

The topology of software risk in scientific models

3. Global hydrological and land use models

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1 Preliminary

```
# PRELIMINARY FUNCTIONS #####
#####

sensobol::load_packages(c("data.table", "tidyverse", "openxlsx", "scales",
                          "cowplot", "readxl", "ggrepel", "tidytext", "here",
                          "tidygraph", "igraph", "foreach", "parallel", "ggraph",
                          "tools", "purrr", "sensobol", "benchmarkme"))

# Create custom theme -----

theme_AP <- function() {
  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")

# Source all .R files in the "functions" folder -----

r_functions <- list.files(path = here("functions"),
                          pattern = "\\..R$", full.names = TRUE)

lapply(r_functions, source)

# Set seed -----
```

```
seed <- 123
```

2 Analysis

```
# CREATE DATASET #####

# Path to folder -----

path <- "./datasets/call_metrics"

# List CSV files -----

files <- list.files(path, pattern = "\\*.csv$", full.names = TRUE)

# Split by language -----

python_files <- grep("python", files, value = TRUE, ignore.case = TRUE)
fortran_files <- grep("fortran", files, value = TRUE, ignore.case = TRUE)

base_fortran <- file_path_sans_ext(basename(fortran_files))
base_python <- file_path_sans_ext(basename(python_files))

model_names_fortran <- models <- sub(".*_", "", base_fortran)
model_names_python <- models <- sub(".*_", "", base_python)

# Load and name files -----

python_list <- lapply(python_files, fread)
fortran_list <- lapply(fortran_files, fread)

names(python_list) <- model_names_python
names(fortran_list) <- model_names_fortran

# RBIND -----

make_callgraph <- function(lst, lang) {
  rbindlist(lst, idcol = "model") %>%
    .[, language := lang] %>%
    .[, .(file, model, language, `function`, call)] %>%
    setnames(., c("function", "call"), c("from", "to"))
}

python_callgraphs <- make_callgraph(python_list, "python")
fortran_callgraphs <- make_callgraph(fortran_list, "fortran")

all_callgraphs <- rbind(python_callgraphs, fortran_callgraphs)

# SOURCE CODE CLASSIFICATION BY FUNCTIONAL ROLE #####
```

```

# Strip leading "./models/" -----
all_callgraphs[, file_clean := sub("^\\.models/", "", file)]

# model_id = first part before "/" -----
all_callgraphs[, model_id := tstrsplit(file_clean, "/", fixed = TRUE, keep = 1L)]

# rest = everything after "model_id/" -----
all_callgraphs[, rest := sub("[^/]+/", "", file_clean)]

# 2) top_level directory inside each model -----
all_callgraphs[, top_level := tstrsplit(rest, "/", fixed = TRUE, keep = 1L)]

## 4) component classification (order matters)

all_callgraphs[nchar(file) == 0L | is.na(file), component := NA_character_]

all_callgraphs[!is.na(file) & nchar(file) > 0L, component := fcase(

  # 1) CI and vendored libraries -----

  top_level == ".github", "ci_cd",
  top_level == ".lib" | grepl("/\\.lib/", rest), "vendored_lib",

  # 2) CIME / CESM / CDEPS infrastructure (framework) -----

  grepl("^cime/CIME/", rest), "framework",
  grepl("^cime_config/", rest), "framework",
  grepl("^cime/doc/", rest), "framework",
  grepl("^components/cdeps/cime_config/", rest), "framework",

  # 3) Tests (incl. SystemTests, case-insensitive) -----

  grepl("SystemTests/", rest, ignore.case = TRUE), "tests",
  grepl("/tests?/|^tests?/", rest, ignore.case = TRUE), "tests",

  # 4) Couplers: NUOPC / LILAC / CESM / cpl -----

  grepl("cpl_|/cesm|/cpl_|/cpl_", rest), "coupler",

  # 5) Drivers: Fortran code clearly in drivers directories -----

  grepl("(^|/)drivers(/|$)", rest) & language == "fortran", "driver",

```

```

# 6) CLI / tools: scripts, setup, CTSM python utilities -----

grepl("tools/|scripts/|cli\\.py$|setup\\.py$", rest), "cli_or_tool",
grepl("^python/ctsm/", rest), "cli_or_tool",

# 7) Everything else: model core -----

default = "model_core"
)]

# Create column to include in risk calculations or not -----

all_callgraphs[, include_in_risk:= (language %chin% c("fortran", "python") &
                                   component %chin% c("model_core", "coupler"))]

# SUMmarize -----

all_callgraphs[, .N, component]

##      component      N
##      <char> <int>
## 1:      ci_cd       5
## 2: vendored_lib   100
## 3:  cli_or_tool  1334
## 4:   framework  2091
## 5:   model_core 19946
## 6:      tests   1851
## 7:     coupler   485

all_callgraphs[, .N, include_in_risk]

##   include_in_risk      N
##   <lgcl> <int>
## 1:      FALSE   5381
## 2:       TRUE  20431

# Remove module calls -----

all_callgraphs <- all_callgraphs[!(from %in% "<module>")] %>%
  .[include_in_risk == TRUE]

# LOAD CYCLOMATIC COMPLEXITY VALUES FOR FUNCTIONS AND SUBROUTINES #####

cc_unique <- fread("./datasets/cyclomatic_complexity_functions.csv")

# CREATE NETWORK FROM CALL GRAPHS #####

all_graphs <- all_callgraphs[, .(graph = list(as_tbl_graph(.SD, directed = TRUE))),
                             .(model, language)]

```

```

# ADD NODE METRICS #####

# Define the weights to characterize risky nodes -----

alpha <- 0.6 # Weight to cyclomatic complexity
beta  <- 0.3 # Weight to in-degree (impact of bug upstream)
gamma <- 0.1 # Weight to betweenness (critical bridge)

# Add node metrics -----

all_graphs[, graph:= Map(function(g, m, lang) {

  comp_sub <- cc_unique[model == m & language == lang]

  # mean cyclomatic complexity for this model & language -----

  mean_cyclo <- mean(comp_sub$cyclomatic_complexity, na.rm = TRUE)

  g %>%
    activate(nodes) %>%

    # Left join with dataset with cyclomatic complexity values -----

    left_join(comp_sub, by = "name") %>%

    # replace NA cyclomatic_complexity with model-language mean -----

    mutate(cyclomatic_complexity = if (!is.na(mean_cyclo)) {

      ifelse(is.na(cyclomatic_complexity), mean_cyclo, cyclomatic_complexity)

    } else {

      # if even the mean is NA (all NA in comp_sub), leave as-is

      cyclomatic_complexity
    }) %>%

    # Remove Python MODULE_AGG / CLASS_AGG nodes from this graph
    # because they are not callable -----

    filter(!(language == "python" & type %in% c("MODULE_AGG", "CLASS_AGG"))) %>%

    # Calculation of key network metrics -----

    mutate(indeg = centrality_degree(mode = "in"),

```

```

    outdeg = centrality_degree(mode = "out"),
    btw = centrality_betweenness(directed = TRUE, weights = NULL),
    cyclo_sc = rescale(cyclomatic_complexity),
    indeg_sc = rescale(indeg),
    btw_sc = rescale(btw),
    risk_score = alpha * cyclo_sc + beta * indeg_sc + gamma * btw_sc)
  },
  graph, model, language)]

# EXTRACT NODE DF #####

all_graphs[, node_df := lapply(graph, as_tibble, what = "nodes")]

# Export full node df -----

full_node_df <- all_graphs %>%
  mutate(node_df = purrr::map(node_df, ~ select(.x, -model, -language))) %>%
  unnest(node_df) %>%
  select(-graph) %>%
  data.table()

write.xlsx(full_node_df, "full_node_df.xlsx")

# COMPUTE ALL PATHS AND THEIR RISK SCORES #####

all_graphs[, paths_tbl := Map(all_paths_fun, node_df, graph)]

# Export full paths df -----

full_paths_df <- all_graphs %>%
  unnest(paths_tbl) %>%
  select(-c(graph, node_df))

write.xlsx(full_paths_df, "full_paths_df.xlsx")

# CONDUCT UNCERTAINTY AND SENSITIVITY ANALYSIS #####

# Define sample size and order of effects -----

N <- 2^11
order <- "first"

# Run the function (we remove the vic and python model implementation because
# there are not paths) -----

all_graphs[!c(model == "VIC" & language == "python"),
  uncertainty_sensitivity := Map(full_ua_sa_risk_fun, node_df, paths_tbl, N, order)]

```



```

# UNNEST APPROPRIATELY #####

unnested_df <- all_graphs %>%
  mutate(us_nodes = map(uncertainty_sensitivity, "nodes"),
         us_paths = map(uncertainty_sensitivity, "paths"))

# Create SA data frame -----

full_sa_df <- unnested_df %>%
  select(us_nodes) %>%
  unnest(cols = c(us_nodes)) %>%
  select(name, model, language, sensitivity_indices) %>%
  unnest(cols = c(sensitivity_indices))

# Export
fwrite(full_sa_df, "full_sa_df.csv")

# Create UA data frame -----

full_ua_df <- unnested_df %>%
  select(model, language, us_paths) %>%
  unnest(cols = c(us_paths)) %>%
  data.table()

# Export
fwrite(full_ua_df, "full_ua_df.csv")

# CALCULATE SOME DESCRIPTIVE METRICS #####

tmp <- data.table(full_paths_df)[, .(n_paths = .N), .(model, language)] %>%
  .[order(-n_paths)]

tmp2 <- data.table(full_node_df)[, .(n_nodes = .N), .(model, language)] %>%
  .[order(-n_nodes)]

# Path to node ratio: how interconnected the model is.
# Model_cc: Proxy for algorithmic complexity of model.
# Avg_path_length: Proxy for depth of dependency chains (risk-highway potential)
# Model fragility: more (error) propagation routes.
models_metrics <- merge(tmp, tmp2) %>%
  .[, `:=`(path_to_node_ratio = n_paths / n_nodes,
          model_cc = n_paths / log(n_nodes),
          avg_path_length = n_nodes / log(n_paths + 1),
          model_fragility_index = n_paths / (n_nodes * (n_nodes - 1)))]

models_metrics

```

```

# Read descriptive_stats_file -----

descriptive_stats <- data.table(read_xlsx("./datasets/descriptive_statistics/descriptive_statistics.xlsx"))
all_descriptive_df <- merge(models_metrics, descriptive_stats)

# Sort by model -----

model_ordered <- all_descriptive_df[, sum(lines), model] %>%
  .[order(V1)]

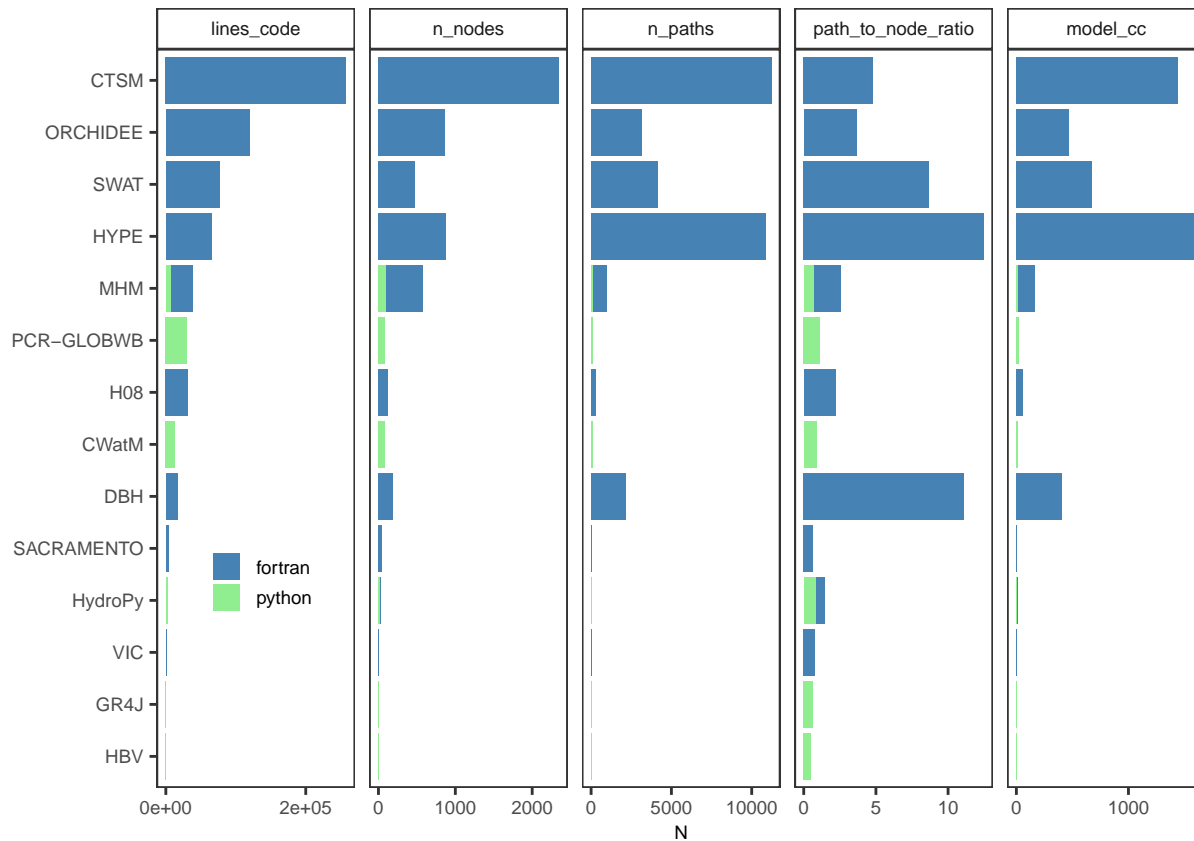
# Plot descriptive measures per model -----

plot_descriptive <- melt(all_descriptive_df, measure.vars = c("lines_code", "n_nodes", "n_paths",
  "path_to_node_ratio", "model_cc")) %>%
  .[, model:= factor(model, levels = model_ordered[, model])] %>%
  ggplot(., aes(model, value, fill = language)) +
  geom_col() +
  coord_flip() +
  scale_y_continuous(breaks = breaks_pretty(n = 2)) +
  scale_fill_manual(values = color_languages, name = "") +
  facet_wrap(~ variable, ncol = 7, scales = "free_x") +
  labs(x = "", y = "N") +
  theme_AP() +
  theme(legend.position = c(0.1, 0.3))

## Warning in melt.data.table(all_descriptive_df, measure.vars = c("lines_code", :
## 'measure.vars' [lines_code, n_nodes, n_paths, path_to_node_ratio, ...] are not
## all of the same type. By order of hierarchy, the molten data value column will
## be of type 'double'. All measure variables not of type 'double' will be coerced
## too. Check DETAILS in ?melt.data.table for more on coercion.

plot_descriptive

```



METRICS AT THE FILE AND FUNCTION LEVEL

```
folder <- "./datasets/results_per_function"
```

Get names of files -----

```
csv_files <- list.files(path = folder, pattern = "\\*.csv$", full.names = TRUE)
```

Split into file_metrics and func_metrics -----

```
file_metric_files <- grep("file_metrics", csv_files, value = TRUE)
```

```
func_metric_files <- grep("func_metrics", csv_files, value = TRUE)
```

Build one named list -----

```
list_metrics <- list(file_metrics = setNames(lapply(file_metric_files, fread),
                                              basename(file_metric_files)),
                    func_metrics = setNames(lapply(func_metric_files, fread),
                                              basename(func_metric_files)))
```

Create function to combine files -----

```
make_combined <- function(subset_list, pattern) {
  rbindlist(subset_list[grepl(pattern, names(subset_list))], idcol = "source_file")
}
```

```

}

# Combine files -----

metrics_combined <- list(file_fortran = make_combined(list_metrics$file_metrics, "fortran"),
                        file_python = make_combined(list_metrics$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)
  sub("^^(file|func)_metrics_\\d+_[A-Za-z0-9-]+_(fortran|python).*", "\\2", x)

extract_lang <- function(x)
  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) {
  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) {
  dt <- as.data.table(metrics_combined[[nm]])
  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(b1 = expression(C %in% "(" * 0 * ", 10" * "]" ),
             b2 = expression(C %in% "(" * 10 * ", 20" * "]" ),
             b3 = expression(C %in% "(" * 20 * ", 50" * "]" ),
             b4 = expression(C %in% "(" * 50 * ", " * infinity * "]" ))

```

```

# Define vector to exclude classes that are not functions -----
excluded_classes_vec <- c("MODULE_AGG", "CLASS_AGG")

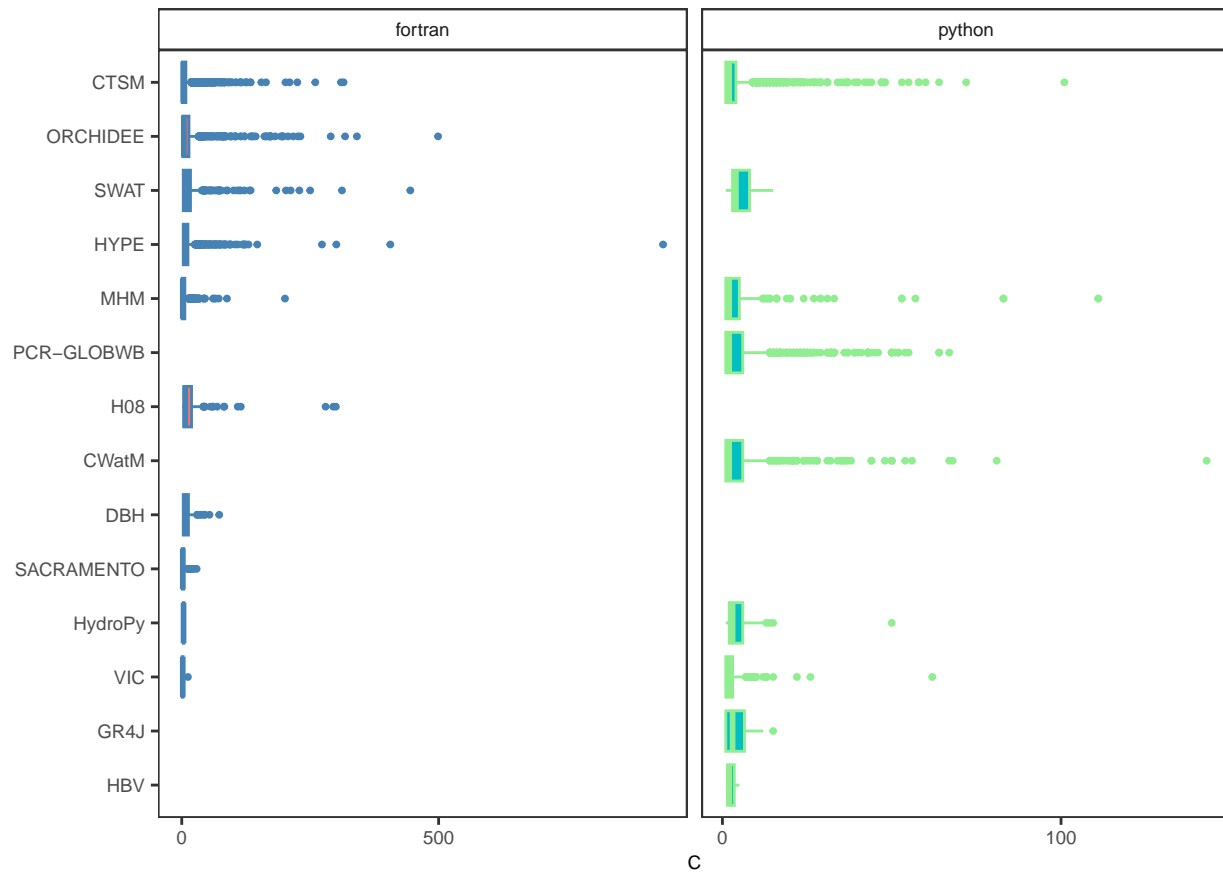
# PLOT #####

## ----plot_c_model, dependson="read_metrics_function_data", fig.height=2.2, fig.width=3.1----

plot_c_model <- metrics_combined[grep("^func_", names(metrics_combined))] %>%
  lapply(., function(x)
    x[, .(model, language, `function`, cyclomatic_complexity, loc, bugs, type))] %>%
rbindlist() %>%
  .[!type %in% excluded_classes_vec] %>%
  .[, model:= factor(model, levels = model_ordered[, model])] %>%
ggplot(., aes(model, cyclomatic_complexity, fill = language, color = language)) +
geom_boxplot(outlier.size = 0.7) +
coord_flip() +
scale_y_continuous(breaks = scales::breaks_pretty(n = 2)) +
facet_wrap(~language, scales = "free_x") +
labs(x = "", y = "C") +
theme_AP() +
scale_color_manual(values = color_languages) +
theme(legend.position = "none",
      plot.margin = margin(0, 2, 0, 0))

plot_c_model

```



```
## ----plot_scatter_and_bar, dependson="read_metrics_function_data", fig.height=2.5, fig.width=10
```

```
# Scatterplot cyclomatic vs lines of code -----
```

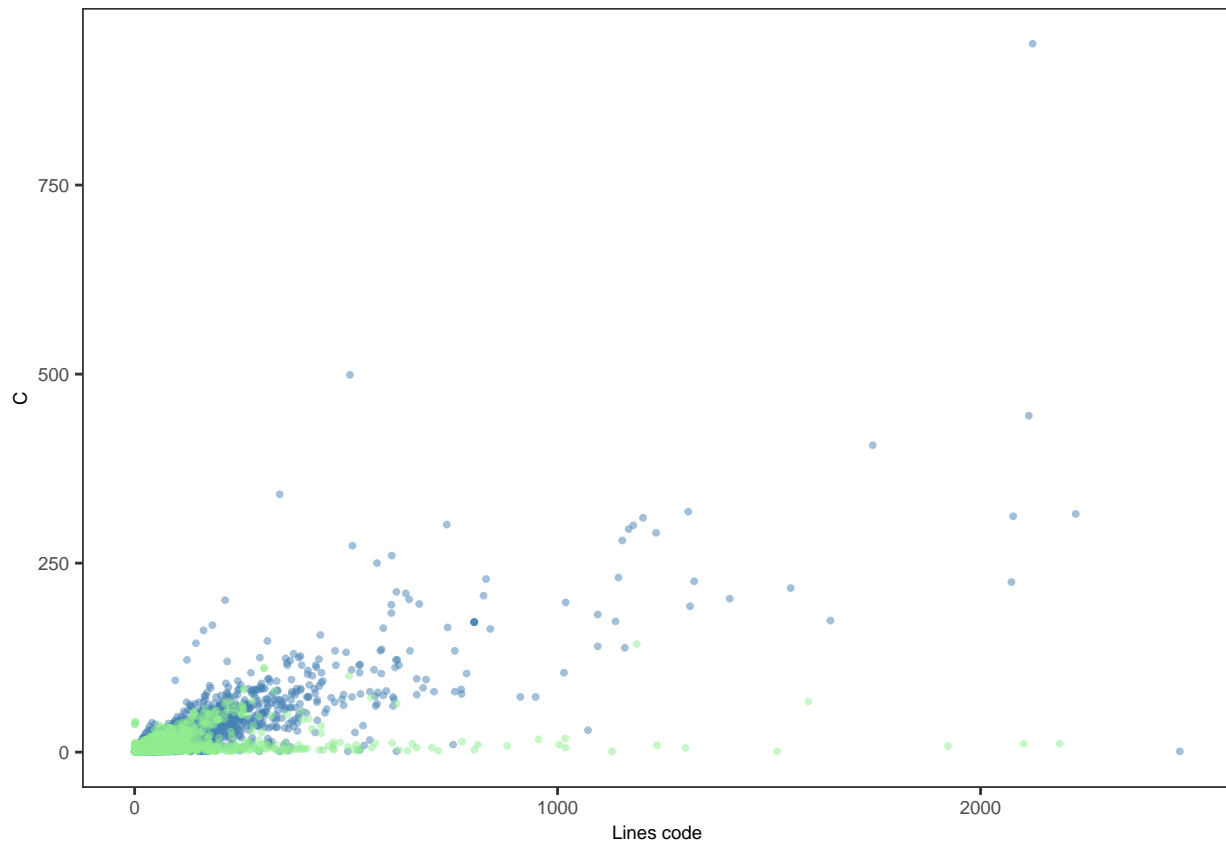
```
plot_c_vs_loc <- metrics_combined[grep("^func_", names(metrics_combined))] %>%
  lapply(., function(x) x[, .(loc, cyclomatic_complexity, language)]) %>%
  rbindlist() %>%
  ggplot(., aes(loc, cyclomatic_complexity, color = language)) +
  geom_point(alpha = 0.5, size = 0.7) +
  scale_x_continuous(breaks = breaks_pretty(n = 3)) +
  labs(x = "Lines code", y = "C") +
  scale_color_manual(values = color_languages) +
  theme_AP() +
  scale_x_continuous(breaks = breaks_pretty(n = 2)) +
  theme(legend.position = "none")
```

```
## Scale for x is already present.
```

```
## Adding another scale for x, which will replace the existing scale.
```

```
plot_c_vs_loc
```

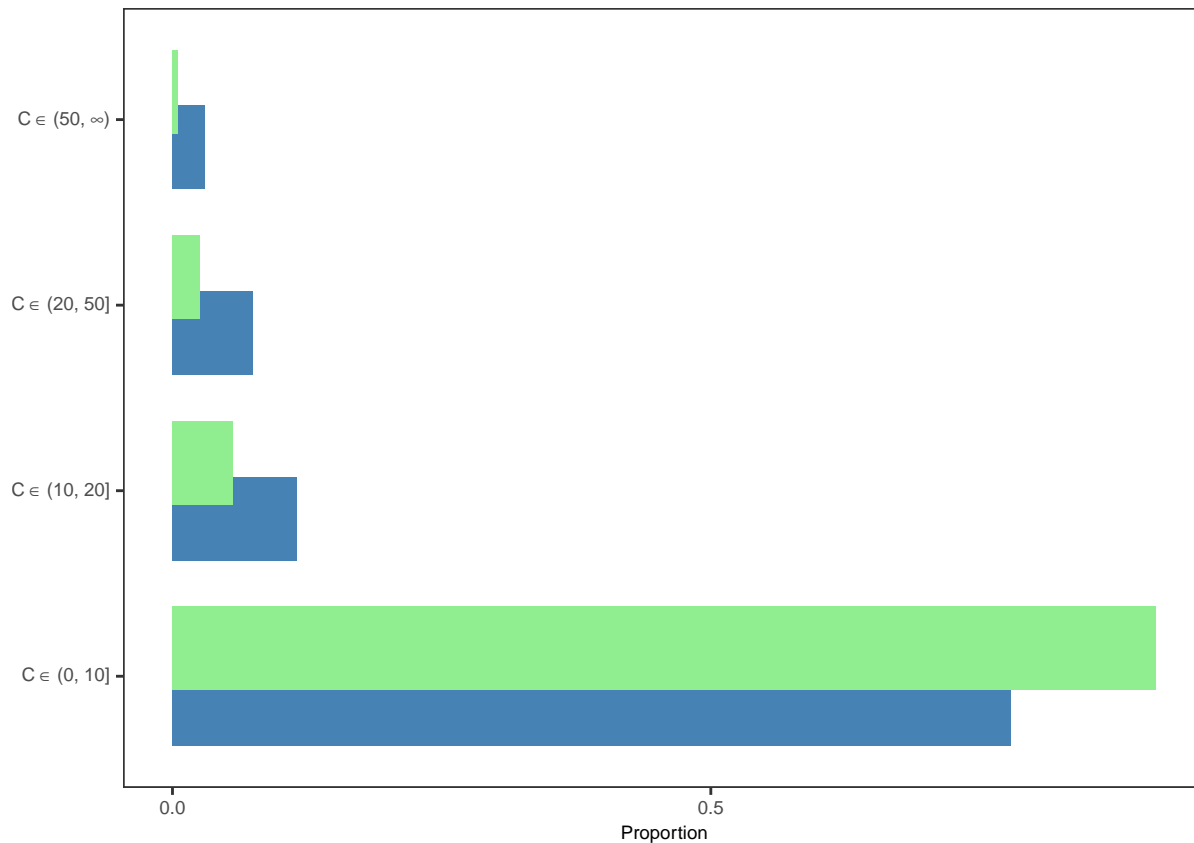
```
## Warning: Removed 1195 rows containing missing values or values outside the scale range
## (`geom_point()`).
```



```
# Count & proportion -----

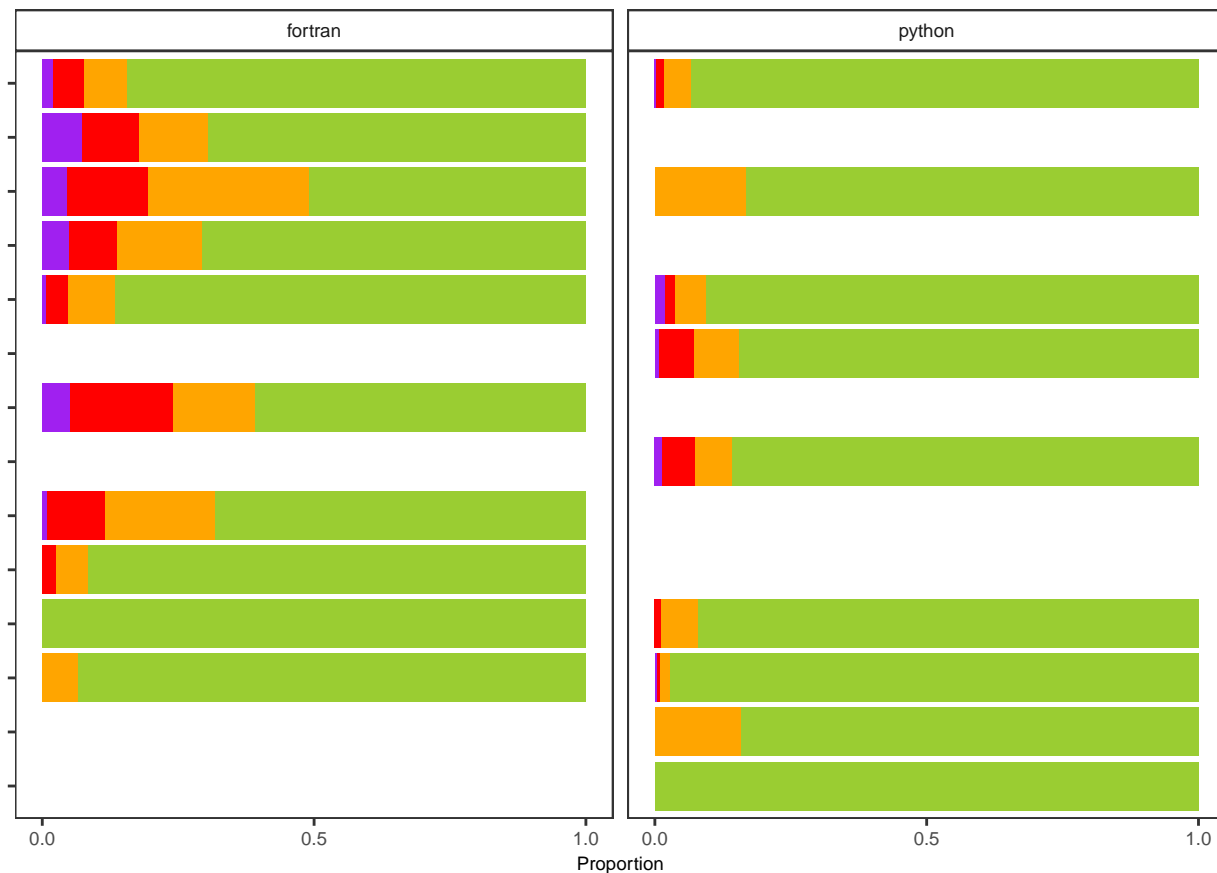
plot_bar_cyclomatic <- metrics_combined[grepl("^func_", names(metrics_combined))] %>%
  lapply(., function(x) x[, .(complexity_category, language, type)]) %>%
  rbindlist() %>%
  .[!type %in% excluded_classes_vec] %>%
  .[, .N, .(complexity_category, language)] %>%
  .[, proportion := N / sum(N), language] %>%
  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 = 3)) +
  scale_x_discrete(labels = lab_expr) +
  labs(x = "", y = "Proportion") +
  coord_flip() +
  theme_AP() +
  theme(legend.position = "none")

plot_bar_cyclomatic
```



```
plot_bar_category <- metrics_combined[grep("^func_", names(metrics_combined))] %>%
  lapply(., function(x)
    x[, .(model, language, complexity_category, type)] %>%
    rbindlist() %>%
    .[!type %in% excluded_classes_vec] %>%
    .[, model := factor(model, levels = model_ordered[, model])] %>%
    .[, .N, .(model, language, complexity_category)] %>%
    .[, proportion := N / sum(N), .(language, model)] %>%
    ggplot(., aes(model, proportion, fill = complexity_category)) +
    geom_bar(stat = "identity") +
    scale_fill_manual(values = c("yellowgreen", "orange", "red", "purple"),
                      labels = lab_expr,
                      name = "") +
    facet_wrap(~language) +
    labs(x = "", y = "Proportion") +
    coord_flip() +
    scale_y_continuous(breaks = scales::breaks_pretty(n = 3)) +
    theme_AP() +
    theme(legend.position = "none") +
    theme(axis.text.y = element_blank(),
          legend.text = element_text(size = 7),
          plot.margin = margin(0, 0, 0, 2))

plot_bar_category
```

3 Descriptive plots

```
# MERGE FIGURES #####
```

```
legend2 <- get_legend_fun(plot_bar_category + theme(legend.position = "top"))
```

```
## Warning: `is.ggplot()` was deprecated in ggplot2 3.5.2.
```

```
## i Please use `is_ggplot()` instead.
```

```
## This warning is displayed once every 8 hours.
```

```
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
```

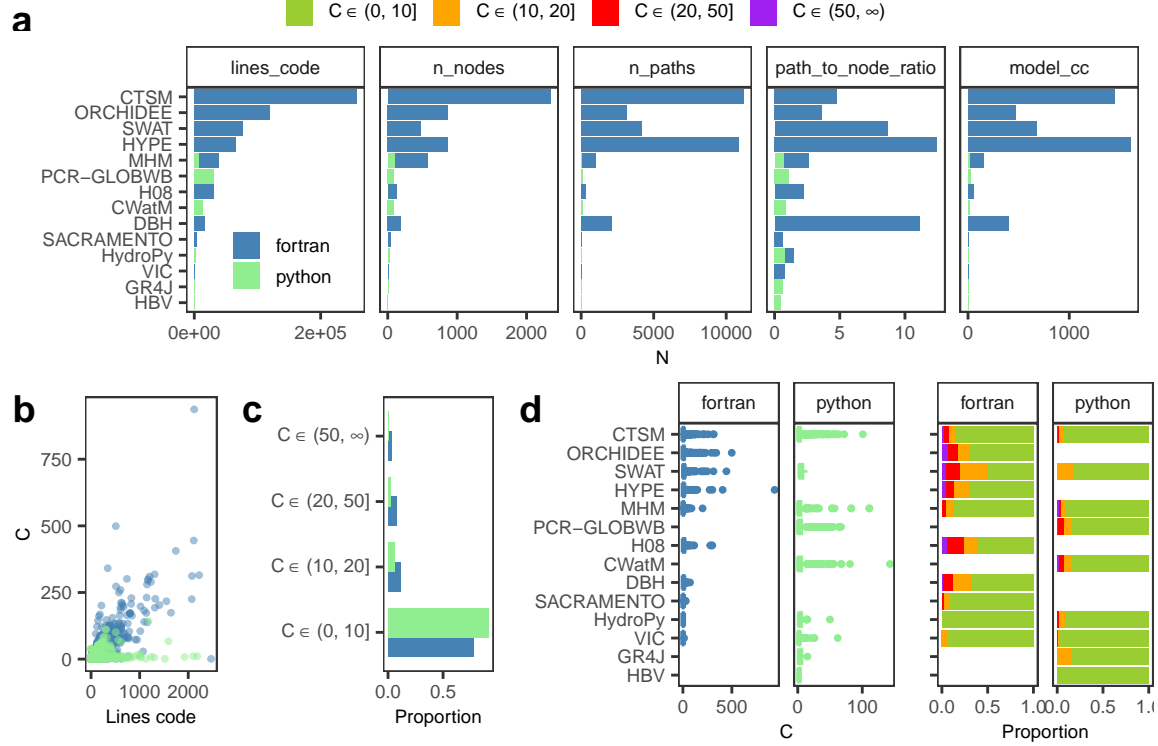
```
## generated.
```

```
top_plot <- plot_grid(legend2, plot_descriptive, rel_heights = c(0.1, 0.9), ncol = 1,  
                      labels = "a")
```

```
bottom <- plot_grid(plot_c_vs_loc, plot_bar_cyclomatic, plot_c_model,  
                    plot_bar_category, ncol = 4, rel_widths = c(0.2, 0.24, 0.34, 0.22),  
                    labels = c("b", "c", "d"))
```

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

```
plot_grid(top_plot, bottom, ncol = 1, rel_heights = c(0.52, 0.48), align = "h",
axis = "tb")
```



4 Figures

```
# PLOT FIGURES #####
```

```
# Plot graphs -----
```

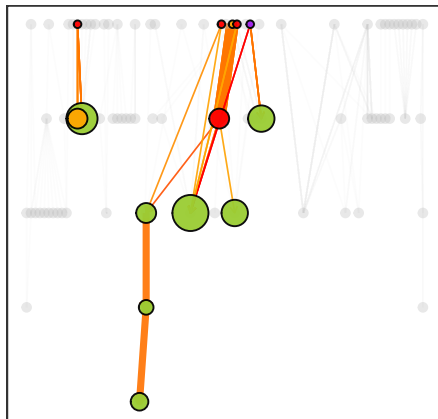
```
set.seed(seed)
```

```
# Thickness of edge: frequency across top-10 risk paths
```

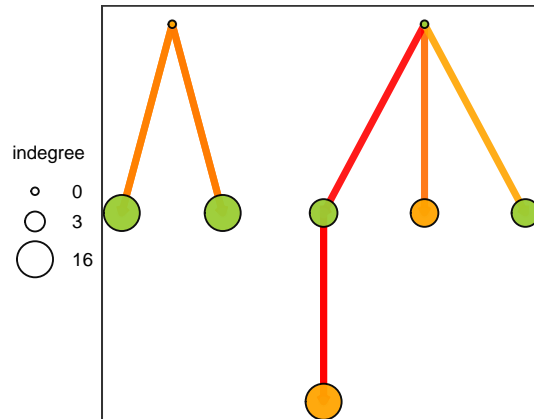
```
# Color of edge: mean risk of paths using that edge
```

```
all_graphs <- all_graphs[, plot_obj := mapply(plot_top_paths_fun, call_g = graph,
                                              paths_tbl = paths_tbl, model.name = model,
                                              language = language, SIMPLIFY = FALSE)]
```

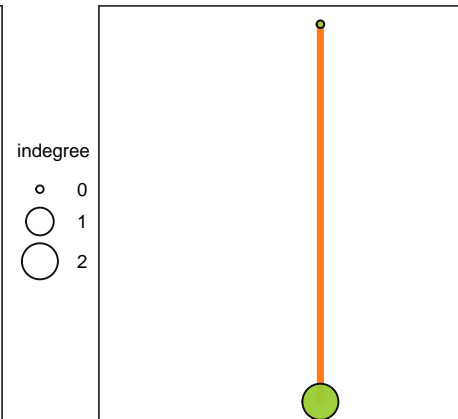
CWatM: python



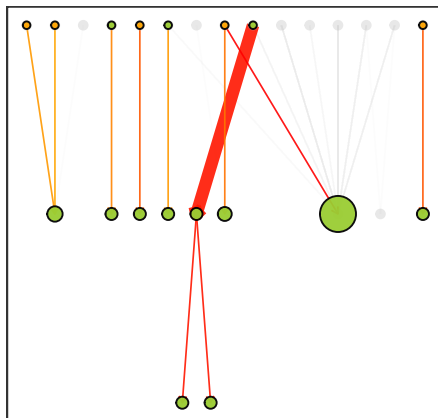
GR4J: python



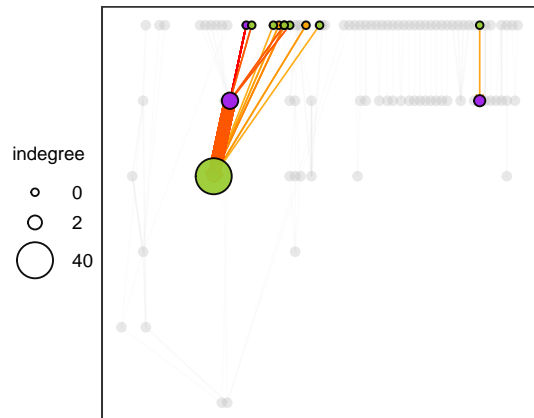
HBV: python



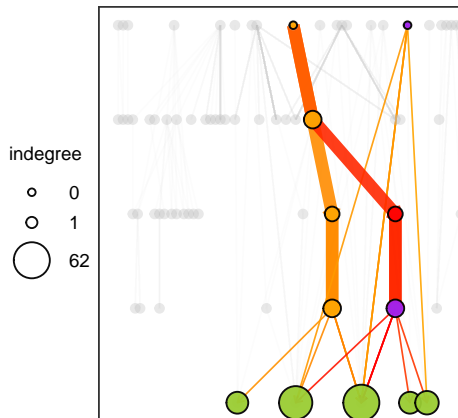
HydroPy: python



MHM: python

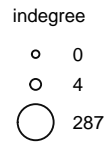
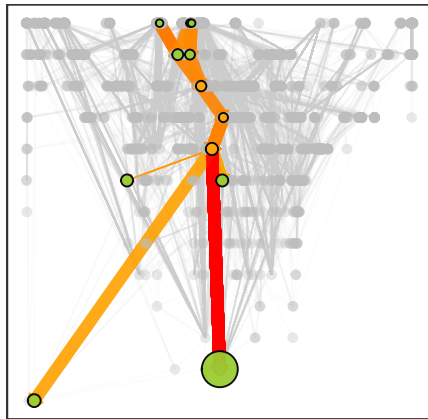


PCR-GLOBWB: python

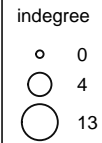
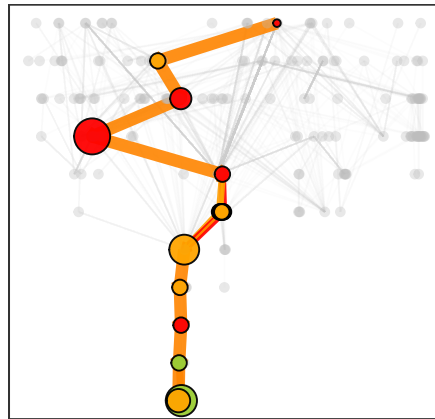


```
## No paths in paths_tbl; skipping plot for: VIC
```

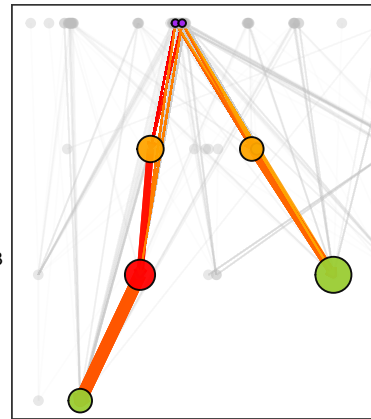
CTSM: fortran



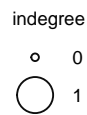
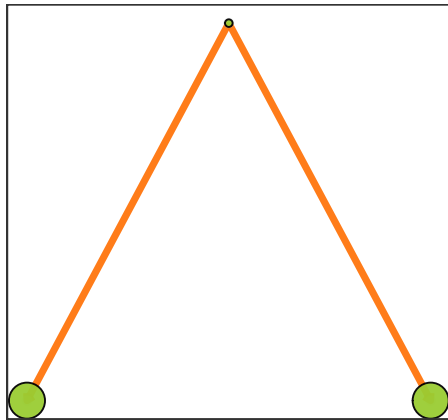
DBH: fortran



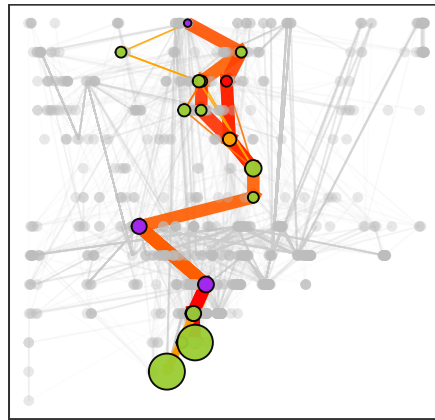
H08: fortran



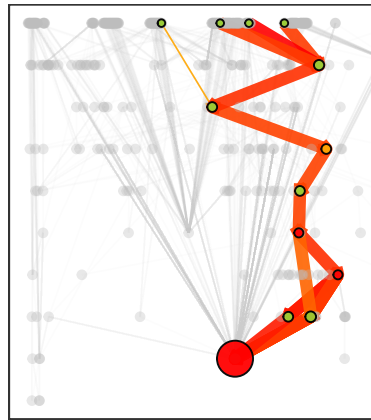
HydroPy: fortran



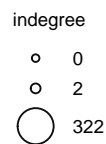
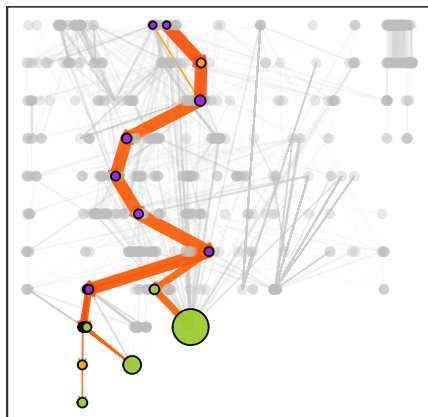
HYPE: fortran



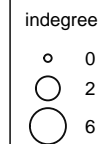
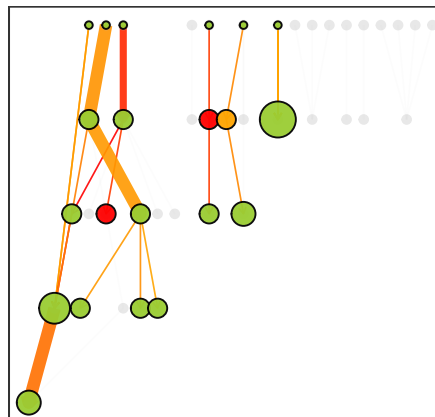
MHM: fortran



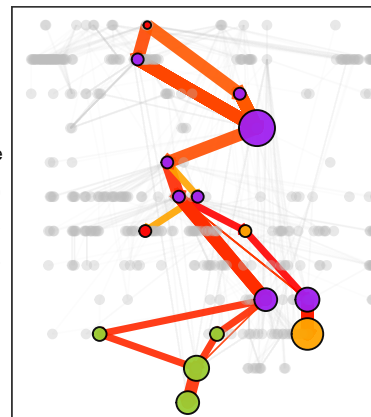
ORCHIDEE: fortran



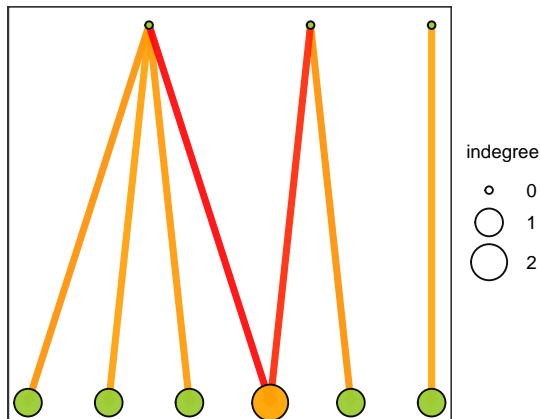
SACRAMENTO: fortran



SWAT: fortran



VIC: fortran



```
# PLOT OTHER FIGURES #####
```

```
selected_models <- data.table(model = c("CTSM", "PCR-GLOBWB", "DBH", "HYPE",
    "ORCHIDEE", "SWAT", "CWatM", "MHM"),
    language = c("fortran", "python", "fortran",
    "fortran", "fortran", "fortran",
    "python", "python"))
```

```
# Plot call graphs -----
```

```
tmp <- all_graphs[selected_models, on = .(model, language)]
plot_all_risky_paths <- plot_grid(plotlist = tmp$plot_obj, ncol = 2, align = "hv")
```

```
# Plot risk_slope -----
```

```
a <- full_paths_df %>%
  data.table() %>%
  .[selected_models, on = .(model, language)] %>%
  .[order(-p_path_fail), .SD[1:10], model] %>%
  ggplot(., aes(reorder(model, risk_slope), risk_slope)) +
  geom_boxplot() +
  scale_y_continuous(breaks = pretty_breaks(n = 3)) +
  geom_hline(yintercept = 0, lty = 2, color = "red") +
  coord_flip() +
  labs(x = "", y = expression(theta[1*k])) +
  theme_AP()
```

```
# Plot Gini metric -----
```

```
b <- full_paths_df %>%
  data.table() %>%
  .[selected_models, on = .(model, language)] %>%
  .[order(-p_path_fail), .SD[1:10], model] %>%
  ggplot(., aes(reorder(model, gini_node_risk), gini_node_risk)) +
```

```

geom_boxplot() +
coord_flip() +
labs(x = "", y = expression(G[k])) +
theme_AP()

# Plot Si values -----

c <- full_sa_df %>%
  data.table() %>%
  .[selected_models, on = .(model, language)] %>%
  .[sensitivity == "Si", .(median = median(original, na.rm = TRUE)), .(model, parameters)] %>%
  ggplot(. , aes(x = parameters, y = model, fill = median)) +
  geom_tile() +
  scale_fill_viridis_c(name = expression("Med(" * S[p] * ")"),
    limits = c(0, 1),
    breaks = c(0, 0.5, 1)) +
  scale_x_discrete(labels = c(a_raw = expression(alpha),
    b_raw = expression(beta),
    c_raw = expression(gamma))) +
  labs(x = NULL, y = NULL) +
  theme_AP() +
  theme(legend.position = "none")

# Plot interaction strength -----

tmp <- split(full_sa_df, full_sa_df$language)
tmp2 <- lapply(tmp, data.table) %>%
  lapply(. , function(x) {
    dcast(x, name + model + language + parameters ~ sensitivity,
      value.var = "original") %>%
    .[, interaction:= Ti - Si]})

d <- do.call(rbind, tmp2) %>%
  .[selected_models, on = .(model, language)] %>%
  .[, .(median = median(interaction, na.rm = TRUE)), .(parameters, model)] %>%
  ggplot(. , aes(x = parameters, y = model, fill = median)) +
  geom_tile() +
  scale_x_discrete(labels = c(a_raw = expression(alpha),
    b_raw = expression(beta),
    c_raw = expression(gamma))) +
  scale_fill_viridis_c(name = expression("Med(" * T[p] - S[p] * ")"),
    limits = c(0, 0.06),
    breaks = c(0, 0.03, 0.06),
    option = "magma") +
  labs(x = NULL, y = NULL) +
  theme_AP() +

```

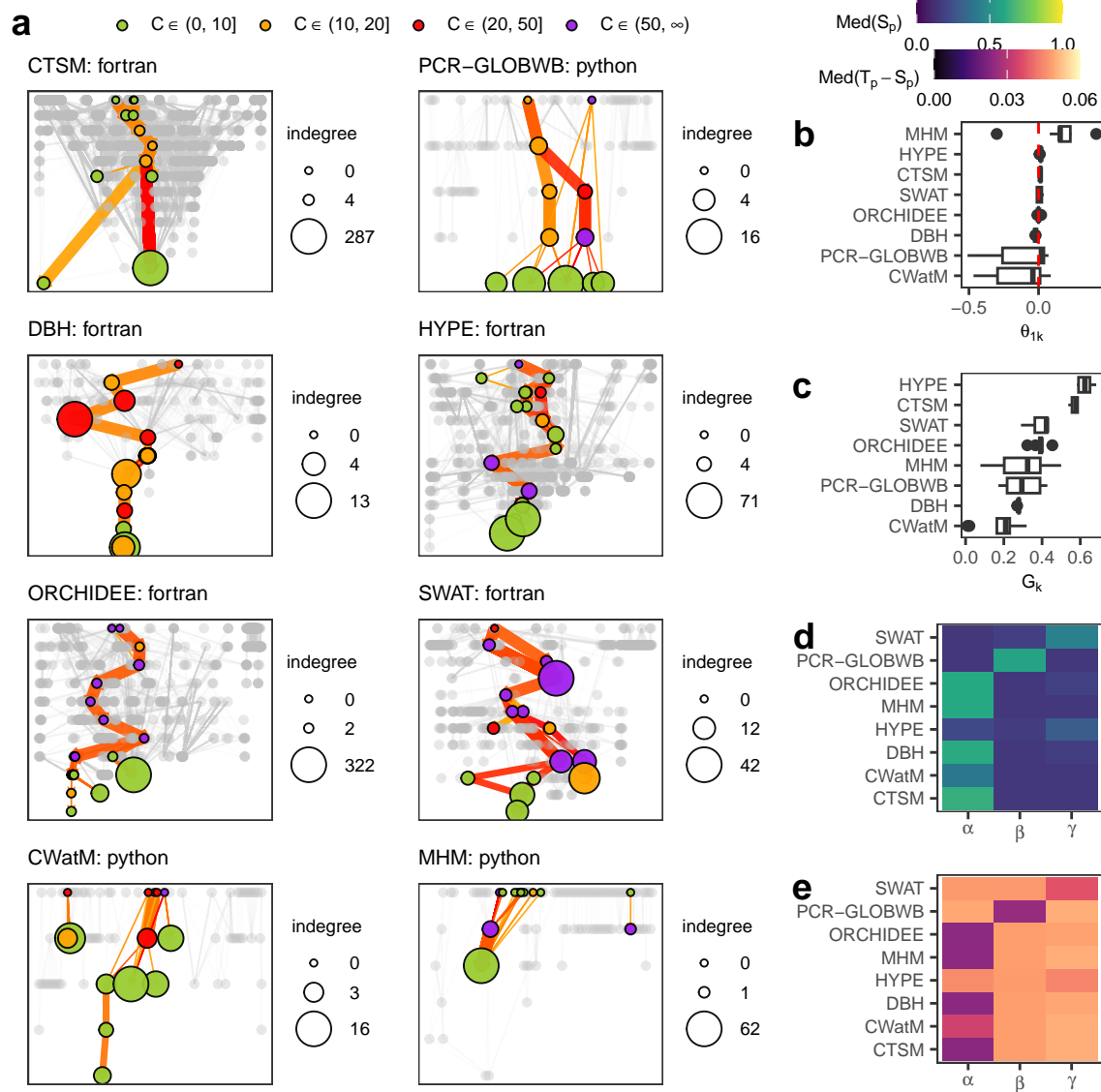
```

theme(legend.position = "none")

# MERGE #####

p_for_fill_legend <- all_graphs$plot_obj[[6]] +
  guides(size = "none", fill = guide_legend(title = ""))
fill_legend <- get_legend_fun(p_for_fill_legend + theme(legend.position = "top"))
plot_top_paths <- plot_grid(fill_legend, plot_all_risky_paths, ncol = 1, rel_heights = c(0.05,
  labels = "a"))
heatmap_legend <- get_legend(c + theme(legend.position = "top"))
ti_legend <- get_legend(d + theme(legend.position = "top"))
dada <- plot_grid(a, b, c, d, ncol = 1, labels = c("b", "c", "d", "e"))
all_legends <- plot_grid(heatmap_legend, ti_legend, ncol = 1)
right_plot <- plot_grid(all_legends, dada, ncol = 1, rel_heights = c(0.1, 0.9))
plot_grid(plot_top_paths, right_plot, ncol = 2, rel_widths = c(0.7, 0.3))

```



PATH-LEVEL RISK ACCOUNTED FOR THE TOP 5% NODES

```
setDT(full_paths_df)
```

To long format -----

```
paths_long <- full_paths_df[, .(node = unlist(path_nodes),
  p_path_fail = p_path_fail,
  gini_node_risk = gini_node_risk,
  risk_slope = risk_slope,
  risk_mean = risk_mean,
  risk_sum = risk_sum),
.(model, language, path_id)]
```



```

# Aggregate at function level -----
node_from_paths <- paths_long[, .(n_paths = .N,
  mean_p_path = mean(p_path_fail, na.rm = TRUE),
  max_p_path = max(p_path_fail, na.rm = TRUE),
  sum_p_path = sum(p_path_fail, na.rm = TRUE),
  mean_gini = mean(gini_node_risk, na.rm = TRUE),
  mean_slope = mean(risk_slope, na.rm = TRUE),
  mean_risksum = mean(risk_sum, na.rm = TRUE)),
  .(model, language, node)]

# Join with nodes -----
node_summary <- merge(node_from_paths, full_node_df, by.x = c("model", "language", "node"),
  by.y = c("model", "language", "name"), all.x = TRUE)

# Calculate risk mass -----
node_summary[, risk_mass := mean_p_path * n_paths]

# share of risk mass in top X% nodes, per model .-----
top_share <- function(X = 0.05) {
  node_summary[!is.na(risk_mass) & risk_mass >= 0, {
    dt <- .SD[order(-risk_mass)]
    n_top <- max(1L, ceiling(.N * X))
    .(X = X, n_nodes = .N, n_top = n_top,
      share_risk_mass_topX = sum(dt$risk_mass[1:n_top]) / sum(dt$risk_mass))
  },
  .(model, language)
]
}

# Run function -----
tmp <- top_share(0.05) %>%
  .[order(-share_risk_mass_topX)]

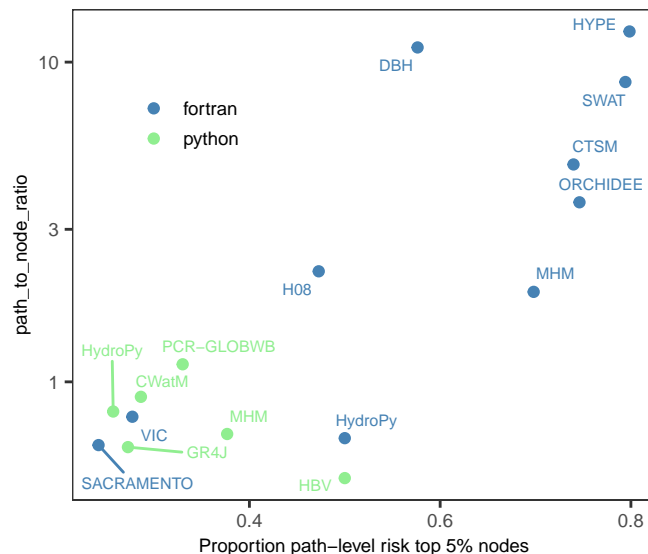
tmp

##      model language      X n_nodes n_top share_risk_mass_topX
##      <char>   <char> <num>   <int> <num>             <num>
##  1:      HYPE  fortran 0.05     872   44             0.7985366
##  2:      SWAT  fortran 0.05     481   25             0.7942209
##  3: ORCHIDEE  fortran 0.05     865   44             0.7460796

```

```
## 4:      CTSM  fortran  0.05    2339   117          0.7398243
## 5:      MHM  fortran  0.05     468    24          0.6980374
## 6:      DBH  fortran  0.05     191    10          0.5763146
## 7:      HBV  python  0.05        2     1          0.5000000
## 8:   HydroPy fortran  0.05        3     1          0.5000000
## 9:      H08  fortran  0.05     129     7          0.4726677
## 10:     MHM  python  0.05      98     5          0.3766507
## 11: PCR-GLOBWB python  0.05      89     5          0.3300054
## 12:    CWatM python  0.05      84     5          0.2862374
## 13:     VIC  fortran  0.05        9     1          0.2772493
## 14:    GR4J  python  0.05        8     1          0.2726486
## 15:   HydroPy python  0.05      26     2          0.2571617
## 16: SACRAMENTO fortran  0.05      41     3          0.2418015
```

```
# Plot-----
merge(all_descriptive_df, tmp, by = c("model", "language")) %>%
  ggplot(., aes(share_risk_mass_topX, path_to_node_ratio, color = language)) +
  geom_point() +
  scale_color_manual(values = color_languages, name = "") +
  geom_text_repel(aes(label = model), size = 2, max.overlaps = Inf, show.legend = FALSE) +
  scale_y_log10() +
  labs(x = "Proportion path-level risk top 5% nodes", y = "path_to_node_ratio") +
  theme_AP() +
  theme(legend.position = c(0.2, 0.8))
```



```
# PLOT THE TOP 50 PATHS PER MODEL #####
tmp <- full_ua_df %>%
  .[order(-P_k_mean), .SD[1:50], .(model, language)] %>%
  split(., list(.$model, .$language)) %>%
  lapply(., na.omit)
```

```

# Remove empty slots -----
tmp2 <- tmp[sapply(tmp, function(x) nrow(x) > 0)]

# Plot in a for loop -----

out <- list()

for ( i in 1:length(tmp2)) {

  out[[i]] <- ggplot(tmp2[[i]], aes(P_k_mean, reorder(path_str, P_k_mean), color = risk_slope),
    geom_point(size = 1) +
    geom_errorbar(aes(xmin = P_k_q025, xmax = P_k_q975), height = 0.2) +
    scale_color_gradient2(low = "blue", mid = "grey80", high = "red", midpoint = 0,
      name = expression(beta[k])) +
    labs(y = "Path ID", x = expression(P[k])) +
    theme_AP() +
    scale_x_continuous(breaks = breaks_pretty(n = 3),
      limits = c(0, 1)) +
    theme(axis.text.y = element_text(size = 4),
      legend.position = "top") +
    ggtitle(names(tmp[i]))
}

out

## [[1]]
## `height` was translated to `width`.

```

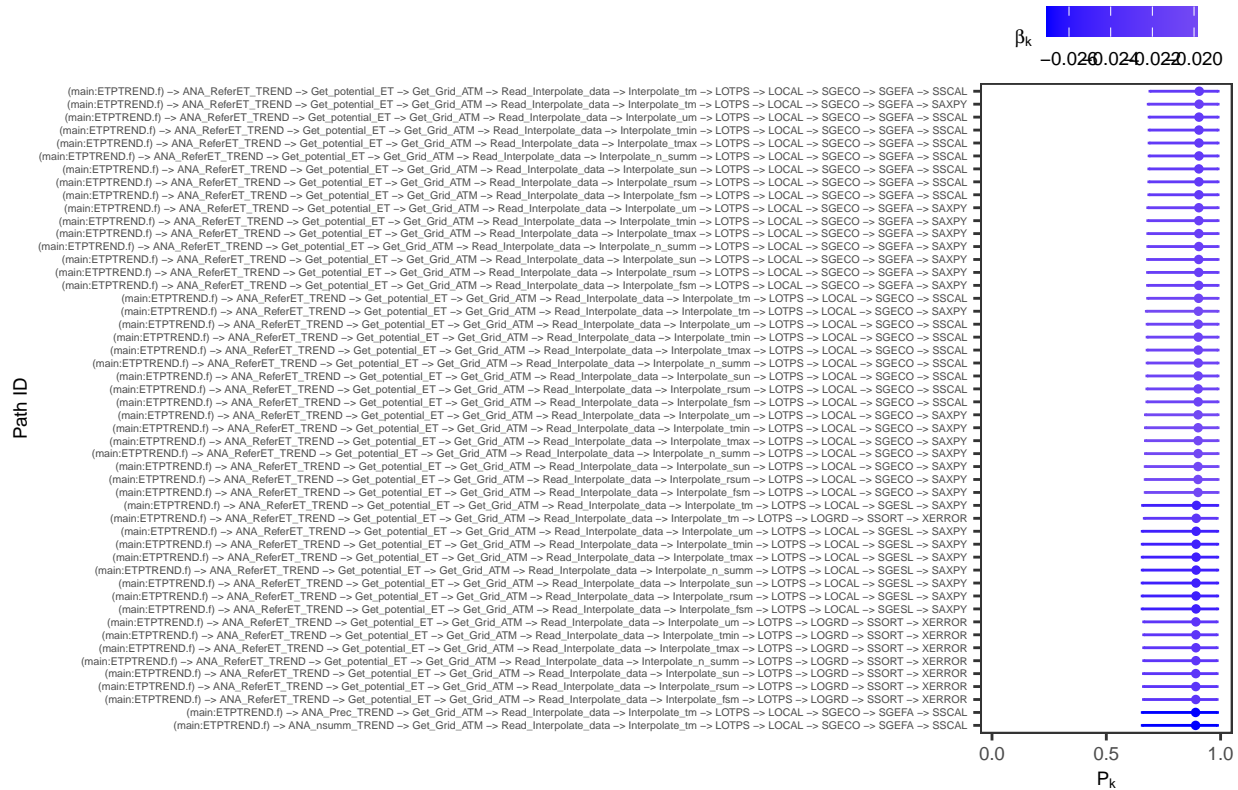
CTSM.fortran



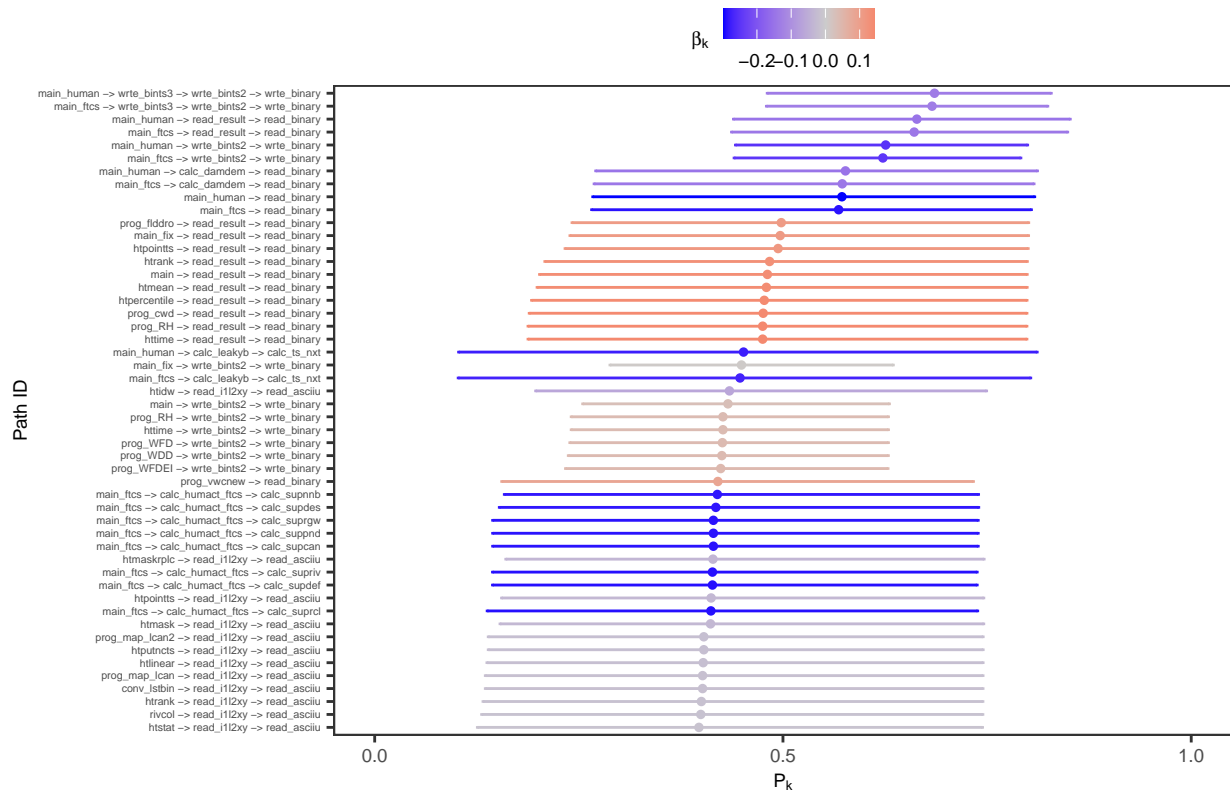
##

[[2]]

`height` was translated to `width`.



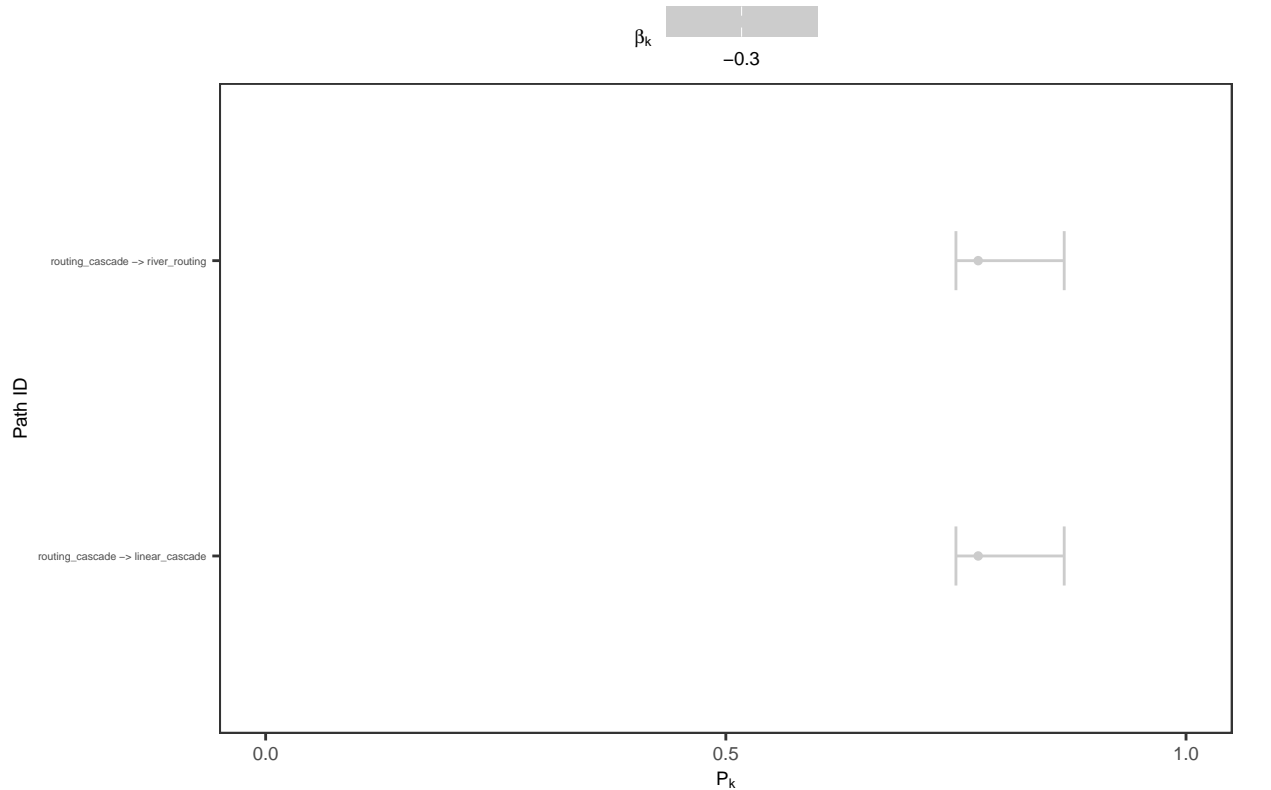
DBH.fortran



##

[[4]]

`height` was translated to `width`.



##

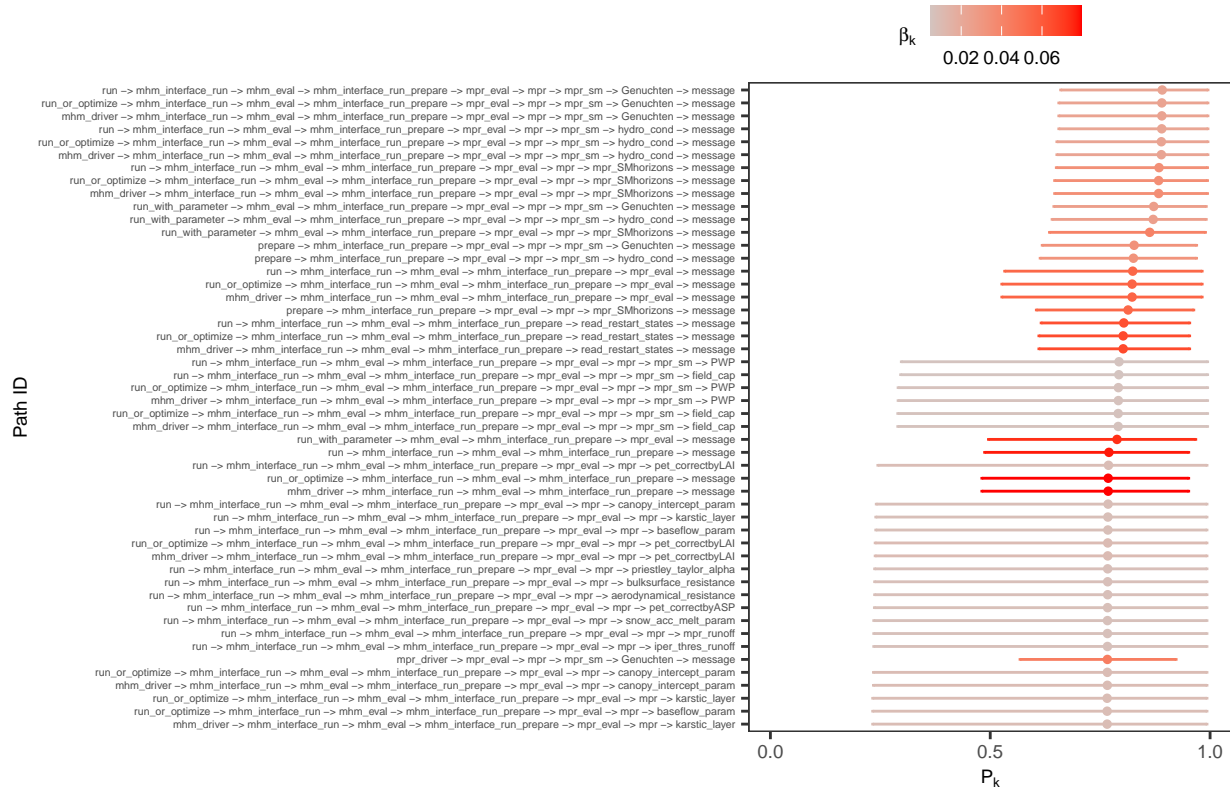
```
## [[5]]
```

```
## `height` was translated to `width`.
```

 β_k
0.0[illegible]

```
## `height` was translated to `width`.
```

HBV.fortran



```
## `height` was translated to `width`.
```


Path ID

##

[[8]]

`height` was translated to `width`.

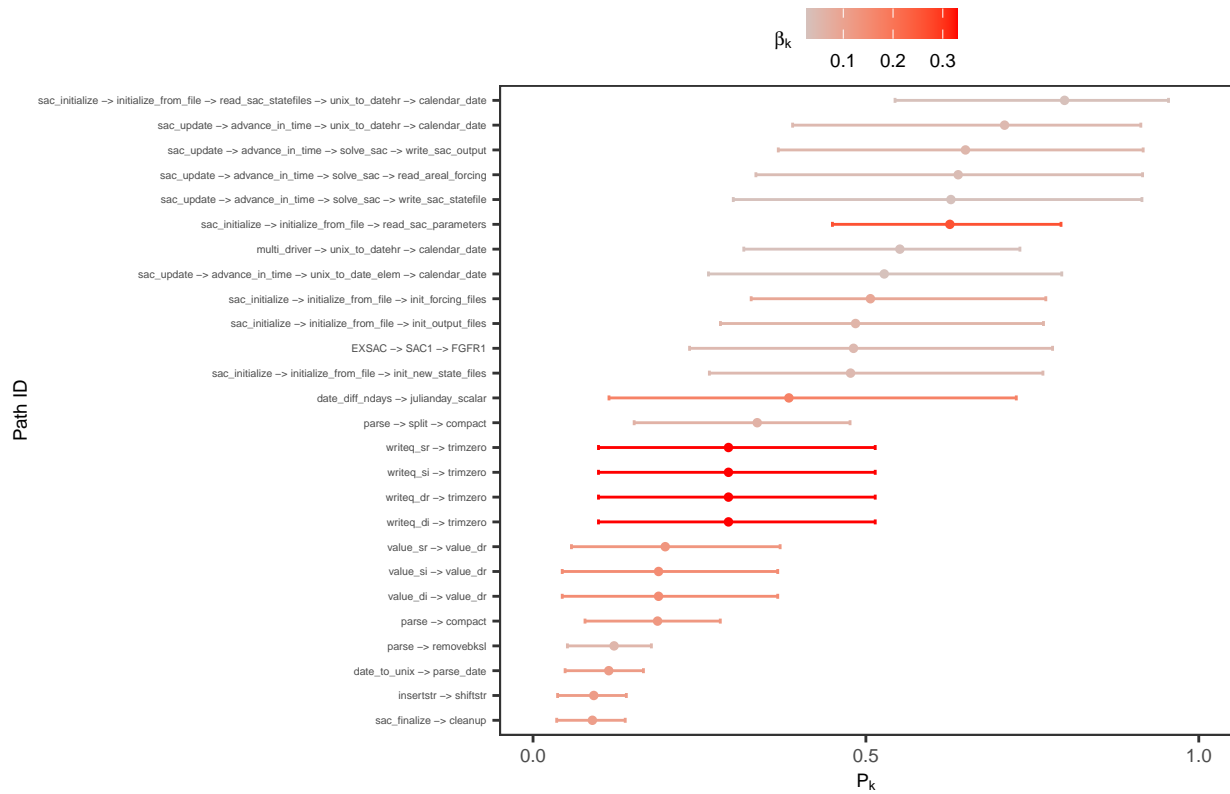
β_k

0.00

0.0

P_k

HYPE.fortran

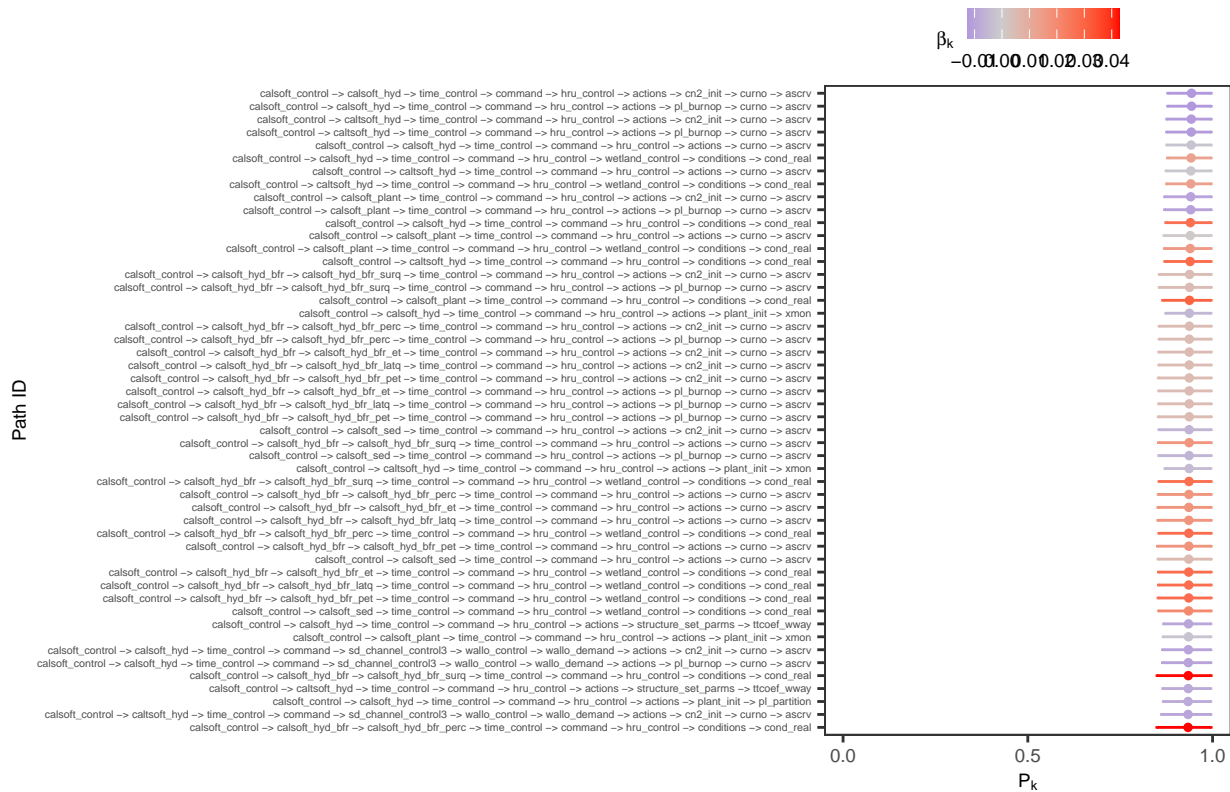


##

[[9]]

`height` was translated to `width`.

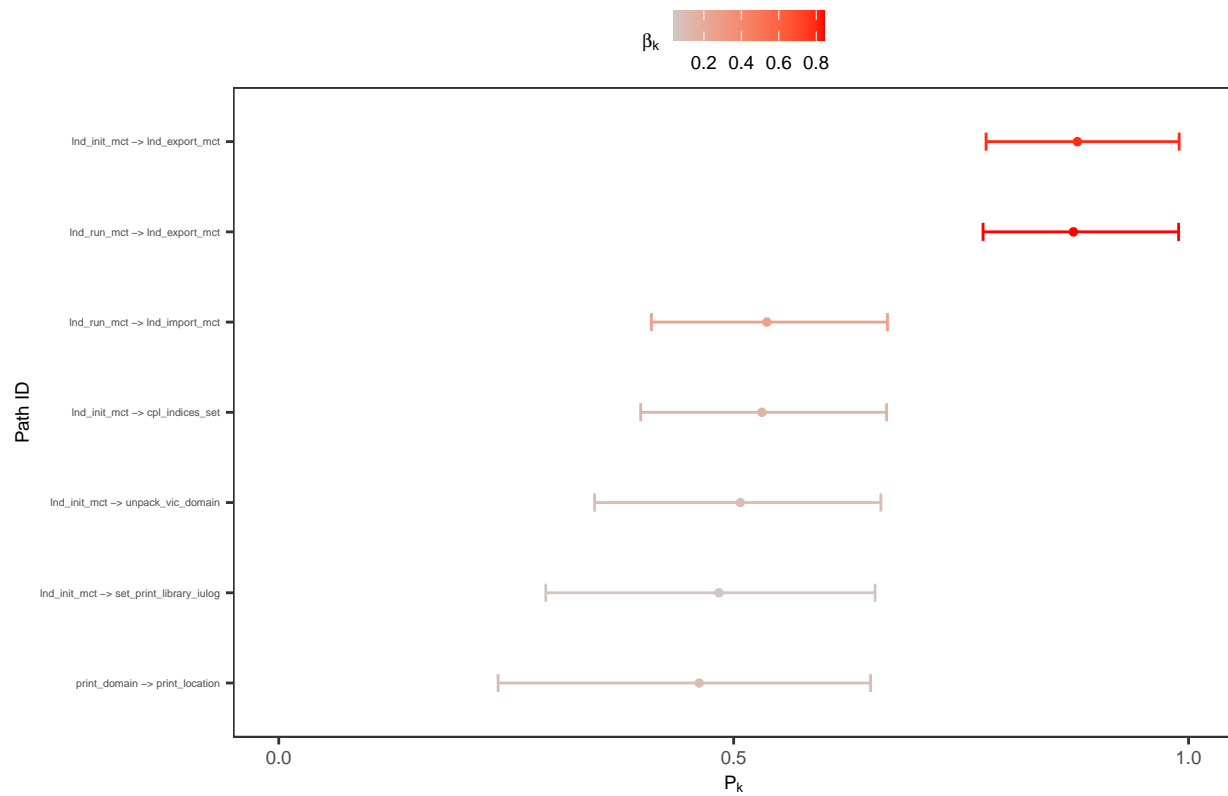
MHM.fortran



##

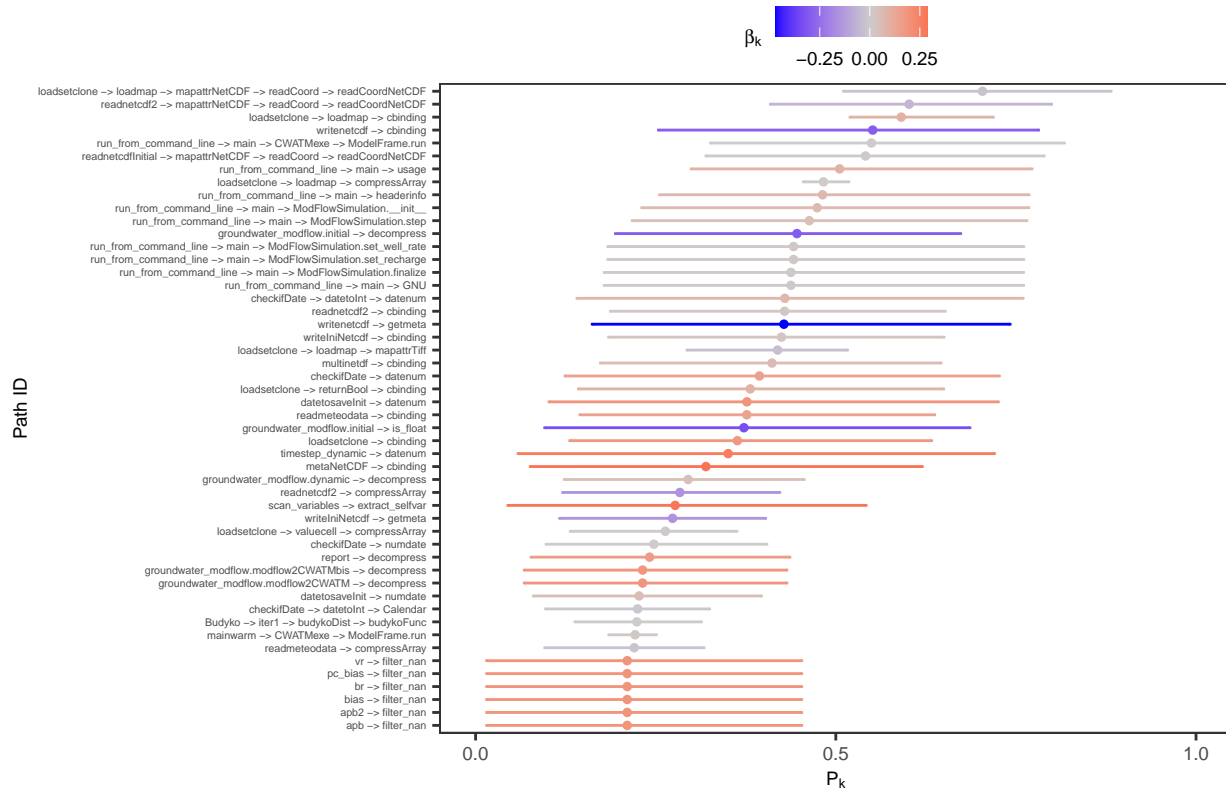
[[10]]

`height` was translated to `width`.



```
##
## [[11]]
## `height` was translated to `width`.
```

PCR-GLOBWB.fortran

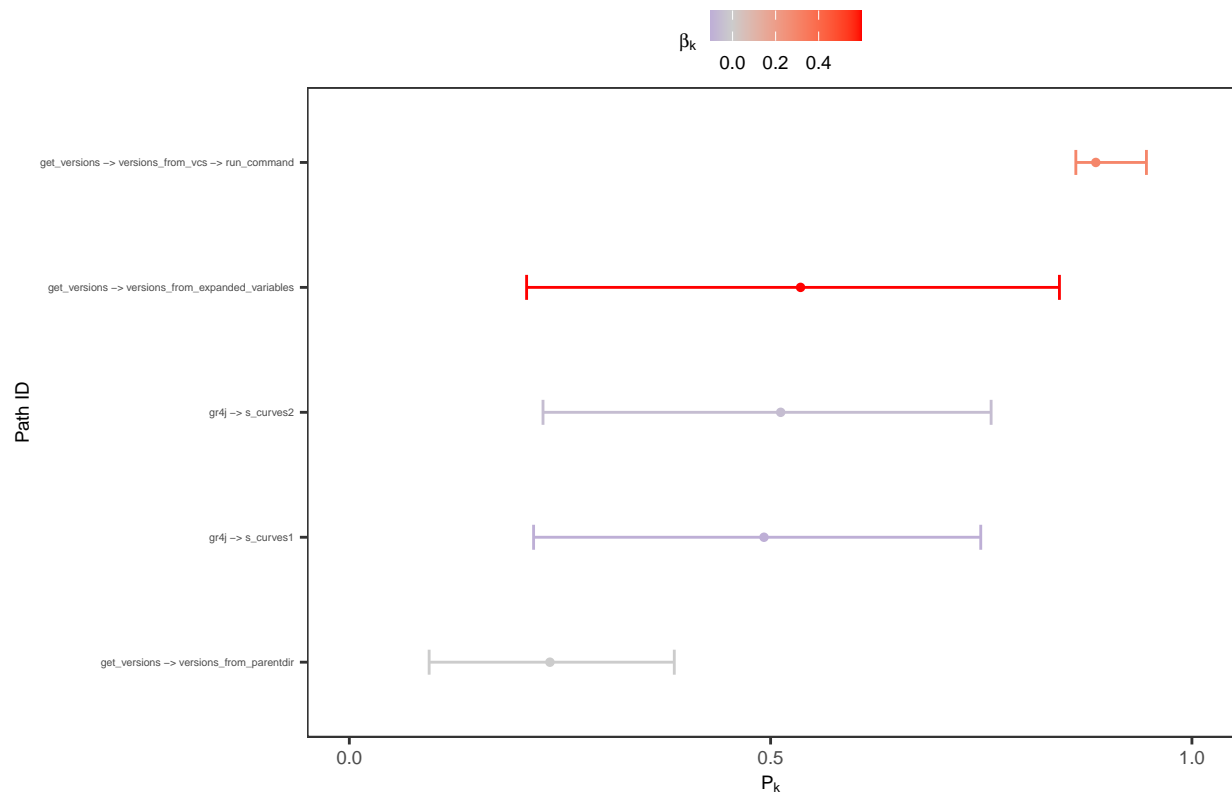


##

[[12]]

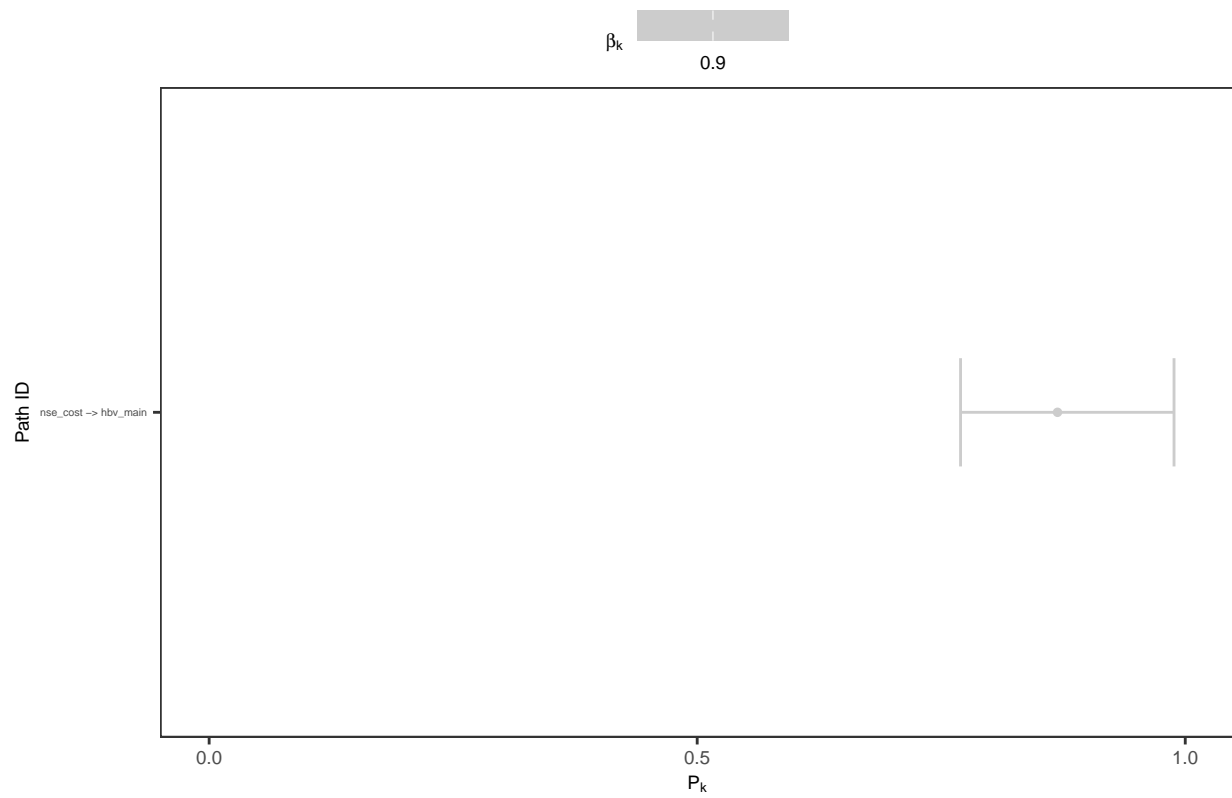
`height` was translated to `width`.

SACRAMENTO.fortran



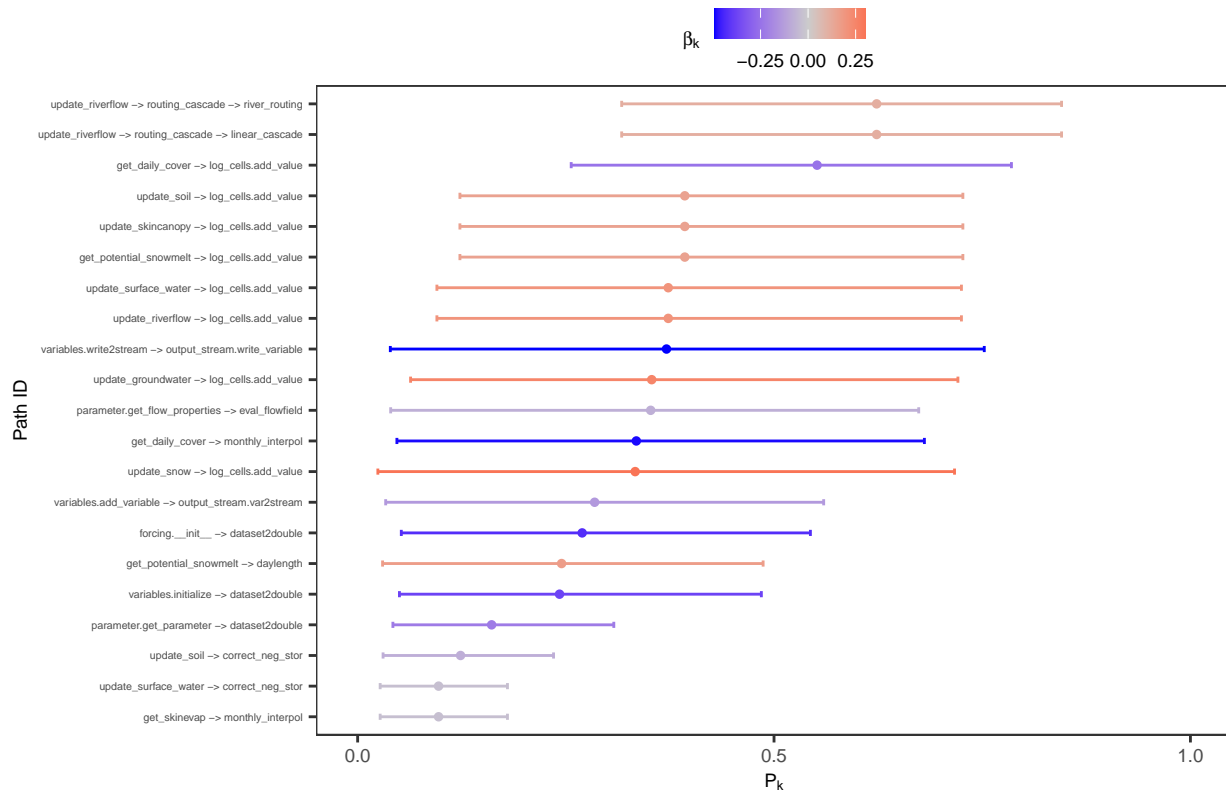
```
##
## [[13]]
## `height` was translated to `width`.
```

SWAT.fortran



```
##  
## [[14]]  
## `height` was translated to `width`.
```

VIC.fortran

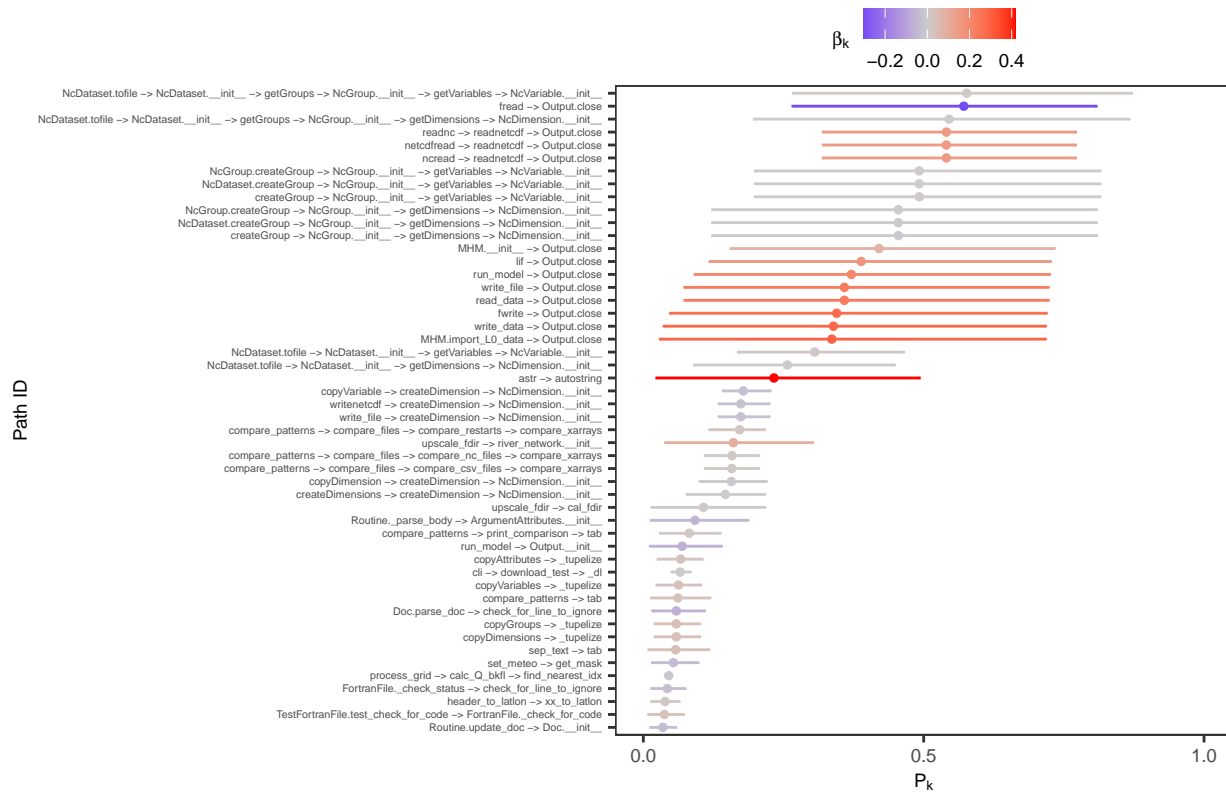


##

[[15]]

`height` was translated to `width`.

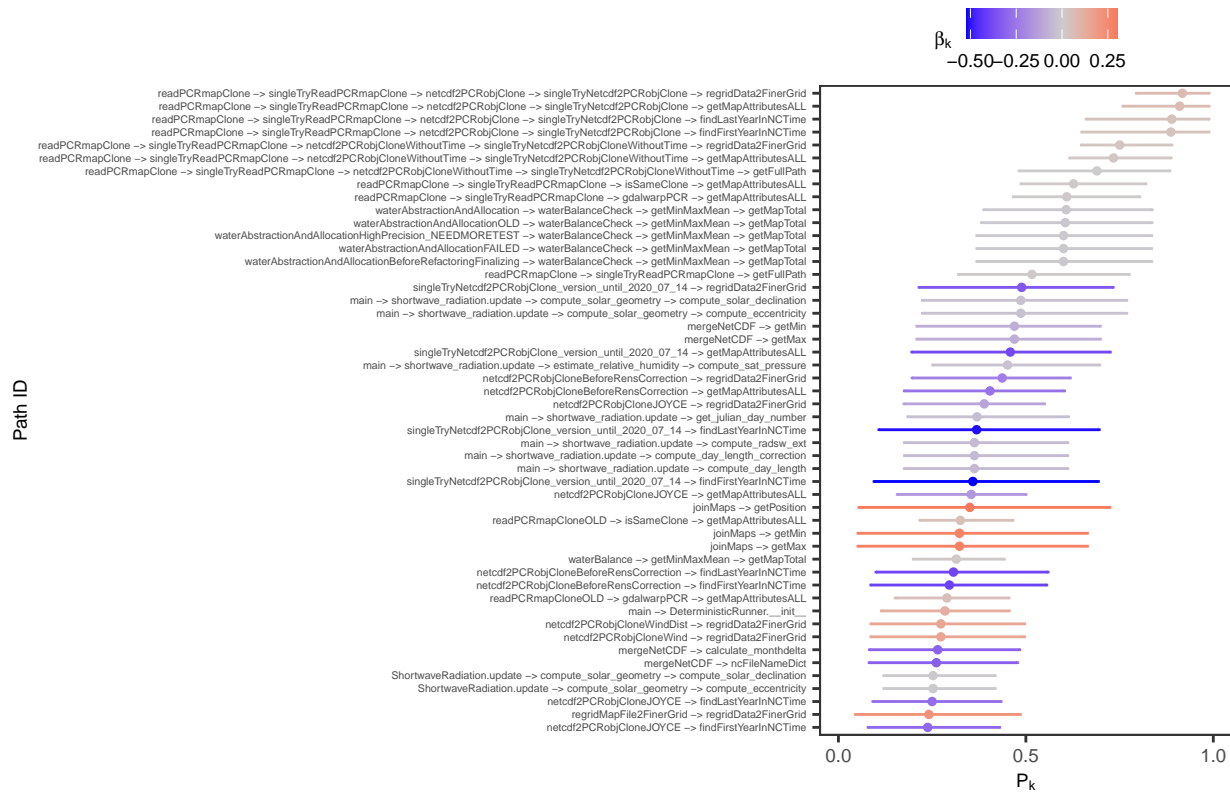
CTSM.python



##

[[16]]

`height` was translated to `width`.



```
# READ RANKING OF THE UA / SA DATASET #####
```

```
top_ten_overlap <- readRDS("top_ten_overlap.rds")
```

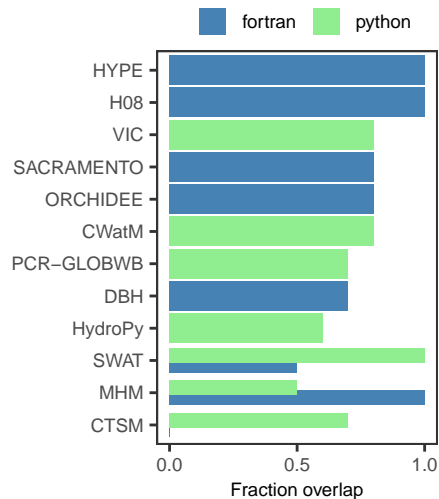
```
# ORDER AND FILTER OUT MODELS WITH LESS THAN 10 PATHS #####
```

```
model_names_ordered <- top_ten_overlap %>%
  .[n_paths > 10] %>%
  .[order(overlap_fraction)] %>%
  .[, model] %>%
  unique()
```

```
# PLOT #####
```

```
top_ten_overlap %>%
  .[n_paths > 10] %>%
  .[, model := factor(model, levels = model_names_ordered)] %>%
  ggplot(. , aes(model, overlap_fraction, fill = language)) +
  geom_bar(stat = "identity", position = position_dodge(0.6)) +
  scale_fill_manual(values = color_languages, name = "") +
  coord_flip() +
  scale_y_continuous(breaks = breaks_pretty(n = 3)) +
  labs(x = "", y = "Fraction overlap") +
```

```
theme_AP() +
theme(legend.position = "top")
```



```
# METRICS AT THE FILE AND FUNCTION LEVEL #####
```

```
folder <- "./datasets/git_logs"
```

```
# Get names of files -----
```

```
csv_files <- list.files(path = folder, pattern = "\\*.csv$", full.names = TRUE)
```

```
# Plot -----
```

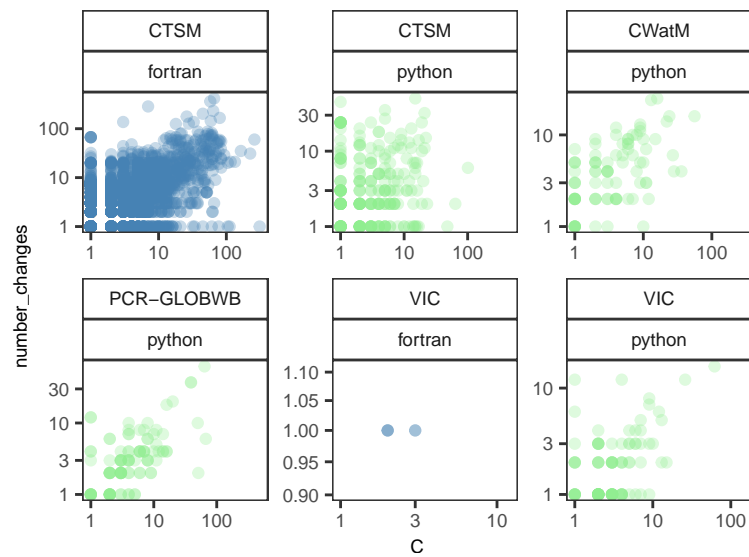
```
plot_logs <- lapply(csv_files, fread) %>%
  lapply(., function(x) x[, .(model, language, cyclomatic_complexity, number_changes,
                             change_per_days, age_days)]) %>%
  rbindlist() %>%
  ggplot(., aes(cyclomatic_complexity, number_changes, color = language)) +
  geom_point(alpha = 0.3) +
  scale_color_manual(values = color_languages, name = "") +
  scale_x_log10() +
  scale_y_log10() +
  labs(x = expression(C), y = "number_changes") +
  facet_wrap(model~language, scales = "free") +
  theme_AP() +
  theme(legend.position = "none")
```

```
plot_logs
```

```
## Warning in scale_x_log10(): log-10 transformation introduced infinite values.
```

```
## Warning: Removed 6629 rows containing missing values or values outside the scale range
```

```
## (`geom_point()`).
```



```
# FUNCTIONS TO SELECT THE TOP TEN RISKY PATHS PER MODEL AND
# PRINT THEM OUT FOR LATEX #####

tmp <- full_paths_df[order(-p_path_fail), .SD[1:10], .(model, language)] %>%
  .[, .(model, language, path_str)]

tmp2 <- split(tmp, list(tmp$model, tmp$language))

tmp3 <- tmp2[sapply(tmp2, nrow) > 0] %>%
  lapply(., function(x) na.omit(x) %>%
    .[, .(path_str)])

to_tex_list_fun(tmp3)
```

5 Session information

```
# SESSION INFORMATION #####
```

```
sessionInfo()
```

```
## R version 4.5.2 (2025-10-31)
## Platform: aarch64-apple-darwin20
## Running under: macOS Sequoia 15.6.1
##
## Matrix products: default
## BLAS: /System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework
## LAPACK: /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRlapack.dylib;
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## time zone: Europe/London
## tzcode source: internal
##
## attached base packages:
## [1] tools parallel stats graphics grDevices utils datasets
## [8] methods base
##
## other attached packages:
## [1] benchmarkme_1.0.8 sensobol_1.1.6 ggraph_2.2.2 foreach_1.5.2
## [5] igraph_2.1.4 tidygraph_1.3.1 here_1.0.2 tidytext_0.4.3
## [9] ggrepel_0.9.6 readxl_1.4.5 cowplot_1.2.0.9000 scales_1.4.0
## [13] openxlsx_4.2.8 lubridate_1.9.4 forcats_1.0.1 stringr_1.5.2
## [17] dplyr_1.1.4 purrr_1.1.0 readr_2.1.5 tidyr_1.3.1
## [21] tibble_3.3.0 ggplot2_4.0.0.9000 tidyverse_2.0.0 data.table_1.17.8
##
## loaded via a namespace (and not attached):
## [1] tidyselect_1.2.1 viridisLite_0.4.2 farver_2.1.2
## [4] viridis_0.6.5 S7_0.2.0 fastmap_1.2.0
## [7] tweenr_2.0.3 janeaustenr_1.0.0 digest_0.6.37
## [10] timechange_0.3.0 lifecycle_1.0.4 tokenizers_0.3.0
## [13] magrittr_2.0.4 compiler_4.5.2 rlang_1.1.6
## [16] yaml_2.3.10 knitr_1.50 labeling_0.4.3
## [19] graphlayouts_1.2.2 RColorBrewer_1.1-3 withr_3.0.2
## [22] grid_4.5.2 polyclip_1.10-7 iterators_1.0.14
## [25] MASS_7.3-65 tinytex_0.57 cli_3.6.5
## [28] crayon_1.5.3 rmarkdown_2.30 generics_0.1.4
## [31] RcppParallel_5.1.11-1 rstudioapi_0.17.1 httr_1.4.7
## [34] tzdb_0.5.0 cachem_1.1.0 ggforce_0.5.0
## [37] cellranger_1.1.0 vctrs_0.6.5 Matrix_1.7-4
## [40] hms_1.1.3 ineq_0.2-13 glue_1.8.0
## [43] benchmarkmeData_1.0.4 codetools_0.2-20 rngWELL_0.10-10
```

```
## [46] stringi_1.8.7      gtable_0.3.6      randtoolbox_2.0.5
## [49] pillar_1.11.1      htmltools_0.5.8.1 R6_2.6.1
## [52] zigg_0.0.2         Rdpack_2.6.4      doParallel_1.0.17
## [55] rprojroot_2.1.1    evaluate_1.0.5    lattice_0.22-7
## [58] rbibutils_2.3      SnowballC_0.7.1   Rfast_2.1.5.1
## [61] memoise_2.0.1      Rcpp_1.1.0        zip_2.3.3
## [64] gridExtra_2.3      xfun_0.53         pkgconfig_2.0.3
```

```
## Return the machine CPU -----
```

```
cat("Machine:      "); print(get_cpu()$model_name)
```

```
## Machine:
```

```
## [1] "Apple M1 Max"
```

```
## Return number of true cores -----
```

```
cat("Num cores:    "); print(detectCores(logical = FALSE))
```

```
## Num cores:
```

```
## [1] 10
```

```
## Return number of threads -----
```

```
cat("Num threads: "); print(detectCores(logical = FALSE))
```

```
## Num threads:
```

```
## [1] 10
```