STOP COMPLAINING, IT SOLVES NOTHING.

My project will provide insights about **waste management**, which is of vital importance to the world and humanity. I hope to convey the awareness and perspective I wish to share with you, since change begins with awareness, and **we have to change our way** so that our children can live in the world they deserve!

RECYCLING WASTE MATERIALS
LIGHT BULBS
PAPER
PLASTIC
ORGANIC
GLASS
BATTERIES
CLOTHES
METAL
E-WASTE

1. Are we aware?

Important fact: Are we aware that when we do not recycle waste or use it for energy consumption, it pollutes our groundwater, our soil, and the air through greenhouse gases emitted by the waste, ultimately reducing the quality of the food produced in our soil and our overall life quality?

We just complain, don't we? Strawberries used to smell like strawberries, tomatoes used to taste different... right?

Unfortunately, complaining doesn't fix anything, and it won't. If we want to deserve to live in this world, we must work hard for our generation. The effort we do not put into our waste will heavily come back to haunt us and our children in this universe created with karma. **Let's quit complaining and start acting!**

The scope: The processes and activities required to handle waste from its inception to its final disposal are called ***waste management.*** These activities include the collection, transport, treatment, and disposal of waste, as well as the monitoring and organization of waste management processes [1]. In this project, insights are attempted to be extracted from several data collections on waste management in Turkiye, with a particular focus on municipal waste statistics. Initially, data are analyzed on a national level, then the analysis is moved to a provincial basis. Then, time series methods are used to forecast waste amount trends in Turkiye. Additionally, the variables that influence the amounts of waste and their effects by province are investigated using regression analysis.

The aim: In this project, the main goals are to increase awareness about waste issues, determine future waste quantities, investigate the waste levels of the provinces, and discuss both prevention strategies and proper disposal and recycling methods for unavoidable waste.

Some information before the analysis: As of 2023, ***Turkiye's population is 85 million 279 thousand 553 people*** and it has a total of 81 provinces, with Istanbul, Ankara, and Izmir being the most populous [2]. According to the data from 2022, ***1,389*** out of 1,391 municipalities in Turkiye ***provide waste management services***, and it is amassed ***a total of 30,283,757 tons of waste***, and the amount of MSW collected per person is ***1.03 kg/day*** [3]. From this total, ***85.9%*** was directed towards waste treatment facilities, ***13.5%*** was allocated to municipal dumping sites, and the remaining ***0.6%*** was disposed of through alternative methods such as open burning, burial, and the dumping into rivers or onto land [3].

2. Data

Municipal Solid Waste (MSW), waste collected by the municipalities that provide waste management services, includes everyday trash from homes, businesses, and public places, along with bulky items and yard waste. It also covers street sweepings and waste from public trash bins and markets, if treated like household trash. However, it doesn't include waste from sewer systems, industrial processes or construction and demolition sites [4].

Multiple data sources are planned to be utilized for the analysis in this area of MSW, primarily focusing on waste quantities, along with Gross Domestic Product (GDP), education, electricity consumption, population figures, and agriculture area for ***Turkiye and its provinces.***

2.1 Data Source

The references from which I have gathered the data include:

- Waste Statistics, TURKSTAT
- Environment Regional Data, Biruni TURKSTAT
- Agriculture area, Biruni TURKSTAT
- Education, Biruni TURKSTAT
- GDP, Biruni TURKSTAT
- Electricity consumption, Biruni TURKSTAT

2.2 General Information About the Main Data

- **First data set:** The municipal waste amount data of Turkiye, which includes information such as the population of Turkiye and its 81 provinces' municipalities, total waste amounts for the year 2022, the average waste amount per person, etc.

```
library(openxlsx)
```

```
Warning: package 'openxlsx' was built under R version 4.3.3
```

```
municipal_waste <- read.xlsx("project/data/municipal_waste.xlsx")
```

- **Second data set:** Data including the amounts of collected municipal waste that are sent to municipal landfills, waste processing facilities (the waste sent to landfill sites, incineration plants and all the waste recovery facilities), and disposed of using other methods (disposals by burning in an open area, dumping into river/onto land and burying).

```
where_to_municipal_waste <- read.xlsx("project/data/where_to_municipal_waste.xlsx")
```

- **Third data set:** Time series data including municipal waste amounts, waste per capita, waste sent to processing facilities, etc., and time series of waste amounts by provinces of Turkiye for the years 1994-2022.

```
time_series_municipal_waste <- read.xlsx("project/data/time_series_municipal_waste.xlsx", colN
ts_province <- read.xlsx("project/data/ts_waste_province.xlsx")
```

2.3 Reason of Choice

This topic was chosen because it was realized that **waste management is not given enough importance** in Turkiye, and it is believed that carelessness should not continue in this matter. The importance of the subject is **indisputable**. By using the data sets mentioned above, it is aimed to reveal and analyze the current situation of waste management, to derive knowledge, and to contribute to the literature and our country.

2.4 Preprocessing

- **For "municipal_waste" dataset:**

Downloadable dataset in .RData version

```
library(tidyverse)
```

```
Warning: package 'stringr' was built under R version 4.3.2
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.3     v readr     2.1.4
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.4.4     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.0
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```r
# remove unnecessary columns
municipal_waste <- select(municipal_waste, -X5)
municipal_waste <- select(municipal_waste, -X6)
# rename columns
municipal_waste <- rename(municipal_waste, "Provinces" ="Belediye.atık.hizmeti.istatistikleri,
municipal_waste <- rename(municipal_waste, "Total municipal population" = "X2")
municipal_waste <- rename(municipal_waste, "Total number of municipalities" ="X3")
municipal_waste <- rename(municipal_waste, "Number of municipalities providing waste services"
municipal_waste <- rename(municipal_waste, "Amount of waste collected (Tonnes)
" ="X7")
municipal_waste <- rename(municipal_waste, "Amount of waste per capita (Kg/capita-day)
" ="X8")
# remove unnecessary rows
municipal_waste <- municipal_waste[-c(1, 2, 85, 86, 87, 88), ]
# reorder row names that is disordered
row.names(municipal_waste) <- NULL
municipal_waste <- municipal_waste %>%
  mutate(row_id = row_number())
municipal_waste <- municipal_waste %>%
  select(row_id, everything())
municipal_waste <- municipal_waste[,-c(1)]
# adjust necessary columns as numbers
municipal_waste <- municipal_waste %>%
  mutate(across(-Provinces, ~as.numeric(as.character(.))))
sapply(municipal_waste,class)
```

```
                                        Provinces
                                      "character"
                       Total municipal population
                                        "numeric"
                   Total number of municipalities
                                        "numeric"
Number of municipalities providing waste services
                                        "numeric"
            Amount of waste collected (Tonnes) \n
                                        "numeric"
    Amount of waste per capita (Kg/capita-day) \n
                                        "numeric"
```

The first six rows of the municipal waste dataset are provided below.

```r
str(municipal_waste)
```

```
'data.frame':   82 obs. of  6 variables:
 $ Provinces                                        : chr  "Türkiye" "Adana" "Adıyaman" "Afyon
 $ Total municipal population                       : num  80785141 2274106 487642 588048 3145
 $ Total number of municipalities                   : num  1391 16 23 60 12 ...
 $ Number of municipalities providing waste services: num  1389 16 22 60 12 ...
 $ Amount of waste collected (Tonnes)
            : num  30283757 665695 179724 198273 181116 ...
 $ Amount of waste per capita (Kg/capita-day)
    : num  1.033 0.807 1.019 0.928 1.58 ...
```

The descriptive statistics for each column are provided below.

```r
summary(municipal_waste)
```

```
  Provinces          Total municipal population Total number of municipalities
 Length:82          Min.   :   41120           Min.   :   4.00               
 Class :character   1st Qu.:  242100           1st Qu.:  11.00               
 Mode  :character   Median :  417945           Median :  16.00               
                    Mean   : 1970369           Mean   :  33.93               
                    3rd Qu.: 1139026           3rd Qu.:  21.00               
                    Max.   :80785141           Max.   :1391.00               
 Number of municipalities providing waste services
 Min.   :   4.00                                  
 1st Qu.:  11.00                                  
 Median :  16.00                                  
 Mean   :  33.88                                  
 3rd Qu.:  21.00                                  
 Max.   :1389.00                                  
 Amount of waste collected (Tonnes) \n
 Min.   :   21392                     
 1st Qu.:   81725                     
 Median :  151235                     
 Mean   :  738628                     
 3rd Qu.:  415882                     
 Max.   :30283757                     
 Amount of waste per capita (Kg/capita-day) \n
 Min.   :0.6498                              
 1st Qu.:0.8730                              
 Median :0.9672                              
 Mean   :1.0679                              
 3rd Qu.:1.1887                              
 Max.   :1.9962                              
```

- **For "where_to_municipal_waste" dataset:**

Downloadable dataset in .RData version

```r
library(tidyverse)
# remove unnecessary columns
where_to_municipal_waste <- select(where_to_municipal_waste, -X2)
where_to_municipal_waste <- select(where_to_municipal_waste, -X4)
where_to_municipal_waste <- select(where_to_municipal_waste, -X6)
where_to_municipal_waste <- select(where_to_municipal_waste, -X8)
where_to_municipal_waste <- select(where_to_municipal_waste, -X9)
# rename columns
where_to_municipal_waste <- rename(where_to_municipal_waste, "Provinces" = `Belediye.atık.yöne
where_to_municipal_waste <- rename(where_to_municipal_waste, "Total amount of waste collected
where_to_municipal_waste <- rename(where_to_municipal_waste, "Municipality's dumping sites" ="
where_to_municipal_waste <- rename(where_to_municipal_waste, "Waste treatment facilities"= "X7
where_to_municipal_waste <- rename(where_to_municipal_waste, "Other disposal methods"= "X10")
# remove unnecessary rows
where_to_municipal_waste <- where_to_municipal_waste[-c(1, 2, 85:94), ]
# reorder row names that is disordered
```

```
row.names(where_to_municipal_waste) <- NULL
where_to_municipal_waste <- where_to_municipal_waste %>%
  mutate(row_id = row_number())
where_to_municipal_waste <- where_to_municipal_waste %>%
  select(row_id, everything())
where_to_municipal_waste <- where_to_municipal_waste[,-c(1)]
# adjust necessary columns as numbers
where_to_municipal_waste <- where_to_municipal_waste %>%
  mutate(across(-Provinces, ~as.numeric(as.character(.))))
sapply(where_to_municipal_waste,class)
```

```
                                 Provinces
                               "character"
Total amount of waste collected  (Tonnes)
                                 "numeric"
             Municipality's dumping sites
                                 "numeric"
               Waste treatment facilities
                                 "numeric"
                   Other disposal methods
                                 "numeric"
```

The first six rows of the dataset showing the distribution of municipal waste disposal methods are provided below.

```
str(where_to_municipal_waste)
```

```
'data.frame':   82 obs. of  5 variables:
 $ Provinces                                : chr  "Türkiye" "Adana" "Adıyaman" "Afyonkarahisa
 $ Total amount of waste collected  (Tonnes): num  30283757 665695 179724 198273 181116 ...
 $ Municipality's dumping sites             : num  4092721 0 178453 20090 131116 ...
 $ Waste treatment facilities               : num  26016988 663895 1271 175952 50000 ...
 $ Other disposal methods                   : num  174048 1800 0 2231 0 ...
```

The descriptive statistics for each column are provided below.

```
summary(where_to_municipal_waste)
```

```
  Provinces         Total amount of waste collected  (Tonnes)
 Length:82          Min.   :   21392
 Class :character   1st Qu.:   81725
 Mode  :character   Median :  151235
                    Mean   :  738628
                    3rd Qu.:  415882
                    Max.   :30283757
 Municipality's dumping sites Waste treatment facilities Other disposal methods
 Min.   :      0              Min.   :       0           Min.   :     0.0
 1st Qu.:   1260              1st Qu.:   52770           1st Qu.:     0.0
 Median :  17376              Median :  109595           Median :     0.0
 Mean   :  99822              Mean   :  634561           Mean   :  4245.1
 3rd Qu.:  56501              3rd Qu.:  333389           3rd Qu.:   557.5
 Max.   :4092721              Max.   :26016988           Max.   :174047.6
```

- **For “time_series_municipal_waste” dataset and “ts_province” dataset:**

Downloadable dataset in .RData version

```
library(tidyverse)
# remove unnecessary rows
time_series_municipal_waste <- time_series_municipal_waste[-c(2:6,10,14:43), ]
time_series_municipal_waste <- rename(time_series_municipal_waste, "Waste/Year" = "X1")
# rename rows
time_series_municipal_waste[1,1] <- "Turkey population"
time_series_municipal_waste[2,1] <- "Amount of municipal waste generated (Thousand tonnes/year
time_series_municipal_waste[3,1] <- "Amount of municipal waste collected (Thousand tonnes/year
time_series_municipal_waste[4,1] <- "Average amount of municipal waste per capita (Kg/capita-d
time_series_municipal_waste[5,1] <- "Waste treatment facilities"
time_series_municipal_waste[6,1] <- "Municipality's dumping sites"
time_series_municipal_waste[7,1] <- "Other disposal methods"
# reorder row names that is disordered
row.names(time_series_municipal_waste) <- NULL
# adjust necessary columns as numbers
time_series_municipal_waste <- time_series_municipal_waste %>%
  mutate(across(-`Waste/Year`, ~as.numeric(as.character(.))))
sapply(time_series_municipal_waste,class)
```

```
 Waste/Year        1994        1995        1996        1997        1998
"character"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric"
       2001        2002        2003        2004        2006        2008
  "numeric"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric"
       2010        2012        2014        2016        2018        2020
  "numeric"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric"
       2022
  "numeric"
```

The attributes of the time series dataset are provided below.

```
str(time_series_municipal_waste)
```

```
'data.frame':   7 obs. of  19 variables:
 $ Waste/Year: chr  "Turkey population" "Amount of municipal waste generated (Thousand tonnes/
 $ 1994      : num  6.28e+07 2.34e+04 1.78e+04 1.10 1.00e+03 ...
 $ 1995      : num  6.28e+07 2.72e+04 2.09e+04 1.27 1.60e+03 ...
 $ 1996      : num  6.28e+07 2.93e+04 2.25e+04 1.37 3.03e+03 ...
 $ 1997      : num  6.28e+07 3.19e+04 2.42e+04 1.46 4.54e+03 ...
 $ 1998      : num  6.28e+07 3.30e+04 2.49e+04 1.51 5.42e+03 ...
 $ 2001      : num  6.78e+07 3.10e+04 2.51e+04 1.35 8.52e+03 ...
 $ 2002      : num  6.78e+07 3.10e+04 2.54e+04 1.34 7.43e+03 ...
 $ 2003      : num  6.78e+07 3.11e+04 2.61e+04 1.38 7.76e+03 ...
 $ 2004      : num  6.78e+07 2.97e+04 2.50e+04 1.31 7.35e+03 ...
 $ 2006      : num  7.06e+07 3.01e+04 2.53e+04 1.21 9.68e+03 ...
 $ 2008      : num  7.06e+07 2.85e+04 2.44e+04 1.15 1.12e+04 ...
 $ 2010      : num  7.37e+07 2.97e+04 2.53e+04 1.14 1.39e+04 ...
 $ 2012      : num  7.56e+07 3.08e+04 2.58e+04 1.12 1.56e+04 ...
 $ 2014      : num  7.77e+07 3.12e+04 2.80e+04 1.08 1.79e+04 ...
 $ 2016      : num  7.98e+07 3.38e+04 3.16e+04 1.17 2.24e+04 ...
 $ 2018      : num  8.20e+07 3.45e+04 3.22e+04 1.16 2.56e+04 ...
 $ 2020      : num  8.36e+07 3.48e+04 3.23e+04 1.13 2.67e+04 ...
 $ 2022      : num  8.53e+07 3.24e+04 3.03e+04 1.03 2.60e+04 ...
```

The attributes of the provinces' time series dataset are provided below.

```
ts_province  <- select(ts_province , -BÖLGE.KODU)
ts_province  <- rename(ts_province , "Year" = YIL)
ts_province  <- rename(ts_province , "Province" = BÖLGE.ADI)
ts_province  <- rename(ts_province , "Waste amount (1000 ton)" = `Belediye.atık.istatistikleri
ts_province$Year <- as.numeric(ts_province$Year)
ts_province$`Waste amount (1000 ton)` <- as.numeric(ts_province$`Waste amount (1000 ton)`)
```

```
Warning: Zorlamadan dolayı ortaya çıkan NAs
```

```
str(ts_province)
```

```
'data.frame':   1134 obs. of  3 variables:
 $ Year                   : num  1998 2001 2002 2003 2004 ...
 $ Province               : chr  "İstanbul" "İstanbul" "İstanbul" "İstanbul" ...
 $ Waste amount (1000 ton): num  6074 6112 5231 5375 4471 ...
```

3. Analysis

In the first phase of this section, *Exploratory Data Analysis (EDA)*, the data prepared for analysis is visualized to enable discoveries that are not immediately apparent at first glance. Later, relationships are determined through *regression analysis*, future predictions are made using *time series methods.*

3.1 Exploratory Data Analysis

For "municipal_waste" dataset:

The relationship between the population size of Turkiye provinces and the amount of waste generated is shown in the scatter plot below. According to the plot, a linear relationship is observed between them.

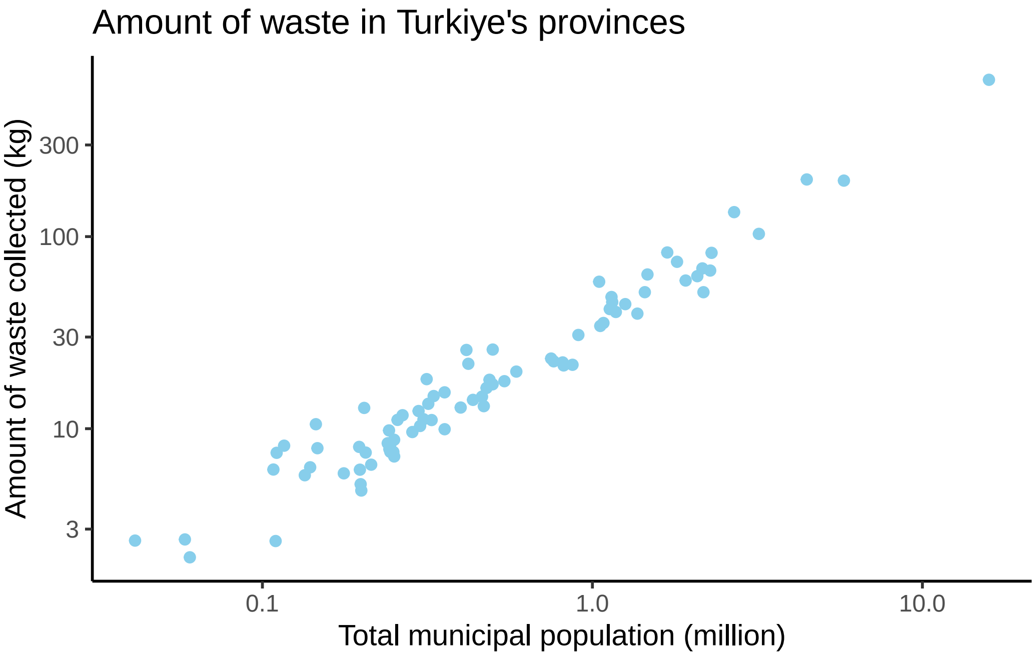
```
library(tidyverse)
library(ggthemes)
```

```
Warning: package 'ggthemes' was built under R version 4.3.2
```

```
library(ggrepel)
```

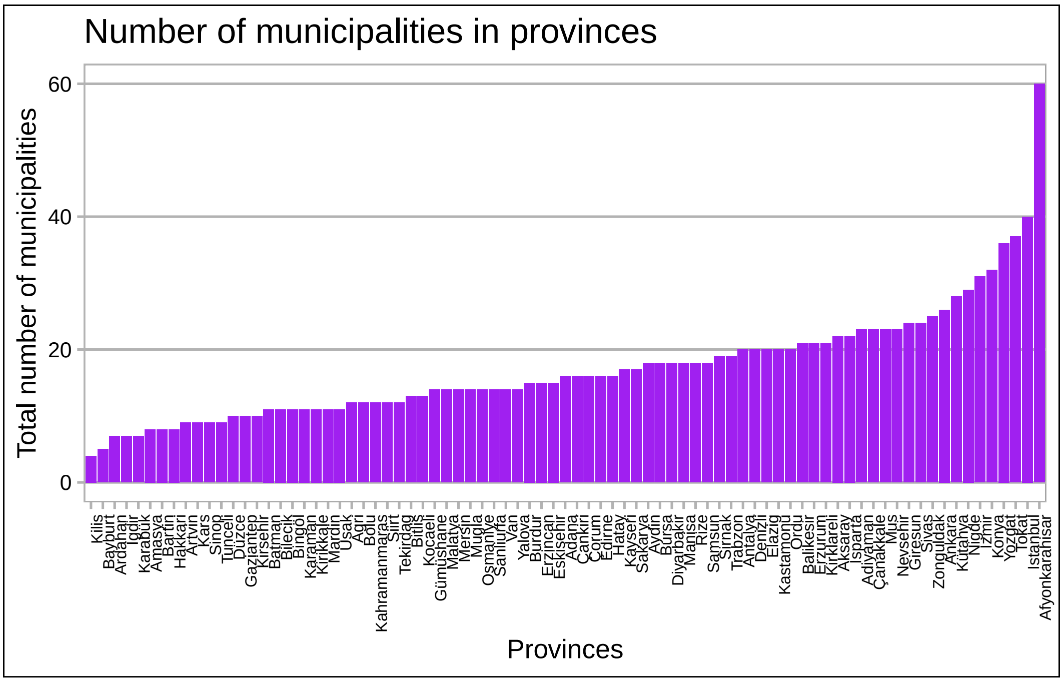
```
Warning: package 'ggrepel' was built under R version 4.3.2
```

```
municipal_waste <- municipal_waste[-c(1), ]

p <- municipal_waste |> ggplot(aes(`Total municipal population`/10^6,
`Amount of waste collected (Tonnes)
`/10^4))
p + geom_point(color = "skyblue") +
scale_x_continuous(trans = "log10") +
scale_y_continuous(trans = "log10") +
xlab("Total municipal population (million)") +
ylab("Amount of waste collected (kg)") +
ggtitle("Amount of waste in Turkiye's provinces")+
theme_classic()
```



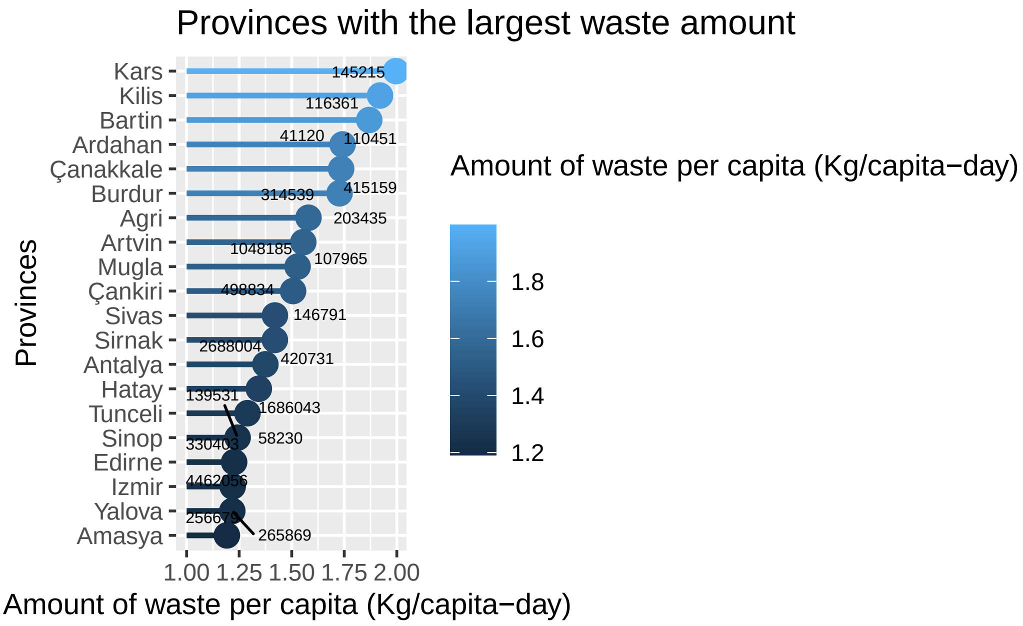
Provinces ranked according to the total number of municipalities can be seen in the below graph together with the number of municipalities.

```
p <- ggplot(municipal_waste, aes(x = reorder(Provinces, `Total number of municipalities`, FUN
p + geom_bar(stat = "identity", fill= "purple") +
  xlab("Provinces") +
  theme_calc() +
  ggtitle("Number of municipalities in provinces") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 6))
```



In the plot below, the first 20 provinces with the highest amount of waste per capita and their populations can be found.

```
# The provinces that produce largest amount of waste
The_largest <- municipal_waste |> arrange(desc(`Amount of waste per capita (Kg/capita-day)
`)) |> head(n = 20)
p <- ggplot(The_largest, aes(x = reorder(Provinces, `Amount of waste per capita (Kg/capita-day
`, FUN = sum),
                             y = `Amount of waste per capita (Kg/capita-day)
`))
ggplot(The_largest, aes(x =`Amount of waste per capita (Kg/capita-day)
`, y = reorder(Provinces, `Amount of waste per capita (Kg/capita-day)
`, FUN = sum), color = `Amount of waste per capita (Kg/capita-day)
`)) +
  geom_point(size = 4) +
  geom_segment(aes(xend = 1, yend = Provinces), linewidth = 1) +
  ylab("Provinces") +
  ggtitle("Provinces with the largest waste amount")+
  geom_text_repel(aes(label =`Total municipal population`), color = "black", size = 2)
```



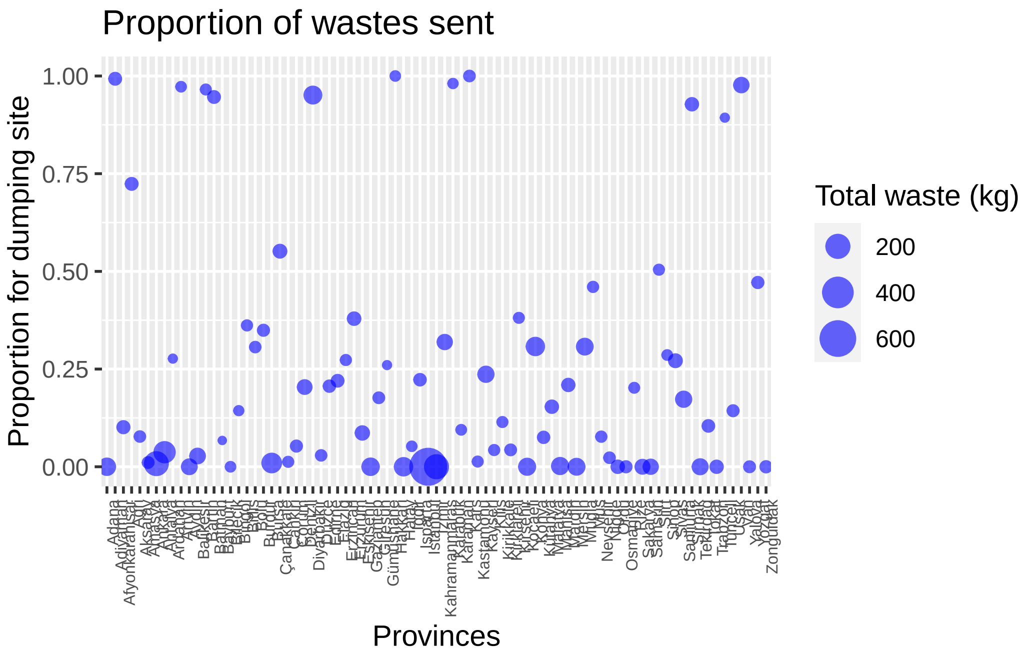
For "where_to_municipal_waste" dataset:

The distribution of waste collected by municipalities according to three disposal methods and provinces is analysed in this section.

```
library(tidyverse)
library(ggthemes)
library(ggrepel)
library(dplyr)

dumping_site <-where_to_municipal_waste |>
  mutate(proportion1 = `Municipality's dumping sites`/`Total amount of waste collected  (Tonne
treatment_facility <-where_to_municipal_waste |>
  mutate(proportion2 =`Waste treatment facilities`/`Total amount of waste collected  (Tonnes)`
other_disposal <-where_to_municipal_waste |>
  mutate(proportion3 =`Other disposal methods`/`Total amount of waste collected  (Tonnes)`)
```

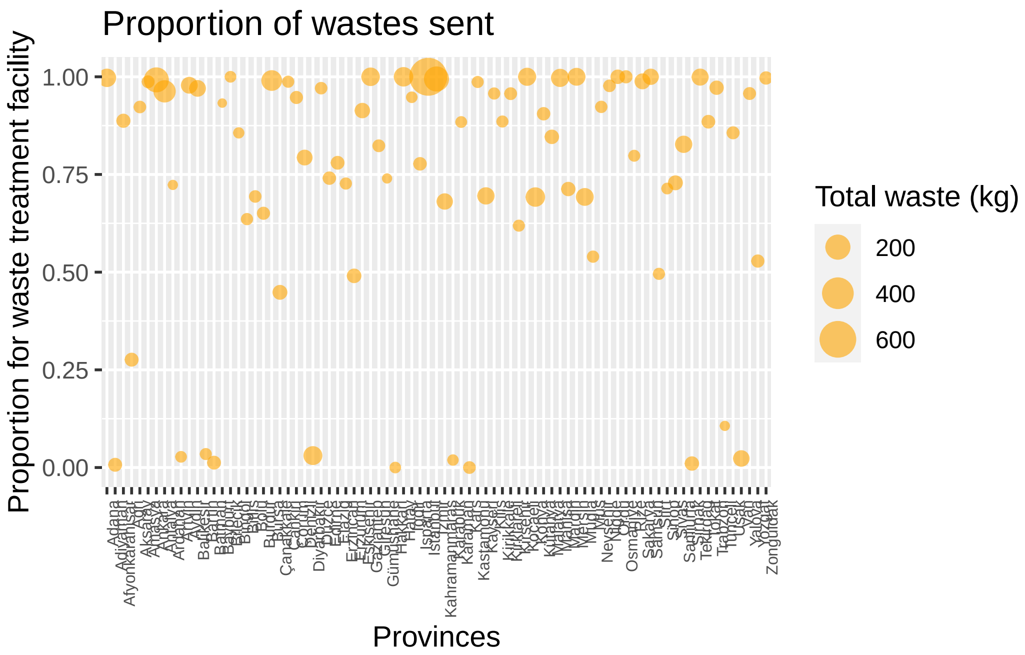
The amount of waste allocated for the *municipality dumping site* can be seen below, plotted by province, with circle diameters representing the total amount of waste.

```
# Dumping site proportion graph
dumping_site <- dumping_site[-c(1), ]
ggplot(dumping_site, aes(Provinces, proportion1, size =`Total amount of waste collected  (Tonn
  geom_point(color = "blue", alpha = 0.6) + theme(axis.text.x = element_text(angle = 90, hjust
  labs (x = "Provinces",y = "Proportion for dumping site", title = "Proportion of wastes sent"
```



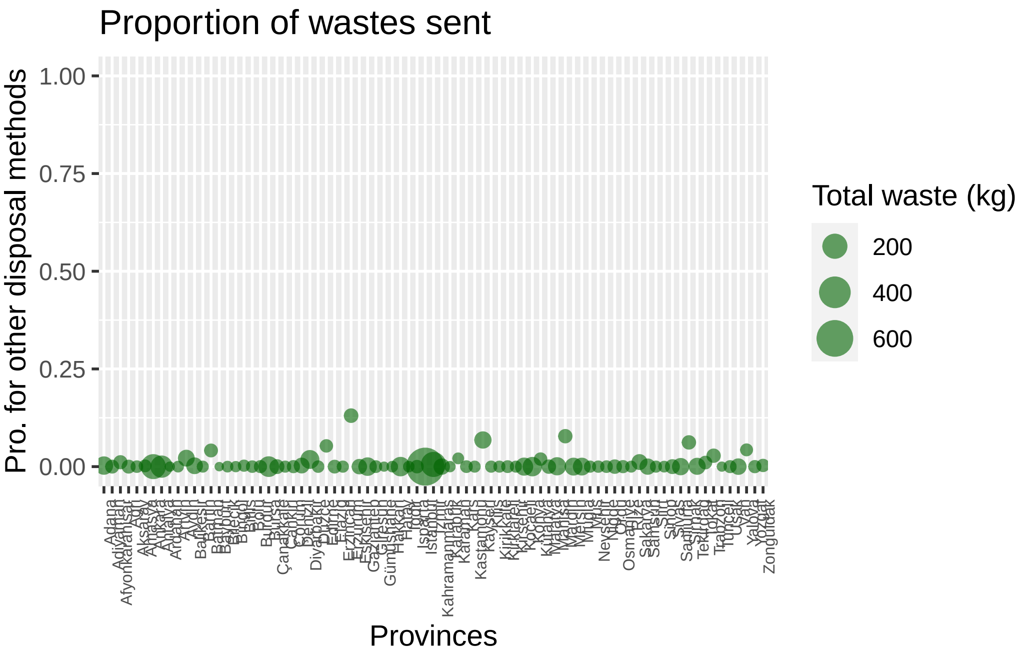
The amount of waste allocated for the *waste treatment facilities* can be seen below, plotted by province, with circle diameters representing the total amount of waste.

```
# Waste treatment facility proportion graph
treatment_facility <- treatment_facility[-c(1), ]
ggplot(treatment_facility, aes(Provinces, proportion2, size =`Total amount of waste collected
  geom_point(color = "orange", alpha = 0.6) +  theme(axis.text.x = element_text(angle = 90, hj
  labs (x = "Provinces",y = "Proportion for waste treatment facility", title = "Proportion of
```



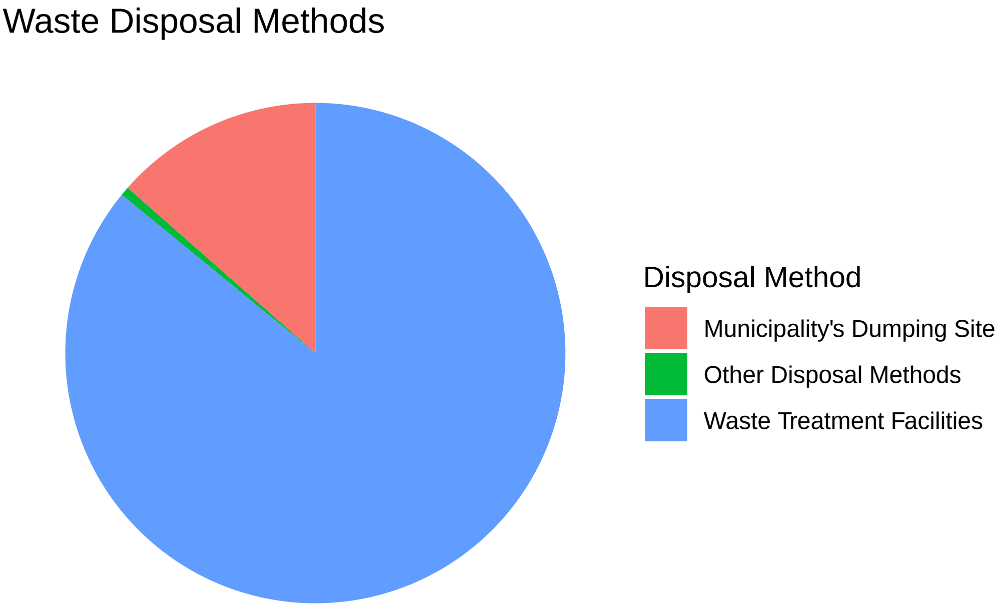
The amount of waste allocated for the *other disposal methods* can be seen below, plotted by province, with circle diameters representing the total amount of waste.

```
# Other disposal methods proportion graph
other_disposal <- other_disposal[-c(1), ]
ggplot(other_disposal, aes(Provinces, proportion3, size =`Total amount of waste collected  (To
  geom_point(color = "darkgreen", alpha = 0.6) + theme(axis.text.x = element_text(angle = 90, 
  labs (x = "Provinces",y = "Pro. for other disposal methods", title = "Proportion of wastes s
```



The pie chart below shows a rough breakdown of the amount of waste sent to these three disposal methods.

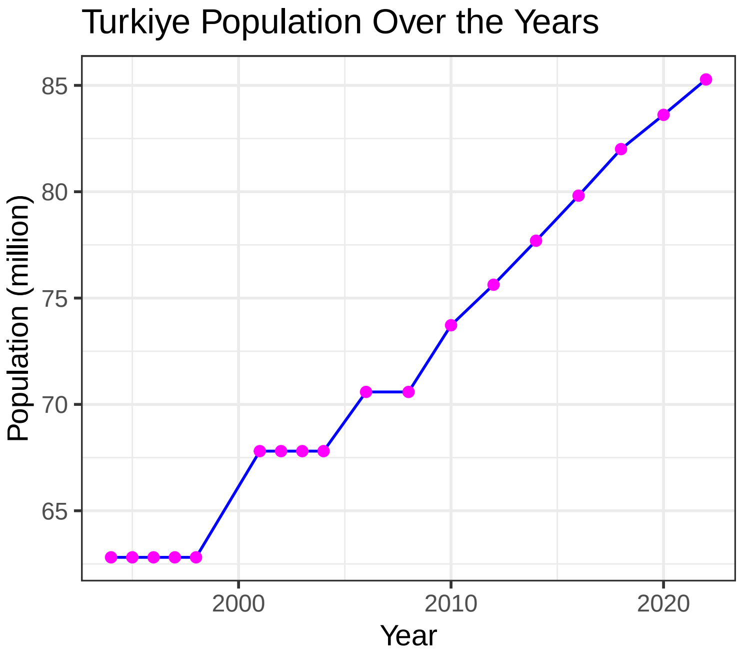
```
# Pie Chart
waste_distr <- data.frame(Method = c("Municipality's Dumping Site", "Waste Treatment Facilitie
ggplot(waste_distr, aes(x = "", y = Amount, fill = Method)) +
  geom_bar(width = 1, stat = "identity") +
  coord_polar(theta = "y") +
  theme_void() +
  labs(title = "Waste Disposal Methods", fill = "Disposal Method")
```



For “time_series_municipal_waste” dataset and “ts_province” dataset:

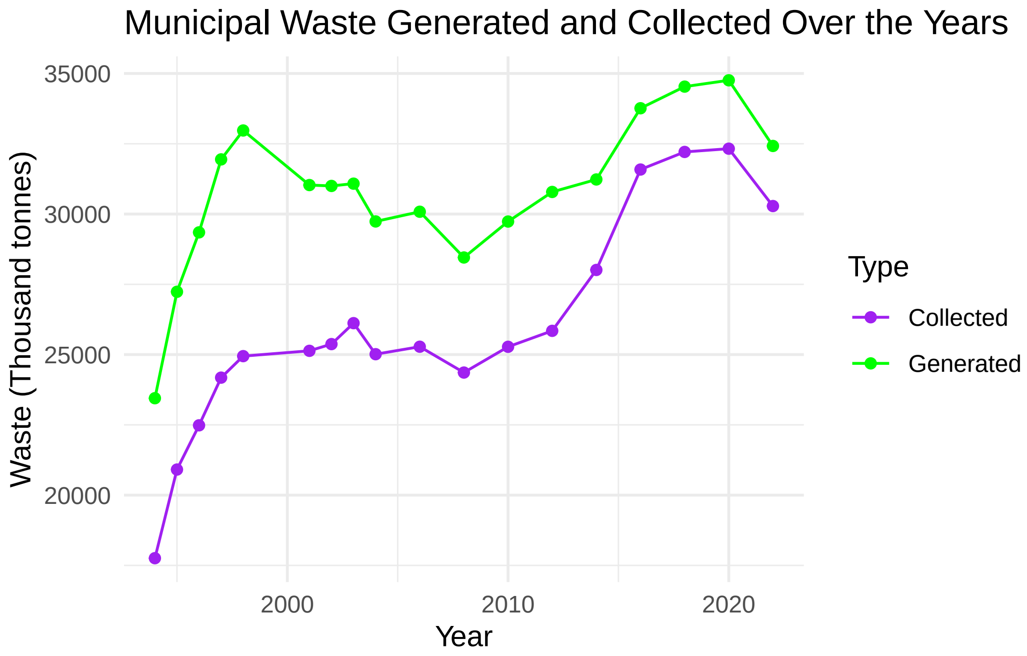
According to the time series data set, Turkiye’s population change over the years is given below.

```
library(tidyverse)
library(ggthemes)
library(ggrepel)
library(dplyr)

ts_data <- time_series_municipal_waste %>%
  pivot_longer(cols = -`Waste/Year`, names_to = "Year", values_to = "Value") %>%
  mutate(Year = as.numeric(Year))

# Türkiye population ts
ggplot(ts_data %>% filter(`Waste/Year` == "Turkey population"),
                          aes(x = Year, y = Value / 10^6)) +
  geom_line(color = "blue") +
  geom_point(color = "magenta") +
  theme_bw() + coord_fixed() +
  labs(title = "Turkiye Population Over the Years", x = "Year", y = "Population (million)")
```



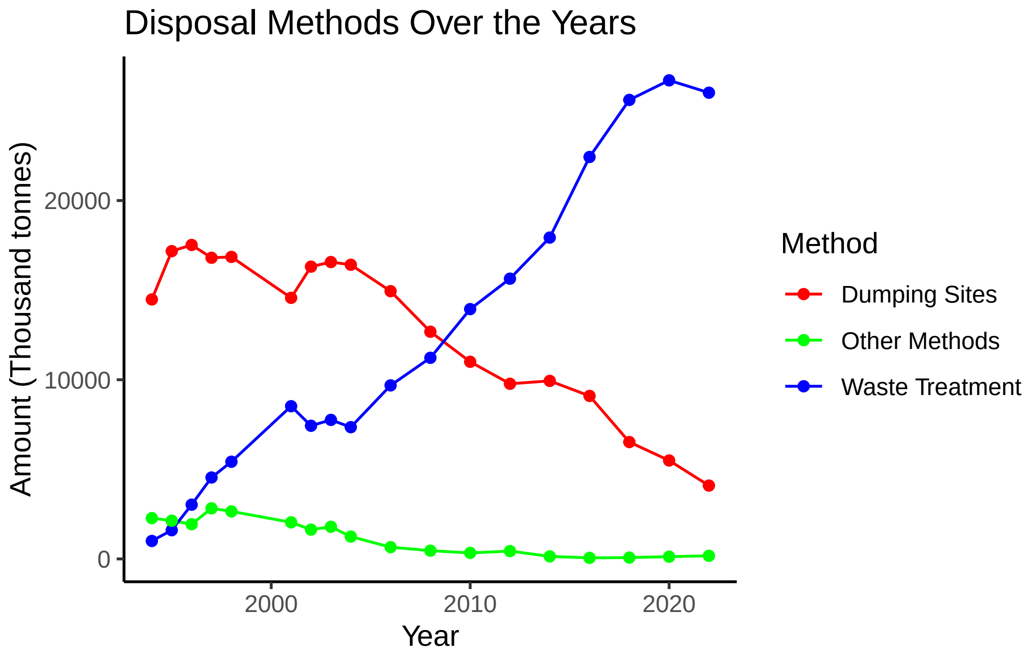
The relationship between the total amount of waste generated in Turkey and the amount collected by municipalities for proper disposal can be accessed from the plot.

```
# Waste graphs
ts_data2 <- ts_data %>%
  filter(`Waste/Year` %in% c("Amount of municipal waste generated (Thousand tonnes/year)",
                             "Amount of municipal waste collected (Thousand tonnes/year)")) %>
  mutate(Type = case_when(
    `Waste/Year` == "Amount of municipal waste generated (Thousand tonnes/year)" ~ "Generated"
    `Waste/Year` == "Amount of municipal waste collected (Thousand tonnes/year)" ~ "Collected"
  ))

ggplot(ts_data2, aes(x = Year, y = Value, color = Type, group = Type)) +
  geom_line() +
  geom_point() +
  scale_color_manual(values = c("Generated" = "green", "Collected" = "purple")) +
  labs(title = "Municipal Waste Generated and Collected Over the Years",
       x = "Year",
       y = "Waste (Thousand tonnes)",
       color = "Type") +
  theme_minimal()
```



Changes in waste amount over the years according to disposal methods are given below.

```
disposal_methods_data <- ts_data %>%
  filter(`Waste/Year` %in% c("Waste treatment facilities",
                              "Municipality's dumping sites",
                              "Other disposal methods")) %>%
  mutate(Type = case_when(
    `Waste/Year` == "Waste treatment facilities" ~ "Waste Treatment",
    `Waste/Year` == "Municipality's dumping sites" ~ "Dumping Sites",
    `Waste/Year` == "Other disposal methods" ~ "Other Methods"
  ))

ggplot(disposal_methods_data, aes(x = Year, y = Value, color = Type, group = Type)) +
  geom_line() +
  geom_point() +
  scale_color_manual(values = c("Waste Treatment" = "blue", "Dumping Sites" = "red", "Other Me
  labs(title = "Disposal Methods Over the Years",
       x = "Year",
       y = "Amount (Thousand tonnes)",
       color = "Method") +
  theme_classic()
```



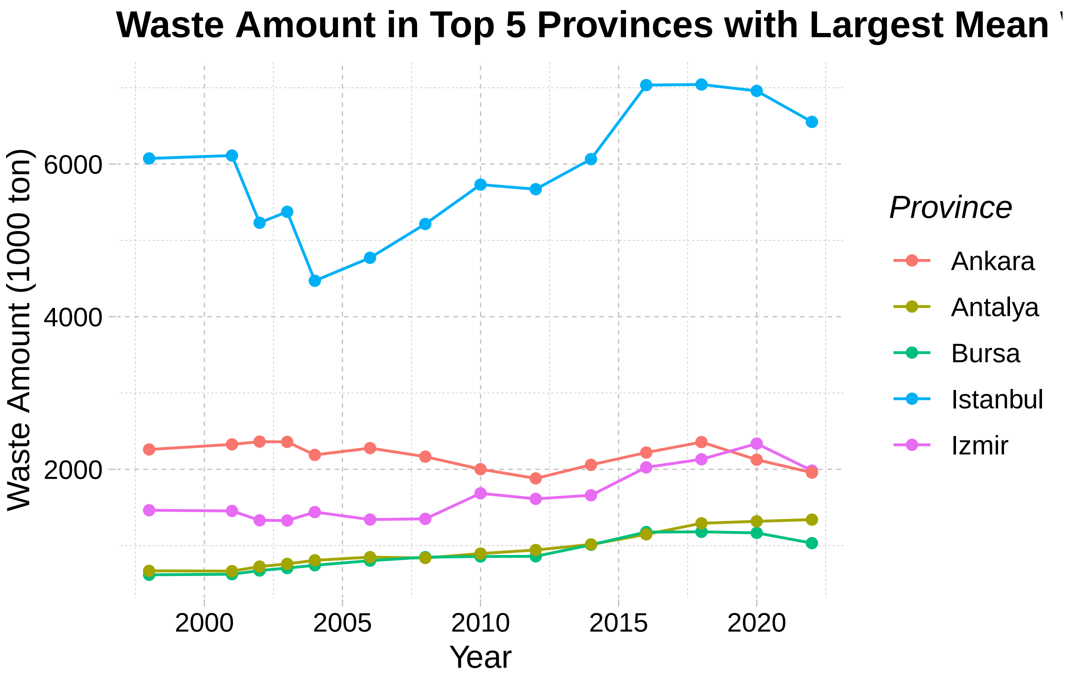
Descriptive statistics for waste amounts by province dataset:

```
summary_stats <- ts_province %>%
  group_by(Province) %>%
  summarise(
    mean_waste = mean(`Waste amount (1000 ton)`, na.rm = TRUE),
    median_waste = median(`Waste amount (1000 ton)`, na.rm = TRUE),
    sd_waste = sd(`Waste amount (1000 ton)`, na.rm = TRUE),
    min_waste = min(`Waste amount (1000 ton)`, na.rm = TRUE),
    max_waste = max(`Waste amount (1000 ton)`, na.rm = TRUE)
  ) %>%
  arrange(desc(mean_waste)) %>%
  top_n(10, mean_waste)
print(summary_stats)
```

```
# A tibble: 10 x 6
   Province mean_waste median_waste sd_waste min_waste max_waste
   <chr>         <dbl>        <dbl>    <dbl>     <dbl>     <dbl>
 1 İstanbul      5879.        5898     824.       4471      7043
 2 Ankara        2182.        2204.    158.       1881      2363
 3 İzmir         1654.        1538.    336.       1329      2337
 4 Antalya        948.         872.    239.        666      1341
 5 Bursa         879           854.    203.        618      1181
 6 Konya          756.         740.     84.7       643       921
 7 Adana          731.         734      63.6       614       826
 8 Mersin         613.         595      97.8       453       819
 9 Kocaeli        539.         534     110.        380       713
10 Muğla          529.         528.     99.9       397       677
```

The line graph of waste amounts over the years for the top 5 cities producing the most waste based on provincial waste amount data is drawn.

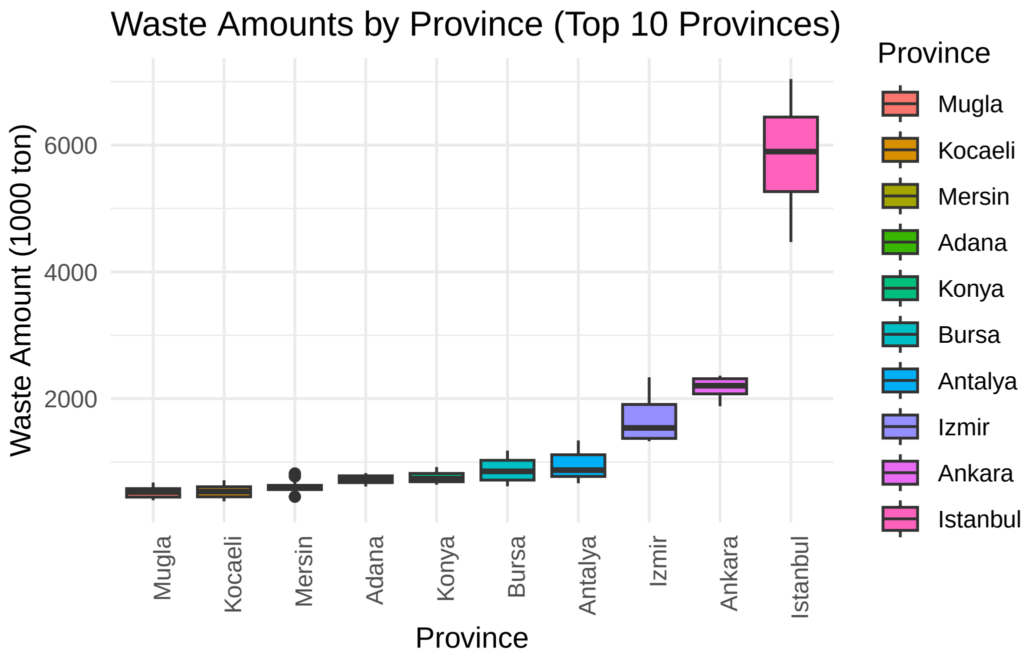
```r
library(tidyverse)
library(ggthemes)
mean_waste <- ts_province %>%
  group_by(Province) %>%
  summarise(mean_waste = mean(`Waste amount (1000 ton)`, na.rm = TRUE)) %>%
  arrange(desc(mean_waste))

top5_provinces <- mean_waste %>%
  top_n(5, mean_waste) %>%
  pull(Province)

top5_data <- ts_province %>%
  filter(Province %in% top5_provinces)

ggplot(top5_data, aes(x = Year, y = `Waste amount (1000 ton)`, color = Province)) +
  geom_line() +
  geom_point() +
  labs(title = "Waste Amount in Top 5 Provinces with Largest Mean Waste Amount",
       x = "Year",
       y = "Waste Amount (1000 ton)") +
  theme_pander()
```



The box plot for the top 10 provinces with the highest average waste amounts is provided below.

```r
top10_summary <- ts_province %>%
  group_by(Province) %>%
  summarise(mean_waste = mean(`Waste amount (1000 ton)`, na.rm = TRUE)) %>%
  arrange(desc(mean_waste)) %>%
  top_n(10, mean_waste)

top10_provinces <- top10_summary$Province
top10_data <- ts_province %>%
  filter(Province %in% top10_provinces)
```

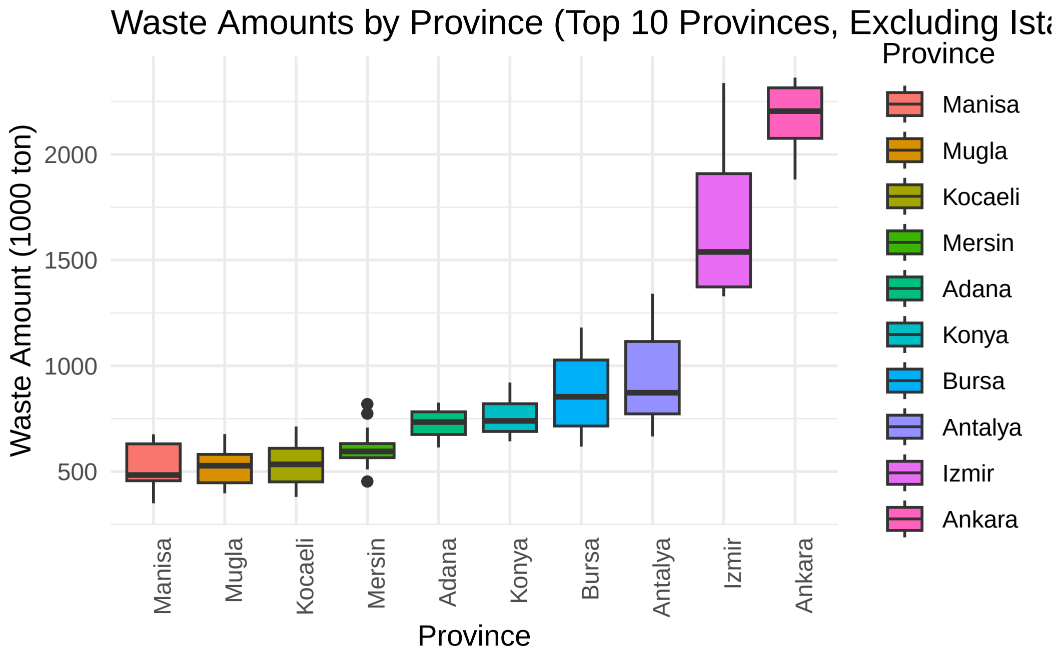
```
top10_data <- top10_data %>%
  mutate(Province = factor(Province, levels = top10_summary$Province[order(top10_summary$mean_

ggplot(top10_data, aes(x = Province, y = `Waste amount (1000 ton)`, fill = Province)) +
  geom_boxplot() +
  labs(title = "Waste Amounts by Province (Top 10 Provinces)",
       x = "Province",
       y = "Waste Amount (1000 ton)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



When İstanbul, which was very dominant in the previous boxplot, is excluded, the results are also examined.

```
ts_province_no_istanbul <- ts_province %>% filter(Province != "İstanbul")
top10_summary_no_istanbul <- ts_province_no_istanbul %>%
  group_by(Province) %>%
  summarise(mean_waste = mean(`Waste amount (1000 ton)`, na.rm = TRUE)) %>%
  arrange(desc(mean_waste)) %>%
  top_n(10, mean_waste)

top10_provinces_no_istanbul <- top10_summary_no_istanbul$Province
top10_data_no_istanbul <- ts_province_no_istanbul %>%
  filter(Province %in% top10_provinces_no_istanbul)

top10_data_no_istanbul <- top10_data_no_istanbul %>%
  mutate(Province = factor(Province, levels = top10_summary_no_istanbul$Province[order(top10_s

ggplot(top10_data_no_istanbul, aes(x = Province, y = `Waste amount (1000 ton)`, fill = Provinc
  geom_boxplot() +
  labs(title = "Waste Amounts by Province (Top 10 Provinces, Excluding İstanbul)",
       x = "Province",
       y = "Waste Amount (1000 ton)") +
```

```r
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



3.2 Regression Analysis

Additional Data

The data sets needed to identify variables contributing to total waste generation and to conduct regression analysis have been preprocessed below.

Data on the agricultural area cultivated in the provinces of Turkiye can be accessed below.

```r
library(openxlsx)
library(tidyverse)
# agriculture area
agriculture_area <- read.xlsx("project/data/agriculture_area.xlsx", colNames = TRUE)
agriculture_area <- select(agriculture_area, -"YIL")
agriculture_area <- select(agriculture_area, -"BÖLGE.KODU")
agriculture_area <- rename(agriculture_area, "Provinces" = "BÖLGE.ADI")
agriculture_area <- rename(agriculture_area, "Agriculture area" =`Toplam.işlenen.tarım.alanı.(
agriculture_area <- agriculture_area [-c(83:87), ]
agriculture_area <- agriculture_area [-c(1), ]
str(agriculture_area)
```

```
'data.frame':   81 obs. of  2 variables:
 $ Provinces       : chr  "İstanbul" "Tekirdağ" "Edirne" "Kırklareli" ...
 $ Agriculture area: num  74041 403706 335499 245224 288589 ...
```

The data on educational status of Turkiye's provinces, categorized by various levels, is provided in education data set.

```r
# education
education <- read.xlsx("project/data/education.xlsx", colNames = TRUE)
education <- select(education, -"YIL")
education <- select(education, -"BÖLGE.KODU")
education  <- rename(education , "Provinces" = "BÖLGE.ADI")
education  <- rename(education , "Total number of faculty members" = `Yükseköğretim.kurumların
education  <- rename(education , "Total number of illiterate people" = `Eğitim.durumuna.göre.n
education  <- rename(education , "Number of associate or bachelor's degree graduates" = `Yükse
education  <- rename(education , "Number of master's degree graduates" = `Eğitim.durumuna.göre
education <- education [-c(1), ]
str(education)
```

```
'data.frame':   81 obs. of  5 variables:
 $ Provinces                                         : chr  "İstanbul" "Tekirdağ" "Edirne" "Kı
 $ Total number of faculty members                   : num  40140 1221 1871 883 1837 ...
 $ Total number of illiterate people                 : num  206140 11573 7011 4462 17368 ...
 $ Number of associate or bachelor's degree graduates: num  167695 3728 6517 3682 7465 ...
 $ Number of master's degree graduates               : num  389440 14458 6914 5137 18318 ...
```

The first six rows of the electricity consumption data for the provinces of Turkiye are as follows.

```r
# electricity consumption
electricity_consumption <- read.xlsx("project/data/electricity_consumption.xlsx", colNames = T
electricity_consumption <- select(electricity_consumption, -"YIL")
electricity_consumption <- select(electricity_consumption, -"BÖLGE.KODU")
electricity_consumption  <- rename(electricity_consumption , "Provinces" = "BÖLGE.ADI")
electricity_consumption  <- rename(electricity_consumption , "Total electricity consumption (M
electricity_consumption  <- rename(electricity_consumption , "Electricity consumption per capi
electricity_consumption <- electricity_consumption [-c(83, 84, 85), ]
electricity_consumption <- electricity_consumption[-c(1), ]
str(electricity_consumption)
```

```
'data.frame':   81 obs. of  3 variables:
 $ Provinces                               : chr  "İstanbul" "Tekirdağ" "Edirne" "Kırklareli"
 $ Total electricity consumption (MWh)     : num  41520357 8502879 1299120 2715585 4276586 ...
 $ Electricity consumption per capita (KWh): num  2621 7637 3152 7412 3420 ...
```

The GDP data for the provinces of Turkiye has been obtained.

```r
# GDP
GDP <- read.xlsx("project/data/GDP.xlsx", colNames = TRUE)
GDP <- select(GDP, -"YIL")
GDP <- select(GDP, -"BÖLGE.KODU")
GDP  <- rename(GDP , "Provinces" = "BÖLGE.ADI")
GDP  <- rename(GDP , "GDP per capita (TL)" = `Kişi.başına.GSYH.(TL)`)
GDP  <- rename(GDP , "GDP per capita ($)" = `Kişi.başına.GSYH.($)`)
GDP <- GDP [-c(83, 84), ]
str(GDP)
```

```
'data.frame':   82 obs. of  3 variables:
 $ Provinces          : chr  "Türkiye" "İstanbul" "Tekirdağ" "Edirne" ...
 $ GDP per capita (TL): num  176651 287524 253501 147752 201355 ...
 $ GDP per capita ($) : num  10659 17349 15296 8915 12150 ...
```

If the response variable is extracted from the municipal data set, the desired variable of waste amount by province can be obtained for the analysis.

```
# Amount of waste
response_variable <- select(municipal_waste, "Provinces")
response_variable <- cbind(response_variable, "Amount of waste collected (Tonnes)" = municipal
`)
str(response_variable)
```

```
'data.frame':   81 obs. of  2 variables:
 $ Provinces                         : chr  "Adana" "Adıyaman" "Afyonkarahisar" "Ağrı" ...
 $ Amount of waste collected (Tonnes): num  665695 179724 198273 181116 111099 ...
```

The regression analysis below has been conducted using the total amount of waste collected at the provincial level as the response variable. The independent variables include GDP per capita, agricultural area, total number of faculty members, total number of illiterate people, number of associate or bachelor's degree graduates, number of master's degree graduates, and electricity consumption. The final table prepared for regression analysis can be found below.

```
regression_data <- data.frame()
regression_data <- full_join(response_variable, agriculture_area, by = "Provinces")
regression_data <- full_join(regression_data, education,  by = "Provinces")
regression_data <- full_join(regression_data, electricity_consumption,  by = "Provinces")
regression_data <- full_join(regression_data, GDP,  by = "Provinces")
str(regression_data)
```

```
'data.frame':   82 obs. of  11 variables:
 $ Provinces                                        : chr  "Adana" "Adıyaman" "Afyonkarahisar
 $ Amount of waste collected (Tonnes)               : num  665695 179724 198273 181116 111099
 $ Agriculture area                                 : num  400819 166921 536127 351566 235758
 $ Total number of faculty members                  : num  2593 925 1647 561 725 ...
 $ Total number of illiterate people                : num  54962 26688 12334 25954 6815 ...
 $ Number of associate or bachelor's degree graduates: num  7987 2453 6787 2065 2870 ...
 $ Number of master's degree graduates              : num  33810 7359 9331 3925 4385 ...
 $ Total electricity consumption (MWh)              : num  7991581 1327087 2131943 495005 706
 $ Electricity consumption per capita (KWh)         : num  3531 2099 2865 944 2106 ...
 $ GDP per capita (TL)                              : num  135798 79223 114168 55296 112044 .
 $ GDP per capita ($)                               : num  8194 4780 6889 3337 6761 ...
```

Regression Analysis

In regression analysis using the forward selection method, the model begins with the variable that exhibits the highest correlation with the response variable, 'Amount of waste collected'. Subsequently, additional variables are incorporated into the model based on their partial correlations.

```
library(ppcor)
```

```
Warning: package 'ppcor' was built under R version 4.3.3
```

```
Zorunlu paket yükleniyor: MASS
```

```
Attaching package: 'MASS'


The following object is masked from 'package:dplyr':

    select
```

```r
library(tidyverse)
library(readxl)
```

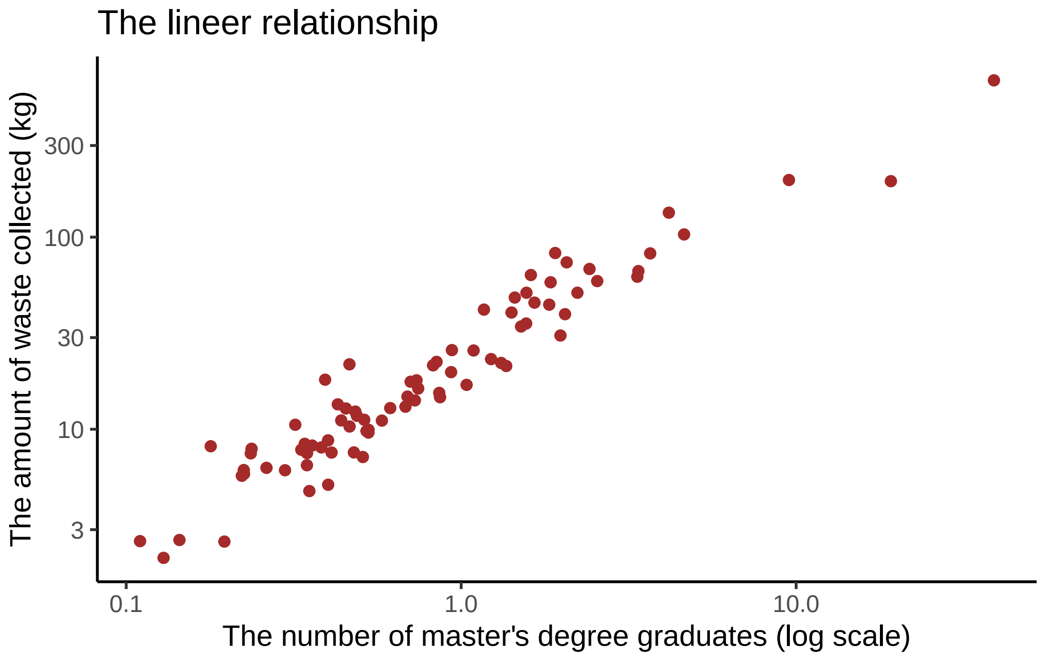
```
Warning: package 'readxl' was built under R version 4.3.3
```

```r
regression_data <- read_excel("regression_data.xlsx")
numeric_cols <- c("Amount of waste collected (Tonnes)", "Agriculture area",
                  "Total number of faculty members", "Total number of illiterate people",
                  "Number of associate or bachelor's degree graduates", "Total electricity con
                  "GDP per capita (TL)", "Number of master's degree graduates")
regression_data[numeric_cols] <- sapply(regression_data[numeric_cols], as.numeric)

if(any(is.na(regression_data[numeric_cols]))) {
  regression_data <- na.omit(regression_data)
}

constant_cols <- sapply(regression_data[numeric_cols], function(x) length(unique(x)) <= 1)
if(any(constant_cols)) {
  regression_data <- regression_data[, !constant_cols]
}

predictor_columns <- names(regression_data) != "Amount of waste collected (Tonnes)"
correlation <- cor(regression_data[predictor_columns], regression_data$`Amount of waste collec
print(correlation)
```

```
                                                        [,1]
Agriculture area                                   0.1237475
Total number of faculty members                    0.9500715
Total number of illiterate people                  0.8469772
Number of associate or bachelor's degree graduates 0.7395918
Number of master's degree graduates                0.9708360
Total electricity consumption (MWh)                0.9327005
GDP per capita (TL)                                0.5047206
```

The plot between the response variable and the independent variable with highest correlation (Number of master's degree graduates):

```r
library(ggthemes)
ggplot(regression_data, aes(`Amount of waste collected (Tonnes)`/10^4,`Number of master's degr
scale_y_log10() + theme_classic() + labs(x = "The amount of waste collected (kg)", y = "The nu
```



Partial correlations: between variables while controlling the variable with the highest correlation:

```
library(ppcor)
partial_cor1 <- pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_dat
partial_cor2 <- pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_dat
partial_cor3 <-pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_data
partial_cor4 <-pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_data
partial_cor5 <-pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_data
partial_cor6 <-pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_data
print(partial_cor5)
```

```
   estimate      p.value statistic  n gp  Method
1 0.5732279 2.742934e-08  6.178469 81  1 pearson
```

When examining the partial correlation values for other columns, taking into account those with significant p-values, the variable with the highest partial correlation is ‘Total electricity consumption’. Therefore, it should be the second variable added to the regression model.

In the next step, partial correlations are examined while controlling for the two variables with the highest correlations this time. Those that pass the significant test from the previous step are included in this calculations.

```
partial_corr1 <- pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_da
partial_corr2 <-pcor.test(regression_data$`Amount of waste collected (Tonnes)`, regression_dat
print(partial_corr2)
```

```
  estimate     p.value statistic  n gp  Method
1 0.334597 0.002578755  3.115659 81  2 pearson
```

When the partial correlations calculated by controlling for the two variables were checked, both were less than 0.5. In other words, there are no remaining variables with a strong relationship. ***In the final model, the independent variables affecting the response variable “Amount of waste***

collected" were selected as "Number of master's degree graduates" and "Total electricity consumption" using the forward selection method.

The results of the multiple regression analysis with the relevant columns are as follows.

```r
ln_version_reg_data <- log10(regression_data)
multiple_regression <- lm(`Amount of waste collected (Tonnes)` ~ `Number of master's degree gr
summary(multiple_regression)
```

```

Call:
lm(formula = `Amount of waste collected (Tonnes)` ~ `Number of master's degree graduates` +
    `Total electricity consumption (MWh)`, data = ln_version_reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.29626 -0.09862 -0.00168  0.07417  0.31978

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                            1.26657    0.18717   6.767 2.18e-09 ***
`Number of master's degree graduates`  0.87283    0.07469  11.687  < 2e-16 ***
`Total electricity consumption (MWh)`  0.09492    0.06526   1.455     0.15
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.13 on 78 degrees of freedom
Multiple R-squared:  0.9254,    Adjusted R-squared:  0.9234
F-statistic: 483.4 on 2 and 78 DF,  p-value: < 2.2e-16
```

Since the variable representing total electricity consumption is not significant, it has been excluded from the model. Therefore, the most suitable and effective version of our model, achieving the highest possible R-squared value, is the simple regression model that solely includes the variable "Number of master's graduates".

```r
regression_model <- lm(`Amount of waste collected (Tonnes)` ~ `Number of master's degree gradu
summary(regression_model)
```

```

Call:
lm(formula = `Amount of waste collected (Tonnes)` ~ `Number of master's degree graduates`,
    data = ln_version_reg_data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.312666 -0.083161 -0.001103  0.064059  0.303947

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                             1.4720     0.1237   11.90   <2e-16 ***
`Number of master's degree graduates`   0.9715     0.0315   30.84   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1309 on 79 degrees of freedom
Multiple R-squared:  0.9233,    Adjusted R-squared:  0.9224
F-statistic: 951.3 on 1 and 79 DF,  p-value: < 2.2e-16
```

```
library(broom)
tidy(regression_model)
```

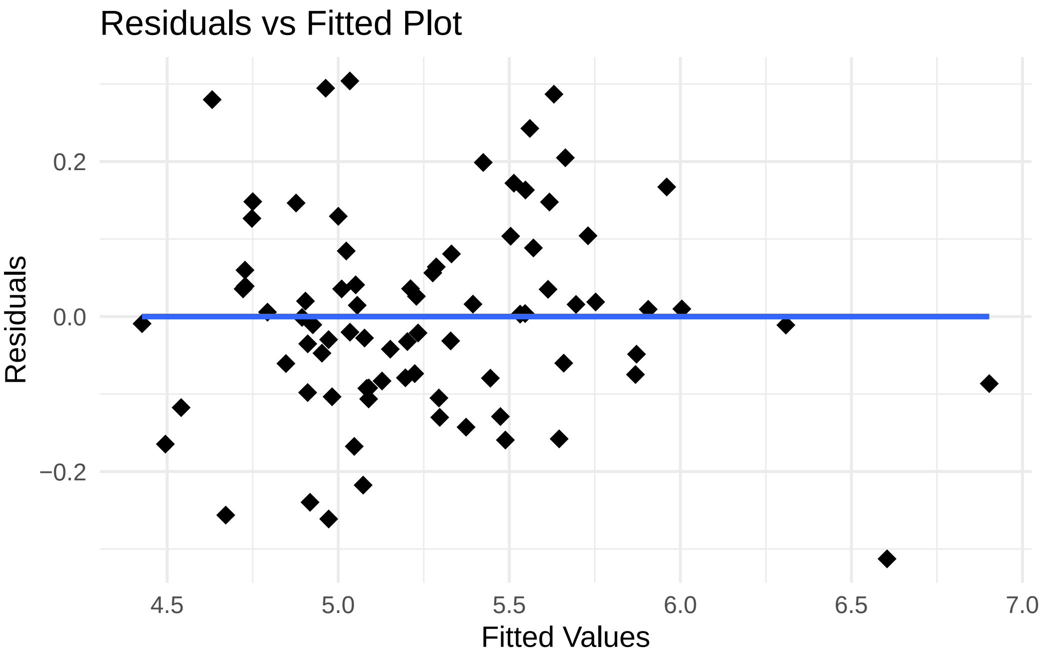
```
# A tibble: 2 x 5
  term                                      estimate std.error statistic  p.value
  <chr>                                        <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)                                  1.47     0.124       11.9 2.68e-19
2 `Number of master's degree graduates`        0.971    0.0315      30.8 8.17e-46
```

Model adequacy checking in a regression model is best achieved by thoroughly analyzing the residuals. Below are the graphs related to residual analysis.

There seems no problem in Residual vs Fitted values plot. This means that ***the assumption of constant variance is satisfied.***

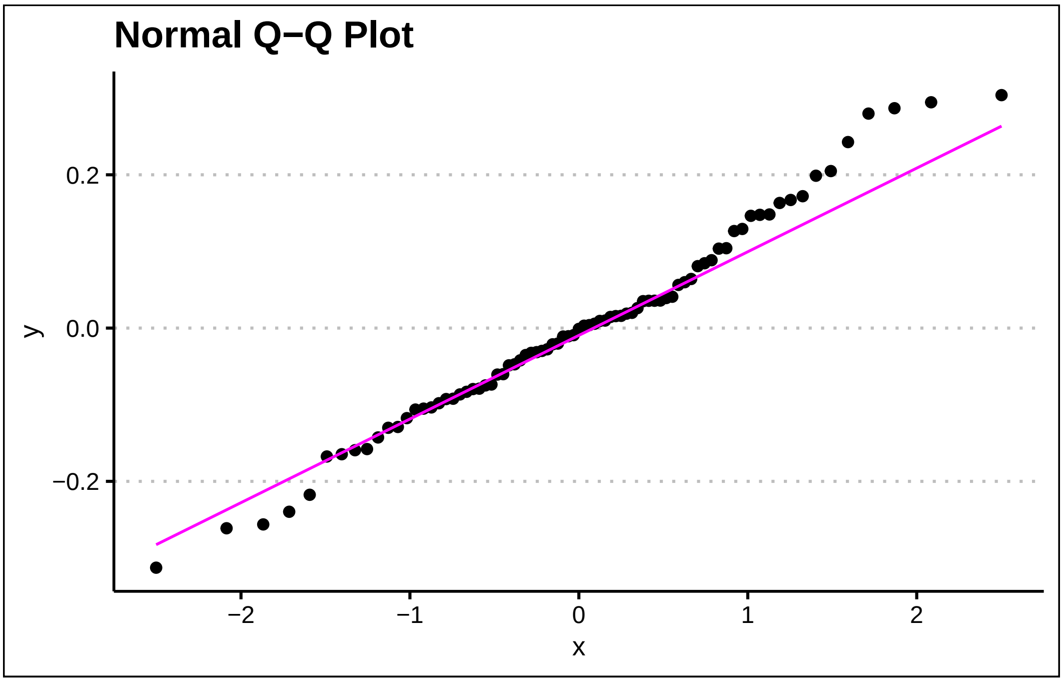
```
ggplot(ln_version_reg_data, aes(x = fitted(regression_model), y = resid(regression_model))) +
  geom_point(size = 3, shape = 18) +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Fitted Values", y = "Residuals", title = "Residuals vs Fitted Plot") +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```



The q-q plot to check if residuals are normally distributed is drawn, and there is no problem with that.

```
library(ggthemes)
ggplot(ln_version_reg_data, aes(sample = resid(regression_model))) +
  stat_qq() +
  stat_qq_line(color = "magenta") +
  labs(title = "Normal Q-Q Plot") +
  theme_clean()
```



In the Q-Q plot, tails are observed on both the right and left sides. To be sure, an Anderson-Darling normality test should also be conducted.

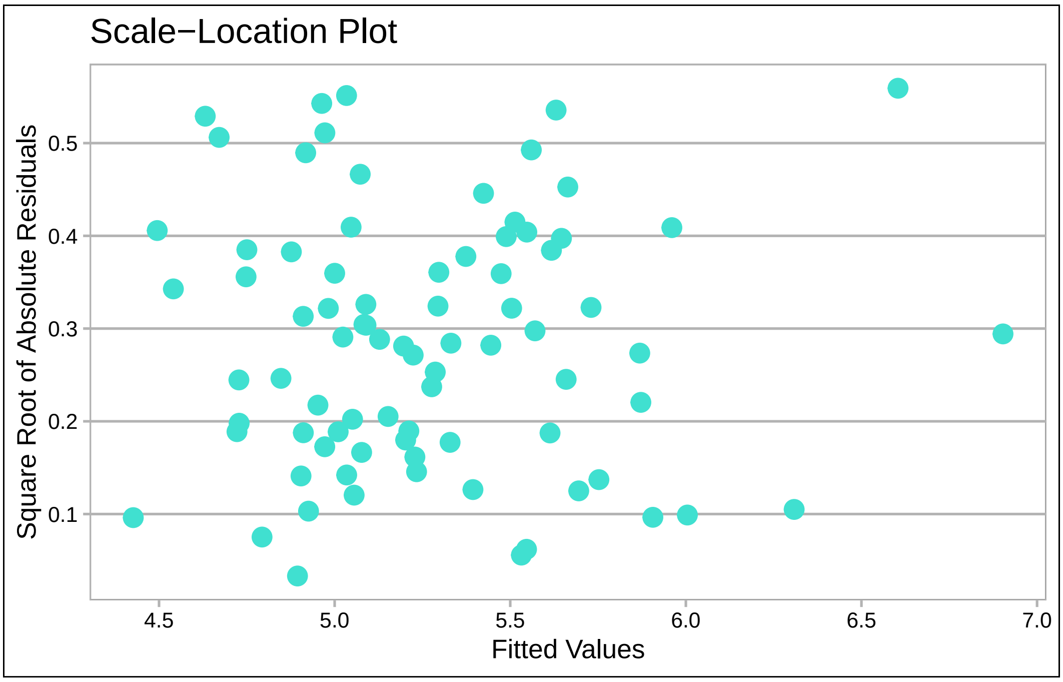
```
library(nortest)
residuals <- resid(regression_model)

ad_test_results <- ad.test(residuals)
print(ad_test_results)
```

```

	Anderson-Darling normality test

data:  residuals
A = 0.43796, p-value = 0.2882
```

A p-value of 0.28 in the Anderson-Darling test indicates that there is not enough evidence to reject the null hypothesis that the residuals are normally distributed. Therefore, it can be assumed that the residuals are normally distributed; ***the normality assumption for the regression model's residuals is considered to be met.***

The plot below helps to check for ***homoscedasticity***. According to it, ***there is no such a problem.***

```
ggplot(ln_version_reg_data, aes(x = fitted(regression_model), y = sqrt(abs(resid(regression_mo
  geom_point(size = 3, color = "turquoise")  +
  labs(x = "Fitted Values", y = "Square Root of Absolute Residuals", title = "Scale-Location P
  theme_calc()
```



3.3 Time Series Analysis

The MSW time series data for Turkiye lacks values for some intermediate years (e.g. 2017, 2019, 2021, etc.), which implies that time series analysis must be conducted under incomplete information. In this respect, **Grey Prediction (GP)** is a powerful forecasting approach to effectively manage the forecast analysis for MSW [6]. This method is particularly advantageous when data availability is limited, as it requires only a few data points to construct reliable models [6]. The core idea of GP involves transforming a complex data series into a more predictable one using a set of operations, such as the Accumulated Generating Operator (AGO), the Inverse Accumulating Operator (IAGO) and Grey Model (GM) [6].

The ExoplanetX greyforecasting R package is used to apply grey prediction models to the MSW time series [7]. All GP models included in the package are applied to the data in the background, and the best model in terms of performance is provided along with its accuracy and 5-year forecasting results.

The GP models in the package are as follows (*):

1. **gm:** Grey Model (1,1), It's a first-order differential equation model with one variable.
2. **gm_1:** GM(1,1)_1, This variant of the GM(1,1) model includes slight modifications or improvements over the standard GM(1,1) model to enhance prediction accuracy or adapt to specific types of data.
3. **gm_2:** GM(1,1)_2, Another variant of the GM(1,1) model, with different modifications from GM(1,1)_1, aiming to improve forecasting performance under certain conditions.
4. **dgm:** Discrete Grey Model, This model is a discrete version of the grey prediction model, which operates on discrete data points rather than continuous data, making it suitable for time series data that are naturally discrete.
5. **verhulst:** Verhulst Model, The Verhulst model is a nonlinear grey prediction model that is particularly useful for data that follow an S-shaped growth curve, such as population growth or diffusion processes.

6. **pgm:** Grey Power Model, The Grey Power Model is another variant of grey models that incorporates power functions into the grey modeling process to handle data with certain types of nonlinearity.

First, the necessary packages are installed, and libraries are called.

```
# Install and load necessary packages
#install.packages("remotes")
#remotes::install_github("exoplanetX/greyforecasting")
# install.packages("Metrics")
# install.packages("readxl")
# install.packages("ggplot2")

library(greyforecasting)
```

```


Attaching package: 'greyforecasting'


The following object is masked from 'package:dplyr':

    combine
```

```
library(Metrics)
```

```

Warning: package 'Metrics' was built under R version 4.3.3


Attaching package: 'Metrics'


The following objects are masked from 'package:greyforecasting':

    ape, mape
```

```
library(readxl)
library(tidyverse)
```

When all models are applied to the data in the background, the method that gives the best result is the **DGM (Discrete Grey Model)** method.

```
file_path <- "time_series_municipal_waste.xlsx"
waste_data <- read_excel(file_path, sheet = "Sheet 1")
waste_collected <- as.numeric(waste_data[3, -1])

# AutoML
fit_and_forecast <- function(model_func, data, forecast_steps = 5) {
  model <- model_func(data)
  fitted_values <- model$fitted
  n <- length(data)
  forecast_values <- numeric(forecast_steps)

  for (i in 1:forecast_steps) {
    extended_data <- c(data, forecast_values[1:(i-1)])
    forecast_model <- model_func(extended_data)
    forecast_values[i] <- tail(forecast_model$fitted, 1)
  }

  list(model = model, fitted = fitted_values, forecast = forecast_values)
}

# Models to evaluate
models <- list(
  gm = gm,
  gm_1 = gm_1,
  gm_2 = gm_2,
  dgm = dgm,
  verhulst = verhulst,
  pgm = pgm
)

# Applying models and calculate accuracy
results <- lapply(models, function(model_func) {
  result <- fit_and_forecast(model_func, waste_collected, forecast_steps = 5)
  accuracy <- rmse(waste_collected[(length(waste_collected)-4):length(waste_collected)], resul
  list(model = result$model, fitted = result$fitted, forecast = result$forecast, accuracy = ac
})

best_model_index <- which.min(sapply(results, function(x) x$accuracy))
best_model_name <- names(results)[best_model_index]
best_model <- results[[best_model_index]]

cat("The best model is:", best_model_name, "\n")
```

```
The best model is: dgm
```

Then, the accuracy metric value and forecast values for the next 5 years are provided for the DGM model.

```
cat("Best model RMSE:", best_model$accuracy, "\n")
```

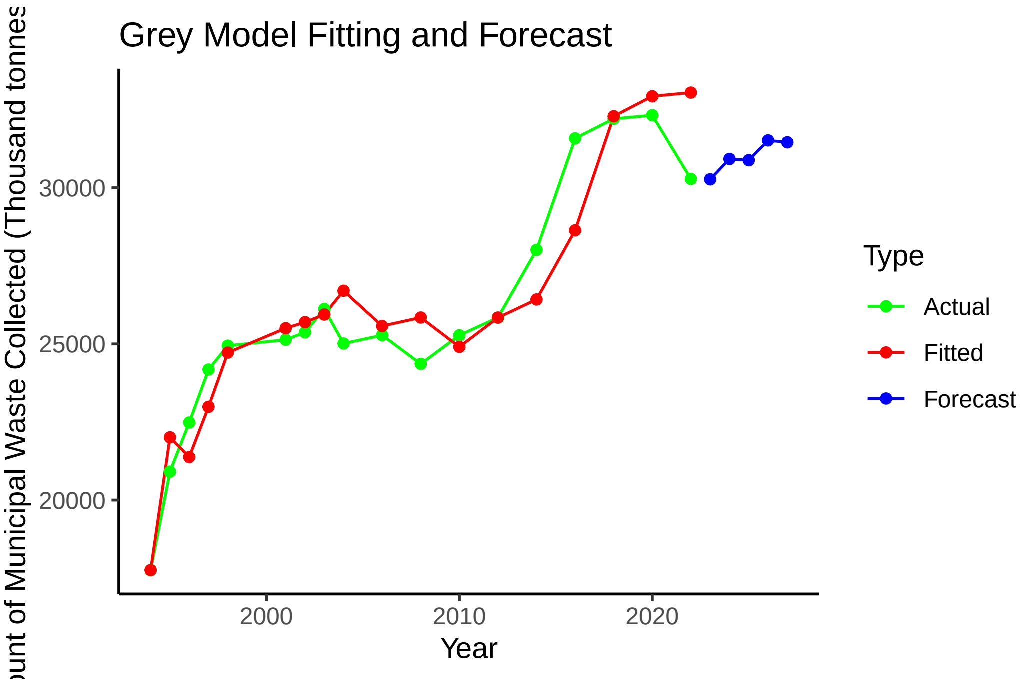
```
Best model RMSE: 1365.859
```

```
print(best_model$forecast)
```

```
[1] 30271.09 30922.96 30883.69 31518.20 31456.93
```

Finally, the original data, fitted values, and forecast points are shown in the graph below.

```
years <- as.numeric(substr(names(waste_data)[-1], 1, 4))
forecast_years <- (max(years) + 1):(max(years) + length(best_model$forecast))
plot_data <- data.frame(
  Year = c(years, forecast_years),
  Value = c(waste_collected, best_model$forecast),
  Type = c(rep("Actual", length(waste_collected)), rep("Forecast", length(best_model$forecast)
)

fitted_data <- data.frame(
  Year = years,
  Value = best_model$fitted,
  Type = "Fitted"
)
plot_data <- rbind(plot_data, fitted_data)

ggplot(plot_data, aes(x = Year, y = Value, color = Type)) +
  geom_line() +
  geom_point() +
  labs(title = "Grey Model Fitting and Forecast",
       x = "Year",
       y = "Amount of Municipal Waste Collected (Thousand tonnes/year)") +
  scale_color_manual(values = c("Actual" = "green", "Fitted" = "red", "Forecast" = "blue")) +
  theme_classic()
```



In the above graph, an increasing trend over the years is observed due to the consideration of total waste amounts. However, Turkiye's population growth is also a factor that must be taken into account. When analyzing the per capita waste production instead of the total amounts, the graph below is obtained.

```
waste_collected <- as.numeric(time_series_municipal_waste[4, -1])
# AutoML
fit_and_forecast <- function(model_func, data, forecast_steps = 5) {
  model <- model_func(data)
  fitted_values <- model$fitted
  n <- length(data)
  forecast_values <- numeric(forecast_steps)

  for (i in 1:forecast_steps) {
```

```r
    extended_data <- c(data, forecast_values[1:(i-1)])
    forecast_model <- model_func(extended_data)
    forecast_values[i] <- tail(forecast_model$fitted, 1)
  }

  list(model = model, fitted = fitted_values, forecast = forecast_values)
}

# Models to evaluate
models <- list(
  gm = gm,
  gm_1 = gm_1,
  gm_2 = gm_2,
  dgm = dgm,
  verhulst = verhulst,
  pgm = pgm
)

# Applying models and calculate accuracy
results <- lapply(models, function(model_func) {
  result <- fit_and_forecast(model_func, waste_collected, forecast_steps = 5)
  accuracy <- rmse(waste_collected[(length(waste_collected)-4):length(waste_collected)], resul
  list(model = result$model, fitted = result$fitted, forecast = result$forecast, accuracy = ac
})

best_model_index <- which.min(sapply(results, function(x) x$accuracy))
best_model_name <- names(results)[best_model_index]
best_model <- results[[best_model_index]]

cat("The best model is:", best_model_name, "\n")
```

```
The best model is: dgm
```

Then, the accuracy metric value and forecast values for the next 5 years are provided for the DGM model.

```r
cat("Best model RMSE:", best_model$accuracy, "\n")
```

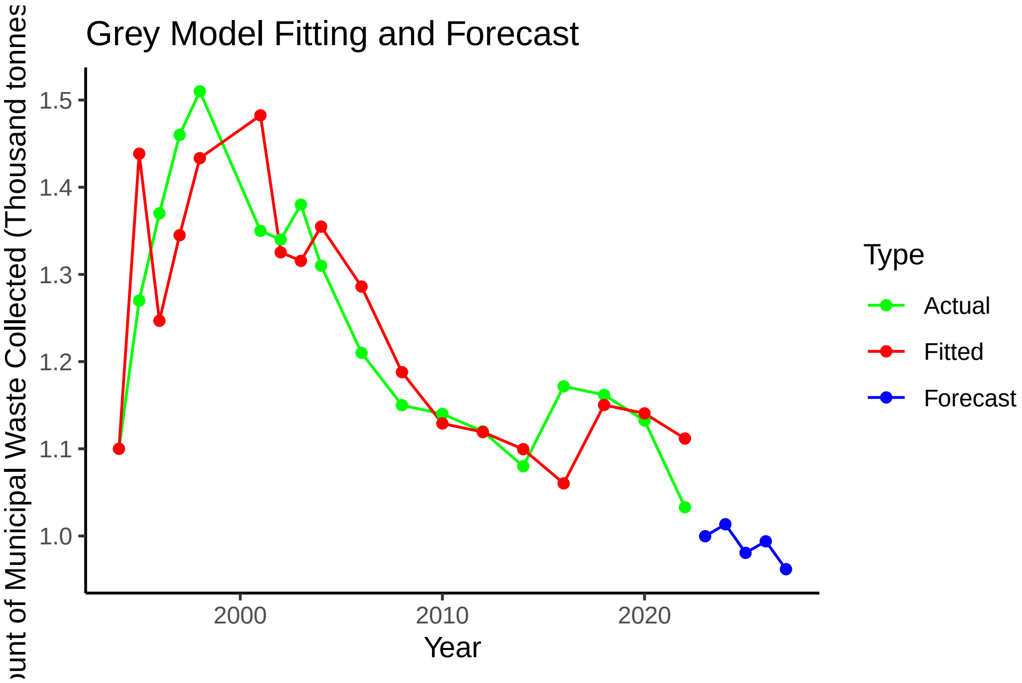
```
Best model RMSE: 0.1330711
```

```r
print(best_model$forecast)
```

```
[1] 0.9997255 1.0134248 0.9806750 0.9938774 0.9619003
```

Finally, the original data, fitted values, and forecast points are shown in the graph below.

```r
years <- as.numeric(substr(names(time_series_municipal_waste)[-1], 1, 4))
forecast_years <- (max(years) + 1):(max(years) + length(best_model$forecast))
plot_data <- data.frame(
  Year = c(years, forecast_years),
  Value = c(waste_collected, best_model$forecast),
  Type = c(rep("Actual", length(waste_collected)), rep("Forecast", length(best_model$forecast)
)

fitted_data <- data.frame(
  Year = years,
  Value = best_model$fitted,
  Type = "Fitted"
)
plot_data <- rbind(plot_data, fitted_data)

ggplot(plot_data, aes(x = Year, y = Value, color = Type)) +
  geom_line() +
  geom_point() +
  labs(title = "Grey Model Fitting and Forecast",
       x = "Year",
       y = "Amount of Municipal Waste Collected (Thousand tonnes/year)") +
  scale_color_manual(values = c("Actual" = "green", "Fitted" = "red", "Forecast" = "blue")) +
  theme_classic()
```



In the waste per capita case, the best fit model according to RMSE is again the DGM. Unlike before, a decreasing trend over the years is noticeable in above figure, indicating that the increasing population must be considered in the analysis.

The following are the results obtained when performing the same grey forecasting analysis for Ankara.

```
library(greyforecasting)
library(Metrics)
library(readxl)
library(tidyverse)
ankara <- ts_province %>% filter(Province == "Ankara") %>% arrange(Year)
ankara_waste <- ankara$`Waste amount (1000 ton)`
```

```r
# AutoML greyforecasting function
fit_and_forecast <- function(model_func, data, forecast_steps = 5) {
  model <- model_func(data)
  fitted_values <- model$fitted
  forecast_values <- numeric(forecast_steps)

  for (i in 1:forecast_steps) {
    extended_data <- c(data, forecast_values[1:(i-1)])
    forecast_model <- model_func(extended_data)
    forecast_values[i] <- tail(forecast_model$fitted, 1)
  }

  list(model = model, fitted = fitted_values, forecast = forecast_values)
}

models <- list(
  gm = gm,
  gm_1 = gm_1,
  gm_2 = gm_2,
  dgm = dgm,
  verhulst = verhulst,
  pgm = pgm
)

results <- lapply(models, function(model_func) {
  result <- fit_and_forecast(model_func, ankara_waste, forecast_steps = 5)
  accuracy <- rmse(tail(ankara_waste, min(5, length(ankara_waste))), result$forecast)
  list(model = result$model, fitted = result$fitted, forecast = result$forecast, accuracy = ac
})

best_model_index <- which.min(sapply(results, function(x) x$accuracy))
best_model_name <- names(results)[best_model_index]
best_model <- results[[best_model_index]]

cat("The best model is:", best_model_name, "\n")
```

```
The best model is: dgm
```

```r
cat("Best model RMSE:", best_model$accuracy, "\n")
```

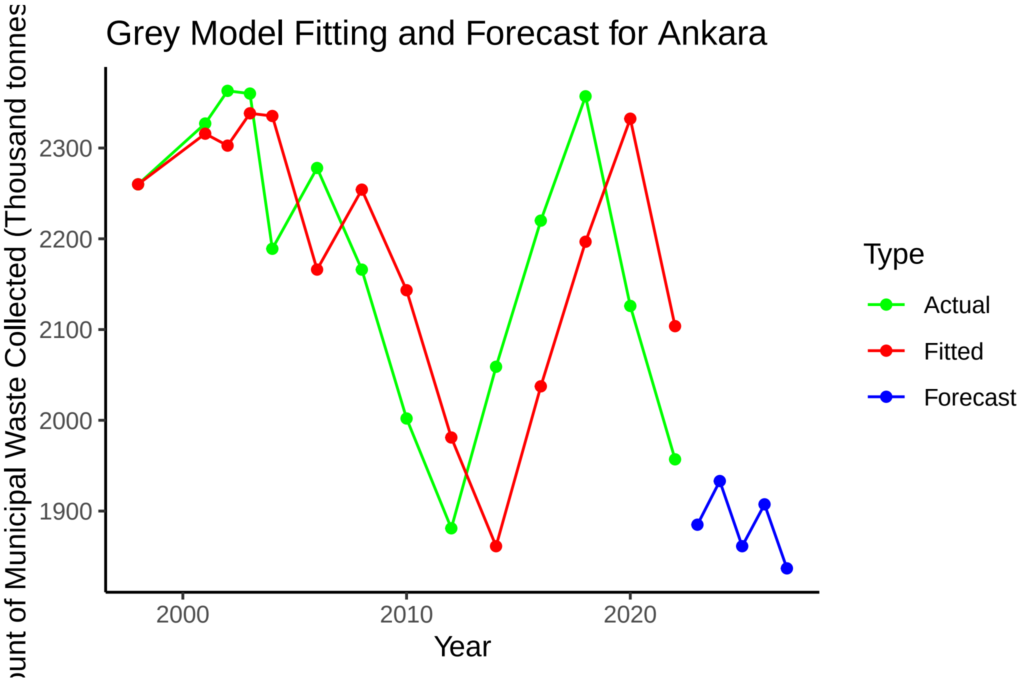
```
Best model RMSE: 290.0232
```

```r
print(best_model$forecast)
```

```
[1] 1884.965 1933.066 1861.282 1907.419 1836.855
```

The graph:

```
# Prepare data for plotting
years <- ankara$Year
forecast_years <- (max(years) + 1):(max(years) + length(best_model$forecast))

plot_data <- data.frame(
  Year = c(years, forecast_years),
  Value = c(ankara_waste, best_model$forecast),
  Type = c(rep("Actual", length(ankara_waste)), rep("Forecast", length(best_model$forecast)))
)
fitted_data <- data.frame(
  Year = years,
  Value = best_model$fitted,
  Type = "Fitted"
)

plot_data <- rbind(plot_data, fitted_data)

ggplot(plot_data, aes(x = Year, y = Value, color = Type)) +
  geom_line() +
  geom_point() +
  labs(title = "Grey Model Fitting and Forecast for Ankara",
       x = "Year",
       y = "Amount of Municipal Waste Collected (Thousand tonnes/year)") +
  scale_color_manual(values = c("Actual" = "green", "Fitted" = "red", "Forecast" = "blue")) +
  theme_classic()
```



Based on the time series analysis, it was concluded that the DGM model is the most appropriate time series model for the data containing total MSW quantities. The fact that data is not available at irregular intervals of time already tells us that the model suitable for the data should be discrete. The DGM model forecasted the next five years with the following values: 30,271.09, 30,922.96, 30,883.69, 31,518.20, and 31,456.93 tonnes. As shown in plots above, the model closely fits the historical data and strengthens the reliability of these forecast values. It is also the best method according to the RMSE performance metric.

The observed increasing trend is consistent with Turkiye's historical waste generation patterns and highlights the increasing waste management challenge posed by urbanization and population growth. In addition, considering Turkiye's population growth, waste generation per capita was also analysed in the study. The per capita waste forecasts have shown a decreasing trend over the years.

In addition, the MSW time series analysis of our city (Ankara) is also included. The DGM model was again dominant, which is logical since it is again an interval time data.

4. Conclusion

Effective planning of solid waste management systems depends on analysing and forecasting MSW flows. Accordingly, analysing waste quantity data is crucial for informed decision-making and strategic planning related to waste management in Turkiye. In this respect, the aim of this study is to analyse and forecast municipal solid waste (MSW) quantities in Turkiye by examining socio-economic factors through regression analysis and applying time series models for forecasting.

Firstly, EDA was applied to the dataset to reveal the underlying relationships and patterns in the data. Factors (economic, education, agriculture, electricity, etc.) that are thought to affect the amount of waste are added as data and a regression analysis is performed. As a result, a model using the number of master's degree graduates in relation to the amount of waste was established and proved to be accurate.

Then, time series models were evaluated to predict future MSW quantities. Since the structure of the dataset is discrete with no regular values in intermediate periods, it was decided that GP methods are appropriate. Among the GP models, the DGM model was found to be the most appropriate model for the given data due to its discrete nature and high accuracy, as indicated by the RMSE performance measure. The observed upward trend in waste generation is in line with Turkiye's historical data and emphasizes the increasing challenge of waste management in urban areas.

Strategic decision-making in waste management systems are crucial to overcome these challenges. The findings underline the necessity of sustainable waste management practices and sound policies to reduce the environmental impacts of increasing waste generation.

References

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(*) ChatGPT