EDS 230/ESM 232 Assignment with Latin Hypercube Sampling (LHS)

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Introduction

For this assignment, we are interested in estimating vegetation or crop water by first estimating atmospheric conductance, which is how easily water diffuses into the air. Atmospheric conductance depends on factors such as windspeed (you get more evaporation in windier conditions), the vegetation itself, and the turbulence it creates.

1. Code a function to compute atmospheric conductance C_{at} (how easily vapor diffuses from vegetation surfaces)

$$C_{at} = \frac{v_m}{6.25 * ln(\frac{z_m - z_d}{z_0})^2}$$

$$z_d = k_d * h$$

$$z_0 = k_0 * h$$

Figure 1: Equation for atmospheric conductance C_{at}, how easily vapor diffuses from vegetation surfaces

Note that:

- ***zm***: *height at which windspeed is measured (usually 200cm above the vegetation)*
- ***h***: *vegetation height (cm)*
- ***v***: *windspeed (cm/sec)*
- ***kd***: *0.7*
- ***ko***: *0.1*

```
#source in atmospheric conductance (cat) function
source(here("functions", "compute_cat.R"))
```

2. Run your model

*You are estimating the atmospheric conductance for a forest that is 10 m high (the accuracy of that measurement is +/- 0.5 m) Windspeeds (**v**) in this region are normally distributed with a mean of 250 cm/s with a standard deviation of 30 cm/sec.*

Come up with a single estimate of atmospheric conductance for this forest.

Set up the C_{at} model parameters:

- number of samples
- `h`: vegetation height (m)
- `v`: windspeed (cm/sec)

```
#parameters
nsamples = 100

#convert m to cm to match the windspeed units
h_default <- 10 * 100
h_deviation = 0.5 * 100

#sample from the uniform distribution of plant heights based on the given forest height accuracy of +/-
h <- runif(min = h_default - h_deviation,
           max = h_default + h_deviation,
           n=nsamples)

v_mean <- 250
v_sd <- 30

#sample the normal distribution of windspeeds based on the given mean and SD values
v <- rnorm(mean = v_mean, sd = v_sd, n = nsamples)

#bind vegetation height (h) and windspeed (v) into a parameters dataframe
parameters <- cbind.data.frame(h, v)
```

Run the model

```
results <- compute_cat(h = parameters$h, v = parameters$v)

mean_cat <- round(mean(results), digits = 2)
```

The model estimates that the mean atmospheric conductance for this forest is approximately 15.57 cm/sec.

3. Now do a sensitivity analysis as follows

Consider the sensitivity of your estimate to uncertainty in the following parameters and inputs

- ***h***: vegetation height (cm)
- ***kd***
- ***ko***
- ***v***: windspeed (cm/sec)

*Windspeeds (**v**) are normally distributed with a mean of 250 cm/sec with a standard deviation of 30 cm/sec.*

For vegetation height assume that height is somewhere between 9.5 and 10.5 m (but any value in that range is equally likely).

*For the **kd** and **ko** parameters you can assume that they are normally distributed with standard deviation of 1% of their default values.*

```
#set default parameters
kd_default = 0.7
k0_default = 0.1

#calculate SD
kd_sd = 0.01 * kd_default
k0_sd = 0.01 * k0_default
```

a) *Use LHS to generate parameter values for the 4 parameters*

Note the following sample distribution types:

1. v - normally distributed
2. h - uniform distribution
3. k0 - normally distributed
4. kd - normally distributed

```
#consider the 4 parameters
factors = c("v", "h", "k0", "kd")

#decide how many parameter sets to generate
nsets=100

#note which parameter uses which type of distribution
q = c("qnorm", "qunif", "qnorm", "qnorm")

#generate the distributions for each parameter
q.arg = list(list(mean = 250, sd = 30),               #v
             list(min = 9.5 * 100, max = 10.5 * 100), #h
             list(mean = k0_default, sd = k0_sd),     #k0
             list(mean = kd_default, sd = kd_sd))     #kd

# generate samples from LHS
```

```
sens_cat = LHS(NULL, factors, nsets, q, q.arg)
sens_parameters = get.data(sens_cat)

head(sens_parameters, n = 10) #check that we have 100 parameter sets
```

```
##           v      h         k0        kd
## 1  267.9328  994.5 0.09951827 0.6966279
## 2  254.9098  971.5 0.10078919 0.7087750
## 3  240.4408  974.5 0.09975957 0.6903946
## 4  237.2156 1022.5 0.09902589 0.6981358
## 5  247.3647  978.5 0.10051007 0.7029830
## 6  184.8973  992.5 0.09981088 0.7046119
## 7  212.3930  981.5 0.10120036 0.7071066
## 8  199.1381 1045.5 0.09924458 0.7096054
## 9  232.0672 1004.5 0.09993729 0.7126834
## 10 280.4567 1023.5 0.09894188 0.7151906
```

b) *Run you atmospheric conductance model for these parameters and return aerodynamic conductances*

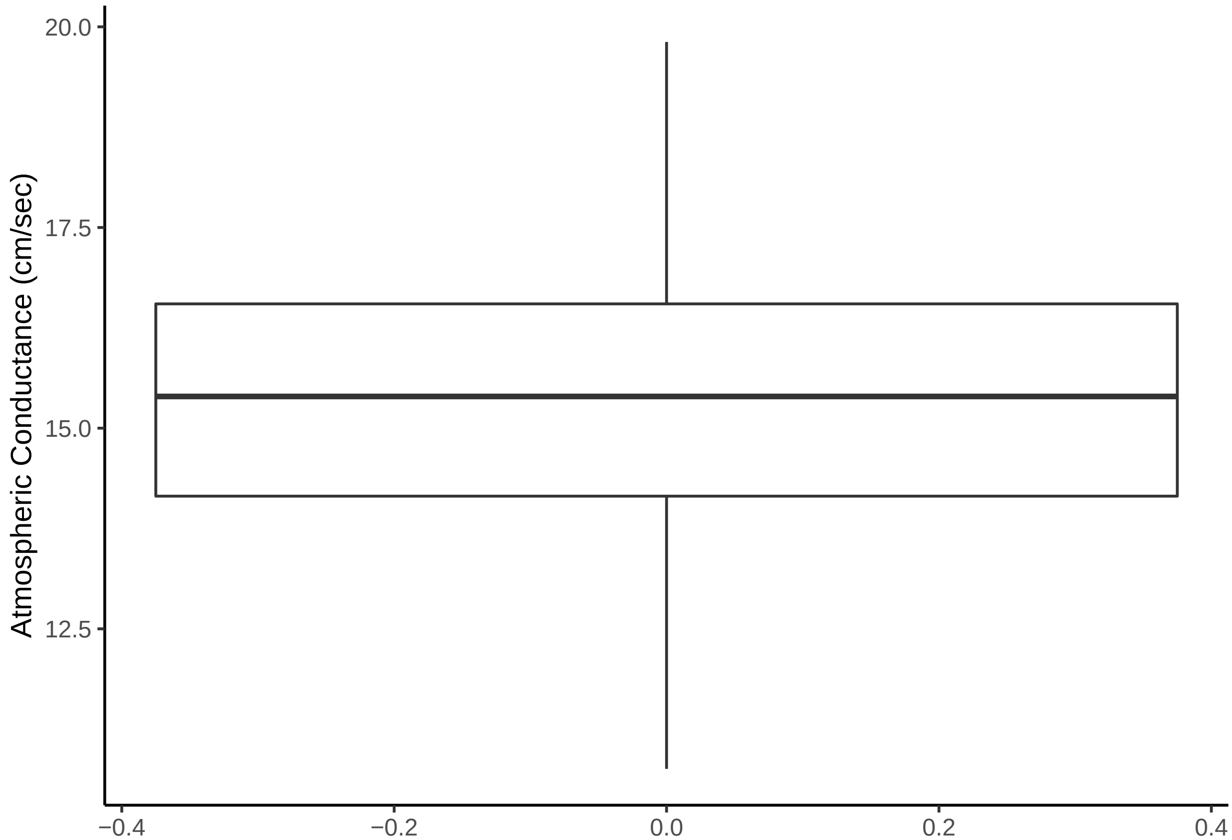
```
conductances <- sens_parameters %>% pmap(compute_cat)
conductances_df <- as.data.frame(unlist(conductances)) %>%
  rename(conductances = "unlist(conductances)")

sens_cat = pse::tell(sens_cat, t(as.matrix(conductances_df)),
                        res.names=c("conductance"))
```

c) *Plot conductance estimates in a way that accounts for parameter uncertainty*

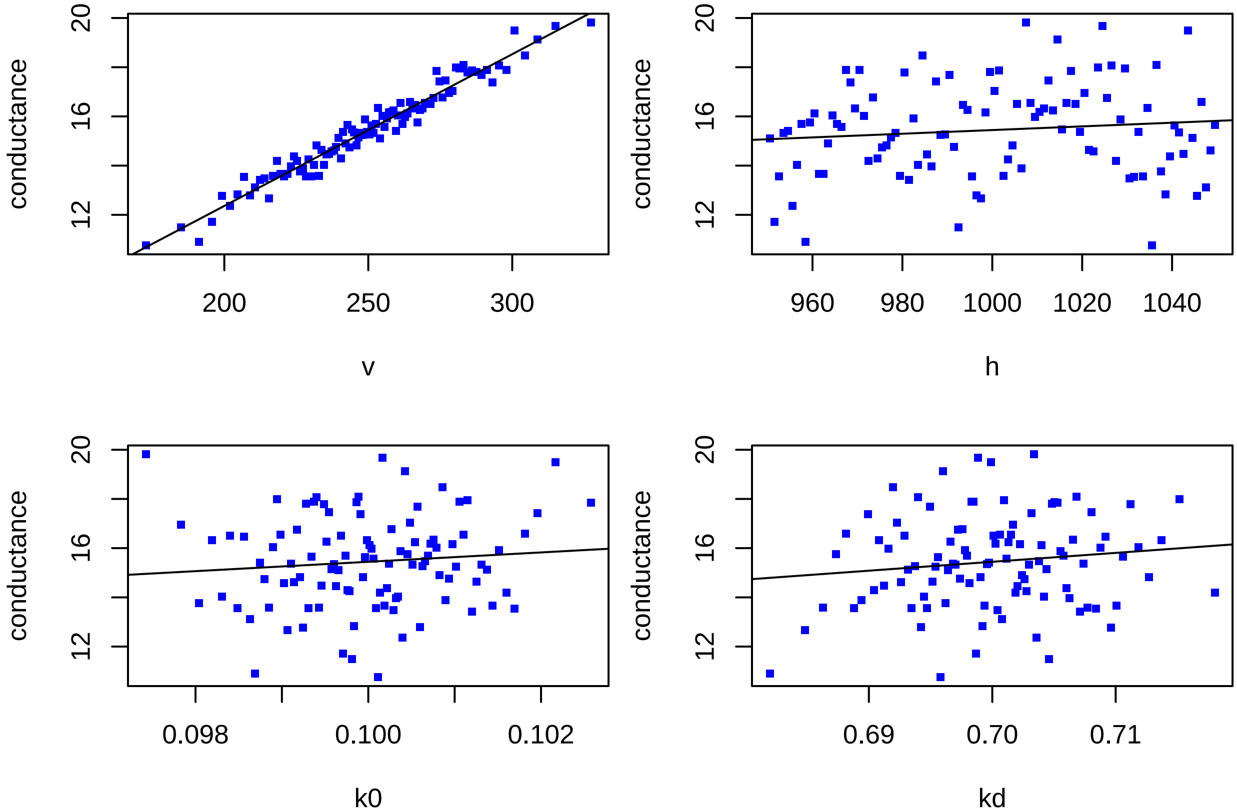
```
tmp = conductances_df %>% gather(value="conductances", key="conductances")

ggplot(tmp, aes(y = conductances)) +
  geom_boxplot() +
  theme(axis.title.x=element_blank(), axis.title.y=element_blank()) +
  labs(y="Atmospheric Conductance (cm/sec)") +
  theme_classic()
```



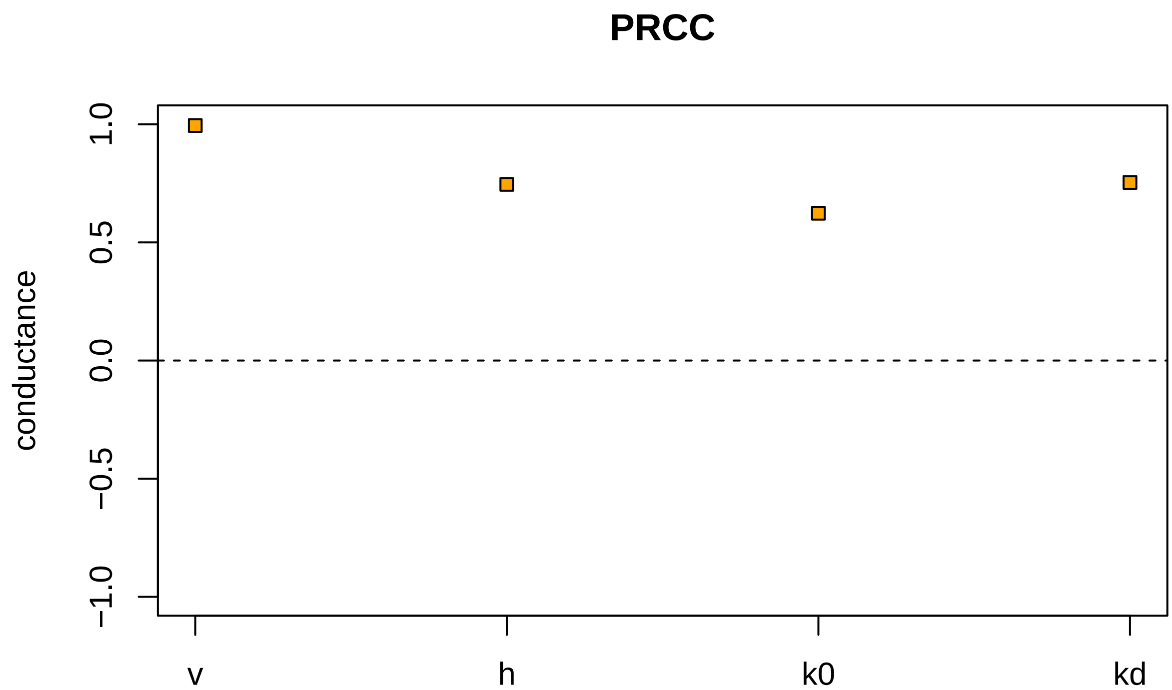
d) Plot conductance estimates against each of your parameters

```
pse::plotscatter(sens_cat, col="blue", cex=5)
```



e) Estimate the Partial Rank Correlation Coefficients

```
pse::plotprcc(sens_cat)
```




```r
# list PRCC value for each parameter
sens_cat$prcc
```

```
## [[1]]
##
## Call:
## pcc.default(X = L, y = r, rank = T, nboot = nboot)
##
## Partial Rank Correlation Coefficients (PRCC):
##     original
## v  0.9946830
## h  0.7455604
## k0 0.6232170
## kd 0.7536805
```

```r
#set object values to reference in text
v = round(0.9929307, digits = 2)
h = round(0.6190269, digits = 2)
k0 = round(0.5826310, digits = 2)
kd = round(0.7463957, digits = 2)

# compare PRCC with parameter values
#head(sens_cat, n = 10)
```

f) Discuss what your results tell you about how aerodynamic conductance varies with the different parameters.

What does it suggest about what you should focus on if you want to reduce uncertainty in aerodynamic conductance estimates? Does this tell you anything about the sensitivity of plant water use to climate change?

Based on the scatterplots, aerodynamic conductance has the strongest positive relationship to the windspeed (`v`) parameter. An increase in windspeed leads to an increase in aerodynamic conductance, which leads to the data points clustering very closely to the line of best fit.

Although aerodynamic conductance varies with vegetation height (`h`), `kd`, and `k0` parameters, there does not appear to be any strong trends or relationships based on the exploratory scatterplots. Those trend lines are much flatter compared to the windspeed plot, and the data points are more scattered.

Windspeed has the largest PRCC value (0.99) of all parameters, indicating a strong correlation to aerodynamic conductance. In contrast, the other parameters have PRCC's ranging from 0.58 to 0.75, indicating moderate correlations.

These results are logical, as windspeed likely impacts plant water use the most (due greater evaporation in windier conditions), compared to plant height (`h`), `kd`, and `k0` parameters. Therefore, based on our sensitivity analysis results, we should focus on the windspeed parameter (`v`) to reduce uncertainty in aerodynamic conductance estimates.

As climate change progresses, windspeed will most likely change and thus impact both aerodynamic conductance and plant water use.