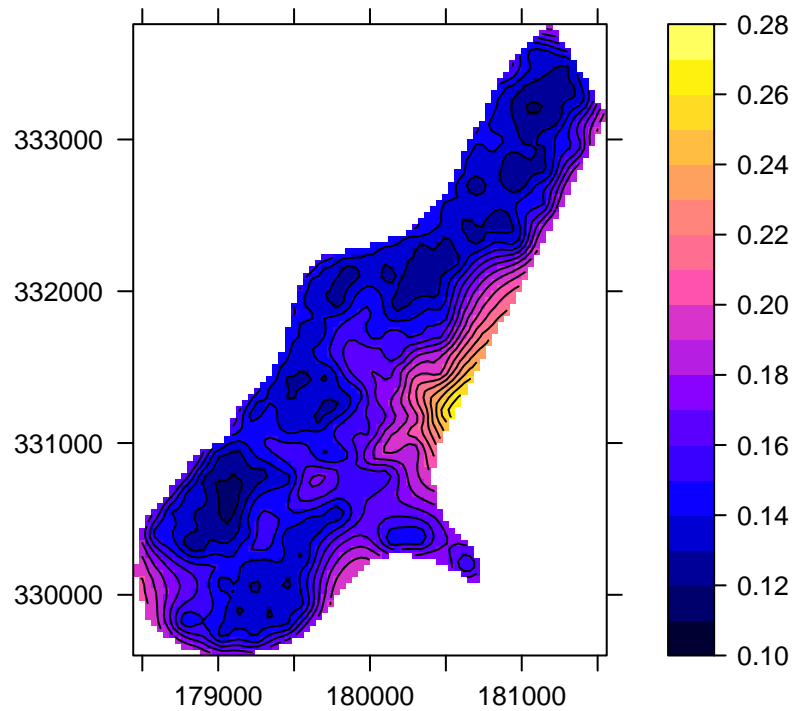
spplot(meuse1.grid, zcol="lCu.dR0.pred", pretty=T, contour=T,
       col.regions=bpy.colors(64),
       main="Predicciones Kriging Residual", scales=list(draw=T))
```

Predicciones Kriging Residual



```
spplot(meuse1.grid, zcol="lCu.dR0.var", pretty=T, contour=T,
       col.regions=bpy.colors(64),
       main="Varianza Predicciones Kriging Residual", scales=list(draw=T))
```

Varianza Predicciones Kriging Residual

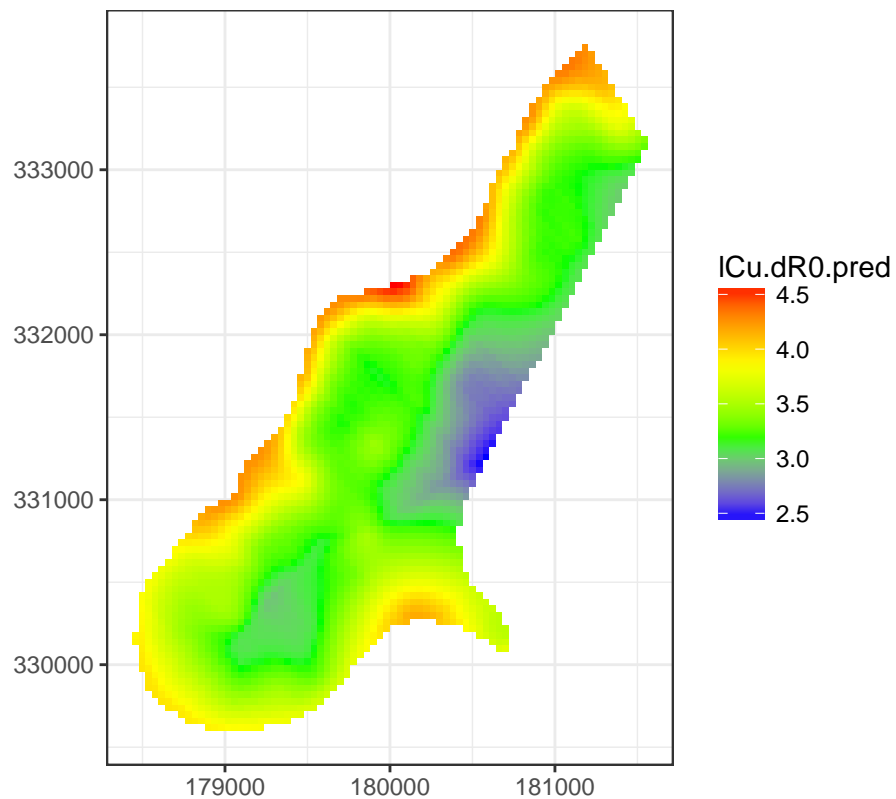


```
df.meuse1.grid = as.data.frame(meuse1.grid)
head(df.meuse1.grid)
```

```
##   part.a part.b      dist      soil      ffreq lCu.dR0.pred lCu.dR0.var
## 1      1      0 0.0000000 calcáreo cada 2 años      4.256912      0.1834901
## 2      1      0 0.0000000 calcáreo cada 2 años      4.294004      0.1713494
## 3      1      0 0.0122243 calcáreo cada 2 años      4.272068      0.1739989
## 4      1      0 0.0434678 calcáreo cada 2 años      4.215448      0.1746580
## 5      1      0 0.0000000 calcáreo cada 2 años      4.322968      0.1566332
## 6      1      0 0.0122243 calcáreo cada 2 años      4.304508      0.1597092
##           x           y
## 1 181180 333740
## 2 181140 333700
## 3 181180 333700
## 4 181220 333700
## 5 181100 333660
## 6 181140 333660
```

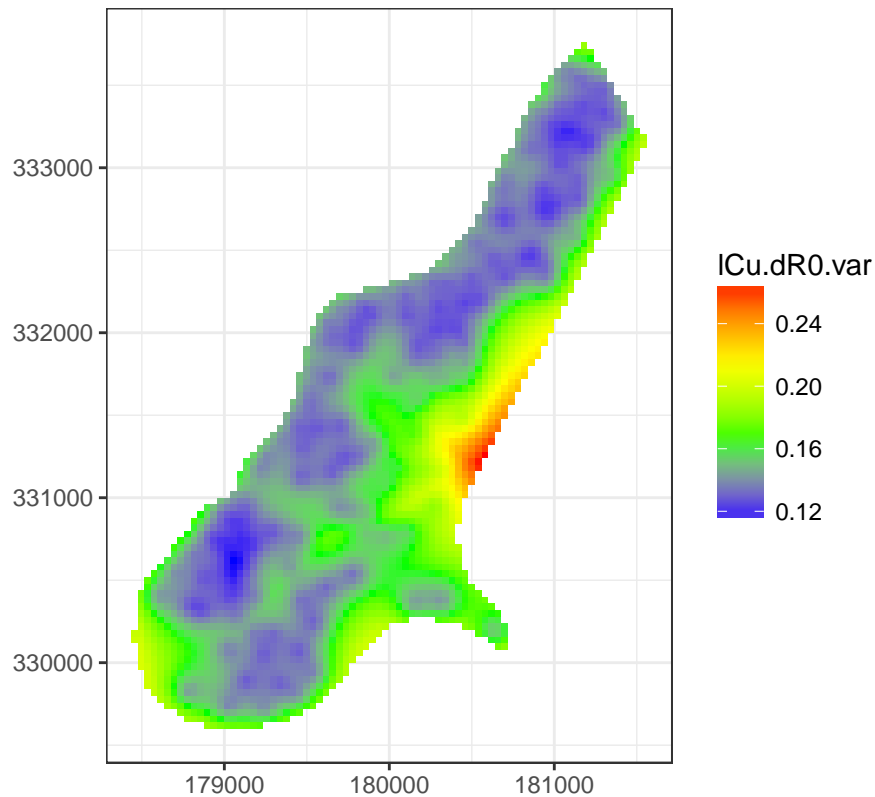
```
ggplot(df.meuse1.grid, aes(x,y,fill=lCu.dR0.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Predicción Kriging Residual. Log(Cobre).')
```

Predicción Kriging Residual. Log(Cobre).



```
ggplot(df.meuse1.grid, aes(x,y,fill=lCu.dR0.var)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradientn(colors=c('blue','green','yellow','red')) +
  labs(x=NULL,y=NULL,
       title='Varianza de Predicción Kriging Residual. Log(Cobre).')
```

Varianza de Predicción Kriging Residual. Log(Cobre).



14.7 Comparativa

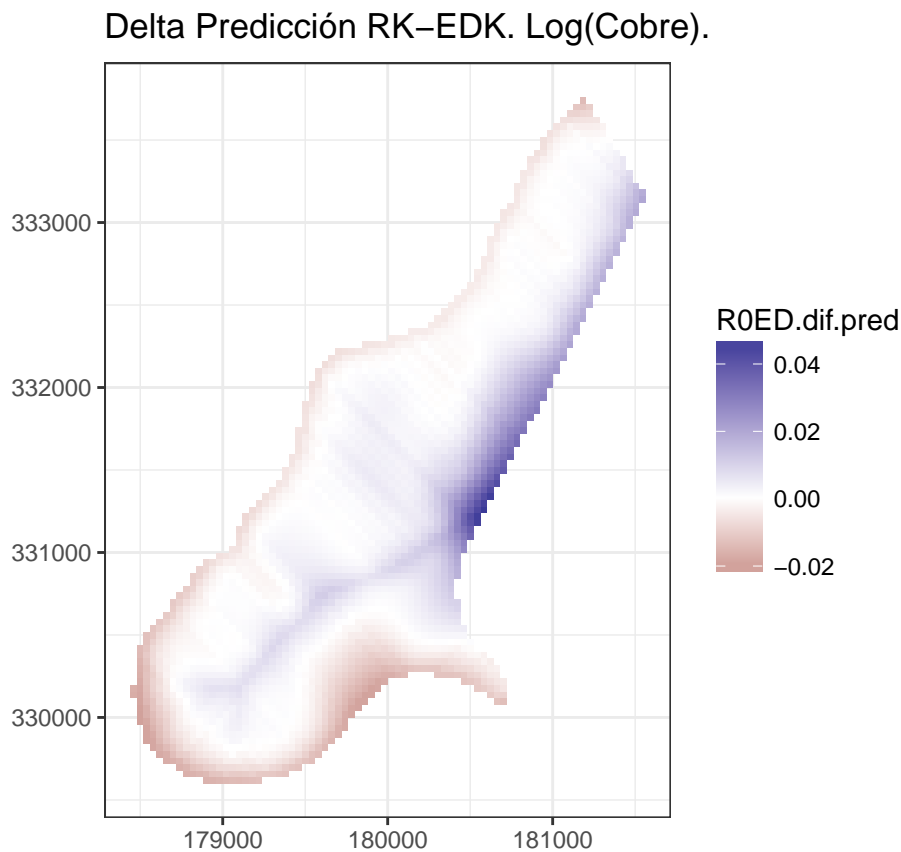
```
df.lCu.preds = data.frame(df.lCu.kriged,
  U.pred = lCu.Ukriged$var1.pred, U.var = lCu.Ukriged$var1.var,
  U0.dif.pred = lCu.Ukriged$var1.pred - lCu.kriged$var1.pred,
  U0.dif.var = lCu.Ukriged$var1.var - lCu.kriged$var1.var,
  ED.pred = lCu.EDkriged$var1.pred, ED.var = lCu.EDkriged$var1.var,
  EDU.dif.pred = lCu.EDkriged$var1.pred - lCu.Ukriged$var1.pred,
  EDU.dif.var = lCu.EDkriged$var1.var - lCu.Ukriged$var1.var,
  RO.pred = lCu.dR0.pred, RO.var = lCu.dR0.var,
  ROED.dif.pred = lCu.dR0.pred - lCu.EDkriged$var1.pred,
  ROED.dif.var = lCu.dR0.var - lCu.EDkriged$var1.var
)
```

```
summary(df.lCu.preds)
```

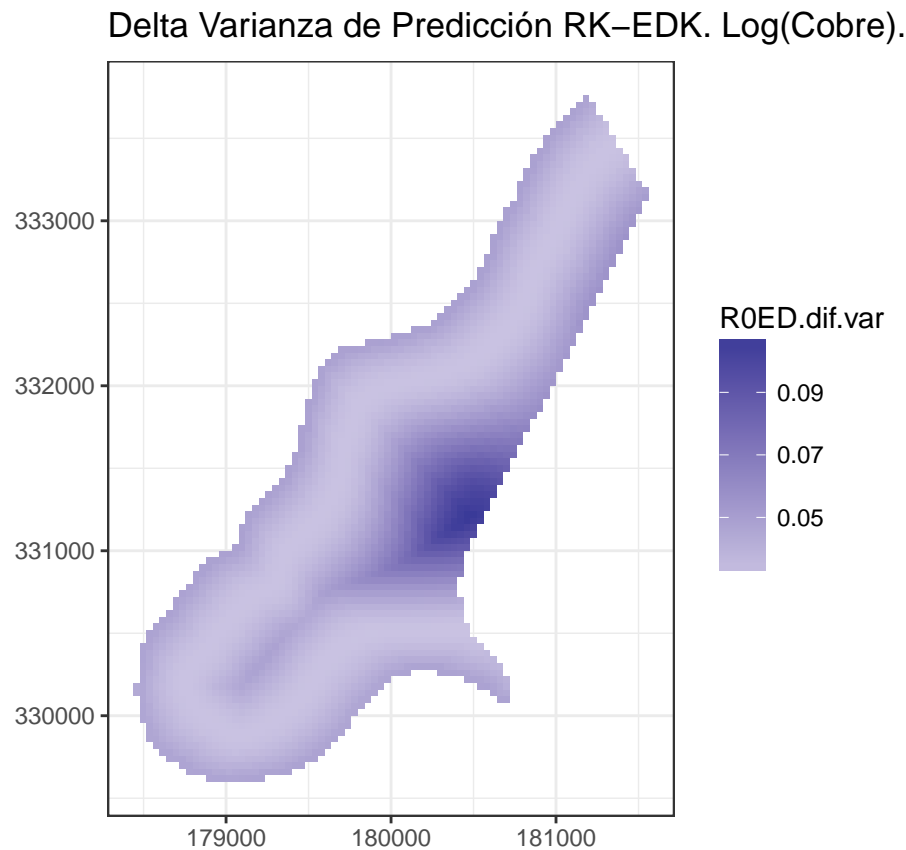
##	x	y	var1.pred	var1.var
##	Min. :178460	Min. :329620	Min. :2.775	Min. :0.08361
##	1st Qu.:179420	1st Qu.:330460	1st Qu.:3.191	1st Qu.:0.10879
##	Median :179980	Median :331220	Median :3.367	Median :0.12083
##	Mean :179985	Mean :331348	Mean :3.447	Mean :0.13192
##	3rd Qu.:180580	3rd Qu.:332140	3rd Qu.:3.637	3rd Qu.:0.14536
##	Max. :181540	Max. :333740	Max. :4.625	Max. :0.26575
##	U.pred	U.var	U0.dif.pred	U0.dif.var
##	Min. :2.772	Min. :0.07894	Min. :-0.444217	Min. :-0.061627


```
## 1st Qu.:3.191 1st Qu.:0.10212 1st Qu.: -0.034734 1st Qu.: -0.013732
## Median :3.335 Median :0.11256 Median : 0.003102 Median : -0.008372
## Mean :3.424 Mean :0.11955 Mean : -0.023218 Mean : -0.012369
## 3rd Qu.:3.610 3rd Qu.:0.13166 3rd Qu.: 0.019132 3rd Qu.: -0.006629
## Max. :4.614 Max. :0.20703 Max. : 0.193378 Max. : -0.004670
## ED.pred ED.var EDU.dif.pred EDU.dif.var
## Min. :2.434 Min. :0.08370 Min. : -0.527312 Min. : -0.050320
## 1st Qu.:3.181 1st Qu.:0.09752 1st Qu.: -0.042246 1st Qu.: -0.012627
## Median :3.362 Median :0.10458 Median : -0.005182 Median : -0.008097
## Mean :3.434 Mean :0.10975 Mean : 0.009642 Mean : -0.009799
## 3rd Qu.:3.699 3rd Qu.:0.11863 3rd Qu.: 0.026527 3rd Qu.: -0.004845
## Max. :4.545 Max. :0.16252 Max. : 0.757908 Max. : 0.009885
## R0.pred R0.var ROED.dif.pred ROED.dif.var
## Min. :2.482 Min. :0.1151 Min. : -0.0202130 Min. : 0.03072
## 1st Qu.:3.186 1st Qu.:0.1350 1st Qu.: -0.0017122 1st Qu.: 0.03314
## Median :3.364 Median :0.1467 Median : 0.0007157 Median : 0.03939
## Mean :3.435 Mean :0.1533 Mean : 0.0016831 Mean : 0.04357
## 3rd Qu.:3.695 3rd Qu.:0.1654 3rd Qu.: 0.0038744 3rd Qu.: 0.04709
## Max. :4.540 Max. :0.2645 Max. : 0.0480805 Max. : 0.10804
```

```
ggplot(df.lCu.preds, aes(x,y,fill=ROED.dif.pred)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Predicción RK-EDK. Log(Cobre).')
```



```
ggplot(df.lCu.preds, aes(x,y,fill=R0ED.dif.var)) +
  geom_raster() + coord_equal() + theme_bw() +
  scale_fill_gradient2() +
  labs(x=NULL,y=NULL,
       title='Delta Varianza de Predicción RK-EDK. Log(Cobre).')
```



Conclusión: No existen grandes diferencias pero Kriging con Deriva Externa sobre la variable Distancia al Río es preferible al Kriging Residual Directo sobre dicha misma variable mostrando una menor varianza de las predicciones.

El orden de preferencia para los distintos métodos estudiados sería el siguiente:

EDK (Distancia al Río) > UK > OK > RK (Distancia al Río)