Software quality analysis of fourteen hydrological models

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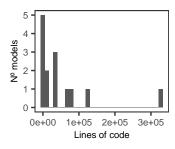
1 Preliminary functions

```
sensobol::load_packages(c("data.table", "tidyverse", "openxlsx", "scales",
                        "cowplot", "readxl", "ggrepel", "tidytext"))
# Create custom theme -----
theme_AP <- function() {</pre>
 theme_bw() +
   theme(panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         legend.background = element_rect(fill = "transparent", color = NA),
         legend.key = element_rect(fill = "transparent", color = NA),
         strip.background = element_rect(fill = "white"),
         legend.text = element_text(size = 7.3),
         axis.title = element text(size = 10),
         legend.key.width = unit(0.4, "cm"),
         legend.key.height = unit(0.4, "cm"),
         legend.key.spacing.y = unit(0, "lines"),
         legend.box.spacing = unit(0, "pt"),
         legend.title = element_text(size = 7.3),
         axis.text.x = element text(size = 7),
         axis.text.y = element_text(size = 7),
         axis.title.x = element_text(size = 7.3),
         axis.title.y = element_text(size = 7.3),
         plot.title = element_text(size = 8),
         strip.text.x = element_text(size = 7.4),
         strip.text.y = element_text(size = 7.4))
# Select color palette -----
color_languages <- c("fortran" = "steelblue", "python" = "lightgreen")</pre>
```

2 Results

2.1 Descriptive statistics

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

```
2 fortran python

2 0.2 0.4 0.6 0.2 0.4 0.6

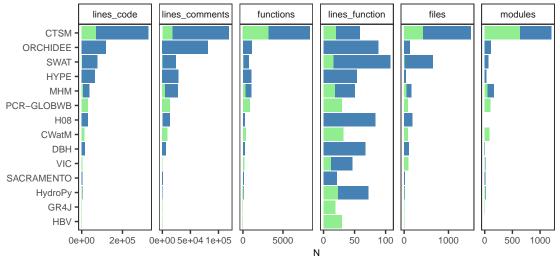
Comment density
```

```
##
           model
                     V1
##
          <char> <num>
## 1:
             \mathtt{HBV}
                   180
## 2:
            GR4J
                    423
         HydroPy
                   3739
## 3:
## 4: SACRAMENTO
                   5294
## 5:
             VIC
                   5952
             DBH 24334
## 6:
## 7:
           CWatM 27745
             H08 42917
## 8:
## 9: PCR-GLOBWB
                  52686
## 10:
             MHM
                  76286
## 11:
            HYPE 89137
## 12:
            SWAT 99976
## 13:
        ORCHIDEE 211871
## 14:
            CTSM 491592
```

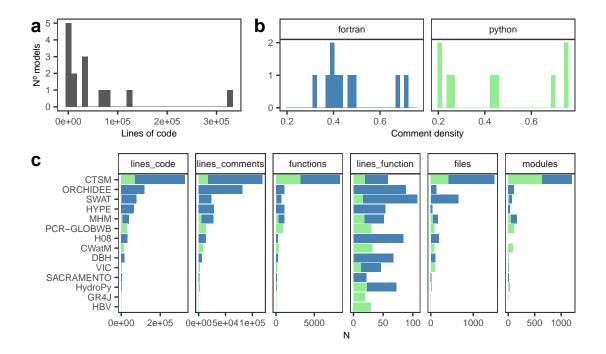
```
plot_per_model <- melt(dt$descriptive_stats, measure.vars = col_names[-c(1, length(col_names))]
.[, variable:= factor(variable, levels = facet_order)] %>%
.[, model:= factor(model, levels = model_ordered[, model])] %>%
.[!variable == "lines"] %>%
ggplot(., aes(model, value, fill = language)) +
geom_col() +
coord_flip() +
scale_y_continuous(breaks = breaks_pretty(n = 2)) +
scale_fill_manual(values = color_languages) +
facet_wrap(~ variable, ncol = 7, scales = "free_x") +
labs(x = "", y = "N") +
theme_AP() +
theme(legend.position = "none")

plot_per_model
```

Warning: Removed 3 rows containing missing values or values outside the scale range
(`geom_col()`).



р1



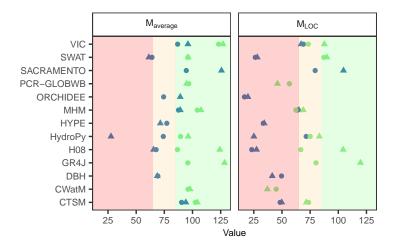
2.2 Maintainability index

```
# Define vector of interpretation -----
vec_interpretation <- c("low", "moderate", "high")</pre>
# Calculate -----
dt$maintainability_index %>%
 melt(., measure.vars = c("M loc", "M average")) %>%
 .[, interpretativity:= ifelse(value > 85, vec_interpretation[3],
                            ifelse(value <=85 & value >= 65, vec_interpretation[2],
                                  vec_interpretation[1]))] %>%
 .[, .N, .(language, interpretativity, variable)] %>%
 dcast(., variable + language ~ interpretativity, value.var = "N") %>%
 .[, total:= rowSums(.SD, na.rm = TRUE), .SDcols = vec_interpretation] %>%
 .[, paste(vec_interpretation, "prop", sep = "_"):= lapply(.SD, function(x)
   x / total), .SDcols = vec_interpretation] %>%
 print()
## Key: <variable, language>
##
      variable language high
                             low moderate total low_prop moderate_prop
##
        <fctr>
               <char> <int> <int>
                                   <int> <num>
                                                 <num>
                                                              <num>
## 1:
        M loc fortran
                         1
                                       5
                                           20 0.7000000
                                                          0.2500000
## 2:
        M_{loc}
              python
                         5
                              5
                                      8
                                           18 0.2777778
                                                          0.444444
                      9 3
## 3: M_average fortran
                                     8
                                           20 0.1500000
                                                          0.400000
## 4: M_average python
                        18
                              NA
                                    NA
                                         18
                                                    NA
                                                                 NA
```

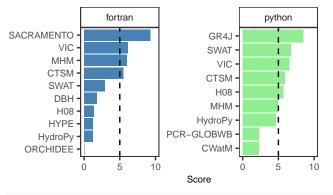
```
## high_prop
## <num>
## 1: 0.0500000
## 2: 0.2777778
## 3: 0.4500000
## 4: 1.0000000
```

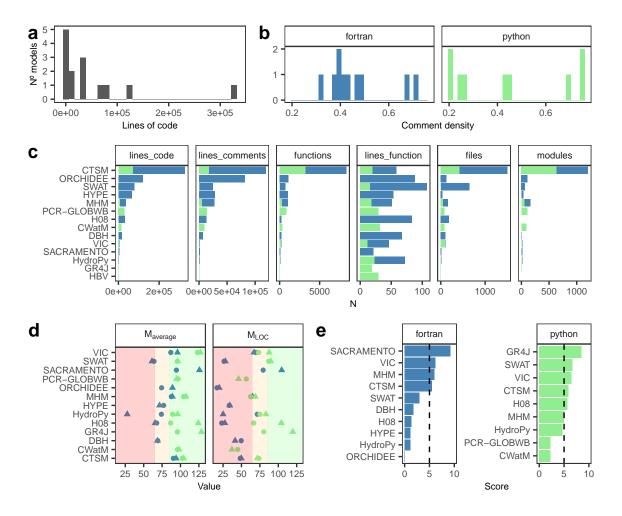
By combining the classic and extended versions of the maintainability index, our analysis reveals differences between Fortran and Python implementations. Using the weighted measure $(M_{\rm LOC})$, 70% of Fortran code falls into the "low" maintainability category, compared with only 15% when using the unweighted average $(M_{\rm average})$. This discrepancy indicates that a few complex, poorly maintainable routines dominate the overall profile of the Fortran codebase. In contrast, Python routines present a more favorable profile: 27% achieve high maintainability under $M_{\rm LOC}$, and all are classified as "highly maintainable" under $M_{\rm average}$.

```
plot_maintainability_index <- dt$maintainability_index %>%
 melt(., measure.vars = c("M_loc", "M_average")) %>%
 .[, variable:= factor(variable, levels = c("M_average", "M_loc"))] %>%
 ggplot(., aes(model, value, color = language, shape = type)) +
 geom_point() +
 annotate("rect", xmin = -Inf, xmax = Inf, ymin = -Inf, ymax = 65,
          fill = "red", alpha = 0.18) +
 annotate("rect", xmin = -Inf, xmax = Inf, ymin = 65, ymax = 85,
          fill = "orange", alpha = 0.1) +
 annotate("rect", xmin = -Inf, xmax = Inf, ymin = 85, ymax = Inf,
          fill = "green", alpha = 0.1) +
 facet_wrap(~variable, labeller = as_labeller(c(M_loc = "M[LOC]",
                                           M_average = "M[average]"),
                                         default = label parsed)) +
 labs(x = "", y = "Value") +
 scale_color_manual(values = color_languages, guide = "none") +
 theme_AP() +
 theme(legend.position = "none") +
 coord_flip()
plot_maintainability_index
```



2.3 Score



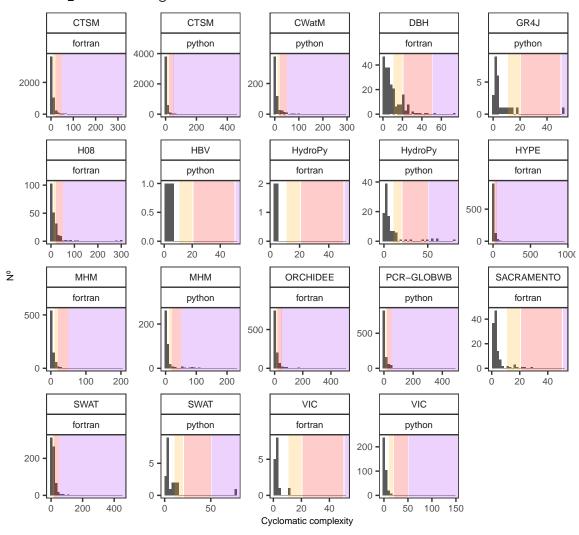


2.4 Metrics at the function level

```
basename(func_metric_files)))
# Create function to combine files -----
make combined <- function(subset list, pattern) {</pre>
 rbindlist(subset_list[grep(pattern, names(subset_list))], idcol = "source_file")
}
# Combine files ------
metrics_combined <- list(file_fortran = make_combined(list_metrics$file_metrics, "fortran"),</pre>
                       file_python = make_combined(list_metrics$file_metrics, "python"),
                       func_fortran = make_combined(list_metrics$func_metrics, "fortran"),
                       func_python = make_combined(list_metrics$func_metrics, "python"))
# Functions to extract name of model and language from file ------
extract_model <- function(x)</pre>
  sub("^(file|func)_metrics_\\d+_([A-Za-z0-9-]+)_(fortran|python).*", "\\2", x)
extract_lang <- function(x)</pre>
  sub("^(file|func)_metrics_{d+_([A-Za-z0-9-]+)_(fortran|python).*", "\\3", x)
# Extract name of model and language -----
metrics_combined <- lapply(metrics_combined, function(dt) {</pre>
 dt[, source_file:= sub("\\.csv$", "", basename(source_file))]
 dt[, model:= extract_model(source_file)]
 dt[, language:= extract_lang(source_file)]
 dt
})
# Add column of complexity category -----
metrics_combined <- lapply(names(metrics_combined), function(nm) {</pre>
 dt <- as.data.table(metrics_combined[[nm]])</pre>
  if (grepl("^func_", nm) && "cyclomatic_complexity" %in% names(dt)) {
   dt[, complexity_category := cut(
     cyclomatic_complexity,
     breaks = c(-Inf, 10, 20, 50, Inf),
     labels = c("b1","b2","b3","b4")
   )]
 }
  dt
}) |> setNames(names(metrics_combined))
# Define labels -----
```

```
lab_expr <- c(</pre>
 b1 = expression(C %in% "(" * 0 * ", 10" * "]"),
 b2 = expression(C \%in\% "(" * 10 * ", 20" * "]"),
 b3 = expression(C %in% "(" * 20 * ", 50" * "]"),
 b4 = expression(C %in% "(" * 50 * ", " * infinity * ")")
# set output folder inside "datasets" -----
outdir <- file.path("datasets", "merged_results")</pre>
# write each slot to its own CSV ------
lapply(names(metrics_combined), function(nm) {
 out_file <- file.path(outdir, paste0(nm, ".csv"))</pre>
 fwrite(metrics_combined[[nm]], out_file)
})
## [[1]]
## NULL
##
## [[2]]
## NULL
##
## [[3]]
## NULL
##
## [[4]]
## NULL
# Cyclomatic complexity at the model level ------
metrics_combined[grep("^func_", names(metrics_combined))] %>%
 lapply(., function(x) x[, .(cyclomatic_complexity, model, language)]) %>%
 rbindlist() %>%
 ggplot(., aes(cyclomatic_complexity)) +
 geom_histogram() +
 annotate("rect",
        xmin = 11, xmax = 20,
         ymin = -Inf, ymax = Inf,
        fill = "orange", alpha = 0.2) +
 annotate("rect",
        xmin = 21, xmax = 50,
```

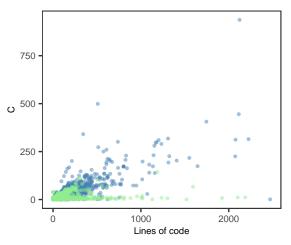
`stat_bin()` using `bins = 30`. Pick better value `binwidth`.



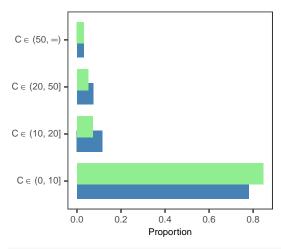
```
# Scatterplot cyclomatic vs lines of code ------
plot_c_vs_loc <- metrics_combined[grep("^func_", names(metrics_combined))] %>%
    lapply(., function(x) x[, .(loc, cyclomatic_complexity, language)]) %>%
    rbindlist() %>%
```

```
ggplot(., aes(loc, cyclomatic_complexity, color = language)) +
geom_point(alpha = 0.5, size = 0.7) +
scale_x_continuous(breaks = breaks_pretty(n = 3)) +
labs(x = "Lines of code", y = "C") +
scale_color_manual(values = color_languages) +
theme_AP() +
theme(legend.position = "none")
```

Warning: Removed 1195 rows containing missing values or values outside the scale range
(`geom_point()`).



```
# Count & proportion -
plot_bar_cyclomatic <- metrics_combined[grep("^func_", names(metrics_combined))] %>%
  lapply(., function(x) x[, .(complexity_category, language)]) %>%
 rbindlist() %>%
  .[, .N, .(complexity_category, language)] %>%
  .[, proportion := N / sum(N), language] %>%
  ggplot(., aes(complexity_category, proportion, fill = language)) +
  geom_bar(stat = "identity", position = position_dodge(0.6)) +
  scale_fill_manual(values = color_languages) +
  scale_y_continuous(breaks = scales::breaks_pretty(n = 4)) +
  scale_x_discrete(labels = lab_expr) +
 labs(x = "", y = "Proportion") +
  coord flip() +
 theme AP() +
  theme(legend.position = "none")
plot_bar_cyclomatic
```



Warning: Removed 1195 rows containing missing values or values outside the scale range
(`geom_point()`).

