

Impact of Oil Palm Production on Forest Cover and Carbon Emissions in Malaysia and Indonesia

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Contents

Load your datasets	3
Rationale and Research Questions	3
Dataset Information	5
Exploratory Analysis	6
Analysis	9
Summary and Conclusions	18
References	19

Table 1: List of Tables

Table	Name
1	Palm Production
2	Forest Area
3	Carbon Emissions

Table 2: List of Figures

Figures	Name
1	Palm Production
2	Forest Area
3	Carbon Emissions

Load your datasets

```
#dataset on palm cultivation
palm_production <- read.csv("./Raw /palm-oil-production.csv", stringsAsFactors = TRUE)
#filtering for only Indonesia and Malaysia, making a new column with an adjusted scale for oil palm cul
palm_production <- palm_production %>%
  filter(Entity == "Indonesia" | Entity == "Malaysia", Year %in% (1990:2020)) %>%
  mutate(Oil.Palm = Palm.oil...00000257....Production...005510....tonnes/1000) %>%
  dplyr::select(Entity, Year, Oil.Palm)

#dataset on forest area
forest_area <- read.csv("./Raw /forest-area-primary-planted.csv", stringsAsFactors = TRUE)
#filtering for Indonesia and Malaysia, adjusting scales for planted and natural forests
forest_area <- forest_area %>%
  filter(Entity == "Indonesia" | Entity == "Malaysia") %>%
  mutate(Planted.Forest =
    Planted.Forest...00006716....Area...005110....hectares/1000000 ) %>%
  mutate(Natural.Forest =
    Naturally.regenerating.forest...00006717....Area...005110....hectares/1000000) %>%
  dplyr::select(Entity, Year, Planted.Forest, Natural.Forest)

#datasets on carbon emissions
carbon_emissions <- read.csv("./Raw /ghg-emissions-by-sector_indonesia.csv", stringsAsFactors = TRUE)
#filtering for Indonesia and Malaysia, adjusting scales for co2 emissions variable
carbon_emissions <- carbon_emissions %>%
  filter(Entity == "Indonesia" | Entity == "Malaysia") %>%
  mutate(CO2.emissions = Greenhouse.gas.emissions.from.land.use.change.and.forestry/1000000) %>%
  dplyr::select(Entity, Year, CO2.emissions)

#merge the datasets into one for analysis
merged_dataset <- merge(palm_production, forest_area, by = c("Entity", "Year"),
  all = TRUE)
dataset <- merge(merged_dataset, carbon_emissions, by = c("Entity", "Year"),
  all = TRUE)
dataset <- dataset %>%
  mutate(Total.Forest = Planted.Forest + Natural.Forest)
```

Rationale and Research Questions

The oil palm tree is a productive and useful crop, as it can be cultivated at a lower price, providing high-quality oil (WWF, n.d.). It is used not only as food but for other purposes, such as in detergents/ cosmetics and for bioenergy (Ritchie, 2021). This has led to a rapid expansion in the oil palm industry, particularly across Asia, Africa, and Latin America (WWF, n.d.). For example, the yield increased from 2 million tonnes in 1970 to 71 million tonnes in 2018 (Ritchie, 2021). According to the Food and Agriculture Organization of the United Nations, Indonesia and Malaysia contributed to 57% and 27% of global production respectively (Ritchie, 2021). However, the expansion of the industry has been linked to some negative impacts on the environment, becoming one of the major contributors to deforestation, carbon emissions, and tropical biodiversity loss (WWF, n.d.). In this project, we will explore the oil palm cultivation industry in Indonesia and Malaysia. We want to measure how the cultivation of oil palm has contributed to deforestation and carbon emissions in the two countries from 1990 to 2020.” H0: The cultivation of oil

pam has not significantly changed forest cover (carbon emissions) in Indonesia and Malaysia. Ha:
The cultivation of oil palm has significantly changed forest cover (carbon emissions) in Indonesia
and Malaysia.

Dataset Information

After loading the datasets, we filter for Indonesia and Malaysia and then create a new column for adjusted scales of the interested variables. Provided below is a breakdown of our datasets.

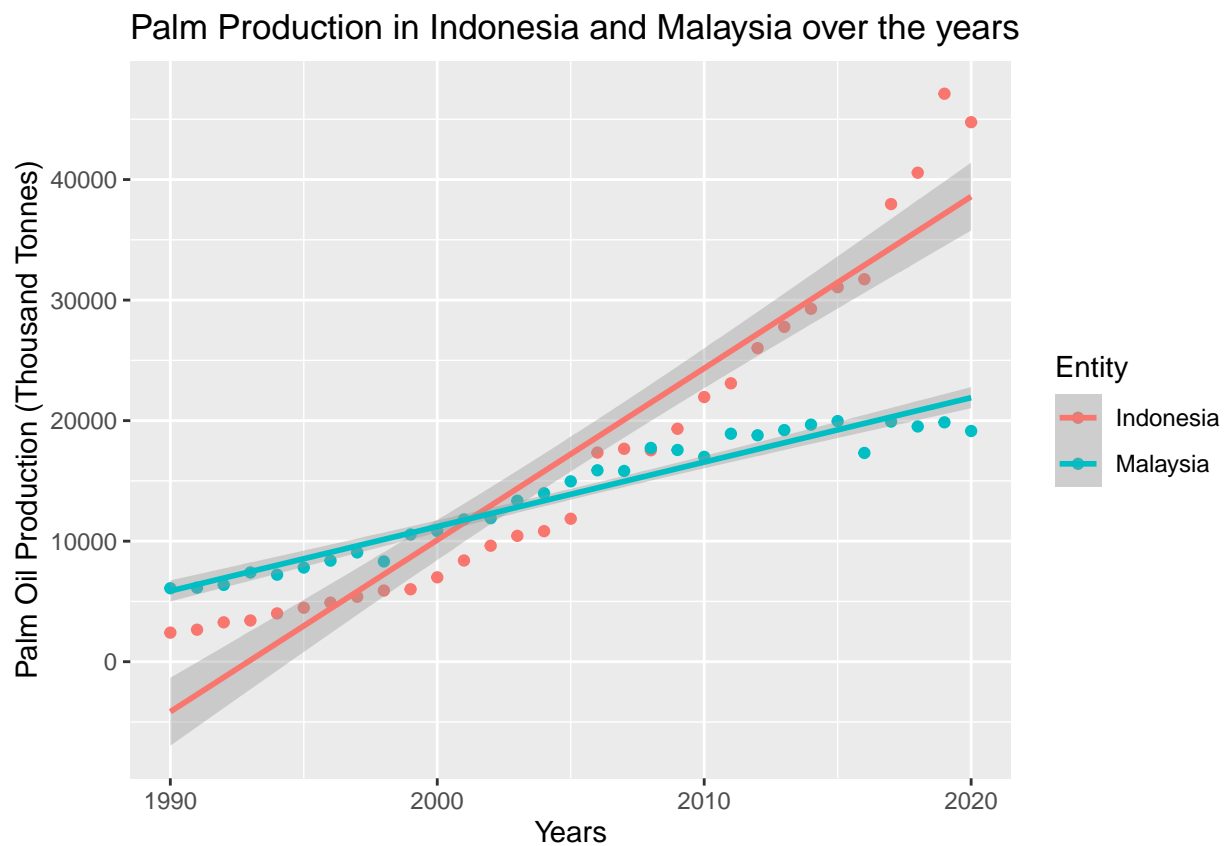
Data	Name	Source	Variables of Interest
Oil Palm Production	palm-oil-production.csv	Food and Agriculture 2020	Entity, Year, Palm.oil. . . 00000257. . . Production
Primary Forests	forest-area-primary-planted.csv	Food and Agriculture 2020	Entity, Year, Planted.Forest. . . 00006716. . . Area
Natural Forests	forest-area-primary-planted.csv	Food and Agriculture 2020	Entity, Year, Naturally.regenerating.forest. . . 00006716. . . Area
Carbon Emissions	ghg-emissions-by-sector_indonesia.csv	Climate Watch 2033	Entity, Year, Greenhouse. gas emissions.from.land.use .change.and.forestry

Exploratory Analysis

```
#plotting oil palm cultivation over the years to see the trend
options(scipen = 999)
palm_production_graph <- ggplot(palm_production, aes(x=Year, y = Oil.Palm, color = Entity)) +
  geom_point()+
  geom_smooth(method = lm)+
  labs(x= "Years", y = "Palm Oil Production (Thousand Tonnes)", title = "Palm Production in Indonesia and Malaysia")

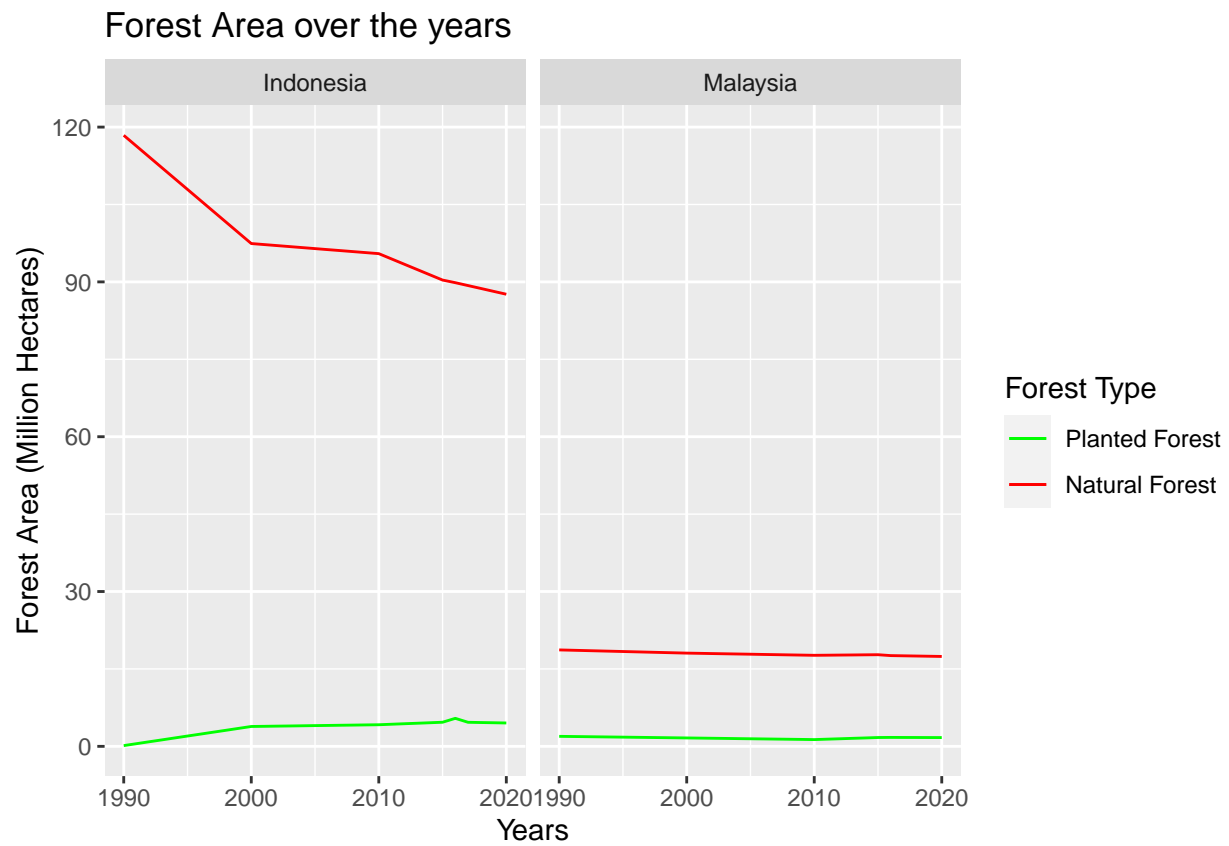
palm_production_graph
```

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



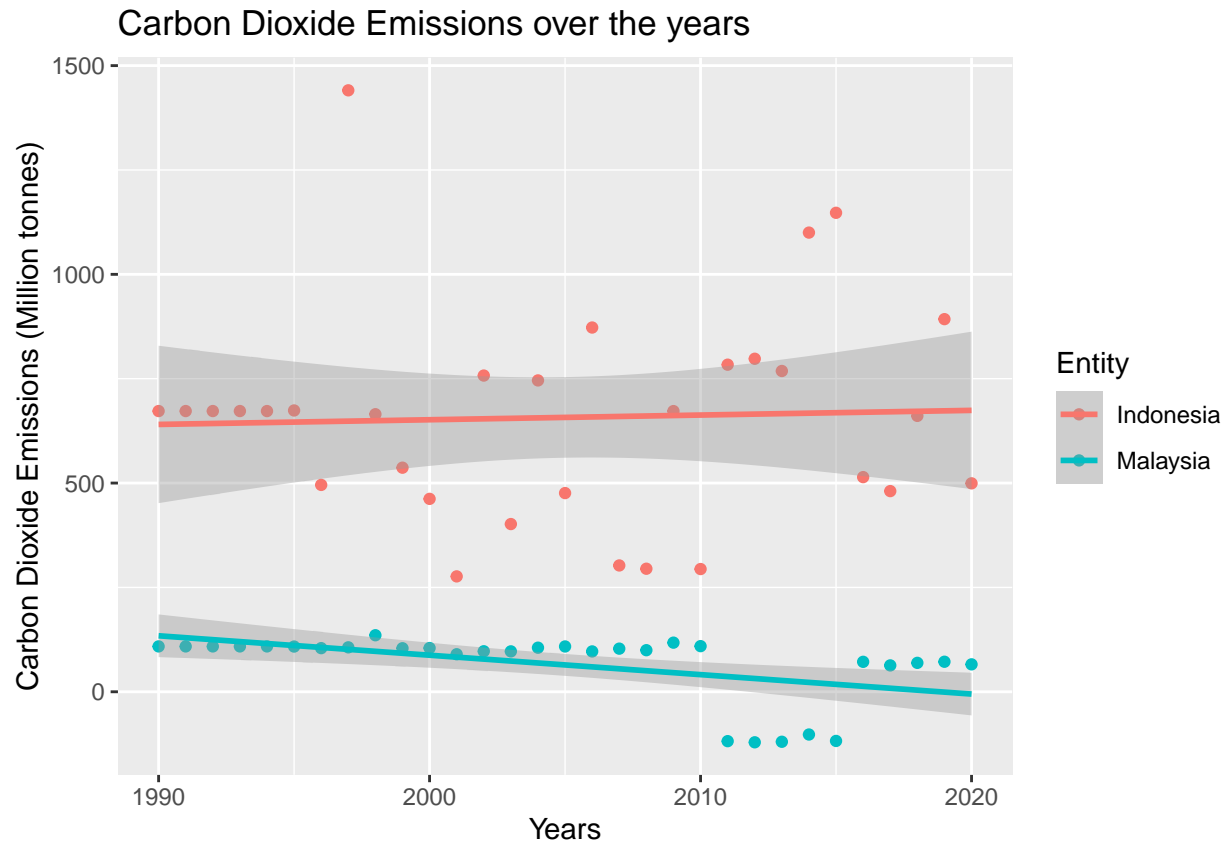
```
#graphing the data on forest area
forest_area_graph <- ggplot(forest_area, aes(x = Year)) +
  geom_line(aes(y = Planted.Forest, color = "green")) +
  geom_line(aes(y = Natural.Forest, color = "red")) +
  scale_color_manual(name = "Forest Type",
    values = c("green" = "green", "red" = "red"),
    labels = c("Planted Forest", "Natural Forest"))+
  facet_wrap(vars(Entity))+
  labs(x= "Years", y = "Forest Area (Million Hectares)", title =
    "Forest Area over the years")
```

```
forest_area_graph
```



```
#graphing dataset on carbon emissions
carbon_emissions_graph <- ggplot(carbon_emissions, aes(x=Year, y = CO2.emissions, color = Entity)) +
  geom_point()+
  geom_smooth(method = lm)+
  labs(x= "Years", y = "Carbon Dioxide Emissions (Million tonnes)", title = "Carbon Dioxide Emissions over the years")
carbon_emissions_graph
```

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



Analysis

#MULTIPLE LINEAR REGRESSION

#checking best fit models through AIC

```
natural_AIC <- lm(data = dataset, Natural.Forest ~ Year + Oil.Palm)
step(natural_AIC)
```

```
## Start: AIC=460.46
## Natural.Forest ~ Year + Oil.Palm
##
##           Df Sum of Sq    RSS    AIC
## <none>                94575 460.46
## - Oil.Palm   1     7353.2 101928 463.10
## - Year       1     8165.3 102740 463.60

##
## Call:
## lm(formula = Natural.Forest ~ Year + Oil.Palm, data = dataset)
##
## Coefficients:
## (Intercept)      Year      Oil.Palm
## 5100.969627   -2.531462    0.002114
```

```
planted_AIC <- lm(data = dataset, Planted.Forest ~ Year + Oil.Palm)
step(planted_AIC)
```

```
## Start: AIC=14.45
## Planted.Forest ~ Year + Oil.Palm
##
##           Df Sum of Sq    RSS    AIC
## <none>                71.056 14.453
## - Year       1      2.9184 73.974 14.948
## - Oil.Palm   1     20.9457 92.001 28.470

##
## Call:
## lm(formula = Planted.Forest ~ Year + Oil.Palm, data = dataset)
##
## Coefficients:
## (Intercept)      Year      Oil.Palm
##  96.7642003   -0.0478585    0.0001128
```

```
total_AIC <- lm(data = dataset, Total.Forest ~ Year + Oil.Palm)
step(total_AIC)
```

```
## Start: AIC=462.76
## Total.Forest ~ Year + Oil.Palm
##
##           Df Sum of Sq    RSS    AIC
## <none>                98143 462.76
## - Oil.Palm   1     8159.0 106302 465.71
## - Year       1     8476.9 106620 465.89
```

```
##
## Call:
## lm(formula = Total.Forest ~ Year + Oil.Palm, data = dataset)
##
## Coefficients:
## (Intercept)      Year      Oil.Palm
## 5197.733827    -2.579320     0.002227

#include both oil palm and year, they have the lowest AIC

#Planted Forests in Indonesia
planted_ind <- lm(data = filter(dataset, Entity == "Indonesia") , Planted.Forest ~ Oil.Palm + Year)
summary(planted_ind)

##
## Call:
## lm(formula = Planted.Forest ~ Oil.Palm + Year, data = filter(dataset,
##      Entity == "Indonesia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.41140 -0.23182 -0.05122  0.23901  0.62207
##
## Coefficients:
##              Estimate      Std. Error t value      Pr(>|t|)
## (Intercept) -670.09805117    44.19770752  -15.161 0.000000000000000499 ***
## Oil.Palm      -0.00014286     0.00001491   -9.581 0.00000000024563750 ***
## Year          0.33718573     0.02216642   15.212 0.000000000000000460 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3154 on 28 degrees of freedom
## Multiple R-squared:  0.9505, Adjusted R-squared:  0.9469
## F-statistic: 268.6 on 2 and 28 DF,  p-value: < 0.00000000000000022

#Natural Forests in Indonesia
natural_ind <- lm(data = filter(dataset, Entity == "Indonesia") ,
                  Total.Forest ~ Oil.Palm + Year)
summary(natural_ind)

##
## Call:
## lm(formula = Total.Forest ~ Oil.Palm + Year, data = filter(dataset,
##      Entity == "Indonesia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.2989 -1.2130  0.3197  1.4283  2.5704
##
## Coefficients:
##              Estimate      Std. Error t value      Pr(>|t|)
## (Intercept) 2752.30375651    249.92173495   11.013 0.00000000000110 ***
## Oil.Palm      0.00040478     0.00008432    4.801 0.0000478080285 ***
```

```
## Year          -1.32527929    0.12534293 -10.573 0.00000000000277 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.783 on 28 degrees of freedom
## Multiple R-squared:  0.9426, Adjusted R-squared:  0.9385
## F-statistic: 230 on 2 and 28 DF, p-value: < 0.00000000000000022
```

#Total Forests in Indonesia

```
total_ind <- lm(data = filter(dataset, Entity == "Indonesia") ,
                Total.Forest ~ Oil.Palm + Year)
summary(total_ind)
```

```
##
## Call:
## lm(formula = Total.Forest ~ Oil.Palm + Year, data = filter(dataset,
##   Entity == "Indonesia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.2989 -1.2130  0.3197  1.4283  2.5704
##
## Coefficients:
##              Estimate      Std. Error t value      Pr(>|t|)
## (Intercept) 2752.30375651    249.92173495   11.013 0.0000000000110 ***
## Oil.Palm      0.00040478     0.00008432    4.801 0.0000478080285 ***
## Year         -1.32527929     0.12534293  -10.573 0.00000000000277 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.783 on 28 degrees of freedom
## Multiple R-squared:  0.9426, Adjusted R-squared:  0.9385
## F-statistic: 230 on 2 and 28 DF, p-value: < 0.00000000000000022
```

#Planted Forests in Malaysia

```
planted_mly <- lm(data = filter(dataset, Entity == "Malaysia") ,
                  Planted.Forest ~ Oil.Palm + Year)
summary(planted_mly)
```

```
##
## Call:
## lm(formula = Planted.Forest ~ Oil.Palm + Year, data = filter(dataset,
##   Entity == "Malaysia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.23672 -0.06197 -0.02353  0.07960  0.23074
##
## Coefficients:
##              Estimate      Std. Error t value      Pr(>|t|)
## (Intercept) -77.28376941    18.77951404   -4.115 0.000308 ***
## Oil.Palm     -0.00009040     0.00001722  -5.249 0.000014 ***
## Year          0.03998286     0.00948208    4.217 0.000234 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1134 on 28 degrees of freedom
## Multiple R-squared:  0.594, Adjusted R-squared:  0.565
## F-statistic: 20.48 on 2 and 28 DF,  p-value: 0.000003309

#Natural Forests in Malaysia
natural_mly <- lm(data = filter(dataset, Entity == "Malaysia") ,
                  Natural.Forest ~ Oil.Palm + Year)
summary(natural_mly)

##
## Call:
## lm(formula = Natural.Forest ~ Oil.Palm + Year, data = filter(dataset,
##   Entity == "Malaysia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.10560 -0.07516 -0.00737  0.04423  0.21435
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  67.81268039  14.80190920   4.581 0.0000871 ***
## Oil.Palm     -0.00002664   0.00001357  -1.962  0.05973 .
## Year         -0.02468443   0.00747372  -3.303  0.00262 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.08935 on 28 degrees of freedom
## Multiple R-squared:  0.9443, Adjusted R-squared:  0.9403
## F-statistic: 237.2 on 2 and 28 DF,  p-value: < 0.00000000000000022

#Total Forests in Malaysia
total_mly <- lm(data = filter(dataset, Entity == "Malaysia") ,
                 Total.Forest ~ Oil.Palm + Year)
summary(total_mly)

##
## Call:
## lm(formula = Total.Forest ~ Oil.Palm + Year, data = filter(dataset,
##   Entity == "Malaysia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.34232 -0.14158 -0.02986  0.13638  0.44509
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -9.47108903  33.01389840  -0.287 0.776315
## Oil.Palm     -0.00011703   0.00003027  -3.866 0.000602 ***
## Year          0.01529843   0.01666925   0.918 0.366581
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1993 on 28 degrees of freedom
## Multiple R-squared:  0.8465, Adjusted R-squared:  0.8355
## F-statistic: 77.2 on 2 and 28 DF,  p-value: 0.000000000004035
```

#Results and Discussions on Forest Area >By running linear regression models, we found that natural, planted, and total forest areas all have high r values (>0.90) for Indonesia, indicating that there is a high statistical significance in the high correlation between forest areas and oil palm production over the years. Oil palm production over the years can explain more than 90% of the forest cover change While total forest area and natural forest area have positive intercepts, planted forest has a negative coefficient for oil palm production. This may be because of practices that plant oil palm in natural forests. The reason for the negative coefficient for planted forests and oil palm production requires further investigation. Overall, we were able to reject the H0 and understand that oil palm production over time do contribute significantly to the forest cover change in Indonesia.

On the other hand, the coefficients for all three forest types and oil palm production are all negative, indicating that oil palm production negatively correlates with forests of all types for Malaysia. The r-squared values for planted and total forest areas are high (>0.8), and it is medium (0.59) for natural forests. Overall, there is a medium to high correlation between oil palm production and forest cover change in Malaysia (oil palm production over the years accounts for about 60% to 90% of forest cover change). Interestingly, total and natural forest cover have positive intercepts with oil palm production. This may also be because of practices that plant oil palm in natural forests. Overall, we were able to reject the H0 and understand that oil palm production over time do contribute significantly to the forest cover change in Malaysia.

#checking best fit models through AIC

```
co2_AIC <- lm(data = dataset, CO2.emissions ~ Year + Oil.Palm + Natural.Forest + Total.Forest + Planted
step(co2_AIC)
```

```
## Start:  AIC=656.86
## CO2.emissions ~ Year + Oil.Palm + Natural.Forest + Total.Forest +
##   Planted.Forest
##
##
## Step:  AIC=656.86
## CO2.emissions ~ Year + Oil.Palm + Natural.Forest + Total.Forest
##
##           Df Sum of Sq    RSS    AIC
## - Natural.Forest  1      2471 2108524 654.93
## - Total.Forest   1      8410 2114463 655.10
## <none>                        2106053 656.86
## - Year           1     100444 2206496 657.75
## - Oil.Palm       1      120851 2226904 658.32
##
## Step:  AIC=654.93
## CO2.emissions ~ Year + Oil.Palm + Total.Forest
##
##           Df Sum of Sq    RSS    AIC
## <none>                        2108524 654.93
## - Year           1     100450 2208974 655.82
## - Oil.Palm       1      163884 2272408 657.57
## - Total.Forest   1     4471271 6579796 723.49
```

```
##
## Call:
## lm(formula = CO2.emissions ~ Year + Oil.Palm + Total.Forest,
##     data = dataset)
##
## Coefficients:
## (Intercept)      Year      Oil.Palm  Total.Forest
## 18343.84392    -9.25447     0.01039     6.74973
```

#model to be used is with year, oil palm and total forests - has the lowest AIC

#MLR checking for CO2 in Indonesia

```
CO2_ind <- lm(data = filter(dataset, Entity == "Indonesia") ,
              CO2.emissions ~ Total.Forest + Oil.Palm + Year)
summary(CO2_ind)
```

```
##
## Call:
## lm(formula = CO2.emissions ~ Total.Forest + Oil.Palm + Year,
##     data = filter(dataset, Entity == "Indonesia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -337.24 -154.07  -29.57  129.96  797.92
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 36100.93496 86460.32996   0.418   0.680
## Total.Forest  -0.21459   28.31483  -0.008   0.994
## Oil.Palm      0.01316    0.01706   0.771   0.447
## Year         -17.77970   41.96204  -0.424   0.675
##
## Residual standard error: 267.2 on 27 degrees of freedom
## Multiple R-squared:  0.03962, Adjusted R-squared: -0.06708
## F-statistic: 0.3713 on 3 and 27 DF, p-value: 0.7743
```

#MLR checking for CO2 in Malaysia

```
CO2_mly <- lm(data = filter(dataset, Entity == "Malaysia") ,
              CO2.emissions ~ Total.Forest + Oil.Palm + Year)
summary(CO2_mly)
```

```
##
## Call:
## lm(formula = CO2.emissions ~ Total.Forest + Oil.Palm + Year,
##     data = filter(dataset, Entity == "Malaysia"))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -117.510  -23.483   -5.332   35.225   87.485
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -17633.61877 8965.46703  -1.967  0.059557 .
```

```
## Total.Forest    -199.50890      51.24598   -3.893   0.000587 ***
## Oil.Palm        -0.04711       0.01017   -4.634   0.0000814 ***
## Year           11.10126       4.58766    2.420   0.022535 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 54.04 on 27 degrees of freedom
## Multiple R-squared:  0.6083, Adjusted R-squared:  0.5648
## F-statistic: 13.98 on 3 and 27 DF,  p-value: 0.00001086
```

#Results and Discussions on Carbon Emissions > CO2.emissions which is our variable of interest in the release of carbon emissions through land use change and forestry. We feel this is best suited for our analysis as the variable carbon emissions from agriculture explains emissions from livestock. To begin the analysis, we first use the AIC to gauge which variables best impact carbon dioxide emissions. The lowest AIC from this stepwise regression suggests that we use Total Forests (including natural and planted growth), Oil Palm cultivation and year. This suggests that planted forests too impact carbon emissions which makes for a positive argument in support of their credibility. >The MLR for Indonesia reports a very low R squared(3.96%). We see a negative correlation between carbon emissions and total forests (-0.21) and year(-17.77) with the former having a smaller impact than the later. As expected, carbon emissions increase with oil palm cultivation (0.013). Due to the low significance, we fail to reject the H0 that oil palm production, time, and total forest area do not contribute significantly to the CO2 emission in Indonesia. We believe this is due to a few factors. First, there are limitations to our measure of oil palm in that it is on the mass of oil palm production as opposed to the geographical area of oil palm production. Technology could change the relationship between oil palm production and deforestation. In addition, there are still many aspects of the oil palm industry as well as deforestation that is unregulated, which means that the two datasets do not reflect the actual values of oil palm production or deforestation.

> The MLR for Malaysia reports an R squared of 60.83%. The low p value in this analysis suggests a highly significant result (p value= 0.00001086). We see a large negative correlation between carbon emissions and total forests (-199.5). Surprisingly, oil palm cultivation too has an inverse relationship with carbon emissions in Malaysia (-0.04) while it is a relatively smaller number. Due to the medium to high R squared value, we can semi-confidently reject the H0 and understand that oil palm production, time, and total forest area do contribute significantly to the CO2 emission in Indonesia.

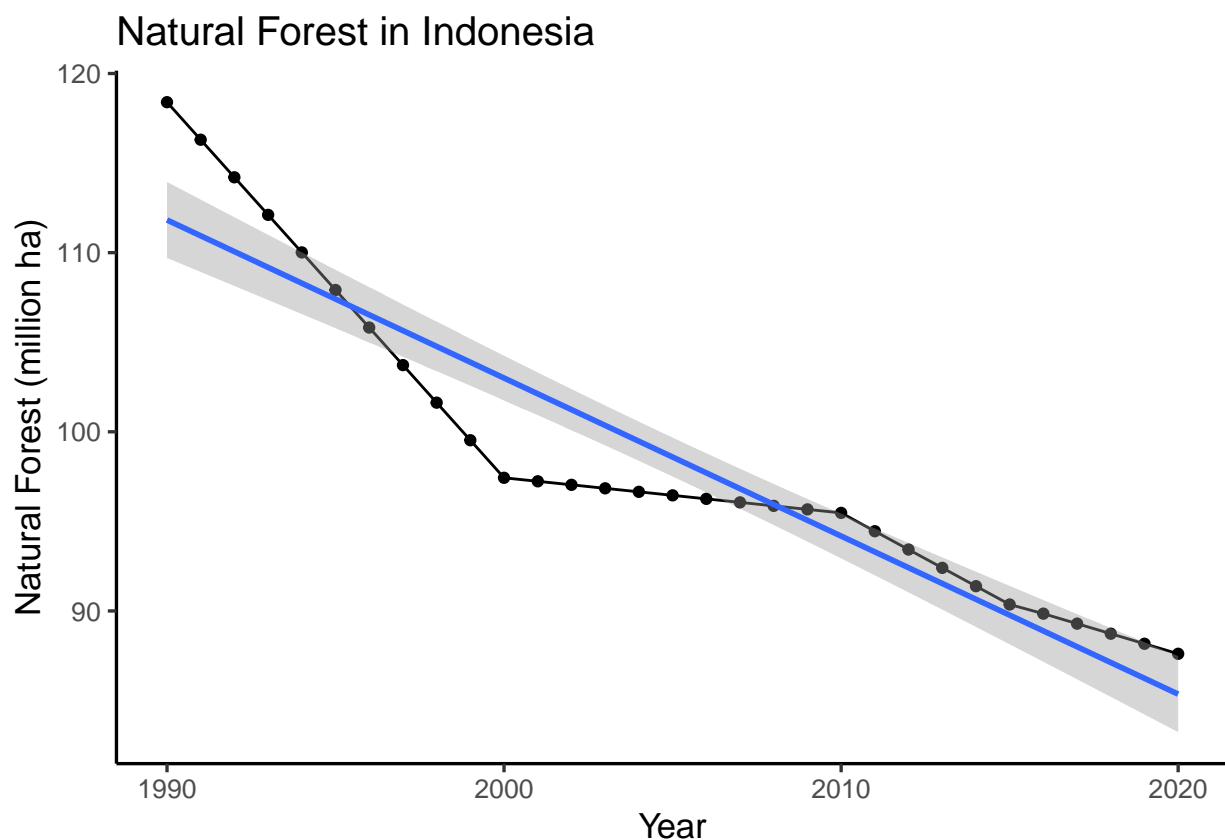
```
dataset_ind <- dataset %>%
  subset(Entity == "Indonesia") %>%
  mutate(Date = paste(Year, "-", 01, "-", 01))
dataset_ind$Date <- ymd(dataset_ind$Date)

#TIME SERIES ANALYSIS
##create ts object
natural_forest_ind_ts <- ts(dataset_ind$Natural.Forest, start = c(1990,01,01), frequency = 1)
#run a mann-kendall test on this data
mk.test(natural_forest_ind_ts)
```

```
##
## Mann-Kendall trend test
##
## data:  natural_forest_ind_ts
## z = -7.8863, n = 31, p-value = 0.000000000000003112
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##      S      varS      tau
## -465.000 3461.667  -1.000
```

```
##plot the data
natural_forest_ind_plot <-
ggplot(dataset_ind, aes(x = Date, y = Natural.Forest)) +
  geom_point() +
  geom_line() +
  ylab("Natural Forest (million ha)") +
  xlab("Year") +
  geom_smooth(method = lm ) +
  labs(title = "Natural Forest in Indonesia") +
  mytheme
print(natural_forest_ind_plot)
```

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



```
##repeat the same for Malaysia
dataset_mly <- dataset %>%
  subset(Entity == "Malaysia") %>%
  mutate(Date = paste(Year, "-", 01, "-", 01))
dataset_mly$Date <- ymd(dataset_mly$Date)
##create ts object
natural_forest_mly_ts <- ts(dataset_mly$Natural.Forest, start = c(1990,01,01), frequency = 1)
#run a mann-kendall test on this data
mk.test(natural_forest_mly_ts)
```

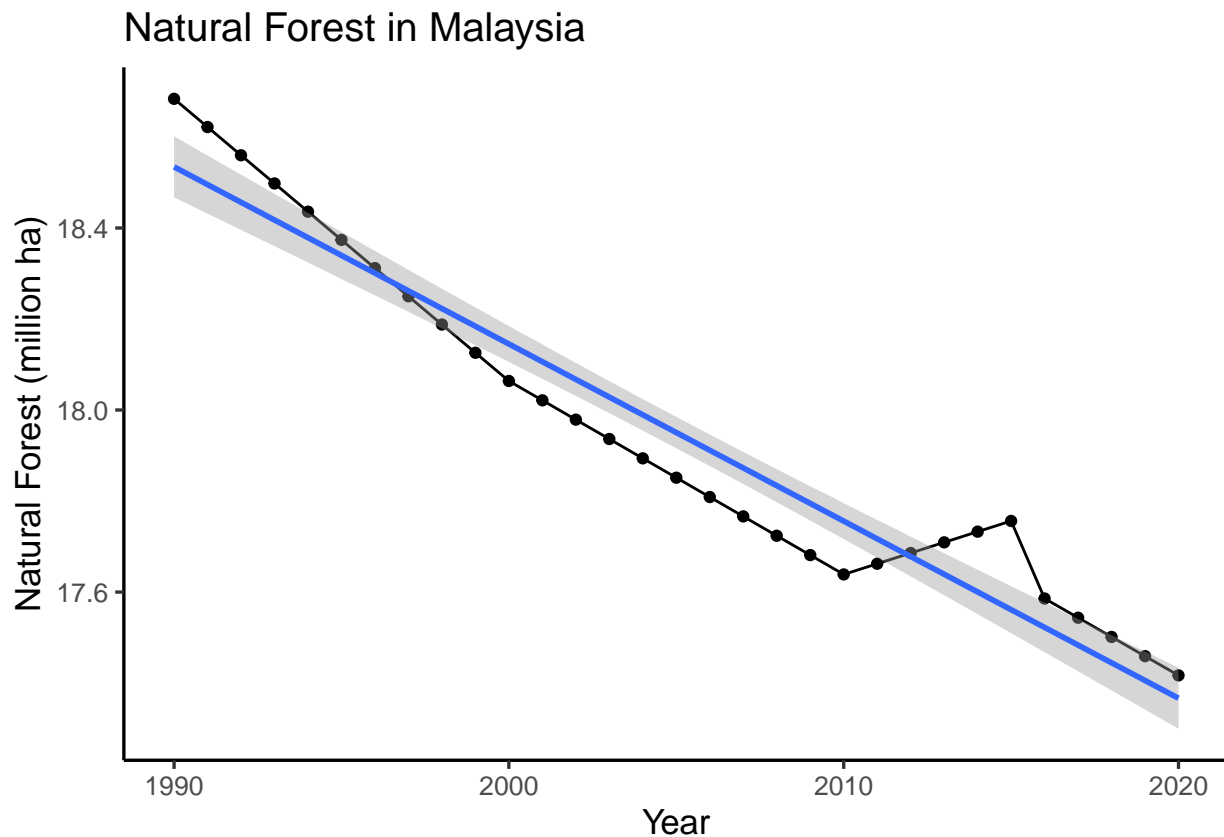
```
##
```



```
## Mann-Kendall trend test
##
## data: natural_forest_mly_ts
## z = -7.1725, n = 31, p-value = 0.0000000000007365
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## -423.0000000 3461.6666667 -0.9096774
```

```
##plot the data
natural_forest_mly_plot <-
ggplot(dataset_mly, aes(x = Date, y = Natural.Forest)) +
  geom_point() +
  geom_line() +
  ylab("Natural Forest (million ha)") +
  xlab("Year") +
  geom_smooth(method = lm ) +
  labs(title = "Natural Forest in Malaysia") +
  theme
print(natural_forest_mly_plot)
```

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



#Results and Discussions on Time Series Analysis >In the time-series analysis, we used natural forest data cover because natural forests are more important in terms of supporting biodiversity and providing ecosystem services. They are also able to store and capture more CO₂ than planted forests. Since we only have annual data with no apparent seasonal trend, we opted to using Mann-Kendall test for the two countries' natural forest cover changes. For Indonesia, we found that there is a strong statistical significance (p-value: 0.00000000000003112) of a strong downward trend (z: -7.8863) in the natural forest area in Indonesia. The -1 tau also confirms the strong downward trend.

Similarly, there is also a strong statistical significance (p-value: 0.0000000000007365) of a strong downward trend (z: -7.1725) in the natural forest area in Malaysia. The -0.910 tau also confirms the strong downward trend.

Summary and Conclusions

Overall, we found that using the best fit model, oil palm production as well as time and total forest cover contribute to a very small portion of CO₂ emission from forestry and land-use change in Indonesia and more than half of the CO₂ emission from forestry and land-use change in Malaysia. We were hence able to reject the null hypothesis for Malaysia and were not able to reject the null hypothesis for Indonesia on oil palm's contribution to forest cover. As for forest cover, we found that oil palm contributes significantly to forest cover change in both countries over the years. Hence, we can confidently reject the null hypothesis for both countries when it comes to oil palm production and forest cover change.

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