# Calibration

# Calibration

Choosing parameter sets based on comparison with observed data

- calibration is very similar to sensitivity analysis
- we could use LHS or SOBEL function to generate parameter sets and model runs
- compute performance metrics for each run

# A key step: Designing your performance metric

What does it mean to be "good"?

First we need to think about how to compare models and observations

- can be simple if output is a single number e.g increase in profit
- often we are predicing things through time (many numbers)

# Comparing model and observed time series output

When evaluating a model - Always plot first!

What plotting can tell you

- plot through time
  - *look for differences in performance in different periods*
  - *does model capture variation through time (long term increase/descrease; seasonalibty)*
- plot x-y (observed vs model)
  - *look for bios (error) (using a 1 to 1 line are points always above or below)*
  - *look for errors associated with particular magnitdues (e.g high or low values)*
- NOTE: some things to think about that might help make it easier to "see" differences betwee observed time series and mdoelled time series
  - *consider appropriate y-axis (log-scale for large fluctuations in patterns)*
  - *consider picking a window (subset in x-axis)*

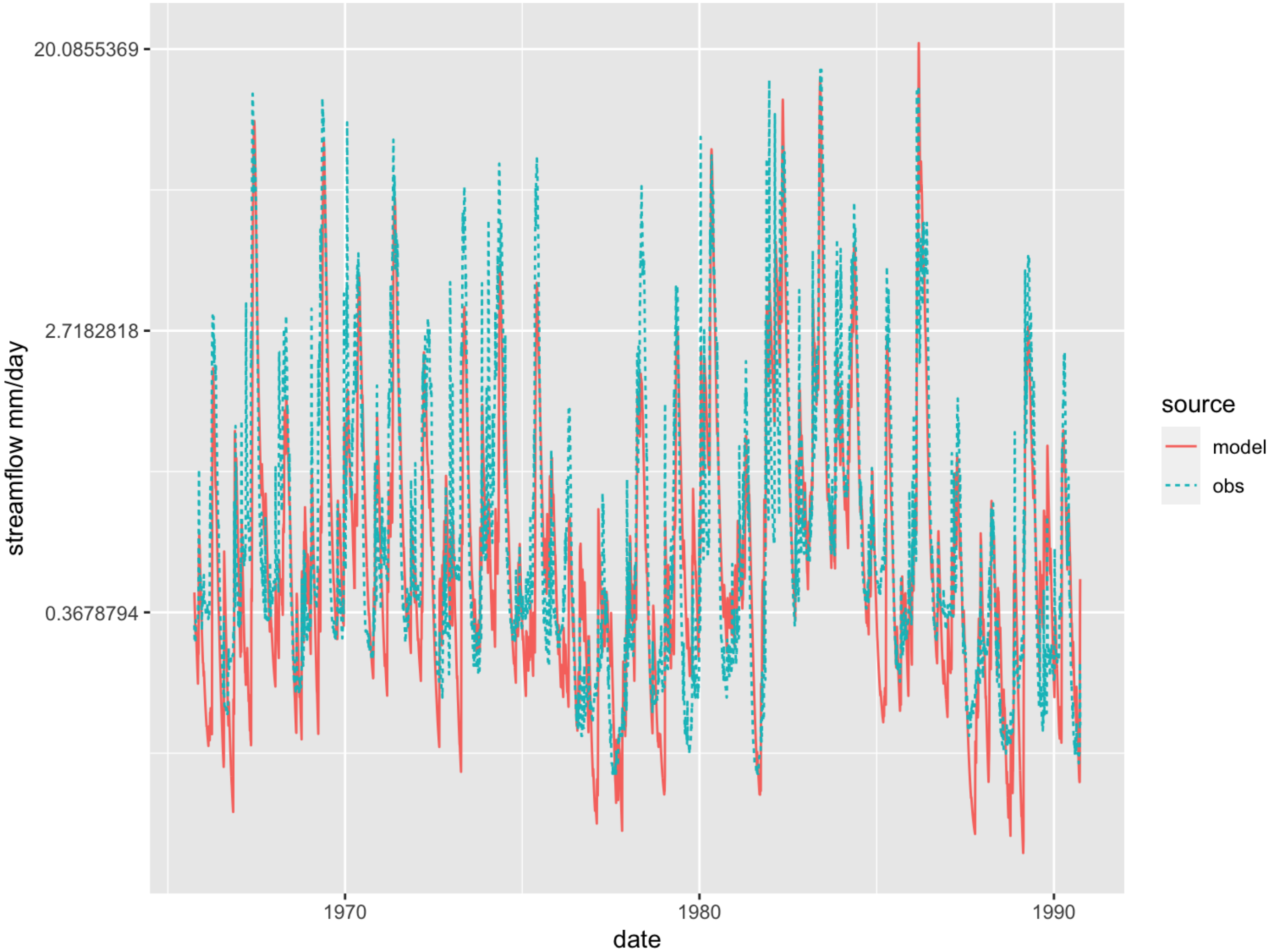
```
sager = read.table("../Data/sager.txt", header=T)
head(sager)
```

```
##       model       obs month day year   wy wyd
## 1 0.4238063 0.3358678    10   1 1965 1966   1
## 2 0.4133587 0.3208737    10   2 1965 1966   2
```

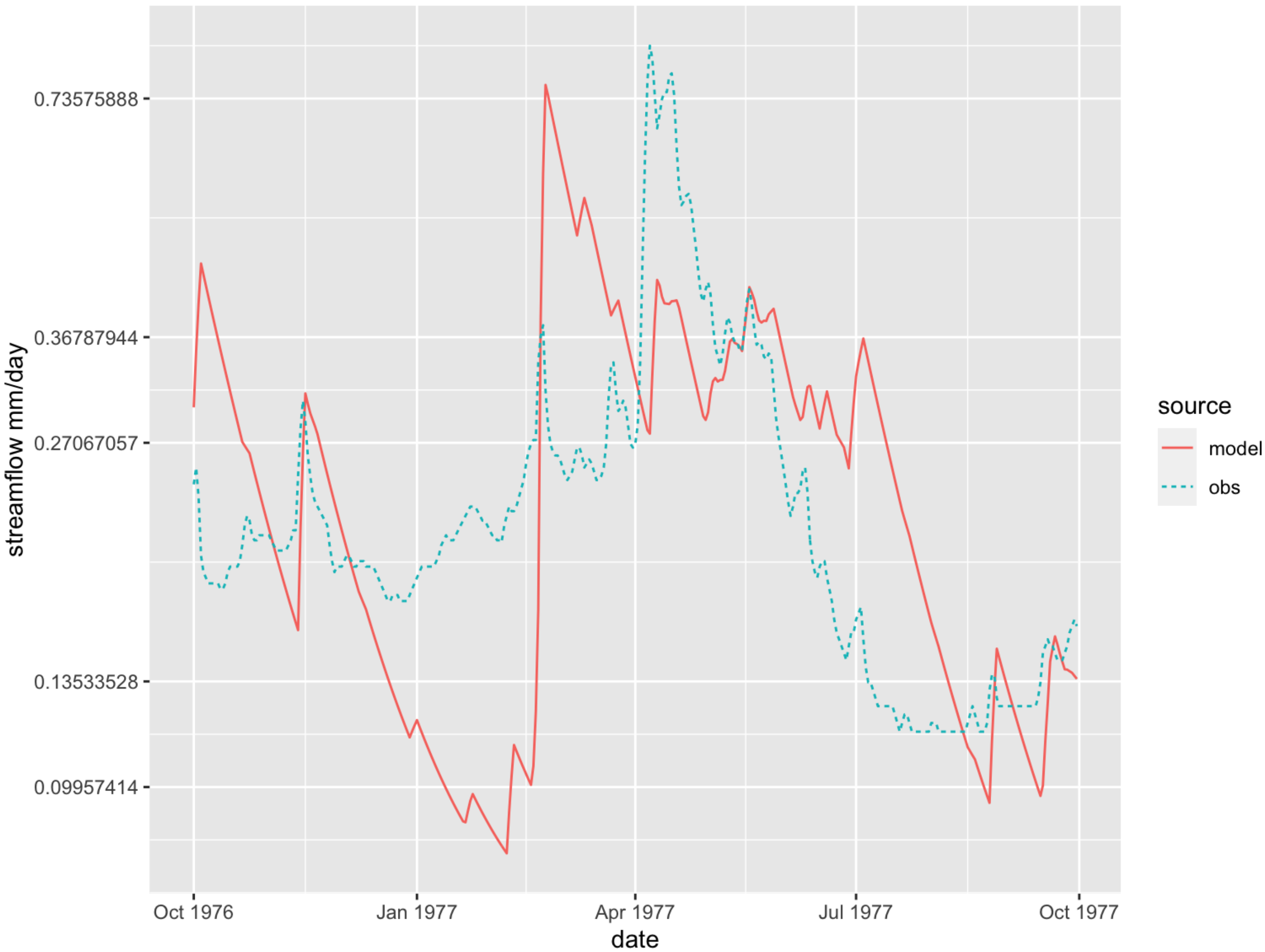
```
## 3 0.4032640 0.3058796    10   3 1965 1966   3
## 4 0.3935287 0.2968832    10   4 1965 1966   4
## 5 0.3841480 0.2968832    10   5 1965 1966   5
## 6 0.3751000 0.2968832    10   6 1965 1966   6
```

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

# plot
sagerl = sager %>% pivot_longer(cols=c("model","obs"), names_to="source",
                                values_to="flow")

# basic plot
ggplot(sagerl, aes(date, flow, col=source, linetype=source))+geom_line()
```

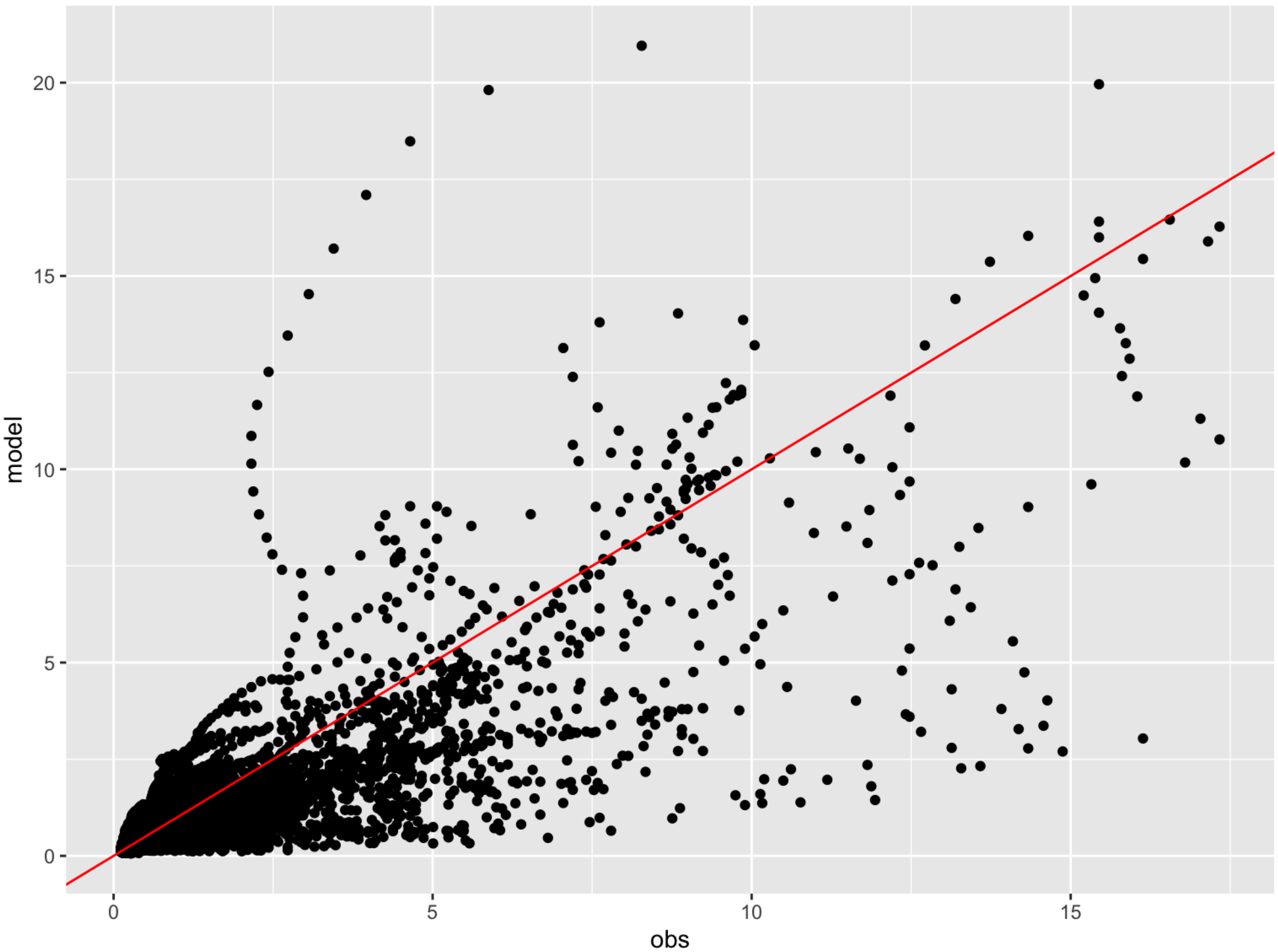

```
# change axis to get a closer look at performance at low values
# when you have high dynamic range (lots of large and small values), taking log can help
# with visualization
ggplot(sagerl, aes(date, flow, col=source,
        linetype=source))+geom_line()+scale_y_continuous(trans="log")+labs(y="streamflow
        mm/day")
```




```r
# focus on a shorter time period to see more closely
ggplot(subset(sagerl, wy==1977), aes(date, flow, col=source,
        linetype=source))+geom_line()+scale_y_continuous(trans="log")+labs(y="streamflow
        mm/day")
```




```
# consider as x-y graph to find biass
ggplot(sager, aes(obs, model))+geom_point()+geom_abline(intercept=0, slope=1, col="red")
```



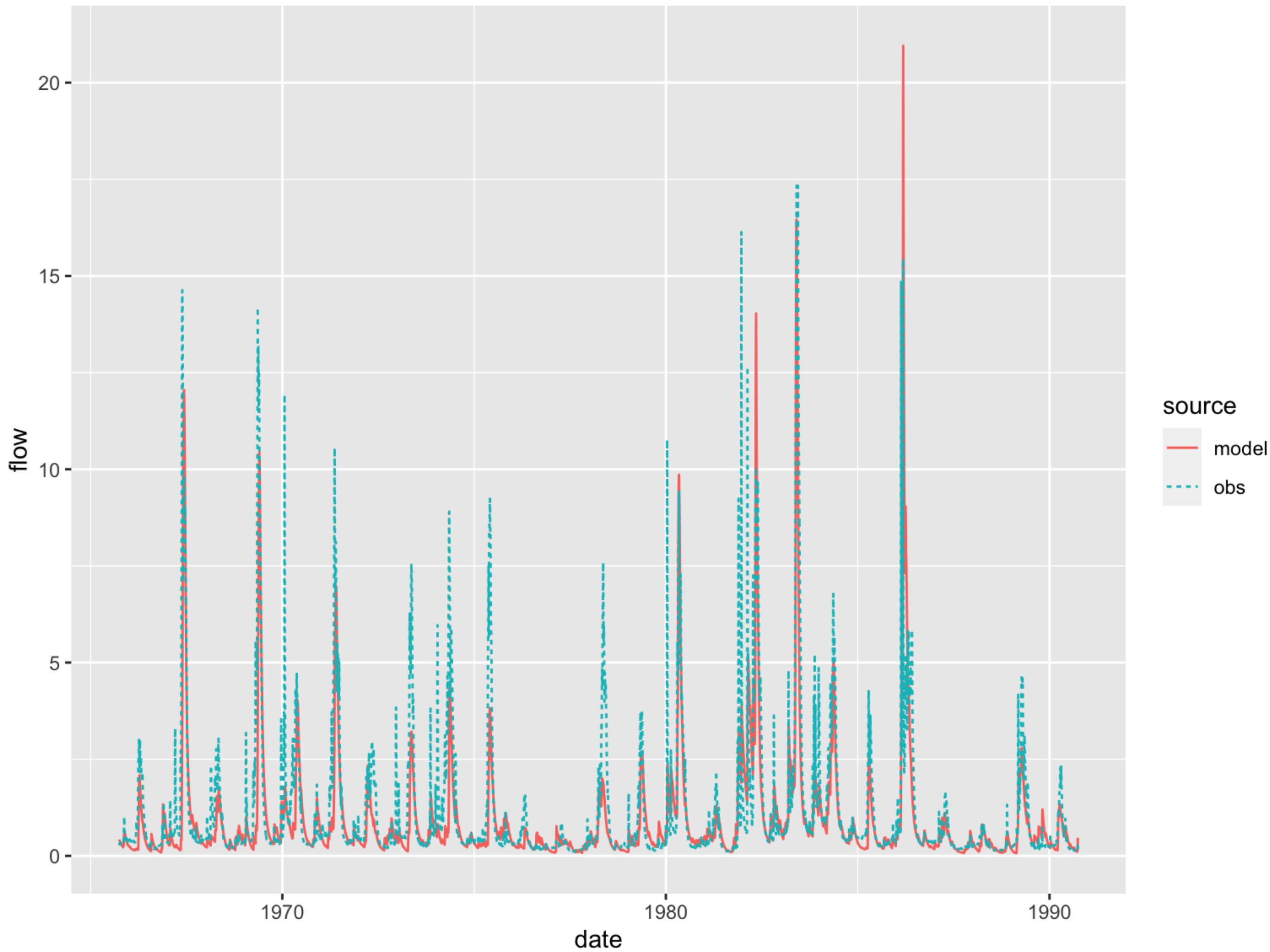

Some examples of model evaluation using results from a hydrologic model applied to a Sierra watershed

# Graph

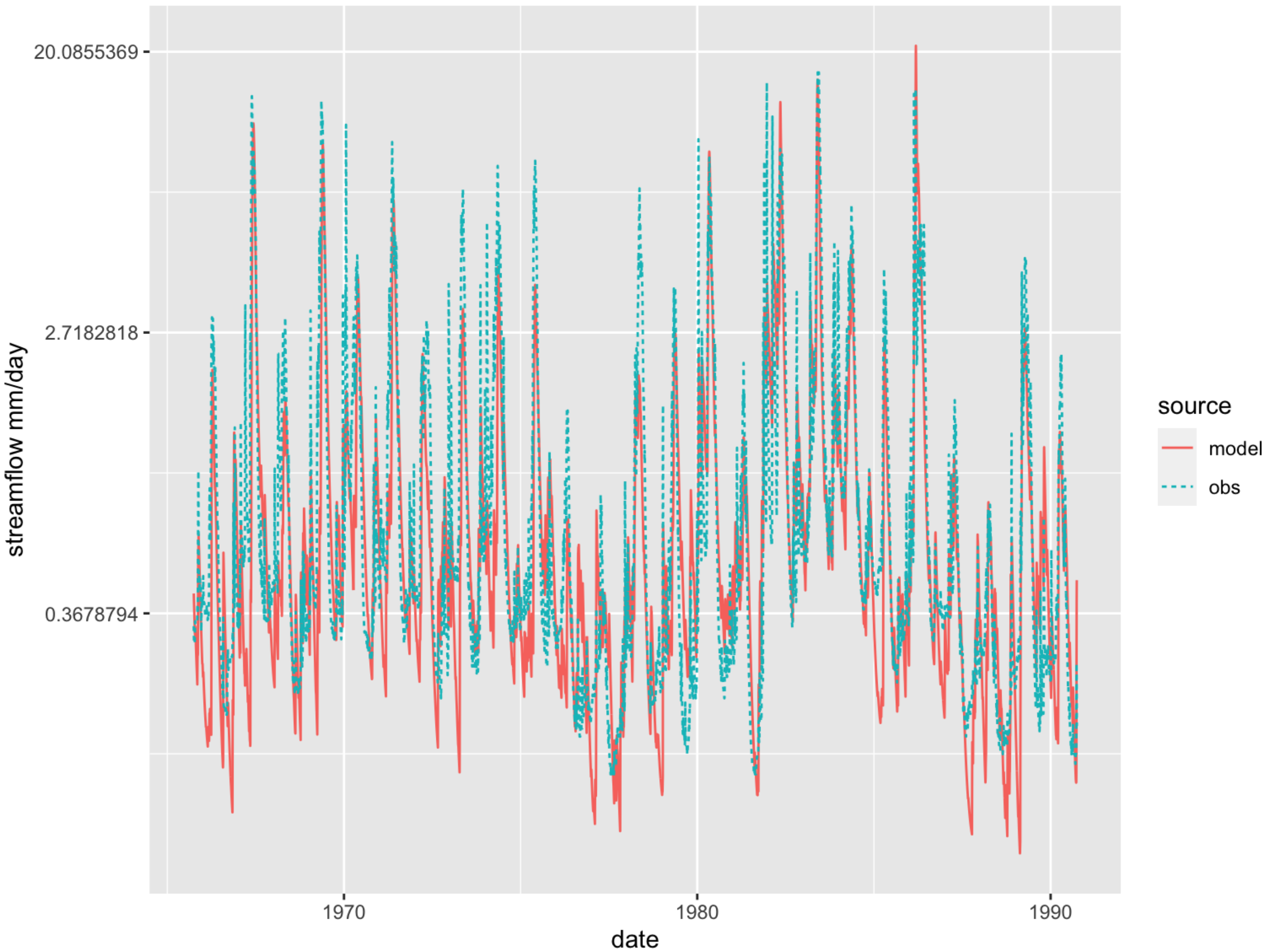
```
sager = read.table("../Data/sager.txt", header=T)
head(sager)
```

```
##       model       obs month day year   wy wyd
## 1 0.4238063 0.3358678    10   1 1965 1966   1
## 2 0.4133587 0.3208737    10   2 1965 1966   2
## 3 0.4032640 0.3058796    10   3 1965 1966   3
## 4 0.3935287 0.2968832    10   4 1965 1966   4
## 5 0.3841480 0.2968832    10   5 1965 1966   5
## 6 0.3751000 0.2968832    10   6 1965 1966   6
```

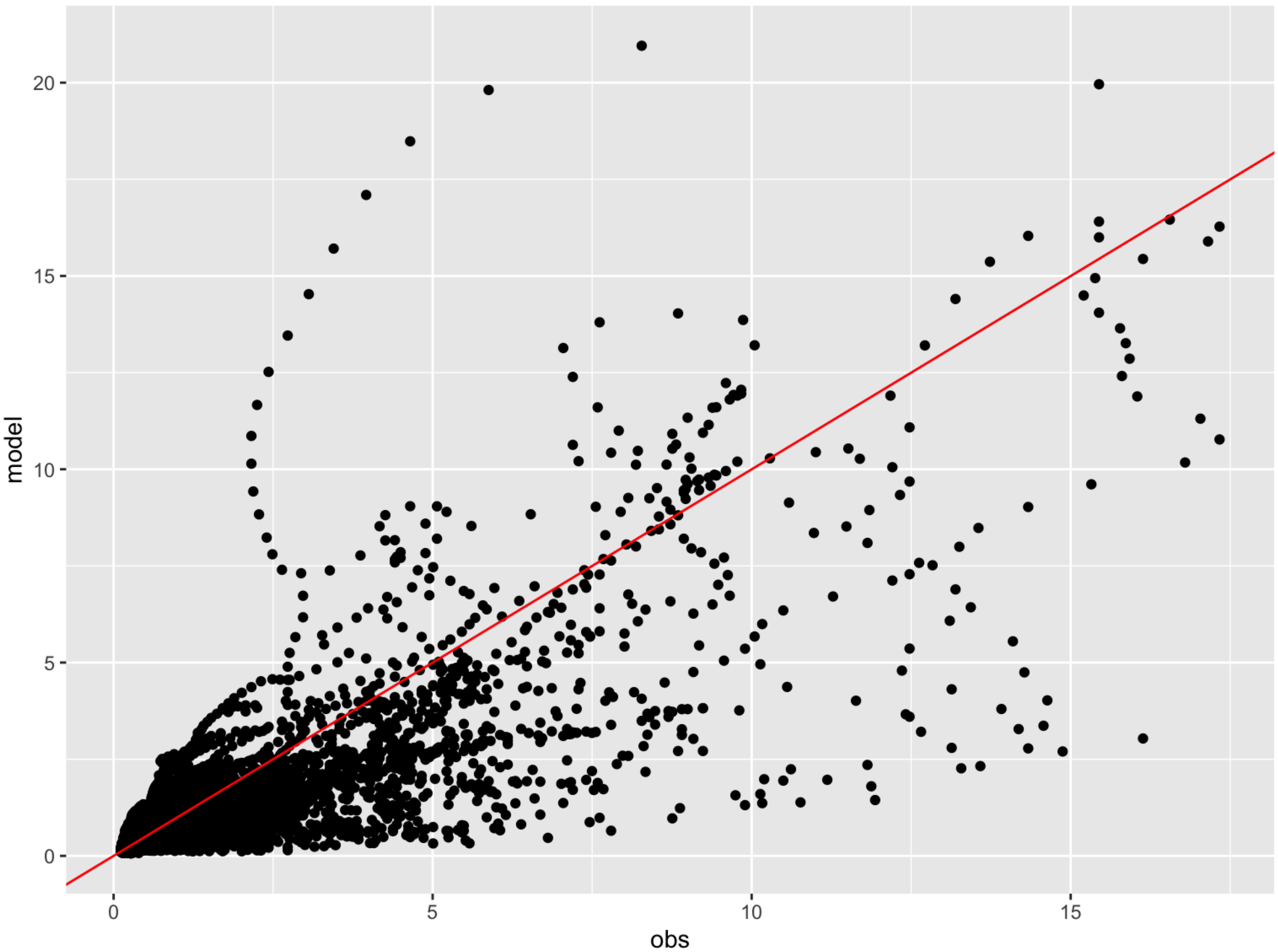
```
# add date
sager = sager %>% mutate(date = paste(day,month,year, sep="/"))
sager$date = as.Date(sager$date,"%d/%m/%Y")

# plot
sagerl = sager %>% pivot_longer(cols=c("model","obs"), names_to="source",
                                 values_to="flow")

# basic plot
ggplot(sagerl, aes(date, flow, col=source, linetype=source))+geom_line()
```




```r
# change access to get a closer look at performance at low values
# when you have high dynamic range (lots of large and small values), taking log can help
# with visualization
ggplot(sagerl, aes(date, flow, col=source,
        linetype=source))+geom_line()+scale_y_continuous(trans="log")+labs(y="streamflow
        mm/day")
```




```
# look at it another way with 1:1 line
ggplot(sager, aes(obs, model))+geom_point()+geom_abline(intercept=0, slope=1, col="red")
```


model
obs
0
5
10
15
20
0
5
10
15

# Measure Performance using different metrics

Once you’ve plotted, consider some metrics that summarize performance

Think about what part of the time-series is of interest

- long term means
- year to year variablity
- peak or minimum events

Create performance metrics that are relevant to the model application

# Lets start though with some simple metrics

### Root Mean Squared Error (RMSE)

- average deviations between observed and model
- squared so that over and under estimates doen't cancel each other

### Bias (Percent Error)

- unlike RMSE not squared - tell you if you generally are over or underestimating

### Nah Sutcliffe Efficiency (NSE)

- like mean squared error expect normalized by output variance
- does a better job of accounting for accuracy under different (high/low) conditions

```
source("../R/nse.R")

source("../R/relerr.R")

source("../R/cper.R")

nse
```

```
## function (m, o)
## {
##     err = m - o
##     meanobs = mean(o)
##     mse = sum(err * err)
##     ovar = sum((o - meanobs) * (o - meanobs))
##     nse = 1 - mse/ovar
```

```
##     return(nse)
## }
```

```
relerr
```

```
## function (m, o)
## {
##     err = m - o
##     meanobs = mean(o)
##     meanerr = mean(err)
##     res = meanerr/meanobs
##     return(res)
## }
```

```
cper
```

```
## function (m, o, weight.nse = 0.5, weight.relerr = 0.5)
## {
##     nse = nse(m, o)
##     mnse = max(nse, 0)
##     rel.err = relerr(m, o)
##     merr = 1 - min(1, abs(rel.err)/max(abs(rel.err)))
##     combined = weight.nse * mnse + weight.relerr * merr
##     return(combined)
## }
```

```
nse(m=sager$model, o=sager$obs)
```

```
## [1] 0.6253416
```

```
relerr(m=sager$model, o=sager$obs)*100
```

```
## [1] -18.9577
```

```
cper(m=sager$model, o=sager$obs, weight.nse=0.8)
```

```
## [1] 0.5002733
```

# Scale and subsetting

Performance also depends on the time scale and period that you are evaluating

- time steps (annual, daily, monthly)
- selection of particular periods of time e.g just August flows
- the same *metric* eg. correlation coefficient or NSE will look different applied to annual versus daily values,
- what matters depends on application (e.g for fish habitat maybe summer, for flood maybe winter peaks?)

```
# try a different time step
sager_wy = sager %>% group_by(wy) %>% summarize(model=sum(model), obs=sum(obs))

nse(sager_wy$model, sager_wy$obs)
```

```
## [1] 0.7702007
```

```
cper(m=sager_wy$model, o=sager_wy$obs, weight.nse=0.8)
```

```
## [1] 0.6161606
```

```
# just look at august flow
# first sum by month
tmp = sager %>% group_by(wy, month) %>% summarize(model=sum(model), obs=sum(obs))
```

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

```
# now extract august
sager_aug = subset(tmp, month==8)
cor(sager_aug$model, sager_aug$obs)
```

```
## [1] 0.8248351
```

# Exercise on your own

- Read in the *sager.txt* data
- Think of a new metric that might be interesting from a particular environmental context
- Code that metric as a function - and then apply it
- To help us use this metric later for multiple model outputs structure your function so that model and observed inputs are separate

*For example*

mymetric = function(model, obs, …other inputs) {…

NOT

mymetric = function(combinedataframe) {…

# Using multiple metrics.

- depends on what you want the model to get right
- type of data that you have for evaluation (its resolution and accuracy)

```
# turn your evaluation metric into a function
source("../R/compute_lowflowmetrics.R")
compute_lowflowmetrics
```

```
## function (m, o, month, day, year, wy, low_flow_months = 8)
## {
##     flow = cbind.data.frame(m, o, month, day, year, wy)
##     tmp = flow %>% group_by(wy) %>% summarize(mino = min(o),
##         minm = min(m))
##     annual_min_err = mean(tmp$minm - tmp$mino)
##     annual_min_cor = cor(tmp$minm, tmp$mino)
##     tmp = flow %>% group_by(month, year) %>% summarize(model =
sum(m),
##         obs = sum(o))
##     low = subset(tmp, month %in% low_flow_months)
##     low_month_err = mean(low$model - low$obs)
##     low_month_cor = cor(low$model, low$obs)
##     return(list(annual_min_err = annual_min_err, annual_min_cor =
annual_min_cor,
##         low_month_err = low_month_err, low_month_cor =
low_month_cor))
## }
```

```
compute_lowflowmetrics(m=sager$model,o=sager$obs, month=sager$month, day=sager$day,
        year=sager$year, wy=sager$wy)
```

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

```
## $annual_min_err
## [1] -0.03759139
##
## $annual_min_cor
## [1] 0.8101656
##
## $low_month_err
## [1] 3.320798
##
```

```
## $low_month_cor
## [1] 0.8248351
```

```
# use different low flow months
compute_lowflowmetrics(m=sager$model,o=sager$obs, month=sager$month, day=sager$day,
        year=sager$year, wy=sager$wy, low_flow_months = c(7:9))
```

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

```
## $annual_min_err
## [1] -0.03759139
##
## $annual_min_cor
## [1] 0.8101656
##
## $low_month_err
## [1] 2.005931
##
## $low_month_cor
## [1] 0.8884455
```

# Combining multiple metrics into a single value

- if you want a quantitative comparison between multiple models
- useful for calibration
- *IF* all the metrics are on the same scale, for example between 0 and 1 where 1 is perfect performance and 0 is the worst you can simply add or multiply metrics together
- you can transform metrics to put them on the same scale

# Example of a transformation of a metric to get on the same "scale"

**This is a bit tricky, try to go through but not essential for homework**

- Imagine we want a combined metric that uses the corelation coeffcient and a relative error (model-obs)/obs
- Relative Error can't be combined with a correlation coefficient because they are on different scale
- Correlation coefficient (0 to 1) increase with performance
- Relative Error larger values are worse perforance

# *Transform* our relative error metric

1. Create a new metric,

- transform to 0-1 scale;
- flip so that good values are higher values

To transform to a 0-1 scale, choose a maximum possible error as the "worst" value and then normailizes by that

Lets take the absolute value (so everything is positive)

$$\mathrm{relErr}_{\mathrm{normalized}} = \frac{\mathrm{abs}(\mathrm{relErr})}{\mathrm{abs}(\mathrm{relErr}_{\mathrm{max}})}$$

The maximum error $\mathrm{relerr}_{\mathrm{max}}$ is a user defined value above which you don't care how much worse the performance is For example if error is more than 50% of maximum observed streamflow, you might consider that unacceptibly bad, or perhaps beyond 50% of *mean* observed streamflow is too poor to be meaningful if you are using your model to estimate how climate is influencing streamflow

- now flip so that worse values are lower values; I'm also making sure values don't go below 0 (below 0 doesn't matter its already *bad*)

$$\mathrm{relErr}_{\mathrm{transformed}} = 1.0 - \min(1.0, \frac{\mathrm{abs}(\mathrm{relErr})}{\mathrm{abs}(\mathrm{relErr}_{\mathrm{max}})})$$

```
perf = compute_lowflowmetrics(m=sager$model,o=sager$obs, month=sager$month, day=sager$day,
        year=sager$year, wy=sager$wy, low_flow_months = c(7:9))
```

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

```
perf = as.data.frame((perf))

# remember you want error to be low but correlation to be high
# so we need to transform in some way

# normalize by max error = if error is greater than this we don't care
# can try many ideas -  maybe 50% of mean daily summer observed low flow
tmp = sager %>% subset(month %in% c(7:9))
errmax = mean(tmp$obs)*0.5
errmax
```

```
## [1] 0.2255891
```

```
perf = perf %>% mutate(annual_min_err_trans = max(0,(1-abs(annual_min_err/errmax) )))

# for monthly we can do a similar thing to find maximum allowable error
tmp = sager %>% subset(month %in% c(7:9)) %>% group_by(wy, month) %>% summarize(obs=sum(obs))
```

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

```
errmax = mean(tmp$obs)*0.5

perf = perf %>% mutate(low_month_err_trans = max(0,(1-abs(low_month_err/errmax) )))

# now we have 4 measures that we can combine together

perf = perf %>% mutate(combined = (annual_min_cor + annual_min_err_trans + low_month_err_trans
        + low_month_cor)/4)
perf
```

```
##   annual_min_err annual_min_cor low_month_err low_month_cor
## 1    -0.03759139      0.8101656      2.005931     0.8884455
##   annual_min_err_trans low_month_err_trans  combined
## 1            0.8333635           0.7099185 0.8104733
```

```
# or weight differently - we know that minimum flows are hard to get so we can weight those
        differently

perf = perf %>% mutate(combined2 = 0.1*annual_min_cor + 0.1*annual_min_err_trans +
        0.4*low_month_err_trans+ 0.4*low_month_cor)


perf
```

```
##   annual_min_err annual_min_cor low_month_err low_month_cor
## 1    -0.03759139      0.8101656      2.005931     0.8884455
##   annual_min_err_trans low_month_err_trans  combined combined2
## 1            0.8333635           0.7099185 0.8104733 0.8036985
```

```
# easier to put all this in a function
source("../R/compute_lowflowmetrics_all.R")

compute_lowflowmetrics_all
```

```
## function (m, o, month, day, year, wy, low_flow_months = 8,
max_err_annual_min = NULL,
##     max_err_low_month = NULL, wts = c(0.25, 0.25, 0.25, 0.25))
## {
##     flow = cbind.data.frame(m, o, month, day, year, wy)
##     tmp = flow %>% group_by(wy) %>% dplyr::summarize(mino = min(o),
##         minm = min(m))
##     annual_min_err = mean(tmp$minm - tmp$mino)
##     annual_min_cor = cor(tmp$minm, tmp$mino)
##     if (is.null(max_err_annual_min)) {
##         max_err_annual_min = 0.5 * mean(tmp$mino)
##     }
##     tmp = flow %>% group_by(month, year) %>% dplyr::summarize(model =
sum(m),
##         obs = sum(o))
##     low = subset(tmp, month %in% low_flow_months)
##     low_month_err = mean(low$model - low$obs)
##     low_month_cor = cor(low$model, low$obs)
##     if (is.null(max_err_low_month)) {
##         max_err_low_month = 0.5 * mean(low$obs)
##     }
##     annual_min_err_trans = max(0, (1 -
abs(annual_min_err/max_err_annual_min)))
##     low_month_err_trans = max(0, (1 -
abs(low_month_err/max_err_low_month)))
##     wts = wts/sum(wts)
##     combined = wts[1] * annual_min_err_trans + wts[2] *
annual_min_cor +
##         wts[3] * low_month_cor + wts[4] * low_month_err_trans
##     return(list(annual_min_err = annual_min_err, annual_min_cor =
annual_min_cor,
##         low_month_err = low_month_err, low_month_cor = low_month_cor,
##         combined = combined))
## }
```

# Your turn! Part 1: Come up with a combined metric that you think is interesting

- if you can, try to include at least one "sub" metric that needs to be transformed (for example, the `annual_min_err_trans` above)

- Be creative

  - *you can subset, aggregate, focus only on particular type of years or days*
  - *think about ecological or human water uses that depend on certain flow conditions*

# Calibration

Calibration is picking parameter sets based on performance evaluation

Apply metrics over multiple outputs (generated by running across many parameters sets) - like we've done in our sensitivity analysis work

**Example** - a dataset where each column is a different model run for Sagehen Creek (using different parameters) - don't worry about the parameters for now

- sagerm.txt

**Split-sample**: split time period into * calibration time period (used to pick parameter sets) * validation time period (used to see how well chose paramter sets perform)

In many cases - you just run calibration sample first - and then only run validation for parameters that you choose

here I ran for all parameters sets for the full time period so that we can explore

We could also envision this as a 'lab' where we only had a few years of observed streamflow data for calibration and want to see going forward how much parameter selection influences results

Some code to help organize things

```
# multiple results - lets say we've run the model for multiple years,
#each column  is streamflow for a different parameter set
msage = read.table("../Data/sagerm.txt", header=T)
```

```
# keep track of number of simulations (e.g results for each parameter set)
# use as a column names
nsim = ncol(msage)
snames = sprintf("S%d",seq(from=1, to=nsim))
colnames(msage)=snames


# lets say we know the start date from our earlier output
msage$date = sager$date
msage$month = sager$month
msage$year = sager$year
msage$day = sager$day
msage$wy = sager$wy

# lets add observed
msage = left_join(msage, sager[,c("obs","date")], by=c("date"))

head(msage)
```

```
##            S1        S2         S3        S4         S5        S6
S7
## 1 0.07191767 0.3316747 0.04331200 0.1875757 0.07469700 0.2454343
0.1347037
## 2 0.06689267 0.3179167 0.04020500 0.1819137 0.06790767 0.2412470
0.1286780
## 3 0.06221900 0.3047440 0.03732067 0.1764227 0.06173567 0.2371983
0.1229220
## 4 0.05787167 0.2921237 0.03464333 0.1710973 0.05612433 0.2332663
0.1174237
## 5 0.05382833 0.2800427 0.03215800 0.1659330 0.05102333 0.2294617
0.1121710
## 6 0.05006733 0.2684613 0.02985100 0.1609243 0.04638600 0.2257630
0.1071530
##             S8        S9         S10       S11       S12        S13
S14
## 1 0.0003533333 0.2383413 0.003331333 0.2431933 0.3644930 0.05328633
0.005250000
## 2 0.0003400000 0.2321840 0.003039333 0.2355610 0.3583200 0.05014967
0.004755333
## 3 0.0003273333 0.2261857 0.002773000 0.2281683 0.3522187 0.04719767
0.004307333
## 4 0.0003150000 0.2203423 0.002530000 0.2210077 0.3463190 0.04441933
0.003901333
## 5 0.0003033333 0.2146500 0.002308333 0.2140717 0.3404873 0.04180433
0.003533667
## 6 0.0002920000 0.2091047 0.002106333 0.2073533 0.3347960 0.03934333
0.003200667
##          S15         S16       S17        S18        S19       S20
S21
## 1 0.5948570 0.012760333 0.2362903 0.01888033 0.12594367 0.4374097
0.2176843
## 2 0.5860857 0.011643667 0.2341553 0.01800533 0.11671333 0.4312180
0.2053780
## 3 0.5774453 0.010624667 0.2320393 0.01717100 0.10815933 0.4251140
```

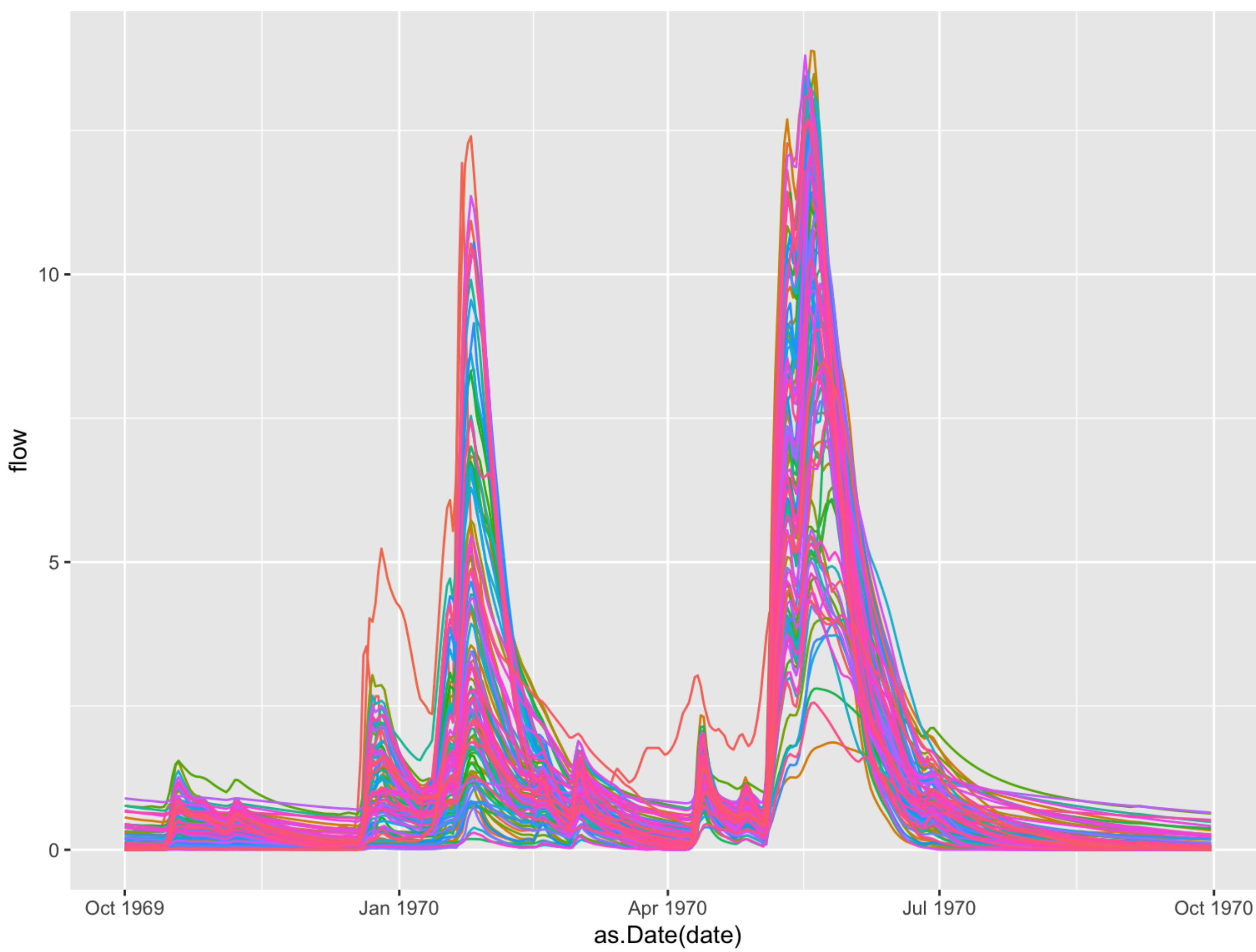
```
0.1937673
## 4 0.5689357 0.009695000 0.2299423 0.01637500 0.10023233 0.4190963
0.1828130
## 5 0.5605520 0.008846667 0.2278643 0.01561600 0.09288633 0.4131640
0.1724780
## 6 0.5522937 0.008072333 0.2258053 0.01489200 0.08607867 0.4073157
0.1627270
##          S22         S23        S24         S25         S26         S27
S28
## 1 0.03378267 0.06285833 0.1675450 0.01840800 0.07664567 0.08750367
0.06550033
## 2 0.03198167 0.05886167 0.1607863 0.01818167 0.07178267 0.07925833
0.06094633
## 3 0.03027667 0.05511900 0.1543007 0.01795833 0.06722800 0.07178967
0.05670900
## 4 0.02866267 0.05161433 0.1480763 0.01773767 0.06296233 0.06502500
0.05276633
## 5 0.02713500 0.04833233 0.1421033 0.01752000 0.05896733 0.05889767
0.04909767
## 6 0.02568833 0.04525933 0.1363710 0.01730467 0.05522600 0.05334767
0.04568400
##         S29       S30       S31       S32       S33       S34
S35
## 1 0.4238063 0.1451923 0.2529733 0.5392687 0.2826070 0.3202217
0.09478400
## 2 0.4133587 0.1420453 0.2425717 0.5297423 0.2725720 0.3132013
0.08795600
## 3 0.4032640 0.1389667 0.2325977 0.5207750 0.2628933 0.3063350
0.08161967
## 4 0.3935287 0.1359547 0.2230337 0.5123903 0.2535583 0.2996190
0.07573967
## 5 0.3841480 0.1330080 0.2138630 0.5044643 0.2445547 0.2930503
0.07028333
## 6 0.3751000 0.1301250 0.2050693 0.4969153 0.2358707 0.2866257
0.06522000
##          S36         S37         S38         S39      S40       S41
S42
## 1 0.06635500 0.11842967 0.06669433 0.04664267 0.300477 0.2028417
0.012289333
## 2 0.06367833 0.11037967 0.06533933 0.04223633 0.294672 0.1982920
0.011173667
## 3 0.06110933 0.10287700 0.06401167 0.03824633 0.289076 0.1938443
0.010159667
## 4 0.05864433 0.09588400 0.06271100 0.03463333 0.283719 0.1894963
0.009237667
## 5 0.05627867 0.08936667 0.06143667 0.03136167 0.278557 0.1852460
0.008399333
## 6 0.05400833 0.08329200 0.06018833 0.02839900 0.273602 0.1810907
0.007637000
##          S43         S44        S45        S46        S47        S48
S49
## 1 0.06128400 0.02764267 0.1804390 0.2829493 0.1520090 0.2241143
0.7156417
## 2 0.06053600 0.02508200 0.1691530 0.2743833 0.1437337 0.2130743
0.7082513
## 3 0.05979700 0.02275867 0.1585730 0.2660767 0.1359090 0.2025780
```

```
0.7009373
## 4 0.05906700 0.02065067 0.1486547 0.2580213 0.1285100 0.1925987
0.6936990
## 5 0.05834567 0.01873767 0.1393567 0.2502097 0.1215140 0.1831110
0.6865357
## 6 0.05763333 0.01700167 0.1306403 0.2426347 0.1148987 0.1740907
0.6794463
##         S50       S51        S52        S53        S54        S55
S56
## 1 0.2459190 0.2593303 0.04046233 0.10185033 0.06195833 0.10997067
0.009269667
## 2 0.2405390 0.2468773 0.03690200 0.09695700 0.05648833 0.10079000
0.008794000
## 3 0.2352767 0.2350223 0.03365500 0.09229867 0.05150133 0.09237700
0.008343000
## 4 0.2301293 0.2237367 0.03069367 0.08786433 0.04695433 0.08466767
0.007915000
## 5 0.2250950 0.2129927 0.02799267 0.08364300 0.04280867 0.07760267
0.007509000
## 6 0.2201707 0.2027647 0.02552933 0.07962467 0.03902933 0.07112800
0.007123667
##          S57        S58       S59        S60       S61        S62
S63
## 1 0.08622433 0.10054867 0.2285157 0.08376633 0.5664663 0.10368200
0.06505233
## 2 0.07895133 0.09925867 0.2167053 0.07812267 0.5552560 0.09547367
0.06421500
## 3 0.07229167 0.09798533 0.2055057 0.07285900 0.5442673 0.08791533
0.06338833
## 4 0.06619400 0.09672833 0.1948847 0.06795000 0.5334960 0.08095500
0.06257267
## 5 0.06061067 0.09548733 0.1848123 0.06337167 0.5229380 0.07454600
0.06176733
## 6 0.05549833 0.09426233 0.1752607 0.05910200 0.5125890 0.06864433
0.06097233
##          S64       S65        S66       S67       S68        S69
S70
## 1 0.03208967 0.1484727 0.02082133 0.1788070 0.2103860 0.05299600
0.08575100
## 2 0.02934900 0.1428527 0.01943867 0.1768543 0.2058670 0.05246267
0.08295733
## 3 0.02684233 0.1374453 0.01814767 0.1749230 0.2015403 0.05194533
0.08025467
## 4 0.02454967 0.1322427 0.01694233 0.1730127 0.1974167 0.05144067
0.07764000
## 5 0.02245300 0.1272373 0.01581733 0.1711233 0.1934500 0.05095233
0.07511067
## 6 0.02053500 0.1224213 0.01476667 0.1692543 0.1896473 0.05047133
0.07266367
##          S71          S72       S73        S74       S75       S76
S77
## 1 0.08208500 0.0007126667 0.3321513 0.08189933 0.3378253 0.1432480
0.7430853
## 2 0.07795867 0.0006753333 0.3250353 0.07565067 0.3255447 0.1332823
0.7382633
## 3 0.07404000 0.0006400000 0.3180720 0.06987867 0.3137103 0.1240100
```

```
0.7334727
## 4 0.07031800 0.0006063333 0.3112577 0.06454733 0.3023063 0.1153827
0.7287130
## 5 0.06678333 0.0005746667 0.3045897 0.05962267 0.2913170 0.1073557
0.7239843
## 6 0.06342633 0.0005446667 0.2980643 0.05507367 0.2807270 0.0998870
0.7192863
##         S78       S79        S80       S81       S82        S83
S84
## 1 0.1609307 0.1326143 0.08507667 0.5321190 0.6998950 0.06295467
0.4064717
## 2 0.1496117 0.1302127 0.07844300 0.5224367 0.6909930 0.05740367
0.4009937
## 3 0.1390887 0.1278543 0.07232633 0.5129303 0.6822040 0.05234233
0.3955893
## 4 0.1293057 0.1255390 0.06668667 0.5035970 0.6735270 0.04772733
0.3902580
## 5 0.1202110 0.1232657 0.06148667 0.4944333 0.6649603 0.04351900
0.3849987
## 6 0.1117560 0.1210333 0.05669233 0.4854367 0.6565027 0.03968167
0.3798100
##         S85         S86       S87        S88       S89       S90
S91
## 1 0.1612057 0.011333000 0.5693913 0.10873833 0.3803070 0.5337300
0.1945403
## 2 0.1501753 0.010880000 0.5595980 0.10389400 0.3671423 0.5310793
0.1823263
## 3 0.1398997 0.010444667 0.5499730 0.09926567 0.3544333 0.5284417
0.1708793
## 4 0.1303273 0.010027000 0.5405137 0.09484367 0.3421643 0.5258170
0.1601510
## 5 0.1214097 0.009626000 0.5312170 0.09061867 0.3303200 0.5232057
0.1500963
## 6 0.1131023 0.009241333 0.5220803 0.08658167 0.3188857 0.5206070
0.1406727
##          S92       S93       S94       S95        S96       S97
S98
## 1 0.02710667 0.1718877 0.2836493 0.1334437 0.07881167 0.2935460
0.2200570
## 2 0.02649667 0.1624967 0.2761773 0.1266033 0.07252633 0.2823550
0.2093427
## 3 0.02590033 0.1536187 0.2689023 0.1201153 0.06674233 0.2715907
0.1991500
## 4 0.02531767 0.1452257 0.2618187 0.1139563 0.06141933 0.2612367
0.1894533
## 5 0.02474800 0.1372913 0.2549220 0.1081093 0.05652100 0.2512777
0.1802290
## 6 0.02419133 0.1297903 0.2482067 0.1025590 0.05201333 0.2416983
0.1714537
##           S99       S100       S101       date month year day   wy
obs
## 1 0.011247667 0.07537933 0.04625600 1965-10-01    10 1965   1 1966
0.3358678
## 2 0.010750333 0.07278433 0.04515367 1965-10-02    10 1965   2 1966
0.3208737
## 3 0.010282667 0.07027900 0.04407767 1965-10-03    10 1965   3 1966
```

```
0.3058796
## 4 0.009823000 0.06785967 0.04302733 1965-10-04    10 1965   4 1966
0.2968832
## 5 0.009406333 0.06552400 0.04200200 1965-10-05    10 1965   5 1966
0.2968832
## 6 0.008985333 0.06326867 0.04100100 1965-10-06    10 1965   6 1966
0.2968832
```

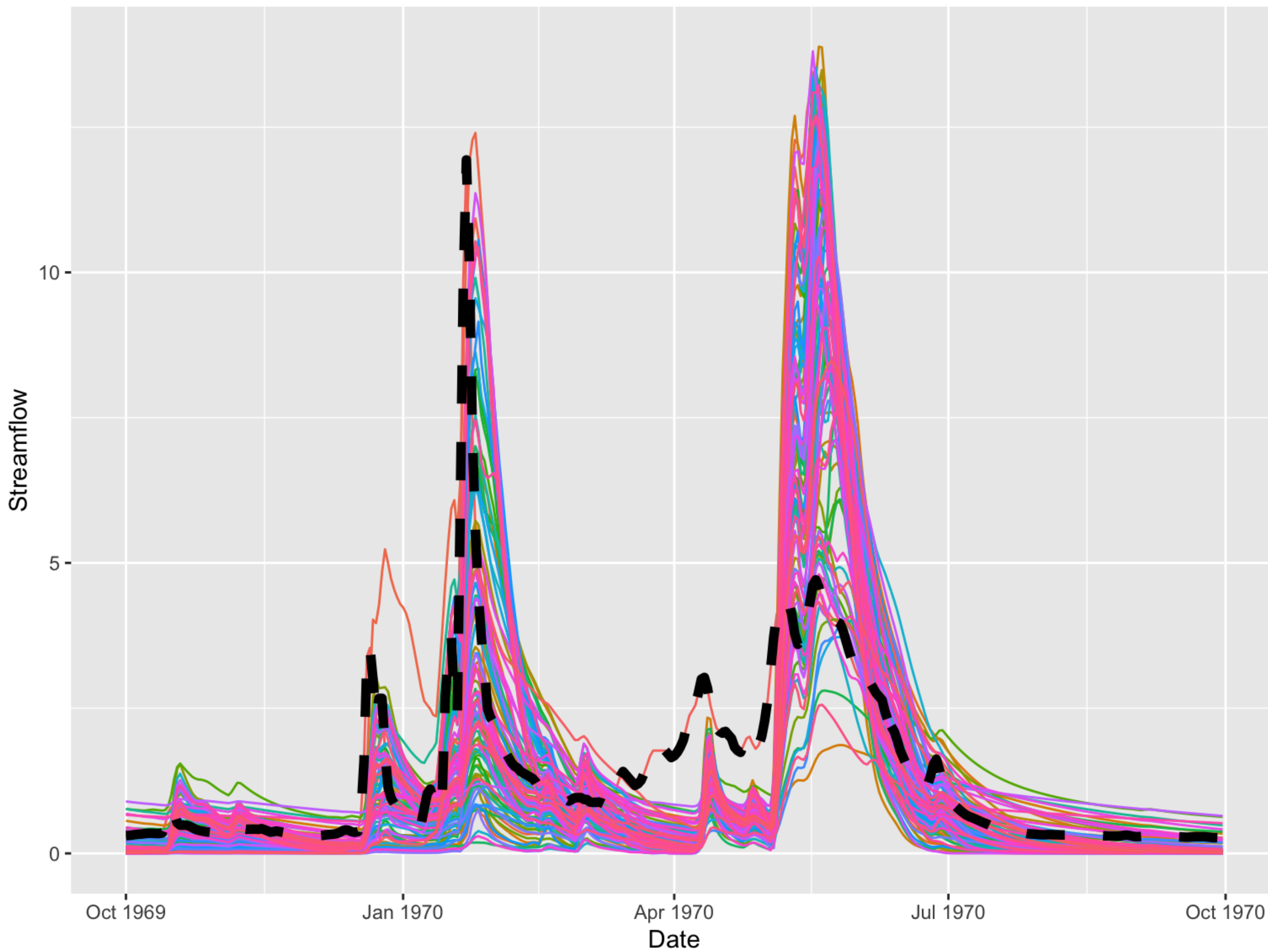
```
# how can we plot all results - lets plot water year 1970 otherwise its hard to see
msagel = msage %>% pivot_longer(cols=!c(date, month, year, day,wy), names_to="run",
        values_to="flow")

p1=ggplot(subset(msagel, wy == 1970), aes(as.Date(date), flow,
        col=run))+geom_line()+theme(legend.position = "none")
p1
```




```
# lets add observed streamflow
p1+geom_line(data=subset(sager, wy == 1970), aes(as.Date(date), obs), size=2, col="black",
        linetype=2)+labs(y="Streamflow", x="Date")
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2
3.4.0.
```

```
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning
was
## generated.
```




```
# subset for split sample calibration
short_msage = subset(msage, wy < 1975)

# compute performance measures for output from all parameters
res = short_msage %>% select(!c("date","month","year","day","wy","obs")) %>%
      map_dbl(nse, short_msage$obs)
# purrr function here! map_dbl will apply the function nse() to each column in our data frame
        against the observed and returns a vector

head(res)
```

```
##         S1         S2         S3         S4         S5         S6
## -0.4724480  0.5330579  0.3692951  0.2700532  0.3606149  0.4573876
```

```
# another example using our low flow statistics
# use apply to compute for all the data
source("../R/compute_lowflowmetrics_all.R")
res = short_msage %>% select(-date, -month, -day, -year, -wy, -obs ) %>%
  map_df(compute_lowflowmetrics_all, o=short_msage$obs, month=short_msage$month,
        day=short_msage$day, year=short_msage$year, wy=short_msage$wy)
```

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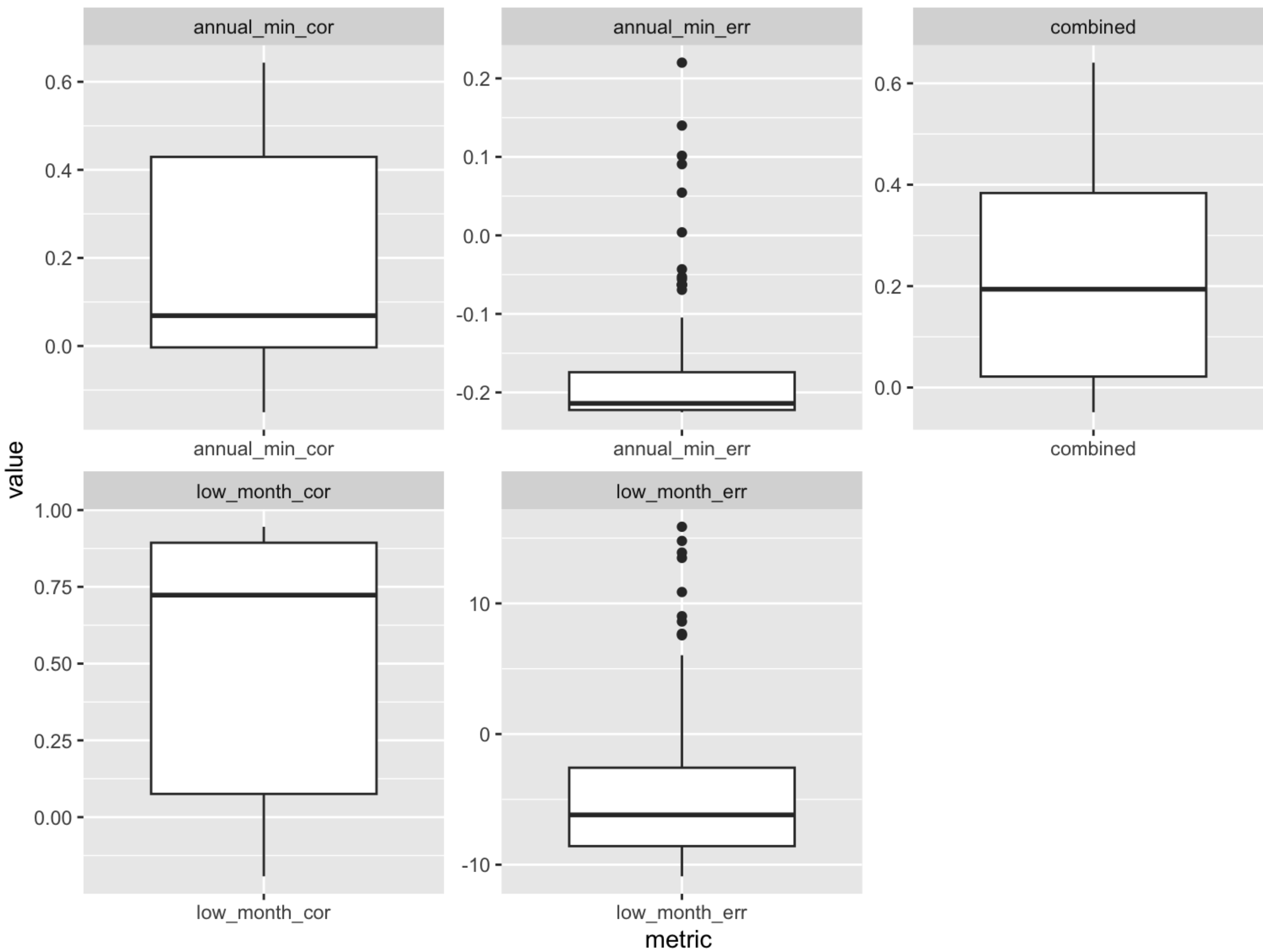
```
# note here we use map_df to get a dataframe back


# interesting to look at range of metrics - could use this to decide on
# acceptable values
summary(res)
```

```
##  annual_min_err    annual_min_cor      low_month_err
low_month_cor
##  Min.   :-0.2252   Min.   :-0.150353   Min.   :-10.890   Min.
:-0.19268
##  1st Qu.:-0.2223   1st Qu.:-0.003188   1st Qu.: -8.579   1st Qu.:
0.07569
##  Median :-0.2140   Median : 0.068846   Median : -6.188   Median :
0.72298
##  Mean   :-0.1756   Mean   : 0.176563   Mean   : -4.368   Mean   :
0.52731
##  3rd Qu.:-0.1743   3rd Qu.: 0.429427   3rd Qu.: -2.576   3rd Qu.:
0.89349
##  Max.   : 0.2200   Max.   : 0.643432   Max.   : 15.866   Max.   :
0.94551
##     combined
```

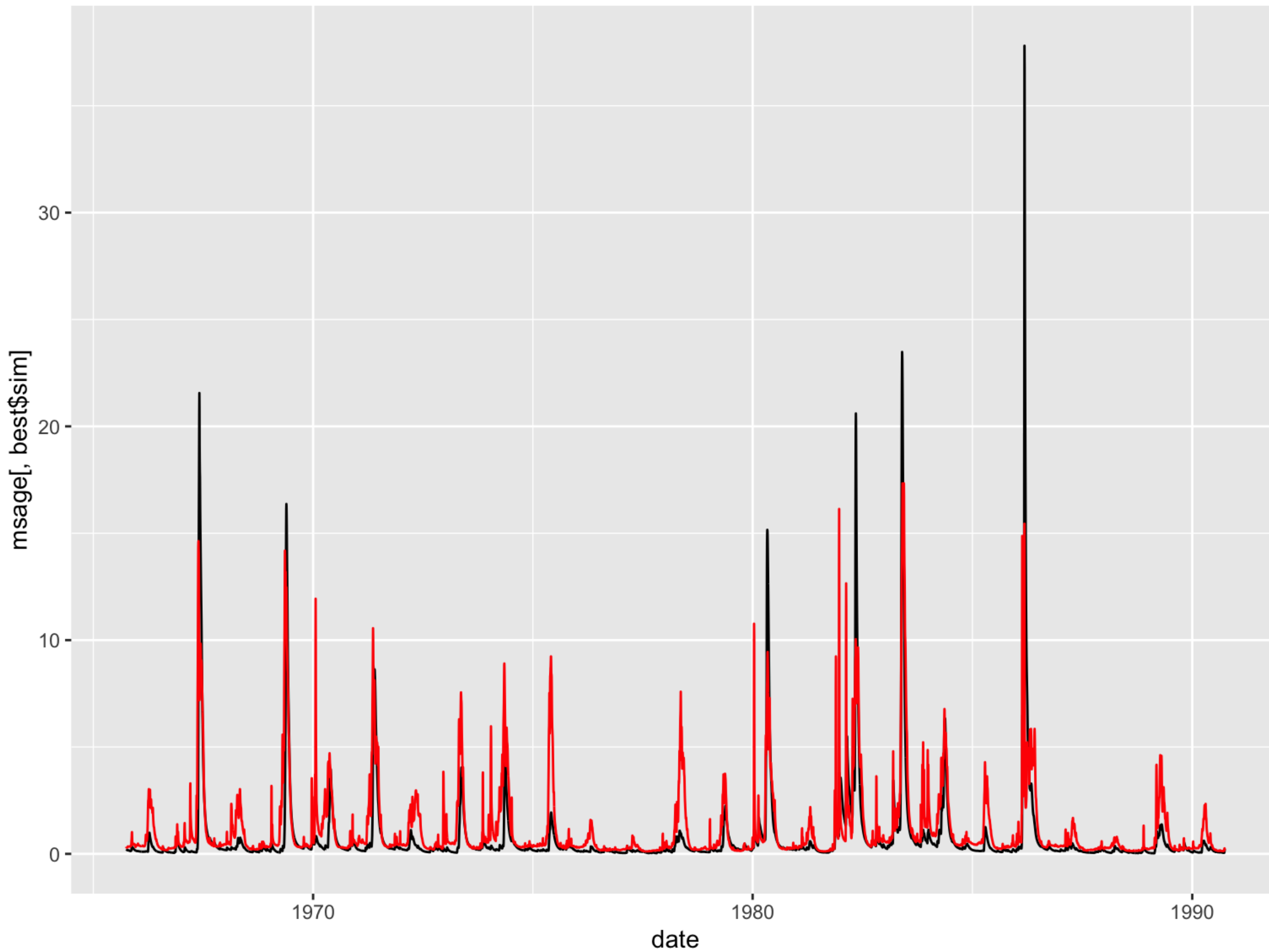
```
##  Min.   :-0.04867
##  1st Qu.: 0.02162
##  Median : 0.19392
##  Mean   : 0.22239
##  3rd Qu.: 0.38361
##  Max.   : 0.64072
```

```
# we can add a row that links with simulation number
res$sim = snames

# graph range of performance measures
resl = res %>% pivot_longer(-sim, names_to="metric", values_to="value")

ggplot(resl, aes(metric, value))+geom_boxplot()+facet_wrap(~metric, scales="free")
```




```
# select the best one based on the combined metric
best = res[which.max(res$combined),]

# running the model forward
# so we can look at the full time series
```

```
# lets start with streamflow estimates from best performing parameter set
ggplot(msage, aes(date, msage[,best$sim])) + geom_line()+geom_line(aes(date, obs), col="red")
```




```
# for comparison lets consider how worst and best parameters perform for subsequent simulations
# focusing specifically on August streamflow
worst = res[which.min(res$combined),]

compruns = msage %>% select(best$sim, worst$sim, date, obs, month, day, year, wy)
compruns = subset(compruns, wy > 1970)
compruns_mwy = compruns %>% select(-c(day,date, year)) %>% group_by(month, wy) %>%
       summarize(across(everything(), mean))
```

```
## `summarise()` has grouped output by 'month'. You can override using
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```
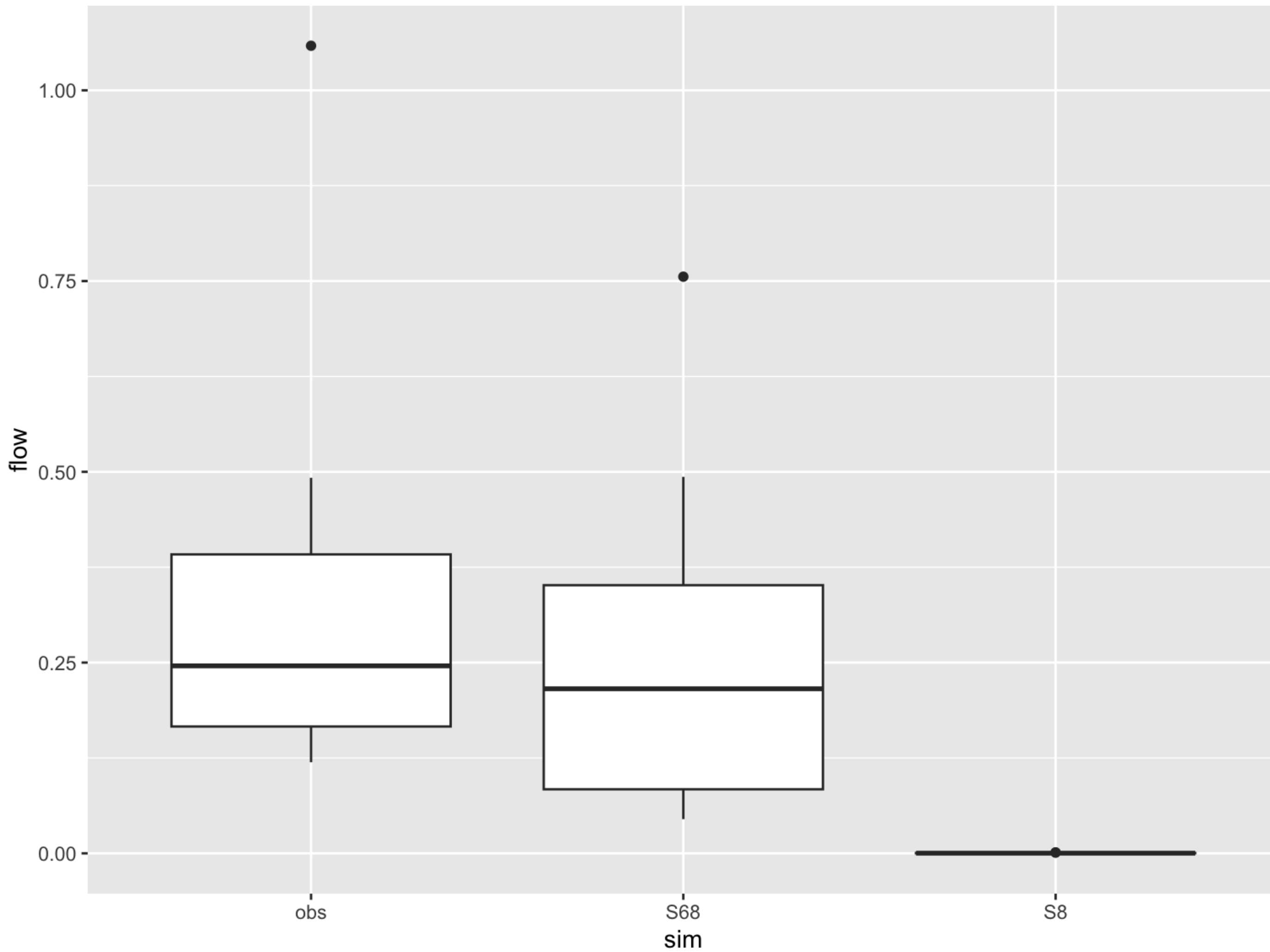

```
compruns_mwyl = compruns_mwy %>% pivot_longer(cols=!c(month,wy), names_to="sim",
       values_to="flow")
compruns_mwyl %>% subset(month==8) %>% ggplot(aes(sim,flow ))+geom_boxplot()
```


1.00
0.75
0.50
0.25
0.00
flow
obs
S68
S8
sim

# Your turn! Part 2: Using your performance metric

- Perform a split-sample calibration - you can decide what year to use for calibration (its an experiment!) on the Sagehen model output dataset that we've been working with
- Find the best and worst parameter set, and then graph something about streamflow (e.g daily, mean August, or ?) for the best parameter set
- Compute and plot how the performance of the model using the best parameter set changed in pre and post calibration periods (that you chose)

On the canvas survey - add the 'best' parameter set column number number (so we can compare how different metrics influence which parameter you pick)

To hand in - an Rmarkdown and R function. Please knit and turn in either an html or pdf of the markdown. AND submissing of best parmaeter set column number on CANVAS discussion

# Rubric 40 pts

- R function (10pts)
  - *combines at least 2 performance metrics (5)*
  - *function is applied to part of Sagehen data set (5)*
- Calibration (10pts)
  - *your function is applied to the `msage` dataset across all parameter sets (5)*
  - *your metrics are used to select the best and worst parameter set (5)*
- Graphs (10pts)
  - *1 plots of summary of performance over calibration period (5)*
  - *graphing style (axis labels, legibility) (5)*
- Discussion (10pts)
  - *short explanation of why you designed the metrics you used (5)*
  - *1 sentence on how well the model performed given you model goal*