Supporting Information:

Human histories shape the biodiversity data that decide our future

Abstract:

While rapidly growing repositories of biodiversity data provide unprecedented insight into ecological patterns at global scales, the application of species observations often belies the reality that the species these data tell us most about is the one they were never intended to include: humans. Biodiversity data trace not only cities and roads but the rise of surveillance technology, shadows of colonial histories, and echoes of contemporary racial and economic disparities. However, these same data are increasingly used as the starting point to inform the implementation of global policy and the investment of billions of dollars to protect and restore nature over the next decade. Effectively leveraging large-scale biodiversity data to benefit both people and nature requires expertise in social, cultural, and political processes underlying data infrastructures and their histories, just as much as it requires more data and increasingly complex statistical methods.

Here we synthesize examples of the social, political and economic dimensions of human society reflected in global biodiversity data.

Exploring social and political dimensions of biodiversity data

In Figure 1, we leverage the Global Biodiversity Information Facility (GBIF) to reproduce, update, and expand upon the cited social and political dimensions of biodiversity data presented throughout the scientific literature.

GBIF releases full occurrence "snapshots" monthly. In this paper, we leverage the Sept 31, 2023 Snapshot, which was the most recent at the time of submission. (https://doi.org/10.15468/dl.ua9nww) (GBIF.Org User 2023)

We provide code to reproduce each panel of the figure and explain how it relates to previously published work cited in the paper.

Throughout the code we use the following packages (Cameron and Brand 2022; Mühleisen and Raasveldt 2023; Boettiger 2023; "Global Biodiversity Information Facility (GBIF) Species Occurrences" 2021; Wickham et al. 2019; Pebesma and Bivand 2023; Hijmans 2023b, 2023a; Mills 2022; Massicotte and South 2023; Arel-Bundock, Enevoldsen, and Yetman 2018; Richardson et al. 2023; Di Lorenzo 2023):

```r
library(geomtextpath)
library(duckdbfs)
library(gbifdb)
library(tidyverse)
library(fst)
library(sf)
library(terra)
library(raster)
library(MetBrewer)
library(rnaturalearth)
library(countrycode)
library(arrow)
library(usmap)
library(svglite)
```

Connect to a GBIF snapshot

We use a local version of of the Sept 31 2023 GBIF snapshot and the `gbifdb` package to query the >2.6 billion observations in the database.

```r
gbif <- gbif_local("/home/shared-data/gbif/occurrence/2023-10-01/occurrence.parquet/",
                   backend="duckdb")
```

All analysis here can alternatively be done by querying the GBIF AWS snapshot (leveraging the `arrow` package, see code below).

```r
# snapshot <- "s3://gbif-open-data-eu-central-1/occurrence/2023-10-01/occurrence.parquet"
# gbif <- open_dataset(gbif_snapshot)
```

Panel A: Global map

We summarize the count of observations at 0.1 decimal degrees. All observations in GBIF with coordinates from the year 1800 onward are included in this map.

```
df <- gbif |>
  mutate(latitude = round(decimallatitude,1),
         longitude = round(decimallongitude,1)) |>
  filter(year >1800) |>
  count(longitude, latitude) |>
  collect()
```

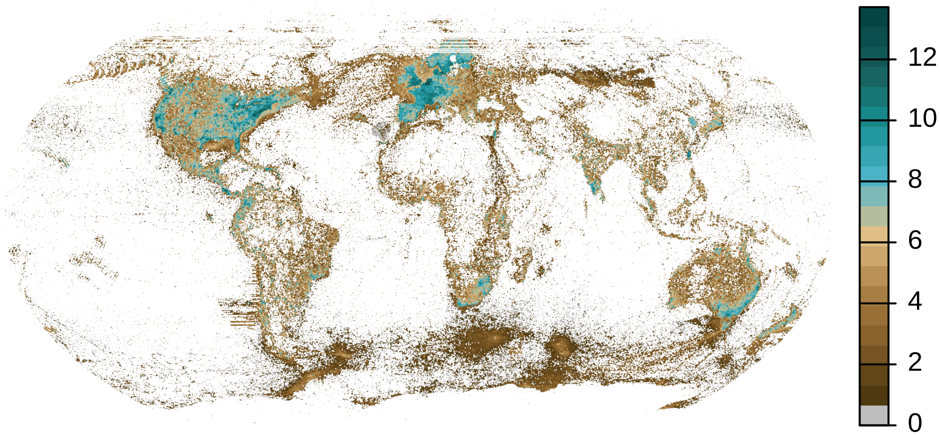
We convert the lat/long to spatial points using the `sf` package

```
df_spatial <- df |>
  filter(!is.na(latitude),
         !is.na(longitude)) |>
  st_as_sf(coords = c("longitude", "latitude"),
           crs = "epsg:4326")
```

The log of the sum of observations at each point is converted into a global raster at 0.1 degrees.

```
ras_temp <-raster(xmn=-180, xmx=180, ymn=-90, ymx=90,
                  resolution=c(0.1,0.1), vals=NA)
global_plot <- rasterize(df_spatial, ras_temp,
                         field = "n", fun='sum')
rm(df_spatial) #remove unnecessary data
rm(ras_temp) #remove unnecessary data
```

```
crs <- "+proj=robin +lon_0=0 +x_0=0 +y_0=0 +datum=WGS84 +units=m"
global_plot <- terra::rast(global_plot)
global_plot <- global_plot * 1 # to deal with NAs in this dataset
# reproject for viz
global_plot <- terra::project(global_plot, crs, mask=TRUE)
# define color gradient
colors <- c("grey", met.brewer(name="Isfahan1",n=20,type="continuous"))
# take log for viz
terra::plot(log(global_plot), col = colors, axes = FALSE)
```



Panel B: Macroeconomic patterns

In panel B, we show the number of observations (log) per year collected in countries across different income groups.

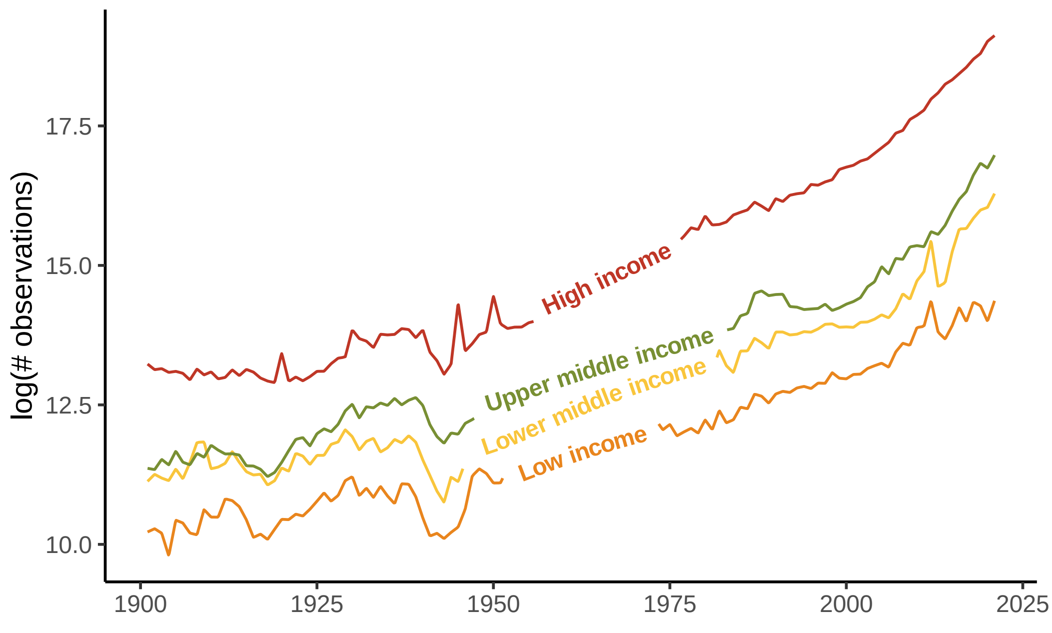
```
world <- ne_countries(type = "countries", scale = "medium")
world <- st_as_sf(world) |>
  dplyr::select(iso_a2, income_grp) |>
  st_make_valid() |>
  mutate(area = st_area(geometry)) |>
  as_tibble() |>
  dplyr::select(-geometry) |>
  mutate(area = as.numeric(area)) |>
  rename(countrycode = iso_a2)
```

Collect count of observations per year per country

```
country_year <-  gbif |>
    count(countrycode, year) |>
    collect()
```

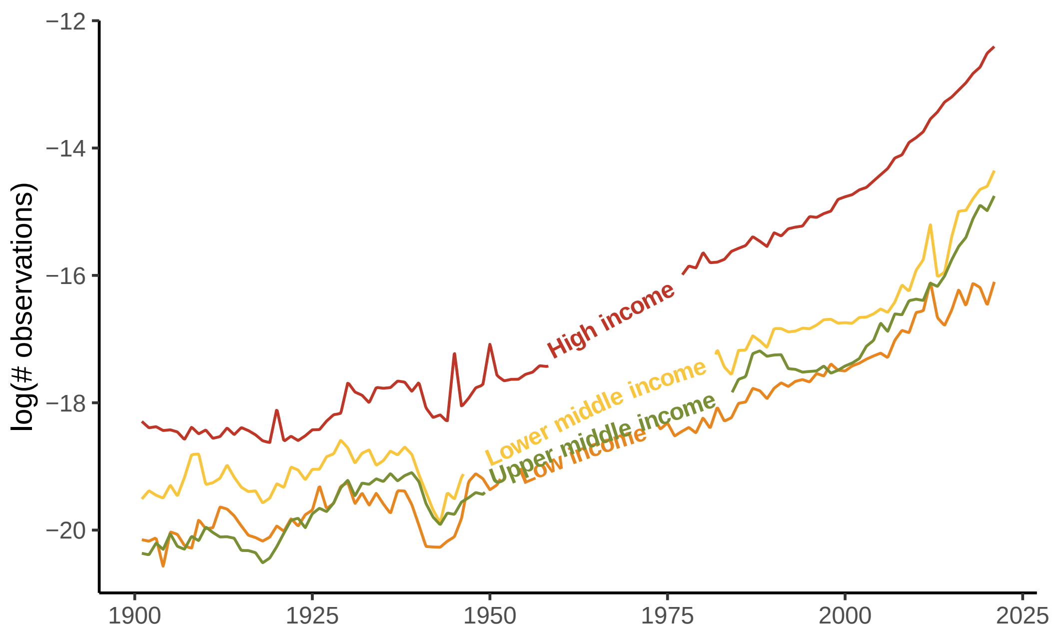
Filter to years 1900-2022 and get the sum of observations per country, plot log

```r
macroeconomics <- country_year |>
  filter(year >1900 & year < 2022) |>
  mutate(n = replace_na(n, 0)) |>
  left_join(world) |>
  mutate(income_grp = str_sub(income_grp, 4, -1),
         #INCOME_GRP = gsub("\\s", "\n", INCOME_GRP),
         income_grp = gsub("\\:.*","",income_grp)) |>
  group_by(year, income_grp) |>
  summarise(n = sum(n, na.rm = TRUE), area = sum(area)) |>
  mutate(density = n/area) |>
  drop_na() |>
  ggplot(aes(year, log(n), color = income_grp, label = income_grp)) +
  geom_textline(size = 3, fontface = 2, spacing = 30, text_smoothing = 50) +
  theme_classic() +
  theme(legend.position = "none", legend.title = element_blank()) +
  labs(x = "", y = "log(# observations)") +
  scale_color_manual(values=met.brewer("Homer2", 4)) +
  theme(legend.background =
          element_rect(colour = 'black', fill = 'white', linetype='solid'))
macroeconomics
```



We can see that these patterns hold true if we look at the log(observations) per unit area

```r
macroeconomics_density <- country_year |>
  filter(year >1900 & year < 2022) |>
  mutate(n = replace_na(n, 0)) |>
  left_join(world) |>
  mutate(income_grp = str_sub(income_grp, 4, -1),
         #INCOME_GRP = gsub("\\s", "\n", INCOME_GRP),
         income_grp = gsub("\\:.*","",income_grp)) |>
  group_by(year, income_grp) |>
  summarise(n = sum(n, na.rm = TRUE), area = sum(area)) |>
  mutate(density = n/area) |>
  drop_na() |>
  ggplot(aes(year, log(density), color = income_grp, label = income_grp)) +
  geom_textline(size = 3, fontface = 2, spacing = 30, text_smoothing = 50) +
  theme_classic() +
  theme(legend.position = "none", legend.title = element_blank()) +
  labs(x = "", y = "log(# observations)") +
  scale_color_manual(values=met.brewer("Homer2", 4)) +
  theme(legend.background =
          element_rect(colour = 'black', fill = 'white', linetype='solid'))
macroeconomics_density
```



Panel C: Redlining

Redlining data

Redlining data is downloaded from Mapping Inequality (https://dsl.richmond.edu/panorama/redlining/) (Robert K. Nelson, n.d.). While Ellis-Soto et al., 2023 (Ellis-Soto, Chapman, and Locke 2023) show these patterns in bird data throughout the United States, here we show that similar patterns hold true across all taxa (in aggregate) in GBIF.

```
holc <-
  st_read("https://dsl.richmond.edu/panorama/redlining/static/fullDownload.geojson") |>
  dplyr::select(state, city, holc_grade, geometry) |>
  dplyr::filter(!is.na(holc_grade) & holc_grade != 'E') |>
  sf::st_make_valid()
```

```
Reading layer `fullDownload' from data source
  `https://dsl.richmond.edu/panorama/redlining/static/fullDownload.geojson'
  using driver `GeoJSON'
replacing null geometries with empty geometries
Simple feature collection with 8878 features and 7 fields (with 3 geometries empty)
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -122.7675 ymin: 25.70537 xmax: -70.9492 ymax: 47.72251
Geodetic CRS:  WGS 84
```

```
holc <- holc |>
  dplyr::mutate(valid =st_is_valid(holc)) |>
  dplyr::filter(valid=="TRUE")

holc_area  <- holc |>
  mutate(area = st_area(geometry)) |>
  as_tibble() |>
  dplyr::select(-geometry) |>
  group_by(holc_grade) |>
  summarise(area = sum(area)) |>
  mutate(area = as.numeric(area)) |>
  ungroup()
```

Map of US observations

Observations in the US are queried and summed at 0.001 decimal degrees.

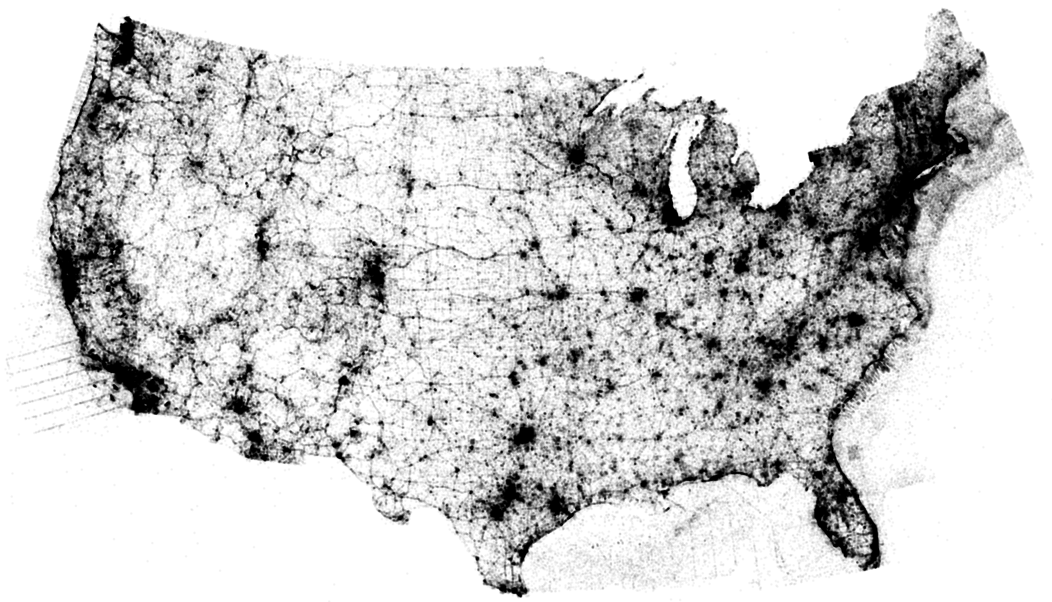
```r
states <- sf::st_as_sf(maps::map("state",
                                 plot = FALSE, fill = TRUE)) |>
  filter(ID!= "alaska" & ID!= "hawaii" )
ext_states <- ext(states)

US_pts <- gbif |>
   filter(countrycode == "US") |>
   mutate(latitude = round(decimallatitude,3),
         longitude = round(decimallongitude,3)) |>
  count(latitude, longitude) |>
  collect() |>
  filter(longitude > ext_states[1] & longitude < ext_states[2] &
           latitude > ext_states[3] & latitude < ext_states[4])
```

These are converted to a spatial data frame

```r
US_pts_sf_all <- US_pts |>
  filter(!is.na(latitude),
         !is.na(longitude)) |>
  st_as_sf(coords = c("longitude", "latitude"),
           crs = st_crs(holc))

US_pts_sf <- US_pts_sf_all |>  head(1000000) |>
  st_transform(crs = usmap::usmap_crs())
```

For the US map we plot a subset of 1 million points to allow for visualization of point density in cities and around major roads.

```r
plot_gbif <- US_pts_sf |>
  ggplot() +
  geom_sf(aes(geometry = geometry), alpha = 0.05,
            size = 0.001, color= "black") +
  theme(legend.position = "none") +
  theme_void()

plot_gbif
```



Map of LA: observation and redlining

All observation points are shown as an example in LA.

```
la <- holc |> filter(city == "Los Angeles")
ext_la <- ext(la)
pts_la <- US_pts |>
  dplyr::select(longitude, latitude, n) |>
```

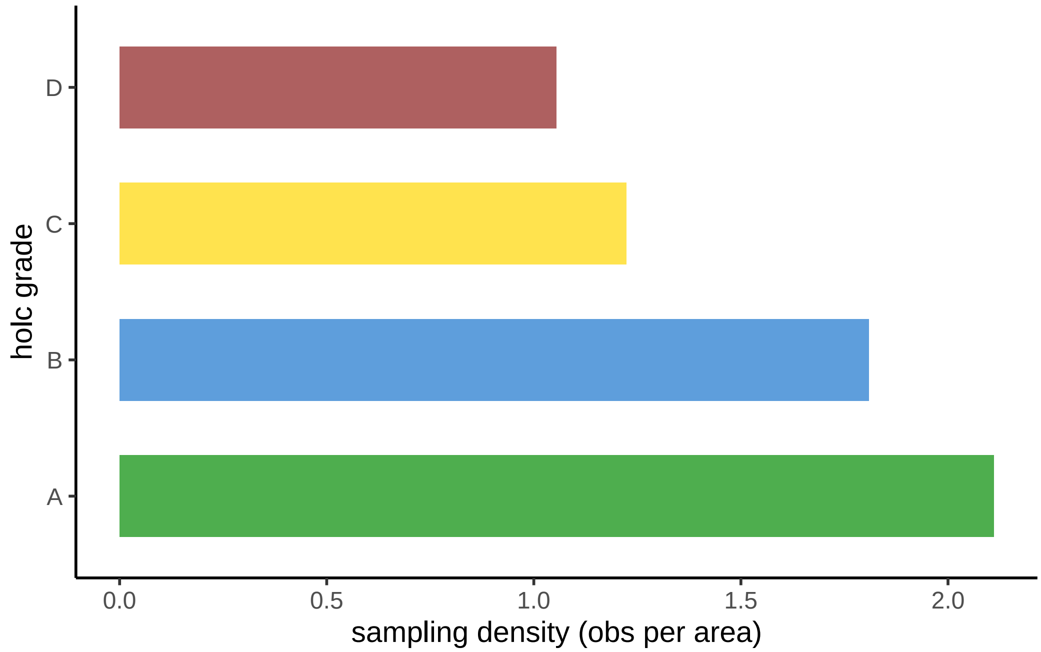
```
  rename(lon = longitude, lat = latitude) |>
  filter(lon > ext_la[1] & lon < ext_la[2] &
           lat > ext_la[3] & lat < ext_la[4])

holc_la <- holc |> filter(city == "Los Angeles") |>
  ggplot() +
  geom_sf(aes(fill = holc_grade), alpha = 0.7, lwd = 0) +
    scale_fill_manual(
      values=c("green4","dodgerblue3", "gold1", "firebrick4")) +
  theme_void() +
  geom_point(data = pts_la, aes(x = lon, y = lat),
             color = "black", alpha= 0.1, size = 0.01) +
ggspatial::annotation_scale() + theme(legend.position = "none")
```

Redlining observations summary

The bar chart shows the number of observations per unit area in each holc grad across all cities included in the Mapping Inequality dataset.

```
holc_obs <- st_join(US_pts_sf_all, holc, join = st_within)
```

```
redlining <- as_tibble(holc_obs) |>
  drop_na() |>
  group_by(holc_grade) |>
  summarise(counts = sum(n)) %>% ungroup() |>
  left_join(holc_area) |>
  mutate(density = counts/area) |>
  ggplot(aes(x = holc_grade, y = density*1000, fill = holc_grade)) +
  scale_fill_manual(
    values=c("green4","dodgerblue3", "gold1", "firebrick4")) +
  geom_col(width = 0.6, alpha = 0.7) + theme_classic() +
  theme(legend.position = "none") +
  labs(x = "holc grade", y = "sampling density (obs per area)") + coord_flip()

redlining
```




```
as_tibble(holc_obs) |>
  drop_na() |>
  group_by(holc_grade) |>
  summarise(counts = sum(n)) |>
  ungroup() |>
  left_join(holc_area) |>
  mutate(density = counts/area*1000) |>
  dplyr::select(holc_grade, density) |>
  write_csv("../data/panels/panelC_holc_bar_data.csv")
```

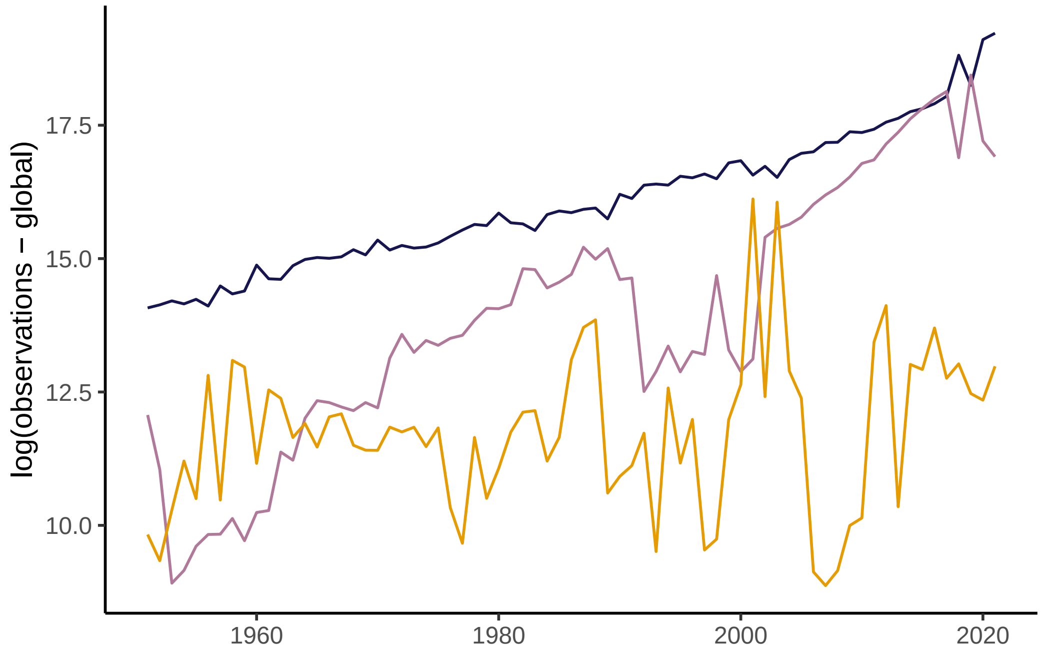
Panel D: Conflict

Following analysis in (Zizka et al. 2021) and leveraging the yearly conflict data from the Uppsala Conflict Data Program (UCDP) (Davies, Pettersson, and Öberg 2023; GLEDITSCH et al. 2002), we show how biodiversity data observations track conflict both (i) globally and (ii) in Cambodia (Zizka et al. 2021) since 1950.

```
country_year <-  gbif |>
    count(countrycode, year) |>
    collect()
```

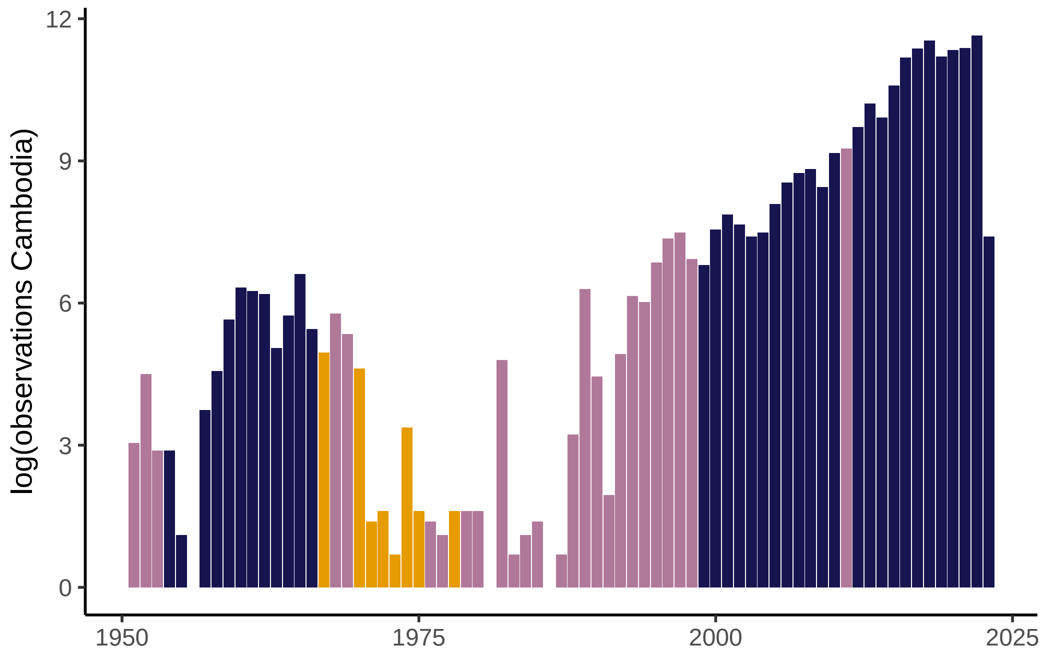
```r
#download.file(url = "https://ucdp.uu.se/downloads/ucdpprio/ucdp-prio-acd-231-rds.zip", dest
#unzip("data/conflict.zip", exdir = "data/")

conflict <- readRDS("../data/UcdpPrioConflict_v23_1.rds") |>
  dplyr::select(location, year, intensity_level) |>
  separate_rows(location, sep = ",") |>
  mutate(countrycode =
           countrycode(location,
                       origin = 'country.name',
                       destination = 'iso2c'))
```

```r
conflict_plot_i <- country_year |>
  left_join(conflict) |>
  dplyr::select(-location) |>
  filter(year >1950 & year <2022) |>
  mutate(intensity_level = replace_na(intensity_level, 0)) |>
  mutate(n = replace_na(n, 0)) |>
  group_by(year, intensity_level) |>
  summarise( n = sum(n, na.rm = TRUE)) |>
  unique() |>
  ggplot() +
  geom_line(aes(year, log(n), col = as.factor(intensity_level), group=as.factor(intensity_lev
  #scale_color_manual(values= c("darkgrey", "#FF4433", "darkred")) +
  scale_color_manual(values=met.brewer("Renoir", 4)) +
  #geom_line(aes(year, v2xcl_dmove*10), lwd = 1.5, color = "black") +
  theme_classic() +
  theme(legend.position = "none", axis.title.x = element_blank()) +
  scale_y_continuous(
    # Features of the first axis
    name = "log(observations - global)"#,
    # Add a second axis and specify its features
    #sec.axis = sec_axis( trans=~./10, name="freedom of movement")
  ) #+ geom_line(aes(x = year, y = intensity_level*5)) +

conflict_plot_i
```




```
conflict_plot_ii <- country_year |>
  left_join(conflict) |>
  dplyr::select(-location) |>
  filter(year >1950) |>
  mutate(intensity_level = replace_na(intensity_level, 0)) |>
  mutate(n = replace_na(n, 0)) |>
  filter(countrycode == "KH") |>
  group_by(countrycode, year) |>
  summarise(intensity_level = max(intensity_level),
            n = mean(n, na.rm = TRUE)) |>
  unique() |>
  ggplot() +
  geom_col(aes(year, (log(n)), fill = as.factor(intensity_level))) +
  #scale_fill_manual(values= c("darkgrey", "#FF4433", "darkred")) +
  scale_fill_manual(values=met.brewer("Renoir", 4)) +
  #geom_line(aes(year, v2xcl_dmove*10), lwd = 1.5, color = "black") +
  theme_classic() +
  theme(legend.position = "none", axis.title.x = element_blank()) +
  scale_y_continuous(
    # Features of the first axis
    name = "log(observations Cambodia)"#,
    # Add a second axis and specify its features
```

```
    #sec.axis = sec_axis( trans=~./10, name="freedom of movement")
  ) #+ geom_line(aes(x = year, y = intensity_level*5)) +

conflict_plot_ii
```




```
country_year |>
  left_join(conflict) |>
  dplyr::select(-location) |>
  filter(year >1950 & year <2022) |>
  mutate(intensity_level = replace_na(intensity_level, 0)) |>
  mutate(n = replace_na(n, 0)) |>
  group_by(year, intensity_level) |>
  summarise( n = sum(n, na.rm = TRUE)) |>
  unique() |>
  write_csv("../data/panels/panelD_i_data.csv")
```

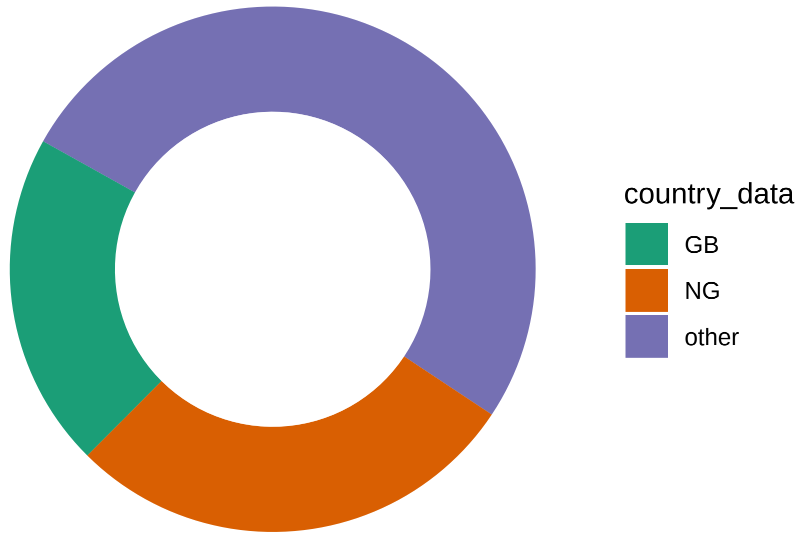
Panel E: Colonialism

As explored in (Zizka et al. 2021), social and political factors impact who has collected biodiversity data. We reproduce this analysis using the update GBIF snapshot. We can see that the publishing country before and after Nigeria's independence (1960) is drastically different (Zizka et al. 2021).

```
NG_year <- gbif |>
    filter(countrycode == "NG") |>
    count(year, basisofrecord, datasetkey) |>
    collect()

# download dataset keys to keep track of publishing country
orgs <- read_tsv("https://api.gbif.org/v1/dataset/search/export?format=TSV&") |>
  dplyr::select(publishing_country, dataset_key, title) |>
  rename(datasetkey = dataset_key)

NG_year_summary <- NG_year |>
  left_join(orgs) |>
  mutate() |>
  mutate(country_data = ifelse(publishing_country == "GB", "GB",
                               ifelse(publishing_country == "NG", "NG", "other"))) |>
  mutate(precol = ifelse(year <1961,"1","2")) |>
  group_by(country_data, precol) |>
  summarise(n = sum(n)) |>
  drop_na()
```

Observations in Nigeria pre-independence

```
t1 <- NG_year_summary |>
  group_by(precol) |> mutate(total_obs = sum(n)) |> ungroup()|>
  mutate(perc_obs = n/total_obs) |> filter(precol == "1") |>
  arrange(desc(perc_obs)) %>%
  mutate(lab.pos = cumsum(perc_obs)-.5*perc_obs)

panelE_i <- ggplot(data = t1,
      aes(x = 2, y = perc_obs, fill = country_data))+
  geom_bar(stat = "identity")+
  coord_polar("y", start = 200) +
  theme_void() +
  scale_fill_brewer(palette = "Dark2") + xlim(.2,2.5)

panelE_i
```



Observations in Nigeria post-independence

```
t2 <- NG_year_summary |>
  group_by(precol) |> mutate(total_obs = sum(n)) |> ungroup()|>
  mutate(perc_obs = n/total_obs) |> filter(precol == "2") |>
  arrange(desc(perc_obs)) %>%
  mutate(lab.pos = cumsum(perc_obs)-.5*perc_obs)

panelE_ii <- ggplot(data = t2,
       aes(x = 2, y = perc_obs, fill = country_data))+
  geom_bar(stat = "identity")+
  coord_polar("y", start = 200) +
  theme_void() +
  scale_fill_brewer(palette = "Dark2") + xlim(.2,2.5)
```

References

Arel-Bundock, Vincent, Nils Enevoldsen, and CJ Yetman. 2018. "Countrycode: An r Package to Convert Country Names and Country Codes" 3: 848. https://doi.org/10.21105/joss.00848.

Boettiger, Carl. 2023. "Duckdbfs: High Performance Remote File System Access Using 'Duckdb'." https://github.com/cboettig/duckdbfs.

Cameron, Allan, and Teun van den Brand. 2022. "Geomtextpath: Curved Text in 'Ggplot2'." https://allancameron.github.io/geomtextpath/.

Davies, Shawn, Therése Pettersson, and Magnus Öberg. 2023. "Organized Violence 1989–2022, and the Return of Conflict Between States." *Journal of Peace Research* 60 (4): 691–708. https://doi.org/10.1177/00223433231185169.

Di Lorenzo, Paolo. 2023. "Usmap: US Maps Including Alaska and Hawaii." https://usmap.dev.

Ellis-Soto, Diego, Melissa Chapman, and Dexter H. Locke. 2023. "Historical Redlining Is Associated with Increasing Geographical Disparities in Bird Biodiversity Sampling in the United States." *Nature Human Behaviour*, September. https://doi.org/10.1038/s41562-023-01688-5.

GBIF.Org User. 2023. "Occurrence Download." The Global Biodiversity Information Facility. https://doi.org/10.15468/DL.UA9NWW.

GLEDITSCH, NILS PETTER, PETER WALLENSTEEN, MIKAEL ERIKSSON, MARGARETA SOLLENBERG, and HÅVARD STRAND. 2002. "Armed Conflict 1946-2001: A New Dataset." *Journal of Peace Research* 39 (5): 615–37. https://doi.org/10.1177/0022343302039005007.

"Global Biodiversity Information Facility (GBIF) Species Occurrences." 2021. https://registry.opendata.aws/gbif.

Hijmans, Robert J. 2023a. "Raster: Geographic Data Analysis and Modeling." https://rspatial.org/raster.

———. 2023b. "Terra: Spatial Data Analysis." https://rspatial.org/.

Massicotte, Philippe, and Andy South. 2023. "Rnaturalearth: World Map Data from Natural Earth." https://docs.ropensci.org/rnaturalearth/ https://github.com/ropensci/rnaturalearth.

Mills, Blake Robert. 2022. "MetBrewer: Color Palettes Inspired by Works at the Metropolitan Museum of Art."

Mühleisen, Hannes, and Mark Raasveldt. 2023. "Duckdb: DBI Package for the DuckDB Database Management System." https://duckdb.org/.

Pebesma, Edzer, and Roger Bivand. 2023. "{Spatial Data Science: With Applications in r}." https://doi.org/10.1201/9780429459016.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, and Apache Arrow. 2023. "Arrow: Integration to 'Apache' 'Arrow'." https://github.com/apache/arrow/.

Robert K. Nelson, Richard Marciano, LaDale Winling. n.d. "Mapping Inequality." https://dsl.richmond.edu/panorama/redlining/#loc=5/39.1/-94.58&text=downloads.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the {Tidyverse}" 4: 1686. https://doi.org/10.21105/joss.01686.

Zizka, Alexander, Oskar Rydén, Daniel Edler, Johannes Klein, Allison Perrigo, Daniele Silvestro, Sverker C. Jagers, Staffan I. Lindberg, and Alexandre Antonelli. 2021. "Bio-Dem, a Tool to Explore the Relationship Between Biodiversity Data Availability and

Socio-Political Conditions in Time and Space." *Journal of Biogeography* 48 (11): 2715–26. https://doi.org/10.1111/jbi.14256.