

Coding Challenge 5

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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 Diversity-Data.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_Imbided
## 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 errors
```

```
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.

- Using mutate, create a new column to calculate Pielou's evenness index.
- 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.

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

```
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.
```

```
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

- Start with the alpha_average dataframe

- Select relevant columns: select the columns Time_Point, Crop, and mean.even.
- 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.
- 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.
- 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 wide
  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
```

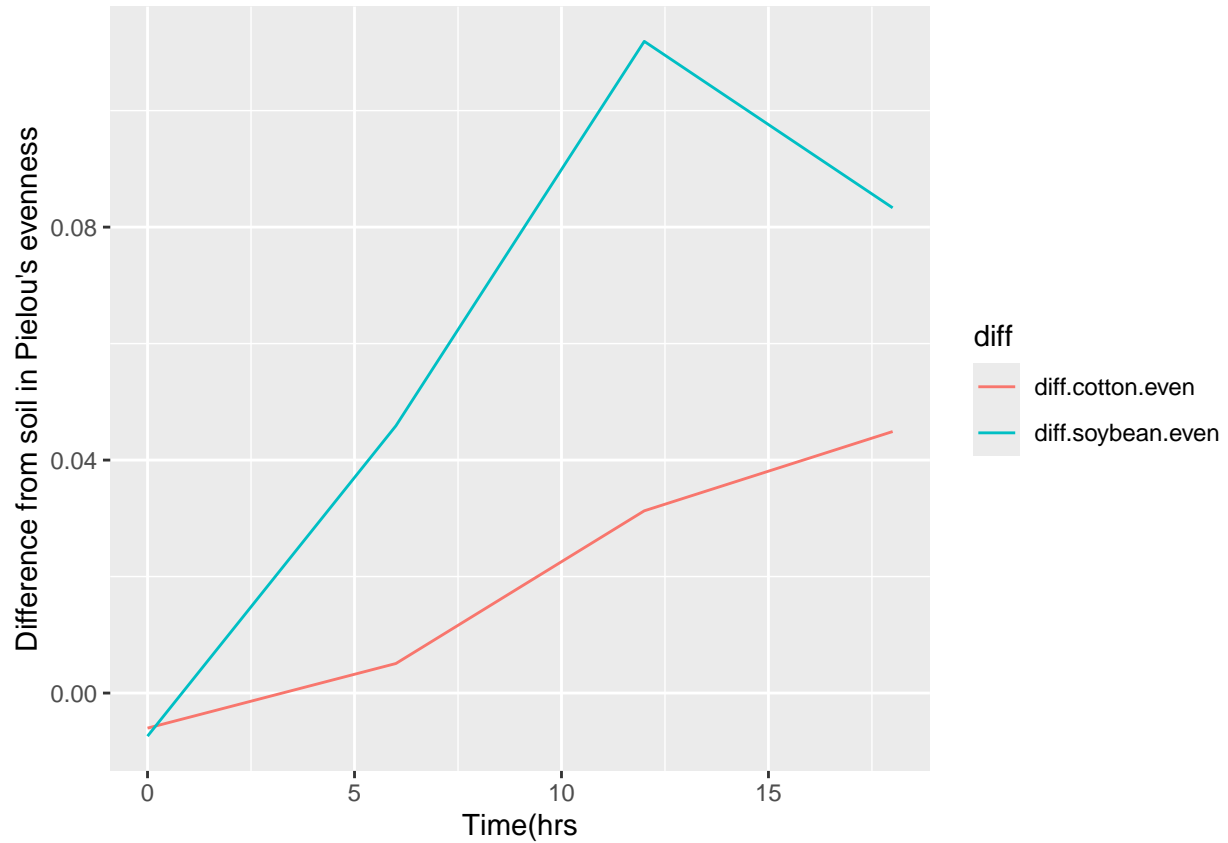
6. 4 pts. Connecting it to plots

- Start with the alpha_average2 dataframe
- Select relevant columns: select the columns Time_Point, diff.cotton.even, and diff.soybean.even.
- 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.
- 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")
```

- 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 format to long
  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