Comparing VAST and sdmTMB GOA indices

Contents

```
#remotes::install_github("pbs-assess/sdmTMB", dependencies = TRUE)
library(VAST)
library(sp)
library(sdmTMB)
library(dplyr)
library(ggplot2)
library(here)

species <- "Sebastes_variabilis" #Gadus_macrocephalus Sebastes_alutus Sebastes_polyspinis Sebastes_poly
```

We will fit geostatistical spatiotemporal models with VAST and sdmTMB for the purposes of index standardization and compare the outputs given the same data. We will use data from the GOA AFSC GAP bottom trawl survey for the species specified above. The density units are kg/km^2.

```
dat_ll <- readRDS(here("species_specific_code", "GOA", species, "production",
                       "data", paste0("Data_Geostat_", species, ".rds")))

dat_ll <-  dplyr::transmute(dat_ll,
                          cpue_kg_km2 = Catch_KG,
                          year = as.integer(Year),
                          vessel = "missing",
                          effort = AreaSwept_km2,
                          lat = Lat,
                          lon = Lon,
                          pass = 0) %>%
                as.data.frame() # ensure not a tibble
```

We begin by specifying the VAST model. To specify the mesh used to approximate the spatial process, which is used in the SPDE calculations, we use the k-means method in VAST. Rather than specifying the cutoff distance, meshes in VAST are typically generated by specifying only the number of knots, which we will later pass, along with other model settings to the function make_settings. We will use 750 knots, the same number in the mesh created in the existing production VAST index for this stock and region.

We will include a factor predictor that represents the mean estimate for each time slice. Settings used for index standardization are applied by specifying `purpose = "index2"`.

Unlike in sdmTMB, the fitting and predicting steps are all accomplished with the function `fit_model()` and thus we need to specify the prediction grid (referred to as the "extrapolation grid" in VAST). Here, X and Y are coordinates in UTM zone 5.

```
GOAgrid <- read.csv(here("extrapolation_grids", "GOAThorsonGrid_Less700m.csv"))
input_grid <- cbind(Lat=GOAgrid$Latitude,
                    Lon=GOAgrid$Longitude,
```

```
                    Area_km2=GOAgrid$Shape_Area/1000000)

settings <- make_settings(
  n_x = 750, # number of vertices in the SPDE mesh
  Region = "user",
  purpose = "index2", # index of abundance with Gamma for positive catches
  fine_scale = TRUE, # use bilinear interpolation from the INLA 'A' matrix
  zone = NA, # detects automatically
  Options = c("Calculate_Range" = TRUE, "Calculate_effective_area" = TRUE,
              "treat_nonencounter_as_zero" = FALSE),
  ObsModel = c(2, 1), # conventional logit-linked delta-Gamma; (2,4) if there are years with 100% encou
  bias.correct = TRUE,
  use_anisotropy = TRUE,
  max_cells = Inf, # use all grid cells from the extrapolation grid, production model used 2000
  knot_method = "grid", # or "samples"
  strata.limits = data.frame(STRATA = as.factor('All_areas')) # customize to sp.
)
```

Next we will fit a GLMM (generalized linear mixed effects model).

```
# create folder for saved output:
dir.create(paste0(here("species_specific_code", "GOA", species,
                       "index_comparison")), showWarnings = FALSE)

f <- here("species_specific_code", "GOA", species, "index_comparison", "VASTfit.RDS")
if (!file.exists(f)) {
  fit <- fit_model(
    settings = settings,
    Lat_i = dat_ll[, "lat"],
    Lon_i = dat_ll[, "lon"],
    t_i = dat_ll[, "year"],
    b_i = dat_ll[, "cpue_kg_km2"],
    a_i = dat_ll[, "effort"],
    input_grid = input_grid,
    working_dir = paste0(here("species_specific_code", "GOA",
                              species, "index_comparison"), "/")
  )
  saveRDS(fit, file = f)
} else {
  fit <- readRDS(f)
  fit <- reload_model(fit)
}
#> Maximum absolute gradient of 2.8e-07: No evidence of non-convergence
```

We can look at parameter estimates. First we see estimates from the binomial component and second we see estimates from the positive Gamma component.

```
fit$parameter_estimates$diagnostics
#>          Param starting_value     Lower         MLE     Upper final_gradient
#> 1   ln_H_input     0.22431634 -5.000000  0.22431782  5.000000  -5.376359e-09
#> 2   ln_H_input     0.13141468 -5.000000  0.13141574  5.000000  -7.357404e-09
#> 3     beta1_ft    -3.50992317      -Inf -3.50991755       Inf  -1.238694e-09
#> 4     beta1_ft    -2.53414281      -Inf -2.53414460       Inf  -1.161650e-09
```

```
#> 5       beta1_ft    -2.86122138      -Inf -2.86122149       Inf  -8.500614e-10
#> 6       beta1_ft    -2.92061916      -Inf -2.92060913       Inf  -8.290613e-10
#> 7       beta1_ft    -2.84134737      -Inf -2.84130929       Inf   6.675836e-09
#> 8       beta1_ft    -2.67699818      -Inf -2.67698582       Inf  -2.407088e-10
#> 9       beta1_ft    -2.60573764      -Inf -2.60573457       Inf  -1.039933e-09
#> 10      beta1_ft    -2.68948717      -Inf -2.68949463       Inf  -6.489778e-10
#> 11      beta1_ft    -2.85404062      -Inf -2.85403671       Inf  -1.266466e-09
#> 12      beta1_ft    -2.91090288      -Inf -2.91090356       Inf  -5.331646e-10
#> 13      beta1_ft    -2.72227845      -Inf -2.72225608       Inf   1.047644e-09
#> 14      beta1_ft    -2.74259387      -Inf -2.74258882       Inf  -6.351435e-10
#> 15      beta1_ft    -2.45426843      -Inf -2.45429340       Inf  -1.752198e-11
#> 16      beta1_ft    -2.18951239      -Inf -2.18950986       Inf  -6.409753e-10
#> 17      beta1_ft    -2.49502666      -Inf -2.49498281       Inf   3.166615e-09
#> 18      beta1_ft    -2.45344190      -Inf -2.45344826       Inf  -5.118466e-10
#> 19    L_omega1_z     1.69122361      -Inf  1.69121068       Inf  -3.191666e-09
#> 20 L_epsilon1_z     0.44268706      -Inf  0.44268935       Inf  -2.326690e-08
#> 21     logkappa1    -3.14173940 -6.765487 -3.14173040 -1.659642   3.699228e-09
#> 22      beta2_ft     5.19539975      -Inf  5.19550592       Inf   6.635052e-09
#> 23      beta2_ft     5.11226637      -Inf  5.11233579       Inf   4.082985e-09
#> 24      beta2_ft     5.66667169      -Inf  5.66680022       Inf   6.663633e-09
#> 25      beta2_ft     5.34051015      -Inf  5.34059811       Inf   3.406569e-09
#> 26      beta2_ft     5.85663403      -Inf  5.85673609       Inf   4.101942e-09
#> 27      beta2_ft     5.77305189      -Inf  5.77318374       Inf   9.887014e-09
#> 28      beta2_ft     5.98076258      -Inf  5.98088718       Inf   6.606189e-09
#> 29      beta2_ft     5.67361609      -Inf  5.67373826       Inf   6.725838e-09
#> 30      beta2_ft     5.43681805      -Inf  5.43690668       Inf   3.609181e-09
#> 31      beta2_ft     5.49391404      -Inf  5.49401794       Inf   4.343857e-09
#> 32      beta2_ft     5.82868288      -Inf  5.82880495       Inf   5.012975e-09
#> 33      beta2_ft     5.62396814      -Inf  5.62407540       Inf   4.460620e-09
#> 34      beta2_ft     5.47400675      -Inf  5.47409154       Inf   2.885571e-09
#> 35      beta2_ft     5.43856397      -Inf  5.43865850       Inf   4.211280e-09
#> 36      beta2_ft     5.59496343      -Inf  5.59505576       Inf   4.433950e-09
#> 37      beta2_ft     5.37130570      -Inf  5.37139262       Inf   3.954288e-09
#> 38    L_omega2_z     1.27968716      -Inf  1.27969953       Inf  -1.647631e-07
#> 39 L_epsilon2_z     1.64733848      -Inf  1.64736284       Inf  -1.264471e-07
#> 40     logkappa2    -2.47470640 -6.765487 -2.47465890 -1.659642   1.257782e-07
#> 41     logSigmaM     0.06254715      -Inf  0.06255359 10.000000  -2.821395e-07
```

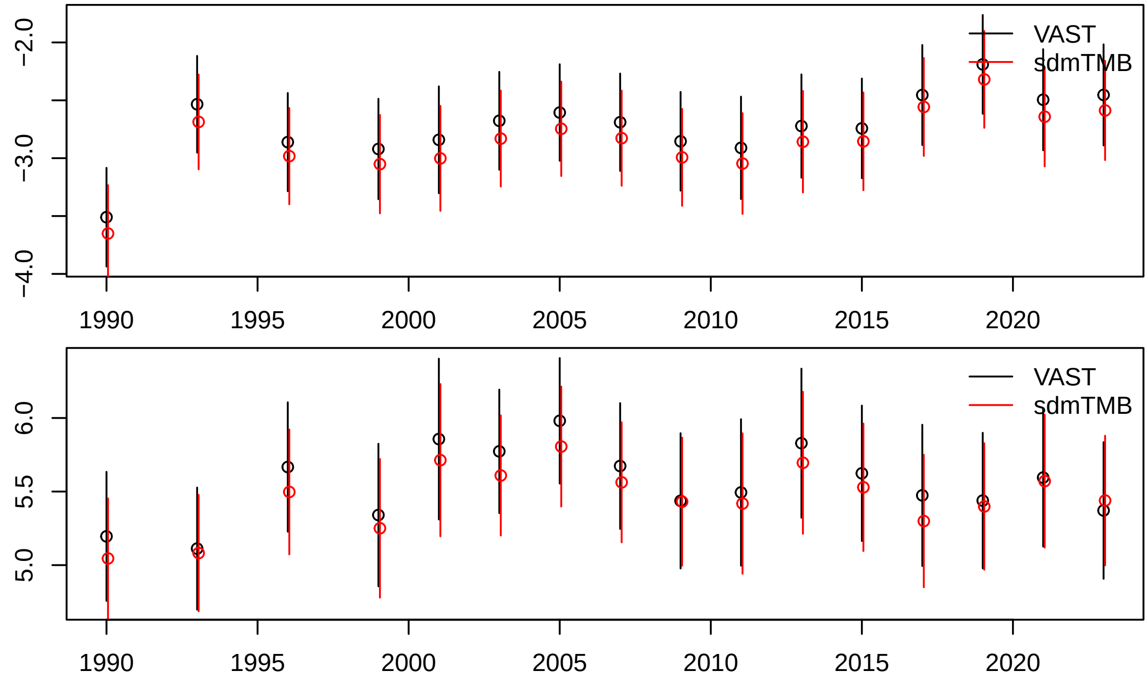
Now we fit the same model in sdmTMB:

```
dat <- dat_ll %>%
  rename(X = lon, Y = lat)

dat$year_f <- as.factor(dat$year)

coordinates(dat) <- ~ X + Y
proj4string(dat) <- CRS("+proj=longlat +datum=WGS84")
dat <- as.data.frame(spTransform(dat, CRS("+proj=utm +zone=5")))
# scale to km so values don't get too large
dat$X <- dat$coords.x1 / 1000
dat$Y <- dat$coords.x2 / 1000

f1 <- here("species_specific_code", "GOA", species,
           "index_comparison", "fit_sdmTMB.RDS")
```

```
if (!file.exists(f1)) {
# make mesh and fit model
mesh <-  make_mesh(dat, xy_cols = c("X", "Y"), mesh = fit$spatial_list$MeshList$anisotropic_mesh) #pass
#mesh <-  make_mesh(dat, xy_cols = c("X", "Y"), n_knots = 50, type = "kmeans") #coarser mesh for experi

fit_sdmTMB <- sdmTMB(
  cpue_kg_km2 ~ 0 + year_f,
  data = dat,
  mesh = mesh,
  family = delta_gamma(type = "poisson-link"),
  time = "year",
  spatial = "on",
  spatiotemporal = "iid",
  silent = FALSE,
  anisotropy = TRUE,
  do_fit = TRUE
  #, do_index = TRUE (to compute index at same time, requires passing args)
)
fit_sdmTMB
saveRDS(fit_sdmTMB, file = here("species_specific_code", "GOA",
                                species, "index_comparison",
                                "fit_sdmTMB.RDS"))
} else {
fit_sdmTMB <- readRDS(f1)
}

# diagnose estimation issues due to model structure
#TMBhelper::check_estimability(fit_sdmTMB$tmb_obj)
```

We wrote some custom code to extract comparable parameters (not shown above). Here are the annual mean estimates in link space with 95% confidence intervals for the two components to the delta model:

```
par(mfrow = c(2, 1), cex = 0.8, mar = c(1.5, 1, 1, 1), oma = c(2, 3, 1, 1))
plot_betas(fit, fit_sdmTMB, "beta1_ft", sdmTMB_pars = 1)
plot_betas(fit, fit_sdmTMB, "beta2_ft", sdmTMB_pars = 2)
```



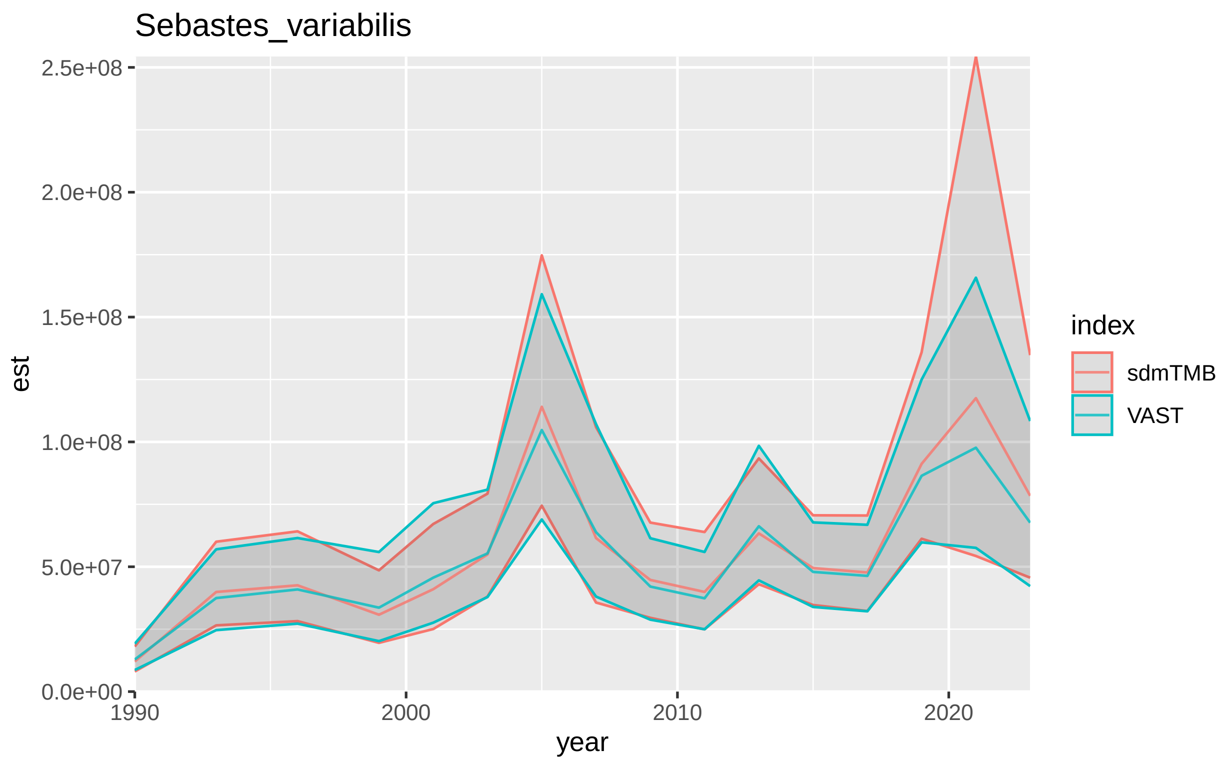
We can compare the index we would get using sdmTMB.

```
# prep prediction grid and transform to UTM projection
grid_ll <- as.data.frame(input_grid)
names(grid_ll) <- tolower(names(grid_ll))
coordinates(grid_ll) <- ~ lon + lat
proj4string(grid_ll) <- CRS("+proj=longlat +datum=WGS84")
grid <- as.data.frame(spTransform(grid_ll, CRS("+proj=utm +zone=5")))

# rename and scale to km so values don't get too large
grid$X <- grid$coords.x1 / 1000
grid$Y <- grid$coords.x2 / 1000

# or with sf:
# grid_ll <- sf::st_as_sf(
#   x = grid_ll,
#   coords = c("lon", "lat"),
#   crs = "+proj=longlat +datum=WGS84"
# )
# grid <- sf::st_transform(grid_ll, crs = "+proj=utm +zone=5")

# replicate extrapolation grid for each year in data
pred_grid <- replicate_df(grid, "year_f", unique(dat$year_f))
pred_grid$year <- as.integer(as.character(factor(pred_grid$year_f)))

# make predictions and get index
f2 <- here("species_specific_code", "GOA", species,
           "index_comparison", "predictions.RDS")
if (!file.exists(f2)) {
```

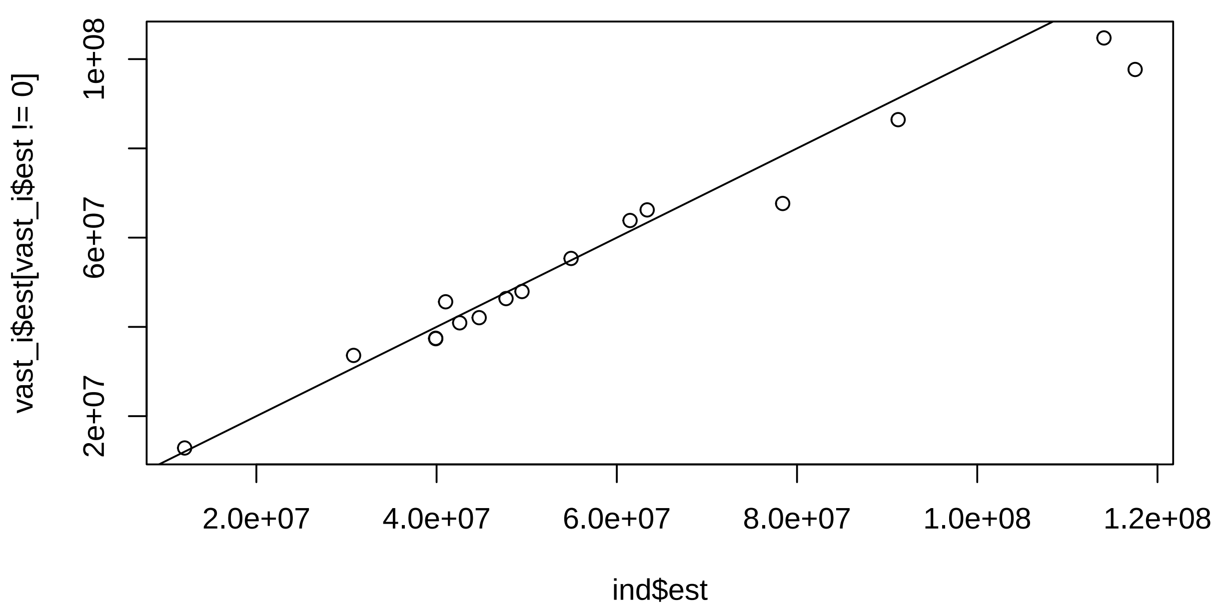
```
p <- predict(fit_sdmTMB, newdata = pred_grid, return_tmb_object = TRUE)
saveRDS(p, file = here("species_specific_code", "GOA", species, "index_comparison", "predictions.RDS"))
} else {
p <- readRDS(f2)
}

f3 <- here("species_specific_code", "GOA", species,
           "index_comparison", "index.RDS")
if (!file.exists(f3)) {
ind <- get_index(p, bias_correct = TRUE, area = p$data$area_km2)
saveRDS(ind, file = here("species_specific_code", "GOA", species, "index_comparison", "index.RDS"))
} else {
ind <- readRDS(f3)
}
```

Now, we can compare the indices.

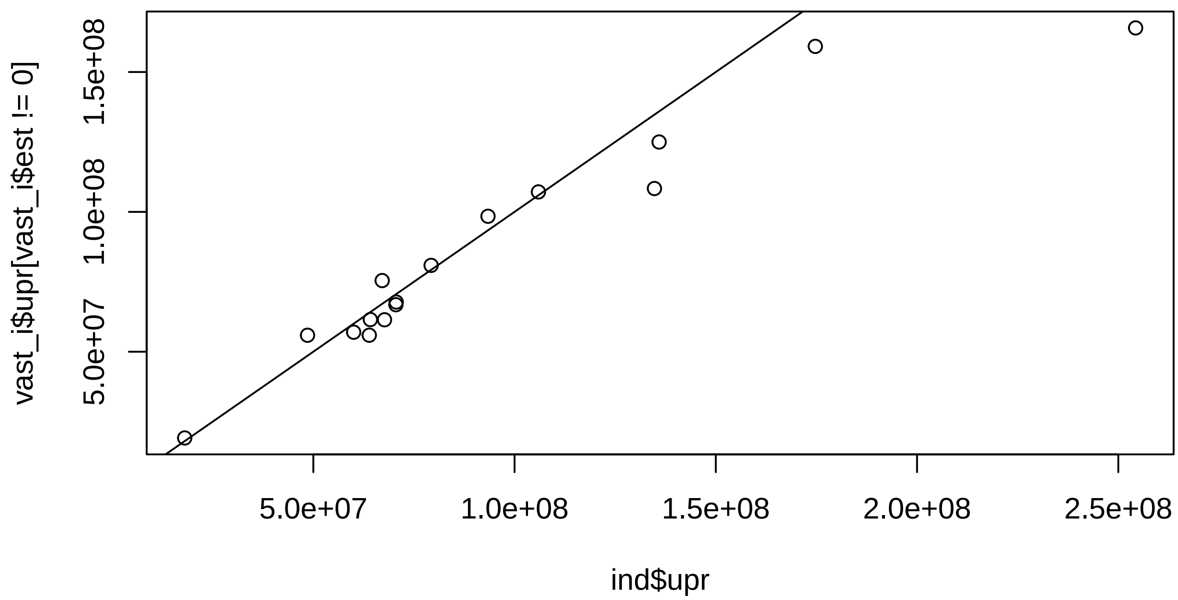
```
sdm_i <- ind %>% mutate(index = "sdmTMB")
vast_i <- read.csv(here("species_specific_code", "GOA", species, "index_comparison", "Index.csv")) %>%
  mutate(index = "VAST", year = as.numeric(Time), est = Estimate,
    se = Std..Error.for.ln.Estimate.) %>%
  select(index, year, est, se) %>%
  filter(year %in% unique(sdm_i$year)) %>%
  mutate(lwr = exp(log(est) + qnorm(0.025) * se)) %>%
  mutate(upr = exp(log(est) + qnorm(0.975) * se))
both_i <- bind_rows(sdm_i, vast_i) %>% filter(est > 0)

ggplot(both_i, aes(x = year, y = est, ymin = lwr, ymax = upr, colour = index)) +
  geom_ribbon(alpha = 0.1) +
  geom_line(alpha = 0.8) +
  ylim(0, max(both_i$upr)) +
  ggtitle(species) +
  coord_cartesian(expand = FALSE)
```



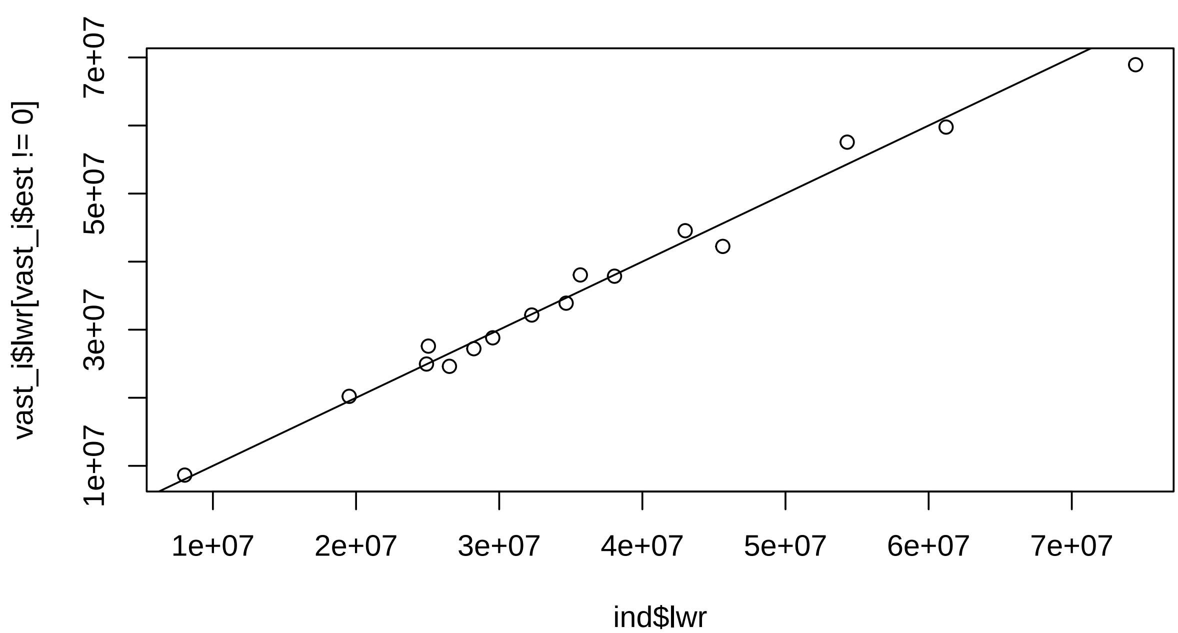

```
plot(ind$est, vast_i$est[vast_i$est != 0]);abline(0, 1)
```




```
plot(ind$upr, vast_i$upr[vast_i$est != 0]);abline(0, 1)
```




```
plot(ind$lwr, vast_i$lwr[vast_i$est != 0]);abline(0, 1)
```




```
(ind$est - vast_i$est[vast_i$est != 0]) / vast_i$est[vast_i$est != 0]
```

```
#>  [1] -0.064197978  0.065312921  0.040464747 -0.083971484 -0.101307827
#>  [6] -0.007477008  0.088909518 -0.037184976  0.063183633  0.068226133
#> [11] -0.043011308  0.032378051  0.029304485  0.055373409  0.203131799
#> [16]  0.158967474
(ind$upr - vast_i$upr[vast_i$est != 0]) / vast_i$upr[vast_i$est != 0]
#>  [1] -0.05818895  0.05344194  0.04349982 -0.13128715 -0.11051229 -0.01985106
#>  [7]  0.09777135 -0.01122308  0.10204794  0.14288187 -0.05114117  0.04198073
#> [13]  0.05563908  0.08751413  0.53408839  0.24371329
(ind$lwr - vast_i$lwr[vast_i$est != 0]) / vast_i$lwr[vast_i$est != 0]
#>  [1] -0.070168665  0.077317676  0.037438500 -0.034078707 -0.092008119
#>  [6]  0.005053261  0.080119223 -0.062465204  0.025689899 -0.001552911
#> [11] -0.034811785  0.022863870  0.003626851  0.024182583 -0.056425866
#> [16]  0.079996182
```

This document was built using:

```
R.Version()$version.string
#> [1] "R version 4.3.0 (2023-04-21 ucrt)"
packageVersion("VAST")
#> [1] '3.11.2'
packageVersion("FishStatsUtils")
#> [1] '2.13.1'
```