

How has the Brazilian Amazon been constructed as a problem - presidential speeches and transnational politics since 1985

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We need to protect the Amazon from foreign interests.

We need to exploit the Amazon's natural resources.

We need to provide better living standards for the people in the Amazon.

We need to preserve the Amazon as a standing ecosystem.

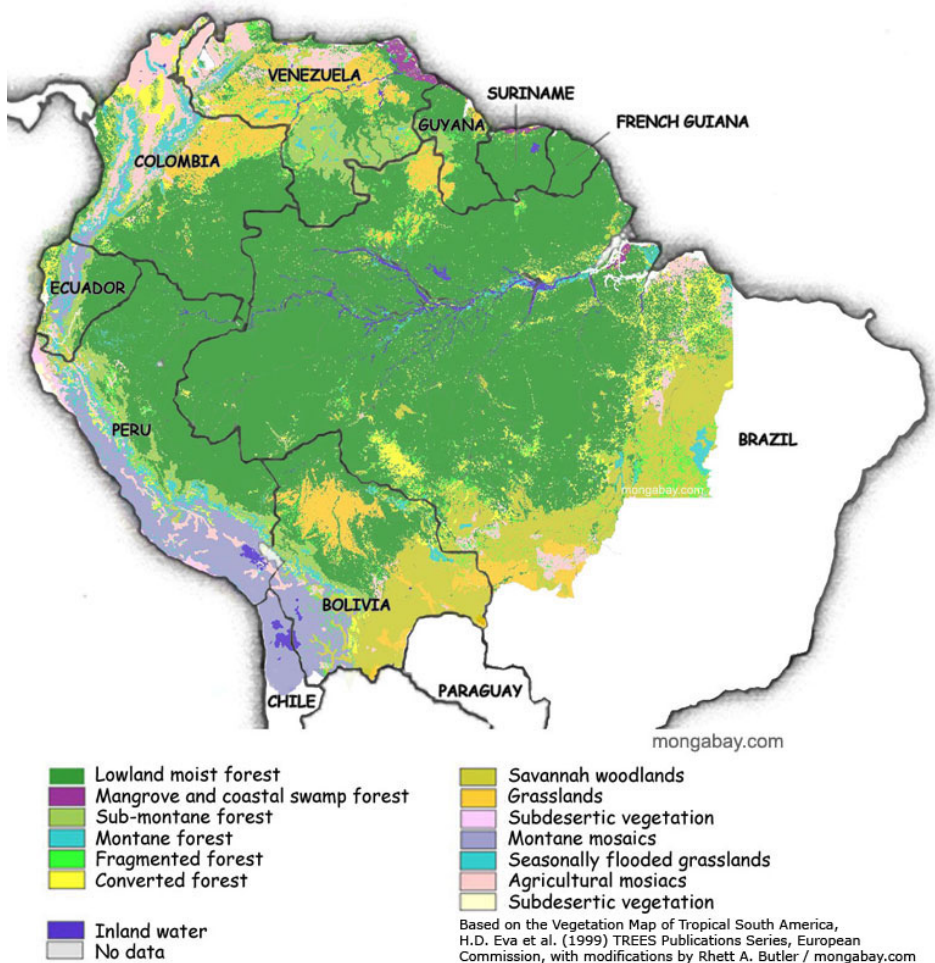


Figure 1: The Amazon Forest

Question

How the Brazilian Amazon has been constructed as a problem in transnational presidential speeches since 1985?

Data and methods

- Dataset containing all 6130 official speeches by presidents since 1985
- Subset of 2014 “amazonian statements”
- Location
- Hand-coding and supervised machine learning
- Can you think of some limitations with this approach?

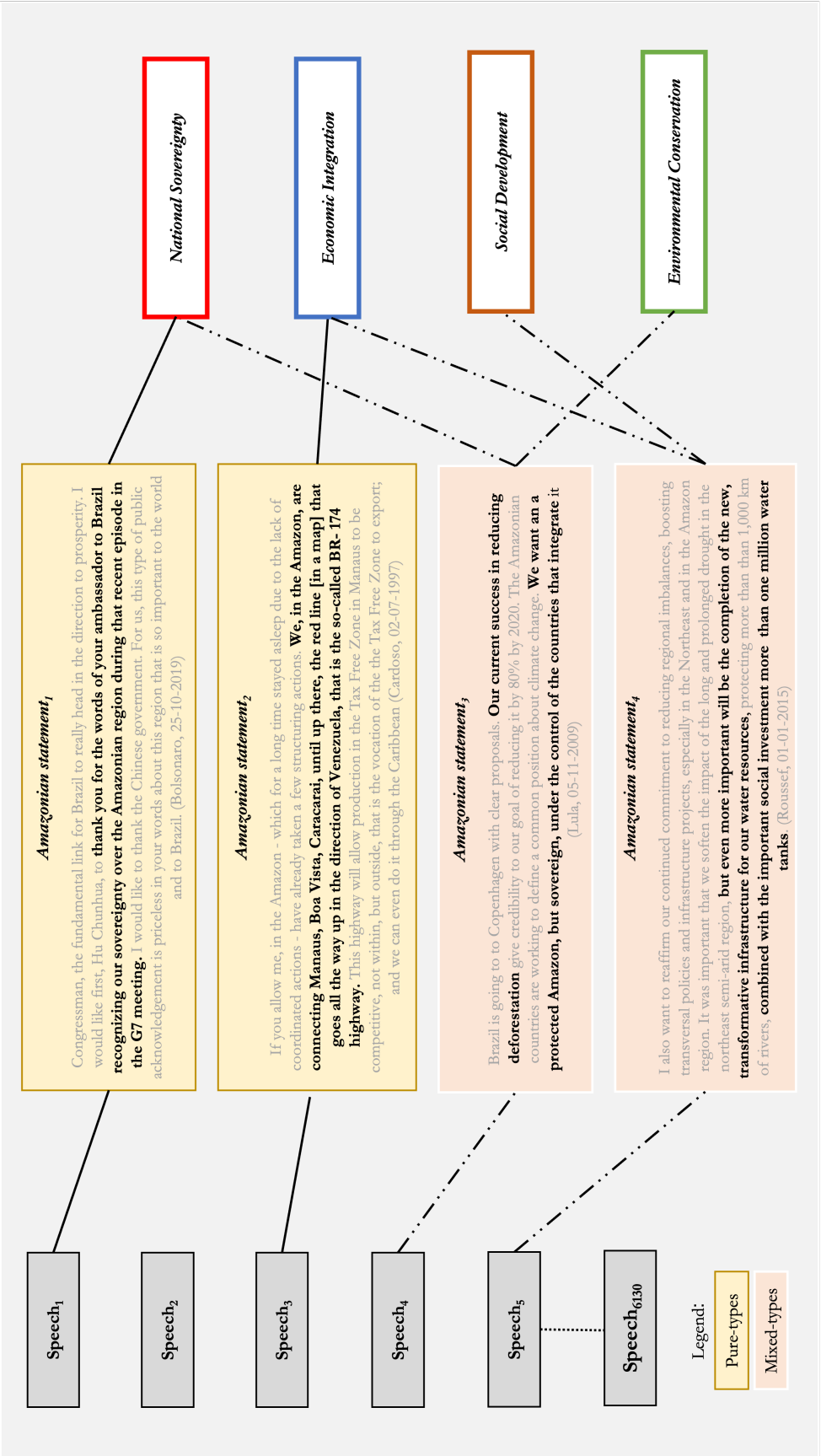


Figure 2: Operationalization of problem-constructions

```
summary(ama)
```

```
##      ID      president      year      party
## Min.   :1001   Length:1895   Min.   :1985   Length:1895
## 1st Qu.:1289   Class :character   1st Qu.:1996   Class :character
## Median :1522   Mode  :character   Median :2003   Mode  :character
## Mean   :1522                      Mean   :2003
## 3rd Qu.:1772                      3rd Qu.:2009
## Max.   :2000                      Max.   :2021
##
##      location      mixed_type      hand_coded      other
## Length:1895      Length:1895      Min.   :0.0000   Min.   :0.0000
## Class :character   Class :character   1st Qu.:0.0000   1st Qu.:0.0000
## Mode  :character   Mode  :character   Median :0.0000   Median :0.0000
##                      Mean   :0.4902   Mean   :0.2106
##                      3rd Qu.:1.0000   3rd Qu.:0.0000
##                      Max.   :1.0000   Max.   :1.0000
##
##      location_cat      AAI      km_to_manaus      def_year
## International      :165   Min.   : 1.65   Min.   : 0   Min.   : 4.571
## Amazonian States    :533   1st Qu.: 4.52   1st Qu.: 0   1st Qu.:10.129
## Amazonian Countries :153   Median : 6.41   Median : 1934   Median :14.286
## Brasilia           :597   Mean   : 239.93   Mean   : 1950   Mean   :15.366
## Non Amazonian States:444   3rd Qu.: 12.53   3rd Qu.: 2675   3rd Qu.:18.226
## NA's               : 3   Max.   :2477.15   Max.   :15979   Max.   :29.059
##
##      area      mx_cat      election_year
## Min.   : 4571   Pure Economic Integration      :465   Min.   :0.000
## 1st Qu.:10129   Other                          :399   1st Qu.:0.000
## Median :14286   Pure Environmental Conservation:275   Median :0.000
## Mean   :15366   Pure Social Development          :205   Mean   :0.258
## 3rd Qu.:18226   Economic Conservation           :130   3rd Qu.:1.000
## Max.   :29059   Pure National Sovereignty       :105   Max.   :1.000
##                      (Other)                      :316
```

```
# library(skimmr)
# skimr::skim(ama)
```

When Brazilian presidents speak about conservation in the context of the Amazon, where are they?

A simple logistic regression

Why do we use a logistic model and not a linear one here?

```
ama_model <- filter(ama, location_cat != "Non Identified",
                    mx_cat != "Other Mixed-types") %>%
  mutate(con_vs_all = ifelse(mx_cat == "Pure Environmental Conservation", 1, 0),
         EI_vs_all = ifelse(mx_cat == "Pure Economic Integration", 1, 0),
         SD_vs_all = ifelse(mx_cat == "Pure Social Development", 1, 0),
```

```

    sov_vs_all = ifelse(mx_cat == "Pure National Sovereignty", 1, 0))
# model
model_logit_con <- glm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                      family=binomial(link = "logit"), data = ama_model)
summary(model_logit_con)

```

```

##
## Call:
## glm(formula = con_vs_all ~ km_to_manaus + election_year + def_year +
##      AAI, family = binomial(link = "logit"), data = ama_model)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.3118  -0.5825  -0.5130  -0.4377   2.3245
##
## Coefficients:
##              Estimate Std. Error z value      Pr(>|z|)
## (Intercept) -1.71845866  0.19066729  -9.013 < 0.0000000000000002 ***
## km_to_manaus  0.00011555  0.00002145   5.386  0.0000000719 ***
## election_year  0.28790781  0.15665954   1.838   0.066093 .
## def_year     -0.03173895  0.01129821  -2.809   0.004966 **
## AAI           0.00038679  0.00010404   3.718   0.000201 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1549.3  on 1841  degrees of freedom
## Residual deviance: 1497.3  on 1837  degrees of freedom
## AIC: 1507.3
##
## Number of Fisher Scoring iterations: 4

```

Estimates are in log odds... But what are log-odds?

Need an easy publication table? No worries!

```
stargazer::stargazer(model_logit_con, header = FALSE)
```

Table 1:

	<i>Dependent variable:</i>
	con_vs_all
km_to_manaus	0.0001*** (0.00002)
election_year	0.288* (0.157)
def_year	-0.032*** (0.011)
AAI	0.0004*** (0.0001)
Constant	-1.718*** (0.191)
Observations	1,842
Log Likelihood	-748.648
Akaike Inf. Crit.	1,507.296
Note:	*p<0.1; **p<0.05; ***p<0.01

What about time effects?

```
pooled_ols <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
  data = ama_model, model = "pooling", index = c("year"))
summary(pooled_ols)
```

```
## Pooling Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##   def_year + AAI, data = ama_model, model = "pooling", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Residuals:
##      Min.    1st Qu.    Median    3rd Qu.     Max.
## -0.470289 -0.158090 -0.126625 -0.082295  0.953062
##
## Coefficients:
##              Estimate      Std. Error t-value      Pr(>|t|)
```

```
## (Intercept)    0.1429802958  0.0235559575  6.0698 0.000000001552 ***
## km_to_manaus   0.0000178431  0.0000032303  5.5237 0.000000037934 ***
## election_year  0.0359069945  0.0199552120  1.7994  0.0721228 .
## def_year       -0.0033476666  0.0012965902 -2.5819  0.0099026 **
## AAI            0.0000552053  0.0000146958  3.7565  0.0001776 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    233.24
## Residual Sum of Squares: 226.09
## R-Squared:    0.030665
## Adj. R-Squared: 0.028555
## F-statistic: 14.5286 on 4 and 1837 DF, p-value: 0.0000000001099

fixed <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                  data = ama_model, model = "within", index = c("year"))
summary(fixed)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##   def_year + AAI, data = ama_model, model = "within", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Residuals:
##      Min.    1st Qu.    Median    3rd Qu.    Max.
## -0.729676 -0.166751 -0.117960 -0.045981  0.970345
##
## Coefficients:
##              Estimate Std. Error t-value Pr(>|t|)
## km_to_manaus 0.0000152831 0.0000033197  4.6037 0.000004441 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    220.46
## Residual Sum of Squares: 217.9
## R-Squared:    0.011612
## Adj. R-Squared: -0.0086599
## F-statistic: 21.194 on 1 and 1804 DF, p-value: 0.0000044405
```

Not a good choice here, why? (tip: is this a balanced panel)

```
random <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                  data = ama_model, model = "random", index = c("president"))
summary(random)
```

```
## Oneway (individual) effect Random Effect Model
##   (Swamy-Arora's transformation)
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
```

```
##      def_year + AAI, data = ama_model, model = "random", index = c("president"))
##
## Unbalanced Panel: n = 8, T = 22-589, N = 1842
##
## Effects:
##              var  std.dev share
## idiosyncratic 0.122010 0.349300 0.952
## individual    0.006187 0.078657 0.048
## theta:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.3125  0.7306  0.8171  0.7599  0.8200  0.8200
##
## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.54501 -0.16392 -0.12262 -0.00199 -0.08238  0.94123
##
## Coefficients:
##              Estimate Std. Error z-value Pr(>|z|)
## (Intercept)  0.1301289997  0.0414516964  3.1393  0.001694 **
## km_to_manaus  0.0000177485  0.0000032289  5.4968 0.00000003867 ***
## election_year  0.0464289206  0.0211305356  2.1972  0.028003 *
## def_year      -0.0015416390  0.0017175629 -0.8976  0.369413
## AAI           0.0000460187  0.0000242763  1.8956  0.058010 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    230.69
## Residual Sum of Squares: 224.29
## R-Squared:    0.02777
## Adj. R-Squared: 0.025653
## Chisq: 41.8736 on 4 DF, p-value: 0.000000017719
```

Better, but not a good choice here, why? (tip: is this a balanced panel)

Nominal outcome (depenedent) variables, multinomial is the name of the game!

```
library(nnet)
# model
model_multi <- nnet::multinom(mx_cat ~ location_cat + election_year + def_year + AAI,
                             data = ama_model, model = TRUE, trace = FALSE)
# summary statistics
summary(model_multi)
```

But very hard to interpret as there are, often, multiple reference categories... Above the reference categories are Pure Economic Inegration in International settings?!

The Amazon multi-level game: talking to the people inside

Predicted probability of each problem–construction as a function of dis

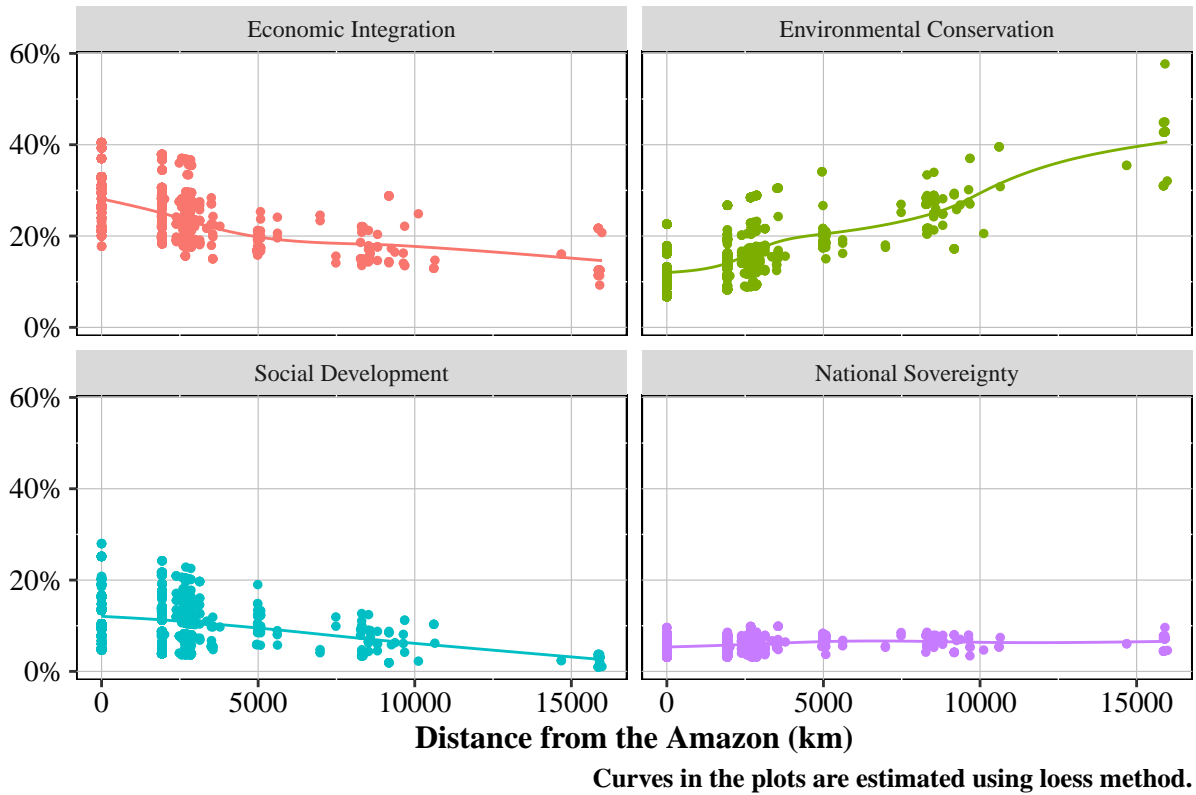


Figure 3: Logistic Regression predicted values

Can you see the relationship?

The Amazon multi-level game: boasting policy outside

Table 2: Logistic Regression Models

	<i>Dependent variable:</i>			
	Conservation (1)	Economic Integration (2)	Social Development (3)	Sovereignty (4)
Distance from the Amazon in 1000s of km	0.11554*** (0.021453)	-0.056590** (0.023979)	-0.101285** (0.039849)	0.009384 (0.038080)
Election year	0.287908* (0.156660)	-0.022328 (0.132762)	0.328917* (0.171163)	-0.448696* (0.269325)
Yearly Deforestation	-0.031739*** (0.011298)	0.040870*** (0.008404)	-0.072349*** (0.013232)	-0.031859* (0.016768)
Yearly Inflation	0.000387*** (0.000104)	-0.000231** (0.000104)	-0.000205 (0.000151)	0.000215 (0.000177)
Constant	-1.718459*** (0.190667)	-1.568837*** (0.159988)	-0.909845*** (0.213791)	-2.300558*** (0.280849)
Observations	1,842	1,842	1,842	1,842
Log Likelihood	-748.648200	-1,022.790000	-620.264400	-399.290500
Akaike Inf. Crit.	1,507.296000	2,055.579000	1,250.529000	808.581000
<i>Note:</i>	* p<0.1; ** p<0.05; *** p<0.01			

Why distances to Manaus by 1000km?