Coding Challenge 5

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Contents

1. 3 pts. Download two .csv files from Canvas called DiversityData.csv and Metadata.csv, and read them into R using relative file paths. **2**

2. 4 pts. Join the two dataframes together by the common column 'Code'. Name the resulting dataframe alpha. **5**

3. 4 pts. Calculate Pielou's evenness index: Pielou's evenness is an ecological parameter calculated by the Shannon diversity index (column Shannon) divided by the log of the richness column. **8**

4. 4. Pts. Using tidyverse language of functions and the pipe, use the summarise function and tell me the mean and standard error evenness grouped by crop over time. **11**

5. 4. Pts. Calculate the difference between the soybean column, the soil column, and the difference between the cotton column and the soil column **11**

6. 4 pts. Connecting it to plots **12**

7. 2 pts. Commit and push a gfm .md file to GitHub inside a directory called Coding Challenge 5. Provide me a link to your github written as a clickable link in your .pdf or .docx **13**

Data wrangling – 25 pts

PLEASE READ THIS BEFORE CONTINUING

This assignment will help you practice integrating some of the tidyverse functions into your R scripts. It will also involve some more practice with GitHub. You may collaborate with a partner to enhance your learning experience. Please ensure the following:

• Collaboration: If you work with a partner, include both names on the final submission by editing the YAML header. • Submission: Only one person should submit the assignment to Canvas in a Word document or .pdf file generated through R markdown. Additionally, you should provide a link to your GitHub, where the assignment should be viewable by rendering it as a GitHub-flavored markdown file. • Setup: It is also assumed you already have a GitHub repository for this class. • Time: This should take you no longer than the class period to complete.

1. 3 pts. Download two .csv files from Canvas called DiversityData.csv and Metadata.csv, and read them into R using relative file paths.

```
DiversityData <- read.csv("DiversityData.csv")  #loading data in R
DiversityData
```

```
##       Code  shannon invsimpson   simpson richness
## 1   S01_13 6.624921  210.72795 0.9952545     3319
## 2   S02_16 6.612413  206.86664 0.9951660     3079
## 3   S03_19 6.660853  213.01843 0.9953056     3935
## 4   S04_22 6.660671  204.69080 0.9951146     3922
## 5   S05_25 6.610965  200.25523 0.9950064     3196
## 6   S06_28 6.650812  199.32110 0.9949830     3481
## 7   S61_32 6.570679  200.23177 0.9950058     3250
## 8   S62_35 6.492227  171.27965 0.9941616     3170
## 9   S63_38 6.610986  192.08535 0.9947940     3657
## 10  S64_41 6.472259  163.99814 0.9939024     3177
## 11  S65_44 6.508824  181.69248 0.9944962     2985
## 12  S66_47 6.482495  176.90684 0.9943473     2770
## 13 S121_51 6.276073  126.56259 0.9920988     3040
## 14 S122_54 6.461118  152.98152 0.9934633     3192
## 15 S123_57 6.334648  138.92556 0.9928019     2673
## 16 S124_60 6.461988  171.13732 0.9941567     3180
## 17 S125_63 6.501973  172.97532 0.9942188     3320
## 18 S126_66 6.354387  142.61016 0.9929879     2773
## 19 S181_70 6.299381  142.64506 0.9929896     2806
## 20 S182_74 6.340644  145.48656 0.9931265     3047
## 21 S183_78 6.282807  150.39829 0.9933510     2190
## 22 S184_82 6.268316  141.14138 0.9929149     2488
## 23 S186_90 6.289000  140.45260 0.9928802     2684
## 24  C01_11 6.618126  220.66218 0.9954682     3076
## 25  C02_14 6.627206  211.03921 0.9952615     3180
## 26  C03_17 6.616958  216.06631 0.9953718     2938
## 27  C04_20 6.626465  215.93901 0.9953691     3371
## 28  C05_23 6.642822  211.08960 0.9952627     3435
## 29  C06_26 6.679131  216.31351 0.9953771     3629
## 30  C61_30 6.454741  170.03639 0.9941189     2767
## 31  C62_33 6.484032  172.35279 0.9941979     3377
## 32  C63_36 6.517958  173.41489 0.9942335     3804
## 33  C64_39 6.476069  167.13138 0.9940167     3204
## 34  C65_42 6.569722  197.01186 0.9949242     3250
## 35  C66_45 6.482145  172.96394 0.9942184     3009
## 36 C121_49 5.944568   71.55607 0.9860249     2779
## 37 C122_52 6.187755   96.43939 0.9896308     3193
## 38 C123_55 6.129460   81.26646 0.9876948     2859
## 39 C124_58 6.028523   75.49726 0.9867545     2950
## 40 C125_61 6.148179   98.94468 0.9898933     3018
## 41 C126_64 6.347332  150.05708 0.9933359     2946
## 42 C181_68 6.301392  132.36230 0.9924450     3266
## 43 C182_72 6.000205   83.90929 0.9880824     2969
```

```
## 44  C183_76 5.981284   82.44127 0.9878702     2636
## 45  C184_80 5.578566   50.73174 0.9802885     2043
## 46  C185_84 6.064655   87.82732 0.9886140     3113
## 47  SB01_12 6.644864  216.86110 0.9953888     3203
## 48  SB02_15 6.615662  211.32573 0.9952680     3055
## 49  SB03_18 6.693987  230.45439 0.9956607     3595
## 50  SB04_21 6.647502  234.80343 0.9957411     3253
## 51  SB05_24 6.605749  198.57265 0.9949641     3187
## 52  SB06_27 6.640696  215.26494 0.9953546     3190
## 53  SB61_31 6.044229   89.13912 0.9887816     2371
## 54  SB62_34 6.437589  154.21624 0.9935156     3248
## 55  SB63_37 6.194632   83.11681 0.9879687     2976
## 56  SB64_40 6.117393   87.20257 0.9885324     3006
## 57  SB65_43 5.439798   29.48338 0.9660826     2809
## 58  SB66_46 6.195816  108.22394 0.9907599     2680
## 59 SB121_50 4.393341   12.39587 0.9193280     2508
## 60 SB122_53 5.630929   52.97931 0.9811247     2403
## 61 SB123_56 5.579523   48.59842 0.9794232     2752
## 62 SB124_59 5.406651   34.08685 0.9706632     2946
## 63 SB125_62 5.863941   63.33020 0.9842097     3165
## 64 SB126_65 5.738025   57.88780 0.9827252     2705
## 65 SB181_69 5.671024   57.37726 0.9825715     2642
## 66 SB182_73 5.489406   43.16854 0.9768350     2773
## 67 SB183_77 5.713960   60.47882 0.9834653     2454
## 68 SB184_81 5.467076   44.06798 0.9773078     2365
## 69 SB185_85 5.729473   55.95864 0.9821297     2789
## 70 SB186_89 5.556356   54.34527 0.9815991     2050
```

```
Metadata <- read.csv("Metadata.csv",na.strings ="na") #loading data in R
Metadata
```

```
##        Code    Crop Time_Point Replicate Water_Imbibed
## 1    S01_13    Soil          0         1            NA
## 2    S02_16    Soil          0         2            NA
## 3    S03_19    Soil          0         3            NA
## 4    S04_22    Soil          0         4            NA
## 5    S05_25    Soil          0         5            NA
## 6    S06_28    Soil          0         6            NA
## 7    S61_32    Soil          6         1            NA
## 8    S62_35    Soil          6         2            NA
## 9    S63_38    Soil          6         3            NA
## 10   S64_41    Soil          6         4            NA
## 11   S65_44    Soil          6         5            NA
## 12   S66_47    Soil          6         6            NA
## 13  S121_51    Soil         12         1            NA
## 14  S122_54    Soil         12         2            NA
## 15  S123_57    Soil         12         3            NA
## 16  S124_60    Soil         12         4            NA
## 17  S125_63    Soil         12         5            NA
## 18  S126_66    Soil         12         6            NA
## 19  S181_70    Soil         18         1            NA
## 20  S182_74    Soil         18         2            NA
## 21  S183_78    Soil         18         3            NA
## 22  S184_82    Soil         18         4            NA
```

```
## 23  S186_90    Soil         18         6            NA
## 24   C01_11  Cotton          0         1        0.0042
## 25   C02_14  Cotton          0         2        0.0091
## 26   C03_17  Cotton          0         3        0.0013
## 27   C04_20  Cotton          0         4        0.0087
## 28   C05_23  Cotton          0         5        0.0075
## 29   C06_26  Cotton          0         6        0.0046
## 30   C61_30  Cotton          6         1        0.0580
## 31   C62_33  Cotton          6         2        0.0440
## 32   C63_36  Cotton          6         3        0.0569
## 33   C64_39  Cotton          6         4        0.0841
## 34   C65_42  Cotton          6         5        0.0535
## 35   C66_45  Cotton          6         6        0.0029
## 36  C121_49  Cotton         12         1        0.0651
## 37  C122_52  Cotton         12         2        0.0527
## 38  C123_55  Cotton         12         3        0.0675
## 39  C124_58  Cotton         12         4        0.0545
## 40  C125_61  Cotton         12         5        0.0623
## 41  C126_64  Cotton         12         6        0.0021
## 42  C181_68  Cotton         18         1        0.0034
## 43  C182_72  Cotton         18         2        0.0632
## 44  C183_76  Cotton         18         3        0.0514
## 45  C184_80  Cotton         18         4        0.0577
## 46  C185_84  Cotton         18         5        0.0554
## 47  SB01_12 Soybean          0         1        0.1664
## 48  SB02_15 Soybean          0         2        0.0942
## 49  SB03_18 Soybean          0         3        0.1248
## 50  SB04_21 Soybean          0         4        0.1150
## 51  SB05_24 Soybean          0         5        0.0993
## 52  SB06_27 Soybean          0         6        0.1005
## 53  SB61_31 Soybean          6         1        0.2308
## 54  SB62_34 Soybean          6         2        0.2603
## 55  SB63_37 Soybean          6         3        0.2111
## 56  SB64_40 Soybean          6         4        0.2808
## 57  SB65_43 Soybean          6         5        0.2712
## 58  SB66_46 Soybean          6         6        0.2887
## 59 SB121_50 Soybean         12         1        0.2822
## 60 SB122_53 Soybean         12         2        0.2557
## 61 SB123_56 Soybean         12         3        0.2982
## 62 SB124_59 Soybean         12         4        0.2489
## 63 SB125_62 Soybean         12         5        0.2573
## 64 SB126_65 Soybean         12         6        0.2285
## 65 SB181_69 Soybean         18         1        0.2528
## 66 SB182_73 Soybean         18         2        0.2706
## 67 SB183_77 Soybean         18         3        0.3196
## 68 SB184_81 Soybean         18         4        0.2437
## 69 SB185_85 Soybean         18         5        0.2461
## 70 SB186_89 Soybean         18         6        0.3010
```

2. 4 pts. Join the two dataframes together by the common column 'Code'. Name the resulting dataframe alpha.

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become error
```

```
library(ggplot2)
library(knitr)
library(markdown)
alpha <- left_join(DiversityData, Metadata, by = "Code") #combining two dataframes together by common c
alpha
```

```
##       Code  shannon invsimpson   simpson richness    Crop Time_Point Replicate
## 1    S01_13 6.624921  210.72795 0.9952545     3319    Soil          0         1
## 2    S02_16 6.612413  206.86664 0.9951660     3079    Soil          0         2
## 3    S03_19 6.660853  213.01843 0.9953056     3935    Soil          0         3
## 4    S04_22 6.660671  204.69080 0.9951146     3922    Soil          0         4
## 5    S05_25 6.610965  200.25523 0.9950064     3196    Soil          0         5
## 6    S06_28 6.650812  199.32110 0.9949830     3481    Soil          0         6
## 7    S61_32 6.570679  200.23177 0.9950058     3250    Soil          6         1
## 8    S62_35 6.492227  171.27965 0.9941616     3170    Soil          6         2
## 9    S63_38 6.610986  192.08535 0.9947940     3657    Soil          6         3
## 10   S64_41 6.472259  163.99814 0.9939024     3177    Soil          6         4
## 11   S65_44 6.508824  181.69248 0.9944962     2985    Soil          6         5
## 12   S66_47 6.482495  176.90684 0.9943473     2770    Soil          6         6
## 13  S121_51 6.276073  126.56259 0.9920988     3040    Soil         12         1
## 14  S122_54 6.461118  152.98152 0.9934633     3192    Soil         12         2
## 15  S123_57 6.334648  138.92556 0.9928019     2673    Soil         12         3
## 16  S124_60 6.461988  171.13732 0.9941567     3180    Soil         12         4
## 17  S125_63 6.501973  172.97532 0.9942188     3320    Soil         12         5
## 18  S126_66 6.354387  142.61016 0.9929879     2773    Soil         12         6
## 19  S181_70 6.299381  142.64506 0.9929896     2806    Soil         18         1
## 20  S182_74 6.340644  145.48656 0.9931265     3047    Soil         18         2
## 21  S183_78 6.282807  150.39829 0.9933510     2190    Soil         18         3
## 22  S184_82 6.268316  141.14138 0.9929149     2488    Soil         18         4
## 23  S186_90 6.289000  140.45260 0.9928802     2684    Soil         18         6
## 24   C01_11 6.618126  220.66218 0.9954682     3076  Cotton          0         1
## 25   C02_14 6.627206  211.03921 0.9952615     3180  Cotton          0         2
## 26   C03_17 6.616958  216.06631 0.9953718     2938  Cotton          0         3
## 27   C04_20 6.626465  215.93901 0.9953691     3371  Cotton          0         4
## 28   C05_23 6.642822  211.08960 0.9952627     3435  Cotton          0         5
```

```
## 29   C06_26 6.679131  216.31351 0.9953771     3629  Cotton          0          6
## 30   C61_30 6.454741  170.03639 0.9941189     2767  Cotton          6          1
## 31   C62_33 6.484032  172.35279 0.9941979     3377  Cotton          6          2
## 32   C63_36 6.517958  173.41489 0.9942335     3804  Cotton          6          3
## 33   C64_39 6.476069  167.13138 0.9940167     3204  Cotton          6          4
## 34   C65_42 6.569722  197.01186 0.9949242     3250  Cotton          6          5
## 35   C66_45 6.482145  172.96394 0.9942184     3009  Cotton          6          6
## 36  C121_49 5.944568   71.55607 0.9860249     2779  Cotton         12          1
## 37  C122_52 6.187755   96.43939 0.9896308     3193  Cotton         12          2
## 38  C123_55 6.129460   81.26646 0.9876948     2859  Cotton         12          3
## 39  C124_58 6.028523   75.49726 0.9867545     2950  Cotton         12          4
## 40  C125_61 6.148179   98.94468 0.9898933     3018  Cotton         12          5
## 41  C126_64 6.347332  150.05708 0.9933359     2946  Cotton         12          6
## 42  C181_68 6.301392  132.36230 0.9924450     3266  Cotton         18          1
## 43  C182_72 6.000205   83.90929 0.9880824     2969  Cotton         18          2
## 44  C183_76 5.981284   82.44127 0.9878702     2636  Cotton         18          3
## 45  C184_80 5.578566   50.73174 0.9802885     2043  Cotton         18          4
## 46  C185_84 6.064655   87.82732 0.9886140     3113  Cotton         18          5
## 47  SB01_12 6.644864  216.86110 0.9953888     3203 Soybean          0          1
## 48  SB02_15 6.615662  211.32573 0.9952680     3055 Soybean          0          2
## 49  SB03_18 6.693987  230.45439 0.9956607     3595 Soybean          0          3
## 50  SB04_21 6.647502  234.80343 0.9957411     3253 Soybean          0          4
## 51  SB05_24 6.605749  198.57265 0.9949641     3187 Soybean          0          5
## 52  SB06_27 6.640696  215.26494 0.9953546     3190 Soybean          0          6
## 53  SB61_31 6.044229   89.13912 0.9887816     2371 Soybean          6          1
## 54  SB62_34 6.437589  154.21624 0.9935156     3248 Soybean          6          2
## 55  SB63_37 6.194632   83.11681 0.9879687     2976 Soybean          6          3
## 56  SB64_40 6.117393   87.20257 0.9885324     3006 Soybean          6          4
## 57  SB65_43 5.439798   29.48338 0.9660826     2809 Soybean          6          5
## 58  SB66_46 6.195816  108.22394 0.9907599     2680 Soybean          6          6
## 59 SB121_50 4.393341   12.39587 0.9193280     2508 Soybean         12          1
## 60 SB122_53 5.630929   52.97931 0.9811247     2403 Soybean         12          2
## 61 SB123_56 5.579523   48.59842 0.9794232     2752 Soybean         12          3
## 62 SB124_59 5.406651   34.08685 0.9706632     2946 Soybean         12          4
## 63 SB125_62 5.863941   63.33020 0.9842097     3165 Soybean         12          5
## 64 SB126_65 5.738025   57.88780 0.9827252     2705 Soybean         12          6
## 65 SB181_69 5.671024   57.37726 0.9825715     2642 Soybean         18          1
## 66 SB182_73 5.489406   43.16854 0.9768350     2773 Soybean         18          2
## 67 SB183_77 5.713960   60.47882 0.9834653     2454 Soybean         18          3
## 68 SB184_81 5.467076   44.06798 0.9773078     2365 Soybean         18          4
## 69 SB185_85 5.729473   55.95864 0.9821297     2789 Soybean         18          5
## 70 SB186_89 5.556356   54.34527 0.9815991     2050 Soybean         18          6
##    Water_Imbibed
## 1             NA
## 2             NA
## 3             NA
## 4             NA
## 5             NA
## 6             NA
## 7             NA
## 8             NA
## 9             NA
## 10            NA
## 11            NA
```

```
## 12           NA
## 13           NA
## 14           NA
## 15           NA
## 16           NA
## 17           NA
## 18           NA
## 19           NA
## 20           NA
## 21           NA
## 22           NA
## 23           NA
## 24       0.0042
## 25       0.0091
## 26       0.0013
## 27       0.0087
## 28       0.0075
## 29       0.0046
## 30       0.0580
## 31       0.0440
## 32       0.0569
## 33       0.0841
## 34       0.0535
## 35       0.0029
## 36       0.0651
## 37       0.0527
## 38       0.0675
## 39       0.0545
## 40       0.0623
## 41       0.0021
## 42       0.0034
## 43       0.0632
## 44       0.0514
## 45       0.0577
## 46       0.0554
## 47       0.1664
## 48       0.0942
## 49       0.1248
## 50       0.1150
## 51       0.0993
## 52       0.1005
## 53       0.2308
## 54       0.2603
## 55       0.2111
## 56       0.2808
## 57       0.2712
## 58       0.2887
## 59       0.2822
## 60       0.2557
## 61       0.2982
## 62       0.2489
## 63       0.2573
## 64       0.2285
## 65       0.2528
```

```
## 66         0.2706
## 67         0.3196
## 68         0.2437
## 69         0.2461
## 70         0.3010
```

3. 4 pts. Calculate Pielou's evenness index: Pielou's evenness is an ecological parameter calculated by the Shannon diversity index (column Shannon) divided by the log of the richness column.

a. Using mutate, create a new column to calculate Pielou's evenness index.
b. Name the resulting dataframe alpha_even.

```
alpha_even <- alpha %>%
mutate(logRich = log(richness)) %>%  #adding a column named logRich containing log values of richness c
mutate(alpha, Pielousevennessindex = shannon/logRich) #adding a column Pielousevennessindex by calculat

alpha_even
```

```
##        Code  shannon invsimpson   simpson richness    Crop Time_Point Replicate
## 1    S01_13 6.624921  210.72795 0.9952545     3319    Soil          0         1
## 2    S02_16 6.612413  206.86664 0.9951660     3079    Soil          0         2
## 3    S03_19 6.660853  213.01843 0.9953056     3935    Soil          0         3
## 4    S04_22 6.660671  204.69080 0.9951146     3922    Soil          0         4
## 5    S05_25 6.610965  200.25523 0.9950064     3196    Soil          0         5
## 6    S06_28 6.650812  199.32110 0.9949830     3481    Soil          0         6
## 7    S61_32 6.570679  200.23177 0.9950058     3250    Soil          6         1
## 8    S62_35 6.492227  171.27965 0.9941616     3170    Soil          6         2
## 9    S63_38 6.610986  192.08535 0.9947940     3657    Soil          6         3
## 10   S64_41 6.472259  163.99814 0.9939024     3177    Soil          6         4
## 11   S65_44 6.508824  181.69248 0.9944962     2985    Soil          6         5
## 12   S66_47 6.482495  176.90684 0.9943473     2770    Soil          6         6
## 13  S121_51 6.276073  126.56259 0.9920988     3040    Soil         12         1
## 14  S122_54 6.461118  152.98152 0.9934633     3192    Soil         12         2
## 15  S123_57 6.334648  138.92556 0.9928019     2673    Soil         12         3
## 16  S124_60 6.461988  171.13732 0.9941567     3180    Soil         12         4
## 17  S125_63 6.501973  172.97532 0.9942188     3320    Soil         12         5
## 18  S126_66 6.354387  142.61016 0.9929879     2773    Soil         12         6
## 19  S181_70 6.299381  142.64506 0.9929896     2806    Soil         18         1
## 20  S182_74 6.340644  145.48656 0.9931265     3047    Soil         18         2
## 21  S183_78 6.282807  150.39829 0.9933510     2190    Soil         18         3
## 22  S184_82 6.268316  141.14138 0.9929149     2488    Soil         18         4
## 23  S186_90 6.289000  140.45260 0.9928802     2684    Soil         18         6
## 24   C01_11 6.618126  220.66218 0.9954682     3076  Cotton          0         1
## 25   C02_14 6.627206  211.03921 0.9952615     3180  Cotton          0         2
## 26   C03_17 6.616958  216.06631 0.9953718     2938  Cotton          0         3
## 27   C04_20 6.626465  215.93901 0.9953691     3371  Cotton          0         4
## 28   C05_23 6.642822  211.08960 0.9952627     3435  Cotton          0         5
## 29   C06_26 6.679131  216.31351 0.9953771     3629  Cotton          0         6
## 30   C61_30 6.454741  170.03639 0.9941189     2767  Cotton          6         1
## 31   C62_33 6.484032  172.35279 0.9941979     3377  Cotton          6         2
```

```
## 32   C63_36 6.517958  173.41489 0.9942335     3804  Cotton          6          3
## 33   C64_39 6.476069  167.13138 0.9940167     3204  Cotton          6          4
## 34   C65_42 6.569722  197.01186 0.9949242     3250  Cotton          6          5
## 35   C66_45 6.482145  172.96394 0.9942184     3009  Cotton          6          6
## 36  C121_49 5.944568   71.55607 0.9860249     2779  Cotton         12          1
## 37  C122_52 6.187755   96.43939 0.9896308     3193  Cotton         12          2
## 38  C123_55 6.129460   81.26646 0.9876948     2859  Cotton         12          3
## 39  C124_58 6.028523   75.49726 0.9867545     2950  Cotton         12          4
## 40  C125_61 6.148179   98.94468 0.9898933     3018  Cotton         12          5
## 41  C126_64 6.347332  150.05708 0.9933359     2946  Cotton         12          6
## 42  C181_68 6.301392  132.36230 0.9924450     3266  Cotton         18          1
## 43  C182_72 6.000205   83.90929 0.9880824     2969  Cotton         18          2
## 44  C183_76 5.981284   82.44127 0.9878702     2636  Cotton         18          3
## 45  C184_80 5.578566   50.73174 0.9802885     2043  Cotton         18          4
## 46  C185_84 6.064655   87.82732 0.9886140     3113  Cotton         18          5
## 47  SB01_12 6.644864  216.86110 0.9953888     3203 Soybean          0          1
## 48  SB02_15 6.615662  211.32573 0.9952680     3055 Soybean          0          2
## 49  SB03_18 6.693987  230.45439 0.9956607     3595 Soybean          0          3
## 50  SB04_21 6.647502  234.80343 0.9957411     3253 Soybean          0          4
## 51  SB05_24 6.605749  198.57265 0.9949641     3187 Soybean          0          5
## 52  SB06_27 6.640696  215.26494 0.9953546     3190 Soybean          0          6
## 53  SB61_31 6.044229   89.13912 0.9887816     2371 Soybean          6          1
## 54  SB62_34 6.437589  154.21624 0.9935156     3248 Soybean          6          2
## 55  SB63_37 6.194632   83.11681 0.9879687     2976 Soybean          6          3
## 56  SB64_40 6.117393   87.20257 0.9885324     3006 Soybean          6          4
## 57  SB65_43 5.439798   29.48338 0.9660826     2809 Soybean          6          5
## 58  SB66_46 6.195816  108.22394 0.9907599     2680 Soybean          6          6
## 59 SB121_50 4.393341   12.39587 0.9193280     2508 Soybean         12          1
## 60 SB122_53 5.630929   52.97931 0.9811247     2403 Soybean         12          2
## 61 SB123_56 5.579523   48.59842 0.9794232     2752 Soybean         12          3
## 62 SB124_59 5.406651   34.08685 0.9706632     2946 Soybean         12          4
## 63 SB125_62 5.863941   63.33020 0.9842097     3165 Soybean         12          5
## 64 SB126_65 5.738025   57.88780 0.9827252     2705 Soybean         12          6
## 65 SB181_69 5.671024   57.37726 0.9825715     2642 Soybean         18          1
## 66 SB182_73 5.489406   43.16854 0.9768350     2773 Soybean         18          2
## 67 SB183_77 5.713960   60.47882 0.9834653     2454 Soybean         18          3
## 68 SB184_81 5.467076   44.06798 0.9773078     2365 Soybean         18          4
## 69 SB185_85 5.729473   55.95864 0.9821297     2789 Soybean         18          5
## 70 SB186_89 5.556356   54.34527 0.9815991     2050 Soybean         18          6
##    Water_Imbibed  logRich Pielousevennessindex
## 1             NA 8.107419            0.8171431
## 2             NA 8.032360            0.8232216
## 3             NA 8.277666            0.8046776
## 4             NA 8.274357            0.8049774
## 5             NA 8.069655            0.8192376
## 6             NA 8.155075            0.8155427
## 7             NA 8.086410            0.8125582
## 8             NA 8.061487            0.8053387
## 9             NA 8.204398            0.8057856
## 10            NA 8.063693            0.8026420
## 11            NA 8.001355            0.8134652
## 12            NA 7.926603            0.8178151
## 13            NA 8.019613            0.7825905
## 14            NA 8.068403            0.8007927
```

```
## 15            NA 7.890957            0.8027732
## 16            NA 8.064636            0.8012745
## 17            NA 8.107720            0.8019483
## 18            NA 7.927685            0.8015438
## 19            NA 7.939515            0.7934213
## 20            NA 8.021913            0.7904154
## 21            NA 7.691657            0.8168340
## 22            NA 7.819234            0.8016534
## 23            NA 7.895063            0.7965737
## 24        0.0042 8.031385            0.8240330
## 25        0.0091 8.064636            0.8217613
## 26        0.0013 7.985484            0.8286233
## 27        0.0087 8.122965            0.8157692
## 28        0.0075 8.141772            0.8158938
## 29        0.0046 8.196712            0.8148549
## 30        0.0580 7.925519            0.8144250
## 31        0.0440 8.124743            0.7980600
## 32        0.0569 8.243808            0.7906489
## 33        0.0841 8.072155            0.8022726
## 34        0.0535 8.086410            0.8124399
## 35        0.0029 8.009363            0.8093209
## 36        0.0651 7.929846            0.7496447
## 37        0.0527 8.068716            0.7668822
## 38        0.0675 7.958227            0.7702042
## 39        0.0545 7.989560            0.7545500
## 40        0.0623 8.012350            0.7673379
## 41        0.0021 7.988204            0.7945881
## 42        0.0034 8.091321            0.7787840
## 43        0.0632 7.995980            0.7504026
## 44        0.0514 7.877018            0.7593336
## 45        0.0577 7.622175            0.7318864
## 46        0.0554 8.043342            0.7539969
## 47        0.1664 8.071843            0.8232153
## 48        0.0942 8.024535            0.8244294
## 49        0.1248 8.187299            0.8176063
## 50        0.1150 8.087333            0.8219646
## 51        0.0993 8.066835            0.8188774
## 52        0.1005 8.067776            0.8231136
## 53        0.2308 7.771067            0.7777862
## 54        0.2603 8.085795            0.7961603
## 55        0.2111 7.998335            0.7744902
## 56        0.2808 8.008366            0.7638754
## 57        0.2712 7.940584            0.6850627
## 58        0.2887 7.893572            0.7849191
## 59        0.2822 7.827241            0.5612885
## 60        0.2557 7.784473            0.7233538
## 61        0.2982 7.920083            0.7044778
## 62        0.2489 7.988204            0.6768294
## 63        0.2573 8.059908            0.7275444
## 64        0.2285 7.902857            0.7260697
## 65        0.2528 7.879291            0.7197378
## 66        0.2706 7.927685            0.6924349
## 67        0.3196 7.805475            0.7320451
## 68        0.2437 7.768533            0.7037462
```

```
## 69        0.2461 7.933438            0.7221929
## 70        0.3010 7.625595            0.7286456
```

4. 4. Pts. Using tidyverse language of functions and the pipe, use the summarise function and tell me the mean and standard error evenness grouped by crop over time.

a. Start with the alpha_even dataframe
b. Group the data: group the data by Crop and Time_Point.
c. Summarize the data: Calculate the mean, count, standard deviation, and standard error for the even variable within each group.
d. Name the resulting dataframe alpha_average

```r
alpha_average <- alpha_even %>%
  group_by(Crop, Time_Point) %>%    #grouping the data by Crop and Time point
  summarise(Mean = mean(Pielousevennessindex),  #calculating mean of evenness by group
            n = n(),    #counting number of rows based on group
            sd.dev = sd(Pielousevennessindex)) %>%  #calculating standard deviation of the evenness by
  mutate(std.err = sd.dev/sqrt(n))   #calculating standard error by group
```

```
## `summarise()` has grouped output by 'Crop'. You can override using the
## `.groups` argument.
```

```r
alpha_average
```

```
## # A tibble: 12 x 6
## # Groups:   Crop [3]
##    Crop    Time_Point  Mean     n  sd.dev std.err
##    <chr>        <int> <dbl> <int>   <dbl>   <dbl>
##  1 Cotton           0 0.820     6 0.00556 0.00227
##  2 Cotton           6 0.805     6 0.00920 0.00376
##  3 Cotton          12 0.767     6 0.0157  0.00640
##  4 Cotton          18 0.755     5 0.0169  0.00755
##  5 Soil             0 0.814     6 0.00765 0.00312
##  6 Soil             6 0.810     6 0.00587 0.00240
##  7 Soil            12 0.798     6 0.00782 0.00319
##  8 Soil            18 0.800     5 0.0104  0.00465
##  9 Soybean          0 0.822     6 0.00270 0.00110
## 10 Soybean          6 0.764     6 0.0400  0.0163
## 11 Soybean         12 0.687     6 0.0643  0.0263
## 12 Soybean         18 0.716     6 0.0153  0.00626
```

5. 4. Pts. Calculate the difference between the soybean column, the soil column, and the difference between the cotton column and the soil column

a. Start with the alpha_average dataframe

b. Select relevant columns: select the columns Time_Point, Crop, and mean.even.
c. Reshape the data: Use the pivot_wider function to transform the data from long to wide format, creating new columns for each Crop with values from mean.even.
d. Calculate differences: Create new columns named diff.cotton.even and diff.soybean.even by calculating the difference between Soil and Cotton, and Soil and Soybean, respectively.
e. Name the resulting dataframe alpha_average2

```
alpha_average2 <- alpha_average %>%
  select(Time_Point, Crop, Mean) %>%    #selecting the relevant columns
  pivot_wider(names_from = Crop, values_from = Mean) %>%   #transforming data from longer format to wid
  mutate(diff.cotton.even = Soil - Cotton) %>%  #calculating difference in mean between soil and cotton
  mutate(diff.soybean.even = Soil - Soybean) #calculating difference in mean between soil and soybean a
alpha_average2
```

```
## # A tibble: 4 x 6
##   Time_Point Cotton  Soil Soybean diff.cotton.even diff.soybean.even
##        <int>  <dbl> <dbl>   <dbl>            <dbl>             <dbl>
## 1          0  0.820 0.814   0.822         -0.00602          -0.00740
## 2          6  0.805 0.810   0.764          0.00507           0.0459
## 3         12  0.767 0.798   0.687          0.0313            0.112
## 4         18  0.755 0.800   0.716          0.0449            0.0833
```

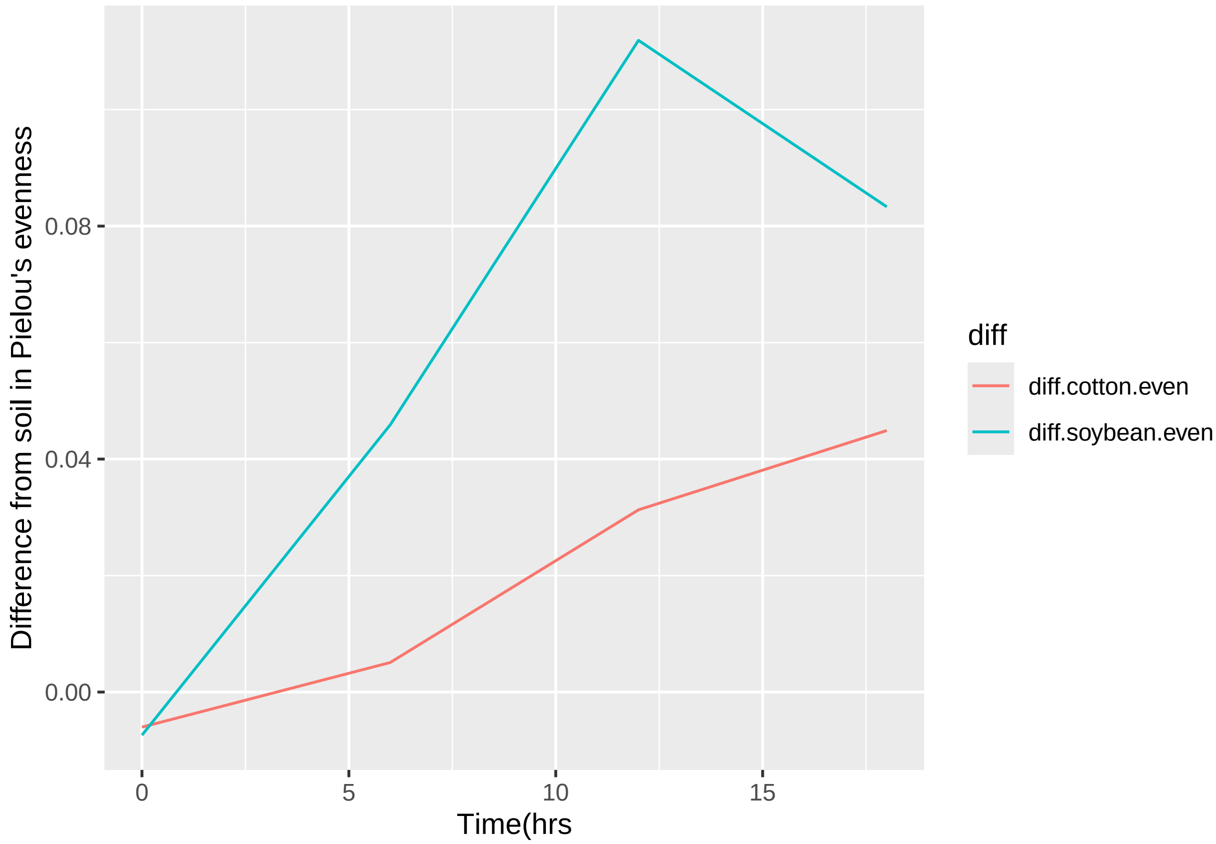
6. 4 pts. Connecting it to plots

a. Start with the alpha_average2 dataframe
b. Select relevant columns: select the columns Time_Point, diff.cotton.even, and diff.soybean.even.
c. Reshape the data: Use the pivot_longer function to transform the data from wide to long format, creating a new column named diff that contains the values from diff.cotton.even and diff.soybean.even.
d. This might be challenging, so I'll give you a break. The code is below.

pivot_longer(c(diff.cotton.even, diff.soybean.even), names_to = "diff")

d. Create the plot: Use ggplot and geom_line() with 'Time_Point' on the x-axis, the column 'values' on the y-axis, and different colors for each 'diff' category. The column named 'values' come from the pivot_longer. The resulting plot should look like the one to the right.

```
alpha_average2 %>%
  select(Time_Point, diff.cotton.even, diff.soybean.even) %>% #selecting relevant columns
  pivot_longer(c(diff.cotton.even, diff.soybean.even), names_to = "diff") %>%  #transforming wide forma
  ggplot(aes(x= Time_Point, y = value, color = diff))+ #creating a line graph with time point as x axis
  geom_line()+
  xlab("Time(hrs)")+ #labeling x axis
  ylab("Difference from soil in Pielou's evenness") #labeling y axis
```



7. 2 pts. Commit and push a gfm .md file to GitHub inside a directory called Coding Challenge 5. Provide me a link to your github written as a clickable link in your .pdf or .docx

Link to my GitHub