Part 1 from above: R function that codes a metric for performance evaluation - must be a combination of at least two performance measures - include some comments that explain 'why' this metric

This combined metric can be used to evaluate the model performance considering both the discrepancy between the observed and modeled flow values as well as the linear relationship between them. Here's the reasoning behind this metric and an overview of the steps:

Transformed Difference: This measure captures the difference between the observed and modeled flow values at the annual scale. By calculating the difference between the sum of observed and modeled values for each water year, we can assess how well the model is reproducing the overall annual flow. The difference is then normalized by the standard deviation of the differences to account for the variations in the dataset and to have a comparable value across different datasets.

Correlation Coefficient: This measure captures the linear relationship between the observed and modeled flow values. A high correlation coefficient indicates that the model is able to reproduce the overall pattern of the flow values throughout the dataset.

Combining the measures: The transformed difference and correlation coefficient are combined by calculating their arithmetic mean. This provides a single value representing the model's performance, considering both the discrepancy between observed and modeled flow values and their linear relationship.

In summary, the combined_metric function evaluates the performance of a hydrologic model by considering both the difference between the observed and modeled flow values at the annual scale and the linear relationship between them. This combined metric can be used to compare the performance of different models and assess how well they reproduce the flow values in a given dataset.

```r
combined_metric <- function(data) {
  sager_differences  <- data |>
    group_by(wy) |>
    summarize(difference_obs_mod = sum(model) - sum(obs))

  # Calculate the mean difference
  mean_difference <- mean(sager_differences$difference_obs_mod)
  # Calculate the standard deviation of the differences
  std_dev_difference <- sd(sager_differences$difference_obs_mod)

  # Compute the transformed difference (e.g., normalize by the standard deviation)
  sager_differences <-
    sager_differences |> mutate(transformed_diff = difference_obs_mod / std_dev_difference)
  # Compute the correlation coefficient between obs and model
  correlation_coefficient <- cor(data$obs, data$model)
  # Combine the transformed difference and the correlation coefficient
  combined_metric <-
    (mean(sager_differences$transformed_diff) + correlation_coefficient) / 2

  return(combined_metric)
}
```

- R markdown that does the following steps (with lots of documentation of the work flow):
  - Part 2 from above:
    1. Apply your performance function to a subset of the Sagehen data set (with multiple simulations) that you want to use for calibration

We perform a split-sample calibration using the year 1984 as the calibration threshold. Then find the best parameter set and graph the mean August streamflow for the best parameter set. Finally compute the performance of the model using the best parameter set in pre and post-calibration periods.

```r
# Read and organize the data
sager = read.table(here('data',"sager.txt"), header=T)

# add date
sager = sager %>% mutate(date = paste(day,month,year, sep="/"))
sager$date = as.Date(sager$date,"%d/%m/%Y")

# Read and organize the data
sagerm <- read.table(here('data',"sagerm.txt"), header = T)
nsim <- ncol(sagerm)
snames <- sprintf("S%d", seq(from = 1, to = nsim))
colnames(sagerm) <- snames

sagerm$date <- sager$date
sagerm$month <- sager$month
sagerm$year <- sager$year
sagerm$day <- sager$day
sagerm$wy <- sager$wy

sagerm <- left_join(sagerm, sager[, c("obs", "date")], by = c("date"))

# Split-sample calibration
calibration_data <- subset(sagerm, wy < 1984)
```

```r
# Define a function to compute the combined_metric for each simulation
combined_metric_for_simulation <- function(sname, data, obs) {
  model_data <- data[[sname]]
  wy_data <- data$wy
  cm <- combined_metric(data.frame(obs = obs, model = model_data, wy = wy_data))
  return(data.frame(sim = sname, combined_metric = cm))
}


# Compute the combined_metric for each simulation during the calibration period
res <- map_dfr(snames, combined_metric_for_simulation, data = calibration_data, obs = calibrat
ft <- flextable(head(res))
```

```r
theme_apa(ft)
```

sim	combined_metric
S1	0.50
S2	0.53
S3	-0.50
S4	-0.14
S5	-0.04
S6	-0.46

```r
# Find the best and worst parameter sets
best_parameter <- res %>% slice_max(combined_metric) |> mutate(param_type = 'best', .before = s
worst_parameter <- res %>% slice_min(combined_metric) |> mutate(param_type = 'worst', .before =

params <- bind_rows(best_parameter,worst_parameter) |>
  flextable()

theme_apa(params)
```

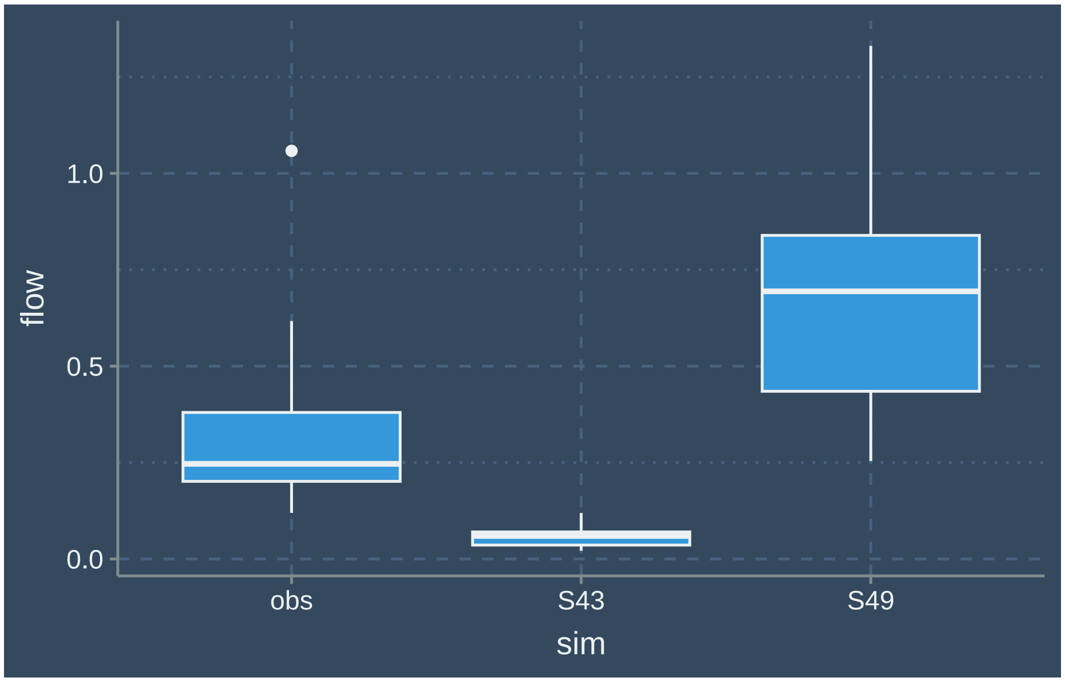
param_type	sim	combined_metric
best	S49	1.04
worst	S43	-0.57

```r
# Compare the performance of the best and worst parameter sets
comparison_data <- sagerm %>%
  select(c(best_parameter$sim, worst_parameter$sim), date, obs, month, day, year, wy)

comparison_data_mwy <- comparison_data %>%
  select(-c(day, date, year)) %>%
  group_by(month, wy) %>%
  summarize(across(everything(), mean))
```

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

```r
comparison_data_mwyl <- comparison_data_mwy %>%
  pivot_longer(cols = !c(month, wy), names_to = "sim", values_to = "flow")
```

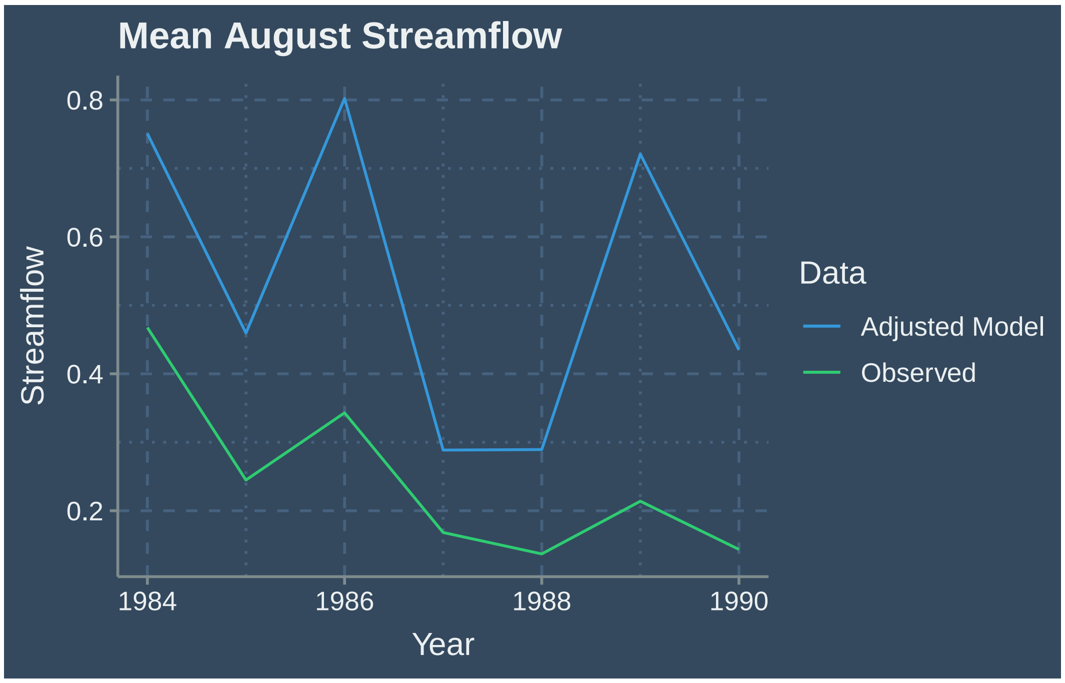
```r
ggplot(subset(comparison_data_mwyl, month == 8), aes(sim, flow)) + geom_boxplot()
```



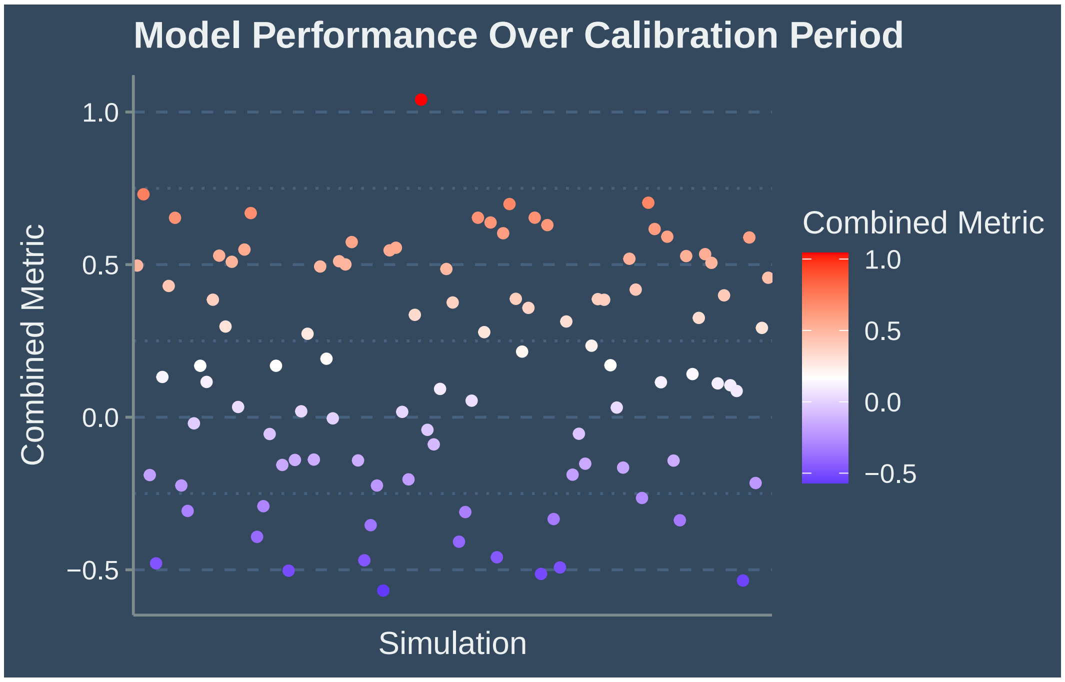
2. Summarize the performance over the calibration period in 1-2 graphs; you can decide what is u

```r
# Apply the best parameter set to the validation data
best_sim <- best_parameter$sim
validation_data <- subset(sagerm, wy >= 1984)

validation_data_adjusted <- validation_data %>%
  mutate(model = !!sym(best_sim))

# Plot the mean August streamflow for the best parameter set
mean_august_streamflow <- validation_data_adjusted %>%
  filter(month == 8) %>%
  group_by(year) %>%
  summarize(mean_obs = mean(obs),
            mean_model = mean(model))
```

```r
ggplot(mean_august_streamflow, aes(x = year)) +
  geom_line(aes(y = mean_obs, color = "Observed")) +
  geom_line(aes(y = mean_model, color = "Adjusted Model"))+
  labs(title = "Mean August Streamflow",
       x = "Year",
       y = "Streamflow",
       color = "Data")
```



```
# Plot the performance over the calibration period
ggplot(res, aes(x = sim, y = combined_metric, color = combined_metric)) +
  geom_point() +
  scale_color_gradient2(low = "blue", mid = "white", high = "red", midpoint = median(res$combi
  scale_x_discrete(breaks = seq(from = 1, to = length(snames), by = 10), labels = snames[seq(f
  labs(title = "Model Performance Over Calibration Period",
       x = "Simulation",
       y = "Combined Metric",
       color = "Combined Metric")
```



```
# Compute the performance of the model using the best parameter set in pre and post-calibratior
pre_calibration_performance <- combined_metric(calibration_data %>% mutate(model = !!sym(best_s
post_calibration_performance <- combined_metric(validation_data_adjusted)

performance_change <- post_calibration_performance - pre_calibration_performance
performance_change
```

```
[1] -0.09090848
```

```
    3.  Record your 'best' and 'worst' parameter set in this [spreadsheet](https://docs.google.co
```