

# Biomass Distribution 1961-2018

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## INTRODUCTION

*This project helps in properly visualising as well as understanding the rapid change in biomass distribution in the last ~60 years. Bar-On, Phillips, and Milo (2018) It is a way to fact check all the different headlines that have been going around recently like how humans contribution to the present state of the planet has been more than 83% but by themselves they only make up 0.01% of the life present on earth. “Humans Just 0.01” (2018)*

*How the population sizes of mammals, fish, birds, reptiles, and amphibians have declined an average of 68% between 1970 and 2016, according to World Wildlife Fund’s (WWF) Living Planet Report 2020. Populations in Latin America and the Caribbean have fared worst, with an average decline of 94%. Global freshwater species have also been disproportionately impacted, declining 84% on average. As an important indicator of planetary health, these drastic species population trends signal a fundamentally broken relationship between humans and the natural world, the consequences of which—as demonstrated by the ongoing COVID-19 pandemic—can be catastrophic. @wwf\_2020*

*In order better understand the actual meaning behind these numbers, biomass distribution has been used which can be used to depict the size of a species with respect to all the lifeforms.*

## DATA

*This project consists of data pulled from 2006 IPCC Guidelines for National Greenhouse Gas Inventories (“2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories” (n.d.)) and Food and Agriculture Organization of the United Nations (“FAO Global Statistical Yearbook, FAO Regional Statistical Yearbooks” (n.d.)) for data regarding the mass index and distribution of poultry and livestock in different regions of the world (North and Latin America, Asia, Indian Subcontinent, Oceania and Africa). The aim of this project was to map out the change in the biomass distribution and analyze how human activities have affected the environment in the past 60 years. The main focus will be on terrestrial lifeforms (animals) and humans.*

*The project can be broken down into two sections: Wrangling and Visualization. As I will be referring to various data sets in this project, cleaning and structuring is a big part of it.*

## WRANGLING

*70% human body is water => 30% carbon x 50% carbon out of the dry weight. Also the average of the human body is being assumed at 50 kgs. Also, 1kg is equal to 0.15 C which is stored in the variable `to_carbon` Hern (1999). `bird_bm` and `mammal_bm` store the total biomass of the birds and mammals on earth and `wild_animal_biomass` stores the total biomass of the wild animals on earth. These values have been used as constants in this notebook for easy conversion. For this project, the total biomass on earth has been assumed to be ~550 Gt C, being such a large number any change in it is bound to be insignificant concerning only a span of 60 years.*

```
regions <- sort(c("Africa", "Latin America", "Asia", "Eastern Europe", "Northern America", "Oceania", "
converter = 1000*0.15/1e15 #kg to Gt
wild_animal_biomass = 550 * 3 * 1e-6
birds_bm = 0.007 #Gt C
mammal_bm = 550 * 3 * 1e-4
```

```
to_carbon = 0.15
human_carbon_mass = 5e4 * to_carbon
```

*Loading the data on human population over the years and converting it into Gt C and calculating the changing biomass and %age biomass over the years*

```
human_pop <- readxl::read_excel("../_data/Data_Extract_From_World_Development_Indicators.xlsx") %>%
  select(! contains("Series") & ! contains("Country")) %>%
  pivot_longer(cols = names(.), names_to = "Year", values_to = "Population") %>%
  mutate(Year = as.numeric(str_extract(Year, '[^\\s]+')) %>%
  mutate(`Total Biomass (Gt C)` = as.double(`Population`) * human_carbon_mass * 1e-15) %>%
  mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)` / (mammal_bm * 1e-2))
```

```
tail(human_pop)
```

```
## # A tibble: 6 x 4
##   Year Population `Total Biomass (Gt C)` `% Mammal Biomass (Gt C)`
##   <dbl>         <dbl>         <dbl>         <dbl>
## 1  2013 7169675197         0.0538         32.6
## 2  2014 7254292848         0.0544         33.0
## 3  2015 7339076654         0.0550         33.4
## 4  2016 7424484741         0.0557         33.7
## 5  2017 7509410228         0.0563         34.1
## 6  2018 7592475615         0.0569         34.5
```

*Loading the mass Index for poultry and modifying the Area name and Region as per the requirement, the areas under focus have been listed down below*

```
birds_index <- read.csv("../_data/birds.csv") %>%
  mutate(Area = case_when(
    Area == "Southern Asia" ~ "Indian Subcontinent",
    Area == "Americas" ~ "Latin America",
    TRUE ~ Area
  )) %>%
  filter(Area %in% regions) %>%
  arrange(Area, Item)
head(birds_index)
```

```
##   Domain.Code   Domain Area.Code   Area Element.Code Element Item.Code
## 1      QA Live Animals    5100 Africa    5112 Stocks    1057
## 2      QA Live Animals    5100 Africa    5112 Stocks    1057
## 3      QA Live Animals    5100 Africa    5112 Stocks    1057
## 4      QA Live Animals    5100 Africa    5112 Stocks    1057
## 5      QA Live Animals    5100 Africa    5112 Stocks    1057
## 6      QA Live Animals    5100 Africa    5112 Stocks    1057
##      Item Year.Code Year   Unit  Value Flag
## 1 Chickens    1961 1961 1000 Head 274201   A
## 2 Chickens    1962 1962 1000 Head 282821   A
## 3 Chickens    1963 1963 1000 Head 292008   A
## 4 Chickens    1964 1964 1000 Head 305707   A
## 5 Chickens    1965 1965 1000 Head 316576   A
## 6 Chickens    1966 1966 1000 Head 330808   A
##                                     Flag.Description
## 1 Aggregate, may include official, semi-official, estimated or calculated data
## 2 Aggregate, may include official, semi-official, estimated or calculated data
```

```
## 3 Aggregate, may include official, semi-official, estimated or calculated data
## 4 Aggregate, may include official, semi-official, estimated or calculated data
## 5 Aggregate, may include official, semi-official, estimated or calculated data
## 6 Aggregate, may include official, semi-official, estimated or calculated data
```

```
unique(as.data.frame(birds_index[, "Area"]))
```

```
##      birds_index[, "Area"]
## 1                Africa
## 291                Asia
## 581            Eastern Europe
## 813    Indian Subcontinent
## 1045            Latin America
## 1277    Northern America
## 1509                Oceania
## 1741            Western Europe
```

Using `bird_index` the information on chicken is extracted out which only the Area, Year and Value columns are selected. The Values of Latin America and Asia are modified by subtracting Northern America and Indian Subcontinent respectively to avoid repetition.

```
chicken <- filter(birds_index, Item == "Chickens") %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`) %>%
  column_to_rownames('Year')
head(chicken)
```

```
##      Africa      Asia Eastern Europe Indian Subcontinent Latin America
## 1961 274201  918518          623953          172296        365212
## 1962 282821  962503          672343          176622        373697
## 1963 292008 1001039          689495          186306        395109
## 1964 305707 1040895          623901          193017        423850
## 1965 316576 1078200          638318          199930        428824
## 1966 330808 1108430          671476          209242        441242
##      Northern America Oceania Western Europe
## 1961          821016    26304          361024
## 1962          847087    27059          364607
## 1963          847720    27313          365832
## 1964          863594    27991          380597
## 1965          904276    28949          386324
## 1966          926914    29316          349822
```

The dataset on chickens laying eggs is loaded and stored in `chicken_layers` and is formatted to match the table above.

```
chicken_layers <- read.csv('../_data/FAOSTAT_egg_chicken.csv') %>%
  mutate(Area = case_when(
    Area == "Southern Asia" ~ "Indian Subcontinent",
    Area == "Americas" ~ "Latin America",
    TRUE ~ Area
  )) %>%
  filter(Area %in% regions & Element == "Laying") %>%
  arrange(Area) %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`) %>%
```

```
column_to_rownames('Year')
```

```
head(chicken_layers)
```

```
##      Africa  Asia Eastern Europe Indian Subcontinent Latin America
## 1961 122114 546011      393793      56750      150247
## 1962 126039 575480      405868      61033      151731
## 1963 129208 568808      390208      64255      153821
## 1964 134420 593492      384892      65305      160602
## 1965 141982 614320      414677      69055      171345
## 1966 145630 628879      438041      74105      167284
##      Northern America Oceania Western Europe
## 1961      323081      18033      167066
## 1962      326236      18301      163560
## 1963      323869      17925      164074
## 1964      327459      18117      169345
## 1965      327171      19248      168955
## 1966      329247      19579      199529
```

To calculate the biomass of chicken first chicken is separated into two categories- broilers and layers. The resulting separate dataframes are multiplied by the avg weight as per the “2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories” (n.d.) standards i.e. 0.9 and 1.8 kgs. The output obtained is then stored together in `chicken_all` where the added weights are converted into Biomass(Gt C) then the actual %age of Total Biomass is calculated as well. The `chicken_all` dataframe adds both the dataframes together. The sum of all the regions are added based on the year using `rowSums()` and the %Total Birds mass is calculated using the constant `birds_bm`

```
chicken_broilers <- (chicken - chicken_layers)*0.9
chicken_layers <- (chicken_layers)* 1.8
```

```
chicken_all <- (chicken_broilers + chicken_layers) %>%
  rowSums() %>%
  as.data.frame() * converter
```

```
names(chicken_all)[1] <- "Total Biomass (Gt C)"
```

```
chicken_all <- chicken_all %>%
  mutate(`% Total Birds` = (`Total Biomass (Gt C)`/birds_bm) * 1e5) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)` * 1e-1)
```

```
tail(chicken_all)
```

```
##      Total Biomass (Gt C) % Total Birds
## 2013      3.656286e-07      52.23266
## 2014      3.694877e-07      52.78396
## 2015      3.786571e-07      54.09388
## 2016      3.962678e-07      56.60968
## 2017      4.023285e-07      57.47550
## 2018      4.086130e-07      58.37328
```

For ducks (and Turkey), the data is first loaded to `ducks(Turkeys)` from `bird_index` similarly as chickens before. The `ducks_all(Turkey_all)` then adds all the different regions together which is then multiplied by their avg weight (as per “2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories” (n.d.)) of 2.7 and then converted into Gt C using `converter`.

```
ducks <- filter(birds_index, Item == 'Ducks') %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  column_to_rownames('Year') %>%
  mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`)

ducks_all <- ducks %>%
  rowSums() %>%
  as.data.frame() * converter * 2.7
names(ducks_all)[1] <- "Total Biomass (Gt C)"
ducks_all <- ducks_all %>%
  #mutate(`% Total Animal Biomass (Gt C)` = `Total Biomass (Gt C)`/(wild_animal_biomass)) %>%
  mutate(`% Total Birds` = `Total Biomass (Gt C)`/birds_bm) * 1e5

head(ducks_all)
```

```
##      Total Biomass (Gt C) % Total Birds
## 1961      0.007619913      1.088559
## 1962      0.007960680      1.137240
## 1963      0.008356851      1.193836
## 1964      0.008590374      1.227196
## 1965      0.008861400      1.265914
## 1966      0.009144859      1.306409
```

```
Turkey <- filter(birds_index, Item == 'Turkeys') %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  column_to_rownames('Year') %>%
  mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`)

Turkey_all <- Turkey %>%
  rowSums() %>%
  as.data.frame() * converter * 2.7
names(Turkey_all)[1] <- "Total Biomass (Gt C)"
Turkey_all <- Turkey_all %>%
  #mutate(`% Total Animal Biomass (Gt C)` = `Total Biomass (Gt C)`/(wild_animal_biomass)) %>%
  mutate(`% Total Birds` = `Total Biomass (Gt C)`/birds_bm) * 1e5

head(Turkey_all)
```

```
##      Total Biomass (Gt C) % Total Birds
## 1961      0.007942334      1.1346191
## 1962      0.006744587      0.9635124
## 1963      0.006216345      0.8880493
## 1964      0.005902389      0.8431984
## 1965      0.005909071      0.8441531
## 1966      0.006389240      0.9127485
```

*Livestock index loads the dataset on the weight of livestock in different regions of the world as per the “2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories” (n.d.). The columns are renamed and rearranged as per the requirement*

```

livestock_index <- read.csv("../_data/animal_weight.csv",
                           col.names = c('Area', 'Cattle_dairy', 'Cattle_non_dairy', 'Buffaloes', 'Swine_market'),
                           as.is = TRUE) %>%
  select(! starts_with("d")) %>%
  filter(! Area == "Middle east") %>%
  arrange(Area) %>%
  column_to_rownames('Area')
livestock_index

```

```

##           Cattle_dairy Cattle_non_dairy Buffaloes Swine_market
## Africa                275             173         380         28
## Asia                  350             391         380         50
## Eastern Europe        550             391         380         50
## Indian Subcontinent   275             110         295         28
## Latin America         400             305         380         28
## Northern America      604             389         380         46
## Oceania               500             330         380         45
## Western Europe        600             420         380         50
##
##           Swine_breeding Sheep Goats Horses Asses Mules Camels
## Africa                28  28.0  30.0   238   130   130   217
## Asia                  180  48.5  38.5   377   130   130   217
## Eastern Europe        180  48.5  38.5   377   130   130   217
## Indian Subcontinent    28  28.0  30.0   238   130   130   217
## Latin America         28  28.0  30.0   238   130   130   217
## Northern America      198  48.5  38.5   377   130   130   217
## Oceania               180  48.5  38.5   377   130   130   217
## Western Europe        198  48.5  38.5   377   130   130   217

```

As for most of the data, similar wrangling is required, `wrangling_livestock` function has been created which helps in loading the `FAOSTAT_livestock` data (in most cases) and then filtering them out based on the category.

```

wrangling_livestock <- function (category, file_name = "FAOSTAT_livestock"){
  temp <- read.csv(sprintf("../_data/%s.csv", file_name)) %>%
    mutate(Area = case_when(
      Area == "Southern Asia" ~ "Indian Subcontinent",
      Area == "Americas" ~ "Latin America",
      TRUE ~ as.character(Area)
    )) %>%
    filter(Area %in% regions) %>%
    arrange(Area, Item) %>%
    filter(Item == sprintf('%s', category)) %>%
    select(Area, Year, Value) %>%
    pivot_wider(names_from = Area, values_from = Value) %>%
    column_to_rownames('Year') %>%
    mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`)

  return(temp)
}

```

Dairy and non-dairy cattles have different diets and hence different weights. So, to make the calculations more accurate the data on dairy cattles is loaded from `FAOSTAT_cattle_dairy.csv` which is then filtered to match the regions which we are focussing on. Due to different column naming `wrangling_livestock` function is skipped but is to load data on non-dairy cattles.

```

cattle_dairy <- read.csv('../_data/FAOSTAT_cattle_dairy.csv') %>%
  mutate(Area = case_when(
    Area == "Southern Asia" ~ "Indian Subcontinent",
    Area == "Americas" ~ "Latin America",
    TRUE ~ Area
  )) %>%
  filter(Area %in% regions) %>%
  arrange(Area, Item) %>%
  filter(Element == 'Milk Animals') %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  column_to_rownames('Year') %>%
  mutate(`Latin America` = `Latin America` - `Northern America`, Asia = Asia - `Indian Subcontinent`)
cattle <- wrangling_livestock('Cattle') - cattle_dairy

```

```
head(cattle)
```

```

##           Africa      Asia Eastern Europe Indian Subcontinent Latin America
## 1961 105529681 86089461      51332404      198560283      158687950
## 1962 107228969 83195165      56757782      200223885      162380226
## 1963 109072042 85148252      60337536      201085315      162233211
## 1964 112410585 87364184      58670982      205939424      168267429
## 1965 115554186 91991748      60065138      206173971      175688128
## 1966 115675777 92478459      66390091      201876014      181666686
##           Northern America Oceania Western Europe
## 1961      88166740 18975600      27582914
## 1962      91504879 19729034      29253640
## 1963      96536759 20297538      29125845
## 1964     100998695 20968039      28375526
## 1965     103289512 20898726      28795538
## 1966     104017227 20502454      30221061

```

```
head(cattle_dairy)
```

```

##           Africa      Asia Eastern Europe Indian Subcontinent Latin America
## 1961 17007415 6862907      45941801      27498908      17161126
## 1962 17237363 7316815      47520221      25057900      17531215
## 1963 17390909 7490111      48870567      24423500      18210796
## 1964 17747291 7761084      49030454      23406763      18519113
## 1965 18469973 7924174      49501925      22818605      19151689
## 1966 19118918 8270102      50004087      28560745      20170925
##           Northern America Oceania Western Europe
## 1961      20230855 5115736      19921153
## 1962      19798540 5224001      20012785
## 1963      19175636 5286648      19724129
## 1964      18584172 5125422      19515994
## 1965      17840320 5081390      19749062
## 1966      16748828 5034903      19855998

```

To calculate the mass of all the cattles they are multiplied by their respective regional masses and category(dairy/non-dairy) from the `livestock_index` dataframe, the resulting dfs are then added together and stored in `cattle_all` where all the different regions are summed together based on the year to get the total biomass/year as well %age total biomass/year



```

for (r in 1:length(regions)){
  cattle[regions[r]] <- as.double(livestock_index[regions[r], 'Cattle_non_dairy']) * cattle[regions[r]]
  cattle_dairy[regions[r]] <- as.double(livestock_index[regions[r], 'Cattle_dairy']) * cattle_dairy[regions[r]]
}
cattle_all <- (cattle + cattle_dairy) %>%
  rowSums() %>%
  as.data.frame() %>%
  `colnames<-`(c("Total Biomass (Gt C)")) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)` * converter) %>%
  mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)` / (mammal_bm * 1e-2))

head(cattle_all)

```

##	Total Biomass (Gt C)	% Mammal Biomass (Gt C)
## 1961	0.04018161	24.35249
## 1962	0.04097010	24.83036
## 1963	0.04172734	25.28930
## 1964	0.04238290	25.68660
## 1965	0.04335895	26.27815
## 1966	0.04436850	26.89000

The uncertainty in these estimates is  $\pm 50\%$ .  
<sup>a</sup>Summarized from 1996 IPCC Guidelines, 1997; European Environmental Agency, 2002; USA EPA National NH<sub>3</sub> Inventory Draft Report, 2004; and data of GHG inventories of Annex I Parties submitted to the Secretariat UNFCCC in 2004.  
<sup>b</sup>Nitrogen excretion for swine are based on an estimated country population of 90% market swine and 10% breeding swine.  
<sup>c</sup>Modified from European Environmental Agency, 2002.  
<sup>d</sup>Data of Hutchings *et al.*, 2001.

Figure 1: Estimated Population of Swine

For swine(pigs) the “2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories” (n.d.) assumption is assumed here where close to 90% of them are used for breeding and only 1% are available for market. Based on this assumption *swine\_breeding* and *swine\_market* dataframes are created using the *wrangling\_livestock* function (loading *FAOSTAT\_livestock.csv*) and then multiplied by their respective weights in different regions. These are then combined to form *swine\_all* where using *rowSums* the data is categorized into Total Biomass/year and %age Total Mammal Biomass/year.

```

swine_breeding <- wrangling_livestock("Pigs") * 0.9
swine_market <- swine_breeding / 9

for (r in 1:length(regions)){
  swine_breeding[regions[r]] <- as.double(livestock_index[regions[r], 'Swine_breeding']) * swine_breeding[regions[r]]
  swine_market[regions[r]] <- as.double(livestock_index[regions[r], 'Swine_market']) * swine_market[regions[r]]
}

swine <- (swine_breeding + swine_market)

swine_all <- swine %>%
  rowSums() %>%
  as.data.frame() %>%
  `colnames<-`(c("Total Biomass (Gt C)")) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)` * converter) %>%

```



```
mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)`/(mammal_bm*1e-2))

head(swine_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.008243982      4.996352
## 1962      0.008659171      5.247982
## 1963      0.009241365      5.600827
## 1964      0.009410881      5.703564
## 1965      0.010282287      6.231689
## 1966      0.010649067      6.453980
```

*In the case of buffaloes, most of the process is same as in cattle except the regions(buffaloes are not present in northern America and west Europe) which are modified to match rest of the tables*

```
buffaloes <- read.csv('../_data/FAOSTAT_livestock.csv') %>%
  mutate(Area = case_when(
    Area == "Southern Asia" ~ "Indian Subcontinent",
    Area == "Americas" ~ "Latin America",
    TRUE ~ Area
  )) %>%
  filter(Area %in% regions) %>%
  arrange(Area, Item) %>%
  filter(Item == "Buffaloes") %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  column_to_rownames('Year') %>%
  mutate(Asia = Asia - `Indian Subcontinent`, `Western Europe` = 0) %>%
  cbind(`Northern America` = 0)

for (r in 1:length(regions)){
  buffaloes[regions[r]] <- (buffaloes[regions[r]] * as.double(livestock_index[r, "Buffaloes"]))
}

buffaloes_all <- buffaloes %>%
  rowSums() %>%
  as.data.frame() %>%
  `colnames<-`(c("Total Biomass (Gt C)")) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)` * converter) %>%
  mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)`/(mammal_bm*1e-2))

head(buffaloes_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.004257691      2.580419
## 1962      0.004305583      2.609444
## 1963      0.004329264      2.623797
## 1964      0.004517807      2.738065
## 1965      0.004568208      2.768611
## 1966      0.004810559      2.915490
```

*Sheeps, Goats, Horses, asses and mules follow the same procedure as in cattle and their final values are stored sheep\_all, horses\_all, asses\_all and mules\_all respectively.*

```
sheep <- wrangling_livestock("Sheep")
```

```
for (r in 1:length(regions)){
  sheep[regions[r]] <- (sheep[regions[r]] * as.double(livestock_index[r, "Sheep"]))
}
```

```
sheep_all <- sheep %>%
  rowSums() %>%
  as.data.frame() %>%
  `colnames<-`(c("Total Biomass (Gt C)")) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)` * converter) %>%
  mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)`/(mammal_bm*1e-2))
```

```
head(sheep_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.005442698      3.298605
## 1962      0.005478983      3.320596
## 1963      0.005519002      3.344850
## 1964      0.005605461      3.397249
## 1965      0.005692616      3.450070
## 1966      0.005742036      3.480022
```

```
goat <- wrangling_livestock("Goats")
```

```
for (r in 1:length(regions)){
  goat[regions[r]] <- goat[regions[r]] * as.double(livestock_index[r, "Goats"])
}
```

```
goat_all <- goat %>%
  rowSums() %>%
  as.data.frame() %>%
  `colnames<-`(c("Total Biomass (Gt C)")) %>%
  mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)`*converter) %>%
  mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)`/(mammal_bm*1e-2))
```

```
head(goat_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.001663703      1.008305
## 1962      0.001747766      1.059252
## 1963      0.001784774      1.081682
## 1964      0.001775618      1.076132
## 1965      0.001765696      1.070119
## 1966      0.001770902      1.073274
```

```
horses <- wrangling_livestock("Horses")
```

```
for (r in 1:length(regions)){
  horses[regions[r]] <- (horses[regions[r]] * as.double(livestock_index[r, "Goats"]))
}
```

```
horses_all <- horses %>%
  rowSums() %>%
  as.data.frame() %>%
```

```
`colnames<-`(c("Total Biomass (Gt C)")) %>%
mutate(`Total Biomass (Gt C)` = `Total Biomass (Gt C)`* converter) %>%
mutate(`% Mammal Biomass (Gt C)` = `Total Biomass (Gt C)`/(mammmal_bm*1e-2))
```

```
head(horses_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.0003073617      0.1862798
## 1962      0.0002959165      0.1793433
## 1963      0.0002889394      0.1751148
## 1964      0.0002845318      0.1724435
## 1965      0.0002904977      0.1760592
## 1966      0.0002938808      0.1781096
```

```
mules <- wrangling_livestock("Mules")
```

```
mules_all <- (mules*130*converter) %>%
  rowSums() %>%
  as.data.frame() %>%
  #mutate(`% Biomass (Gt C)` = `.`/(wild_animal_biomass * 1e-2)) %>%
  mutate(`% Mammal Biomass (Gt C)` = `.`/(mammmal_bm*1e-2)) %>%
  `colnames<-`(c("Total Biomass (Gt C)", "% Mammal Biomass (Gt C)"))
```

```
head(mules_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.0001676369      0.1015981
## 1962      0.0001791703      0.1085880
## 1963      0.0001708586      0.1035507
## 1964      0.0001764372      0.1069317
## 1965      0.0001784144      0.1081299
## 1966      0.0001813179      0.1098896
```

```
asses <- wrangling_livestock("Asses")
```

```
asses_all <- (asses*130*converter) %>%
  rowSums() %>%
  as.data.frame() %>%
  #mutate(`% Biomass (Gt C)` = `.`/(wild_animal_biomass * 1e-2)) %>%
  mutate(`% Mammal Biomass (Gt C)` = `.`/(mammmal_bm*1e-2)) %>%
  `colnames<-`(c("Total Biomass (Gt C)", "% Mammal Biomass (Gt C)"))
```

```
head(asses_all)
```

```
##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.0006781587      0.4110053
## 1962      0.0006521343      0.3952329
## 1963      0.0006479494      0.3926966
## 1964      0.0006640885      0.4024779
## 1965      0.0006817642      0.4131905
## 1966      0.0006959867      0.4218101
```

*Camels are not found in Europe, Northern America, Latin America much as livestock so they have been set to zero for the purpose of calculation. The wild camels in Australia(Oceania) will come under wild Animals (included in analysis later)*

```

camels <- read.csv('../_data/FAOSTAT_livestock.csv') %>%
  mutate(Area = case_when(
    Area == "Southern Asia" ~ "Indian Subcontinent",
    Area == "Americas" ~ "Latin America",
    TRUE ~ Area
  )) %>%
  filter(Area %in% regions) %>%
  arrange(Area, Item) %>%
  filter(Item == "Camels") %>%
  select(Area, Year, Value) %>%
  pivot_wider(names_from = Area, values_from = Value) %>%
  column_to_rownames('Year') %>%
  mutate(Asia = Asia - `Indian Subcontinent`, `Western Europe` = 0) %>%
  cbind(`Northern America` = 0, `Latin America` = 0, `Oceania` = 0)

camels_all <- (camels*217*converter) %>%
  rowSums() %>%
  as.data.frame() %>%
  #mutate(`% Biomass (Gt C)` = `.`/(wild_animal_biomass * 1e-2)) %>%
  mutate(`% Mammal Biomass (Gt C)` = `.`/(mammmal_bm*1e-2)) %>%
  `colnames<-`(c("Total Biomass (Gt C)", "% Mammal Biomass (Gt C)"))

head(camels_all)

```

```

##      Total Biomass (Gt C) % Mammal Biomass (Gt C)
## 1961      0.0004207621      0.2550073
## 1962      0.0004283833      0.2596262
## 1963      0.0004431511      0.2685764
## 1964      0.0004608473      0.2793014
## 1965      0.0004746598      0.2876726
## 1966      0.0004953378      0.3002047

```

The result obtained from poultry and livestock have been clubbed together below to get much more clearer picture of the distribution of biomass.

```

poultry <- (chicken_all + Turkey_all + ducks_all) %>%
  select(`Total Biomass (Gt C)`, `% Total Birds`)

wild_birds <- poultry %>%
  mutate(`Total Biomass (Gt C)` = (100 - `% Total Birds`) * birds_bm * 1e-2) %>%
  mutate(`% Total Birds` = (100 - `% Total Birds`))

livestocks <- (cattle_all + buffaloes_all + sheep_all + goat_all + horses_all + mules_all + asses_all +
  select(`Total Biomass (Gt C)`, `% Mammal Biomass (Gt C)`)

wild_animal_biomass <- livestock %>%
  mutate(`Total Biomass (Gt C)` = (100 - `% Mammal Biomass (Gt C)`) * mammmal_bm*1e-2 - human_pop$`Total
  mutate(`% Mammal Biomass (Gt C)` = (100 - `% Mammal Biomass (Gt C)` - human_pop$`% Mammal Biomass (Gt

```

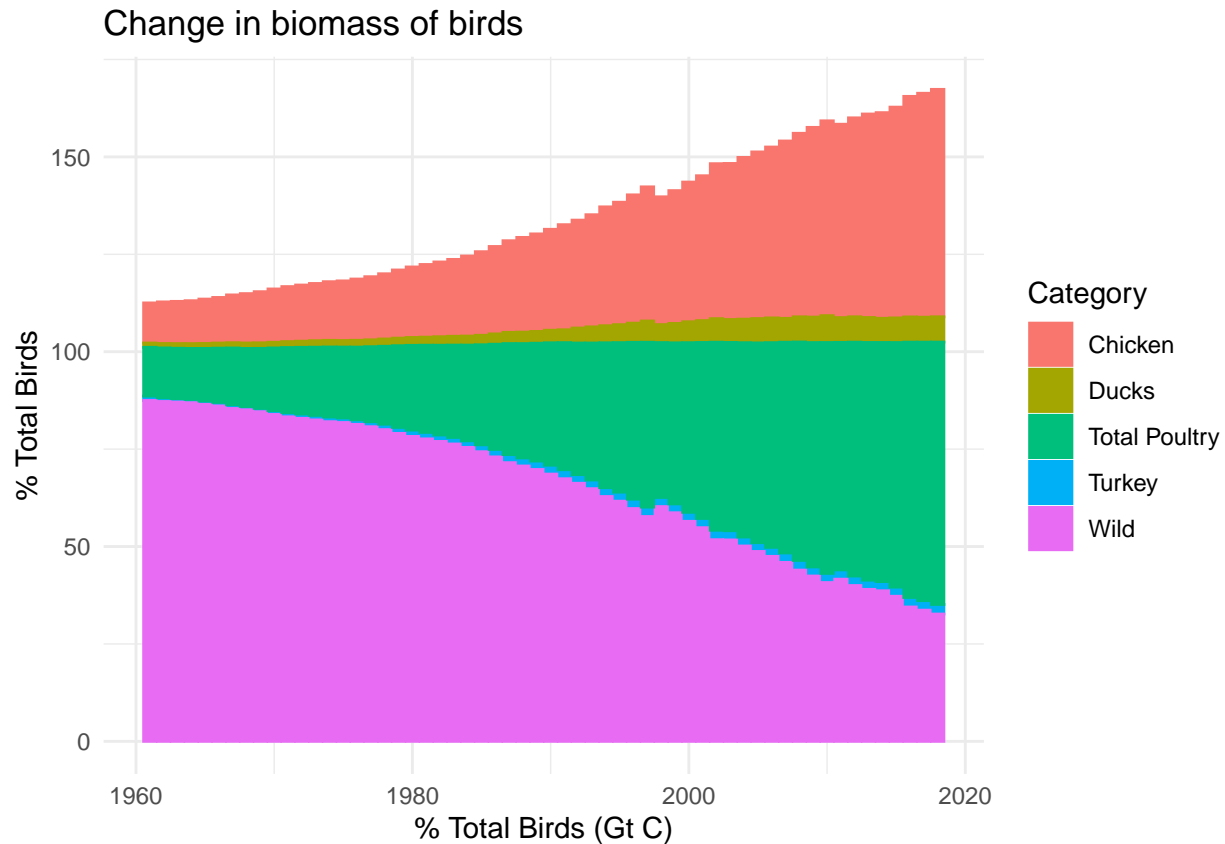
## VISUALIZATION

The graph below helps in the visualization of the change in biomass of the birds from 1961-2018. It is easy to observe from it that there has been a drastic drop in the wild bird population; from occupying more than 60% of the total biomass of the birds they have dropped to 30% in 2018 whereas the poultry is occupying more than 60%.

```

rbind(cbind(chicken_all, Category = "Chicken"), cbind(Turkey_all, Category = "Turkey"), cbind(ducks_all,
  mutate(Time = rep(seq.Date(as.Date('1961-01-01'), length = 58, by = "1 year"),5)) %>%
    ggplot(aes(Time, `"% Total Birds"`, color = Category, fill = Category)) +
    geom_bar(stat = "identity") + theme_minimal() +
    labs(title = "Change in biomass of birds", x = "% Total Birds (Gt C)")

```

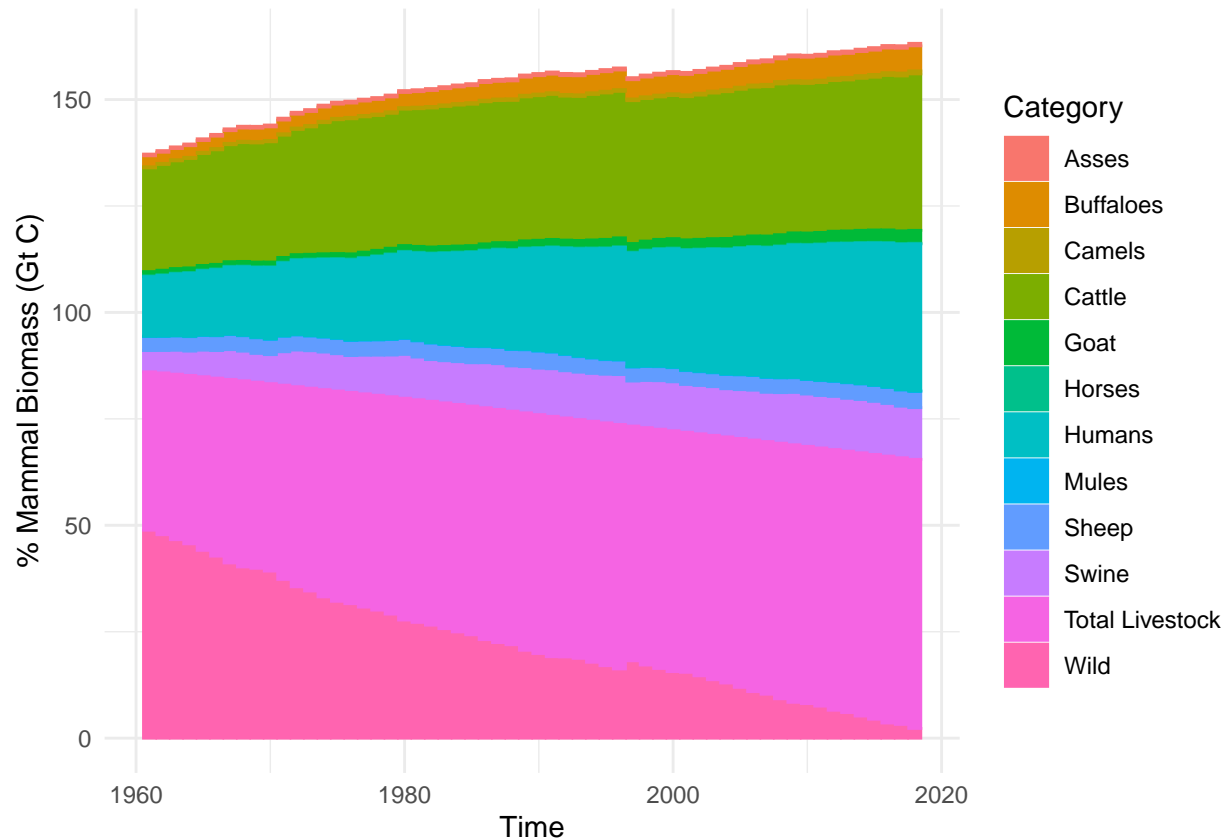


*Like in the case of birds, similar situation can be observed in the mammals where the drop is more significant. The wild animals have dropped from almost 50% to ~2% in less than 60 years. The humans have grown to occupy more than 35% of the total biomass in the mammals and the livestock occupy more than 60% of the total biomass.*

```

rbind(cbind(cattle_all, Category = "Cattle"), cbind(swine_all, Category = "Swine"), cbind(buffaloes_all,
  mutate(Time = rep(seq.Date(as.Date('1961-01-01'), length = 58, by = "1 year"),12)) %>%
    ggplot(aes(Time, `"% Mammal Biomass (Gt C)"`, fill = Category, color = Category)) +
    geom_bar(stat = "identity") + theme_minimal()

```



While most nations have started dealing with carbon emissions, methane(which has a shorter life cycle) is coming under greater focus each year. The largest source of anthropogenic methane emissions is agriculture, responsible for around a quarter of the total, closely followed by the energy sector, which includes emissions from coal, oil, natural gas and bio fuels. With the visualization below I try to showcase the relation between human population growth and methane emission. It is often thought that only livestock are the major contributors but from the visualization obtained it is apparent that other human activities have a significant impact on the emission.

```
methane <- read.csv("../_data/ghg-concentrations_fig-1.csv", skip = 6) %>%
  slice(1860:1964) %>%
  `colnames<-`(c("Year", "d", "Methane (ppm of C02)")) %>%
  select(contains("e")) %>%
  fill(`Methane (ppm of C02)`, .direction = "updown")%>%
  filter(as.numeric(Year) %in% human_pop$Year) %>%
  slice(-c(38))
head(methane)
```

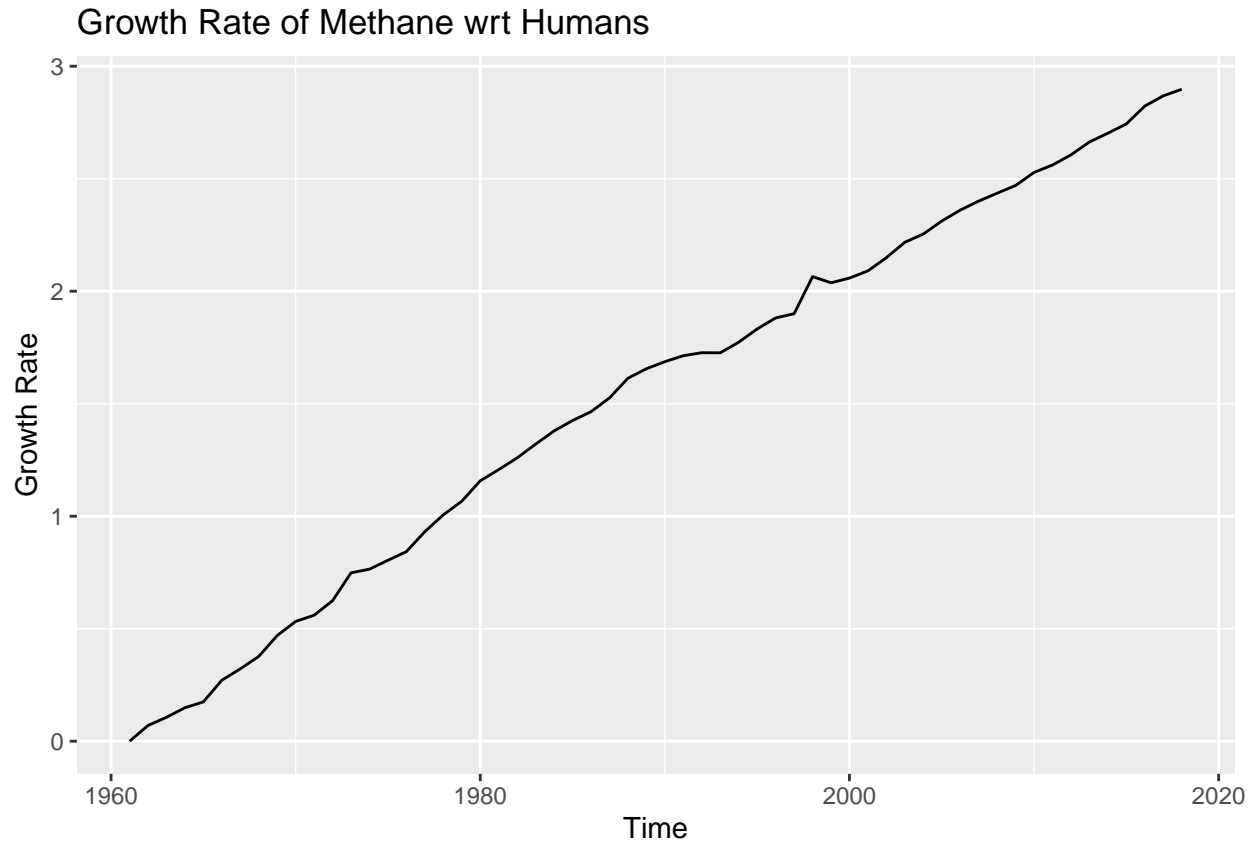
```
##   Year Methane (ppm of C02)
## 1 1961          317.6
## 2 1962          318.5
## 3 1963          319.0
## 4 1964          319.6
## 5 1965          320.0
## 6 1966          321.4
```

```
livestocks %>%
  mutate(Methane = methane$`Methane (ppm of C02)`, Time = seq.Date(as.Date('1961-01-01'), length = 58, by = "year"))
  mutate(Methane = sapply(Methane, function(x){
```

```

    return (100*(x- min(Methane))/(max(Methane) - min(Methane)))
  }) ) %>%
mutate(factor = Methane/Humans) %>%
ggplot(aes(x = Time)) +
geom_line(aes(y = factor)) +
labs(y = "Growth Rate", title = "Growth Rate of Methane wrt Humans")

```

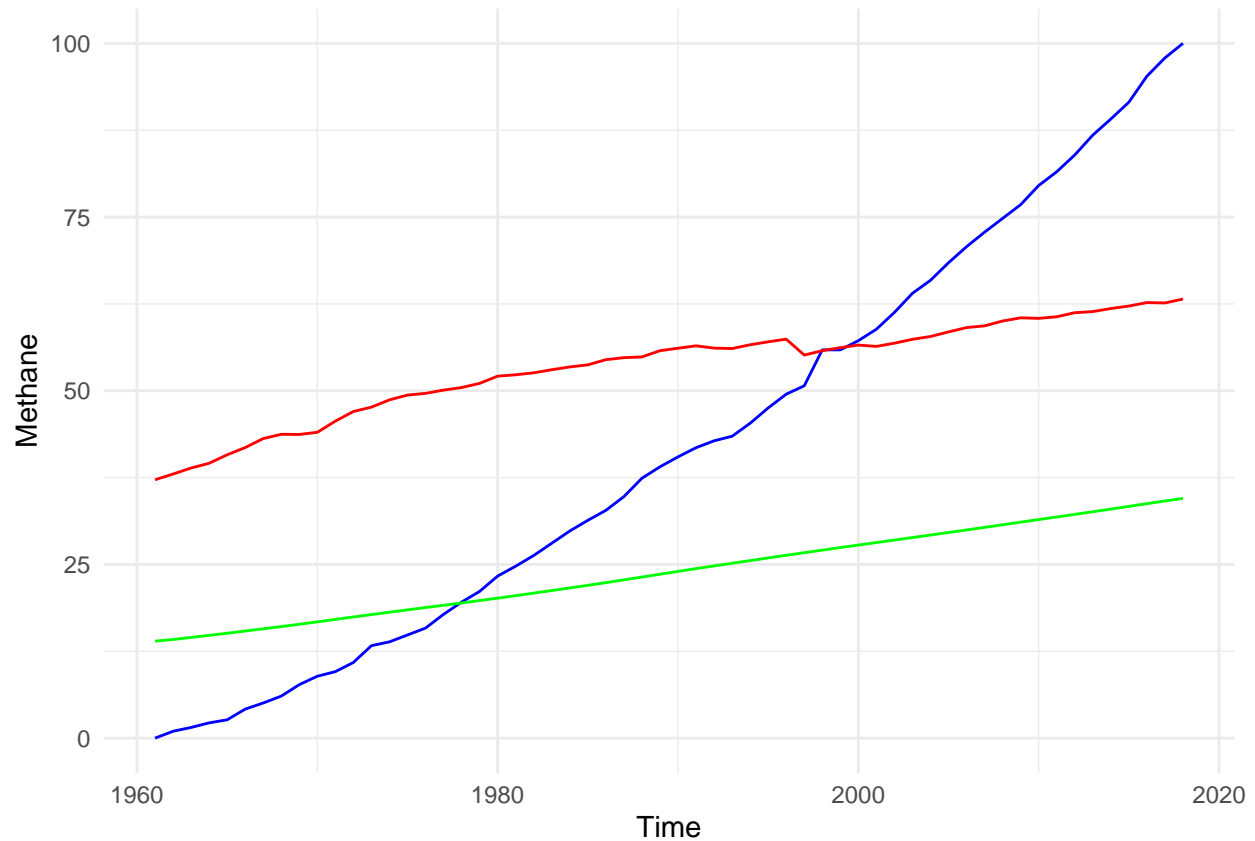


```

livestocks %>%
mutate(Methane = methane$`Methane (ppm of CO2)`, Time = seq.Date(as.Date('1961-01-01'), length = 58, by = "year"),
       Human = humans$`Human (Billion)`, Time = seq.Date(as.Date('1961-01-01'), length = 58, by = "year")) %>%
mutate(Methane = sapply(Methane, function(x){
  return (100*(x- min(Methane))/(max(Methane) - min(Methane)))
})) %>%
ggplot(aes(Time)) +
geom_line(aes(y = Methane), color = "blue", fill = "blue", stat = "identity") +
geom_line(aes(y = `Mammal Biomass (Gt C)`), color = "red", fill = "red", stat = "identity") +
geom_line(aes(y = Humans), color = "green", fill = "green", stat = "identity") + theme_minimal()

```

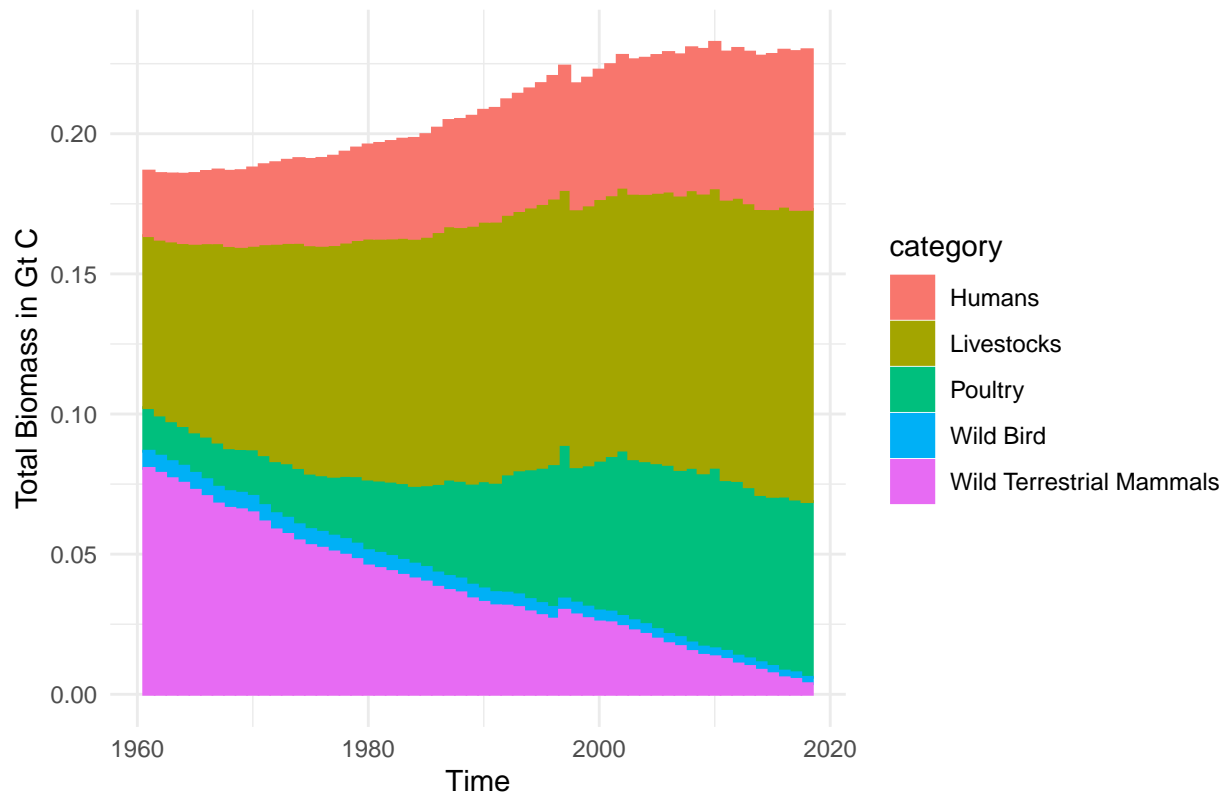




*To sum up all of my findings from this project together, the visualization below showcases the change in biomass of birds and mammals in the past ~60 years in Gt C. Although the share of birds has always been low, the drop in wild animals is very concerning.*

```
as.data.frame(rbind(cbind(poultry$`Total Biomass (Gt C)`, category = "Poultry"), cbind(livestocks$`Total Biomass (Gt C)`, category = "Livestock")),
mutate(Time = rep(seq.Date(as.Date('1961-01-01'), length = 58, by = "1 year"), 5), `Total Biomass` = `Total Biomass (Gt C)`),
ggplot(aes(x = Time, y = `Total Biomass`, fill = category, color = category)) +
  geom_bar(stat = "identity") +
  theme_minimal() +
  labs(title = "Biomass Distributions of Birds and Mammals over the years", y = "Total Biomass in Gt C")
```

## Biomass Distributions of Birds and Mammals over the years



**REFLECTION** Due to dealing with multiple(10) sheets in this project, I had to deal with repetitive coding as structure of each sheet was different. I have used piping extensively in this project in order to decrease the number of variables. I decided to focus on poultry, livestock and humans in this project as I wanted to showcase human impact. I dived deep and segregated the data as much as possible to get an accurate result. For the purpose of maintaining standards and to be able to compare it with actual results in the world I decided to follow IPCC and FAOSTAT for all the information regarding weight and population. As the data was classified on the basis of the regions, I chose to focus on different regions of the world based on the geography. As a result I ended up separating Asia into Asia and Indian Subcontinent and clubbing Australia and surrounding countries Oceania. Also, a major assumption made is that the total biomass on earth 550 Gt C. Although I ended up merging all of the regions together for the sake of visualization, if allowed to continue this project I would like to study all of the different regions separately as well as this might give insights on which region is experiencing most of the changes. Desertification is major problem in Africa and is surely to be major factor in the obtained results

## INFERENCE

Though we have been aware of climate change and importance of a healthy Eco-system for more than three decades, the continuing sharp decline in the wild is concerning and proves that we are much farther away from a solution than we think. Though this project focuses on biomass distribution over the years some of the information can be linked with present situations to get verify the current situations. The rapid decline in the wildlife population is also an indication to the rapid deforestation, which has been a rising problem over the years. Besides this, we can also observe how the livestock have almost doubled in population when compared to humans. Today, the global cattle population amounted to about one billion, which makes it increasingly believable than Iceland has more sheep than human (that's close to 3 sheep per person). This also, raises the topic of till what time will earth be able to sustain the growing food demands. Earth Overshoot Day is the date that marks that we have consumed all the resources that our planet is capable of generating in one year. Each year it is calculated by dividing the planet's bio capacity by humanity's ecological footprint and multiplying by 365, for the number of days in a year. In 2021, 29th July was the Earth Overshoot Day. It was first recorded

in 1970 and the overshoot day was 29 December.

## REFERENCES

- “2006 IPCC Guidelines for NATIONAL Greenhouse Gas Inventories.” n.d. *IPCC*. <https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html>.
- Bar-On, Yinon M., Rob Phillips, and Ron Milo. 2018. “The Biomass Distribution on Earth.” *Proceedings of the National Academy of Sciences* 115 (25): 6506–11. <https://doi.org/10.1073/pnas.1711842115>.
- “FAO Global Statistical Yearbook, FAO Regional Statistical Yearbooks.” n.d. *FAOSTAT*. Food; Agriculture Organization of the United Nations (FAO). <http://www.fao.org/faostat/en/#data/QCL>.
- Hern, Warren M. 1999. “How Many Times Has the Human Population Doubled? Comparisons with Cancer.” *Population and Environment* 21 (1): 59–80. <https://doi.org/10.1023/A:1022153110536>.
- “Humans Just 0.01.” 2018. *The Guardian*. Guardian News; Media. <https://www.theguardian.com/environment/2018/may/21/human-race-just-001-of-all-life-but-has-destroyed-over-80-of-wild-mammals-study>.