Assignment 4: Sobol

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Question 1: Use the Sobel approach to generate parameter values for the 4 parameters

```
source(here("R/Catm.R"))

#windspeed in Catm function is in m/s
# generate two examples of random number from parameter distributions
# v = mean of 300 cm/s (3 m/s) and a SD of 50 cm/s (0.5 m/s)
# height = 3.5 and 5.5 m
# k_o and k_d = SD of 1% of default values


np <- 1000
k_o <- rnorm(mean = 0.1, sd = 0.1 * 0.1, n = np)
k_d <- rnorm(mean = 0.7, sd = 0.7 * 0.1, n = np)
v <- rnorm(mean = 3, sd = 0.5, n = np)
height <- runif(min = 3.5, max = 5.5, n = np)

X1 <- cbind.data.frame(k_o, k_d, v, height = height)

# repeat sampling
k_o <- rnorm(mean = 0.1, sd = 0.1 * 0.1, n = np)
k_d <- rnorm(mean = 0.7, sd = 0.7 * 0.1, n = np)
v <- rnorm(mean = 3, sd = 0.5, n = np)
height <- runif(min = 3.5, max = 5.5, n = np)

X2 <- cbind.data.frame(k_o, k_d, v, height = height)

# Use Sobel to generate parameter values for the 4 parameetes

sens_Catm_Sobol <- sobolSalt(model = NULL, X1, X2, nboot = 100)
```

Question 2: Run the atmospheric conductance model for these parameters

```
# run atmosph conductance model for all parameter sets

parms <- as.data.frame(sens_Catm_Sobol$X)
colnames(parms) <- colnames(X1)
res <- pmap_dbl(parms, Catm)
```

```r
sens_Catm_Sobol <- sensitivity::tell(sens_Catm_Sobol, res, res.names = "ga")

# main effect:  partitions variance (main effect without co-variance) - sums approximately to one
sens_Catm_Sobol$S
```

```
##     original         bias std. error  min. c.i. max. c.i.
## X1 0.1993824 4.345865e-03 0.03282853 0.13221464 0.2681463
## X2 0.1732821 3.998361e-03 0.03300532 0.10698241 0.2427958
## X3 0.5076966 7.638509e-05 0.02358529 0.45629596 0.5571653
## X4 0.1272060 5.954997e-03 0.02971981 0.06254445 0.1813788
```

```r
# add row names
row.names(sens_Catm_Sobol$S) <- colnames(parms)
sens_Catm_Sobol$S
```

```
##         original         bias std. error  min. c.i. max. c.i.
## k_o    0.1993824 4.345865e-03 0.03282853 0.13221464 0.2681463
## k_d    0.1732821 3.998361e-03 0.03300532 0.10698241 0.2427958
## v      0.5076966 7.638509e-05 0.02358529 0.45629596 0.5571653
## height 0.1272060 5.954997e-03 0.02971981 0.06254445 0.1813788
```

```r
# total effect - accounts for parameter interactions, is the T in the code
row.names(sens_Catm_Sobol$T) <- colnames(parms)
sens_Catm_Sobol$T
```

```
##         original          bias  std. error min. c.i. max. c.i.
## k_o    0.1944935  0.0002254934 0.012900840 0.1637002 0.2175913
## k_d    0.1793532  0.0001833197 0.015209897 0.1444066 0.2019065
## v      0.5111083 -0.0023775987 0.025984239 0.4577064 0.5778218
## height 0.1192347  0.0003168313 0.007372026 0.1021100 0.1330561
```

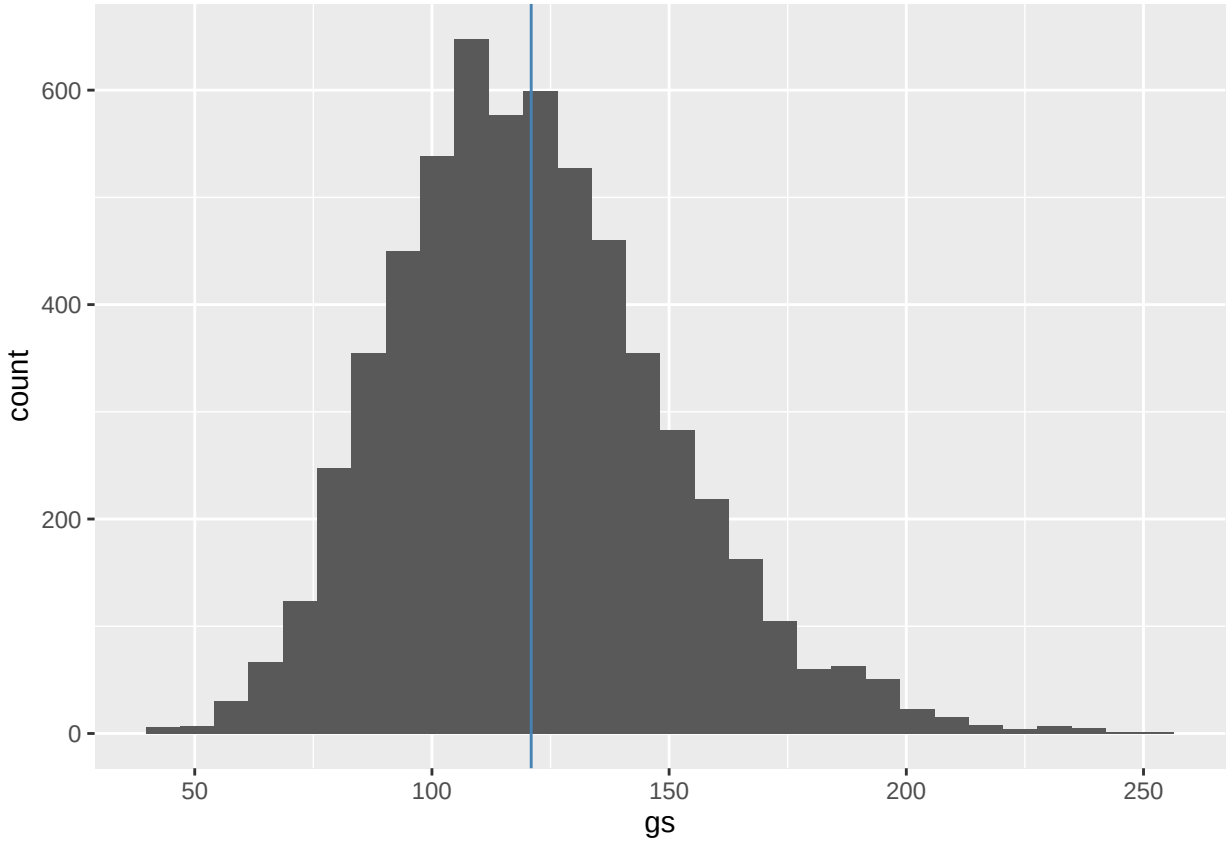
```r
print(sens_Catm_Sobol)
```

```
##
## Call:
## sobolSalt(model = NULL, X1 = X1, X2 = X2, nboot = 100)
##
## Model runs: 6000
##
## Model variance: 814.3801
##
## First order indices:
##         original         bias std. error  min. c.i. max. c.i.
## k_o    0.1993824 4.345865e-03 0.03282853 0.13221464 0.2681463
## k_d    0.1732821 3.998361e-03 0.03300532 0.10698241 0.2427958
## v      0.5076966 7.638509e-05 0.02358529 0.45629596 0.5571653
## height 0.1272060 5.954997e-03 0.02971981 0.06254445 0.1813788
##
## Total indices:
##         original          bias  std. error min. c.i. max. c.i.
## k_o    0.1944935  0.0002254934 0.012900840 0.1637002 0.2175913
## k_d    0.1793532  0.0001833197 0.015209897 0.1444066 0.2019065
## v      0.5111083 -0.0023775987 0.025984239 0.4577064 0.5778218
## height 0.1192347  0.0003168313 0.007372026 0.1021100 0.1330561
```

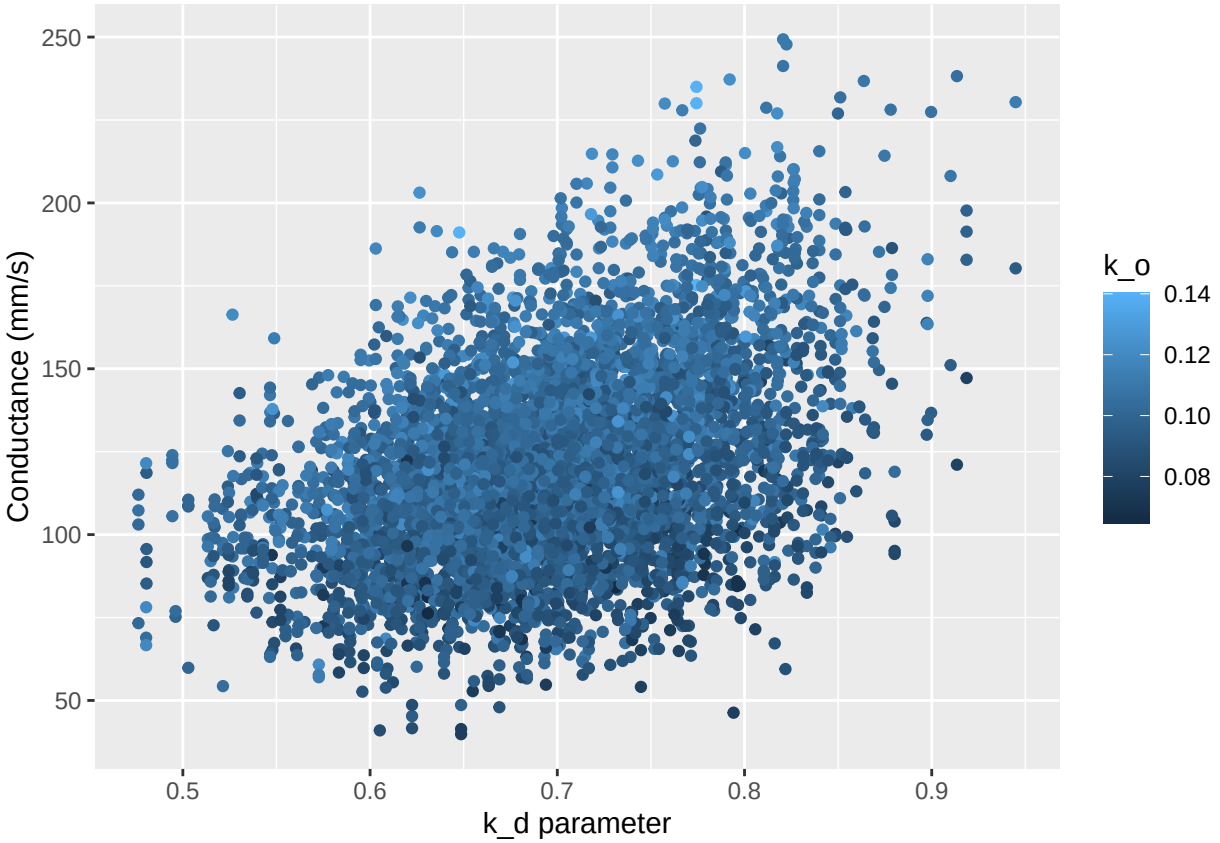
Question 3: Plot conductance estimates in a way that accounts for parameter uncertainty

```
# graph two most sensitive parameters
sens_params <- cbind.data.frame(parms, gs = sens_Catm_Sobol$y)

# look at overall gs sensitvity to uncertainty
ggplot(sens_params, aes(x = gs)) +
  geom_histogram() +
  geom_vline(xintercept = mean(sens_params$gs), col = "steelblue")
```

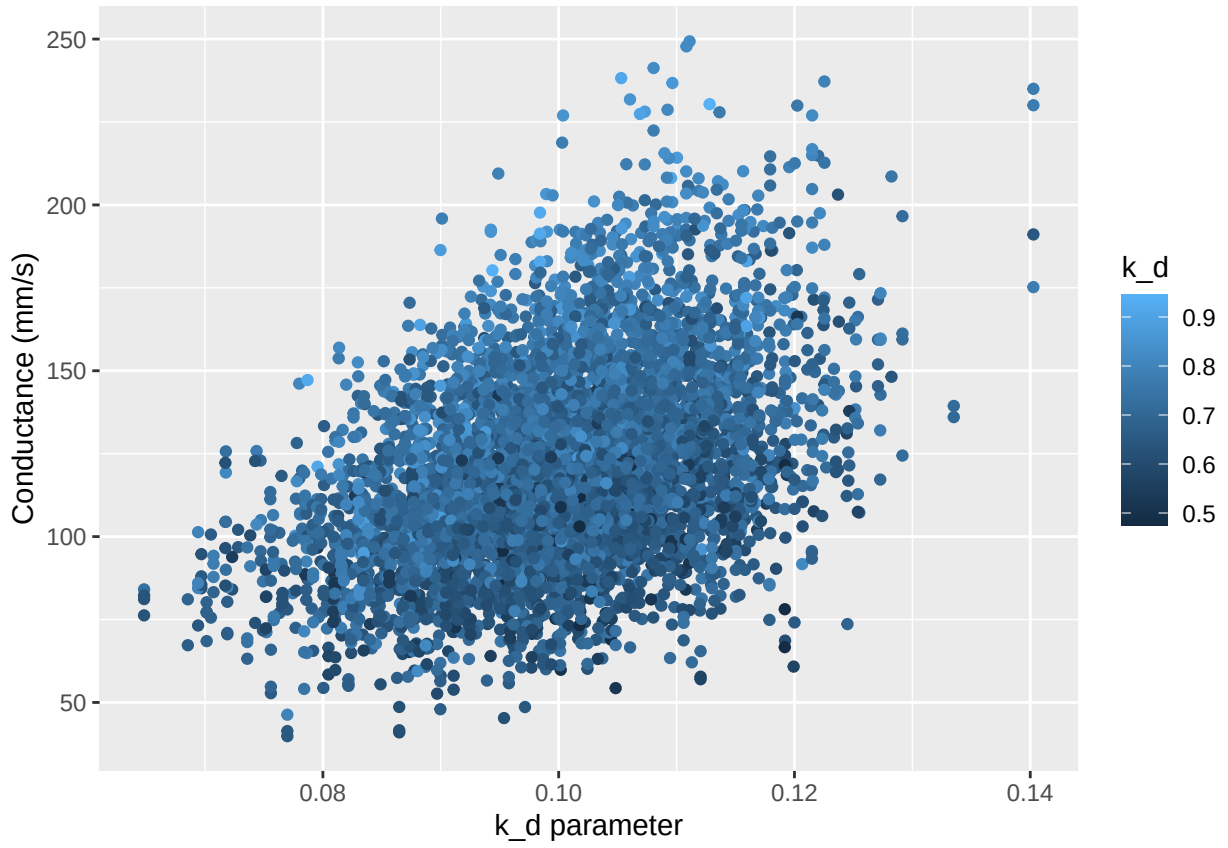
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
############

# (Additional) Plotting conductance estimates against k_d and k_o parameters:
# look at response of conductance to the two most important variables
ggplot(sens_params, aes(k_d, gs, col = k_o)) +
  geom_point() +
  labs(y = "Conductance (mm/s)", x = "k_d parameter")
```




```
# use second most sensitive parameter (using most important as color)
ggplot(sens_params, aes(k_o, gs, col = k_d)) +
  geom_point() +
  labs(y = "Conductance (mm/s)", x = "k_d parameter")
```



Question 4: Plot conductance estimates against windspeed use the parameter that is 2nd in terms of total effect on response

```
#2nd paramater of total effect
T_vals <- sens_Catm_Sobol$T$original
names(T_vals) <- rownames(sens_Catm_Sobol$T)

# Sort descending
sorted_T <- sort(T_vals, decreasing = TRUE)

# View ranking
sorted_T
```

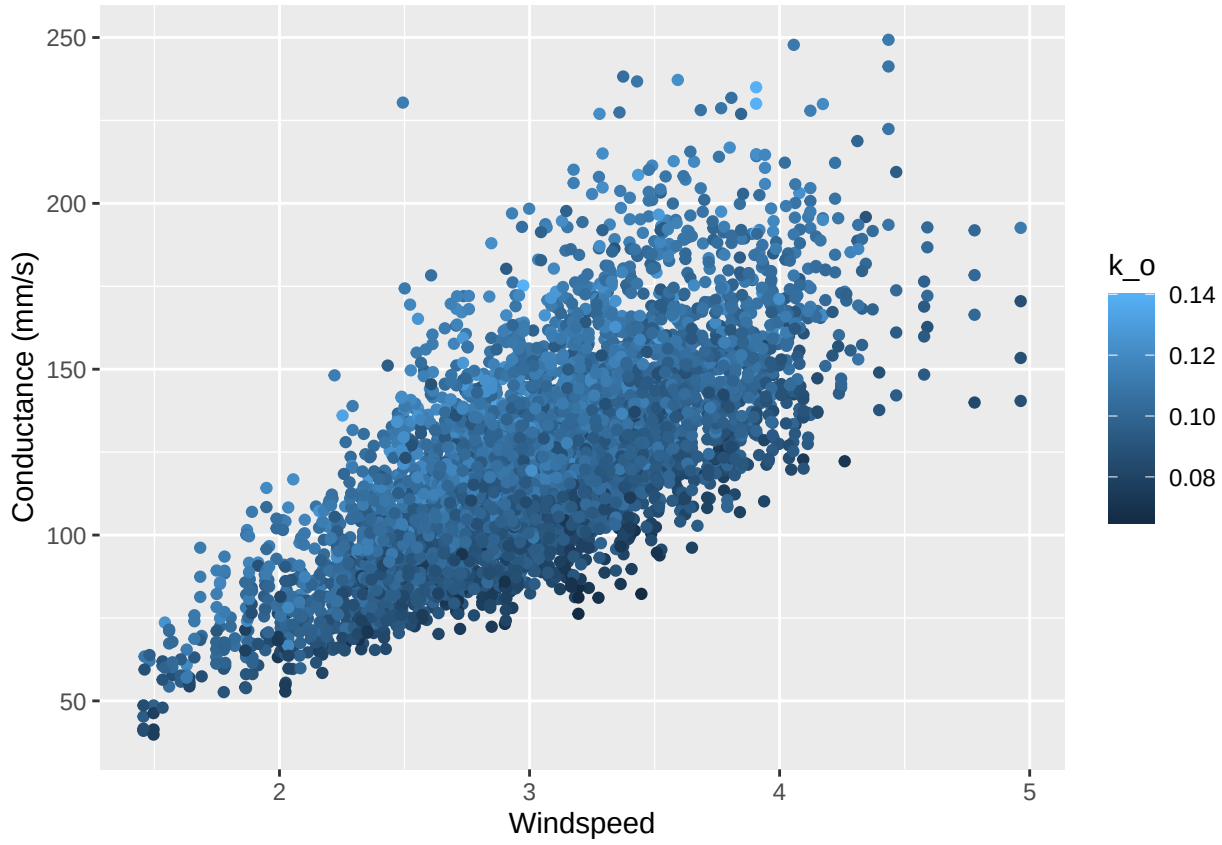
```
##         v       k_o       k_d    height
## 0.5111083 0.1944935 0.1793532 0.1192347
```

```
#2nd paramet of main effect
S_vals <- sens_Catm_Sobol$S$original
names(S_vals) <- rownames(sens_Catm_Sobol$S)

# Sort descending
sorted_S <- sort(S_vals, decreasing = TRUE)
```

```
# View ranking
sorted_S
```

```
##         v       k_o       k_d    height
## 0.5076966 0.1993824 0.1732821 0.1272060
```

```
ggplot(sens_params, aes(v, gs, col = k_o)) +
  geom_point() +
  labs(y = "Conductance (mm/s)", x = "Windspeed")
```



Question 5: Estimate the Sobel Indices for your output

```
sens_Catm_Sobol2 <- sobolSalt(model = NULL, X1, X2, nboot = 100, scheme = "B")

parms2 <- as.data.frame(sens_Catm_Sobol2$X)
colnames(parms2) <- colnames(X1)
res <- pmap_dbl(parms2, Catm)


sens_Catm_Sobol2 <- sensitivity::tell(sens_Catm_Sobol2, res, res.names = "ga")
```

```r
# main effect
row.names(sens_Catm_Sobol2$S) <- colnames(parms2)
sens_Catm_Sobol2$S
```

```
##         original          bias std. error  min. c.i. max. c.i.
## k_o    0.2144623 -0.0026585540 0.03046417 0.14947451 0.2718934
## k_d    0.1620614 -0.0003296345 0.02853285 0.10306398 0.2207947
## v      0.5209522 -0.0028250314 0.02304484 0.47666224 0.5703307
## height 0.1176094 -0.0006875763 0.02822421 0.06676234 0.1647499
```

```r
# total effect
row.names(sens_Catm_Sobol2$T) <- colnames(parms2)
sens_Catm_Sobol2$T
```

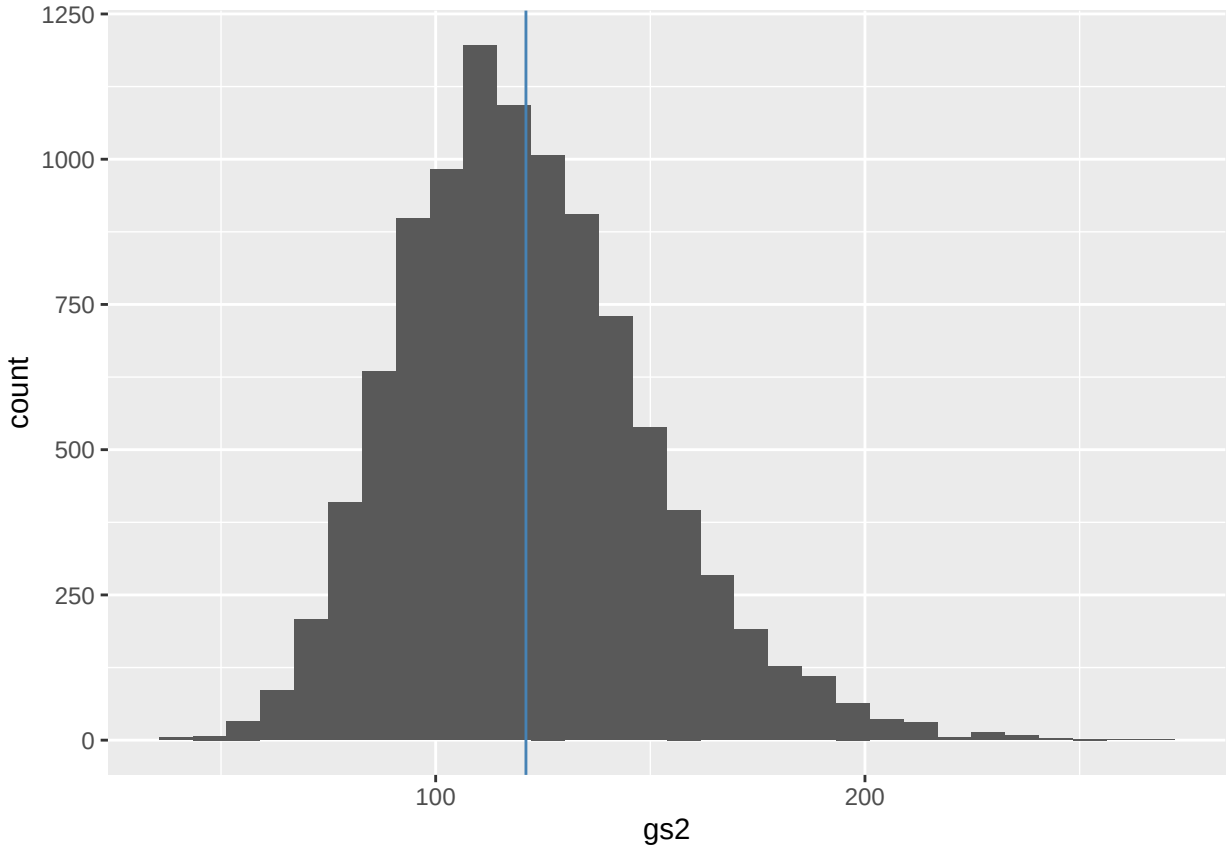
```
##         original         bias  std. error min. c.i. max. c.i.
## k_o    0.1964561 0.0007200344 0.009721906 0.1736072 0.2136321
## k_d    0.1848386 0.0014042787 0.010232188 0.1594014 0.2021913
## v      0.5133257 0.0013534560 0.021867636 0.4695702 0.5572501
## height 0.1232755 0.0015016872 0.005641619 0.1082123 0.1335142
```

```r
# parameters are in order,
sens_Catm_Sobol2$S2
```

```
##          original          bias std. error   min. c.i.  max. c.i.
## X1X2 -0.008440368  0.0010166459 0.03119636 -0.06700114 0.05662368
## X1X3 -0.027028652  0.0018794337 0.03482482 -0.09622361 0.04445720
## X1X4 -0.008563268  0.0027301943 0.03419901 -0.07414313 0.06078896
## X2X3  0.004192131  0.0031084500 0.03595622 -0.07127470 0.08004802
## X2X4  0.008711305 -0.0003241978 0.03054837 -0.05249073 0.06447884
## X3X4 -0.015191347  0.0017368366 0.03087167 -0.07414499 0.05197480
```

```r
#If you cross 0 (negative number) in the Confidence interval, it means it is not signifcant

#Plot the sobol indices

sens_params2 <- cbind.data.frame(parms2, gs2 = sens_Catm_Sobol2$y)

ggplot(sens_params2, aes(x = gs2)) +
  geom_histogram() +
  geom_vline(xintercept = mean(sens_params2$gs2), col = "steelblue")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Question 5: Comment on what this tells you about how atmospheric conductance and its sensitivity to variation in compared to the setting that we examined in class where wind speed was lower and less variable and vegetation was taller.

The sensitivity analysis shows that windspeed (v) is the most influential parameter in determining conductance estimates, with the highest total effect index (~47%). This suggests that variability in windspeed strongly drives model output. The parameters k_o and k_d also contribute meaningfully (~18–19%), but less than windspeed. Vegetation height continues to have the lowest influence (~13%). Compared to the in-calss scenario where wind was lower and vegetation was taller, this setting results in a greater sensitivity to windspeed, likely because taller vegetation in the earlier scenario dampened wind effects. These results highlight how model sensitivity shifts with environmental context and underscore the importance of accounting for wind variability when interpreting atmospheric conductance estimates.