Assignment 3: Data Exploration

Sashoy Milton

OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on Data Exploration.

The completed exercise is due on Sept 30th.

Set up your R session

1. Check your working directory, load necessary packages (tidyverse), and upload two datasets: the ECOTOX neonicotinoid dataset (ECOTOX_Neonicotinoids_Insects_raw.csv) and the Niwot Ridge NEON dataset for litter and woody debris (NEON_NIWO_Litter_massdata_2018-08_raw.csv). Name these datasets "Neonics" and "Litter", respectively. Be sure to include the subcommand to read strings in as factors.

```
#Load packages

library(tidyverse)
library(readr)
library (lubridate)

#Load datasets

getwd() # Check the current working directory for this assignment

Neonics <- read.csv("./ECOTOX_Neonicotinoids_Insects_raw.csv",
                    stringsAsFactors = TRUE)
Neonics
Litter <- read.csv("./NEON_NIWO_Litter_massdata_2018-08_raw.csv",
                   stringsAsFactors = TRUE)
Litter
```

Learn about your system

2. The neonicotinoid dataset was collected from the Environmental Protection Agency's ECOTOX Knowledgebase, a database for ecotoxicology research. Neonicotinoids are a class of insecticides used widely in agriculture. The dataset that has been pulled includes all studies published on insects. Why might we be interested in the ecotoxicology of neonicotinoids on insects? Feel free to do a brief internet search if you feel you need more background information.

   Answer: We might be interested in the ecotoxicology of neonicotinods as it affects the central nervous system of insects, resulting in paralysis and death. It also has widespread agricultural use and is licensed for use in over 100 countries. This means that if the chemical class (neonicotinods) is affecting nontarget species then it has the potential to cause a significant decline in insect populations causing ecosystems to shift to a state of imbalance.

3. The Niwot Ridge litter and woody debris dataset was collected from the National Ecological Observatory Network, which collectively includes 81 aquatic and terrestrial sites across 20 ecoclimatic domains. 32 of these sites sample forest litter and woody debris, and we will focus on the Niwot Ridge long-term ecological research (LTER) station in Colorado. Why might we be interested in studying litter and woody debris that falls to the ground in forests? Feel free to do a brief internet search if you feel you need more background information.

   Answer: It is important for us to understand litter and woody debris that falls to the ground as it gives us insight into the nutrients available in the soil and the overall health of the soil in the forest. In addition, the information provides mass details on the plant functional groups.

4. How is litter and woody debris sampled as part of the NEON network? Read the NEON_Litterfall_UserGuide.pdf document to learn more. List three pieces of salient information about the sampling methods here:

   Answer(s):

   For spatial sampling 1.Random selection of tower plots (plots that contain woody vegetation >2m tall) for sampling. 2.Systematic sampling within each plot (elevated and ground trap deployed for every 400m^2 plot area). 3. Trap placement within plots were either randomized or targeted depending on the vegetation.

Obtain basic summaries of your data (Neonics)

5. What are the dimensions of the dataset?

```r
#Explore data

View(Neonics)
#head(Neonics) #Commented out for ease of viewing of question output
#tail(Neonics) #Commented out for ease of viewing of question output

# Obtain the dimensions of the dataset
dim(Neonics)
```

```
## [1] 4623   30
```

   Answer: There are 4623 rows and 30 columns in the Neonics dataset.

6. Using the `summary` function on the "Effect" column, determine the most common effects that are studied. Why might these effects specifically be of interest?

```r
summary(Neonics$Effect)
```

```
##     Accumulation        Avoidance         Behavior     Biochemistry
##               12              102              360               11
##          Cell(s)      Development        Enzyme(s) Feeding behavior
##                9              136               62              255
```

```
##          Genetics              Growth           Histology         Hormone(s)
##                82                  38                   5                  1
##     Immunological        Intoxication          Morphology          Mortality
##                16                  12                  22               1493
##        Physiology          Population        Reproduction
##                 7                1803                 197
```

Answer: The most common effects studied are population (1803), mortality (1493), behavior (360) and feeding behavior (255). Population and mortality effects are specifically of interest because they give insight into the toxicological impact of neonicotinoid at a population level thereby allowing scientists to understand the community level effects or the long term impacts that neonicotinoid is having on the entire organismal species of interest. This can also provide information, such as is the primary food source of other related organisms that the species of interest interacts with, being disrupted. Meanwhile behavior and feeding behavior effects are of interest as they give insight into molecular level or other internal physiological changes that may be occuring within a species of interest in reaction to exposure to neonicotinoid which may not be perceivable to the eye.

7. Using the `summary` function, determine the six most commonly studied species in the dataset (common name). What do these species have in common, and why might they be of interest over other insects? Feel free to do a brief internet search for more information if needed.

```
summary(Neonics$Species.Common.Name)
```

```
##                          Honey Bee                     Parasitic Wasp
##                                667                                285
##               Buff Tailed Bumblebee               Carniolan Honey Bee
##                                183                                152
##                          Bumble Bee                  Italian Honeybee
##                                140                                113
##                     Japanese Beetle                 Asian Lady Beetle
##                                 94                                 76
##                      Euonymus Scale                          Wireworm
##                                 75                                 69
##                   European Dark Bee                 Minute Pirate Bug
##                                 66                                 62
##                 Asian Citrus Psyllid                     Parastic Wasp
##                                 60                                 58
##              Colorado Potato Beetle                   Parasitoid Wasp
##                                 57                                 51
##                 Erythrina Gall Wasp                      Beetle Order
##                                 49                                 47
##         Snout Beetle Family, Weevil           Sevenspotted Lady Beetle
##                                 47                                 46
##                      True Bug Order             Buff-tailed Bumblebee
##                                 45                                 39
##                        Aphid Family                    Cabbage Looper
##                                 38                                 38
##                Sweetpotato Whitefly                     Braconid Wasp
##                                 37                                 33
##                        Cotton Aphid                    Predatory Mite
##                                 33                                 33
##               Ladybird Beetle Family                        Parasitoid
```

```
##                                   30                              30
##                        Scarab Beetle                    Spring Tiphia
##                                   29                              29
##                          Thrip Order             Ground Beetle Family
##                                   29                              27
##                   Rove Beetle Family                    Tobacco Aphid
##                                   27                              27
##                         Chalcid Wasp           Convergent Lady Beetle
##                                   25                              25
##                        Stingless Bee                Spider/Mite Class
##                                   25                              24
##                  Tobacco Flea Beetle                 Citrus Leafminer
##                                   24                              23
##                      Ladybird Beetle                        Mason Bee
##                                   23                              22
##                             Mosquito                    Argentine Ant
##                                   22                              21
##                               Beetle       Flatheaded Appletree Borer
##                                   21                              20
##                   Horned Oak Gall Wasp               Leaf Beetle Family
##                                   20                              20
##                    Potato Leafhopper      Tooth-necked Fungus Beetle
##                                   20                              20
##                         Codling Moth        Black-spotted Lady Beetle
##                                   19                              18
##                         Calico Scale              Fairyfly Parasitoid
##                                   18                              18
##                          Lady Beetle           Minute Parasitic Wasps
##                                   18                              18
##                            Mirid Bug                 Mulberry Pyralid
##                                   18                              18
##                             Silkworm                   Vedalia Beetle
##                                   18                              18
##                 Araneoid Spider Order                       Bee Order
##                                   17                              17
##                       Egg Parasitoid                     Insect Class
##                                   17                              17
##              Moth And Butterfly Order     Oystershell Scale Parasitoid
##                                   17                              17
## Hemlock Woolly Adelgid Lady Beetle           Hemlock Wooly Adelgid
##                                   16                              16
##                                 Mite                      Onion Thrip
##                                   16                              16
##                Western Flower Thrips                     Corn Earworm
##                                   15                              14
##                    Green Peach Aphid                        House Fly
##                                   14                              14
##                            Ox Beetle               Red Scale Parasite
##                                   14                              14
##                   Spined Soldier Bug            Armoured Scale Family
##                                   14                              13
##                      Diamondback Moth                    Eulophid Wasp
##                                   13                              13
##                    Monarch Butterfly                    Predatory Bug
```

```
##                            13                            13
##          Yellow Fever Mosquito            Braconid Parasitoid
##                            13                            12
##                   Common Thrip  Eastern Subterranean Termite
##                            12                            12
##                         Jassid                    Mite Order
##                            12                            12
##                      Pea Aphid              Pond Wolf Spider
##                            12                            12
##        Spotless Ladybird Beetle        Glasshouse Potato Wasp
##                            11                            10
##                       Lacewing       Southern House Mosquito
##                            10                            10
##         Two Spotted Lady Beetle                    Ant Family
##                            10                             9
##                   Apple Maggot                       (Other)
##                             9                           670
```

Answer: The six most commonly studied species are: honey bee (667), parasitic wasp (285), buff tailed bumblebee (183), carniolan honey bee (152), bumble bee (140) and Italian honeybee (113). These species are all some of the most important pollinators and are not the target species of neonticiotinid insectides. These species might be of interest over other species as numerous plants rely heavily on pollinators to produce seeds and fruit, and humans rely heavily on plants for food. Additionally, studies show that a decline in the number of pollinators correlate to decline in overall ecosystem health. As such, understanding how neonicotinoid insecticides may be affecting these target species provide insight into how interactions within an ecosystem is possibly being disrupted.

8. Concentrations are always a numeric value. What is the class of Conc.1..Author. in the dataset, and why is it not numeric?

```
class(Neonics$Conc.1..Author.)
```

```
## [1] "factor"
```

Answer: The class of Conc.1..Author is factor. This variable is not numeric because factor allows the numeric values of concentration to be categorized into levels. This allows for the flexibility to group concentrations in ranges, for example low, medium or high, which can then allow for the visualization of effects associated with a particular concentration level.

Explore your data graphically (Neonics)

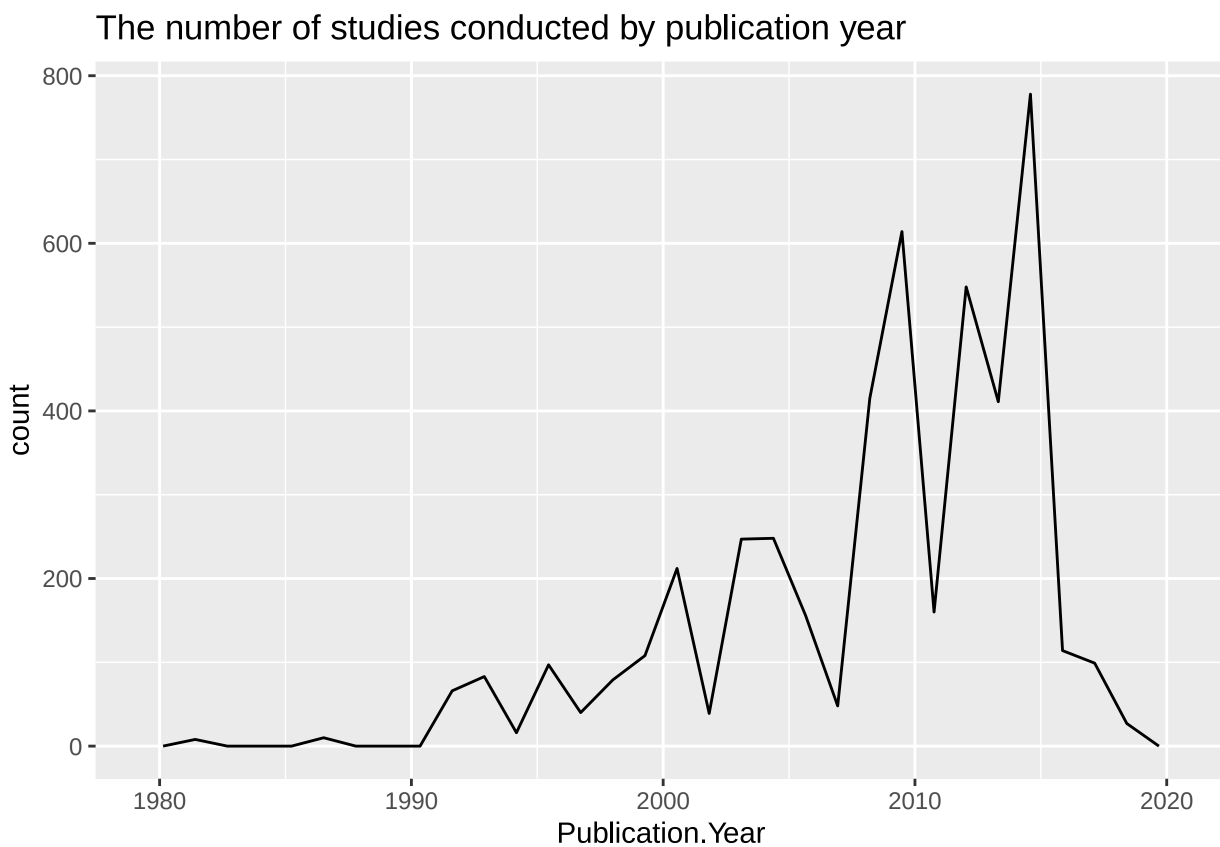
9. Using `geom_freqpoly`, generate a plot of the number of studies conducted by publication year.

```
class(Neonics$Publication.Year) # Check the class of the Publication Year variable
```

```
## [1] "integer"
```

```
#Generate plot

Neonics %>%
  ggplot(aes(x=Publication.Year))+
  geom_freqpoly() +
  ggtitle("The number of studies conducted by publication year")
```

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



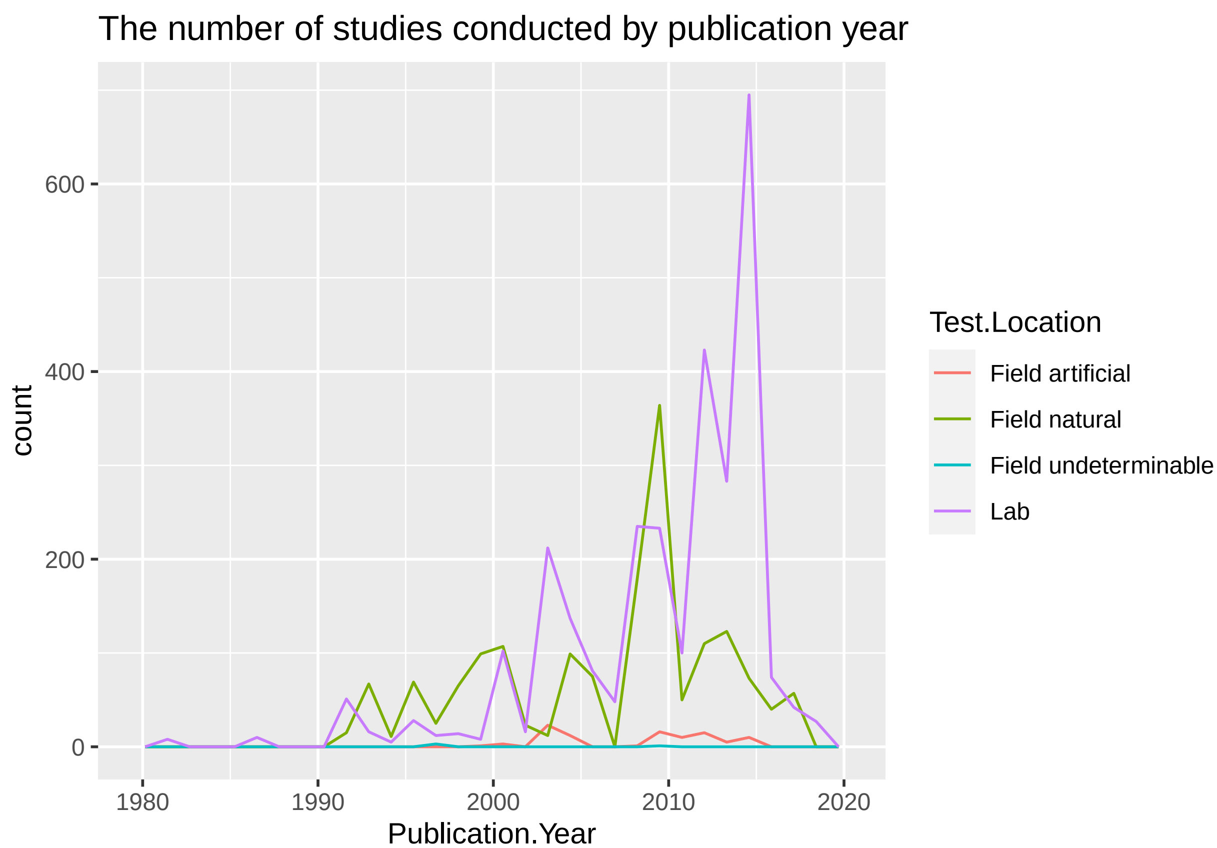
10. Reproduce the same graph but now add a color aesthetic so that different Test.Location are displayed as different colors.

```
class(Neonics$Test.Location) #Check variable class
```

```
## [1] "factor"
```

```
#Generate plot with different test locations displayed as different colors

Neonics %>%
  ggplot(aes(x=Publication.Year, color = Test.Location))+
  geom_freqpoly() +
  ggtitle("The number of studies conducted by publication year")
```

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



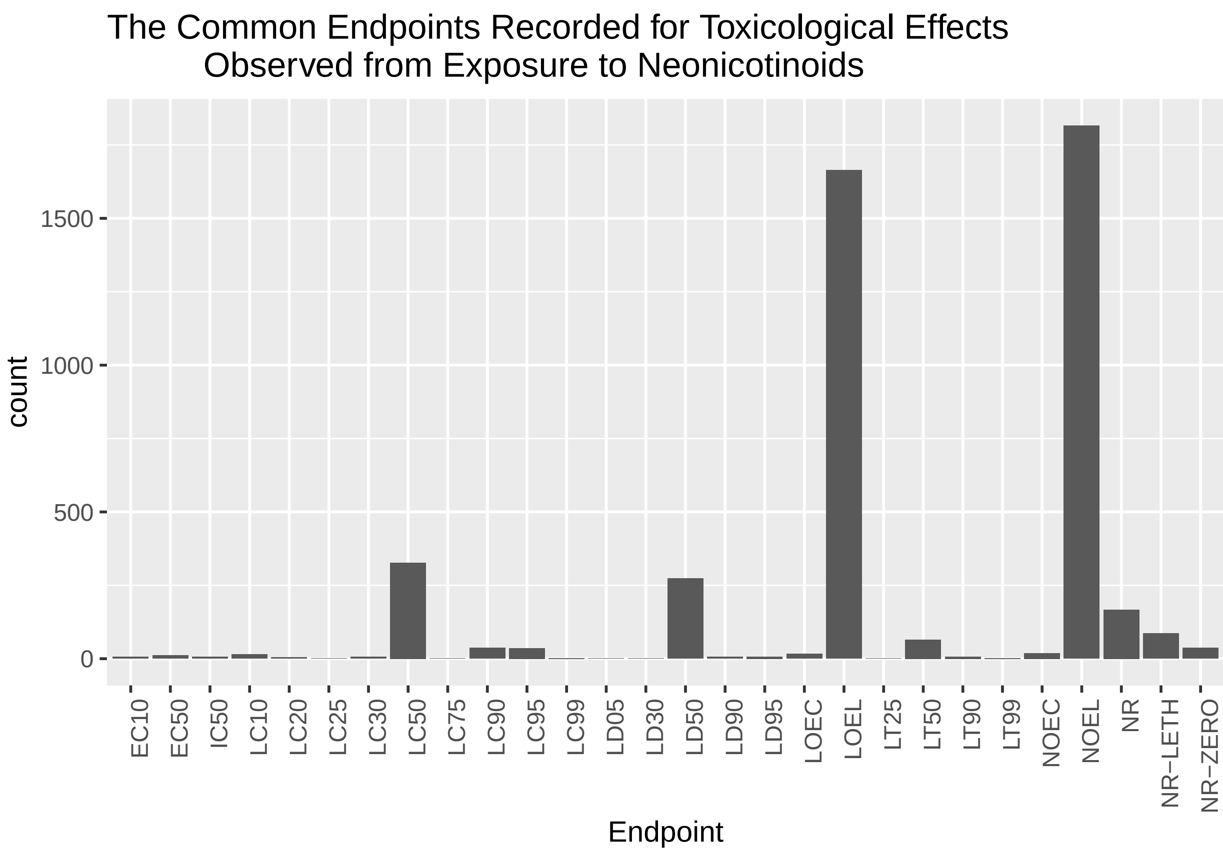
Interpret this graph. What are the most common test locations, and do they differ over time?

> Answer: The most common test locations are lab and field natural.The levels of studies conducted for both test locations saw variantion over time. Starting roughly round 1990, there was an uptick in the number of lab and field natural studies being conducted. However, for lab studies, there was a subsequent sharp decline and immediate leveling off after a few years until right after the year 2000. Over the same time period, the number of field natural studies conducted grew in a haphazard pattern before experiencing steady growth in the late 1990s up to the year 2000. After the year 2000, the number of lab studies conducted increased overall (outpacing field natural studies) from a level of <50 at the beginning of the century to roughly 650 right before 2015. After 2015, the number of lab studies being conducted declined sharply to a level a little less than 50. At this point, the number of studies conducted declined gradually to 0. Over the same period, field natural studies after expeeriencing a sharp decline after the year 2000, continued to grew haphazardly until right before the year 2010 when the test location peaked at a level a little less than 400. After this point, the test location study output declined sharply before experiencing a sharp increase around 2012/2013. The studies conducted at this locationthen declined gradually before falling to a level of 0 right before the year 2020.

11. Create a bar graph of Endpoint counts. What are the two most common end points, and how are they defined? Consult the ECOTOX_CodeAppendix for more information.

```r
# Plot bar graph


Neonics %>%
  ggplot(aes(Endpoint)) +
```

```
  geom_bar() +
  ggtitle("The Common Endpoints Recorded for Toxicological Effects
          Observed from Exposure to Neonicotinoids") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



Answer: The two most common endpoints are lowest observable effect level (LOEL) and no observed effect level (NOEL).

LOEL is defined as the lowest concentration producing effects that were significantly different from responses of the conteol while NOEL is the highest dose producing effects not significantly different from responses of controls according to author's reported statistical test.

Explore your data (Litter)

12. Determine the class of collectDate. Is it a date? If not, change to a date and confirm the new class of the variable. Using the `unique` function, determine which dates litter was sampled in August 2018.

```
# Explore the Litter data

summary(Litter)
```

```
##                                     uid                      namedLocation
##  028eea3d-5c20-4afc-bb7e-a05bab305152:  1   NIWO_040.basePlot.ltr:20
```

```
##  06789d7b-b742-41d9-8556-79d23c193dc0:  1   NIWO_041.basePlot.ltr:19
##  07780a1e-8af9-4b8a-bb9b-be8add15a1e0:  1   NIWO_046.basePlot.ltr:18
##  0a6cae78-ea42-4e68-98c6-9d929068a38a:  1   NIWO_061.basePlot.ltr:17
##  0ae1c621-387e-42a9-bcf3-7ad1c9b97ab4:  1   NIWO_067.basePlot.ltr:17
##  0b274782-8e52-4f6a-bb17-36daa821f929:  1   NIWO_058.basePlot.ltr:16
##  (Other)                             :182   (Other)              :81
##  domainID   siteID         plotID           trapID        weighDate
##  D13:188   NIWO:188   NIWO_040:20   NIWO_040_205:20   2018-08-06:91
##                       NIWO_041:19   NIWO_041_059:19   2018-09-05:97
##                       NIWO_046:18   NIWO_046_155:18
##                       NIWO_061:17   NIWO_061_169:17
##                       NIWO_067:17   NIWO_067_017:17
##                       NIWO_058:16   NIWO_058_101:16
##                       (Other) :81   (Other)     :81
##        setDate       collectDate          ovenStartDate            ovenEndDate
##  2018-07-05:91   2018-08-02:91   2018-08-02T21:00Z:91    2018-08-06T18:02Z:91
##  2018-08-02:97   2018-08-30:97   2018-08-30T22:30Z:97    2018-09-05T19:30Z:97
##
##
##
##
##
##                      fieldSampleID                          massSampleID
##  NEON.LTR.NIWO041059.20180830: 11   NEON.LTR.NIWO040205.20180802.MXT:  2
##  NEON.LTR.NIWO040205.20180802: 10   NEON.LTR.NIWO040205.20180802.NDL:  2
##  NEON.LTR.NIWO040205.20180830: 10   NEON.LTR.NIWO040205.20180830.MXT:  2
##  NEON.LTR.NIWO046155.20180802: 10   NEON.LTR.NIWO040205.20180830.NDL:  2
##  NEON.LTR.NIWO058101.20180802:  9   NEON.LTR.NIWO041059.20180830.MXT:  2
##  NEON.LTR.NIWO061169.20180802:  9   NEON.LTR.NIWO041059.20180830.NDL:  2
##  (Other)                     :129   (Other)                         :176
##      samplingProtocolVersion       functionalGroup    dryMass       qaDryMass
##  NEON.DOC.001710vE:188        Needles       :30     Min.   :0.0000   N:168
##                               Twigs/branches:28     1st Qu.:0.0000   Y: 20
##                               Woody material:26     Median :0.0050
##                               Leaves        :24     Mean   :0.6115
##                               Other         :24     3rd Qu.:0.3200
##                               Flowers       :23     Max.   :8.6300
##                               (Other)       :33
##  remarks                        measuredBy
##  Mode:logical   kstyers@battelleecology.org:91
##  NA's:188       szrillo@battelleecology.org:97
##
##
##
##
##
```

```
head (Litter)
```

```
##                                    uid         namedLocation domainID siteID
## 1 7f065fec-bcb2-4af9-b742-8e520fab7f6e NIWO_061.basePlot.ltr      D13   NIWO
## 2 88df210b-1445-4c3f-b19e-5dabd9305c6e NIWO_061.basePlot.ltr      D13   NIWO
## 3 7f3c549c-1dfa-43bf-a485-c7c2bcb31fd6 NIWO_061.basePlot.ltr      D13   NIWO
## 4 97806ab5-42d2-49c0-8463-db48cd5eab12 NIWO_061.basePlot.ltr      D13   NIWO
```

```
## 5 9d7c89f5-85f8-47b6-b415-1ae208580e6f NIWO_061.basePlot.ltr      D13   NIWO
## 6 6ca7a3e8-4d9e-4062-91a0-845f23b5b925 NIWO_061.basePlot.ltr      D13   NIWO
##     plotID       trapID  weighDate    setDate collectDate     ovenStartDate
## 1 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
## 2 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
## 3 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
## 4 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
## 5 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
## 6 NIWO_061 NIWO_061_169 2018-08-06 2018-07-05  2018-08-02 2018-08-02T21:00Z
##         ovenEndDate                fieldSampleID
## 1 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
## 2 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
## 3 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
## 4 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
## 5 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
## 6 2018-08-06T18:02Z NEON.LTR.NIWO061169.20180802
##                        massSampleID samplingProtocolVersion functionalGroup
## 1 NEON.LTR.NIWO061169.20180802.TWI       NEON.DOC.001710vE  Twigs/branches
## 2 NEON.LTR.NIWO061169.20180802.SDS       NEON.DOC.001710vE           Seeds
## 3 NEON.LTR.NIWO061169.20180802.WDY       NEON.DOC.001710vE  Woody material
## 4 NEON.LTR.NIWO061169.20180802.FLR       NEON.DOC.001710vE         Flowers
## 5 NEON.LTR.NIWO061169.20180802.WDY       NEON.DOC.001710vE  Woody material
## 6 NEON.LTR.NIWO061169.20180802.NDL       NEON.DOC.001710vE         Needles
##   dryMass qaDryMass remarks                 measuredBy
## 1   0.400         N      NA kstyers@battelleecology.org
## 2   0.005         N      NA kstyers@battelleecology.org
## 3   0.040         Y      NA kstyers@battelleecology.org
## 4   0.005         N      NA kstyers@battelleecology.org
## 5   0.070         N      NA kstyers@battelleecology.org
## 6   1.000         N      NA kstyers@battelleecology.org
```

```
tail (Litter)
```

```
##                                      uid         namedLocation domainID siteID
## 183 ebeec5a0-815d-4f3d-a94f-759cca792b11 NIWO_040.basePlot.ltr      D13   NIWO
## 184 d91a07ab-0da7-4182-9e61-a04d01612f83 NIWO_040.basePlot.ltr      D13   NIWO
## 185 cc4285fd-d7cf-40b1-9f67-27aa04b502c3 NIWO_040.basePlot.ltr      D13   NIWO
## 186 93f8312d-c181-4613-80af-4d081b29bf0d NIWO_040.basePlot.ltr      D13   NIWO
## 187 5b7c6e0e-40c8-4bc6-b509-a760cbe1a5e4 NIWO_040.basePlot.ltr      D13   NIWO
## 188 6de90fcf-901c-44c1-88b9-424c92df8c06 NIWO_040.basePlot.ltr      D13   NIWO
##       plotID       trapID  weighDate    setDate collectDate     ovenStartDate
## 183 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
## 184 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
## 185 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
## 186 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
## 187 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
## 188 NIWO_040 NIWO_040_205 2018-09-05 2018-08-02  2018-08-30 2018-08-30T22:30Z
##           ovenEndDate                fieldSampleID
## 183 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
## 184 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
## 185 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
## 186 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
## 187 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
## 188 2018-09-05T19:30Z NEON.LTR.NIWO040205.20180830
```

```
##                        massSampleID samplingProtocolVersion functionalGroup
## 183 NEON.LTR.NIWO040205.20180830.LVS       NEON.DOC.001710vE          Leaves
## 184 NEON.LTR.NIWO040205.20180830.NDL       NEON.DOC.001710vE         Needles
## 185 NEON.LTR.NIWO040205.20180830.TWI       NEON.DOC.001710vE  Twigs/branches
## 186 NEON.LTR.NIWO040205.20180830.MXT       NEON.DOC.001710vE           Mixed
## 187 NEON.LTR.NIWO040205.20180830.NDL       NEON.DOC.001710vE         Needles
## 188 NEON.LTR.NIWO040205.20180830.FLR       NEON.DOC.001710vE         Flowers
##     dryMass qaDryMass remarks                  measuredBy
## 183    0.00         N      NA szrillo@battelleecology.org
## 184    4.55         Y      NA szrillo@battelleecology.org
## 185    0.00         N      NA szrillo@battelleecology.org
## 186    0.61         N      NA szrillo@battelleecology.org
## 187    4.53         N      NA szrillo@battelleecology.org
## 188    0.15         N      NA szrillo@battelleecology.org
```

```
#Determine the class of Litter
class(Litter$collectDate)
```

```
## [1] "factor"
```

```
#Change the class of the variable "Collect Date" to date

Litter$collectDate <- as.Date(Litter$collectDate)

class(Litter$collectDate)  #Check class
```

```
## [1] "Date"
```

```
Litter$collectDate #View data
```

```
##   [1] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##   [6] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [11] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [16] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [21] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [26] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [31] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [36] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [41] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [46] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [51] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [56] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [61] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [66] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [71] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [76] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [81] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [86] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
##  [91] "2018-08-02" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
##  [96] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [101] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [106] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
```

```
## [111] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [116] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [121] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [126] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [131] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [136] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [141] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [146] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [151] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [156] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [161] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [166] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [171] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [176] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [181] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [186] "2018-08-30" "2018-08-30" "2018-08-30"
```

```
#Determine which dates litter was sampled in August 2018

unique(Litter$collectDate)
```

```
## [1] "2018-08-02" "2018-08-30"
```

Answer: August 2, 2018 and August 30, 2018

13. Using the `unique` function, determine how many plots were sampled at Niwot Ridge. How is the information obtained from `unique` different from that obtained from `summary`?

```
# To determine how many plots were sampled at Niwot Ridge

unique(Litter$plotID)
```

```
##  [1] NIWO_061 NIWO_064 NIWO_067 NIWO_040 NIWO_041 NIWO_063 NIWO_047 NIWO_051
##  [9] NIWO_058 NIWO_046 NIWO_062 NIWO_057
## 12 Levels: NIWO_040 NIWO_041 NIWO_046 NIWO_047 NIWO_051 NIWO_057 ... NIWO_067
```

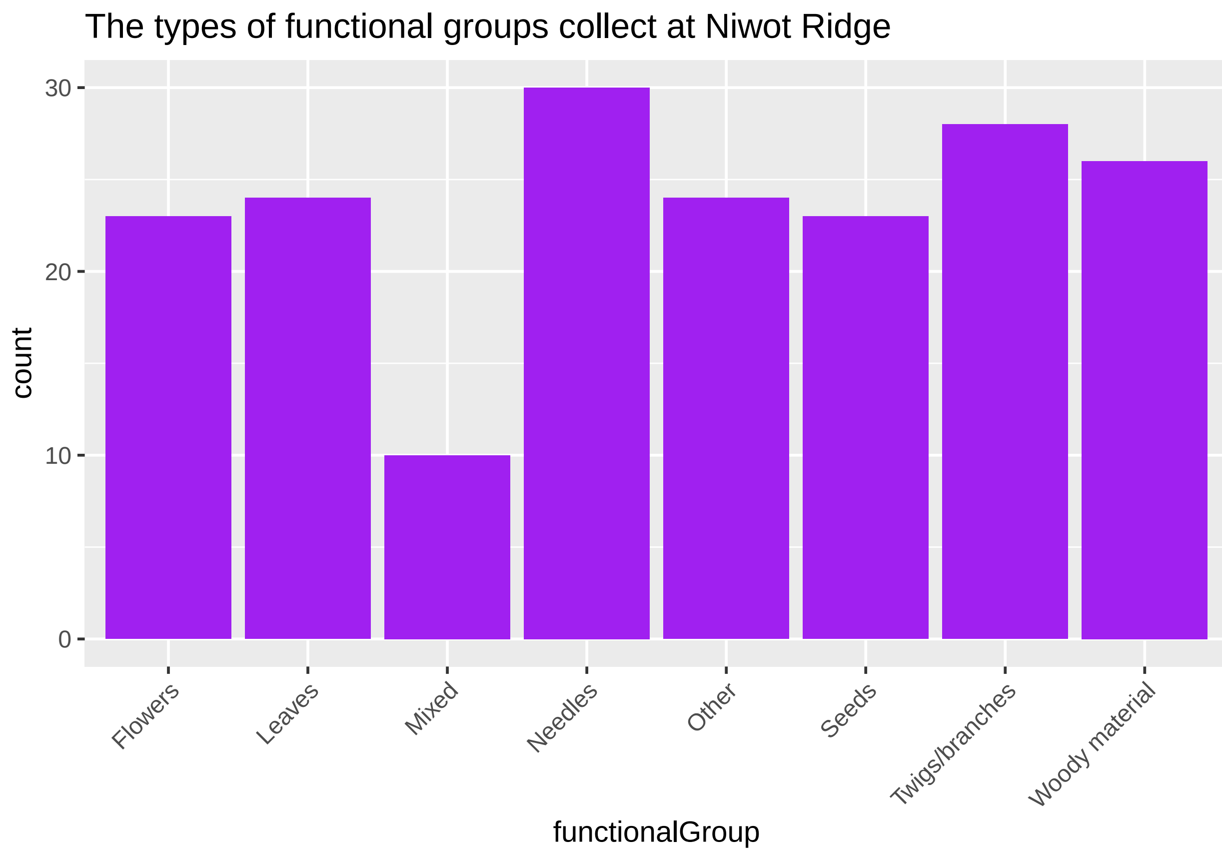
```
#View data frame with unique to compare the result to what was obtained by
#summary

# unique(Litter)
```

Answer: There were 12 plots at Niwot Ridge.

The information obtained from 'unique' is different from 'summary' as 'unique' does not give an overview of the data but simply returns the dataframe without any record(s) that was duplicated.

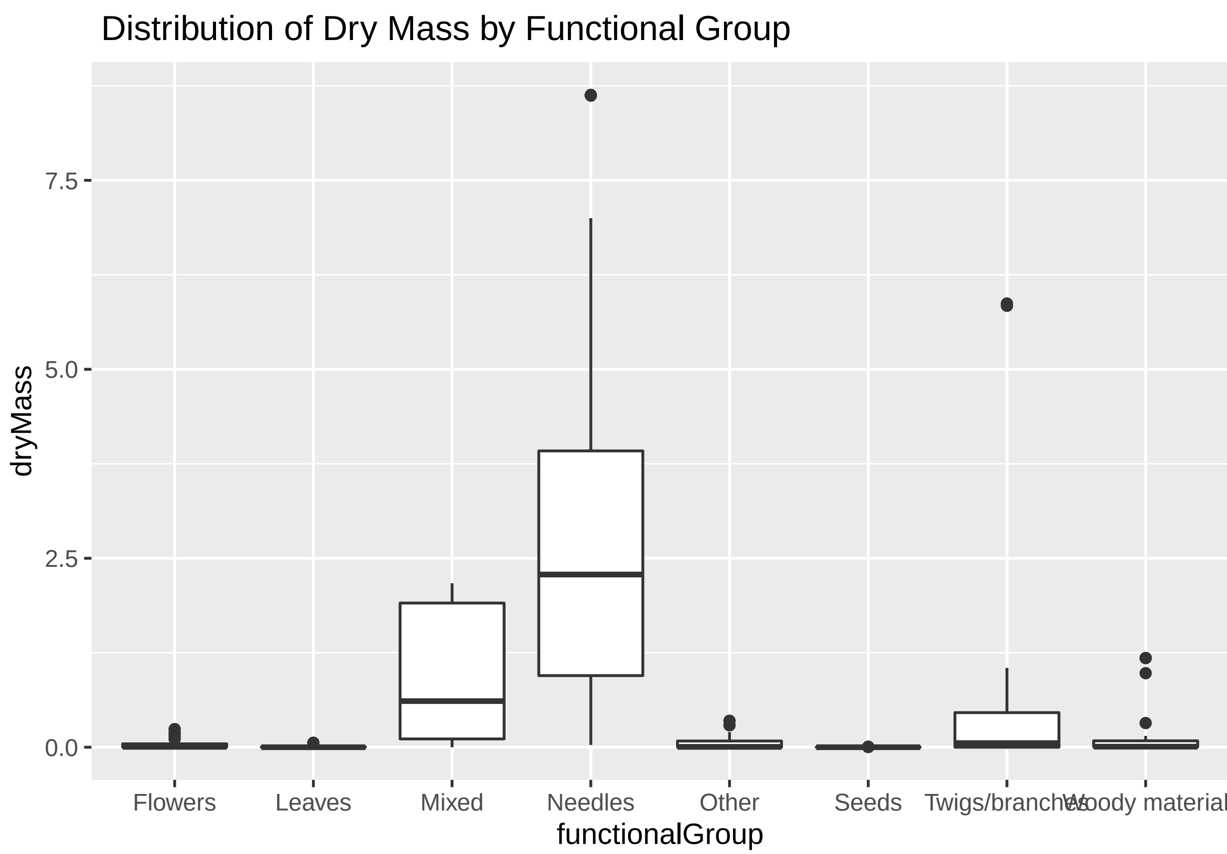
14. Create a bar graph of functionalGroup counts. This shows you what type of litter is collected at the Niwot Ridge sites. Notice that litter types are fairly equally distributed across the Niwot Ridge sites.

```
Litter %>%
  ggplot(aes(functionalGroup)) +
  geom_bar(fill = "purple") +
  ggtitle("The types of functional groups collect at Niwot Ridge") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

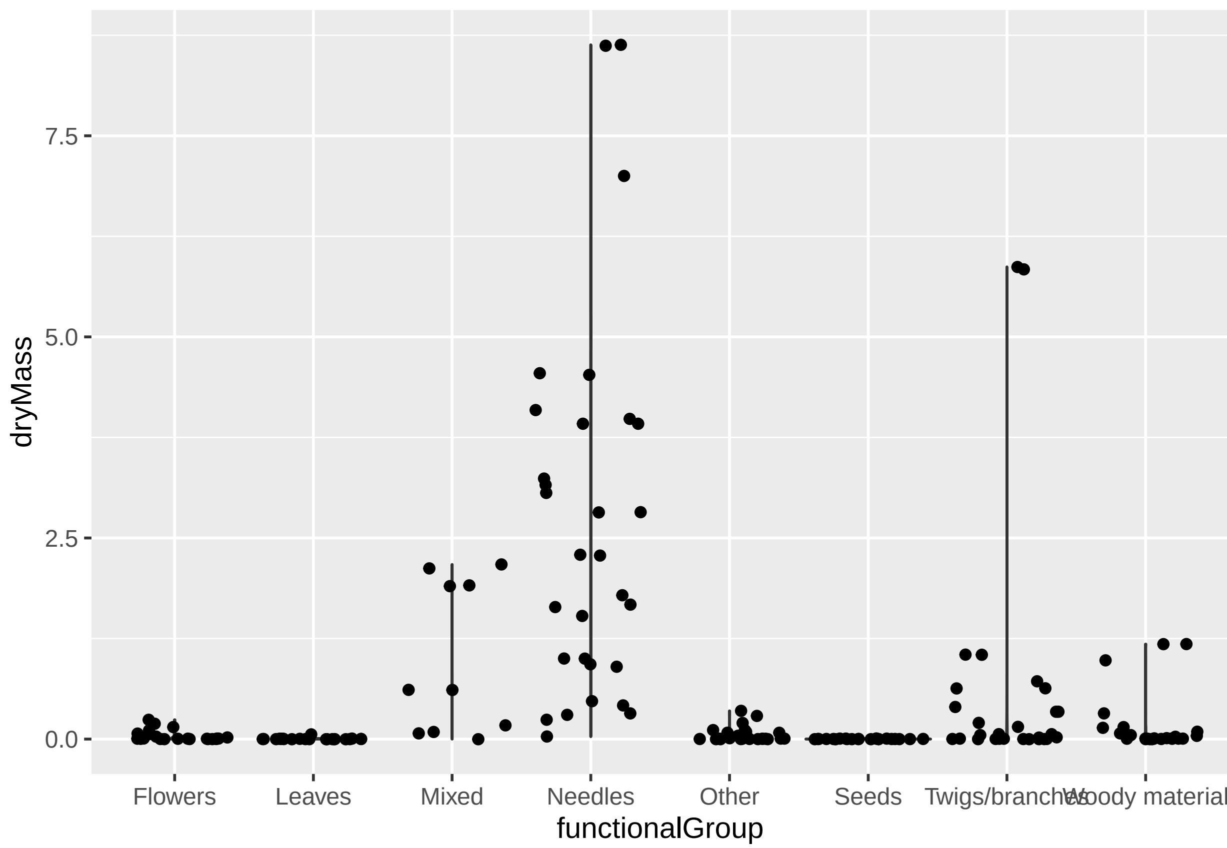


15. Using `geom_boxplot` and `geom_violin`, create a boxplot and a violin plot of dryMass by functionalGroup.

```
#Create box plot of dry mass by functional group

Litter %>%
  ggplot(aes(functionalGroup,dryMass)) +
  geom_boxplot() +
  ggtitle (" Distribution of Dry Mass by Functional Group")
```




```
#Create violin plot of dry mass by functional group

Litter %>%
  ggplot(aes(functionalGroup,dryMass)) +
  geom_violin()+
  geom_jitter()
```




```
  ggtitle (" Distribution of Dry Mass by Functional Group")
```

```
## $title
## [1] " Distribution of Dry Mass by Functional Group"
##
## attr(,"class")
## [1] "labels"
```

Why is the boxplot a more effective visualization option than the violin plot in this case?

> Answer: Box plot is the better visualization option because in this instance we do not have sufficient information to estimate the density of the dry Mass of the various functional groups.

What type(s) of litter tend to have the highest biomass at these sites?

> Answer: Needles followed by mixed tend to have the highest biomass.