

Changes in Land Use between 1990 and 2014

https://github.com/RsMarx/Ag_Forest_Data_Final-

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Abstract

This study uses data spanning 264 countries to explore the causes and impacts of changes in land use from 1990 to 2014. It confirms a slight trend of decreasing levels of forest cover globally which can be explained, in part, by an increase in agriculture cover. In addition to addressing the impacts of agricultural expansion on forest cover, the study considers the roles that electricity access and renewable energy have to play in forest cover trends. Finally, a clear link is drawn between increases in agriculture, decreases in forest, and increases in emissions of methane and nitrous oxide. The study was conducted using a series of linear mixed-effect models with country as a random effect, as well as tests to confirm there are no problems with multicollinearity. While the study looks at trends across all countries in the data set, it also highlights the chain of causes and impacts of land cover change in five countries in five distinct regions. A set of graphs illustrate the differences and similarities of individual country experiences. Overall, the study is a helpful resource for continuing the discussion around protecting forests from conversion to other land uses, such as agriculture.

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<Note: set up autoreferencing for figures and tables in your document>

1 Research Question and Rationale

As the global population continues to grow and require more food and fuel resources, deforestation trends are expected to accelerate. Deforestation can be problematic as forests provide ecosystem services such as carbon storage, nutrient cycling, water filtration, and wildlife habitat. Agriculture is one of the most commonly cited drivers of deforestation, in addition to being a source of emissions. Given that forest and agriculture can be contending land uses, this research examines the relationship between agriculture and forest as land uses and, more broadly, explores the causes and impacts of changes in land use.

This research looks at the trends and tradeoffs in land use across countries from 1990 – 2014. Primary questions include:

- Is there a relationship between the percentage of land area dedicated to forest versus agricultural in countries?
- Is there a relationship between land uses (agriculture or forest) and levels of CO₂, methane, and NO₃ emissions?
- Is there a relationship between access to electricity or renewable electricity output and the percentage of land dedicated to forestry versus agriculture?

The research utilizes a data set from the World Bank that has 135 environment-related variables for 264 countries. I have narrowed the environment variable down to 7 that are relevant to land use. Although the full data set dates back to 1960, I have limited to the time scope of the analysis to between 1990 and 2014 because those are the dates for which forest cover data is available.

2 Dataset Information

2.1 Database Information

Data were collected from the World Bank website. More information can be found here: <https://data.worldbank.org/topic/environment> Data were downloaded as a full data set called “API_6_DS2_en_csv_v2_10518155”. The csv file was saved as “WorldBank_Raw_4.8.19”. Variables from among the raw data set were selected to be used in the data set analysed. Only 7 of a possible 135 environment-related variables were retained in the processed data. This csv file was saved as [“WorldBank_Processed”; “WorldBank_Spread” or “WB_Spread”].

2.2 Data Content Information

Country: Originally named “Country.Name”, the Country variable includes 264 countries.

Year: The Year variable was originally spread horizontally from 1960 – 2018. The years were gathered in to one column named “Year” and formatted as a date.

Forest: The Forest variable was originally named “Forest area (% of land area)”. Its data range is 1990 – 2016.

Agriculture: The Agriculture variable was originally named “Agriculture land (% of land area). Its data range is from 1961 – 2018.

Ag.Methane: The Ag.Methane variable was originally named “Agriculture methane emissions (thousand metric tons of CO2 equivalent). Its data range is 1970 – 2008.

Ag.NO2: The Ag.NO2 variable was originally named “Agriculture nitrous oxide emissions (thousand metric tons of CO2 equivalent). Its data range is 1970 – 2008.

CO2Emissions: The CO2Emissions variable was originally named “CO2 emissions (kt). Its data range is 1960 – 2014.

ElectricityAccess: The ElectricityAccess variable was originally named “Access to electricity (% of total population). Data range is 1990 – 2016.

RenewableElectricity: The RenewableElectricity variable was originally named “Renewable electricity output (% of total electricity output). Its data range is 1990 – 2015.

2.3 Naming conventions and file formats

The files are named according to the following convention: `dbname_datatype_details_stage.format` where: Files are named according to the following naming convention: **dbname** refers to the database from where the data originated **details** are additional descriptive details related to the stage of data wrangling **stage** refers to the stage in data management pipelines (e.g., raw or processed) **format** is a non-proprietary file format (e.g., .csv, .txt)

2.4 Additional Information and Support

For more information, please contact the data assembler, **Rebecca Marx** (rebecca.marx@duke.edu)

Variable	Units	Data Strcuture
Cell 1	Cell 2	Cells
Cell 3	Cell 4	Cells

3 Exploratory Data Analysis and Wrangling

Wrangling the data required multiple operations. First, I used the filter function to select only 7 of a possible 135 variables in the data set. Since the data set was arranged with the years going horizontally, I then had to gather the years in to one column, and create a new column called “Level” that contained the values recorded for each variable in each year. Afterward, I used spread to make each environmental variable its own column. I had to remove an “X” from in front of the Year, and format the Year as a date. I also had to update column names because they were very long. For certain tests, I had to drop na from the data set.

```
World_Bank_Master <- read.csv("../Raw/WorldBank_Raw2_4.8.19.csv")

#Data Subset
World_Bank_Filter <- filter(World_Bank_Master, Indicator.Name == "Forest area (% of land area)")

WorldBank_Gather <- gather(World_Bank_Filter, "Year", "Level", X1960:X2018)

WorldBank_Gather <- select(WorldBank_Gather, -Indicator.Code)

WorldBank_Spread <- spread(WorldBank_Gather, Indicator.Name, Level)

#Format as character
WorldBank_Spread$Year <- as.character(WorldBank_Spread$Year)

#create string
WB_String <- substr(WorldBank_Spread$Year, 2, 5)

#Get rid of X in date
WorldBank_Spread$Year = WB_String

#Format as date
#WB_Fixed$Year <- as.Date(WB_Fixed$Year)
WorldBank_Spread$Year <- as.Date(WorldBank_Spread$Year, format = "%Y") #can I get it to be YYYYMMDD

#Change column names
names(WorldBank_Spread) <- c("Country", "Indicator.Code", "Year", "ElectricityAccess", "ElectricityConsumption", "ElectricityProduction", "ElectricityTransmission")

#Save processed file
#write.csv(WorldBank_Spread, row.names = FALSE, file = "../Processed/WorldBank_Processed.csv")

Five_Countries <- filter(WorldBank_Spread, Country == "Brazil" | Country == "Kenya" | Country == "Mexico" | Country == "Nigeria" | Country == "South Africa")

WB_Spread <- WorldBank_Spread %>%
  na.exclude #check if I need this for my tests
```



```
WB_Spread2 <- WorldBank_Spread %>%
  na.exclude

WB_Brazil <- filter(WorldBank_Spread, Country == "Brazil")
```

<Include R chunks for 5+ lines of summary code (display code and output), 3+ exploratory

After the data was wrangled into a format that would function well with my intended R operations, I was able to begin exploring the data set.

#5+ lines of summary

```
colnames(WorldBank_Spread)
```

```
## [1] "Country"          "Indicator.Code"    "Year"
## [4] "ElectricityAccess" "Agriculture"       "Ag.Methane"
## [7] "Ag.NO2"           "CO2Emissions"     "Forest"
## [10] "RenewableElectricity"
```

```
class(WorldBank_Spread$Year)
```

```
## [1] "Date"
```

```
dim(WorldBank_Spread)
```

```
## [1] 15576    10
```

```
head(WorldBank_Spread)
```

```
##      Country Indicator.Code      Year ElectricityAccess Agriculture
## 1 Afghanistan          AFG 1960-04-16              NA          NA
## 2 Afghanistan          AFG 1961-04-16              NA      57.74592
## 3 Afghanistan          AFG 1962-04-16              NA      57.83782
## 4 Afghanistan          AFG 1963-04-16              NA      57.91441
## 5 Afghanistan          AFG 1964-04-16              NA      58.01091
## 6 Afghanistan          AFG 1965-04-16              NA      58.01397
##   Ag.Methane Ag.NO2 CO2Emissions Forest RenewableElectricity
## 1         NA    NA      414.371    NA              NA
## 2         NA    NA      491.378    NA              NA
## 3         NA    NA      689.396    NA              NA
## 4         NA    NA      707.731    NA              NA
## 5         NA    NA      839.743    NA              NA
## 6         NA    NA     1008.425    NA              NA
```

```
summary(WorldBank_Spread)
```

```
##      Country      Indicator.Code      Year
```

```
## Afghanistan : 59 ABW : 59 Min. :1960-04-16
## Albania : 59 AFG : 59 1st Qu.:1974-04-16
## Algeria : 59 AGO : 59 Median :1989-04-16
## American Samoa: 59 ALB : 59 Mean :1989-04-15
## Andorra : 59 AND : 59 3rd Qu.:2004-04-16
## Angola : 59 ARB : 59 Max. :2018-04-16
## (Other) :15222 (Other):15222
## ElectricityAccess Agriculture Ag.Methane Ag.N02
## Min. : 0.00 Min. : 0.2628 Min. : 0 Min. : 0.0
## 1st Qu.: 53.11 1st Qu.:20.5547 1st Qu.: 120 1st Qu.: 86.9
## Median : 93.94 Median :37.3659 Median : 3300 Median : 2302.9
## Mean : 75.04 Mean :37.0790 Mean : 117609 Mean : 63590.8
## 3rd Qu.:100.00 3rd Qu.:52.3930 3rd Qu.: 24198 3rd Qu.: 15076.6
## Max. :100.00 Max. :93.4407 Max. :3464398 Max. :2242932.7
## NA's :8618 NA's :2521 NA's :5056 NA's :5056
## CO2Emissions Forest RenewableElectricity
## Min. : -81 Min. : 0.00 Min. : 0.000
## 1st Qu.: 964 1st Qu.: 12.50 1st Qu.: 0.465
## Median : 11463 Median : 31.18 Median : 16.961
## Mean : 736069 Mean : 42.70 Mean : 28.211
## 3rd Qu.: 143107 3rd Qu.: 46.96 3rd Qu.: 49.255
## Max. :36138285 Max. :16735.00 Max. :100.000
## NA's :3321 NA's :8717 NA's :8738
```

```
summary(WorldBank_Spread$Agriculture)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
## 0.2628 20.5547 37.3659 37.0790 52.3930 93.4407 2521
```

```
summary(WorldBank_Spread$Forest)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
## 0.00 12.50 31.18 42.70 46.96 16735.00 8717
```

```
summary(WorldBank_Spread$RenewableElectricity)
```

```
## Length Class Mode
## 0 NULL NULL
```

```
summary(WB_Spread$Ag.Methane)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0 687 4638 138432 36696 3464398
```

```
summary(WB_Brazil$Agriculture)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
## 18.01 25.43 28.54 28.07 31.89 33.99 3
```

```
summary(WB_Brazil$Forest)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##  58.93   59.74   61.32   61.66   63.43   65.41      32
```

Figure1 plots agriculture and forest land covers to see if there is a noticeable trend. It appears that there is a tendency for forest cover to decrease as agriculture cover increases. In other words, the scatter plot shows some correlation between the Forest and Agriculture variables.

A second exploratory graph (Figure2) plots forest levels for all 264 countries over time. The resulting graph shows that there is some movement over time, but many countries see constant levels of land use. Similarly, the plot of agriculture over time shows some movement over time, but many countries see constant levels of land use for agriculture. In later graphs I decided to reduce the number of countries included to be able to better visualize changes.

The third exploratory graph (Figure3) is a series of histograms looking at the distribution of forest and agriculture data to determine how to treat the variable in the planned regressions. Although neither forest nor agriculture has a particularly normal distribution and both are measured in terms of percentages, I decided not to log transform either because the logged version of agriculture seemed less interpretable.

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

<Include text sections to accompany these R chunks to explain the reasoning behind your

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Analysis

<Include R chunks for 3+ statistical tests (display code and output) and 3+ final visual

Given that forest cover is my main variable of interest, I started by testing of forest

I used hierarchical or mixed-effect model to include the variable time, expressed in year

I initially attempted three models: a generalized least squares model fit by REML; a linear

The LME model revealed that forest does change over time with a negative coefficient of

#Statistical Test 1: How has forest changed over time

```
Forest.Time1 <- gls(data = WB_Spread,
                    Forest ~ Year,
                    method = "REML")
summary(Forest.Time1)
```

Generalized least squares fit by REML

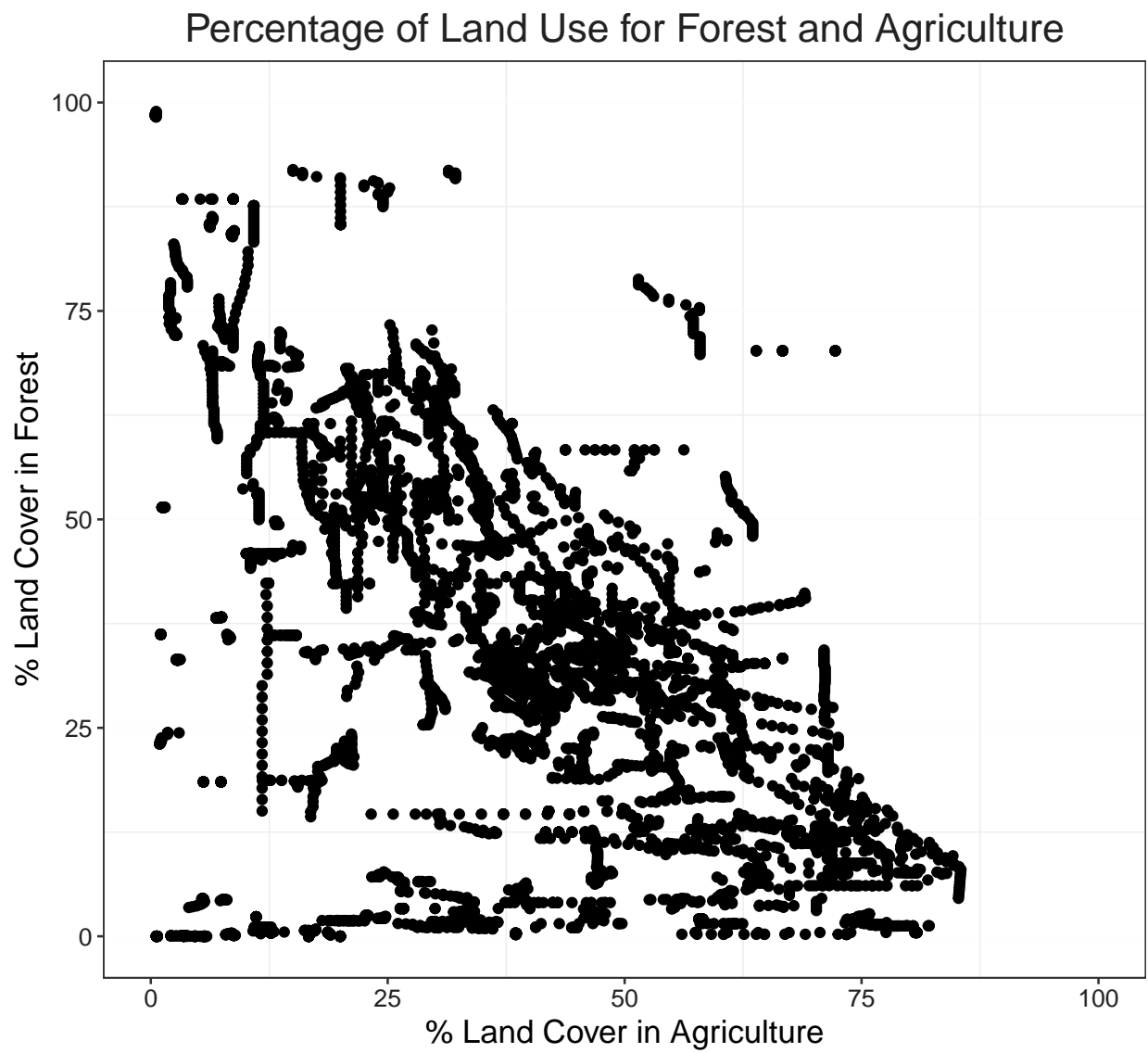


Figure 1: Percentage of Land Use for Forest and Agriculture

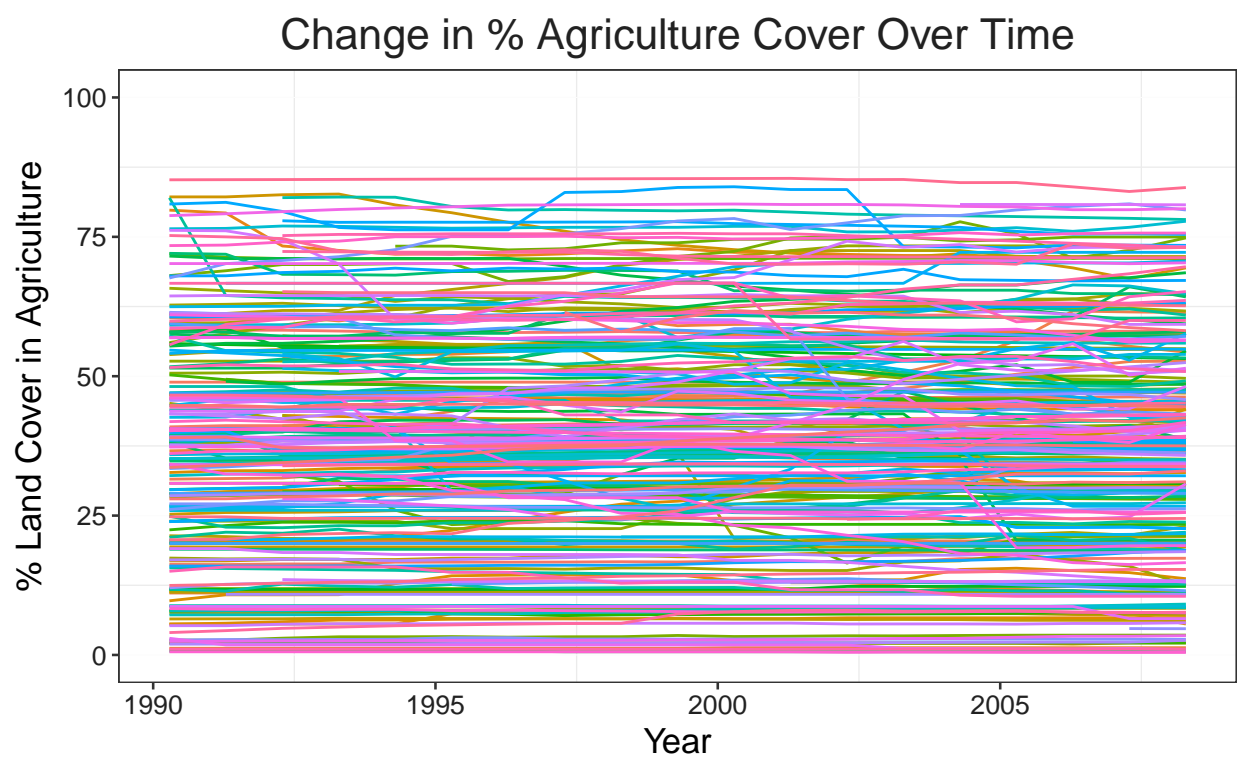
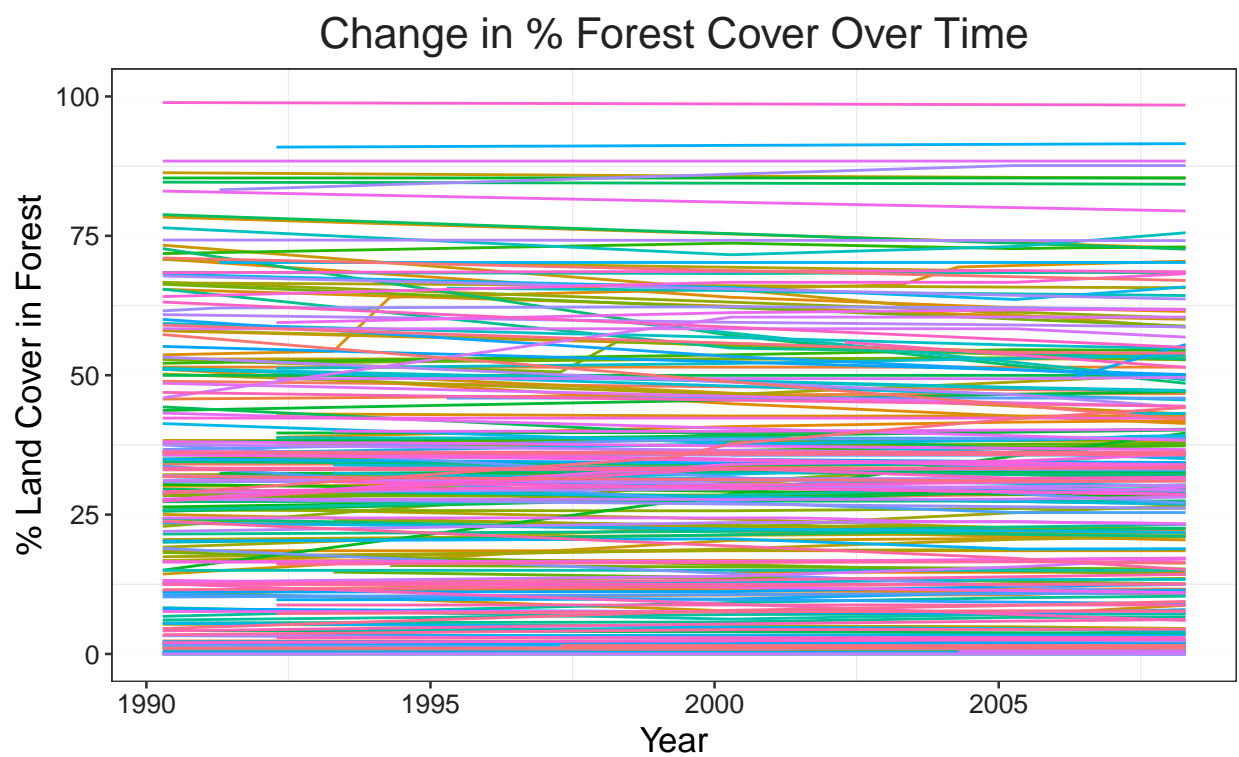


Figure 2: Forest and Agriculture Cover Over Time

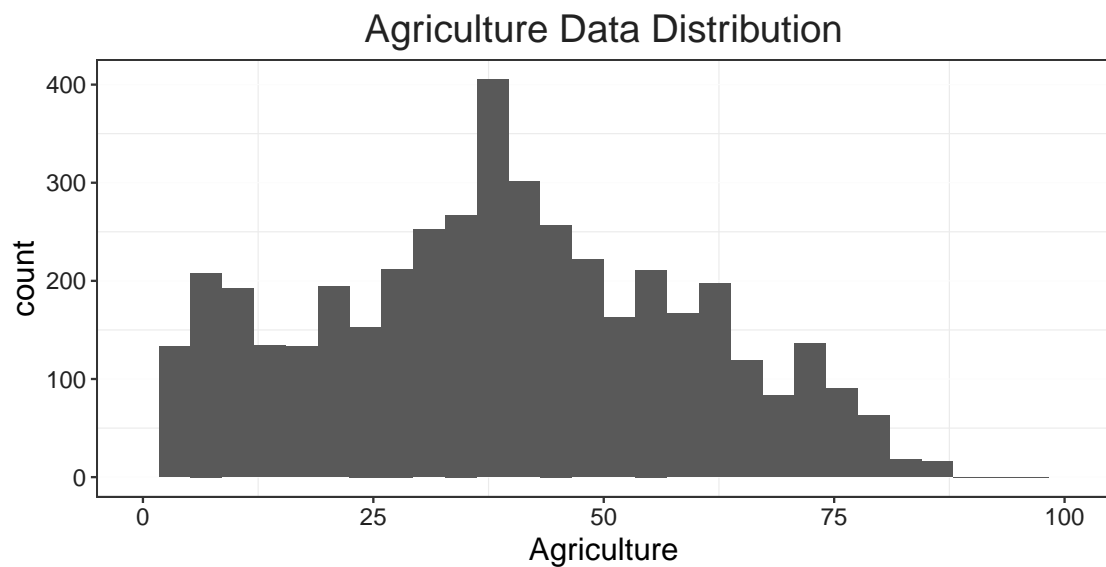
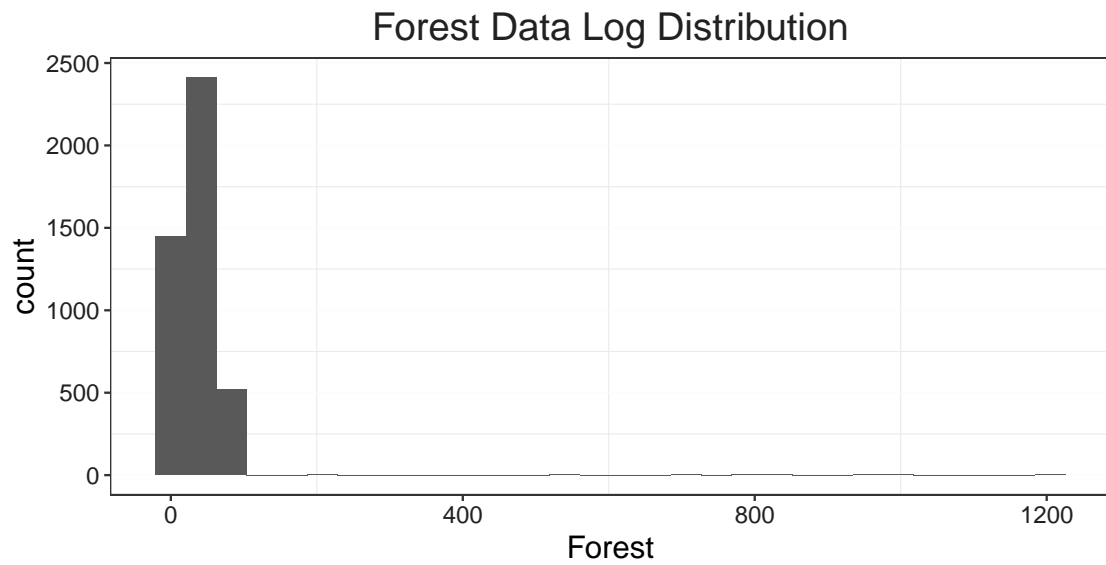
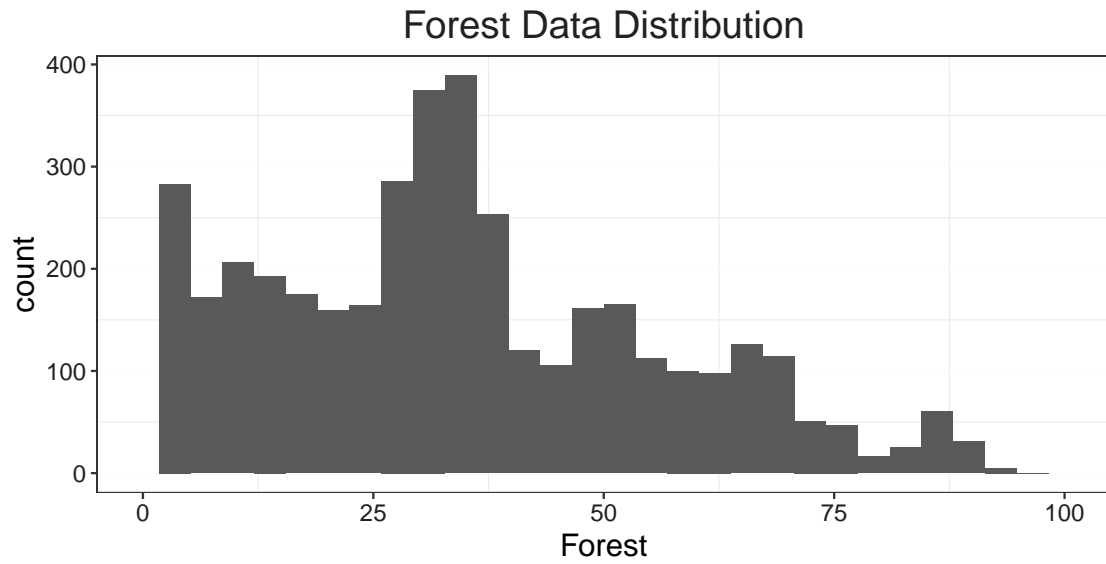


Figure 3: Forest and Agriculture Data Distributions

```
## Model: Forest ~ Year
## Data: WB_Spread
##      AIC      BIC    logLik
## 49977.96 49997.13 -24985.98
##
## Coefficients:
##              Value Std.Error   t-value p-value
## (Intercept) 83.48572  5.840169 14.295086      0
## Year        -0.00425  0.000533 -7.987907      0
##
## Correlation:
##      (Intr)
## Year -0.984
##
## Standardized residuals:
##      Min      Q1      Med      Q3      Max
## -0.74247841 -0.33743857 -0.09641382  0.15552883 16.46833243
##
## Residual standard error: 69.98862
## Degrees of freedom: 4408 total; 4406 residual
```

```
#Forest decreasing over time (-.00424, p-value 0.00)
#AIC 49977.96
```

```
Forest.Time2 <- lme(data = WB_Spread,
                    Forest ~ Year,
                    random = ~1 | Country,
                    method = "REML")
summary(Forest.Time2)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
## 49431.95 49457.52 -24711.98
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:    30.52692 62.84915
##
## Fixed effects: Forest ~ Year
##              Value Std.Error   DF   t-value p-value
## (Intercept) 82.97070  5.654288 4163 14.673944      0
## Year        -0.00421  0.000482 4163 -8.743567      0
## Correlation:
```

```
##      (Intr)
## Year -0.923
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -2.55113019 -0.14187377 -0.01873545  0.09332491 16.07509035
##
## Number of Observations: 4408
## Number of Groups: 244
```

```
#Forest decreasing over time (-.00421, p-value 0.00)
```

```
#AIC 49431.95
```

```
#AIC for the random effect model is lower, so used this going forward.
```

```
Logit_Test <- glm(data = WB_Spread,
                  Forest ~ Year)
summary(Logit_Test)
```

```
##
## Call:
## glm(formula = Forest ~ Year, data = WB_Spread)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -51.97   -23.62    -6.75    10.89   1152.60
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 83.4857163  5.8401690  14.295  < 2e-16 ***
## Year        -0.0042538  0.0005325  -7.988 1.74e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 4898.407)
##
##      Null deviance: 21894930  on 4407  degrees of freedom
## Residual deviance: 21582379  on 4406  degrees of freedom
## AIC: 49967
##
## Number of Fisher Scoring iterations: 2
```

```
#The results were not much different than using gls, and I was not able to account for
```

After establishing that there is a change in forest cover over time, I ran an LME regression to see if agriculture cover can explain any of the change in forest cover. The result of the test

was a statistically significant (p-value = 0.00) negative relationship which, in absolute terms, can be interpreted as a 1% increase in agriculture cover results in a .49% decrease in forest cover.

I used a test for correlation to better understand this relationship. It revealed that there is slight negative correlation between agriculture and forest with a 95% confidence interval of -.16 and -.10.

```
For.Ag.2 <- lme(data = WB_Spread,
  Forest ~ Year + Agriculture,
  random = ~1 | Country,
  method = "REML")
summary(For.Ag.2)

## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
## 49413.7 49445.65 -24701.85
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:      29.32764 62.80075
##
## Fixed effects: Forest ~ Year + Agriculture
##              Value Std.Error   DF   t-value p-value
## (Intercept) 101.79318  6.830657 4162 14.902399     0
## Year         -0.00421  0.000481 4162 -8.754338     0
## Agriculture  -0.49055  0.101138 4162 -4.850333     0
## Correlation:
##      (Intr) Year
## Year         -0.763
## Agriculture  -0.568  0.000
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -2.53066671 -0.13903414 -0.01968184  0.09295492 16.10850732
##
## Number of Observations: 4408
## Number of Groups: 244

cor.test(formula = ~ Forest + Agriculture,
  data = WB_Spread)

##
## Pearson's product-moment correlation
##
```

```
## data: Forest and Agriculture
## t = -8.7073, df = 4406, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.1589757 -0.1009293
## sample estimates:
## cor
## -0.1300639
```

#There is some negative correlation between Agriculture and Forest with a 95% confidence interval

To visualize the relationship between agriculture and forest, I chose to display one country from each of 5 major continents: North America, South America, Europe, Asia and Africa. The country selection within regions was semi-random. I anticipated that Brazil and Indonesia might show increasing agriculture with decreasing forest based on past research; but Canada, Spain and Kenya were chosen at random with the understanding that these five countries represent different regions and states of economic development. The graph shows that forest and agriculture, when they do move, do indeed tend to have an inverse relationship. Agriculture is not always leading to a decrease in forest cover, but three of the five samples are moving in opposite directions while the other two have fairly constant levels.

Zooming in more narrowly on one country, I used Pettitt's test, a nonparametric test that determines if there is a shift in the central tendency of the time series, to determine at what point in time the changepoints occur in Brazil. I applied the test to both Forest Cover and Agriculture Cover to 1) see if there was a change point for agriculture and/or forest and 2) see if the change points occurred in the same year for both forest and agriculture.

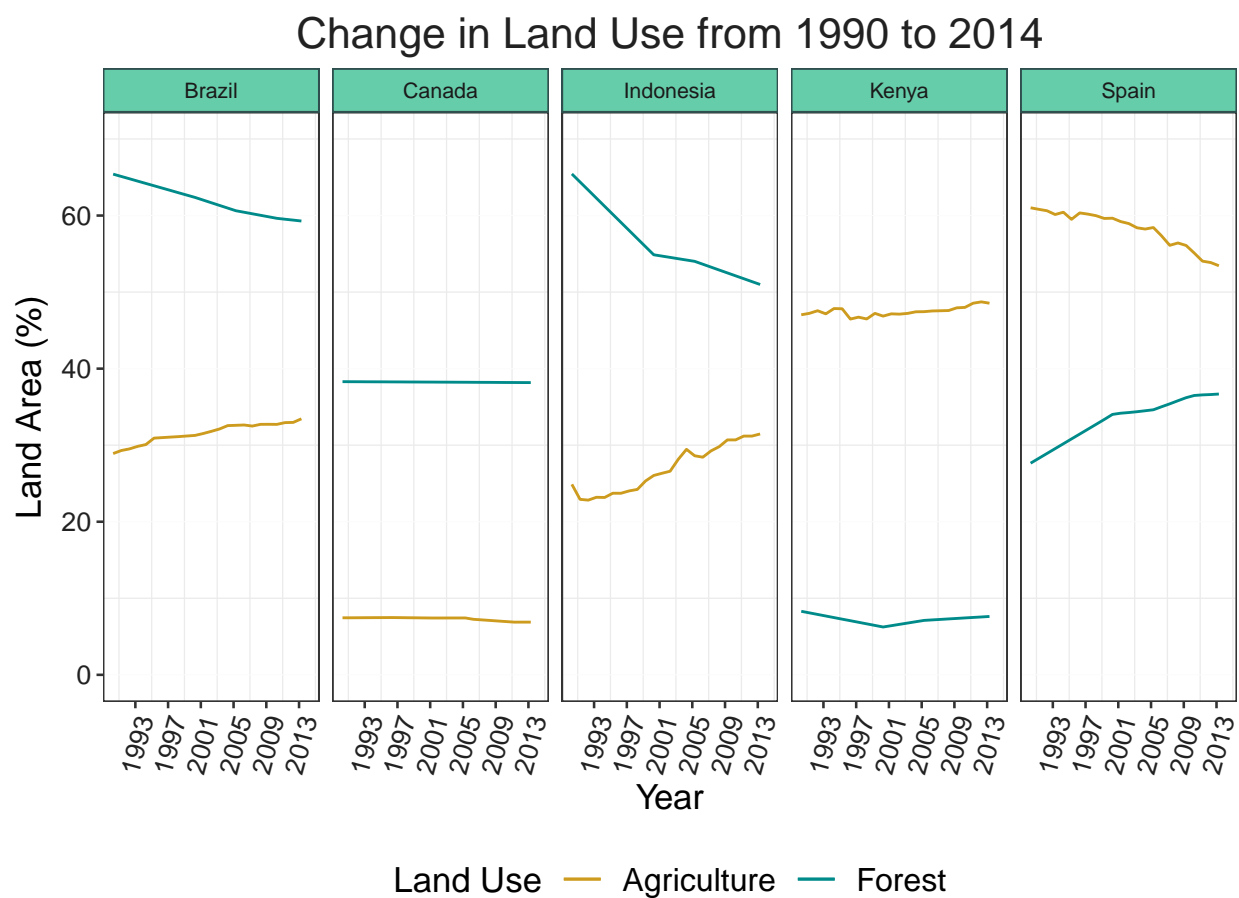
Pettitt's applied to a single country (Brazil) initially detects a change point in Forest and Agriculture in the same year. The change for both was in place 9, which is the year 1998. The significant change points for agriculture and forest in Brazil occurred in the same years (1998 and 2003), further supporting the notion that there is a relationship between the two.

#Statistical Test 2: Pettitt's Test: Looking at Change Points in the Data

#Statistical Test 2: Any change points for full forest data?

```
pettitt.test(WB_Spread$Forest)
```

```
##
## Pettitt's test for single change-point detection
##
## data: WB_Spread$Forest
## U* = 463360, p-value = 5.895e-07
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
## 1739
```



Data Source: World Bank

Figure 4: Change in Land Use from 1990 to 2014 for Five Countries

#Probable change point at time 1428 which doesn't exist.

```
WB_Brazil <- select(WB_Brazil, Forest, Agriculture, Country, Year) %>%  
  na.exclude
```

#Changes in Brazil Forest

```
pettitt.test(WB_Brazil$Forest)
```

```
##  
## Pettitt's test for single change-point detection  
##  
## data: WB_Brazil$Forest  
## U* = 182, p-value = 0.0001182  
## alternative hypothesis: two.sided  
## sample estimates:  
## probable change point at time K <NA>  
## 13 14
```

#13 (of 19): 2002; p-value .0001182 (significant at the .05 level)

```
pettitt.test(WB_Brazil$Forest[13:27])
```

```
##  
## Pettitt's test for single change-point detection  
##  
## data: WB_Brazil$Forest[13:27]  
## U* = 56, p-value = 0.01074  
## alternative hypothesis: two.sided  
## sample estimates:  
## probable change point at time K <NA>  
## 7 8
```

#Changes in Brazil Agriculture

#7 (13+7 = 20: 2009); p-value .01074 (significant at the .01 level)

```
pettitt.test(WB_Brazil$Forest[20:27])
```

```
##  
## Pettitt's test for single change-point detection  
##  
## data: WB_Brazil$Forest[20:27]  
## U* = 16, p-value = 0.139  
## alternative hypothesis: two.sided  
## sample estimates:  
## probable change point at time K  
## 4
```

#4 20 + 4 = 24: 2013 (p-value .139: not significant)

```
pettitt.test(WB_Brazil$Agriculture)
```

```
##
## Pettitt's test for single change-point detection
##
## data: WB_Brazil$Agriculture
## U* = 182, p-value = 0.0001182
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K <NA>
## 13 14
```

#13 (of 19): 2002; p-value .000118 (significant at the .01 level)

```
pettitt.test(WB_Brazil$Agriculture[13:27])
```

```
##
## Pettitt's test for single change-point detection
##
## data: WB_Brazil$Agriculture[13:27]
## U* = 54, p-value = 0.0155
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K <NA>
## 6 7
## <NA>
## 9
```

#6 (13+6 = 19: 2008); p-value .0155 (significant at the .05 level)

```
pettitt.test(WB_Brazil$Agriculture[19:27])
```

```
##
## Pettitt's test for single change-point detection
##
## data: WB_Brazil$Agriculture[19:27]
## U* = 20, p-value = 0.1033
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K <NA>
## 4 5
```

#4 (19 +4 = 2012) p-value .1033 (not significant)

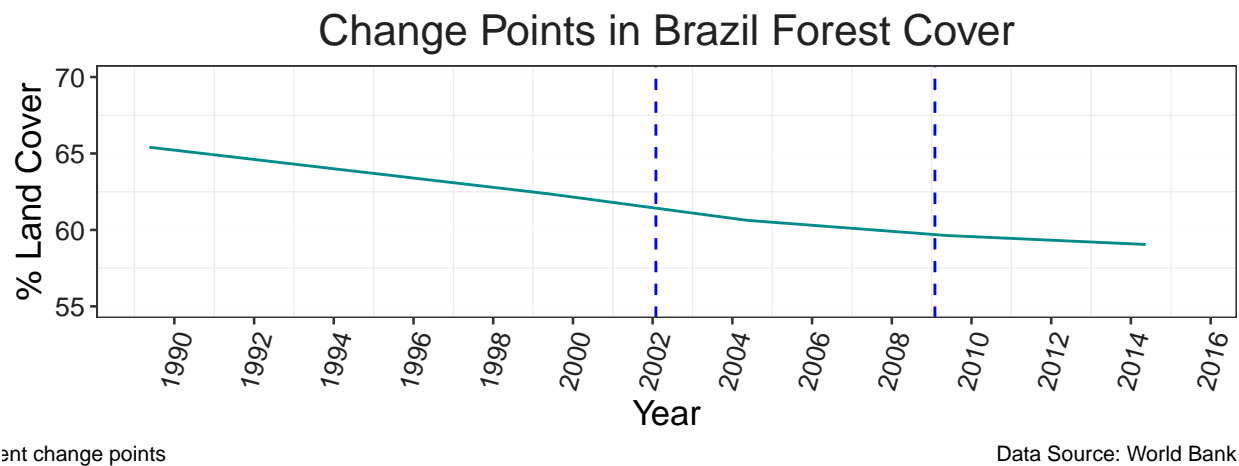
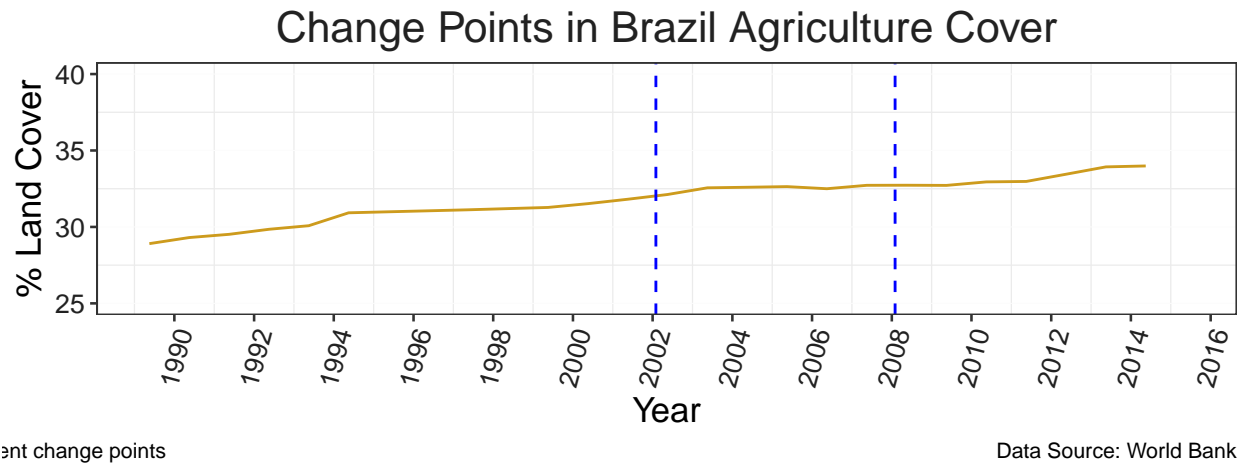


Figure 5: Change Points in Brazil

Having established that agriculture cover has an impact on forest cover, I was also interested in whether access to electricity or the levels of renewable energy produced in countries have a relationship with deforestation. This is because a lack of electricity could drive the use of forest biomass products as an energy source. To the contrary, when included in a model with agriculture electricity access appears to have a negative impact on forest (-.33 coefficient, p-value 0.00). This may be because electricity is needed for some agricultural operations. To test the idea that more agriculture may require more electricity, I ran a variance inflation factor (vif) test to check for multicollinearity in the model. The variance inflation factors were all around 1, meaning multicollinearity is not a problem in the model. I also checked for correlation using the cor.test which revealed that slightly negative correlation between agriculture and electricity access, which I am unable to explain.

A second theory regarding the negative relationship between electricity access and forest cover is that electricity is produced via biofuels, the production of which might require more forest to be converted to agricultural land. With that theory in mind, I was interested in whether there might be a relationship between forested land and renewable energy output because energy produced from biomass is considered to be renewable. However, the result of my LME revealed that a 1 unit increase in renewable energy output is associated with an .20% increase in forest land, meaning the production of biofuels is likely not a main driver of deforestation across the sample, or biofuel is a very small portion of renewable energy.

#Looking at Electricity Accesss and Renewable Energy as a Drive of the Ag. / Forest Tr

```
Forest.Ag.Elec <- lme(data = WB_Spread,
                      Forest ~ Year + Agriculture + ElectricityAccess,
                      random = ~1 | Country,
                      method = "REML")
summary(Forest.Ag.Elec)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
##  49390.4  49428.74 -24689.2
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:      27.83298  62.73873
##
## Fixed effects: Forest ~ Year + Agriculture + ElectricityAccess
##              Value Std.Error   DF   t-value p-value
## (Intercept)   120.57059   7.551404 4161  15.966644     0
## Year          -0.00360   0.000494 4161  -7.293828     0
## Agriculture   -0.54735   0.097884 4161  -5.591834     0
## ElectricityAccess -0.32406   0.059178 4161  -5.475929     0
## Correlation:
```

```
##              (Intr) Year   Agrclt
## Year          -0.567
## Agriculture   -0.542 -0.026
## ElectricityAccess -0.458 -0.227  0.113
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -2.55910898 -0.13847664 -0.01628249  0.09483862 16.10165562
##
## Number of Observations: 4408
## Number of Groups: 244
```

```
car::vif(Forest.Ag.Elec)
```

```
##              Year      Agriculture ElectricityAccess
##      1.054359      1.013011      1.067362
```

```
cor.test(formula = ~ ElectricityAccess + Agriculture,
         data = WB_Spread)
```

```
##
## Pearson's product-moment correlation
##
## data: ElectricityAccess and Agriculture
## t = -9.0997, df = 4406, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.1646811 -0.1067250
## sample estimates:
##      cor
## -0.1358192
```

```
Forest.RE <- lme(data = WB_Spread,
                 Forest ~ Year + RenewableElectricity,
                 random = ~1 | Country,
                 method = "REML")
summary(Forest.RE)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
##  49426.51 49458.46 -24708.26
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:      29.95973  62.8271
```



```
##
## Fixed effects: Forest ~ Year + RenewableElectricity
##               Value Std.Error   DF   t-value p-value
## (Intercept)    75.74745  6.033345 4162 12.554801  0e+00
## Year           -0.00411  0.000482 4162 -8.520768  0e+00
## RenewableElectricity 0.20104  0.059653 4162  3.370074  8e-04
## Correlation:
##               (Intr) Year
## Year           -0.885
## RenewableElectricity -0.355  0.062
##
## Standardized Within-Group Residuals:
##               Min           Q1           Med           Q3           Max
## -2.56121812 -0.14368890 -0.02045123  0.09519242 16.07197971
##
## Number of Observations: 4408
## Number of Groups: 244
```

The next series of tests address the question: Is there a relationship between land uses (agriculture or forest) and levels of CO₂, methane, and NO₃ emissions?

In a model with methane as the dependent variable and forest and agriculture as the explanatory variables, A 1% increase in agriculture leads to an increase of methane of 662.28 thousand metric tons of CO₂ equivalent (p-value 0.00); A 1% increase in forest leads to a decrease of methane of -17.51 thousand metric tons of CO₂ equivalent (p-value .003). I have tested this model for multicollinearity given the significant relationship between agriculture and forest, but it does not seem to be a problem in this model with VIFs around 1. The coefficients are only slightly different that if I made two separate models for agriculture and forest.

In a model with NO₂ as the dependent variable and forest and agriculture as the explanatory variables, A 1% increase in agriculture leads to an increase of nitrous oxide of 491.079 thousand metric tons of CO₂ equivalent (p-value 0.002); A 1% increase in forest leads to a decrease of nitrous oxide of -1.526 thousand metric tons of CO₂ equivalent, but this is not statistically significant with a p-value of .7986.

The results for carbon emissions were not statistically significant, likely because the number includes a large percentage of carbon emissions that are associated with the manufacturing sector as opposed to carbon from land use changes.

#Methane Emissions

```
Ag.For.Meth <- lme(data = WB_Spread,
                  Ag.Methane ~ Year + Agriculture + Forest,
                  random = ~1 | Country,
                  method = "REML")
summary(Ag.For.Meth)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
## 103404.4 103442.8 -51696.22
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:      399120.3 23820.09
##
## Fixed effects: Ag.Methane ~ Year + Agriculture + Forest
##              Value Std.Error   DF   t-value p-value
## (Intercept) 87511.28 26372.723 4161   3.318250  0.0009
## Year          1.93     0.185 4161  10.410309  0.0000
## Agriculture  662.28   160.104 4161   4.136567  0.0000
## Forest      -17.51     5.879 4161  -2.978478  0.0029
## Correlation:
##      (Intr) Year   Agrclt
## Year      -0.082
## Agriculture -0.235  0.021
## Forest     -0.031  0.134  0.052
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -5.12554859 -0.17369030 -0.02167479  0.13084901 14.13409745
##
## Number of Observations: 4408
## Number of Groups: 244
```

```
car::vif(Ag.For.Meth)
```

```
##      Year Agriculture      Forest
## 1.018527 1.002885 1.020821
```

#NO2 Emissions

```
Ag.For.NO2 <- lme(data = WB_Spread,
                  Ag.NO2 ~ Year + Agriculture + Forest,
                  random = ~1| Country,
                  method = "REML")
summary(Ag.For.NO2)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
## 103271.9 103310.3 -51629.97
##
```

```
## Random effects:
## Formula: ~1 | Country
## (Intercept) Residual
## StdDev: 227178.8 24227.78
##
## Fixed effects: Ag.NO2 ~ Year + Agriculture + Forest
## Value Std.Error DF t-value p-value
## (Intercept) 27911.574 15946.871 4161 1.750285 0.0801
## Year 2.963 0.188 4161 15.742913 0.0000
## Agriculture 491.079 160.038 4161 3.068527 0.0022
## Forest -1.526 5.980 4161 -0.255123 0.7986
## Correlation:
## (Intr) Year Agrclt
## Year -0.138
## Agriculture -0.388 0.021
## Forest -0.051 0.134 0.051
##
## Standardized Within-Group Residuals:
## Min Q1 Med Q3 Max
## -6.2159495 -0.2384565 -0.0193730 0.1994855 15.2698912
##
## Number of Observations: 4408
## Number of Groups: 244
```

```
car::vif(Ag.For.NO2)
```

```
## Year Agriculture Forest
## 1.018512 1.002841 1.020782
```

```
#CO2 Emissions
```

```
Ag.For.CO2 <- lme(data = WB_Spread,
  CO2Emissions ~ Year + Agriculture + Forest,
  random = ~1 | Country,
  method = "REML")
summary(Ag.For.CO2)
```

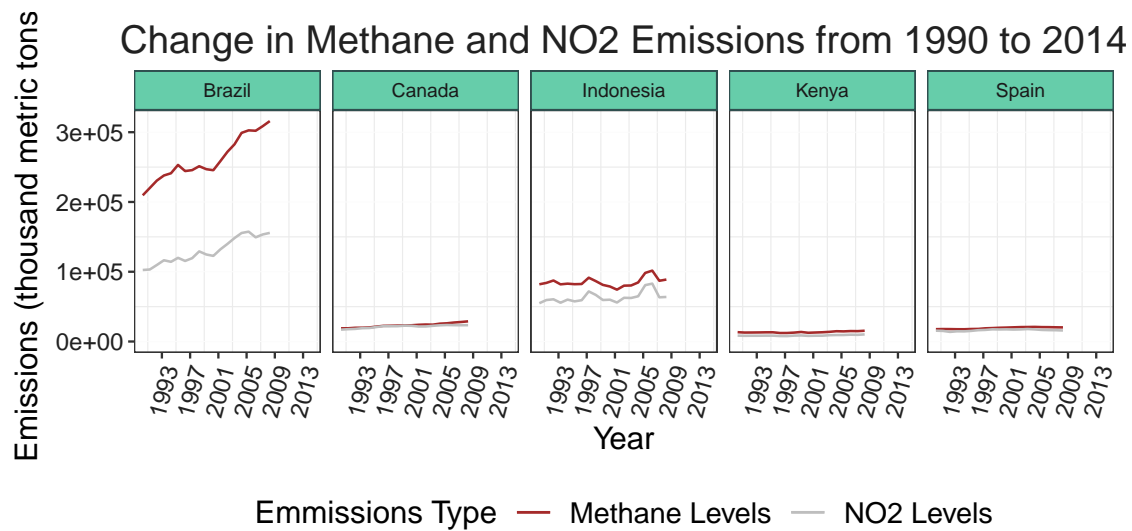
```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
## AIC BIC logLik
## 129304.6 129342.9 -64646.3
##
## Random effects:
## Formula: ~1 | Country
## (Intercept) Residual
## StdDev: 2815249 477534.2
##
```

```
## Fixed effects: CO2Emissions ~ Year + Agriculture + Forest
##               Value Std.Error   DF   t-value p-value
## (Intercept) 237143.25 219216.50 4161   1.081776  0.2794
## Year         62.69      3.71 4161  16.899691  0.0000
## Agriculture  -972.29   3040.95 4161  -0.319733  0.7492
## Forest       -67.45    117.84 4161  -0.572366  0.5671
## Correlation:
##           (Intr) Year   Agrclt
## Year      -0.197
## Agriculture -0.536  0.020
## Forest     -0.072  0.134  0.051
##
## Standardized Within-Group Residuals:
##           Min           Q1           Med           Q3           Max
## -6.645266358 -0.228318747 -0.009787546  0.194387104 13.617669525
##
## Number of Observations: 4408
## Number of Groups: 244
```

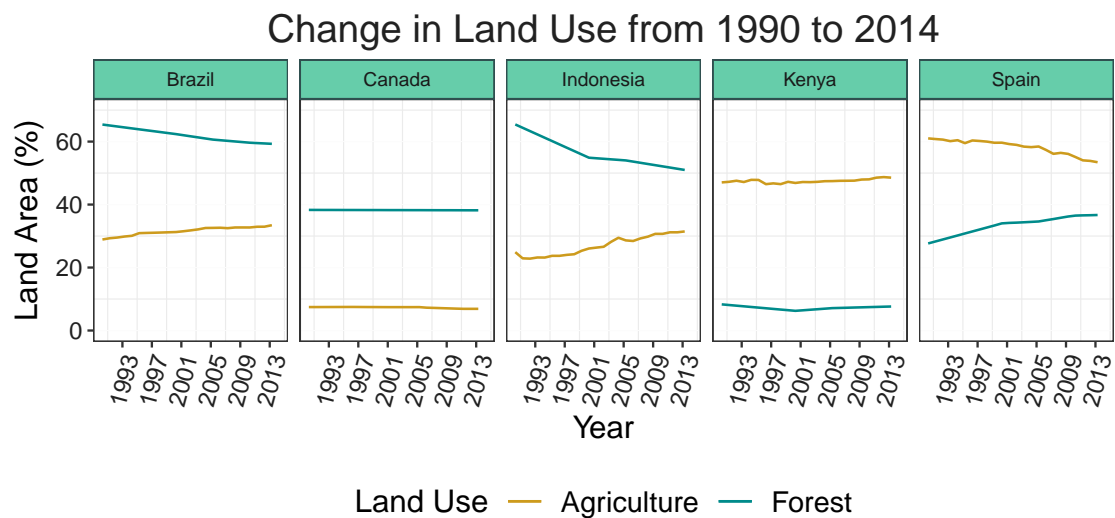
```
ForCO2 <- lme(data = WB_Spread,
              Ag.Methane ~ Year + Forest,
              random = ~1 | Country,
              method = "REML")
summary(ForCO2)
```

```
## Linear mixed-effects model fit by REML
## Data: WB_Spread
##      AIC      BIC    logLik
## 103431.5 103463.5 -51710.76
##
## Random effects:
## Formula: ~1 | Country
##      (Intercept) Residual
## StdDev:    399211.3 23865.83
##
## Fixed effects: Ag.Methane ~ Year + Forest
##               Value Std.Error   DF   t-value p-value
## (Intercept) 113115.75 25642.184 4162   4.411315  0.0000
## Year         1.91      0.185 4162  10.306589  0.0000
## Forest       -18.77     5.883 4162  -3.190742  0.0014
## Correlation:
##           (Intr) Year
## Year      -0.080
## Forest   -0.019  0.133
##
```

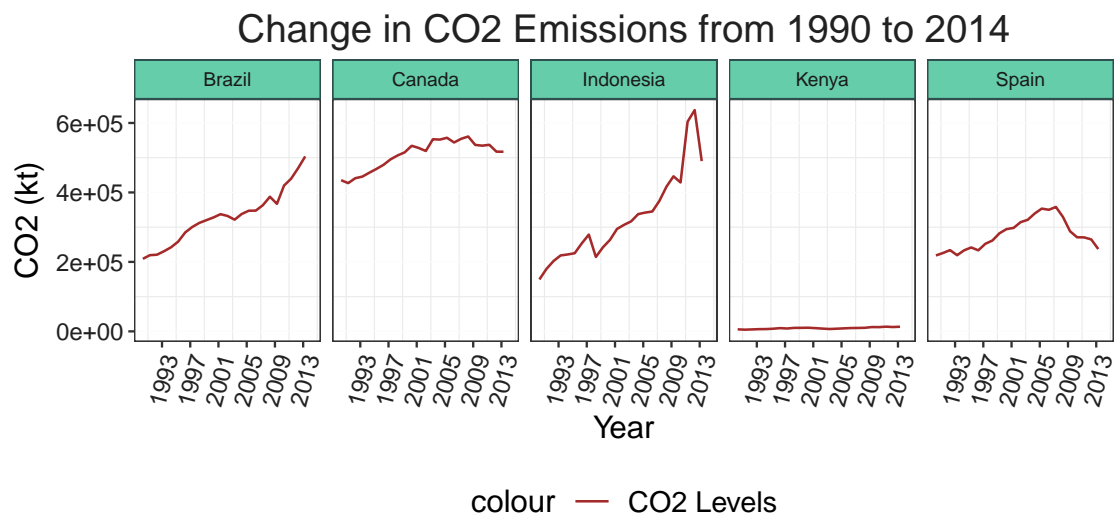
```
## Standardized Within-Group Residuals:
##           Min           Q1           Med           Q3           Max
## -5.11273090 -0.17479056 -0.02340015  0.13160047 14.10832094
##
## Number of Observations: 4408
## Number of Groups: 244
```



Data Source: World Bank



Data Source: World Bank



Data Source: World Bank

Figure 6: Change in Emissions Use from 1990 to 2014 for Five Countries

4 Summary and Conclusions

This research has looked at the causes and impacts of changes in land use from 1990 to 2014 as it pertains to forest cover and agriculture cover. There is a statistically significant trend of slightly decreasing forest cover over time in the full data set of 263 countries, which can partially be attributed to changes in agriculture cover. Renewable electricity output and electricity access also have statistically significant relationships with forest cover. Meanwhile, on the other end of the spectrum, changes in land dedicated to agriculture and to forest have explained increases in emissions of agricultural methane and nitrous oxide, though they were not able to explain changes in carbon.

The questions this research attempts to answer are addressed below:

Is there a relationship between the percentage of land area dedicated to forest versus agricultural in countries?

There is a relationship between the percentage of land area dedicated to forest versus agricultural in countries. A 1% increase in agriculture cover results in a .49% decrease in forest cover, and there is a slight negative correlation between the two variables. The trend of decreasing forest as agriculture increases is not true for all countries as seen by the exploratory plot where many of the countries land covers appear to stay constant, and the plot that highlight five countries where Spain is actually increasing forest cover while agriculture decreases. It does appear that the variables do more or less move together, however, perhaps more in some countries than others. For example, the Pettit's test applied to Brazil showed the first change point being the same for both agriculture cover and forest cover while the second point was just a year apart for the two.

Is there a relationship between access to electricity or renewable electricity output and the percentage of land dedicated to forestry versus agriculture?

This question was explored with forest as the dependent variable to see whether electricity access or renewable electricity levels impact forest cover. There was a statistically significant relationship between both variables and forest cover. Electricity access appears to have a statistically significant negative impact on forest cover, while renewable electricity has a statistically significant positive relationship with forest cover.

Is there a relationship between land uses (agriculture or forest) and levels of CO₂, methane, and NO₃ emissions?

There are statistically significant relationships between methane and nitrous oxide emissions and land covers. An increase in agriculture leads to an increase in both methane and nitrous oxide emissions: a 1% increase in agriculture leading to an increase of 662.28 and 491.08 thousand metric tons of CO₂ equivalent, respectively. Meanwhile, an increase in Forest cover leads to a decrease in both methane and nitrous oxide: a 1% increase in forest leads to a decrease of methane of -17.51 thousand metric tons of CO₂ equivalent. A 1% increase in forest leads to a decrease of nitrous oxide of -1.53 thousand metric tons of CO₂ equivalent but this is not statistically significant with a p-value of .7986. The results for carbon emissions were not statistically significant, likely because the number includes a large percentage of

carbon emissions that are associated with the manufacturing sector as opposed to carbon from land use changes.

Conclusion and applications

Overall this has been valuable exercise in beginning to parse out the chain of results from activities that lead to land conversion to the environmental impacts of land conversion. The results indicate that while agriculture is a driver of deforestation, there are other considerations that should be taken in to account. For example, given that the correlation between agriculture and electricity access is both low and negative, it is difficult to associate the negative relationship between forest and electricity access with an increase in electricity demanded for agricultural activities. The increase in electricity access that has a negative impact on forest cover could actually be indicative of urban development, which may be another driver of deforestation that is not accounted for by this study.

Access to electricity as an explanatory variable could be interesting in a country specific study with multiple data collection sites. This might be a better opportunity to look at whether a lack of electricity could drive deforestation through the use of forest biomass products as an energy source, which was my original reason for including the variable. It is not surprising that deforestation from lack of electricity may not be detected by a model looking at global data because harvest of forest for fuel is likely quite small scale.

While the theory that an increase in renewable energy could actually lead to more forest land being converted to agriculture land for the production of biofuels was not supported by the research results, this could be an interesting question to address using a data set that parses out the quantity of renewable energy that is produced from biofuels. Biofuels are likely a very small portion of the renewable energy data set with other sources like solar, wind, and hydro being bucketed in to the same variable.

The study draws a clear link between increases in agriculture, decreases in forest, and increases in emissions of methane, which should continue to be explored as we continue to make land use decisions in a time of increasing climate change. This study highlights methane as a priority over nitrous oxide when it comes to land conversion both because its impacts were bigger and because the relationship between nitrous oxide and forest cover is not statistically significant. Going forward, it may be prudent to conduct a study that considers emissions from total agricultural activities as opposed to area under agriculture because agricultural intensification—i.e. more production on the same amount of land—may also be driving emissions. It may be interesting to see how agricultural intensification compares to additional land conversion in terms of emissions.

All in all, these findings are they are helpful in continuing the discussion around protecting forests from conversion to other land uses, such as agriculture. Preservation of forest ecosystem services such as carbon storage, nutrient cycling, water filtration, and wildlife habitat should start to be part of the conversation when deciding whether to give up forest land for agriculture, which continues to be a trend.