Pará’s secondary vegetation drivers

Preparing the script

First, let’s upload the data in R markdown (its interface is not connected to R console). To open the command console in R markdown, you have to insert the code
`“ {r}”. From that, the gray area surrounding it is for inserting the commands. To shut it, you type “ ”`
below your commands:

```
library(readxl)

data.set <- read_excel("data.set.xlsx")
data.atributes <- read_excel("variables atributes.xlsx")
```

We will have to load the necessary packages here as well:

Then we can require all sorts of command outputs we want to show in our R markdown file.

Exploring the Dataset

Let’s first visualize some of the data atributes description:

```
print(data.atributes)
```

```
## # A tibble: 105 x 6
##    ATTRIBUTE             CATEGORY DESCRIPTION             OPERATOR SOURCE YEAR
##    <chr>                 <chr>    <chr>                   <chr>    <chr>  <chr>
##  1 id                    -        Cell identifier         -        -      -
##  2 col                   -        Column to which the cel~ -       -      -
##  3 row                   -        Row to which the cell b~ -       -      -
##  4 geocodigo             -        Geocode of the municipa~ Mode    IBGE   2010
##  5 bioma                 -        Biome code in which the~ Coverage IBGE  2015
##  6 EXPLANATORY VARIABLES <NA>     <NA>                    <NA>     <NA>   <NA>
##  7 veg10                 LAND USE Natural vegetation in 2~ Coverage IBGE  2015
##  8 pastn10               LAND USE Natural pasture in 2010 Coverage IBGE   2015
##  9 pastp10               LAND USE Pasture planted in 2010 Coverage IBGE   2015
## 10 agric10               LAND USE Agriculture in 2010     Coverage IBGE   2015
## # ... with 95 more rows
```

The “str” command describes the type of object and displays the internal structure of an R object, in this case our data frame. It gives us the name and type of each variable and the first few observations:

```
str(data.set)
```

```
## tibble [12,527 x 103] (S3: tbl_df/tbl/data.frame)
##  $ id        : chr [1:12527] "C349L519" "C350L519" "C351L519" "C352L519" ...
##  $ col       : num [1:12527] 349 350 351 352 353 354 336 337 338 339 ...
##  $ row       : num [1:12527] 519 519 519 519 519 519 520 520 520 520 ...
##  $ geocodigo : chr [1:12527] "1506708" "1506708" "1506708" "1506708" ...
##  $ bioma     : chr [1:12527] "Amazonia" "Amazonia" "Amazonia" "Amazonia" ...
##  $ veg10     : num [1:12527] 0.458 0.567 0.85 0.618 0.527 ...
##  $ pastn10   : num [1:12527] 0 0 0 0 0.145 ...
##  $ pastp10   : num [1:12527] 0.48 0.4331 0.0938 0.3819 0.3275 ...
##  $ agric10   : num [1:12527] 0 0 0.0563 0 0 ...
##  $ mosc10    : num [1:12527] 0.0625 0 0 0 0 ...
##  $ fores10   : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ outh10    : num [1:12527] 0 0 0 0 0 0.0175 0 0 0 0 ...
##  $ veg14     : num [1:12527] 0.445 0.564 0.613 0.618 0.527 ...
##  $ pastn14   : num [1:12527] 0 0 0 0 0.145 ...
##  $ pastp14   : num [1:12527] 0.4844 0.4363 0.0938 0.3819 0.3275 ...
##  $ agric14   : num [1:12527] 0 0 0.0563 0 0 ...
##  $ mosc14    : num [1:12527] 0.0706 0 0.2375 0 0 ...
##  $ fores14   : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ outh14    : num [1:12527] 0 0 0 0 0 0.0175 0 0 0 0 ...
##  $ va10_3    : num [1:12527] 0.528 0.575 0.674 0.543 0.695 ...
##  $ va15_3    : num [1:12527] 0.518 0.578 0.673 0.538 0.667 ...
##  $ va18_3    : num [1:12527] 0.512 0.561 0.659 0.515 0.656 ...
##  $ va10_4    : num [1:12527] 0.408 0.392 0.294 0.378 0.181 ...
##  $ va15_4    : num [1:12527] 0.397 0.381 0.302 0.343 0.246 ...
##  $ va18_4    : num [1:12527] 0.43 0.402 0.316 0.394 0.278 ...
##  $ va10_5    : num [1:12527] 1.69e-04 9.83e-05 8.02e-05 5.08e-04 1.19e-02 ...
##  $ va15_5    : num [1:12527] 1.78e-04 1.34e-04 8.02e-05 4.10e-04 1.21e-02 ...
##  $ va18_5    : num [1:12527] 1.34e-04 1.16e-04 8.02e-05 5.44e-04 1.16e-02 ...
##  $ Dva3_10_15: num [1:12527] -0.009436 0.00311 -0.000802 -0.005008 -0.02758 ...
##  $ Dva3_15_18: num [1:12527] -0.00629 -0.01743 -0.01403 -0.02257 -0.0112 ...
##  $ Dva4_10_15: num [1:12527] -0.01087 -0.01096 0.00789 -0.03577 0.06553 ...
##  $ Dva4_15_18: num [1:12527] 0.0335 0.0209 0.0143 0.0517 0.0316 ...
##  $ lva10_3   : num [1:12527] -0.277 -0.24 -0.171 -0.265 -0.158 ...
##  $ lva15_3   : num [1:12527] -0.285 -0.238 -0.172 -0.269 -0.175 ...
##  $ lva18_3   : num [1:12527] -0.291 -0.251 -0.181 -0.288 -0.183 ...
##  $ lva10_4   : num [1:12527] -0.39 -0.407 -0.531 -0.422 -0.743 ...
##  $ lva15_4   : num [1:12527] -0.401 -0.419 -0.52 -0.465 -0.608 ...
##  $ lva18_4   : num [1:12527] -0.366 -0.396 -0.5 -0.404 -0.556 ...
##  $ ag_slope_1: num [1:12527] 0.252 0.507 0.74 0.714 0.704 ...
##  $ ag_slope_2: num [1:12527] 0.366 0.439 0.252 0.265 0.274 ...
##  $ ag_slope_3: num [1:12527] 0.1781 0.0325 0.005 0.0213 0.0219 ...
##  $ ag_slope_4: num [1:12527] 0.16312 0.01875 0.00313 0 0 ...
##  $ ag_slope_5: num [1:12527] 0.04063 0.00313 0 0 0 ...
##  $ ag_slope_6: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ ag_apt_MBB: num [1:12527] 1 1 1 0.965 0.166 ...
##  $ ag_apt_MMA: num [1:12527] 0 0 0 0.035 0.834 ...
##  $ mcwda10   : num [1:12527] 43.9 43.9 43.9 43.9 43.9 ...
##  $ loge_roads: num [1:12527] 4.39 4.46 4.44 4.43 4.45 ...
##  $ loge_ports: num [1:12527] 5.93 5.93 5.93 5.94 5.94 ...
##  $ loge_airpo: num [1:12527] 5.42 5.41 5.39 5.37 5.35 ...
##  $ loge_railw: num [1:12527] 5.39 5.37 5.36 5.35 5.33 ...
##  $ loge_hidro: num [1:12527] 4.7 4.62 4.5 4.36 4.15 ...
##  $ loge_river: num [1:12527] 4.31 4.35 4.32 4.31 4.12 ...
##  $ loge_beef : num [1:12527] 4.94 4.98 5.03 5.07 5.1 ...
```

```
##  $ loge_wood : num [1:12527] 5.33 5.32 5.31 5.31 5.3 ...
##  $ loge_soysu: num [1:12527] 5.08 5.11 5.13 5.15 5.18 ...
##  $ loge_min  : num [1:12527] 5.07 5.07 5.08 5.08 5.09 ...
##  $ loge_urb10: num [1:12527] 4.69 4.77 4.75 4.73 4.72 ...
##  $ loge_conpo: num [1:12527] 6.15 6.15 6.14 6.14 6.15 ...
##  $ loge_conmk: num [1:12527] 6.37 6.39 6.39 6.39 6.4 ...
##  $ pland_s_06: num [1:12527] 0.0429 0.0429 0.0429 0.0429 0.0429 ...
##  $ pland_m_06: num [1:12527] 10.2 10.2 10.2 10.2 10.2 ...
##  $ pland_b_06: num [1:12527] 89.8 89.8 89.8 89.8 89.8 ...
##  $ pprop_s_06: num [1:12527] 2.46 2.46 2.46 2.46 2.46 ...
##  $ pprop_m_06: num [1:12527] 66.6 66.6 66.6 66.6 66.6 ...
##  $ pprop_b_06: num [1:12527] 30.9 30.9 30.9 30.9 30.9 ...
##  $ plan_s_17 : num [1:12527] 0.0468 0.0468 0.0468 0.0468 0.0468 ...
##  $ plan_m_17 : num [1:12527] 12.8 12.8 12.8 12.8 12.8 ...
##  $ plan_b_17 : num [1:12527] 87.1 87.1 87.1 87.1 87.1 ...
##  $ ppro_s_17 : num [1:12527] 4.77 4.77 4.77 4.77 4.77 ...
##  $ ppro_m_17 : num [1:12527] 61.6 61.6 61.6 61.6 61.6 ...
##  $ ppro_b_17 : num [1:12527] 33.6 33.6 33.6 33.6 33.6 ...
##  $ c_sett10  : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_nusett10: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ucspas10: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ucspas16: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_apa10   : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_apa16   : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ucpi10  : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ucpi16  : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ussapa10: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_ussapa16: num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ c_allAMZ  : num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
##  $ vnl_1     : num [1:12527] 0.666 0.843 0.313 0 0 ...
##  $ vnl_2     : num [1:12527] 0.334 0.157 0.687 1 0 ...
##  $ vs10_1    : num [1:12527] 0.0259 0.013 0.0162 0.0316 0.0587 ...
##  $ vs10_2    : num [1:12527] 0.0385 0.0197 0.0161 0.0465 0.0535 ...
##  $ vs15_1    : num [1:12527] 0.02838 0.01438 0.00538 0.06004 0.02208 ...
##  $ vs15_2    : num [1:12527] 0.0563 0.0262 0.0198 0.0589 0.0521 ...
##  $ vs18_1    : num [1:12527] 0.019 0.0145 0.0087 0.0419 0.0179 ...
##  $ vs18_2    : num [1:12527] 0.0384 0.0225 0.0162 0.0478 0.0363 ...
##  $ lvs10_1   : num [1:12527] -1.58 -1.88 -1.79 -1.5 -1.23 ...
##  $ lvs10_2   : num [1:12527] -1.41 -1.7 -1.79 -1.33 -1.27 ...
##  $ lvs15_1   : num [1:12527] -1.55 -1.84 -2.26 -1.22 -1.65 ...
##  $ lvs15_2   : num [1:12527] -1.25 -1.58 -1.7 -1.23 -1.28 ...
##  $ lvs18_1   : num [1:12527] -1.72 -1.83 -2.06 -1.38 -1.74 ...
##  $ lvs18_2   : num [1:12527] -1.41 -1.65 -1.79 -1.32 -1.44 ...
##  $ Dvs1_10_15: num [1:12527] 0.00244 0.00133 -0.01077 0.02847 -0.03666 ...
##  $ Dvs2_10_15: num [1:12527] 0.01786 0.00648 0.00369 0.0124 -0.00142 ...
##   [list output truncated]
```

We can similarly display the structure as a list with the "ls.str" command:

```
ls.str(data.set)
```

```
## ad_pmv1 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## ad_pmv2 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## ag_apt_MBB :  num [1:12527] 1 1 1 0.965 0.166 ...
## ag_apt_MMA :  num [1:12527] 0 0 0 0.035 0.834 ...
## ag_slope_1 :  num [1:12527] 0.252 0.507 0.74 0.714 0.704 ...
## ag_slope_2 :  num [1:12527] 0.366 0.439 0.252 0.265 0.274 ...
## ag_slope_3 :  num [1:12527] 0.1781 0.0325 0.005 0.0213 0.0219 ...
## ag_slope_4 :  num [1:12527] 0.16312 0.01875 0.00313 0 0 ...
## ag_slope_5 :  num [1:12527] 0.04063 0.00313 0 0 0 ...
## ag_slope_6 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## agric10 :  num [1:12527] 0 0 0.0563 0 0 ...
## agric14 :  num [1:12527] 0 0 0.0563 0 0 ...
## bioma :  chr [1:12527] "Amazonia" "Amazonia" "Amazonia" "Amazonia" "Amazonia" ...
## c_allAMZ :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_apa10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_apa16 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_nusett10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_sett10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ucpi10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ucpi16 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ucspas10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ucspas16 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ussapa10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## c_ussapa16 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## col :  num [1:12527] 349 350 351 352 353 354 336 337 338 339 ...
## Dva3_10_15 :  num [1:12527] -0.009436 0.00311 -0.000802 -0.005008 -0.02758 ...
## Dva3_15_18 :  num [1:12527] -0.00629 -0.01743 -0.01403 -0.02257 -0.0112 ...
## Dva4_10_15 :  num [1:12527] -0.01087 -0.01096 0.00789 -0.03577 0.06553 ...
## Dva4_15_18 :  num [1:12527] 0.0335 0.0209 0.0143 0.0517 0.0316 ...
## Dvs1_10_15 :  num [1:12527] 0.00244 0.00133 -0.01077 0.02847 -0.03666 ...
## Dvs1_15_18 :  num [1:12527] -0.009338 0.000161 0.003315 -0.018115 -0.004189 ...
## Dvs2_10_15 :  num [1:12527] 0.01786 0.00648 0.00369 0.0124 -0.00142 ...
## Dvs2_15_18 :  num [1:12527] -0.01787 -0.00366 -0.00361 -0.01113 -0.01575 ...
## fores10 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## fores14 :  num [1:12527] 0 0 0 0 0 0 0 0 0 0 ...
## geocodigo :  chr [1:12527] "1506708" "1506708" "1506708" "1506708" "1506708" "1506708" ...
## id :  chr [1:12527] "C349L519" "C350L519" "C351L519" "C352L519" "C353L519" ...
## loge_airpo :  num [1:12527] 5.42 5.41 5.39 5.37 5.35 ...
## loge_beef :  num [1:12527] 4.94 4.98 5.03 5.07 5.1 ...
## loge_conmk :  num [1:12527] 6.37 6.39 6.39 6.39 6.4 ...
## loge_conpo :  num [1:12527] 6.15 6.15 6.14 6.14 6.15 ...
## loge_hidro :  num [1:12527] 4.7 4.62 4.5 4.36 4.15 ...
## loge_min :  num [1:12527] 5.07 5.07 5.08 5.08 5.09 ...
## loge_ports :  num [1:12527] 5.93 5.93 5.93 5.94 5.94 ...
## loge_railw :  num [1:12527] 5.39 5.37 5.36 5.35 5.33 ...
## loge_river :  num [1:12527] 4.31 4.35 4.32 4.31 4.12 ...
## loge_roads :  num [1:12527] 4.39 4.46 4.44 4.43 4.45 ...
## loge_soysu :  num [1:12527] 5.08 5.11 5.13 5.15 5.18 ...
## loge_urb10 :  num [1:12527] 4.69 4.77 4.75 4.73 4.72 ...
## loge_wood :  num [1:12527] 5.33 5.32 5.31 5.31 5.3 ...
## lva10_3 :  num [1:12527] -0.277 -0.24 -0.171 -0.265 -0.158 ...
## lva10_4 :  num [1:12527] -0.39 -0.407 -0.531 -0.422 -0.743 ...
## lva15_3 :  num [1:12527] -0.285 -0.238 -0.172 -0.269 -0.175 ...
## lva15_4 :  num [1:12527] -0.401 -0.419 -0.52 -0.465 -0.608 ...
## lva18_3 :  num [1:12527] -0.291 -0.251 -0.181 -0.288 -0.183 ...
```

```
## lva18_4 :  num [1:12527] -0.366 -0.396 -0.5 -0.404 -0.556 ...
## lvs10_1 :  num [1:12527] -1.58 -1.88 -1.79 -1.5 -1.23 ...
## lvs10_2 :  num [1:12527] -1.41 -1.7 -1.79 -1.33 -1.27 ...
## lvs15_1 :  num [1:12527] -1.55 -1.84 -2.26 -1.22 -1.65 ...
## lvs15_2 :  num [1:12527] -1.25 -1.58 -1.7 -1.23 -1.28 ...
## lvs18_1 :  num [1:12527] -1.72 -1.83 -2.06 -1.38 -1.74 ...
## lvs18_2 :  num [1:12527] -1.41 -1.65 -1.79 -1.32 -1.44 ...
## mcwda10 :  num [1:12527] 43.9 43.9 43.9 43.9 43.9 ...
## mosc10 :  num [1:12527] 0.0625 0 0 0 0 ...
## mosc14 :  num [1:12527] 0.0706 0 0.2375 0 0 ...
## outh10 :  num [1:12527] 0 0 0 0 0 0.0175 0 0 0 0 ...
## outh14 :  num [1:12527] 0 0 0 0 0 0.0175 0 0 0 0 ...
## pastn10 :  num [1:12527] 0 0 0 0 0.145 ...
## pastn14 :  num [1:12527] 0 0 0 0 0.145 ...
## pastp10 :  num [1:12527] 0.48 0.4331 0.0938 0.3819 0.3275 ...
## pastp14 :  num [1:12527] 0.4844 0.4363 0.0938 0.3819 0.3275 ...
## plan_b_17 :  num [1:12527] 87.1 87.1 87.1 87.1 87.1 ...
## plan_m_17 :  num [1:12527] 12.8 12.8 12.8 12.8 12.8 ...
## plan_s_17 :  num [1:12527] 0.0468 0.0468 0.0468 0.0468 0.0468 ...
## pland_b_06 :  num [1:12527] 89.8 89.8 89.8 89.8 89.8 ...
## pland_m_06 :  num [1:12527] 10.2 10.2 10.2 10.2 10.2 ...
## pland_s_06 :  num [1:12527] 0.0429 0.0429 0.0429 0.0429 0.0429 ...
## ppro_b_17 :  num [1:12527] 33.6 33.6 33.6 33.6 33.6 ...
## ppro_m_17 :  num [1:12527] 61.6 61.6 61.6 61.6 61.6 ...
## ppro_s_17 :  num [1:12527] 4.77 4.77 4.77 4.77 4.77 ...
## pprop_b_06 :  num [1:12527] 30.9 30.9 30.9 30.9 30.9 ...
## pprop_m_06 :  num [1:12527] 66.6 66.6 66.6 66.6 66.6 ...
## pprop_s_06 :  num [1:12527] 2.46 2.46 2.46 2.46 2.46 ...
## row :  num [1:12527] 519 519 519 519 519 519 520 520 520 520 ...
## va10_3 :  num [1:12527] 0.528 0.575 0.674 0.543 0.695 ...
## va10_4 :  num [1:12527] 0.408 0.392 0.294 0.378 0.181 ...
## va10_5 :  num [1:12527] 1.69e-04 9.83e-05 8.02e-05 5.08e-04 1.19e-02 ...
## va15_3 :  num [1:12527] 0.518 0.578 0.673 0.538 0.667 ...
## va15_4 :  num [1:12527] 0.397 0.381 0.302 0.343 0.246 ...
## va15_5 :  num [1:12527] 1.78e-04 1.34e-04 8.02e-05 4.10e-04 1.21e-02 ...
## va18_3 :  num [1:12527] 0.512 0.561 0.659 0.515 0.656 ...
## va18_4 :  num [1:12527] 0.43 0.402 0.316 0.394 0.278 ...
## va18_5 :  num [1:12527] 1.34e-04 1.16e-04 8.02e-05 5.44e-04 1.16e-02 ...
## veg10 :  num [1:12527] 0.458 0.567 0.85 0.618 0.527 ...
## veg14 :  num [1:12527] 0.445 0.564 0.613 0.618 0.527 ...
## vnl_1 :  num [1:12527] 0.666 0.843 0.313 0 0 ...
## vnl_2 :  num [1:12527] 0.334 0.157 0.687 1 0 ...
## vs10_1 :  num [1:12527] 0.0259 0.013 0.0162 0.0316 0.0587 ...
## vs10_2 :  num [1:12527] 0.0385 0.0197 0.0161 0.0465 0.0535 ...
## vs15_1 :  num [1:12527] 0.02838 0.01438 0.00538 0.06004 0.02208 ...
## vs15_2 :  num [1:12527] 0.0563 0.0262 0.0198 0.0589 0.0521 ...
## vs18_1 :  num [1:12527] 0.019 0.0145 0.0087 0.0419 0.0179 ...
## vs18_2 :  num [1:12527] 0.0384 0.0225 0.0162 0.0478 0.0363 ...
```

We want to look at the structure of some specific variables, e.g. ‘secondary forest vegetation’, ‘agronomics’, ‘economics’, the number of observations in total, per variable and their data types:

```
str(data.set$loge_roadp)
```

```
## Warning: Unknown or uninitialised column: `loge_roadp`.
```

```
##  NULL
```

Once we have looked at the object, we can check a (statistical) summary of the data as follows:

```
summary(data.set)
```

```
##       id                  col             row         geocodigo
##  Length:12527       Min.   :259.0   Min.   :519.0   Length:12527
##  Class :character   1st Qu.:296.0   1st Qu.:556.0   Class :character
##  Mode  :character   Median :320.0   Median :585.0   Mode  :character
##                     Mean   :323.5   Mean   :584.2
##                     3rd Qu.:351.0   3rd Qu.:612.0
##                     Max.   :404.0   Max.   :656.0
##
##     bioma               veg10           pastn10            pastp10
##  Length:12527       Min.   :0.0000   Min.   :0.00000   Min.   :0.0000
##  Class :character   1st Qu.:0.3897   1st Qu.:0.00000   1st Qu.:0.0000
##  Mode  :character   Median :0.9481   Median :0.00000   Median :0.0000
##                     Mean   :0.7111   Mean   :0.02298   Mean   :0.1196
##                     3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.1113
##                     Max.   :1.0000   Max.   :1.00000   Max.   :1.0000
##
##     agric10             mosc10          fores10              outh10
##  Min.   :0.000000   Min.   :0.0000   Min.   :0.0000000   Min.   :0.000000
##  1st Qu.:0.000000   1st Qu.:0.0000   1st Qu.:0.0000000   1st Qu.:0.000000
##  Median :0.000000   Median :0.0000   Median :0.0000000   Median :0.000000
##  Mean   :0.003949   Mean   :0.0890   Mean   :0.0003851   Mean   :0.053036
##  3rd Qu.:0.000000   3rd Qu.:0.1059   3rd Qu.:0.0000000   3rd Qu.:0.000625
##  Max.   :0.639375   Max.   :1.0000   Max.   :0.6193750   Max.   :1.000000
##
##      veg14           pastn14            pastp14           agric14
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.0000   Min.   :0.000000
##  1st Qu.:0.3262   1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.000000
##  Median :0.9163   Median :0.00000   Median :0.0000   Median :0.000000
##  Mean   :0.6872   Mean   :0.02352   Mean   :0.1342   Mean   :0.004894
##  3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.1631   3rd Qu.:0.000000
##  Max.   :1.0000   Max.   :1.00000   Max.   :1.0000   Max.   :0.778125
##
##      mosc14            fores14              outh14             va10_3
##  Min.   :0.00000   Min.   :0.0000000   Min.   :0.000000   Min.   :0.0000
##  1st Qu.:0.00000   1st Qu.:0.0000000   1st Qu.:0.000000   1st Qu.:0.5807
##  Median :0.00000   Median :0.0000000   Median :0.000000   Median :0.9556
##  Mean   :0.09646   Mean   :0.0006529   Mean   :0.053036   Mean   :0.7731
##  3rd Qu.:0.12750   3rd Qu.:0.0000000   3rd Qu.:0.000625   3rd Qu.:0.9962
##  Max.   :1.00000   Max.   :0.7625000   Max.   :1.000000   Max.   :1.0000
##
##      va15_3            va18_3            va10_4              va15_4
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000000   Min.   :0.0000000
##  1st Qu.:0.5403   1st Qu.:0.5024   1st Qu.:0.0001426   1st Qu.:0.0001604
##  Median :0.9484   Median :0.9369   Median :0.0036801   Median :0.0041078
##  Mean   :0.7605   Mean   :0.7462   Mean   :0.1484585   Mean   :0.1504934
##  3rd Qu.:0.9958   3rd Qu.:0.9948   3rd Qu.:0.2101760   3rd Qu.:0.2314859
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000000   Max.   :1.0000000
##
##      va18_4             va10_5              va15_5              va18_5
##  Min.   :0.000000   Min.   :0.0000000   Min.   :0.0000000   Min.   :0.0000000
##  1st Qu.:0.000286   1st Qu.:0.0000000   1st Qu.:0.0000000   1st Qu.:0.0000000
##  Median :0.007066   Median :0.0004812   Median :0.0004826   Median :0.0004812
##  Mean   :0.161648   Mean   :0.0401332   Mean   :0.0401352   Mean   :0.0401318
##  3rd Qu.:0.261831   3rd Qu.:0.0065850   3rd Qu.:0.0065770   3rd Qu.:0.0065538
##  Max.   :1.000000   Max.   :1.0000000   Max.   :1.0000000   Max.   :1.0000000
```

```
##
##    Dva3_10_15          Dva3_15_18          Dva4_10_15
##  Min.   :-0.5035598   Min.   :-0.4448296   Min.   :-0.370370
##  1st Qu.:-0.0132903   1st Qu.:-0.0161837   1st Qu.:-0.001080
##  Median :-0.0008554   Median :-0.0018445   Median : 0.000000
##  Mean   :-0.0125780   Mean   :-0.0143706   Mean   : 0.002035
##  3rd Qu.:-0.0000178   3rd Qu.:-0.0000894   3rd Qu.: 0.001684
##  Max.   : 0.3703704   Max.   : 0.1620795   Max.   : 0.502865
##
##    Dva4_15_18           lva10_3             lva15_3
##  Min.   :-0.2733437   Min.   :-4.000000   Min.   :-4.000000
##  1st Qu.:-0.0000179   1st Qu.:-0.235965   1st Qu.:-0.267311
##  Median : 0.0003128   Median :-0.019659   Median :-0.022959
##  Mean   : 0.0111547   Mean   :-0.186651   Mean   :-0.198253
##  3rd Qu.: 0.0122392   3rd Qu.:-0.001595   3rd Qu.:-0.001772
##  Max.   : 0.4328090   Max.   : 0.000043   Max.   : 0.000043
##
##     lva18_3            lva10_4             lva15_4
##  Min.   :-4.000000   Min.   :-4.000000   Min.   :-4.000000
##  1st Qu.:-0.298858   1st Qu.:-3.615162   1st Qu.:-3.584372
##  Median :-0.028271   Median :-2.422496   Median :-2.375943
##  Mean   :-0.212460   Mean   :-2.195954   Mean   :-2.166745
##  3rd Qu.:-0.002216   3rd Qu.:-0.677210   3rd Qu.:-0.635288
##  Max.   : 0.000043   Max.   : 0.000043   Max.   : 0.000043
##
##     lva18_4            ag_slope_1        ag_slope_2       ag_slope_3
##  Min.   :-4.000000   Min.   :0.00000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:-3.413418   1st Qu.:0.00750   1st Qu.:0.2231   1st Qu.:0.1500
##  Median :-2.144713   Median :0.04562   Median :0.4456   Median :0.2938
##  Mean   :-2.055448   Mean   :0.12473   Mean   :0.4145   Mean   :0.3104
##  3rd Qu.:-0.581813   3rd Qu.:0.16750   3rd Qu.:0.6031   3rd Qu.:0.4606
##  Max.   : 0.000043   Max.   :1.00000   Max.   :0.9094   Max.   :0.8013
##
##    ag_slope_4        ag_slope_5          ag_slope_6           ag_apt_MBB
##  Min.   :0.00000   Min.   :0.000000   Min.   :0.0000000   Min.   :0.0000
##  1st Qu.:0.00625   1st Qu.:0.000000   1st Qu.:0.0000000   1st Qu.:0.0000
##  Median :0.07062   Median :0.000625   Median :0.0000000   Median :1.0000
##  Mean   :0.13979   Mean   :0.010395   Mean   :0.0001888   Mean   :0.6965
##  3rd Qu.:0.21937   3rd Qu.:0.007500   3rd Qu.:0.0000000   3rd Qu.:1.0000
##  Max.   :0.83437   Max.   :0.307500   Max.   :0.0387500   Max.   :1.0000
##
##    ag_apt_MMA        mcwda10          loge_roads        loge_ports
##  Min.   :0.0000   Min.   :  0.00   Min.   :0.8688   Min.   :3.340
##  1st Qu.:0.0000   1st Qu.: 68.39   1st Qu.:4.2943   1st Qu.:5.253
##  Median :0.0000   Median : 81.21   Median :4.7064   Median :5.483
##  Mean   :0.2986   Mean   : 90.72   Mean   :4.5916   Mean   :5.427
##  3rd Qu.:1.0000   3rd Qu.:106.87   3rd Qu.:4.9903   3rd Qu.:5.657
##  Max.   :1.0000   Max.   :213.91   Max.   :5.4515   Max.   :5.944
##
##    loge_airpo      loge_railw      loge_hidro      loge_river
##  Min.   :3.101   Min.   :2.600   Min.   :1.946   Min.   :1.200
##  1st Qu.:5.093   1st Qu.:4.871   1st Qu.:4.790   1st Qu.:3.458
##  Median :5.298   Median :5.146   Median :5.176   Median :3.835
##  Mean   :5.252   Mean   :5.060   Mean   :5.049   Mean   :3.749
##  3rd Qu.:5.476   3rd Qu.:5.341   3rd Qu.:5.436   3rd Qu.:4.118
##  Max.   :5.740   Max.   :5.623   Max.   :5.747   Max.   :4.819
```

```
##                                  NA's   :2
##    loge_beef       loge_wood       loge_soysu       loge_min
##  Min.   :3.285   Min.   :2.707   Min.   :3.628   Min.   :2.722
##  1st Qu.:5.149   1st Qu.:4.883   1st Qu.:5.502   1st Qu.:4.450
##  Median :5.482   Median :5.124   Median :5.660   Median :4.711
##  Mean   :5.423   Mean   :5.089   Mean   :5.604   Mean   :4.661
##  3rd Qu.:5.760   3rd Qu.:5.346   3rd Qu.:5.762   3rd Qu.:4.914
##  Max.   :6.080   Max.   :5.750   Max.   :5.913   Max.   :5.359
##
##    loge_urb10      loge_conpo      loge_conmk      pland_s_06
##  Min.   :2.480   Min.   :4.305   Min.   :6.261   Min.   : 0.0000
##  1st Qu.:4.550   1st Qu.:5.824   1st Qu.:6.428   1st Qu.: 0.1192
##  Median :4.869   Median :6.047   Median :6.524   Median : 0.2534
##  Mean   :4.826   Mean   :6.004   Mean   :6.517   Mean   : 0.7946
##  3rd Qu.:5.151   3rd Qu.:6.236   3rd Qu.:6.600   3rd Qu.: 1.2033
##  Max.   :5.656   Max.   :6.585   Max.   :6.834   Max.   :28.5589
##                  NA's   :1       NA's   :1
##    pland_m_06        pland_b_06      pprop_s_06        pprop_m_06
##  Min.   : 0.6001   Min.   :11.79   Min.   : 0.7353   Min.   : 1.625
##  1st Qu.: 5.4181   1st Qu.:70.24   1st Qu.: 7.7590   1st Qu.:34.268
##  Median :14.5282   Median :84.65   Median :16.2466   Median :48.638
##  Mean   :17.2260   Mean   :81.98   Mean   :20.0528   Mean   :47.050
##  3rd Qu.:28.5293   3rd Qu.:94.50   3rd Qu.:29.1899   3rd Qu.:61.744
##  Max.   :84.3956   Max.   :99.39   Max.   :95.2733   Max.   :84.435
##
##    pprop_b_06       plan_s_17          plan_m_17        plan_b_17
##  Min.   : 1.213   Min.   :  0.0000   Min.   : 0.000   Min.   : 0.00
##  1st Qu.:21.243   1st Qu.:  0.1226   1st Qu.: 5.845   1st Qu.:61.56
##  Median :28.211   Median :  0.2472   Median :14.510   Median :84.34
##  Mean   :32.898   Mean   :  2.1707   Mean   :20.696   Mean   :77.13
##  3rd Qu.:43.384   3rd Qu.:  1.5687   3rd Qu.:34.732   3rd Qu.:93.67
##  Max.   :76.790   Max.   :100.0000   Max.   :82.683   Max.   :99.62
##
##    ppro_s_17          ppro_m_17       ppro_b_17        c_sett10
##  Min.   :  0.4073   Min.   : 0.00   Min.   : 0.00   Min.   :0.00000
##  1st Qu.:  9.6419   1st Qu.:36.13   1st Qu.:15.45   1st Qu.:0.00000
##  Median : 16.9452   Median :47.13   Median :31.79   Median :0.00000
##  Mean   : 24.5393   Mean   :44.65   Mean   :30.81   Mean   :0.04235
##  3rd Qu.: 35.1852   3rd Qu.:55.64   3rd Qu.:40.87   3rd Qu.:0.00000
##  Max.   :100.0000   Max.   :82.85   Max.   :73.69   Max.   :1.00000
##
##    c_nusett10        c_ucspas10        c_ucspas16        c_apa10
##  Min.   :0.00000   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000
##  Median :0.00000   Median :0.0000   Median :0.0000   Median :0.00000
##  Mean   :0.01267   Mean   :0.3473   Mean   :0.3473   Mean   :0.07168
##  3rd Qu.:0.00000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000
##  Max.   :1.00000   Max.   :1.0000   Max.   :1.0000   Max.   :1.00000
##
##     c_apa16           c_ucpi10          c_ucpi16          c_ussapa10
##  Min.   :0.00000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.00000   Median :0.0000   Median :0.0000   Median :0.0000
##  Mean   :0.07168   Mean   :0.1021   Mean   :0.1022   Mean   :0.1496
##  3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :1.00000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
```

```
##
##    c_ussapa16        c_allAMZ          vnl_1           vnl_2
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000
##  Median :0.0000   Median :1.0000   Median :0.000   Median :0.0000
##  Mean   :0.1501   Mean   :0.5485   Mean   :0.291   Mean   :0.3525
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.000   Max.   :1.0000
##                   NA's   :1
##      vs10_1              vs10_2              vs15_1              vs15_2
##  Min.   :0.0000000   Min.   :0.000000   Min.   :0.0000000   Min.   :0.000000
##  1st Qu.:0.0001158   1st Qu.:0.001078   1st Qu.:0.0001549   1st Qu.:0.001350
##  Median :0.0018356   Median :0.005845   Median :0.0023881   Median :0.007806
##  Mean   :0.0139675   Mean   :0.024315   Mean   :0.0196384   Mean   :0.029186
##  3rd Qu.:0.0182490   3rd Qu.:0.028697   3rd Qu.:0.0272806   3rd Qu.:0.036471
##  Max.   :0.3132814   Max.   :0.565462   Max.   :0.3254177   Max.   :0.644099
##
##      vs18_1              vs18_2             lvs10_1            lvs10_2
##  Min.   :0.0000000   Min.   :0.000000   Min.   :-4.0000   Min.   :-4.0000
##  1st Qu.:0.0003396   1st Qu.:0.001341   1st Qu.:-3.6659   1st Qu.:-2.9288
##  Median :0.0049187   Median :0.008385   Median :-2.7132   Median :-2.2258
##  Mean   :0.0221733   Mean   :0.029871   Mean   :-2.6768   Mean   :-2.2665
##  3rd Qu.:0.0349374   3rd Qu.:0.039448   3rd Qu.:-1.7364   3rd Qu.:-1.5407
##  Max.   :0.3044331   Max.   :0.697991   Max.   :-0.5039   Max.   :-0.2475
##
##     lvs15_1            lvs15_2           lvs18_1            lvs18_2
##  Min.   :-4.0000   Min.   :-4.000   Min.   :-4.0000   Min.   :-4.0000
##  1st Qu.:-3.5958   1st Qu.:-2.839   1st Qu.:-3.3569   1st Qu.:-2.8415
##  Median :-2.6043   Median :-2.102   Median :-2.2994   Median :-2.0714
##  Mean   :-2.5630   Mean   :-2.175   Mean   :-2.4086   Mean   :-2.1630
##  3rd Qu.:-1.5627   3rd Qu.:-1.437   3rd Qu.:-1.4555   3rd Qu.:-1.4029
##  Max.   :-0.4874   Max.   :-0.191   Max.   :-0.5164   Max.   :-0.1561
##  NA's   :1
##    Dvs1_10_15            Dvs2_10_15            Dvs1_15_18
##  Min.   :-0.2683270   Min.   :-0.1504121   Min.   :-0.2703141
##  1st Qu.:-0.0001069   1st Qu.: 0.0000000   1st Qu.:-0.0000980
##  Median : 0.0001158   Median : 0.0003754   Median : 0.0002681
##  Mean   : 0.0056708   Mean   : 0.0048714   Mean   : 0.0025352
##  3rd Qu.: 0.0056170   3rd Qu.: 0.0055692   3rd Qu.: 0.0043661
##  Max.   : 0.3025529   Max.   : 0.2251548   Max.   : 0.2684601
##                                            NA's   :1
##    Dvs2_15_18            ad_pmv1           ad_pmv2
##  Min.   :-0.2155848   Min.   :0.00000   Min.   :0.0000
##  1st Qu.:-0.0004010   1st Qu.:0.00000   1st Qu.:0.0000
##  Median : 0.0000000   Median :0.00000   Median :0.0000
##  Mean   : 0.0006831   Mean   :0.08725   Mean   :0.2215
##  3rd Qu.: 0.0012472   3rd Qu.:0.00000   3rd Qu.:0.0000
##  Max.   : 0.2557719   Max.   :1.00000   Max.   :1.0000
##  NA's   :1
```

Organizing the Dataset

Add subsets as new columns to the dataset

```
df <- data.set %>% mutate(Lvs1_10_15 = ifelse(Dvs1_10_15 < 0, Dvs1_10_15, 0),
                                          Gvs1_10_15 = ifelse(Dvs1_10_15 > 0, Dvs1_10_15, 0),
                                          Lvs2_10_15 = ifelse(Dvs2_10_15 < 0, Dvs2_10_15, 0),
                                          Gvs2_10_15 = ifelse(Dvs2_10_15 > 0, Dvs2_10_15, 0),
                                          Lvs1_15_18 = ifelse(Dvs1_15_18 < 0, Dvs1_15_18, 0),
                                          Gvs1_15_18 = ifelse(Dvs1_15_18 > 0, Dvs1_15_18, 0),
                                          Lvs2_15_18 = ifelse(Dvs2_15_18 < 0, Dvs2_15_18, 0),
                                          Gvs2_15_18 = ifelse(Dvs2_15_18 > 0, Dvs2_15_18, 0))
```

CLEAN DE NAs

```
df.na <- na.omit(df)
```

CLEAN TEXTUAL/DESCRIPTIVE COLLUMNS

```
cs <- df.na[,-c(1:5)]
```

Data Analysis

1 – one ‘multi’ reg with all the candidate variables against the time interval Lvs1_10_15

```
regLvs1 <- lm (

  Lvs1_10_15    ~

    veg10   +

    va10_4  +

    ag_slope_1  +

    ag_slope_4  +

    ag_apt_MBB  +

    ag_apt_MMA  +

    mcwda10 +

    loge_roads  +

    loge_ports  +

    loge_airpo  +

    loge_railw  +

    loge_hidro  +

    loge_river  +

    loge_beef   +

    loge_wood   +

    loge_soysu  +

    loge_urb10  +

    loge_conmk  +

    pprop_s_06  +

    pprop_m_06  +

    pprop_b_06  +

    c_sett10    +

    c_nusett10  +

    c_ucspas10  +

    c_apa10 +

    c_ucpi10    +
```

```
    c_ussapa10  +

    c_allAMZ    +

    vnl_1   +

    ad_pmv1 ,

  cs)



summary(regLvs1)
```

```
##
## Call:
## lm(formula = Lvs1_10_15 ~ veg10 + va10_4 + ag_slope_1 + ag_slope_4 +
##     ag_apt_MBB + ag_apt_MMA + mcwda10 + loge_roads + loge_ports +
##     loge_airpo + loge_railw + loge_hidro + loge_river + loge_beef +
##     loge_wood + loge_soysu + loge_urb10 + loge_conmk + pprop_s_06 +
##     pprop_m_06 + pprop_b_06 + c_sett10 + c_nusett10 + c_ucspas10 +
##     c_apa10 + c_ucpi10 + c_ussapa10 + c_allAMZ + vnl_1 + ad_pmv1,
##     data = cs)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.257098 -0.000505  0.000663  0.002216  0.015278
##
## Coefficients: (1 not defined because of singularities)
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.101e-02  7.648e-03  -1.440 0.149940
## veg10        2.878e-03  4.157e-04   6.924 4.61e-12 ***
## va10_4       3.648e-03  6.619e-04   5.511 3.63e-08 ***
## ag_slope_1   2.147e-04  5.723e-04   0.375 0.707578
## ag_slope_4   1.013e-03  5.126e-04   1.976 0.048223 *
## ag_apt_MBB  -4.303e-03  1.012e-03  -4.252 2.13e-05 ***
## ag_apt_MMA  -4.426e-03  1.016e-03  -4.358 1.32e-05 ***
## mcwda10      2.377e-05  2.929e-06   8.116 5.27e-16 ***
## loge_roads   1.329e-03  2.193e-04   6.060 1.40e-09 ***
## loge_ports   2.787e-03  4.503e-04   6.190 6.21e-10 ***
## loge_airpo  -1.454e-03  3.847e-04  -3.780 0.000158 ***
## loge_railw   1.843e-03  2.443e-04   7.542 4.95e-14 ***
## loge_hidro  -1.998e-03  2.070e-04  -9.651  < 2e-16 ***
## loge_river  -6.278e-04  1.466e-04  -4.282 1.87e-05 ***
## loge_beef   -1.556e-03  3.267e-04  -4.762 1.94e-06 ***
## loge_wood    8.347e-05  3.499e-04   0.239 0.811469
## loge_soysu   5.229e-03  5.018e-04  10.419  < 2e-16 ***
## loge_urb10  -3.325e-05  3.559e-04  -0.093 0.925548
## loge_conmk  -3.553e-03  1.398e-03  -2.542 0.011048 *
## pprop_s_06   4.211e-06  6.097e-06   0.691 0.489762
## pprop_m_06  -3.781e-06  5.463e-06  -0.692 0.488877
## pprop_b_06          NA         NA      NA       NA
## c_sett10     1.046e-04  5.019e-04   0.208 0.834881
## c_nusett10  -6.333e-03  9.286e-04  -6.820 9.52e-12 ***
## c_ucspas10   1.412e-03  3.378e-04   4.181 2.93e-05 ***
## c_apa10      1.817e-03  3.385e-04   5.368 8.11e-08 ***
## c_ucpi10    -1.704e-04  2.863e-04  -0.595 0.551637
## c_ussapa10   1.322e-03  3.499e-04   3.779 0.000158 ***
## c_allAMZ     3.725e-04  2.554e-04   1.458 0.144756
## vnl_1       -1.743e-03  2.311e-04  -7.541 4.98e-14 ***
## ad_pmv1     -1.744e-03  2.687e-04  -6.492 8.78e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.007596 on 12494 degrees of freedom
## Multiple R-squared:  0.1017, Adjusted R-squared:  0.09957
## F-statistic: 48.75 on 29 and 12494 DF,  p-value: < 2.2e-16
```

Considering that values of difference across time intervals are too small, the regressions didn’t show a decent R square (a question to be discussed with the supervisors!). Said that, we approached different ways to address these factors, using a dependent variable that is fixed over time (vs10_1).

2 – one linear simple reg with 1 explanatory variable and a plot

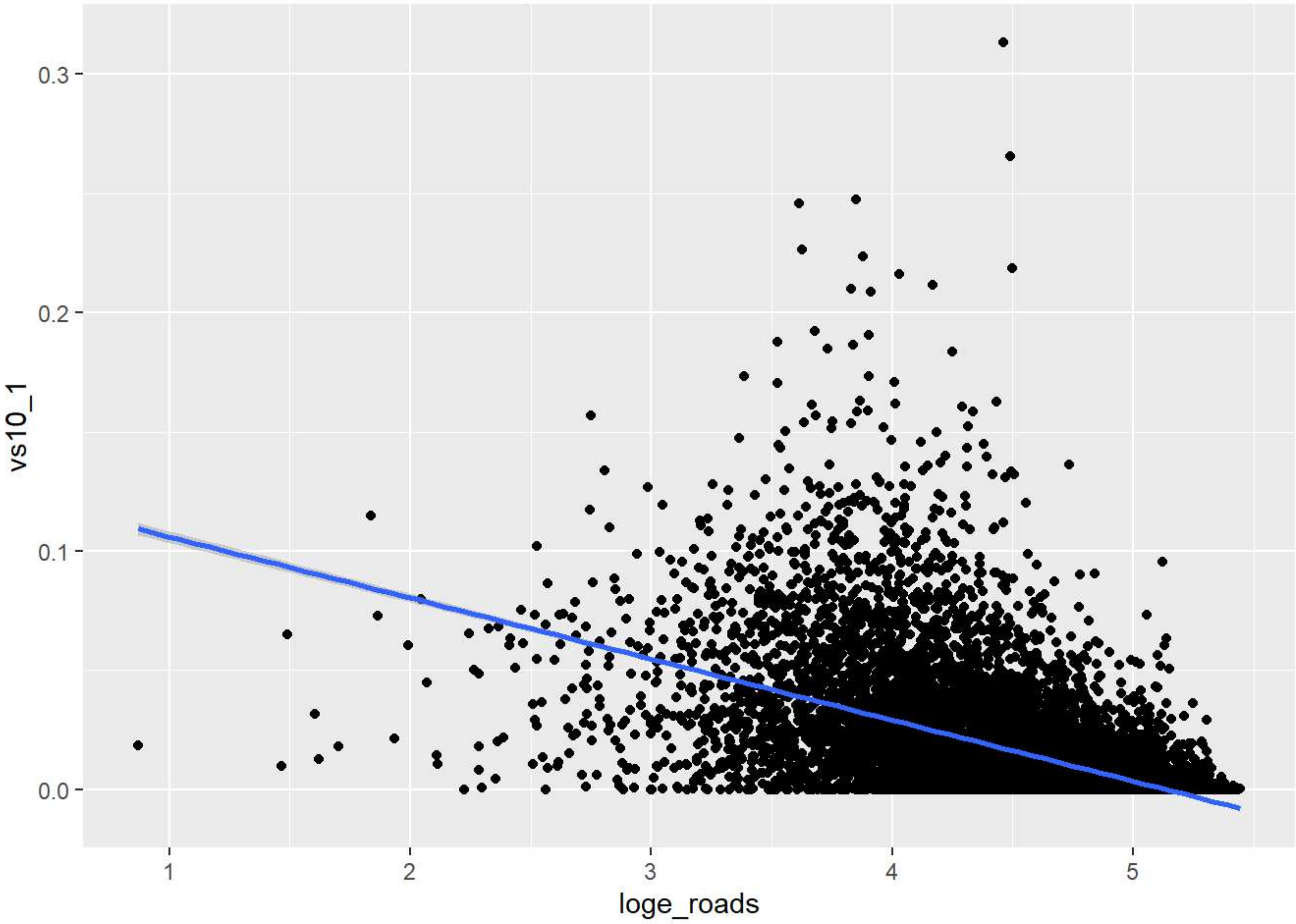
```
reg0 <- lm(vs10_1 ~ loge_roads, cs  )

summary(reg0)
```

```
##
## Call:
## lm(formula = vs10_1 ~ loge_roads, data = cs)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.090688 -0.009623 -0.002783  0.003619  0.295986
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1314856  0.0016270   80.81   <2e-16 ***
## loge_roads  -0.0255940  0.0003521  -72.70   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02064 on 12522 degrees of freedom
## Multiple R-squared:  0.2968, Adjusted R-squared:  0.2967
## F-statistic:  5285 on 1 and 12522 DF,  p-value: < 2.2e-16
```

```
ggplot (reg0, aes(y=vs10_1,x=loge_roads)) + geom_point() + geom_smooth (method="lm")
```

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



In this one we isolated a single explanatory variable with an ‘easy-to-get’ causal relationship. We can see a significative influence of distance to roads to the extent of secondary vegetation from 1 to 5 years old in 2010 (fixed year), with an inverse correlation, meaning the more proximity to roads the less vegetation we have. This was a simple one!

3- linear reg with an added factor (pmv) with a plot

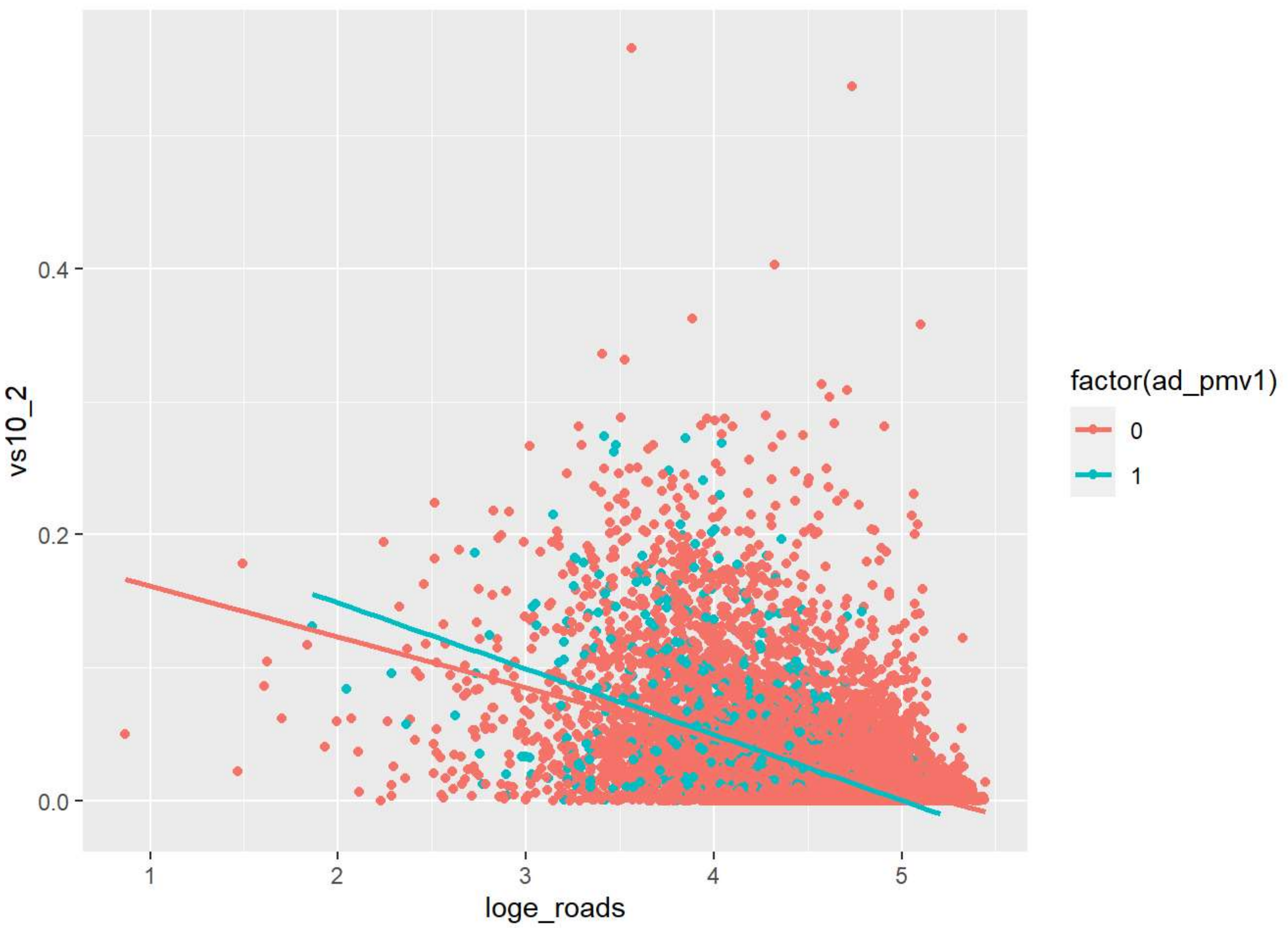
```
reg10 <- lm(vs10_1 ~ loge_roads + ad_pmv1, cs   )

summary(reg10)
```

```
##
## Call:
## lm(formula = vs10_1 ~ loge_roads + ad_pmv1, data = cs)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.090503 -0.009657 -0.002781  0.003635  0.296045
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1312698  0.0016434  79.878   <2e-16 ***
## loge_roads  -0.0255586  0.0003541 -72.179   <2e-16 ***
## ad_pmv1      0.0006129  0.0006571   0.933    0.351
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02064 on 12521 degrees of freedom
## Multiple R-squared:  0.2968, Adjusted R-squared:  0.2967
## F-statistic:  2643 on 2 and 12521 DF,  p-value: < 2.2e-16
```

```
ggplot(cs,aes(y=vs10_2,x=loge_roads,color=factor(ad_pmv1)))+geom_point()+stat_smooth(method
="lm",se=FALSE)
```

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



Here we can see again the same relatioship but with a dummy for the PMV added. This was not significant to the treatment, which makes a lot of sense since PMV doesn’t state anything about roads!

```
reg11 <- lm(vs10_1 ~ veg10 + ad_pmv1, cs    )

summary(reg11)
```

```
##
## Call:
## lm(formula = vs10_1 ~ veg10 + ad_pmv1, data = cs)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.047163 -0.004589 -0.001480  0.001058  0.277686
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.0434210  0.0003750 115.798  < 2e-16 ***
## veg10       -0.0418788  0.0004612 -90.796  < 2e-16 ***
## ad_pmv1      0.0037423  0.0006041   6.195 6.02e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01907 on 12521 degrees of freedom
## Multiple R-squared:  0.3996, Adjusted R-squared:  0.3995
## F-statistic:  4166 on 2 and 12521 DF,  p-value: < 2.2e-16
```

```
ggplot(cs,aes(y=vs10_2,x=veg10,color=factor(ad_pmv1)))+geom_point()+stat_smooth(method="lm",s
e=FALSE)
```

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

On the other hand, when repeating the same test with a different explanatory variable, now the total amount of old growth forests (veg10) things change a little bit: the inclusion of municipalities in the PMV appears to be a significant factor!

4 – one ‘multi’ reg with the fixed value (vs10_1) and up to six explanatory variables and a plot

```
reg2 <- lm(vs10_1 ~ veg10   +

             va10_4 +

             ag_slope_1 +loge_roads +

             loge_ports +

             loge_airpo + c_allAMZ  +

             vnl_1, cs)



summary(reg2)
```

```
##
## Call:
## lm(formula = vs10_1 ~ veg10 + va10_4 + ag_slope_1 + loge_roads +
##     loge_ports + loge_airpo + c_allAMZ + vnl_1, data = cs)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.058478 -0.007208 -0.000833  0.004070  0.277890
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1115901  0.0041904  26.630  < 2e-16 ***
## veg10       -0.0269930  0.0009067 -29.770  < 2e-16 ***
## va10_4       0.0046461  0.0013592   3.418 0.000632 ***
## ag_slope_1  -0.0216550  0.0010320 -20.983  < 2e-16 ***
## loge_roads  -0.0091005  0.0004026 -22.605  < 2e-16 ***
## loge_ports  -0.0100390  0.0006687 -15.013  < 2e-16 ***
## loge_airpo   0.0037066  0.0006676   5.552 2.88e-08 ***
## c_allAMZ    -0.0033551  0.0004210  -7.969 1.74e-15 ***
## vnl_1        0.0076417  0.0005302  14.414  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01765 on 12515 degrees of freedom
## Multiple R-squared:  0.4859, Adjusted R-squared:  0.4856
## F-statistic:  1479 on 8 and 12515 DF,  p-value: < 2.2e-16
```

When adding variables from different categories, testing a multivariate linear regression aiming at explaining change in vs10_1, the results show a significant role for those variables with a good R square.

Thanks for joining us :)

We <3 R!