BioDIGS: Exploring Soil Data

February 11, 2025

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# About this Book

This is a companion training guide for BioDIGS, a GDSCN project that brings a research experience into the classroom. This activity guides students through exploration of the BioDIGS soil data using the tidyverse in R. Students will learn basic data summarization, visualization, and mapping skills. Visit the BioDIGS (BioDiversity and Informatics for Genomics Scholars) website [here](https://biodigs.org/) for more information about this collaborative, distributed research project, including how you can get involved!

The GDSCN (Genomics Data Science Community Network) is a consortium of educators who aim to create a world where researchers, educators, and students from diverse backgrounds are able to fully participate in genomic data science research. You can find more information about its mission and initiatives [here](https://www.gdscn.org/home).



## 0.1 Target Audience

The activities in this guide are written for undergraduate students and beginning graduate students. Some sections require basic understanding of the R programming language, which is indicated at the beginning of the chapter.

## 0.2 Platform

The activities in this guide are demonstrated on NHGRI’s [AnVIL](https://anvilproject.org/) cloud computing platform. AnVIL is the preferred computing platform for the GDSCN. However, all of these activities can be done using your personal installation of R or using the online [Galaxy](usegalaxy.org) portal.



## 0.3 Data

The data generated by the BioDIGS project is available through the [BioDIGS website](biodigs.org), as well as through an [AnVIL workspace](https://anvilproject.org).

Data about the soil itself as well as soil metal content was generated by the [Delaware Soil Testing Program](https://www.udel.edu/canr/cooperative-extension/environmental-stewardship/soil-testing/) at the University of Delaware. Sequences were generated by the [Johns Hopkins University Genetic Resources Core Facility](https://grcf.jhmi.edu/) and by [PacBio](https://www.pacb.com/).

# 1 AnVIL Workspace

You can easily access the data on AnVIL by cloning the dedicated workspace. These sections guide you through creating an AnVIL account and accessing the workspace.

## 1.1 Create Google Account

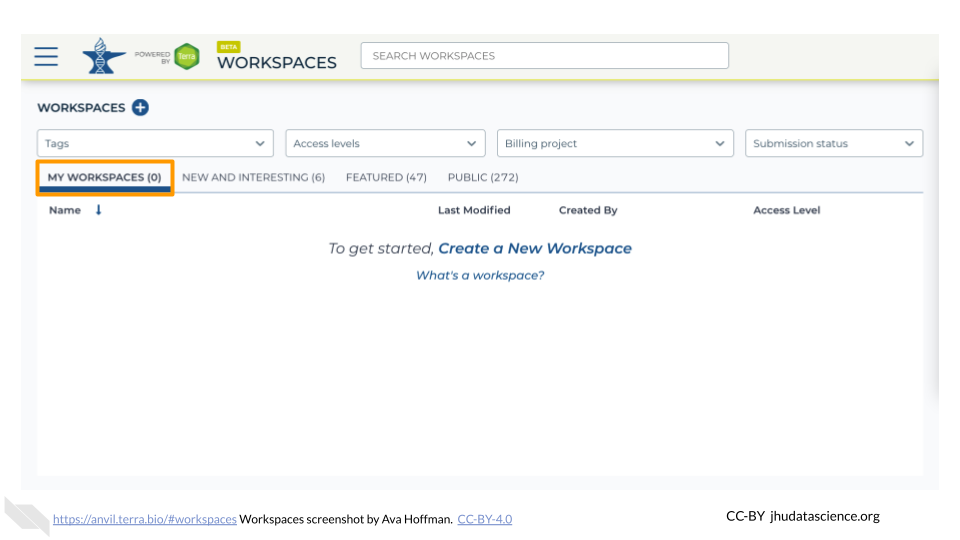
If you do not already have a Google account that you would like to use for accessing Terra, [create one now](https://accounts.google.com/SignUp).

If you would like to create a Google account that is associated with your non-Gmail, institutional email address, follow [these instructions](https://support.terra.bio/hc/en-us/articles/360029186611).

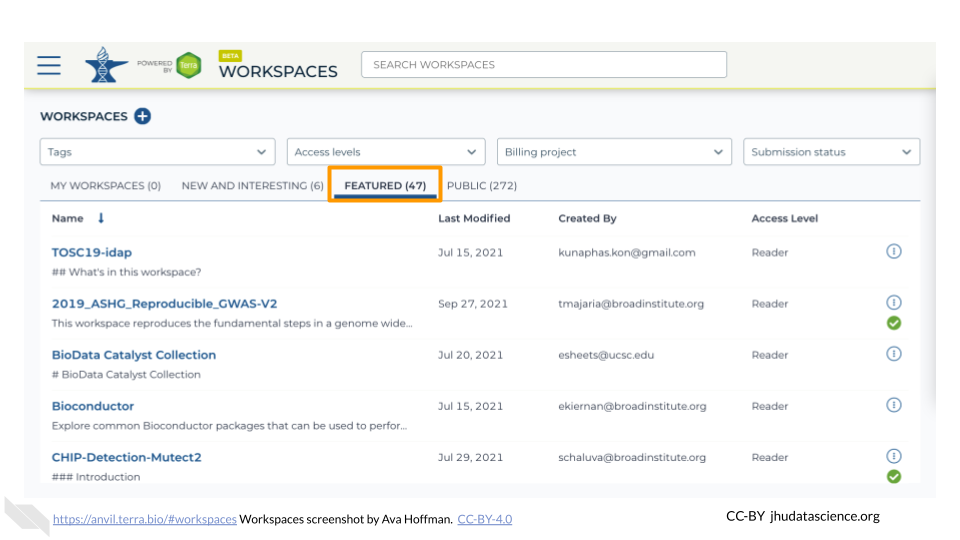
## 1.2 Clone the Workspace

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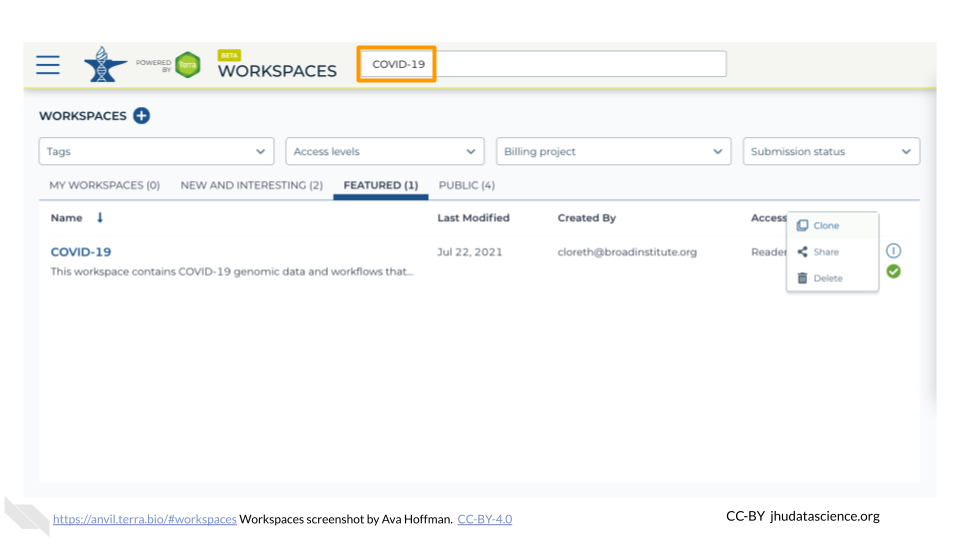
1. [Launch Terra](https://anvil.terra.bio/#workspaces)
2. Locate the Workspace you want to clone. If a Workspace has been shared with you ahead of time, it will appear in “MY WORKSPACES”. You can clone a Workspace that was shared with you to perform your own analyses. In the screenshot below, no Workspaces have been shared.

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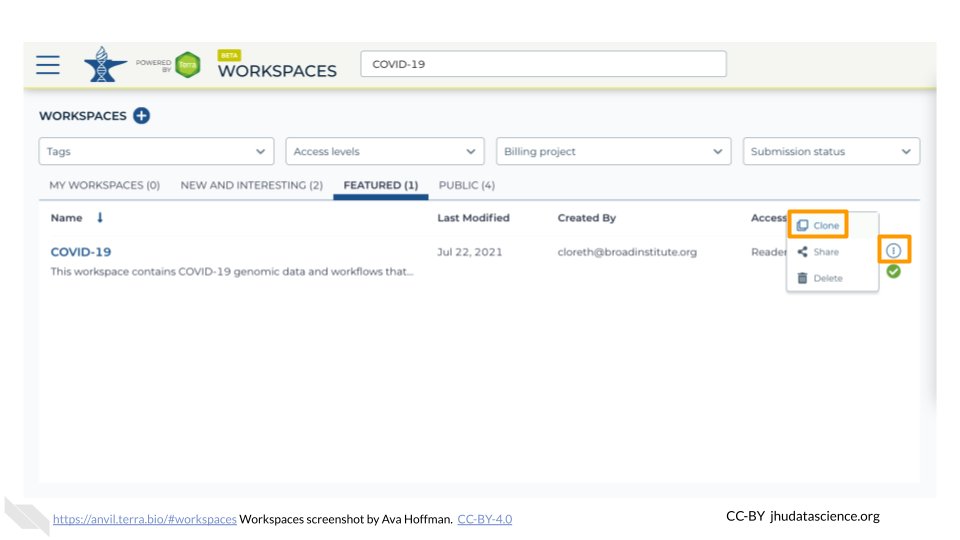
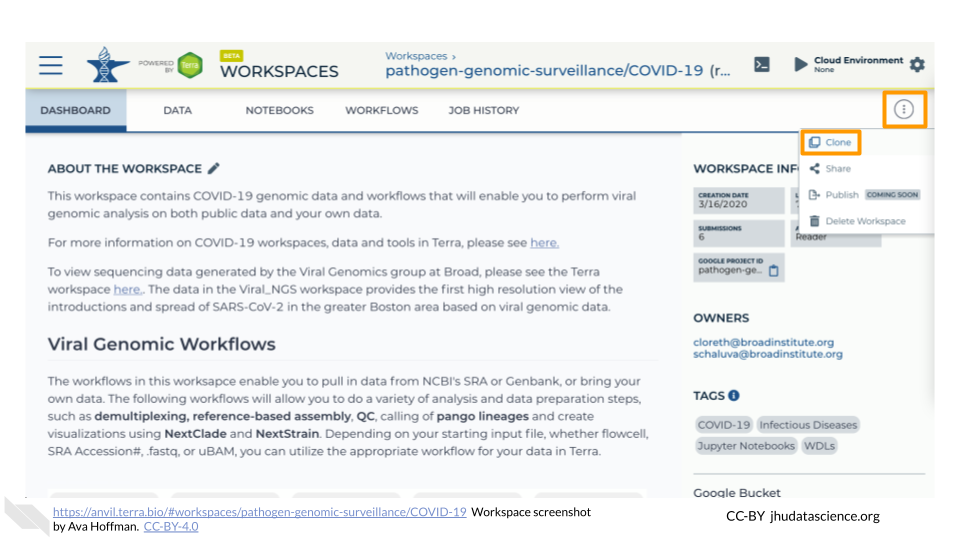
1. If a Workspace hasn’t been shared with you, navigate to the “FEATURED” or “PUBLIC” Workspace tabs.

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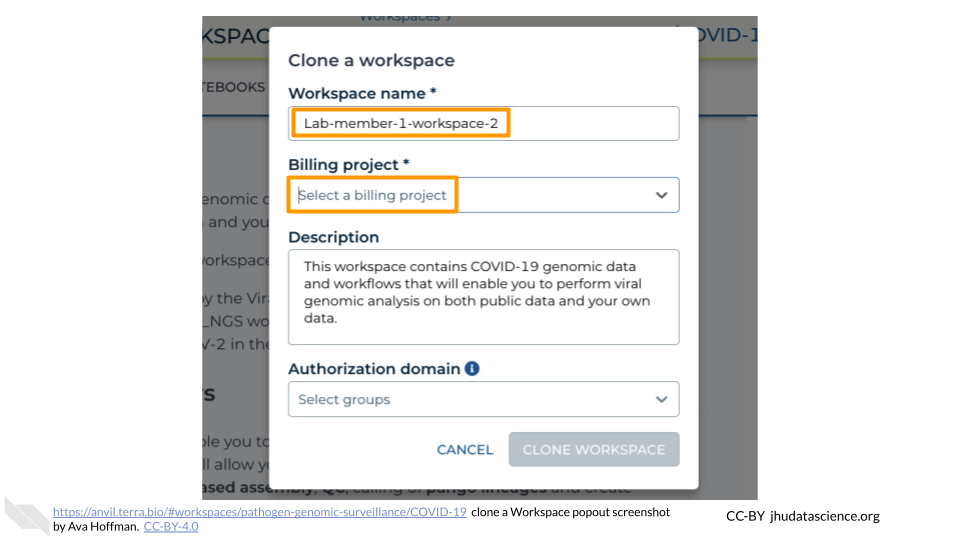
1. Use the search box to find the Workspace you want to clone.

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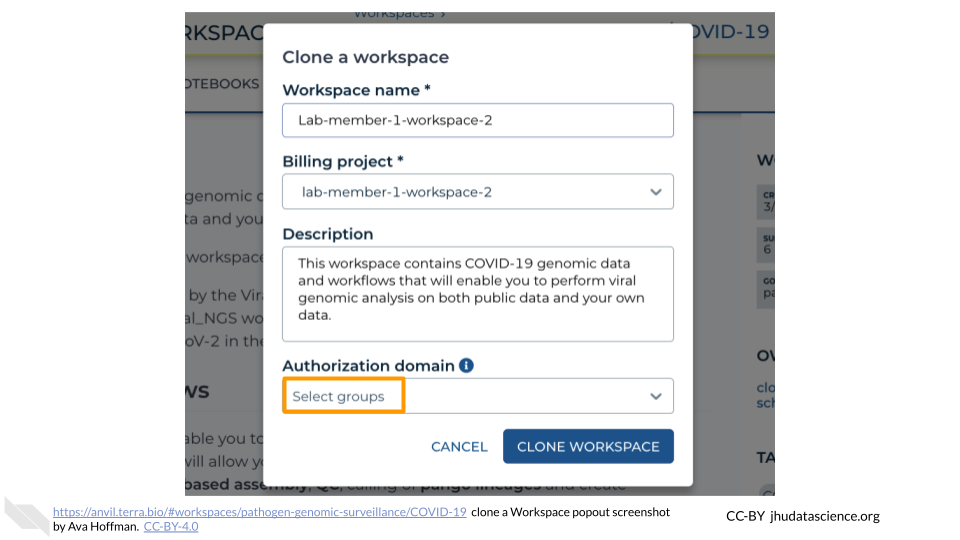
1. Click the teardrop button on the far right next to the Workspace you want to clone. Click “Clone”. You can also clone the Workspace from the Workspace Dashboard instead of the search results.

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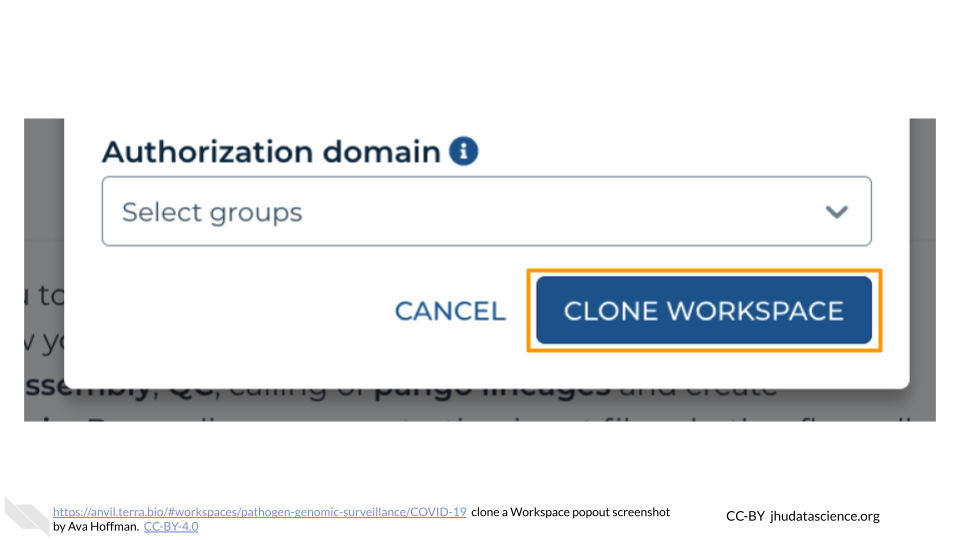
1. You will see a popup box appear. Name your Workspace and select the appropriate Terra Billing Project. **All activity in the Workspace will be charged to this Billing Project** (regardless of who conducted it). Remember that each Workspace should have its own Billing Project.

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1. If you are working with protected data, you can set the **Authorization Domain** to limit who can be added to your Workspace. Note that the Authorization Domain cannot be changed after the Workspace is created (i.e. there is no way to make this Workspace shareable with a larger audience in the future). Workspaces by default are only visible to people you specifically share them with. Authorization domains add an extra layer of enforcement over privacy, but by nature make sharing more complicated. We recommend using Authorization Domains in cases where it is extremely important and/or legally required that the data be kept private (e.g. protected patient data, industry data). For data you would merely prefer not be shared with the world, we recommend relying on standard Workspace sharing permissions rather than Authorization Domains, as Authorization Domains can make future collaborations, publications, or other sharing complicated.

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1. Click “CLONE WORKSPACE”. The new Workspace should now show up under your Workspaces.

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# 2 Using RStudio on AnVIL

In the next few steps, you will walk through how to get set up to use RStudio on the AnVIL platform. AnVIL is centered around different “Workspaces”. Each Workspace functions almost like a mini code laboratory - it is a place where data can be examined, stored, and analyzed. The first thing we want to do is to copy or “clone” a Workspace to create a space for you to experiment.

Use a web browser to go to the AnVIL website. In the browser type:

anvil.terra.bio

**Tip** At this point, it might make things easier to open up a new window in your browser and split your screen. That way, you can follow along with this guide on one side and execute the steps on the other.

Your instructor will give you information on which workspace you should clone.

## 2.1 Video overview of RStudio on AnVIL

Here is a video tutorial that describes the basics of using RStudio on AnVIL.

### 2.1.1 Objectives

* Start compute for your RStudio environment
* Tour RStudio on AnVIL
* Stop compute to minimize expenses

### 2.1.2 Slides

The slides for this tutorial are are located [here](https://docs.google.com/presentation/d/1eypYLLqD11-NwHLs4adGpcuSB07dYEJfAaALSMvgzqw).

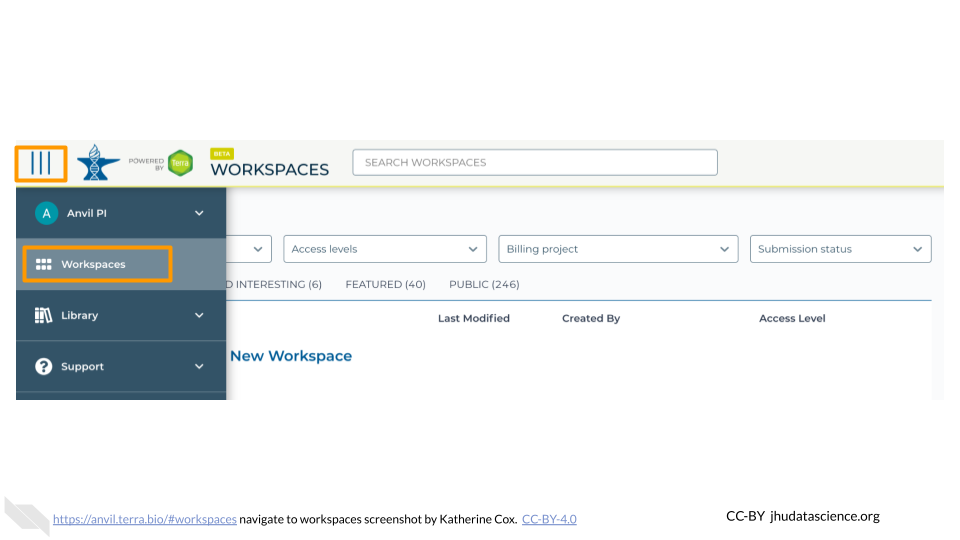
## 2.2 Launching RStudio

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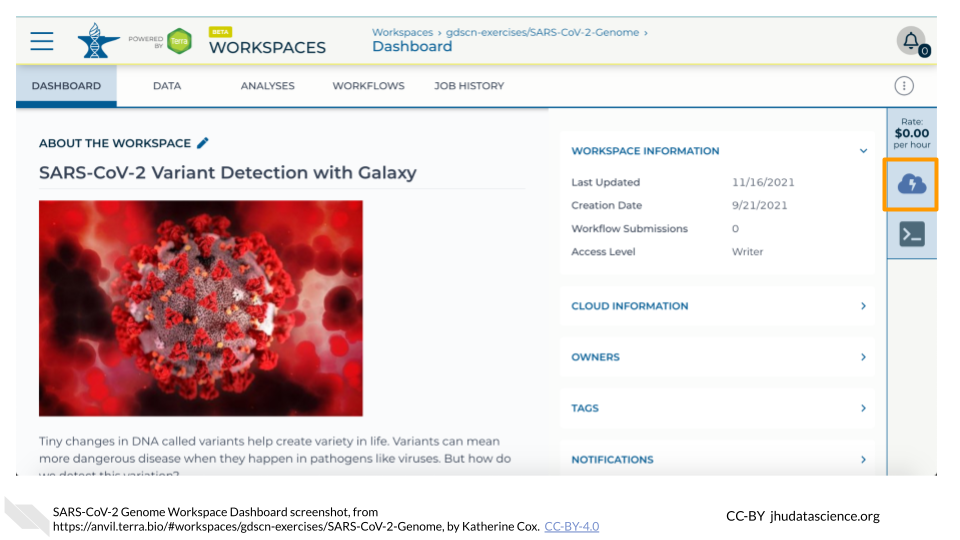
AnVIL is very versatile and can scale up to use very powerful cloud computers. It’s very important that you select a cloud computing environment appropriate to your needs to avoid runaway costs. If you are uncertain, start with the default settings; it is fairly easy to increase your compute resources later, if needed, but harder to scale down.

Note that, in order to use RStudio, you must have access to a Terra Workspace with permission to compute (i.e. you must be a “Writer” or “Owner” of the Workspace).

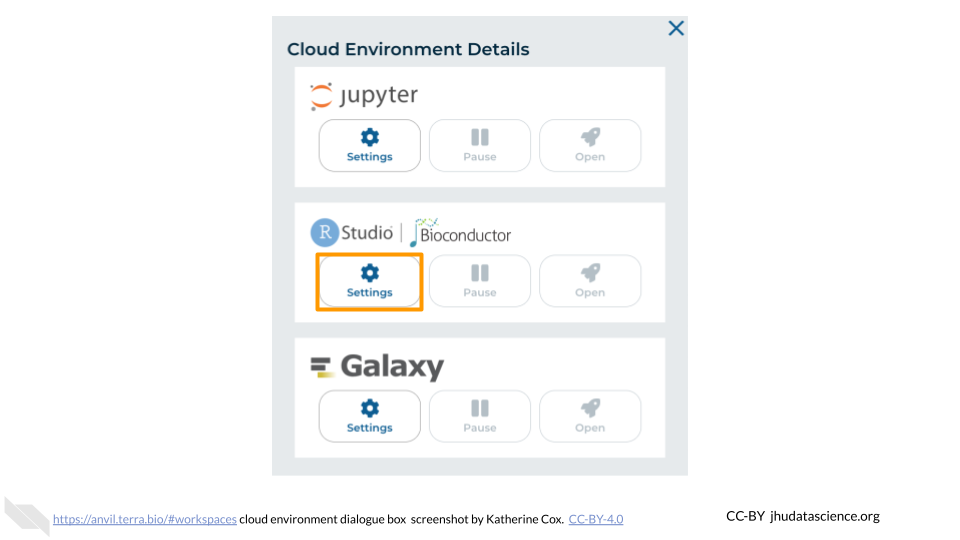
1. Open Terra - use a web browser to go to [anvil.terra.bio](https://anvil.terra.bio/)
2. In the drop-down menu on the left, navigate to “Workspaces”. Click the triple bar in the top left corner to access the menu. Click “Workspaces”.

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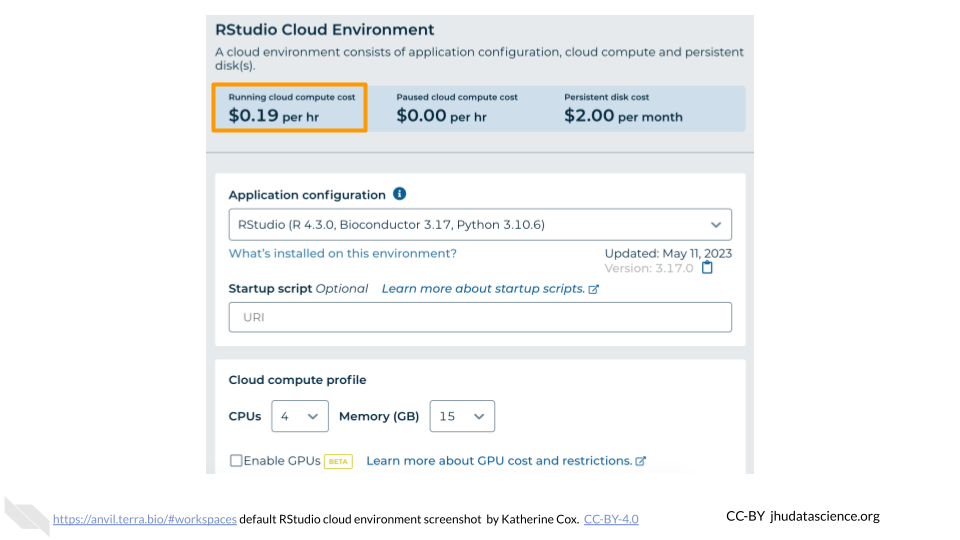
1. Click on the name of your Workspace. You should be routed to a link that looks like: https://anvil.terra.bio/#workspaces/<billing-project>/<workspace-name>.
2. Click on the cloud icon on the far right to access your Cloud Environment options. If you don’t see this icon, you may need to scroll to the right.

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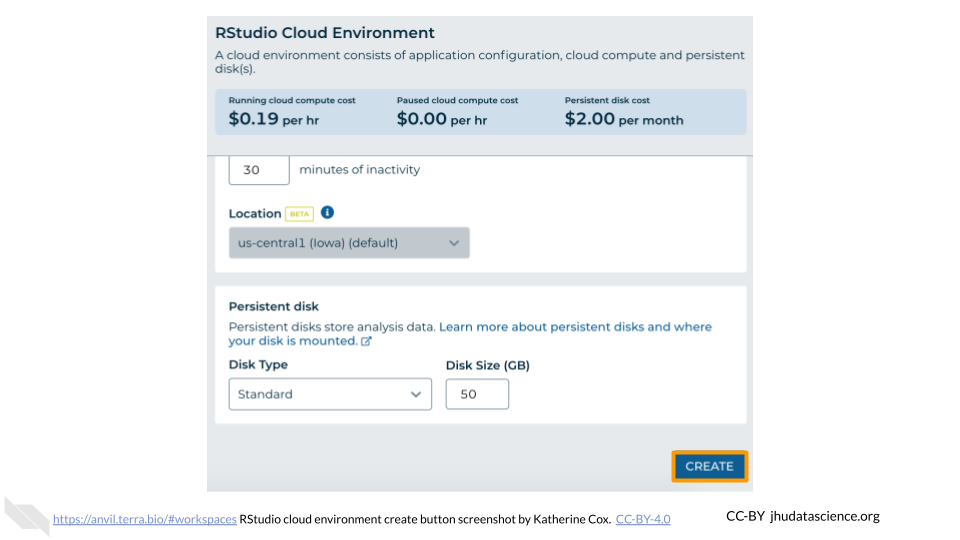
1. In the dialogue box, click the “Settings” button under RStudio.

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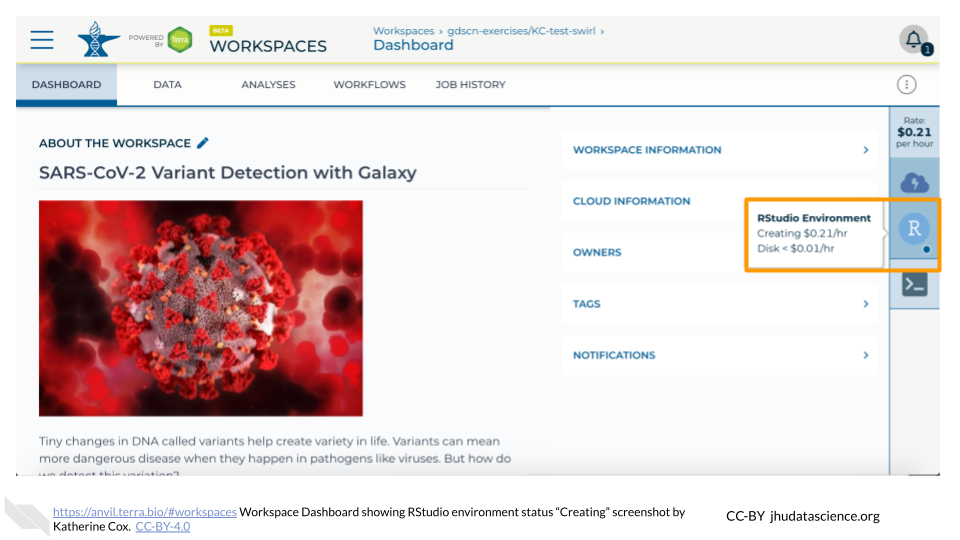
1. You will see some configuration options for the RStudio cloud environment, and a list of costs because it costs a small amount of money to use cloud computing.

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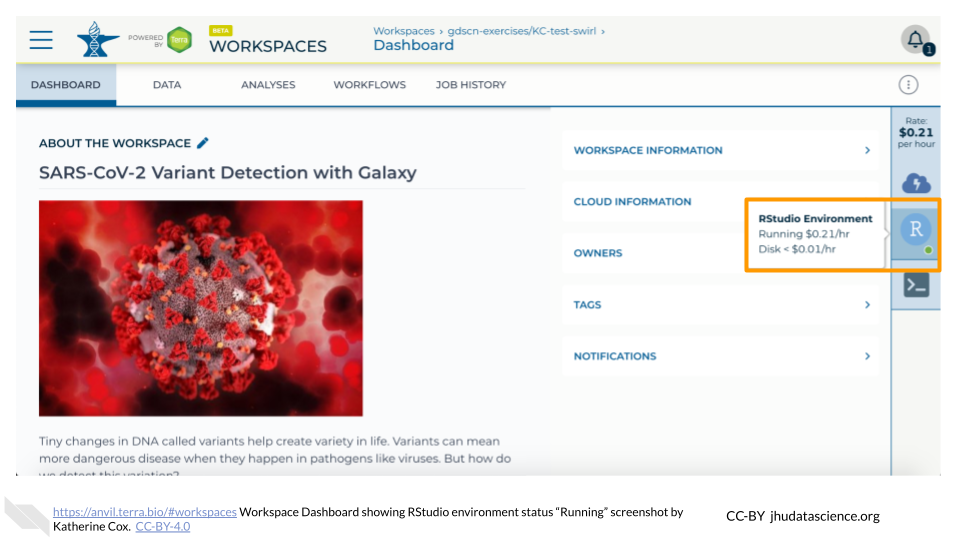
1. Configure any settings you need for your cloud environment. If you are uncertain about what you need, the default configuration is a reasonable, cost-conservative choice. It is fairly easy to increase your compute resources later, if needed, but harder to scale down. Scroll down and click the “CREATE” button when you are satisfied with your setup.

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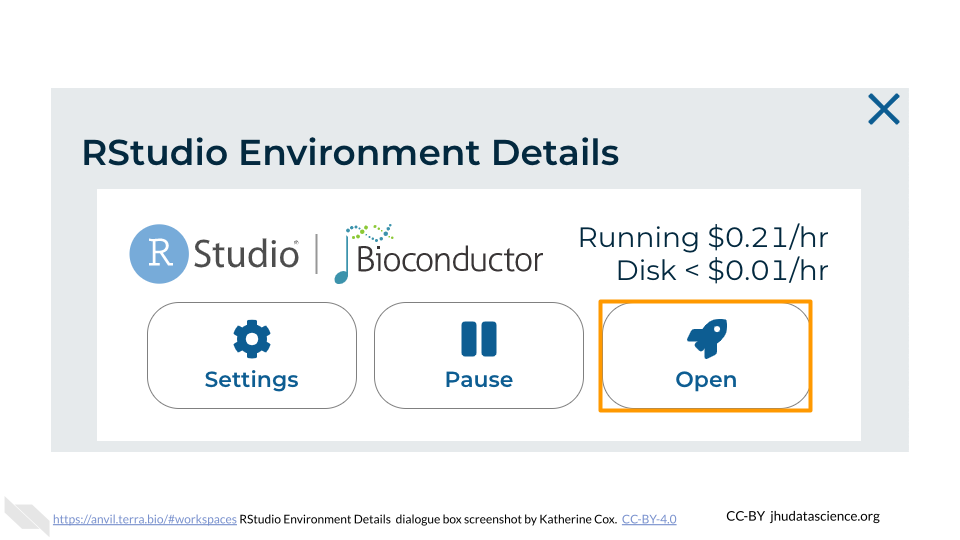
1. The dialogue box will close and you will be returned to your Workspace. You can see the status of your cloud environment by hovering over the RStudio icon. It will take a few minutes for Terra to request computers and install software.

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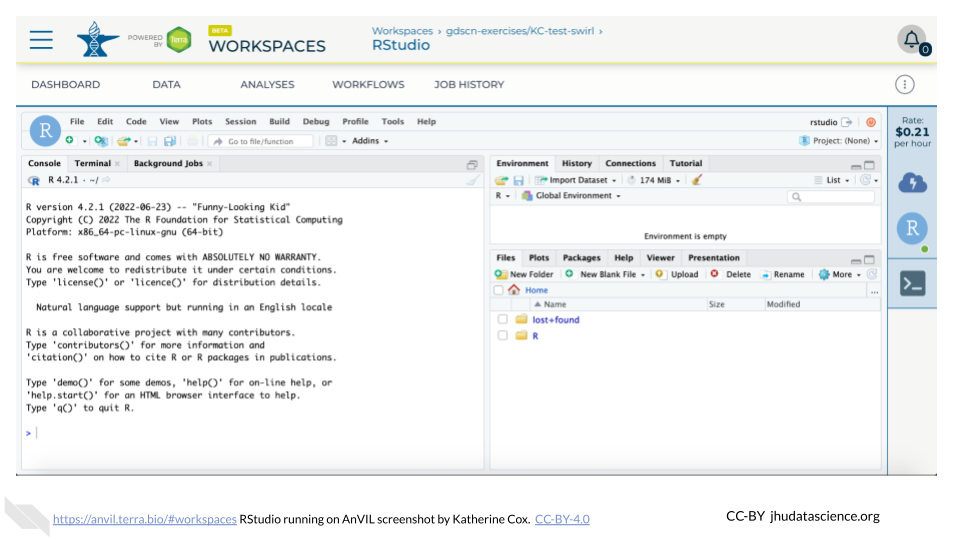
1. When your environment is ready, its status will change to “Running”. Click on the RStudio logo to open a new dialogue box that will let you launch RStudio.

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1. Click the launch icon to open RStudio. This is also where you can pause, modify, or delete your environment when needed.

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1. You should now see the RStudio interface with information about the version printed to the console.

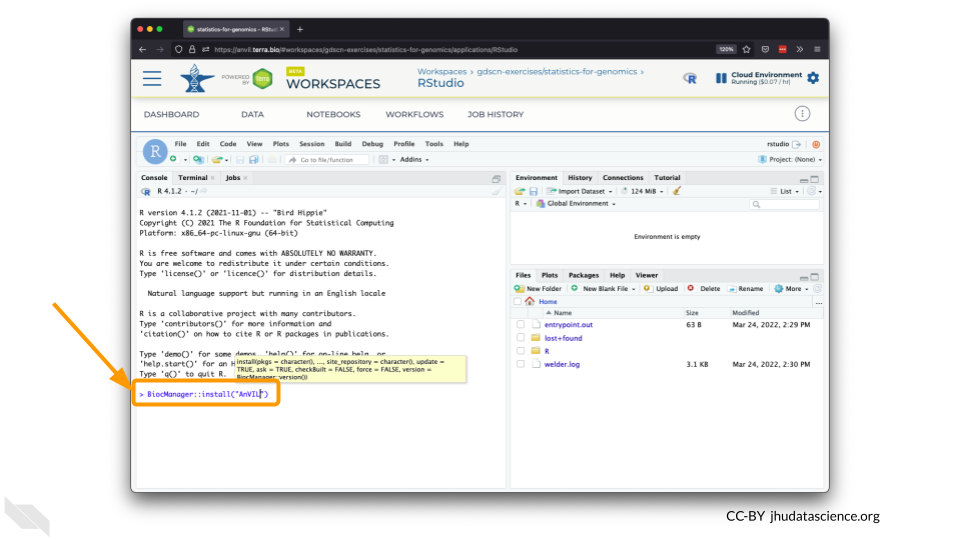
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## 2.3 Touring RStudio

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Next, we will be using RStudio and the package Glimma to create interactive plots. See [this vignette](https://bioconductor.org/packages/release/bioc/vignettes/Glimma/inst/doc/limma_edger.html) for more information.

1. The Bioconductor team has created a very useful package to programmatically interact with Terra and Google Cloud. Install the AnVIL package. It will make some steps easier as we go along.

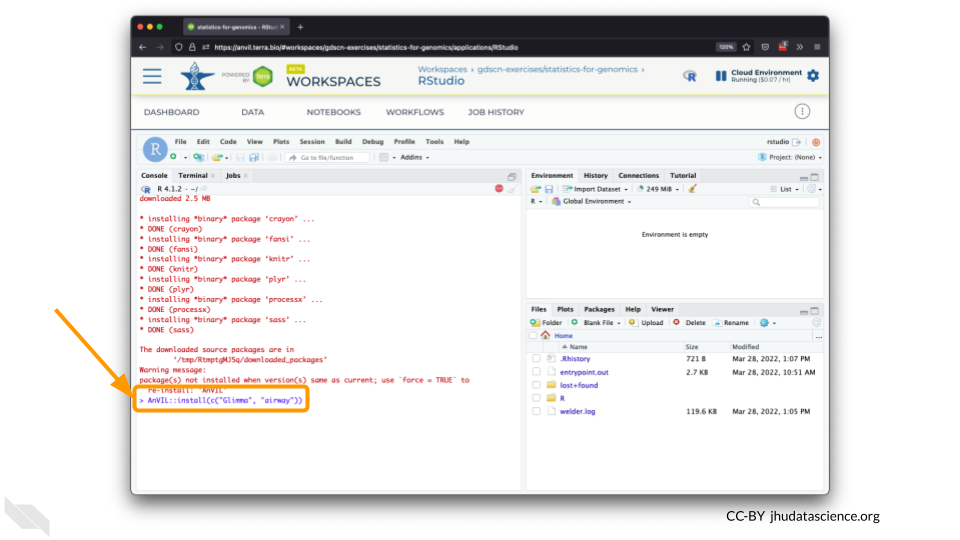
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1. You can now quickly install precompiled binaries using the AnVIL package’s install() function. We will use it to install the Glimma package and the airway package. The airway package contains a SummarizedExperiment data class. This data describes an RNA-Seq experiment on four human airway smooth muscle cell lines treated with dexamethasone.

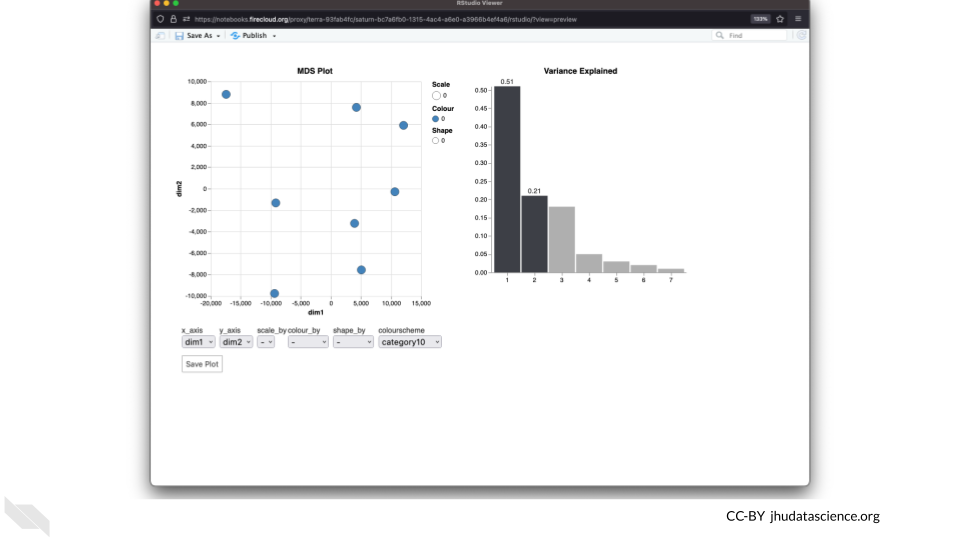
{Note: for some of the packages, you will have to install packaged from the CRAN repository, using the install.packages() function. The examples will show you which install method to use.}

![](resources/images/resources/images/09-student\_guide\_files/figure-docx//1BLTCaogA04bbeSD1tR1Wt-mVceQA6FHXa8FmFzIARrg\_g11f12bc99af\_0\_56.png)

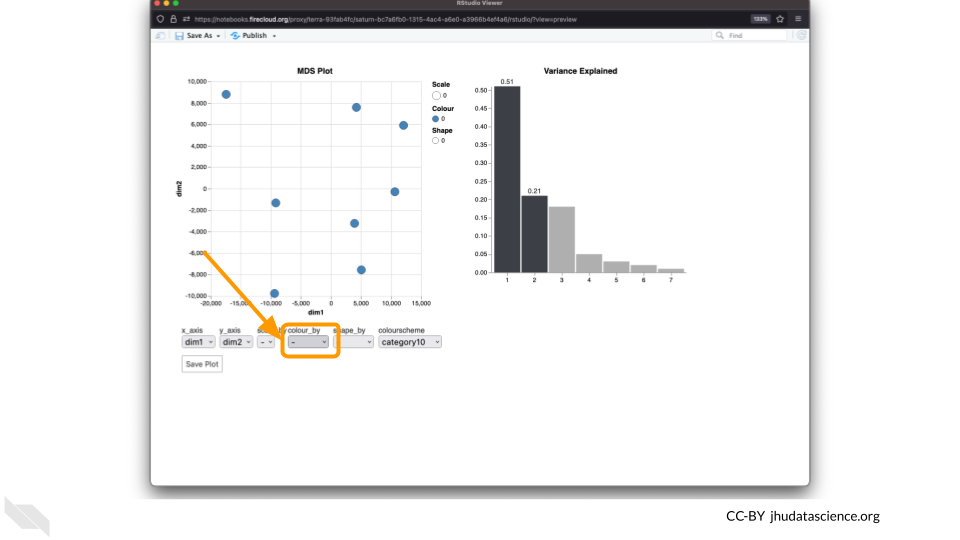
1. Load the example data.

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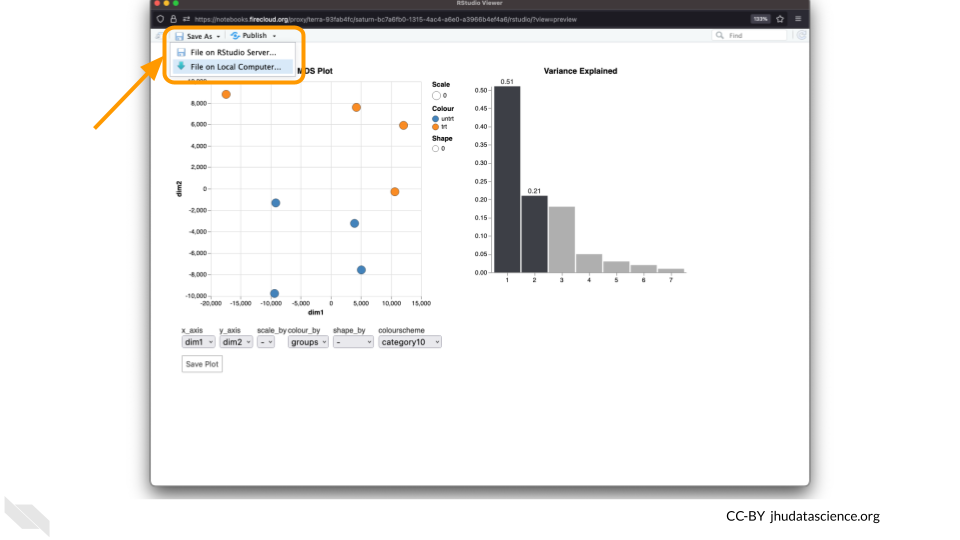
1. The multidimensional scaling (MDS) plot is frequently used to explore differences in samples. When this data is MDS transformed, the first two dimensions explain the greatest variance between samples, and the amount of variance decreases monotonically with increasing dimension. The following code will launch a new window where you can interact with the MDS plot.

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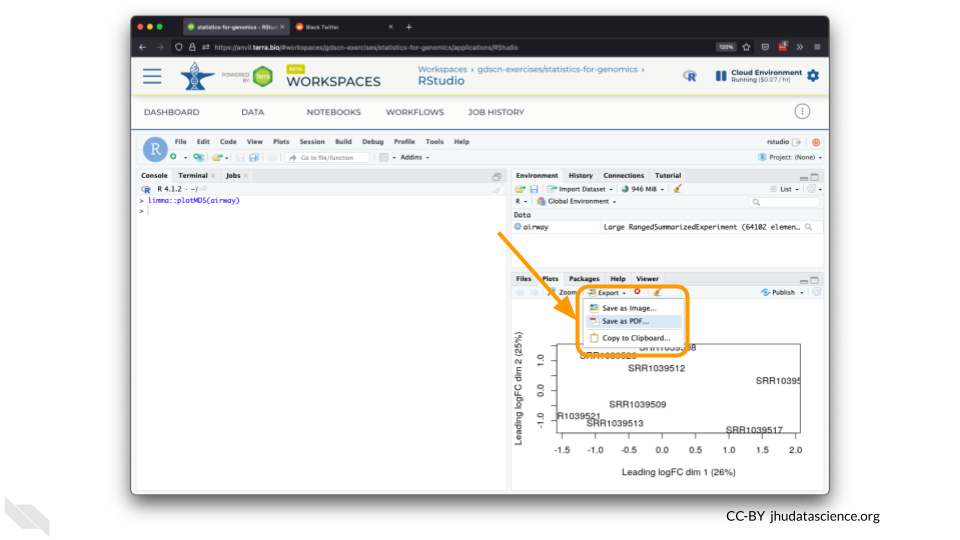
1. Change the colour\_by setting to “groups” so you can easily distinguish between groups. In this data, the “group” is the treatment.

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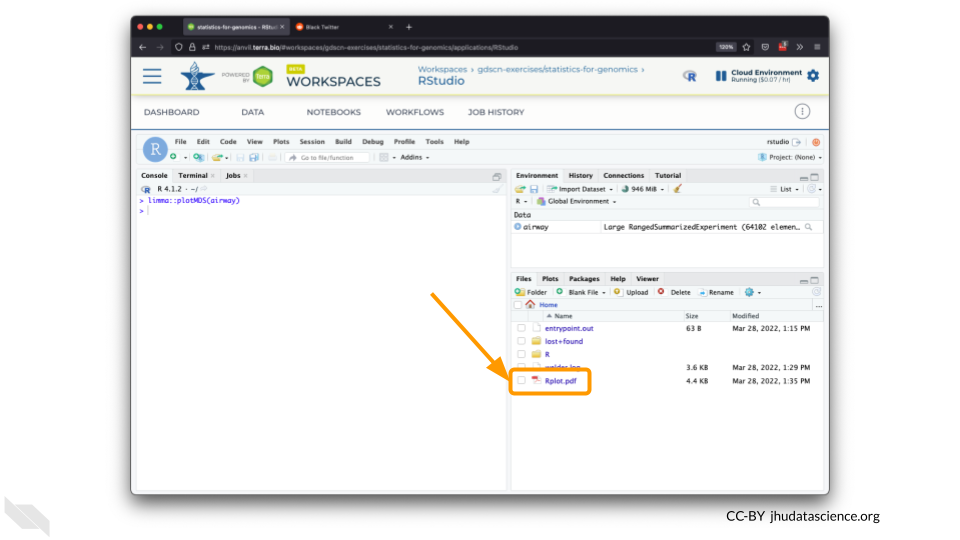
1. You can download the interactive html file by clicking on “Save As”.

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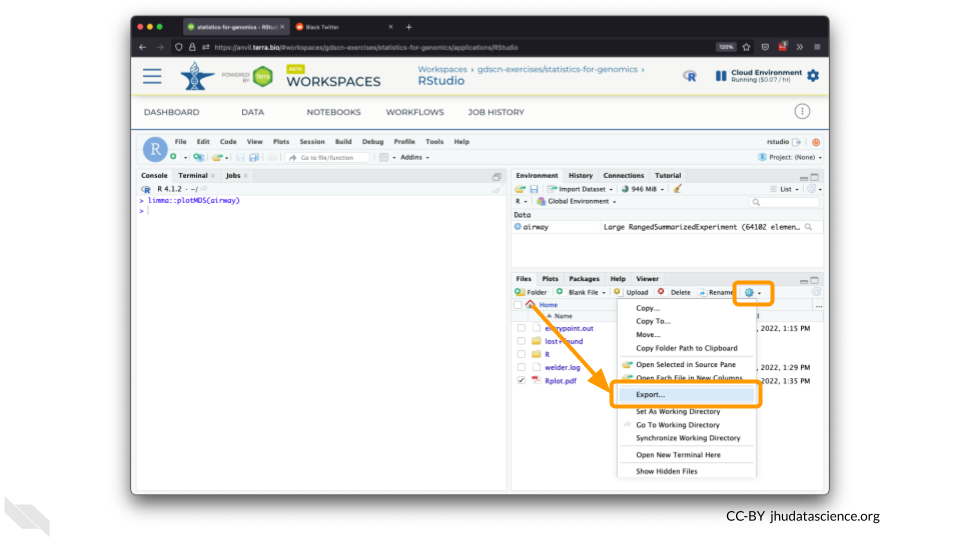
1. You can also download plots and other files created directly in RStudio. To download the following plot, click on “Export” and save in your preferred format to the default directory. This saves the file in your cloud environment.

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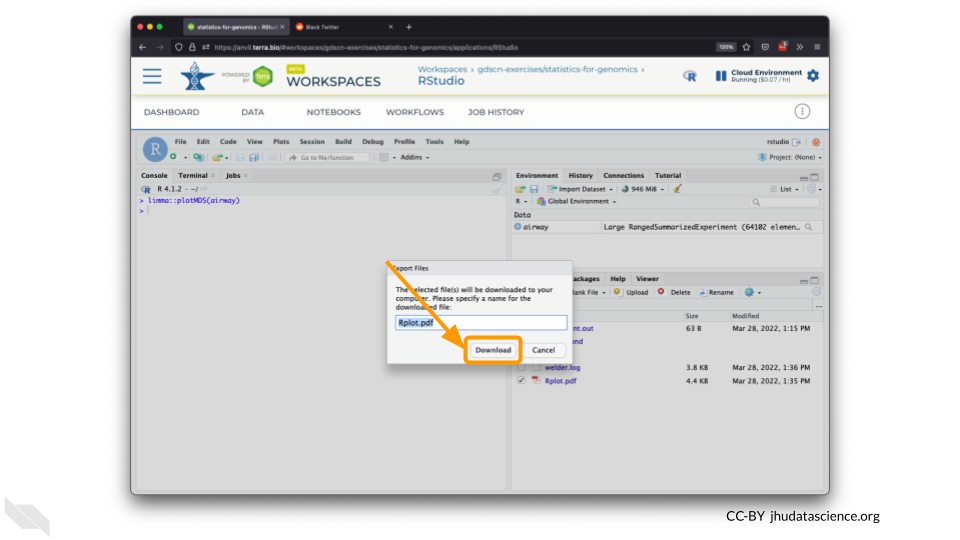
1. You should see the plot in the “Files” pane.

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1. Select this file and click “More” > “Export”

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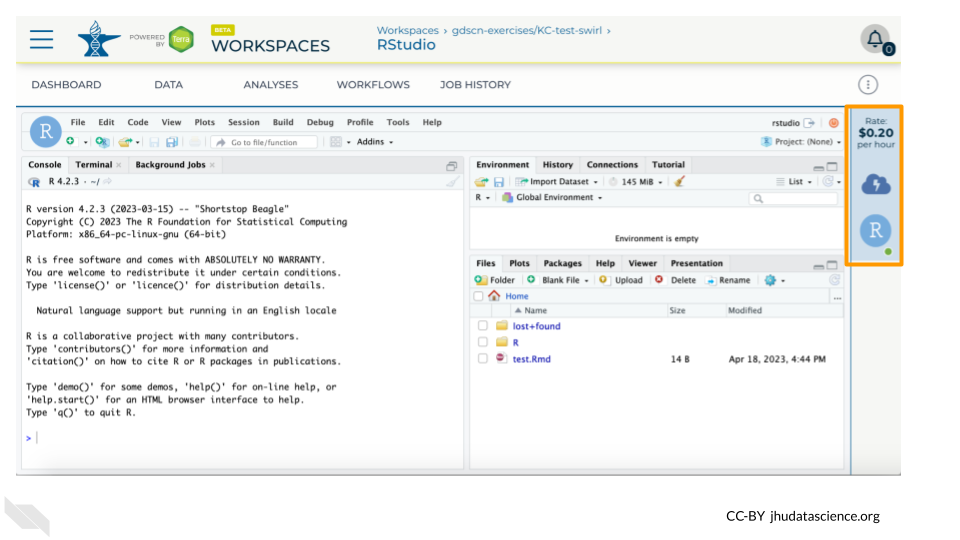
1. Select “Download” to save the file to your local machine.

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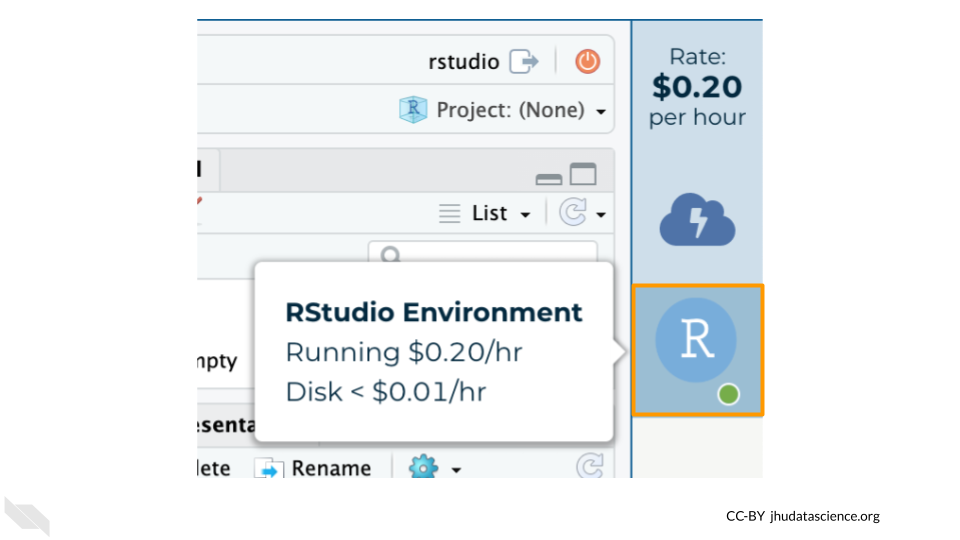
## 2.4 Pausing RStudio

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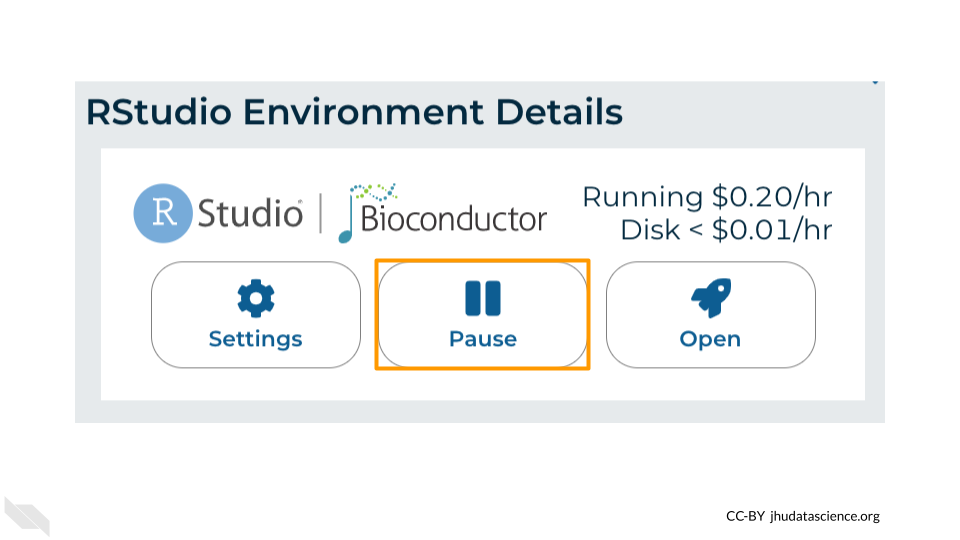
1. You can view costs and make changes to your cloud environments from the panel on the far right of the page. If you don’t see this panel, you may need to scroll to the right. Running environments will have a green dot, and paused environments will have an orange dot.

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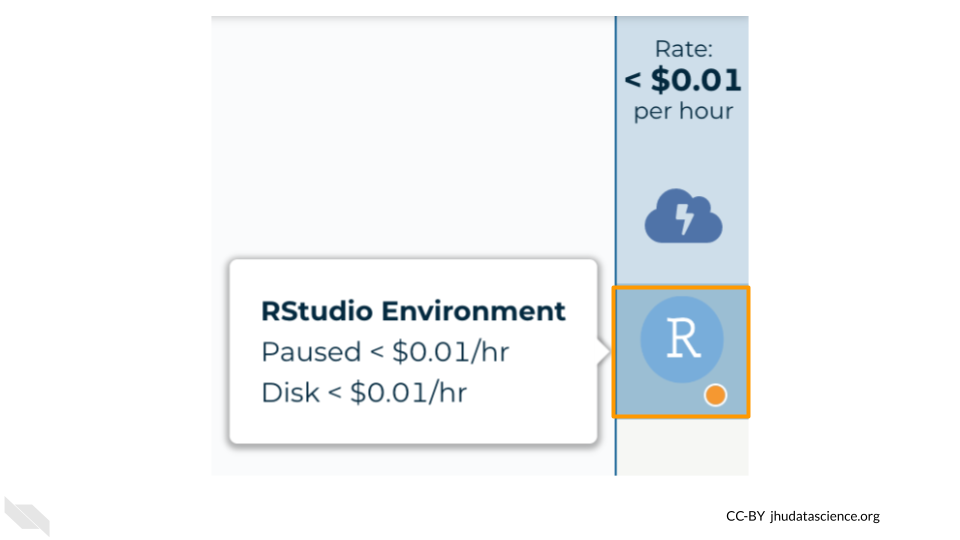
1. Hovering over the RStudio icon will show you the costs associated with your RStudio environment. Click on the RStudio icon to open the cloud environment settings.

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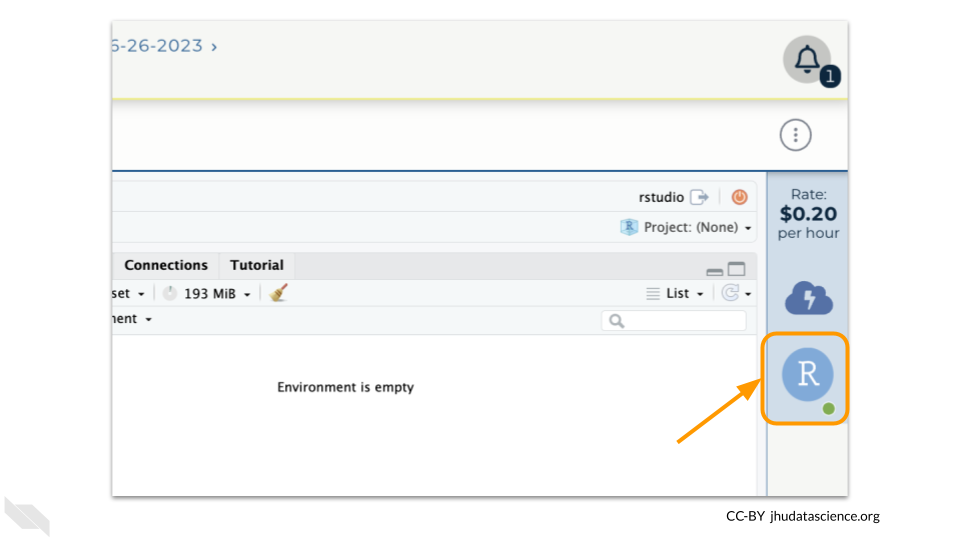
1. Click the Pause button to pause RStudio. This will take a few minutes.

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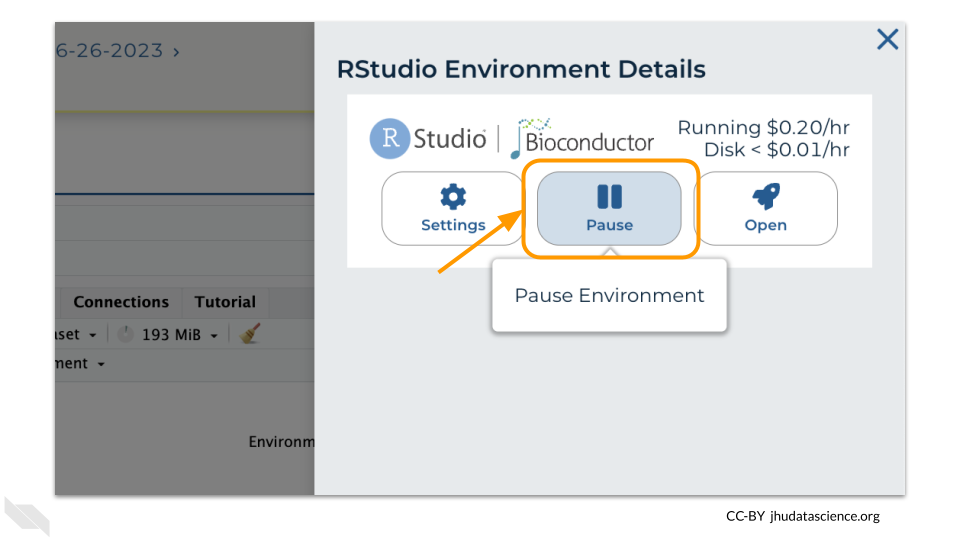
1. When the environment is paused, an orange dot will be displayed next to the RStudio icon. If you hover over the icon, you will see that it is paused, and has a small ongoing cost as long as it is paused. When you’re ready to resume working, you can do so by clicking the RStudio icon and clicking Resume.

* 

1. The right-hand side icon reminds you that you are accruing cloud computing costs. If you don’t see this icon, you may need to scroll to the right.

* 

1. You should minimize charges when you are not performing an analysis. You can do this by clicking on the RStudio icon and selecting “Pause”. This will release the CPU and memory resources for other people to use. Note that your work will be saved in the environment and continue to accrue a very small cost. This work will be lost if the cloud environment gets deleted. If there is anything you would like to save permanently, it’s a good idea to copy it from your compute environment to another location, such as the Workspace bucket, GitHub, or your local machine, depending on your needs.

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You can also pause your cloud environment(s) at <https://anvil.terra.bio/#clusters>.

# 3 Introduction

In this activity, you’ll have a chance to become familiar with the BioDIGS soil testing data. This dataset includes information on the inorganic components of each soil sample, particularly metal concentrations. Human activity can increase the concentration of inorganic compounds in the soil. When cars drive on roads, compounds from the exhaust, oil, and other fluids might settle onto the roads and be washed into the soil. When we put salt on roads, parking lots, and sidewalks, the salts themselves will eventually be washed away and enter the ecosystem through both water and soil. Chemicals from factories and other businesses also leech into our environment. All of this means the concentration of heavy metals and other chemicals will vary among the soil samples collected for the BioDIGS project.

## 3.1 Before You Start

If you do not already have a Google account that you would like to use for accessing Terra, [create one now](https://accounts.google.com/SignUp).

If you would like to create a Google account that is associated with your non-Gmail, institutional email address, follow [these instructions](https://support.terra.bio/hc/en-us/articles/360029186611).

## 3.2 Objectives

This activity will teach you how to use the AnVIL platform to:

1. Open data from an R package
2. Examine objects in R
3. Calculate summary statistics for variables in the soil testing data
4. Create and interpret histograms and boxplots for variables in the soil testing data

# 4 Part 1. Examining the Data

We will use the BioDIGS package to retrieve the data. We first need to install the package from where it is stored on GitHub.

Once you’ve installed the package, we can load the library and assign the soil testing data to an *object*. This command follows the code structure:

dataset\_object\_name <- stored\_BioDIGS\_dataset

It *seems* like the dataset loaded, but it’s always a good idea to verify. There are many ways to check, but the easiest approach (if you’re using RStudio) is to look at the Environment tab on the upper right-hand side of the screen. You should now have an object called soil.values that includes some number of observations for 28 variables. The *observations* refer to the number of rows in the dataset, while the *variables* tell you the number of columns. As long as neither the observations or variables are 0, you can be confident that your dataset loaded.

Let’s take a quick look at the dataset. We can do this by clicking on soil.values object in the Environment tab. (Note: this is equivalent to typing View(soil.values) in the R console.)

This will open a new window for us to scroll through the dataset.

Well, the data definitely loaded, but those column names aren’t immediately understandable. What could **As\_EPA3051** possibly mean? In addition to the dataset, we need to load the *data dictionary* as well.

**Data dictionary:** a file containing the names, definitions, and attributes about data in a database or dataset.

In this case, the data dictionary can help us make sense of what sort of values each column represents. The data dictionary for the BioDIGS soil testing data is available in the R package (see code below), but we have also reproduced it here.

* **site\_id** Unique letter and number site name
* **full\_name** Full site name
* **As\_EPA3051** Arsenic (mg/kg), EPA Method 3051A. Quantities < 3.0 are not detectable.
* **Cd\_EPA3051** Cadmium (mg/kg), EPA Method 3051A. Quantities < 0.2 are not detectable.
* **Cr\_EPA3051** Chromium (mg/kg), EPA Method 3051A
* **Cu\_EPA3051** Copper (mg/kg), EPA Method 3051A
* **Ni\_EPA3051** Nickel (mg/kg), EPA Method 3051A
* **Pb\_EPA3051** Lead (mg/kg), EPA Method 3051A
* **Zn\_EPA3051** Zinc (mg/kg), EPA Method 3051A
* **water\_pH**
* **A-E\_Buffer\_pH**
* **OM\_by\_LOI\_pct** Organic Matter by Loss on Ignition
* **P\_Mehlich3** Phosphorus (mg/kg), using the Mehlich 3 soil test extractant
* **K\_Mehlich3 Potassium** (mg/kg), using the Mehlich 3 soil test extractant
* **Ca\_Mehlich3** Calcium (mg/kg), using the Mehlich 3 soil test extractant
* **Mg\_Mehlich3** Magnesium (mg/kg), using the Mehlich 3 soil test extractant
* **Mn\_Mehlich3** Manganese (mg/kg), using the Mehlich 3 soil test extractant
* **Zn\_Mehlich3** Zinc (mg/kg), using the Mehlich 3 soil test extractant
* **Cu\_Mehlich3** Copper (mg/kg), using the Mehlich 3 soil test extractant
* **Fe\_Mehlich3** Iron (mg/kg), using the Mehlich 3 soil test extractant
* **B\_Mehlich3** Boron (mg/kg), using the Mehlich 3 soil test extractant
* **S\_Mehlich3** Sulfur (mg/kg), using the Mehlich 3 soil test extractant
* **Na\_Mehlich3** Sodium (mg/kg), using the Mehlich 3 soil test extractant
* **Al\_Mehlich3** Aluminum (mg/kg), using the Mehlich 3 soil test extractant
* **Est\_CEC** Cation Exchange Capacity (meq/100g) at pH 7.0 (CEC)
* **Base\_Sat\_pct** Base saturation (BS). This represents the percentage of CEC occupied by bases (Ca2+, Mg2+, K+, and Na+). The %BS increases with increasing soil pH. The availability of Ca2+, Mg2+, and K+ increases with increasing %BS.
* **P\_Sat\_ratio** Phosphorus saturation ratio. This is the ratio between the amount of phosphorus present in the soil and the total capacity of that soil to retain phosphorus. The ability of phosphorus to be bound in the soil is primary a function of iron (Fe) and aluminum (Al) content in that soil.

Using the data dictionary, we find that the values in column As\_EPA3051 give us the arsenic concentration in mg/kg of each soil sample, as determined by [EPA Method 3051A](https://www.epa.gov/sites/default/files/2015-12/documents/3051a.pdf). This method uses a combination of heat and acid to extract specific elements (like arsenic, cadmium, chromium, copper, nickel, lead, and zinc) from soil samples.

While arsenic can occur naturally in soils, higher levels suggest the soil may have been contaminated by mining, hazardous waste, or pesticide application. Arsenic is toxic to humans.

QUESTIONS:

1. What data is found in the column labeled “Fe\_Mehlich3”? Why would we be interested how much of this is in the soil? (You may have to search the internet for this answer.)
2. What data is found in the column labeled “Base\_Sat\_pct”? What does this variable tell us about the soil?

We can also look at just the names of all the columns using the R console using the colnames() command.

[1] “site\_id” “site\_name” “type” “As\_EPA3051”  
[5] “Cd\_EPA3051” “Cr\_EPA3051” “Cu\_EPA3051” “Ni\_EPA3051”  
[9] “Pb\_EPA3051” “Zn\_EPA3051” “water\_pH” “OM\_by\_LOI\_pct” [13] “P\_Mehlich3” “K\_Mehlich3” “Ca\_Mehlich3” “Mg\_Mehlich3”  
[17] “Mn\_Mehlich3” “Zn\_Mehlich3” “Cu\_Mehlich3” “Fe\_Mehlich3”  
[21] “B\_Mehlich3” “S\_Mehlich3” “Na\_Mehlich3” “Al\_Mehlich3”  
[25] “Est\_CEC” “Base\_Sat\_pct” “P\_Sat\_ratio” “region”

Most of the column names are found in the data dictionary, but the very last column (“region”) isn’t. How peculiar! Let’s look at what sort of values this particular column contains. The tab with the table of the soil.views object should still be open in the upper left pane of the RStudio window. If not, you can open it again by clicking on soils.view in the Environment pane, or by using the View() command.

If you scroll to the end of the table, we can see that “region” seems to refer to the city or area where the samples were collected. For example, the first 6 samples all come from Baltimore City.

You may notice that some cells in the soil.values table contain *NA*. This just means that the soil testing data for that sample isn’t available yet. We’ll take care of those values in the next part.

QUESTIONS:

1. How many observations are in the soil testing values dataset that you loaded? What do each of these observations refer to?
2. How many different regions are represented in the soil testing dataset? How many of them have soil testing data available?

# 5 Part 2. Summarizing the Data with Statistics

Now that we have the dataset loaded, let’s explore the data in more depth.

First, we should remove those samples that don’t have soil testing data yet. We *could* keep them in the dataset, but removing them at this stage will make the analysis a little cleaner. In this case, as we know the reason the data are missing (and that reason will not skew our analysis), we can safely remove these samples. This will not be the case for every data analysis.

We can remove the unanalyzed samples using the drop\_na() function from the tidyr package. This function removes any rows from a table that contains *NA* for a particular column. This command follows the code structure:

dataset\_new\_name <- dataset %>% drop\_na(column\_name)

The `%>% is called a pipe and it tells R that the commands after it should all be applied to the object in front of it. (In this case, we can filter out all samples missing a value for “As\_EPA3051” as a proxy for samples without soil testing data.)

Great! Now let’s calculate some basic statistics. For example, we might want to know what the mean (average) arsenic concentration is for all the soil samples. We can use a combination of two functions: pull() and mean(). pull() lets you extract a column from your table for statistical analysis, while mean() calculates the average value for the extracted column.

This command follows the code structure:

OBJECT %>% pull(column\_name) %>% mean()

pull() is a command from the tidyverse package, so we’ll need to load that library before our command.

[1] 5.10875

We can run similar commands to calculate the standard deviation (sd), minimum (min), and maximum (max) for the soil arsenic values.

[1] 5.606926 [1] 0 [1] 27.3

The soil testing dataset contains samples from multiple geographic regions, so maybe it’s more meaningful to find out what the average arsenic values are for each region. We have to do a little bit of clever coding trickery for this using the group\_by and summarize functions. First, we tell R to split our dataset up by a particular column (in this case, region) using the group\_by function, then we tell R to summarize the mean arsenic concentration for each group.

When using the summarize function, we tell R to make a new table (technically, a tibble in R) that contains two columns: the column used to group the data and the statistical measure we calculated for each group.

This command follows the code structure:

dataset %>% group\_by(column\_name) %>% summarize(mean(column\_name))

# 6 A tibble: 2 × 2

region mean(As\_EPA3051) 1 Baltimore City 5.56 2 Montgomery County 4.66

Now we know that the mean arsenic concentration might be different for each region. If we compare the samples from Baltimore City and Montgomery County, the Baltimore City samples appear to have a higher mean arsenic concentration than the Montgomery County samples.

QUESTIONS:

1. All the samples from Baltimore City and Montgomery County were collected from public park land. The parks sampled from Montgomery County were located in suburban and rural areas, compared to the urban parks sampled in Baltimore City. Why might the Montgomery County samples have a lower average arsenic concentration than the samples from Baltimore City?
2. What is the mean iron concentration for samples in this dataset? What about the standard deviation, minimum value, and maximum value?
3. Calculate the mean iron concentration by region. Which region has the highest mean iron concentration? What about the lowest?

Let’s say we’re interested in looking at mean concentrations that were determined using EPA Method 3051. Given that there are 8 of these measures in the soil.values dataset, it would be time consuming to run our code from above for each individual measure.

We can add two arguments to our summarize statement to calculate statistical measures for multiple columns at once: the across argument, which tells R to apply the summarize command to multiple columns; and the ends\_with parameter, which tells R which columns should be included in the statistical calculation.

We are using ends\_with because for this question, all the columns that we’re interested in end with the string ‘EPA3051’.

This command follows the code structure:

dataset %>% group\_by(column\_name) %>% summarize(across(ends\_with(common\_column\_name\_ending), mean))

# 7 A tibble: 2 × 8

region As\_EPA3051 Cd\_EPA3051 Cr\_EPA3051 Cu\_EPA3051 Ni\_EPA3051 Pb\_EPA3051 1 Baltimore C… 5.56 0.359 34.5 35.0 17.4 67.2 2 Montgomery … 4.66 0.402 29.9 24.3 23.4 38.7 # ℹ 1 more variable: Zn\_EPA3051

This is a *much* more efficient way to calculate statistics.

QUESTIONS:

1. Calculate the maximum values for concentrations that were determined using EPA Method 3051. (HINT: change the function you call in the summarize statement.) Which of these metals has the maximum concentration you see, and in which region is it found?
2. Calculate both the mean and maximum values for concentrations that were determined using the Mehlich3 test. (HINT: change the terms in the columns\_to\_include vector, as well as the function you call in the summarize statement.) Which of these metals has the highest average and maximum concentrations, and in which region are they found?

# 8 Part 3. Visualizing the Data

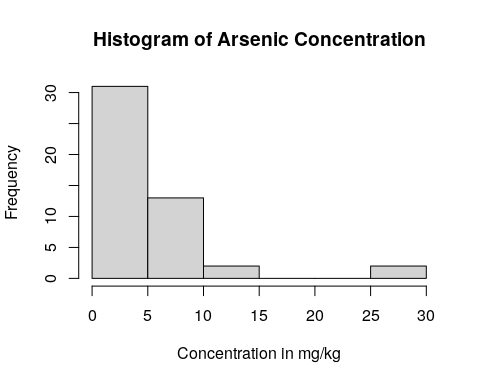
Often, it can be easier to immediately interpret data displayed as a plot than as a list of values. For example, we can more easily understand how the arsenic concentration of the soil samples are distributed if we create histograms compared to looking at point values like mean, standard deviation, minimum, and maximum.

One way to make histograms in R is with the hist() function. This function only requires that we tell R which column of the dataset that we want to plot. (However, we also have the option to tell R a histogram name and a x-axis label.)

We can again use the pull() command and pipes (%>%) to choose the column we want from the soil.values.clean dataset and make a histogram of them.

This combination of commands follows the code structure:

dataset %>% pull(column\_name) %>% hist(main = chart\_title, xlab = x\_axis\_title)



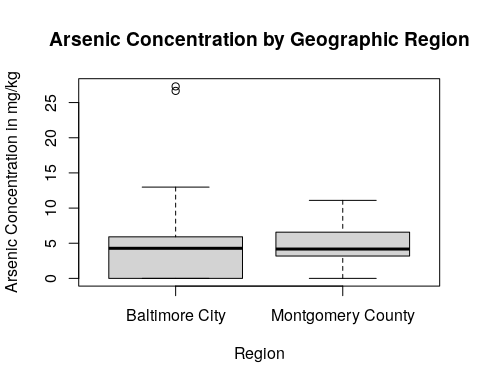
We can see that almost all the soil samples had very low concentrations of arsenic (which is good news for the soil health!). In fact, many of them had arsenic concentrations close to 0, and only one sampling location appears to have high levels of arsenic.

We might also want to graphically compare arsenic concentrations among the geographic regions in our dataset. We can do this by creating boxplots. Boxplots are particularly useful when comparing the mean, variation, and distributions among multiple groups.

In R, one way to create a boxplot is using the boxplot() function. We don’t need to use pipes for this command, but instead will specify what columns we want to use from the dataset inside the boxplot() function itself.

This command follows the code structure:

boxplot(column\_we’re\_plotting ~ grouping\_variable, data = dataset, main = “Title of Graph”, xlab = “x\_axis\_title”, ylab = “y\_axis\_title”)



By using a boxplot, we can quickly see that, while one sampling site within Baltimore City has a very high concentration of arsenic in the soil, in general there isn’t a difference in arsenic content between Baltimore City and Montgomery County.

QUESTIONS:

1. Create a histogram for *iron* concentration, as well as a boxplot comparing iron concentration by region. Is the iron concentration similar among regions? Are there any outlier sites with unusually high or low iron concentrations?
2. Create a histogram for *lead* concentration, as well as a boxplot comparing lead concentration by region. Is the lead concentration similar among regions? Are there any outlier sites with unusually high or low lead concentrations?
3. Look at the maps for [iron](https://biodigs.org/#iron_map) and [lead](https://biodigs.org/#lead_map) on the BioDIGS website. Do the boxplots you created make sense, given what you see on these maps? Why or why not?

# 9 Activity Questions

## 9.1 Part 1. Examining the Data

1. What data is found in the column labeled “Fe\_Mehlich3”? Why would we be interested how much of this is in the soil? (You may have to search the internet for this answer.)
2. What data is found in the column labeled “Base\_Sat\_pct”? What does this variable tell us about the soil?
3. How many observations are in the soil testing values dataset that you loaded? What do each of these observations refer to?
4. How many different regions are represented in the soil testing dataset? How many of them have soil testing data available?

## 9.2 Part 2. Summarizing the Data with Statistics

1. All the samples from Baltimore City and Montgomery County were collected from public park land. The parks sampled from Montgomery County were located in suburban and rural areas, compared to the urban parks sampled in Baltimore City. Why might the Montgomery County samples have a lower average arsenic concentration than the samples from Baltimore City?
2. What is the mean iron concentration for samples in this dataset? What about the standard deviation, minimum value, and maximum value?
3. Calculate the mean iron concentration by region. Which region has the highest mean iron concentration? What about the lowest?
4. Calculate the maximum values for concentrations that were determined using EPA Method 3051. (HINT: change the function you call in the summarize statement.) Which of these metals has the maximum concentration you see, and in which region is it found?
5. Calculate both the mean and maximum values for concentrations that were determined using the Mehlich3 test. (HINT: change the terms in the columns\_to\_include vector, as well as the function you call in the summarize statement.) Which of these metals has the highest average and maximum concentrations, and in which region are they found?

## 9.3 Part 3. Visualizing the Data

1. Create a histogram for *iron* concentration, as well as a boxplot comparing iron concentration by region. Is the iron concentration similar among regions? Are there any outlier sites with unusually high or low iron concentrations?
2. Create a histogram for *lead* concentration, as well as a boxplot comparing lead concentration by region. Is the lead concentration similar among regions? Are there any outlier sites with unusually high or low lead concentrations?
3. Look at the maps for [iron](https://biodigs.org/#iron_map) and [lead](https://biodigs.org/#lead_map) on the BioDIGS website. Do the boxplots you created make sense, given what you see on these maps? Why or why not?