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.

In this SI document, 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) occurrence data set to reproduce, visualize, update, and/or expand upon the cited social and political dimensions of biodiversity data presented in the paper.

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). This snapshot has approximate 2.6 billion occurrence records.

We provide code to reproduce each panel of Figure 1. All data used is accessed within the code and is openly available.

We use the following packages:

```
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)
```

Package citations: (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):

Connect to a GBIF snapshot

We use a local copy of the Sept 31, 2023 GBIF snapshot and the `gbifdb` package ("Global Biodiversity Information Facility (GBIF) Species Occurrences" 2021) to query the >2.6 billion observations in the database.

```
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 (Richardson et al. 2023)) using the following code:

```
# 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 (Pebesma and Bivand 2023).

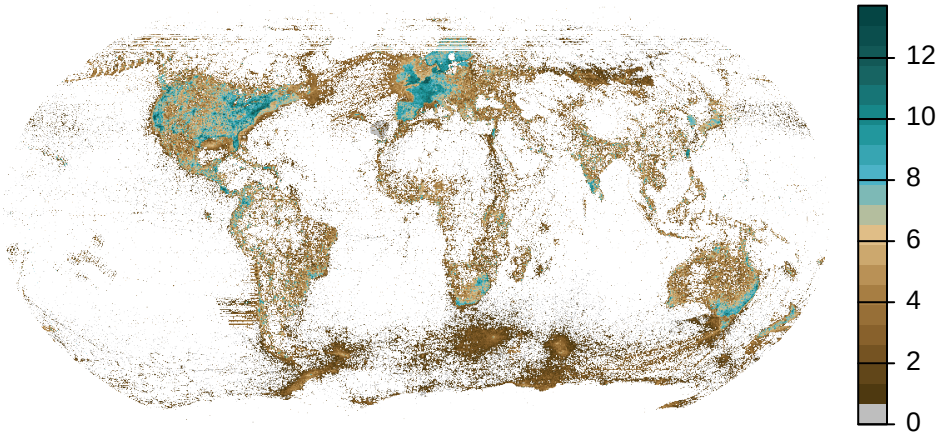
```
df_spatial <- df |>
  filter(!is.na(latitude),
         !is.na(longitude)) |>
  st_as_sf(coords = c("longitude", "latitude"),
           crs = "epsg:4326")
```

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
```

Reproject to the Robinson projection and plot using the terra package (Hijmans 2023b).

```
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. The World Bank classifies economies for analytical purposes into four income groups: **low, lower-middle, upper-middle, and high income**. We use these for our analysis.

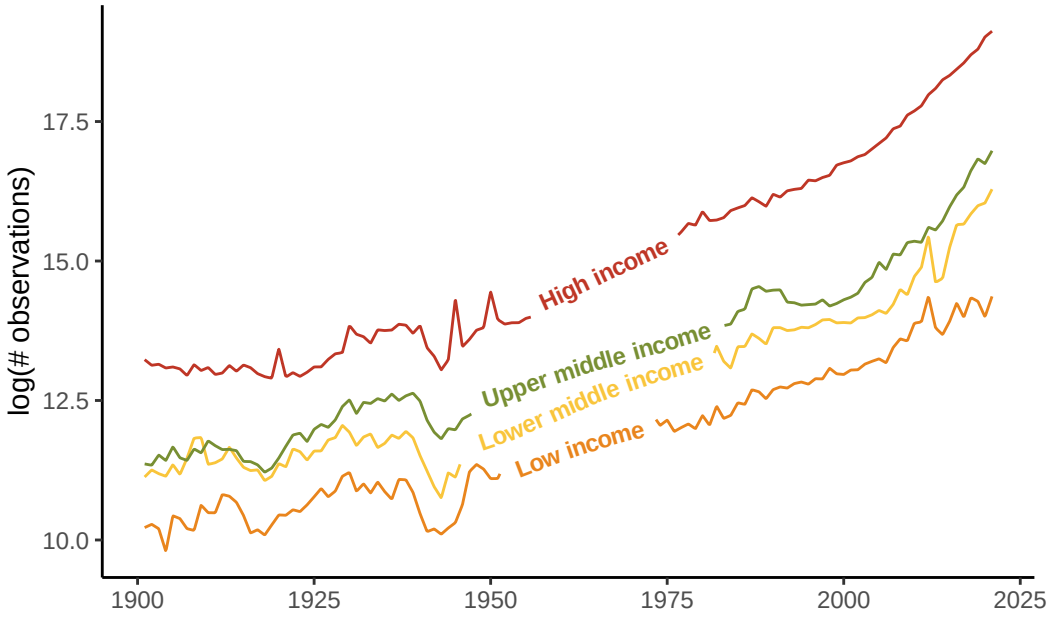
```
world <- ne_countries(type = "countries", scale = "medium")
world <- st_as_sf(world) |>
  dplyr::select(iso_a2, income_grp) |>
  st_make_valid() |>
  mutate(area = st_area(geometry)) |>
  as_tibble() |>
  dplyr::select(-geometry) |>
  mutate(area = as.numeric(area)) |>
  rename(countrycode = iso_a2)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

Collect count of observations per year per country

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

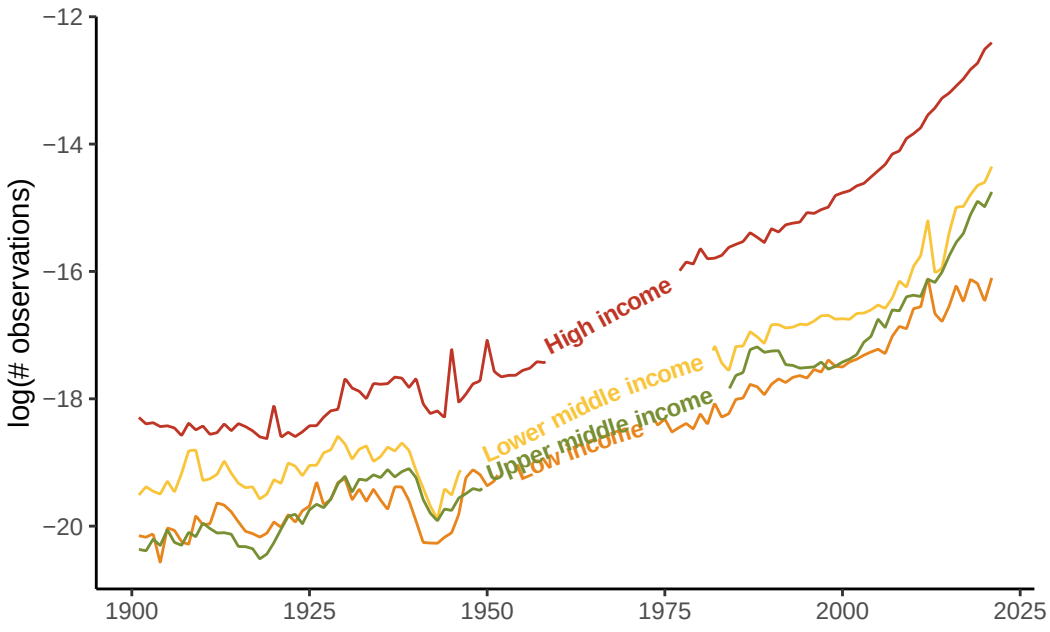
Filter to years 1900-2022 and get the sum of observations per country, plot log

```
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

```
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 similar patterns in bird data throughout redlined cities in the United States, in Panel C we show that qualitatively similar patterns hold true across all taxa (in aggregate) in GBIF.

```
# download redlining geojson
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
```

```
# remove inalid polygons
holc <- holc |>
  dplyr::mutate(valid =st_is_valid(holc)) |>
  dplyr::filter(valid=="TRUE")
# calculate area per neighborhood
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

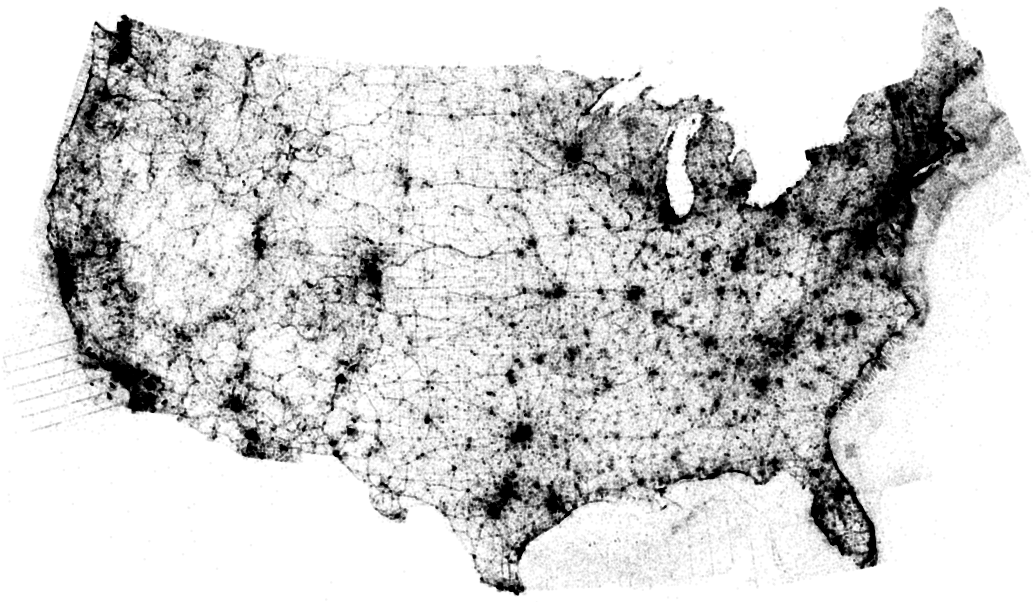
Observations in the US are queried and summerized at 0.001 decimal degrees.

```
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 points are converted to a spatial data frame and reprojected. 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.

```
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())
```

```
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

We zoom in on LA to show point disparities within a given city. All observation points are shown (no subsetting)

```
la <- holc |> filter(city == "Los Angeles")
ext_la <- ext(la)
pts_la <- US_pts |>
```

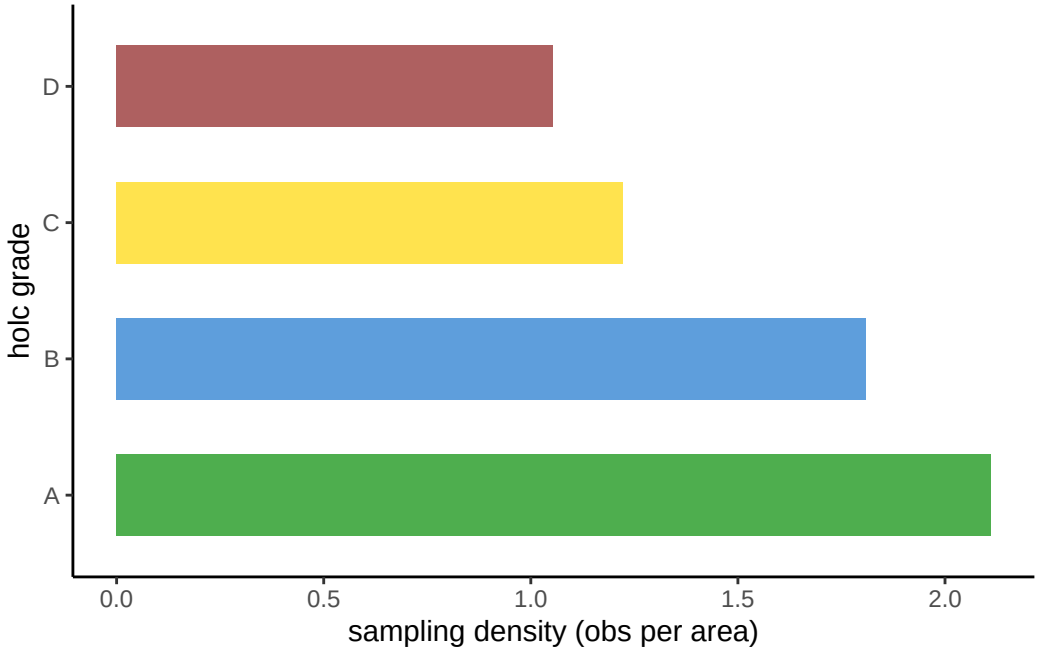
```
  dplyr::select(longitude, latitude, n) |>
  rename(lon = longitude, lat = latitude) |>
  filter(lon > ext_la[1] & lon < ext_la[2] &
           lat > ext_la[3] & lat < ext_la[4])

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 in Panel C 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")
```

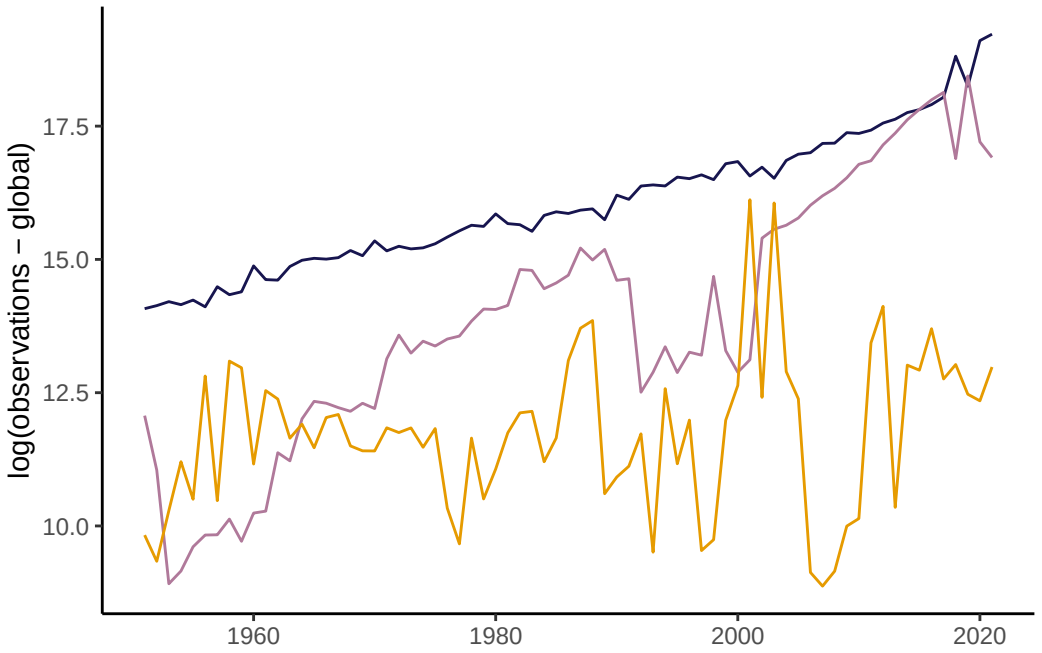
Panel D: Conflict

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()
```

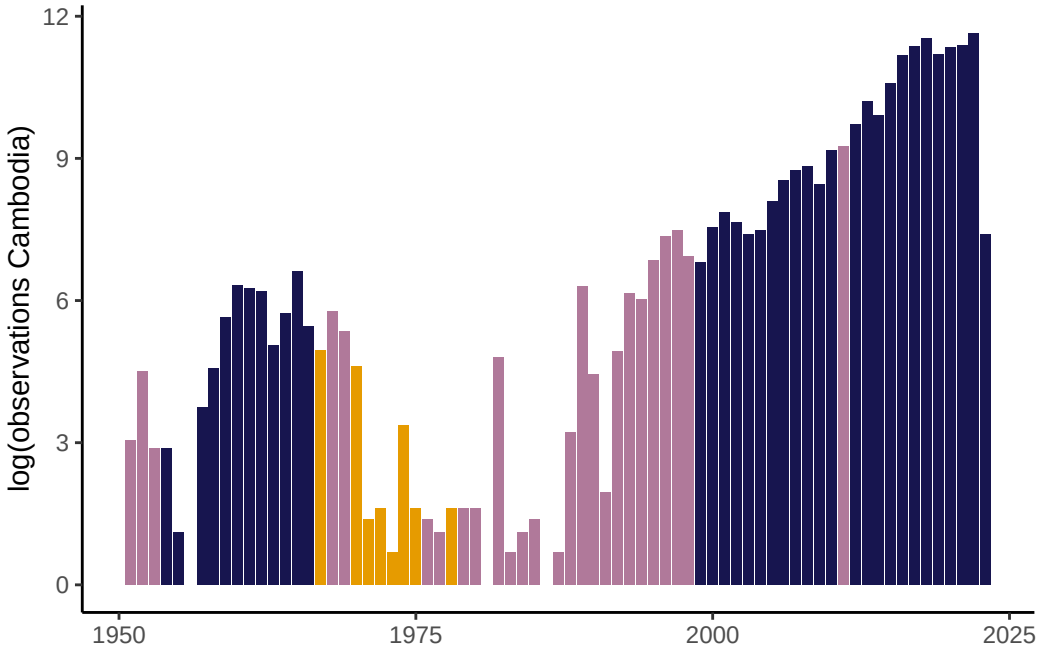
```r
#download.file(url = "https://ucdp.uu.se/downloads/ucdpprio/ucdp-prio-acd-231-rds.zip", dest
#unzip("data/conflict.zip", exdir = "data/")

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

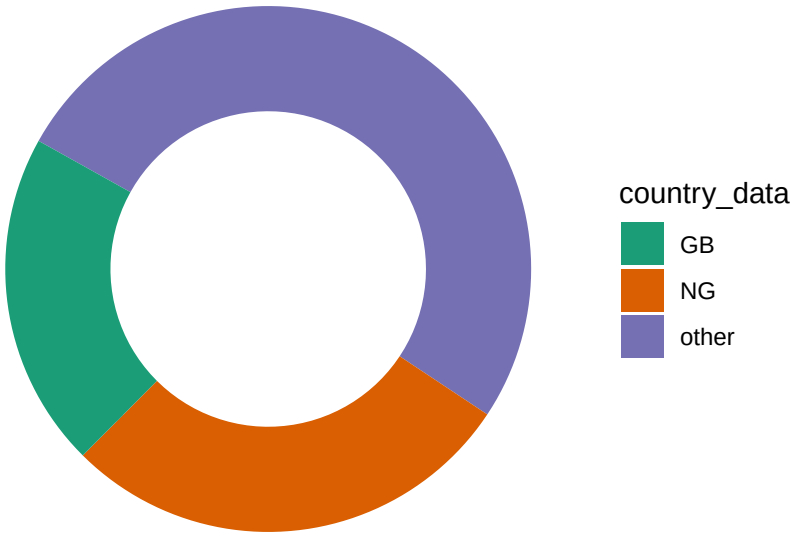
As explored in (Zizka et al. 2021), social and political factors impact who has collected biodiversity data. We reproduce this analysis using the update GBIF snapshot. We can

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

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