Ridgefield to 2022 A horizon spatial analyses

Note: not all the code is shown.

use these packages / options

Read the data

Making our base map of Ridgefield

```
LongLat <- CRS("+proj=longlat +ellps=WGS84
+datum=WGS84 +no_defs") # uses Earth ellipsis specs from WGS84 datum
UTM50S <- CRS("+proj=utm +zone=50 +south") # just for Zone 50, S hemisphere!
```

Map extent object

Getting and plotting the map tile data

```
mtext(side=1, line=2, text="Easting (UTM Zone 50, m)",
      font=2, cex=1.2)
axis(2)
mtext(side=2, line=2, text="Northing (UTM Zone 50, m)",
      font=2, cex=1.2)
source(paste0(git,"rf_map_annot.R"))
with (rf22a, points (Easting, Northing, pch = 19, cex = 0.9, col = "cyan"))
with(rf18a, points(Easting, Northing, pch = 19, cex = 0.9, col = "cyan4"))
addnortharrow(pos="topright", border=1, lwd=1, text.col="white",
              padin=c(0.1,0.2), scale=1.2)
addscalebar(plotepsg = 32750, linecol = "black", label.col = "white",
            widthhint = 0.3, htin = 0.15, label.cex = 1.3)
legend("left", bty="o", bg = 1, inset = 0.01,
       legend = c("Previous data", "New up to 2022"),
       pch = 19, col = c("cyan4", "cyan"), text.col = "white")
box()
```

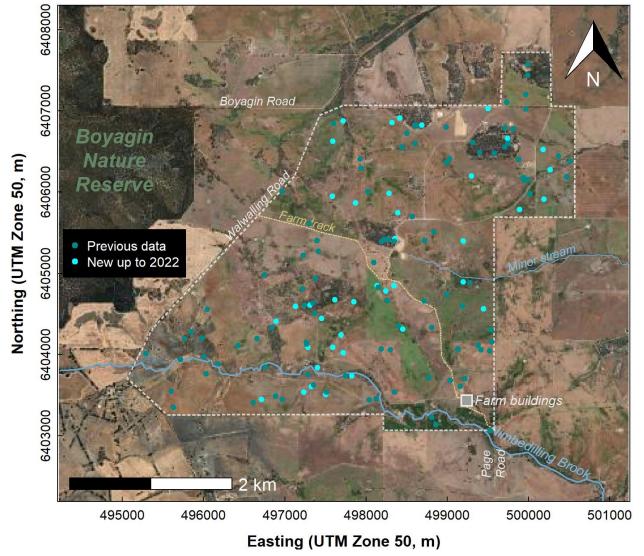


Figure 1: Map of Ridgefield Farm and adjacent area (UTM projection, Zone 50S, EPSG:32750) used subsequently as the base map for spatial analyses. Generated using the maptiles R package, with ESRI WorldTopoMap tiles.

Spatial Autocorrelation

Calculate Global Moran's I

```
var0 <- "C.pct" # choose the variable of interest
# Calculate global Moran's I</pre>
```

Plot local Moran's I

```
palette("default");palette(c(palette(), "gray92", "white", "transparent"))
var0 <- "C.pct" # choose the variable of interest</pre>
data temp <- na.omit(rf22a[,c("Easting", "Northing", var0)])</pre>
Coords <- cbind(data_temp$Easting, data_temp$Northing)</pre>
mI <- moransI(Coords, 8, data_temp[,3]) # log10 minimises skewness</pre>
local_moran <- 1.moransI(Coords, 8, data_temp[,3], scatter.plot = FALSE)</pre>
plotdata <- data.frame(Easting=Coords[,1], Northing=Coords[,2],</pre>
                       MoranI=local_moran$Ii, p_value=local_moran$p.value)
pos0 <- subset(plotdata, plotdata$MoranI>0 & plotdata$p value<=0.05)</pre>
neg0 <- subset(plotdata, plotdata$MoranI<0 & plotdata$p value<=0.05)</pre>
par(oma=c(3,3,1,1), mar=c(4,4,1.5,1.5), mgp=c(1.4,0.2,0),
    lend=2, ljoin=1, tcl=0.3, lwd = 1)
layout (matrix(c(1,1,1,1,2),nrow = 1))
plot(rftiles)
axis(1)
mtext(side=1, line=1.7, text="Easting (UTM Zone 50, m)",
      font=2, cex=1.2)
axis(2)
mtext(side=2, line=1.7, text="Northing (UTM Zone 50, m)",
      font=2, cex=1.2)
addnortharrow(pos="topright", border=1, lwd=1, text.col=10,
              padin=c(0.1,0.2), scale=1.2)
addscalebar(plotepsg = 32750, linecol = "white", label.col = "white",
            widthhint = 0.3, htin = 0.15, label.cex = 1.3)
box()
points(Coords, pch=3, cex=0.5, col = "lemonchiffon")
with(neg0, symbols(Easting, Northing, squares = 250*sqrt(MoranI*-0.04), lwd=2,
                   inches = F, fg = "plum2", bg = \#c0404080", add= TRUE))
plot(c(0,1),c(0,1),type="n",bty="n",axes=F)
legend("top", bty = "o", cex = 1.5, title.cex = 1.5,
       legend = c("Positive I", "Negative I", NA, NA, NA, NA),
       title = paste0(" Local Moran's I for \n", var0,
                       " in rf22a data \n(p \u2264 0.05 only)"),
       pch = c(21, 22, NA, NA, NA), pt.cex = c(3, 2.5, NA, NA, NA, NA),
       col = c("cyan", "plum2"), pt.bg = c("#00808080", "#C0404080"),
text.col = "white", title.col = "pink", y.intersp = 0.9, bg="#384838")
text(0.5, 0.815, col = 10, cex = 1.2,
     labels = paste("Global Moran's I:\n", signif(as.numeric(mI[2]),3),
                            "\nRandomization p:\n", signif(as.numeric(mI[7]),3)))
```

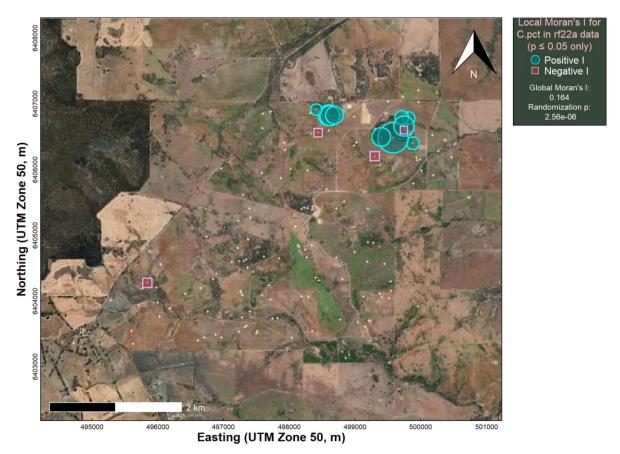


Figure 2: Map of Local Moran's I for TOC concentrations in Ridgefield A horizon soils to 2022. The Global Moran's I parameter is also shown beneath the legend.

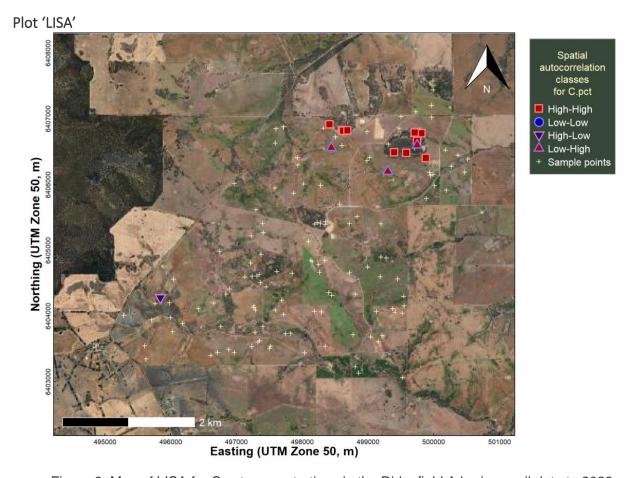


Figure 3: Map of LISA for C.pct concentrations in the Ridgefield A horizon soil data to 2022.

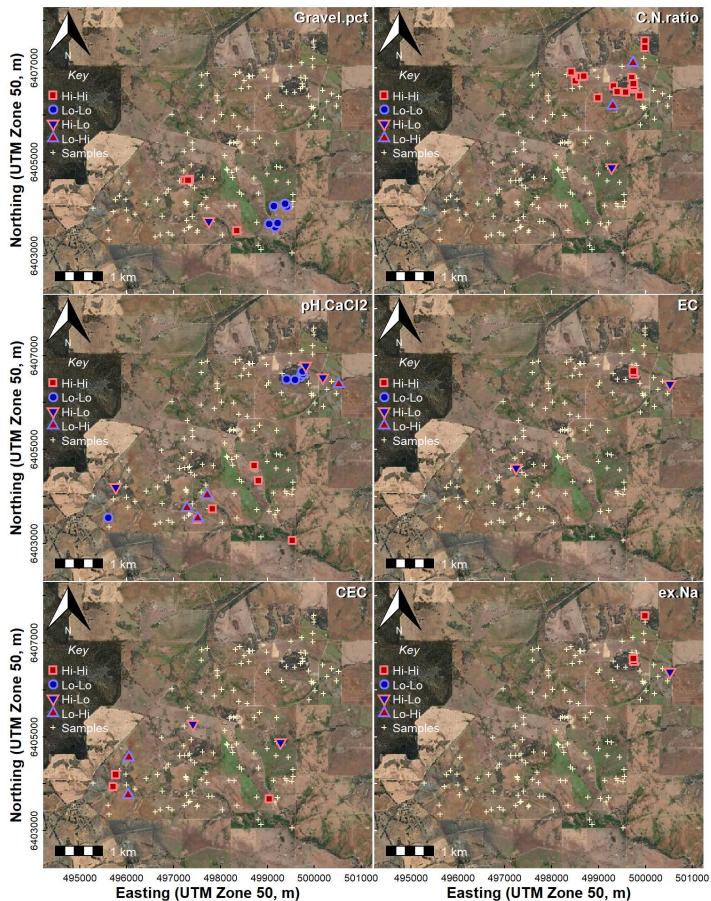


Figure 4: LISA autocorrelation maps for C.pct, Al, Fe, S, As, Cu, Pb, and Zn concentrations in the Ridgefield A horizon soil data to 2022.

Using the gstat package for geostatistics: variograms, kriging, and visualization

Make **sf** & **SpatialPointsDataFrame** objects from a data frame

In this example (as for Moran's I) we \(log_{10}\)-transform our variable if its distribution is highly positively skewed. (Using the untransformed variable would result in too many apparent upper outliers.)

```
data0 <- na.omit(rf22a[,c("Easting","Northing","C.pct")])</pre>
data0[,3] <- log10(data0[,3])</pre>
C.pct_sf <- st_as_sf(data0, coords=c("Easting","Northing"), crs = st_crs(32750))</pre>
C.pct_sp <- as_Spatial(C.pct_sf)</pre>
summary(C.pct_sp)
## Object of class SpatialPointsDataFrame
## Coordinates:
                 min
                          max
## coords.x1 495287
                      500517
## coords.x2 6403063 6407578
## Is projected: TRUE
## proj4string:
## [+proj=utm +zone=50 +south +datum=WGS84 +units=m +no defs]
## Number of points: 140
## Data attributes:
##
        C.pct
## Min. :-1.0458
## 1st Qu.: 0.2082
## Median : 0.3389
## Mean : 0.3410
    3rd Qu.: 0.4948
    Max. : 1.2579
##
```

Plot the spatial object for checking

To quickly check our data, we use the function bubble() from the sp package to make a bubble map of our variable, where the symbol area is proportional to the variable value (in this case, soil TOC concentration).

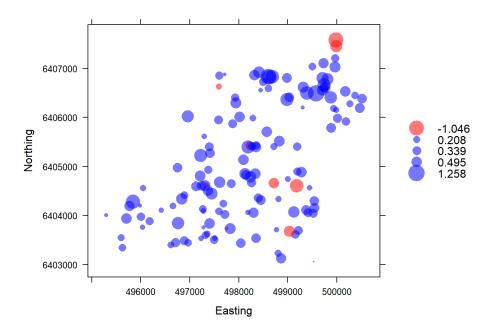


Figure 5: Visualization of spatial point data object for log10-transformed C.pct concentrations in Ridgefield A horizon soil to 2022.

Plot a map with range-class symbols

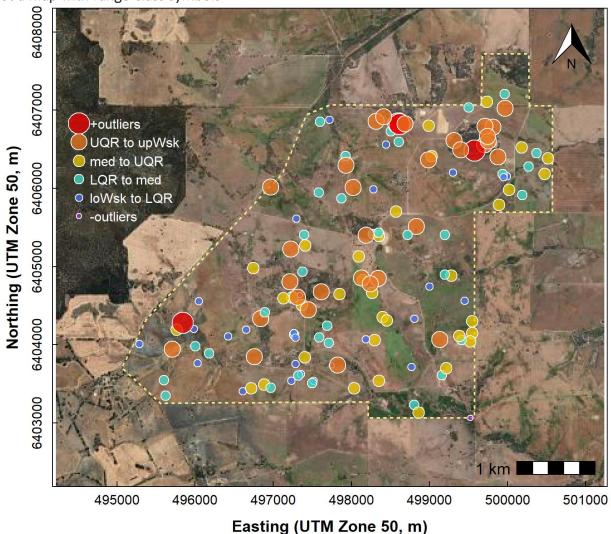


Figure 6: Map of C.pct concentrations expressed as symbols for concentration ranges (UQR is 75th percentile, upWsk is upper whisker, med is median, LQR is 25th percentile, loWsk is lower whisker).

Data are from Ridgefield A horizon soils to 2022.

Table 1: Bins for boxplot-categorised-point map in Figure 6:

bins	logfrom	logto	from	to
-outliers	-4.000	-0.149	0.000	0.710
loWsk to LQR	-0.149	0.207	0.710	1.610
LQR to med	0.207	0.339	1.610	2.182
med to UQR	0.339	0.497	2.182	3.140
UQR to upWsk	0.497	0.888	3.140	7.720
+outliers	0.888	Inf	7.720	Inf

Variograms and Kriging

Make a binned simple variogram object

```
data0 <- na.omit(rf22a[,c("Easting","Northing","Gravel.pct")])
keeprows <- which(data0$Gravel.pct > 1e-6) # find nonzeros
data0 <- data0[keeprows,] # remove zeros
data0[,3] <- log10(data0[,3])
Gravel.pct_sf <- st_as_sf(data0, coords=c("Easting","Northing"), crs = st_crs(32750))
Gravel.pct_sp <- as_Spatial(Gravel.pct_sf)

par(mar = c(3,3,1,1), mgp = c(1.7,0.3,0), font.lab=2, tcl=0.3)</pre>
```

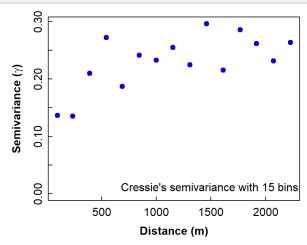


Figure 7: Plot of experimental binned variogram for C.pct in Ridgefield A horizon soils to 2022.

n_points_in_bin	dist_metres	semivariance
70	94	0.137
142	234	0.135
236	389	0.210
295	540	0.272
323	689	0.187
408	844	0.242
442	999	0.233
461	1,150	0.255
446	1,306	0.225
468	1,458	0.297
482	1,613	0.216
504	1,768	0.286
487	1,917	0.262
500	2,073	0.231
473	2,228	0.264

Fit a variogram model using weighted least squares

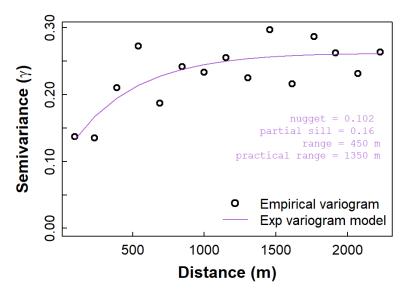


Figure 8: Plot of experimental binned variogram, and exponential variogram model, for Gravel.pct in Ridgefield A horizon soils to 2022.

Perform kriging interpolation

first make a grid mask

```
grid0 <- expand.grid(seq(round(min(Gravel.pct_sp@coords[,1]),1),</pre>
                               round(max(Gravel.pct_sp@coords[,1]),1), 10),
                          seq(round(min(Gravel.pct_sp@coords[,2]),1),
    round(max(Gravel.pct_sp@coords[,2]),1), 10))
rfgrid <- SpatialPoints(grid0, proj4string = UTM50S)</pre>
irregpoly <- Polygon(rf_boundary[,c(1,2)], hole=F)</pre>
irregPolys = Polygons(list(irregpoly), 1)
gridMask = SpatialPolygons(list(irregPolys),
                              proj4string = UTM50S)
inOrOut <- as.vector(over(rfgrid, gridMask))</pre>
rfgrid <- rfgrid[which(inOrOut>0)]
cat("Prediction grid:\n"); summary(rfgrid)
## Prediction grid:
## Object of class SpatialPoints
## Coordinates:
##
             min
## Var1 495287
                  500517
## Var2 6403073 6407573
## Is projected: TRUE
## proj4string :
## [+proj=utm +zone=50 +south +datum=WGS84 +units=m +no defs]
## Number of points: 146250
```

Krige to grid

```
## [using ordinary kriging]
## Object of class SpatialPointsDataFrame
## Coordinates:
           min
## Var1 495287 500517
## Var2 6403073 6407573
## Is projected: TRUE
## proj4string :
## [+proj=utm +zone=50 +south +datum=WGS84 +units=m +no defs]
## Number of points: 146250
## Data attributes:
##
     var1.pred
                        var1.var
## Min. :-1.0000 Min. :0.0000
## 1st Qu.: 0.7900 1st Qu.:0.1733
## Median: 0.9202 Median: 0.1883
## Mean : 0.8442 Mean :0.1894
   3rd Qu.: 1.0252
##
                     3rd Qu.:0.2038
## Max. : 1.6590 Max. :0.2543
##
##
## [inverse distance weighted interpolation]
## Object of class SpatialPointsDataFrame
## Coordinates:
##
          min
                   max
## Var1 495287 500517
## Var2 6403073 6407573
## Is projected: TRUE
## proj4string:
## [+proj=utm +zone=50 +south +datum=WGS84 +units=m +no defs]
## Number of points: 146250
## Data attributes:
##
     var1.pred
## Min. :-1.3001
##
   1st Qu.: 0.8283
## Median : 0.9348
## Mean : 0.8601
## 3rd Qu.: 1.0158
## Max. : 1.9651
```

Simple plot of kriging output

We can then us the spplot() function from sp to visualise the kriging predictions and variance, but without a background map.

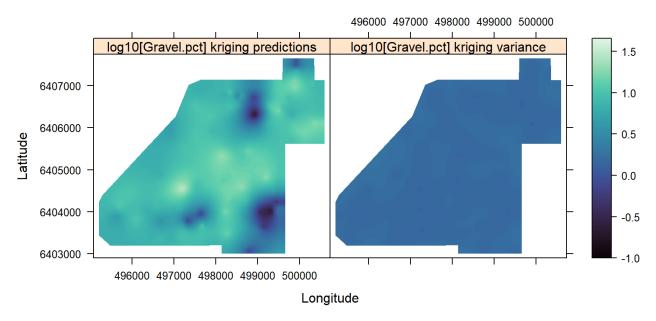


Figure 9: Plots of simple kriging predictions and variance for log-transformed Gravel.pct in Ridgefield A horizon soils to 2022.

Plot a map with overlay of the kriging predictions & kriging variance

```
par(mfrow=c(2,1), oma=c(4,4,1.5,1.5), mgp=c(1.4,0.3,0), lend=2, ljoin=1, tcl=0.3)
plot(rftiles)
axis(1, mgp=c(2, 0.3, 0), labels=F)
# mtext(side=1, line=1.5, text="Easting (UTM Zone 50, m)",
        font=2, cex=1.2)
axis(2, mgp=c(2, 0.3, 0), cex.axis = 1)
mtext(side=2, line=1.5, text="Northing (UTM Zone 50, m)",
      font=2, cex=1.2)
axtx <- c(1,2,3,5,10,20,30,50,100,200,300,500,1000)
colgrad <- gsub("FF","98", viridis::mako(128)[round(seq(1, 128, 1=6),0)])</pre>
rect(494500, 6402250, 501000, 6403000, col="#FFFFFF80", border=NA)
quilt.plot(rfgrid@coords[,1], rfgrid@coords[,2],kriged_Gravel.pct@data[,1],
           add = T, horizontal=T,
           col = colorRampPalette(colgrad, alpha = TRUE)(64),
           legend.lab = expression(bold("Kriging prediction of Gravel.pct (mg/kg)")),
           legend.mar = 6, legend.cex = 1, legend.line = 1.2, text.col=10,
           axis.args = list(at=log10(axtx), labels=axtx, mgp=c(1.2,0.1,0)))
addnortharrow(border=1, lwd=1, text.col=1, padin=c(0.1,0.1), scale = 0.9)
addscalebar(plotepsg = 32750, pos = "topleft")
points(rf22a[,c("Easting","Northing")], pch=16, cex=0.1, col = "gold")
box(); mtext("(a)",3,-1.5, cex=1.5,col=10)
plot(rftiles)
axis(1, mgp=c(2, 0.3, 0), cex.axis = 1)
mtext(side=1, line=1.5, text="Easting (UTM Zone 50, m)",
      font=2, cex=1.2)
axis(2, mgp=c(2, 0.3, 0), cex.axis = 1)
mtext(side=2, line=1.5, text="Northing (UTM Zone 50, m)",
      font=2, cex=1.2)
axtx <- pretty(kriged Gravel.pct@data[,2])</pre>
colgrad <- qsub("FF", "80", viridis::turbo(128)[round(seq(1, 128, 1=6),0)])
rect(494500, 6402250, 501000, 6403000, col="#FFFFFF80", border=NA)
quilt.plot(rfgrid@coords[,1], rfgrid@coords[,2],kriged Gravel.pct@data[,2],
           add = T, horizontal=T,
           col = colorRampPalette(colgrad, alpha = TRUE)(64),
           legend.lab = expression(bold("Kriging variance in Gravel.pct (mg/kg)")),
           legend.mar = 6, legend.cex = 1, legend.line = 1.2, legend.col="white",
           axis.args = list(at=axtx, labels=axtx, mgp=c(1.2,0.1,0)))
addnortharrow(border=1, lwd=1, text.col=1, padin=c(0.1,0.1), scale = 0.9)
addscalebar(plotepsg = 32750, pos = "topleft")
points(rf22a[,c("Easting","Northing")], pch=16, cex=0.1, col="orchid")
box(); mtext("(b)",3,-1.5, cex=1.5,col=10)
```

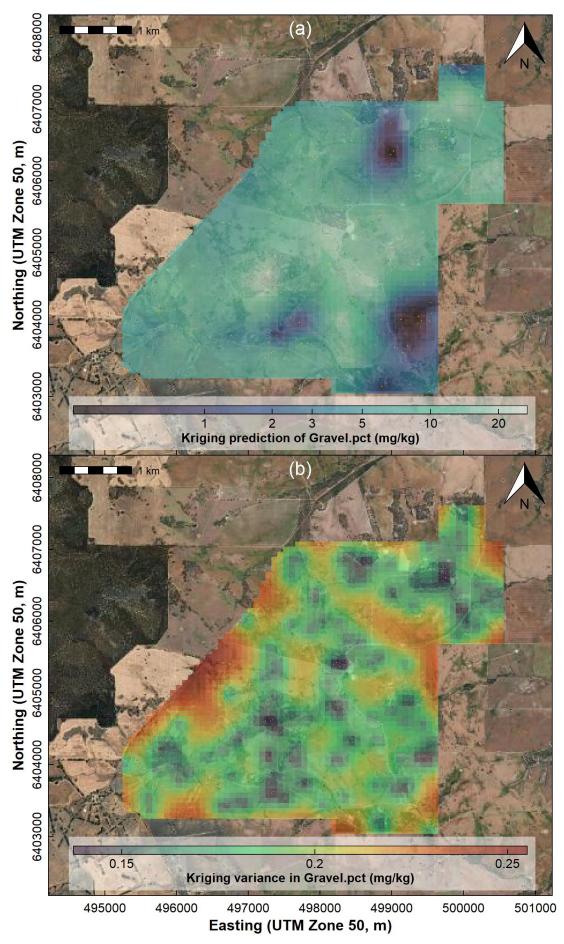


Figure 10: Map showing (a) predictions and (b) variance for kriging model of Gravel.pct in Ridgefield A horizon soils to 2022. Sample points are tiny dots.