

# Assignment 3: Data Exploration

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## OVERVIEW

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

The completed exercise is due on Sept 30th.

Note: I tried to use the following suggested code to make the output of the functions summary, head and tail not run off the pdf but it did not work. It actually additionally make my code flow off the page. I was advised to include it here as note that I did try but was unsuccessful in getting it to work. I did not include in a chunk because I did not want it to run as it causes additional issues as mentioned above.

```
library(formatR)
```

```
r set-up, include = FALSE
```

```
knitr::opts_chunk$set(tidy.opts=list(width.cutoff = 60), tidy=TRUE, echo=TRUE)
```

## 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 neonicotinoids 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 (neonicotinoids) 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<sup>2</sup> 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?

```
#Explore data
```

```
View(Neonics)
```

```
#summary(Neonics) #Commented out as I was unable to get the output to not run off the page.
```

```
#head(Neonics) #Commented out as I was unable to get the output to not run off the page.
```

```
#tail(Neonics) #Commented out as I was unable to get the output to not run off the page.
```

```
# 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?

```
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 occurring within a species of interest in reaction to exposure to neonicotinoid which may not be perceivable to the eye.

- 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 Woolly 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 neonticotinid insecticides. 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.

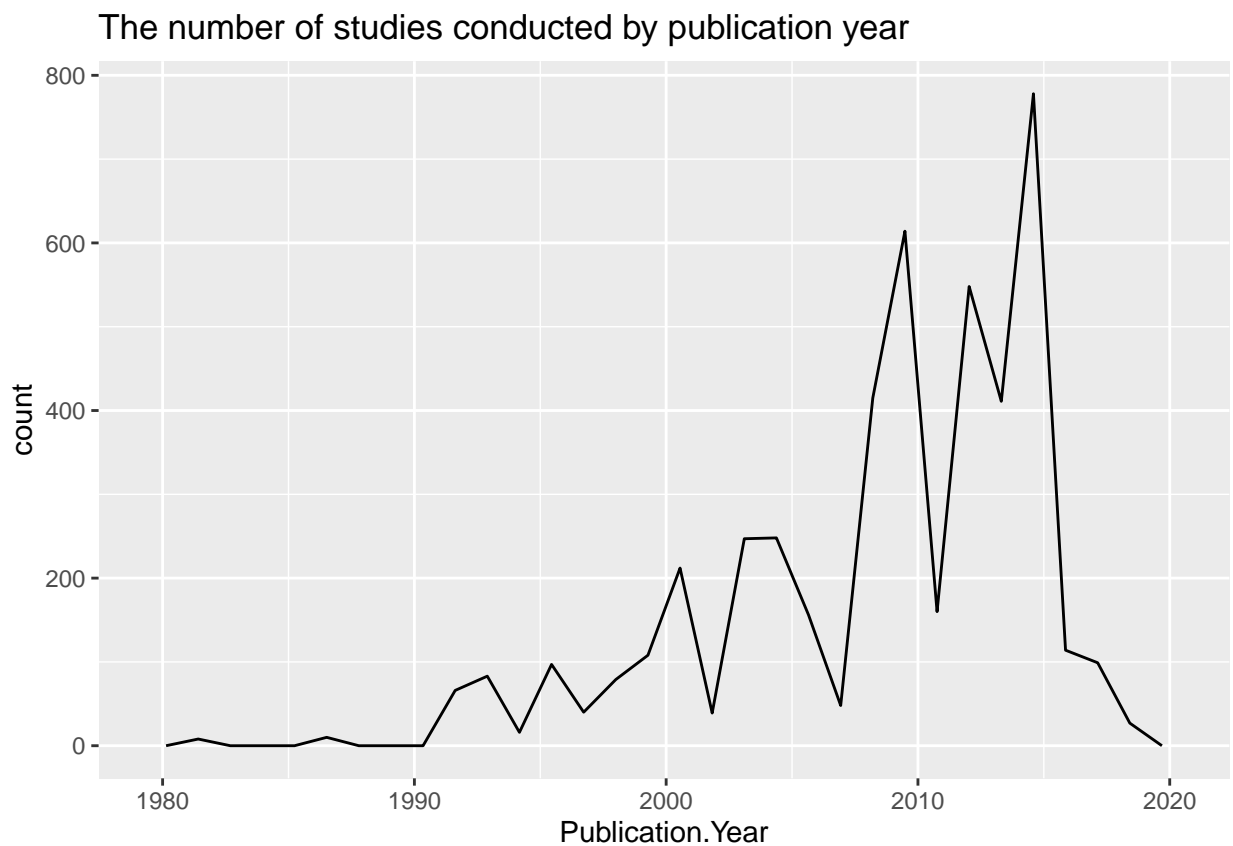
```
class(Neonics$Publication.Year) # Check the class of the Publication Year variable
```

```
## [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.

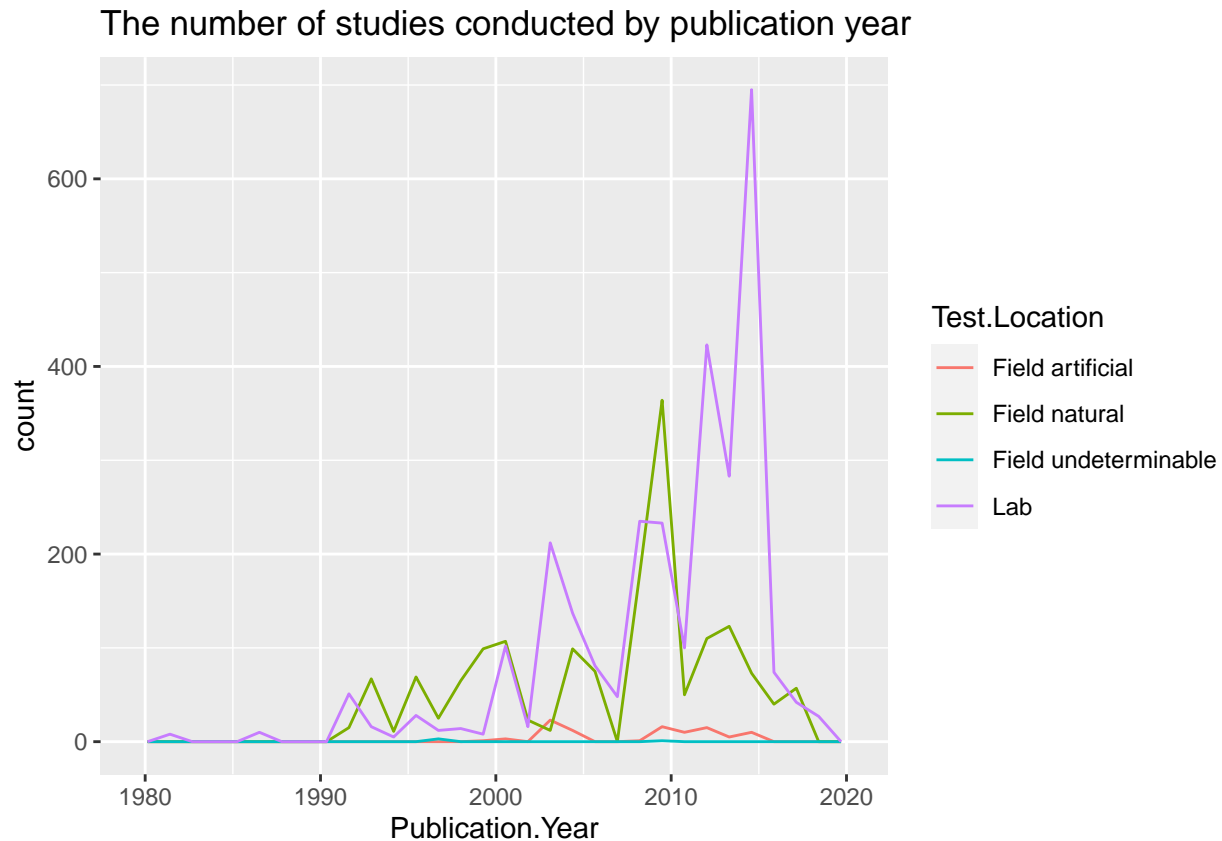
```
class(Neonics$Test.Location) #Check variable class
```

```
## [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'.
```



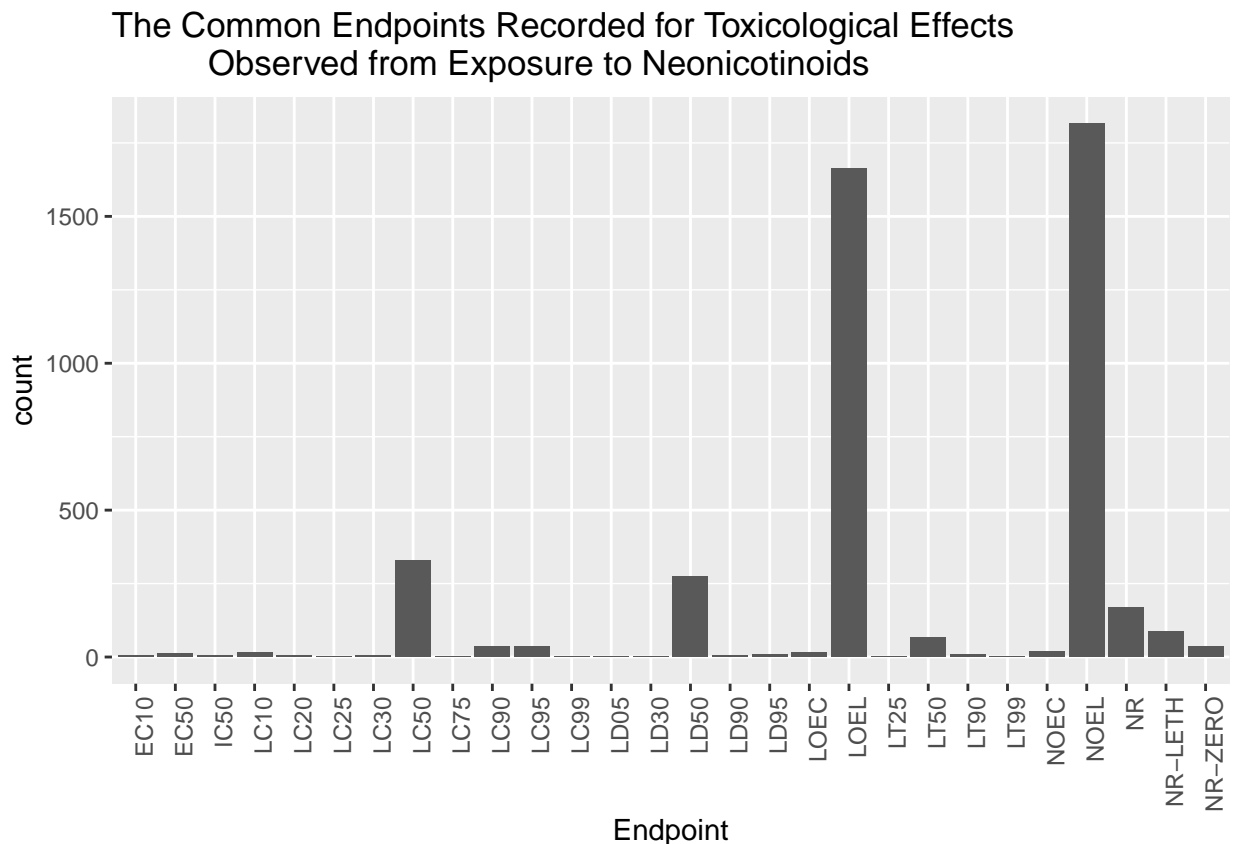
Interpret this graph. What are the most common test locations, and do they differ over time?

Answer: The most common test locations are lab and field natural. The levels of studies conducted for both test locations saw variation over time. Starting roughly around 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 experiencing a sharp decline after the year 2000, continued to grow 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 location then 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.

```
# 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 control 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.NIW0041059.20180830: 11 NEON.LTR.NIW0040205.20180802.MXT: 2
## NEON.LTR.NIW0040205.20180802: 10 NEON.LTR.NIW0040205.20180802.NDL: 2
## NEON.LTR.NIW0040205.20180830: 10 NEON.LTR.NIW0040205.20180830.MXT: 2
## NEON.LTR.NIW0046155.20180802: 10 NEON.LTR.NIW0040205.20180830.NDL: 2
## NEON.LTR.NIW0058101.20180802: 9 NEON.LTR.NIW0041059.20180830.MXT: 2
## NEON.LTR.NIW0061169.20180802: 9 NEON.LTR.NIW0041059.20180830.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.NIW0040205.20180830
## 184 2018-09-05T19:30Z NEON.LTR.NIW0040205.20180830
## 185 2018-09-05T19:30Z NEON.LTR.NIW0040205.20180830
## 186 2018-09-05T19:30Z NEON.LTR.NIW0040205.20180830
## 187 2018-09-05T19:30Z NEON.LTR.NIW0040205.20180830
## 188 2018-09-05T19:30Z NEON.LTR.NIW0040205.20180830
##          massSampleID samplingProtocolVersion functionalGroup
## 183 NEON.LTR.NIW0040205.20180830.LVS      NEON.DOC.001710vE      Leaves
## 184 NEON.LTR.NIW0040205.20180830.NDL      NEON.DOC.001710vE      Needles
## 185 NEON.LTR.NIW0040205.20180830.TWI      NEON.DOC.001710vE      Twigs/branches
## 186 NEON.LTR.NIW0040205.20180830.MXT      NEON.DOC.001710vE      Mixed
## 187 NEON.LTR.NIW0040205.20180830.NDL      NEON.DOC.001710vE      Needles
## 188 NEON.LTR.NIW0040205.20180830.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" "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
```

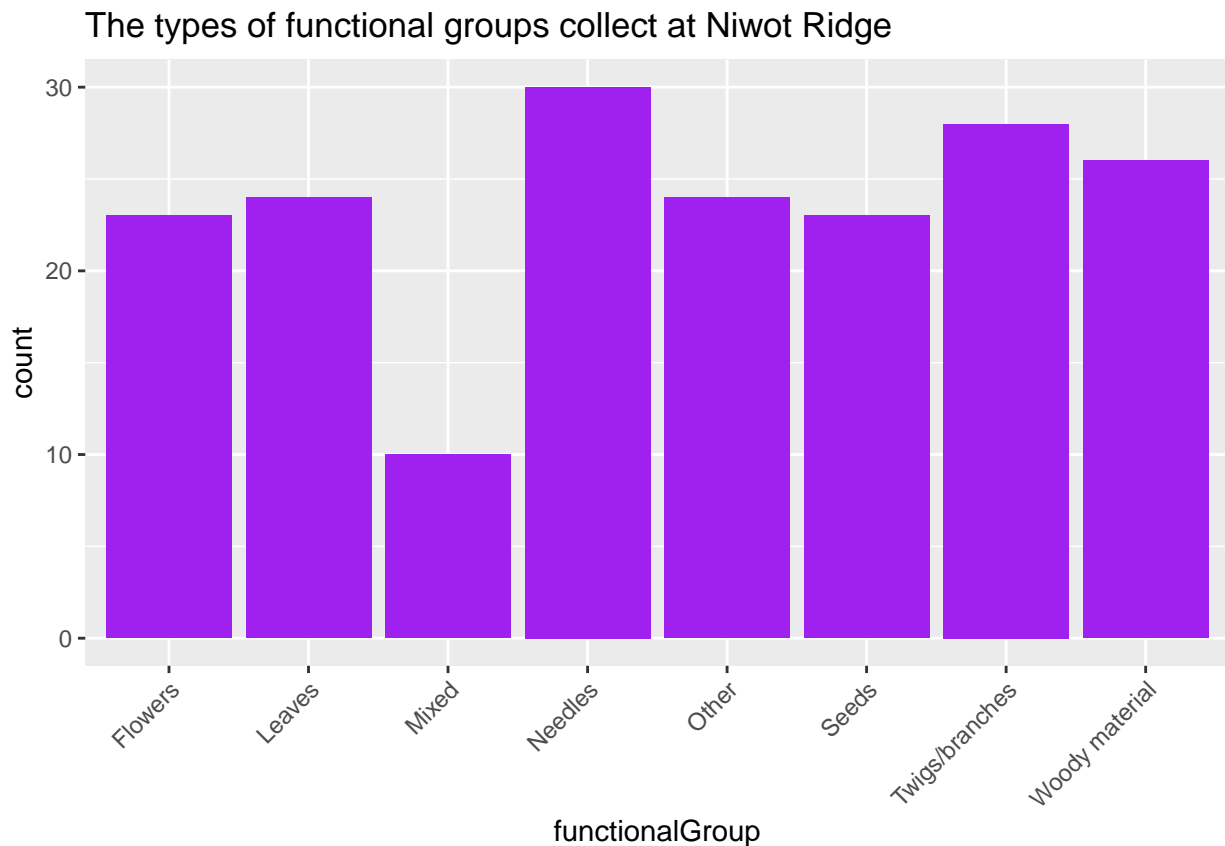
```
# unique(Litter)
```

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.

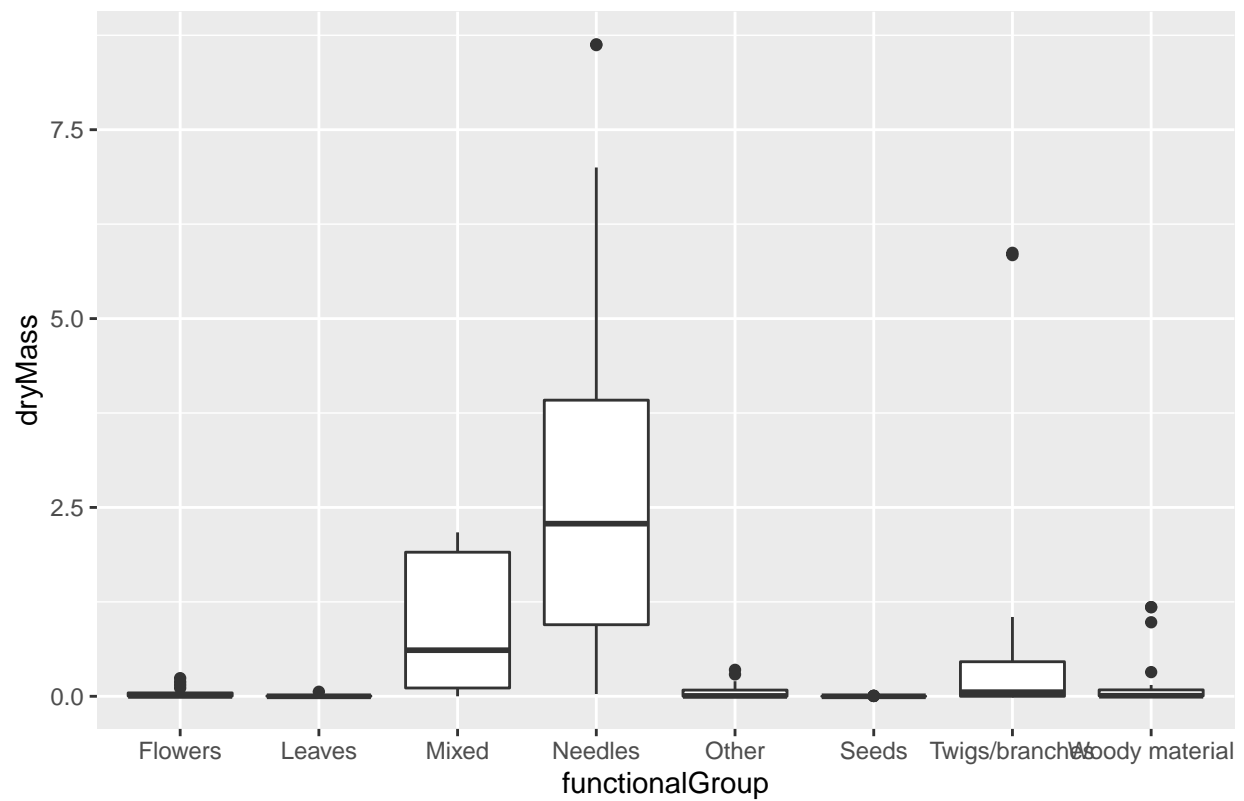
```
Litter %>%  
  ggplot(aes(functionalGroup)) +  
  geom_bar(fill = "purple") +  
  ggtitle("The types of functional groups collect at Niwot Ridge") +  
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



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

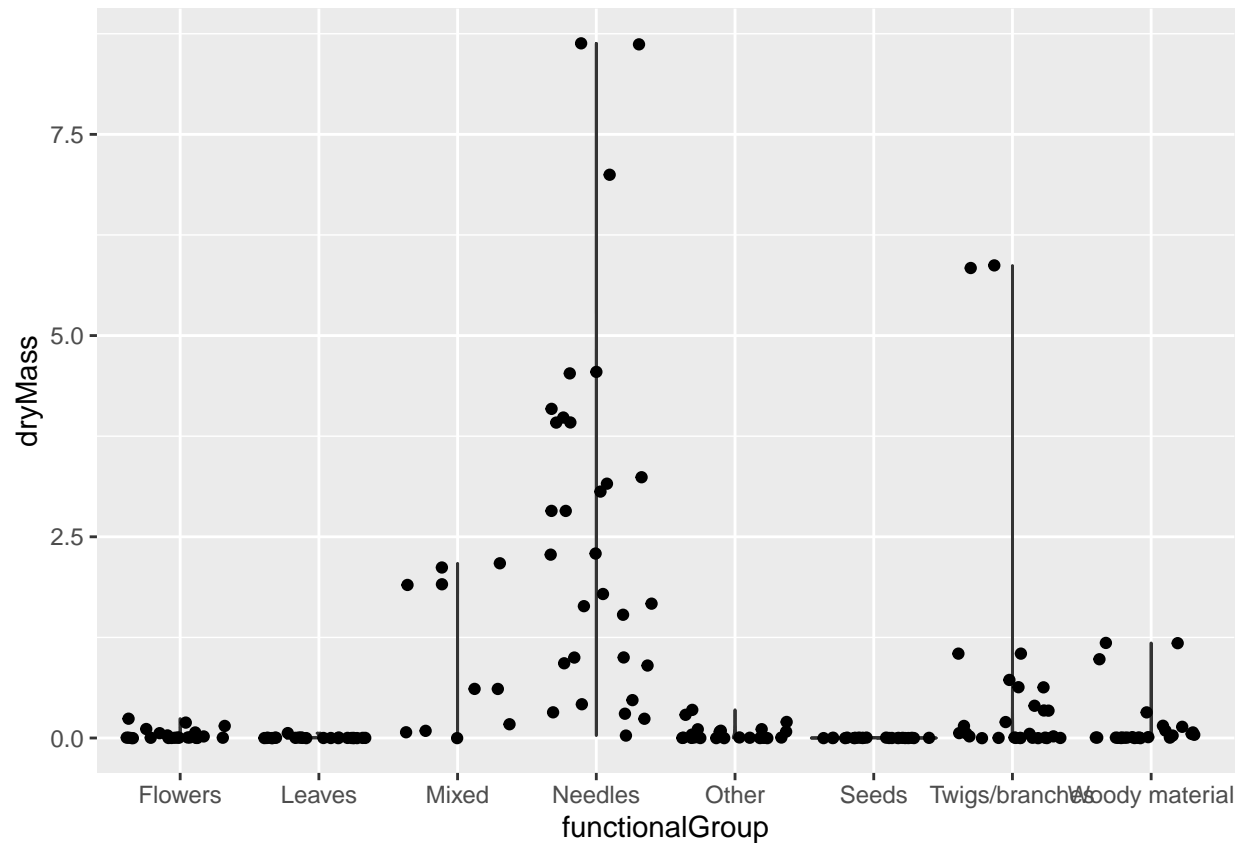
```
#Create box plot of dry mass by functional group  
  
Litter %>%  
  ggplot(aes(functionalGroup, dryMass)) +  
  geom_boxplot() +  
  ggtitle("Distribution of Dry Mass by Functional Group")
```

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.