**Assessing River Herring Migration Using Nonparametric Analysis:** Lesson Background

**By: Timothy M. Owen** *May 10, 2021*

**STUDENT VERSION**

*This document is intended to set the stage for the associated interactive lesson “WalkersDamHerring.rmd”, and also contains background information and supporting documents for the quantitative R Markdown lesson. For additional information, please contact* [*owent2@vcu.edu*](mailto:owent2@vcu.edu)



**Topics Covered in this QUBES Lesson (30 minutes total)**

**Ecological Backstory**

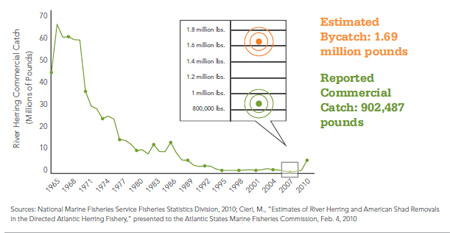
In the state of Virginia, Alewife (*Alosa pseudoharengus*) and Blueback Herring (*Alosa aestivalis*) are collectively referred to as river herring (Figure 1). These fish are members of the clupeid family, and demonstrate an anadromous life history; meaning that they hatch as fry in freshwater rivers, but spend the majority of their lives in the ocean. During the ocean-phase of their life, they function as a vital food source for birds, mammals, and predatory fish. River herring begin to sexually mature at age 3, and after years of filter-feeding on zooplankton in the ocean, they begin their migration back to their natal freshwater streams, driven by their own instinct to reproduce and continue the cycle. Herring typically migrate as several schools, in episodic pulses. As they push further upstream, homing to their own hatch location, they become increasingly concentrated and subject to predation from striped bass, bald eagles, osprey, and even humans.

Figure 1. Alewife (top) and Blueback Herring (bottom)



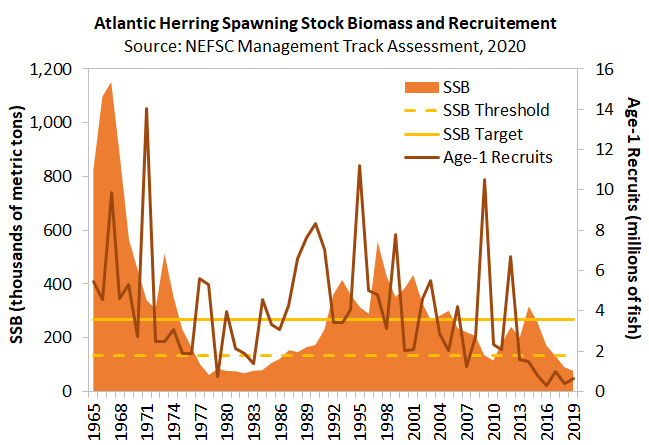
Native Americans developed the first fishery for river herring by developing artificial tidal traps that used shifting tides to strand fish as tidal waters retreat along natural cycles. River herring became vital to several coastal tribes, and were used for direct consumption, fertilizer, and trade. As post-colonial-era human populations grew throughout the eastern United States, the commercialization of the river herring fishery exploded, and the commercial harvest of river herring peaked at over 70 million pounds in the 1950s. This harvest-boom persisted throughout the 1970s, but by 1980, less than 10 million pounds were commercially harvested. A declining trend continued, and by 2006, less than 1 million pounds were commercially harvested (Figure 2). In response, the governing body of Virginia’s marine fisheries, the Virginia Marine Resource Commission, placed a moratorium on the harvest and sale of all river herring species in the state of Virginia in 2011. Despite this measure, river herring continue to be caught as bycatch among commercial and recreational anglers targeting other species of fish.

Figure 2. Commercial River Herring Harvest by Year



As a means of tracking the population of these fish, herring stocks are often quantified by a number of annual abundance indices throughout the Atlantic. The most recent data shows no evidence of river herring populations beginning to rebound (2020; Figure 3). Additionally concerning, these indices are often derived from a combination of sampling gears that include gill netting, electrofishing, and push-netting surveys. Although these methods have proven to be reliable in fish population assessments, they come with one ominous drawback: each of the aforementioned gears is associated with an assumed level of mortality to river herring. Gill net and push-net gears are particularly damaging, as they result in nearly 100% mortality of the fish collected – which can number in the tens of thousands for a single collection event.

Figure 3. Atlantic River Herring Spawning Stock Biomass and Recruitment



Furthermore, these methods interfere with river herring during their most vulnerable life stage, and at the life-stage most important to their recovery: reproduction. Ultimately, tracking populations of river herring is likely a necessary, instrumental component to aiding and documenting the recovery of the species. However, some researchers believe these efforts should not be simultaneously associated with such negative impacts if avoidable. As river herring in Virginia are one of, if not the most, important food sources for wildlife throughout the Chesapeake Bay region, their recovery is tied to the health of the Chesapeake Bay ecosystem, several sectors of the Virginia economy, and the cultural heritage of many Tribal Nations.

Figure 4. A Native Bowfin (Amia calva) feasts on blueback herring during a fish collection event (Chickahominy River, Virginia, 2020)



**Source Data and Methodology**

While it is probably not feasible to completely eliminate human factors of river herring mortality, some scientists are piloting alternative survey methodologies to reduce the footprint of their research on the recovery of the resource. One such example of this is the use of an electronic fish counter, which has been installed as a means of quantifying adult river herring migration on the Chickahominy River, a major tributary to the James River of the Chesapeake Bay Watershed (Figure 5).



**L. Alan Weaver**

Mr. Weaver is the lead researcher at the Walker’s Dam Fishway, and the Statewide Manager of the Virginia Fish Passage Program. Beginning in 1991, Mr. Weaver has made it his mission to reduce aquatic passage barriers for the fishes of Virginia. This has included dam removals, fishway construction, and culvert removals. You can learn more about several of Mr. Weaver’s projects by exploring the following resource:

[Virginia Department of Wildlife Resources: Fish Passage Program](https://dwr.virginia.gov/fishing/fish-passage/)

Figure 5. Location of the Walker's Dam Fishway

This electronic fish counting project was initiated by Mr. Alan Weaver, the Fish Passage Coordinator for Virginia’s Department of Wildlife Resources. The data is collected at the Walker’s Dam Fishway on the Chickahominy River, a double-Denil fishway which resulted in the addition of 30 miles of upstream habitat for migratory fishes when it was constructed in the 1980s (Figure 6).

Figure 6. The Double-Denil Fishway Channels at Walker's Dam



In the Spring of 2020, this electronic fish counter was installed to monitor both of the fishway channels at Walker’s Dam, with the intent of quantifying the total number of river herring migrating up the Chickahominy River system to spawn. The idea is that this technology could replace more harmful monitoring gears, if proven to be reliable. The electronic fish counter functions by funneling migrating fish through a matrix of tubes. Each of these 16 tubes (8 in each fishway; Fig. 6), is fitted with a series of sensors that detect fish passage by measuring upstream disruptions in water conductivity. As a fish passes from the downstream sensor across the upstream sensor, the shift in conductivity causes a count to be tallied for that specific tube.

In order to test the accuracy of these automated fish counts, periodic trapping events were conducted by trapping fish exiting the counter’s tunnels. For these trapping observations, the number of fish counted were recorded for both the electronic count and the number of fish physically captured. This data is presented to us in this lesson within the “TrapDataV2.xlsx” file, and contains 4 columns of data as observed in Figure 7 below, where “Obs” is the unique observation number for each comparison, Date is the timing at which the comparison took place, “SRCount” is the electronic count for each interval, and “TrapCount” is the physical fish count for the same interval. Additionally, the “DailyCounts\_20.xlsx” file contains the total daily river herring (“River Herring”) passed for each day (“Date”) the counter was operational. Each of these 2020 datasets was obtained via email request from the Virginia Department of Wildlife Resources.

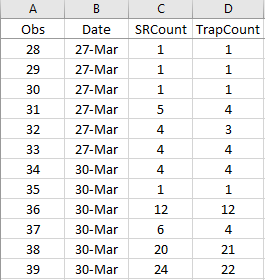


Figure 7. Top Left: Electronic Counts used to generate “SRCount”; Top Right: Physical Fish Counts used to generate “TrapCount”; Bottom: TrapDataV2.xlsx

**Lesson Objectives**

In a perfect world, the electronic fish counts would perfectly match the number of fish physically counted within each observation interval, but this is often not the nature of research in natural resources; and fisheries science is no exception. This is where you come in. In this lesson, you will be the Fisheries Biologist tasked with deciding whether or not the electronic fish counter can be used to reliably estimate river herring migration in the Chickahominy River. Your decision will have ecological and scientific implications, as accepting the electronic counts may result in less incidental river herring mortality, as more researchers see efficacy in the methodology and reduce more destructive monitoring gears. Choosing to decline the validity of the electronic counts will likely result in the continued use of conventional gears. During your analysis, consider that no individual sampling technique is perfect, and researchers must often weigh the costs and benefits of their chosen sampling gears.

To help you accomplish this task you’ve been given, you will use the associated R Markdown file titled “WalkersDamHerring.rmd”. Students with prior experience in R Studio will benefit most from interacting with the lesson within R Studio, while the “WalkersDamHerrin.html” provides an alternative medium for those unfamiliar with the software, but still wish to do a walk-through of the lesson and observe the methods used. In either case, students will be taught how to:

**R Markdown Lesson (*RHerringLesson.Rmd*)**

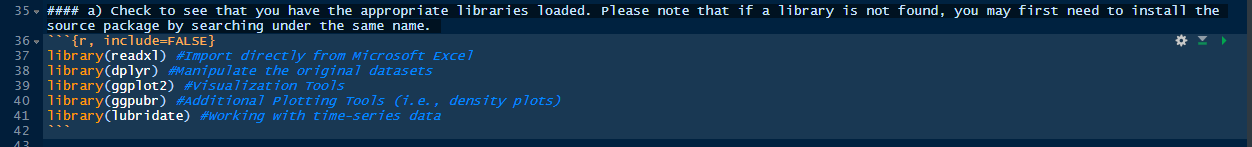
Although each of the concepts required to complete the objectives in this lesson will be taught within the R Markdown document itself, an overview of these concepts is provided in this section for reference. Please note that in R Markdown, many symbols within the *“.Rmd*” are used as formatting operators for the chosen output file. If you wish to see how these symbols function (i.e., # and >), use the Knit feature on the file’s top toolbar to view the file output, which in this case, has been specified as an html document.

The “*RHerringLesson.Rmd”* starts by giving instructions (Line 18) to the user/student. As per the instructions, each user is advised to first read the “*RHerringBackground*” document, and watch the “*RHerringBackground*” video. These documents set the stage for the quantitative lesson that will be given throughout the R Markdown portion of the QUBES lesson. A quick ecological refresher introduction (Line 25) is then provided to reignite the appropriate thought processes before continuing on to the coding portions.

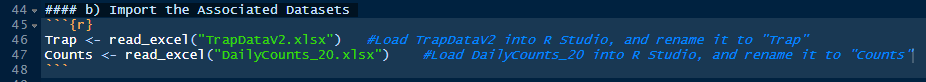
Starting on Line 35, each of the packages necessary to complete the analysis is loaded into R Studio using the “library” function, followed by the name of the package. This command, and all commands in R Studio, can be executed by pressing the green triangle in the upper-right corner of the code chunk, as seen in Figure 8. Note that text lines that begin with a “#” symbol, even if within a code “chunk”, signify that text as non-executable text, and is simply used to annotate chunks and lines of code, or specify the size of the font in the output file.

Figure 8. Lines 35 through 42 from RHerringLesson.Rmd. Note that Line 35 is not within a “Code Chunk”, while lines 36 through 42 are executable code, as signified by being constrained by **```{r} code here```**

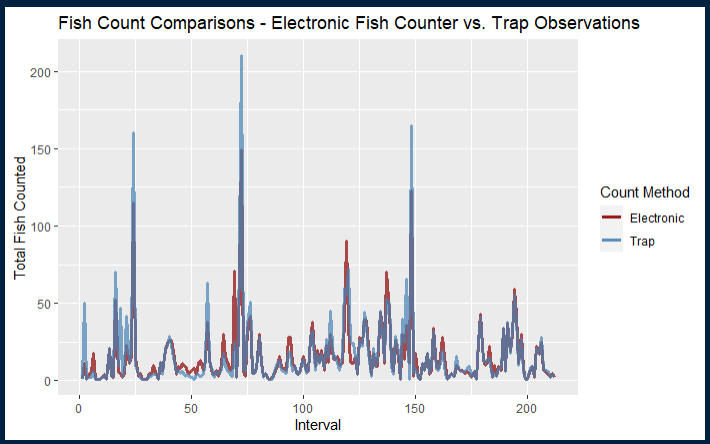
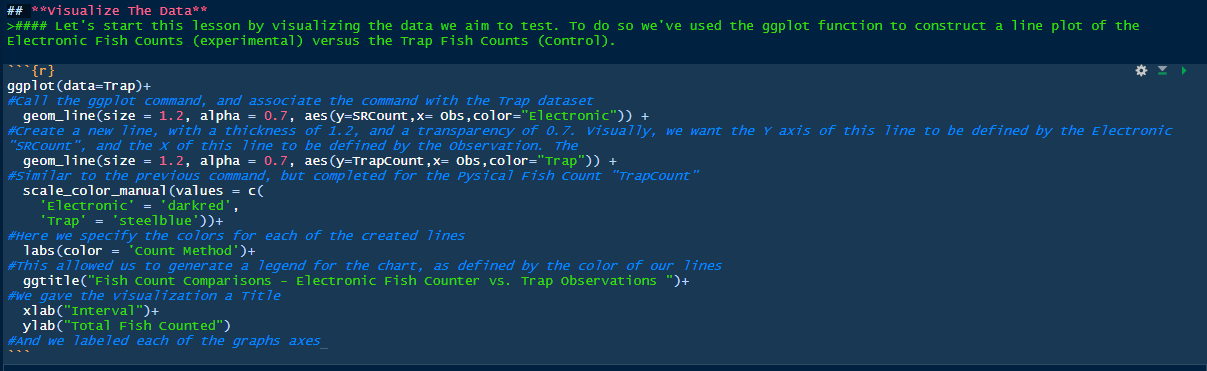
Figure 7 Top Left: Electronic Counts used to generate “SRCount”; Top Right: Physical Fish Counts used to generate “TrapCount”



In Lines 44 through 48, we import each of the necessary datasets we will be working with. Because these files are in excel format, we will use the “read\_excel” command. In the same lines, we have renamed each of the files with the “<-” command. Meaning that we can now reference each of the datasets by now simply typing “Trap” or “Counts”.

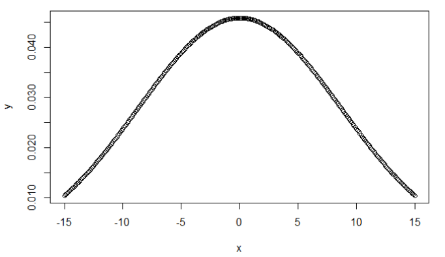
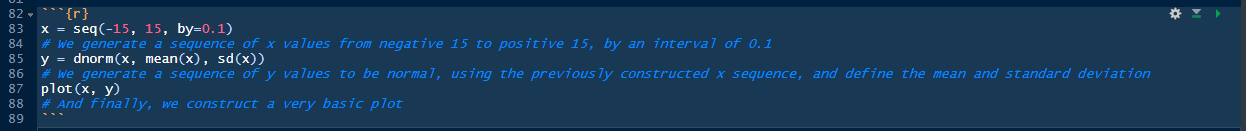


Next, we begin by visualizing one of the datasets we will be working with. To do so, we use the ggplot library, and the associated ggplot commands. This allows us to specify a number of visualization tools, such as the line graph we’ve constructed for our “Trap.xlsx” data.

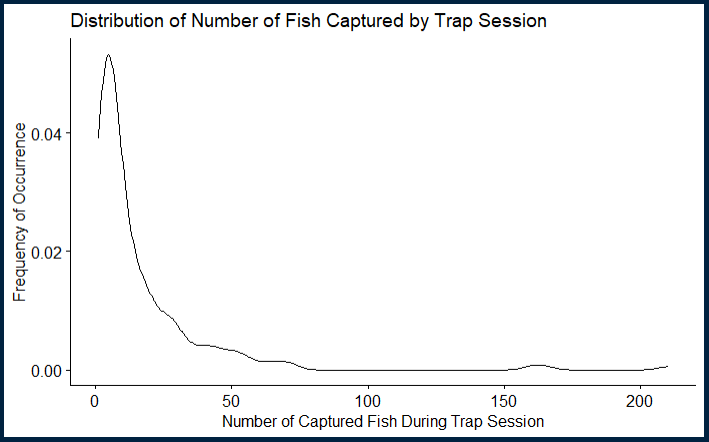
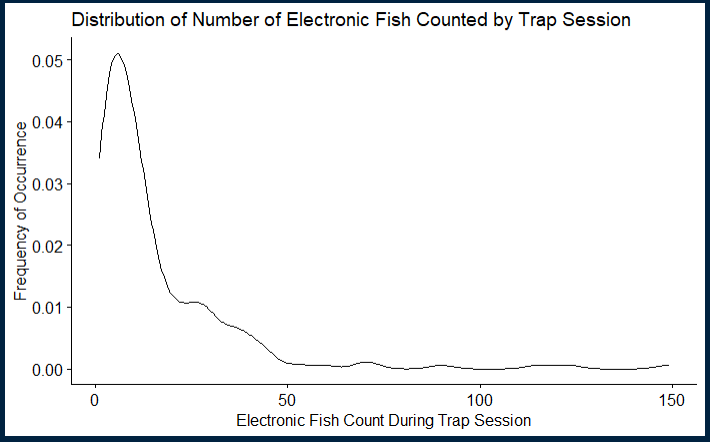


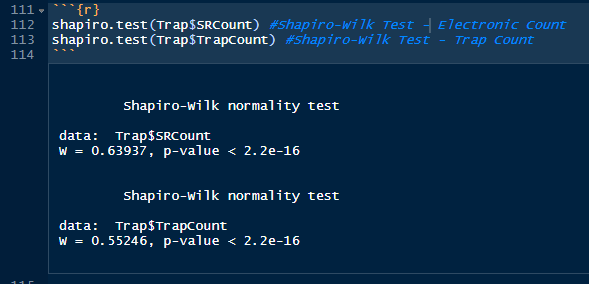
Although our visualization shows that the electronic counts and the physical fish counts appear to be correlated, we also see instances in which the methods have noticeable disparities between the counts. While this graphic is useful for descriptive inferences, it does not allow us to make statistical inferences as to whether the electronic counts are statistically valid. To do this, more sophisticated quantitative techniques are required.

In order to perform many statistical tests, your data must meet several assumptions for the associated test. For some of the most common tests performed, such as simple linear regression, Pearson correlation, and T-tests, one of the primary assumptions is that of data normality. These types of tests are referred to as Parametric Statistics, and only work properly if data is classified as normal. As data becomes less normalized, these tests increase in bias, and at some point, lose all validity. Before we test our own data for normality, lets visualize what normal data looks like. Perfectly normal data resembles a bell-shaped distribution curve, and consequently, is characterized by identical values for the mean, median, and mode. In lines 82 through 89, we use R to visually display a perfectly normal dataset.

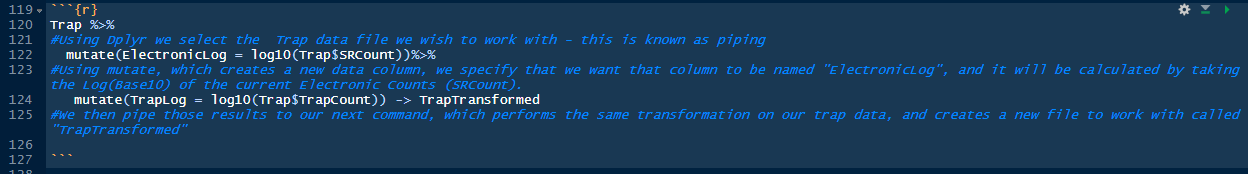


Now that we know what a normal distribution visually looks like, we can perform a similar visualization to assess the variables for the data we wish to test (Lines 93 through 107).

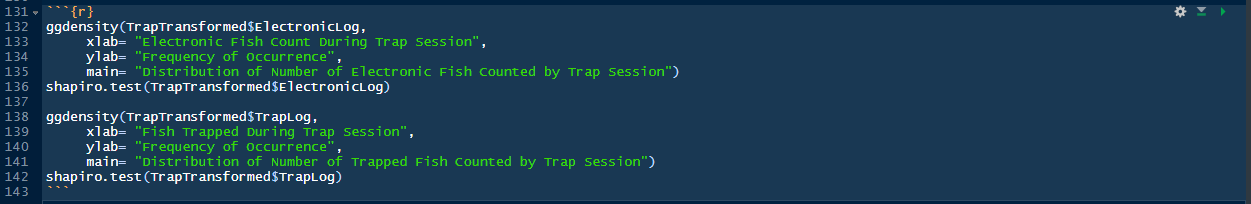
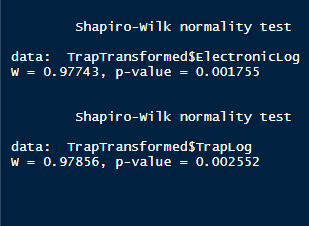
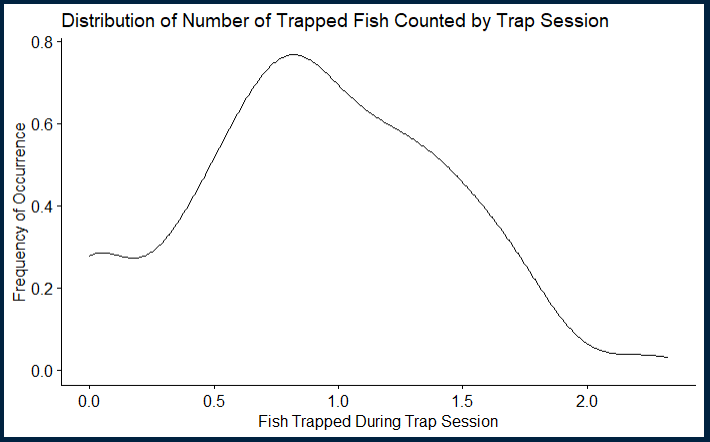
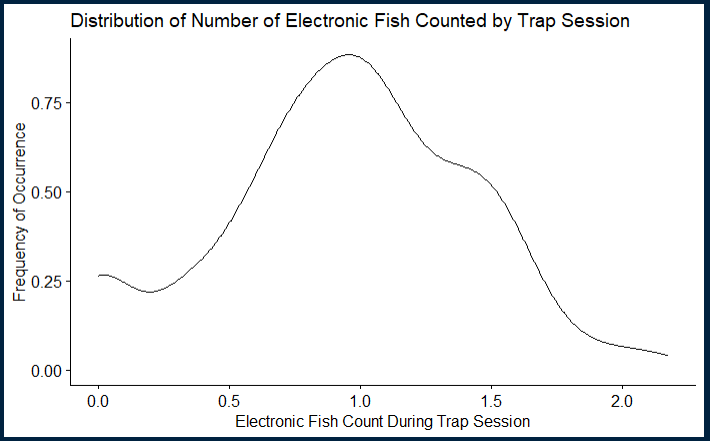


For both variables, we see that our data is very positively skewed, or skewed to the right. As both variables are derived from "Count" data, this is expected, as counts are often not of a continuous nature. Therefore, we can visually infer that our variables are not normally distributed, and cannot be currently assessed using parametric statistics. We can validate this inference statistically by using a Shapiro-Wilk Test for normality, as performed below (Lines 111 through 114). To interpret the results of this test, remember that the \*\*NULL HYPOTHESIS\*\* of this test states that our assessed variable \*\*IS NORMALLY DISTRIBUTED\*\*. In order to accept, or “fail to reject” this hypothesis, which we wish to do, the resulting p-value must be greater than 0.05. In both of our variables, we see that our p-value is much smaller than 0.05 (< 2.2e-16); so we reject the NULL, and confirm our visual inferences that the data is indeed not normal.

What can be done if our data is not normal? Is it useless? Probably not. One of the more common techniques used to address data normality involves transforming the non-normalized variables, which adjusts the shape of that variable's distribution. In our case, we have previously observed that both of our variables are positively skewed. For positively skewed distributions, a Log Transformation is perhaps the most common transformation technique used. This works by taking the original value, and replacing it with the log (10) of that value. R allows us to complete this task quickly, which we will do below (Lines 119 through 127):



Now that we’ve transformed our data, it’s time to reassess normality by repeating the previous visualization and Shapiro-Wilk normality test for each of the variables (Lines 131 through 143).

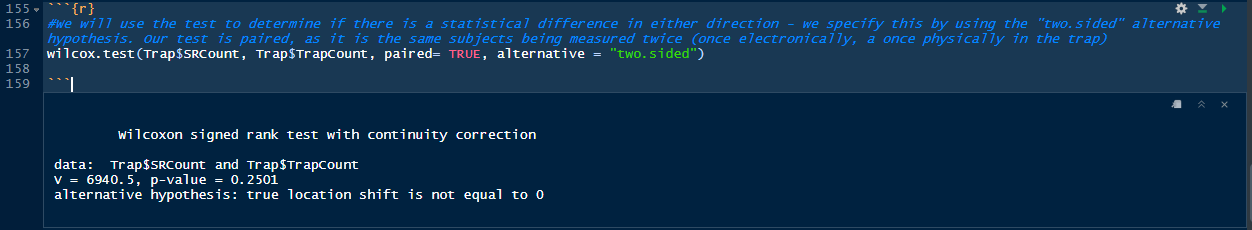


While it is both visually and statistically (both p-values increased) evident that this transformation greatly improved the normality of our variables. We still lack the threshold (p-value > 0.05) to perform a parametric test without introducing an unknown level of bias.

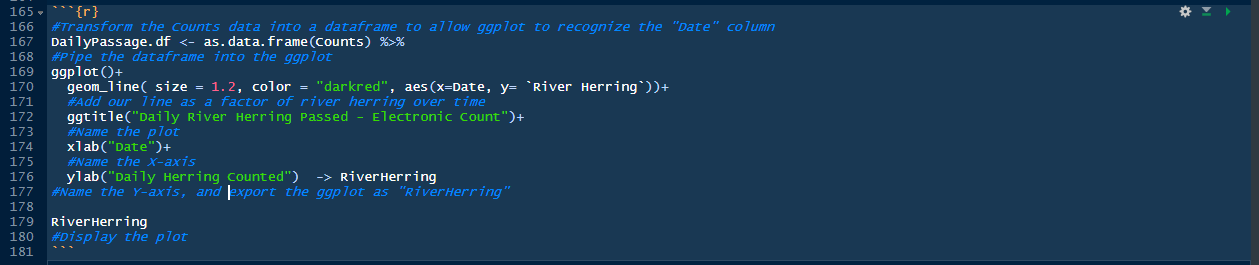
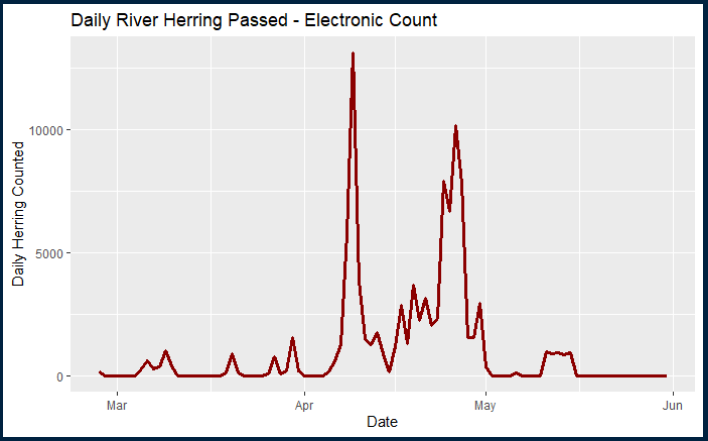
Although many other data transformation techniques exist, let's just pretend we've tried them all – without any of the transformations resulting in a normal distribution for our variables. What other options do we have? One common alternative is to bypass the assumption of normality by using a nonparametric statistical test. While parametric tests are used often more powerful, particularly in studies with a limited sample size, nonparametric alternatives exist for every parametric test. In our case, we have many samples in our data, and therefore we can properly implement the use of the Paired Samples Wilcoxon Signed Rank Test, a nonparametric alternative of the more common parametric paired t-test.

Similar to the t-test, the Paired Samples Wilcoxon Signed Rank Test will pair the values of the two variables – as they are technically the same fish being measured twice (electronically and physically). The test then assigns a rank value for the absolute difference between each pair, and ranks them in order from the least different to the most different. Pairs with a difference of 0 are not used in the calculation, and therefore this is a conservative test of similarity. The least different score (in theory, a difference of 1) is assigned the rank of 1. If multiple pairs have the same difference, as is present in our situation, the rank for all of the pairs sharing that deviation is assigned to the average in which those ranks span. For example, let’s say we have 3 observation intervals, and each pair has a value difference of 1. These pairs would be assigned as the 1st, 2nd, and 3rd ranked pairs – but would all receive a score of 2 (the average of 1+2+3). Remember that the signed rank can also be reported as a negative value, as the variation between the variables is either positive or negative. The test statistic, reported as V in R Studio, is the sum of the signed ranks, and in a test of two variables with the same values, would be reported as V = 0. In practical application, the V score is only indicative of the degree of variation when comparing tests with the same number of variables. Because we know our variables already differ, and we are only interested in whether they are statistically different, we can not use the v score to make any interpretation.

For our analysis, the more useful output for us to focus on is the reported p-value of the test. The alternative hypothesis of the Paired Samples Wilcoxon Signed Rank Test states that “the difference between the two variables IS NOT ZERO”. In order to “fail to reject” this hypothesis, we would therefore require a p-value of < 0.05. In this case, our p-value is 0.2501, which means that we accept our NULL HYPOTHESIS, or, that the difference between the electronic fish counts and physical trap count is statistically insignificant. The true power of R is revealed below, in which the entire Paired Samples Wilcoxon Signed Rank Test is conducted almost instantaneously in Lines 151 to 159 below:



Now that we've statistically validated our electronic fish counts, let's use the data manipulation, R markdown formatting, and visualization plotting functions we learned above to graph the daily total count of river herring detected by the electronic fish counter throughout their 2020 spawning migration.



**R Markdown – External Resources**

The following links contain information for broader understanding of the quantitative concepts covered within the R Markdown document.

[**R Markdown**](https://www.rstudio.com/wp-content/uploads/2015/02/rmarkdown-cheatsheet.pdf)

[**Data Normality**](https://www.analyticsvidhya.com/blog/2017/09/6-probability-distributions-data-science/)

**[Parametric and Nonparametric Tests](https://www.mayo.edu/research/documents/parametric-and-nonparametric-demystifying-the-terms/doc-20408960" \l ":~:text=Parametric%20statistical%20procedures%20rely%20on,deviations)%20of%20the%20assumed%20distribution.)**

[**GGPlot**](https://www.rstudio.com/wp-content/uploads/2015/03/ggplot2-cheatsheet.pdf)

**Requirements to Complete Lesson**

* **RHerringBackground.docx** (Instructor and Student Version)
* **RHerringLesson.rmd** (for those with R Studio)
* **RHerringLesson.html** (for those not wanting to use R Studio)
* **TrapDataV2.xlsx** (validate the name during download and import in R Studio)
* **DailyCounts\_20.xlsx** (validate the name during download and import in R Studio)
* **R Studio**

**Lesson Answers**

**Q1) Why is it important to check for normality before running parametric statistics?**

A1) Data normality is a fundamental assumption of running parametric statistics. The lack of normality introduces bias, and nullifies the results of these techniques.

**Q2) Pretend you are consulted for input on whether or not recreational fishing should be temporarily closed near the Walker's Fishway in order to allow river herring to migrate without additional harassment. Which week(s) or month(s) would you choose to close, and how would you justify this decision?**

A2) Students can choose any timeframe, but must validate their reasoning. For instance, choosing the middle of April to close the fishery in an effort to reduce mortality during the peak of the river herring migration.

**Q3) Let's pretend that we were only interested in whether or not the electronic fish counts overestimated river herring migration. We test this by manipulating our Paired Samples Wilcoxon Test as seen below. Does the electronic counter overestimate fish at a statistically significant threshold?**

A3) No, although we adjusted the test to only check for a greater – or overestimate – count, the p-value of the test still remains > 0.05.

**Q4) In this lesson, we highlighted mortality reduction as the primary advantage to using an electronic fish counter over more invasive fish monitoring gears. Can you think of any other advantageous qualities?**

A4) There are several answers here, but the objective is to get students thinking about the complexity of fisheries biology. Concepts discussed should include that conventional methods only offer snapshots into population numbers, while the electronic fish counter is automatically counting fish 24/7. Other considerations may not be direct mortality, but the likelihood of delayed mortality or behavior alteration that is associated with conventional sampling gears.

**References**

ASMFC. (no date). “Shad and River Herring.” *Atlantic States Marine Fisheries Commission.* <http://www.asmfc.org/species/shad-river-herring>

Hoskin, T. (no date). “Parametric and Nonparametric: Demystifying the Terms.” *The Mayo Clinic Department of Health Sciences Research*. <https://www.mayo.edu/research/documents/parametric-and-nonparametric-demystifying-the-terms/doc-20408960#:~:text=Parametric%20statistical%20procedures%20rely%20on,deviations)%20of%20the%20assumed%20distribution>.

Vidhya, Analytics. (2017). “Six common probability distributions every data science professional should know.” *Analytics Vidhya*. <https://www.analyticsvidhya.com/blog/2017/09/6-probability-distributions-data-science/>

Virginia Department of Wildlife Resources. (no date). “Fish Passage Program”. *Virginia DWR Website*. <https://dwr.virginia.gov/fishing/fish-passage/>

Virginia Department of Wildlife Resources. (no date). “Shad Cam”. *Virginia DWR Website.* <https://dwr.virginia.gov/shad-cam/>