

Global Drivers of Natural Forest Loss: a visual workflow for functions in the *caroline* R-package (Version 1.1.2)

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1 Introduction

Beyond use for lumber and paper products, trees provide a host of other direct and indirect benefits to human-kind. Beside from the personal benefits—bestowing us with shade and a pleasing aesthetic to our everyday visual backdrop—they can also do the more patiently earnest work of protecting fauna, preventing erosion, buffering the water-table, as well as performing many other ecosystem services, including both the production of the oxygen we breathe and the uptake of carbon-dioxide (acting as a net-CO₂ sink) [1] [2] [3] [4]. Unfortunately, the world’s forests are being depleted almost entirely due to human behaviors [5]. These activities include: clearing land to feed our growing population (eg, *agriculture*), housing people by restructuring felled [woody] vegetation (eg, *logging*), powering our increasingly technology [machine & computer] driven industries (eg, *mining*), and indirectly as a result of ([anthropogenic] global-warming fueled) *wildfires*.

Here I showcase the data science (esp. plotting) tools in the *caroline* (R [9]) package (version 1.1.2) [11] that can serve to uncover these biodiversity-imperiling factors. Such degradations are escalating—not only from the Holocene into the Anthropocene (esp. agriculture), but also this century—especially in certain continents, nations, and jungles—as explored here by way of analyzing the Global Forest Watch dataset [6] [7] [8]. In the following pages, I spotlight these evolving quandaries while expounding upon the principal findings previewed above. Most notably that—while several African ([D.]R. Congo, & Madagascar) and South American countries (Brazil, Peru, Bolivia, & Venezuela) have recently approached the highest of world-wide [tropical] forest loss numbers—South [East] Asian nations (Indonesia, Malaysia, Laos, Myanmar, India) and Oceania (Papua New Guinea) may be on a trajectory for [collectively] superseding such extreme [especially extractive] losses in more current decades. Furthermore, mining and (especially) wildfire appear to be gaining on logging and agriculture, both of which have begun to flatten slightly over the past decade. These findings are previewed below via demonstration of the many useful functions built into the package (eg, multi-variable plots that can help untangle confounding).

Such an analysis function, debuting here as the ‘sparse plot’, combines modern plotting innovations with the archetype of distributional summary schema: the boxplot [10]. Other canonical functions, such as `stem()` & `leaf` plots and `rug()` representations, contrast to any such abstraction by instead revealing unadulterated, datum-level detail of entire distributions—but are therefore also limited by space constraints (character/line limits or [1-D] overplotting) that restrict their utility to only smaller datasets. A more concise work-around for these shortcomings, such as in the `stripchart()` [12], may utilize calls to `jitter()` to venture beyond 1-D and broaden distributional swaths into wide strips—so as to alleviate any obscurity arising from superposition (albeit still width-limited in larger datasets). Because 1-D & 2-D planar shapes—in both *violins* and to the `boxplot` itself—may abstract-away often important point-level detail, newer plots have migrated toward jitter-like approaches, where all points are splayed out flat in this extra pseudo-dimension (eg, violin-shaped `sina()` and bush-like `beeswarm()` plots). Like the hybrid approach of the `vioplot()`, even more recent successors may deploy a minimalistic ribbon of `rug()`—as in the `beanplot()` [13]—or a thin quantile box along or inside polygons or points—as in the three-pronged approach of `raincloud()` plots [15]. Many of the above, however, like their `stem()` & `rug()` predecessors, may still tend to over-occupy [axis-orthogonal] space or inevitably break-down when attempting to visualize all points of a larger dataset.

My own data-point accommodating innovation, `plot.sparse()`, also succeeds in revealing myriad possible subtleties underlying distributional density, but in a more efficiently compact way (via narrow rectangular strips of point-nebula). It accomplishes this primarily by leveraging the broad continuum of possible shades of overlapping translucent points, thus circumventing engineering difficulties of smoothing or positioning algorithms en route. The added essentialistic scaffolding of a boxplot (with auto-adjusting grayscale-shaded outlines) overlaid atop the underlying data, acts as a quantitative visual guide in alleviation of any coordinate opacity. This becomes especially helpful in more congested areas—with the overlay importantly demarcating, not only the quartiles [& median]—but also the whiskers, and thus also, conversely, the many possible outliers that spill out-of-bounds—often an artifact of the immense array of possible values which are so routinely generated by automated systems, increasingly typical in our data-abundant era.

2 Software

```
> # wget https://cran.r-project.org/src/contrib/Archive/caroline/caroline_1.1.2.tar.gz  
> # R CMD INSTALL caroline_1.0.1.tar.gz
```

Building the *caroline* package from source can be easily done by downloading from CRAN. Installation can typically be accomplished via the following commands from within the R command line environment:

```
install.packages('caroline')
```

After a successful installation the *caroline* package can be loaded in the normal way: by starting R and invoking the following `library` command:

```
> library(caroline)
```

No other software is required! The `sparge` function (dissimilar to many analogous functions: *vioplot()*, *sinaplot*, *beeswarm()*, *beanplot()*, *raincloud()*) is efficiently coded—and lightweight, in not depending on any other software packages (eg, *tidyr*, *dplyr*, *plotly*, *ggplot*).

3 Data

The primary dataset used here derives from the Global Forest Watch repository [6]. After minimal external recoding (eg, consolidation of some loss 'driver' levels) as well as subsequent merging and regrouping, I will demonstrate analysis of the [~100K] records of this compact database. Below I read in these tree cover data sets (+ country/driver DB-lookups, and the jungle & continent tables) and merge them together. (*Note that in the current release of GFW the sub-national level data are not only an order of magnitude greater than the national level data, but there are a few countries where these numbers juxtapose prominently (in [higher vs lower] relative standing) such as Indonesia vs Congo, Papua New Guinea vs India, & Mexico vs Bolivia)

```
> tl.outcome.var <- 'tc_loss_ha_log' # the main "treeloss" outcome variable (log of total hectares lost)
> C.df <- read.csv(system.file("extdata", 'countries.contients.csv', package="caroline")); C.df$X <- NULL; #, ro
> c.dup <- table(C.df$country)>1; C.df <- subset(C.df, !country%in%names(c.dup)[c.dup]); rownames(C.df)<-C.df$
> continents <- nv(C.df, 2:1)
> jungle.DF <- read.csv(system.file("extdata", 'jungle', "jungle-nats.csv", package="caroline"))
> ## Global Forest Watch downloaded datafiles
> # National level
> alltrees.loss.n <- read.csv(system.file("extdata", 'forest', "GFW-loss-alltrees.national-drivers.DB.csv", pac
> tropical.loss.n <- read.csv(system.file("extdata", 'forest', "GFW-loss-tropical.national-drivers.DB.csv", pac
> # SUB-National level (first level just be low nation: eg: state/province)
> tropical.loss.sn <- read.csv(system.file("extdata", 'forest', "GFW-loss-tropical.subnatnl-drivers.DB.csv", pac
> ## three corresponding (2-column) database-style lookup tables to reduce packaged/storage size of [SubNation
> nats.alltre.lu <- read.csv(system.file("extdata", 'forest', "GFW-loss-alltrees.national-drivers-country.LU.csv
> nats.tropic.lu <- read.csv(system.file("extdata", 'forest', "GFW-loss-tropical.national-drivers-country.LU.csv
> nats.trp.sn.lu <- read.csv(system.file("extdata", 'forest', "GFW-loss-tropical.subnatnl-drivers-country.LU.csv
> subnats.trp.lu <- read.csv(system.file("extdata", 'forest', "GFW-loss-tropical.subnatnl-drivers-subnation.LU.c
> drivers.lu <- read.csv(system.file("extdata", 'forest', "GFW-loss-driver.LU.csv", package="caroline")) #s
> alltrees.loss.n <- nerge(all.x=T, method='lookup', ## demo of the 'nerge()' and 'nv()' caroline package R fun
+ l=list(all=alltrees.loss.n, country=nv(nats.alltre.lu),
+ driver=nv(drivers.lu)))
> tropical.loss.n <- nerge(all.x=T, method='lookup', ## demo of the 'nerge()' and 'nv()' caroline package R fun
+ l=list(tl1=tropical.loss.n, country=nv(nats.tropic.lu),
+ driver=nv(drivers.lu)))
> tropical.loss.sn <- nerge(all.x=T, method='lookup', ## demo of the 'nerge()' and 'nv()' caroline package R fu
+ l=list(tl2=tropical.loss.sn, country=nv(nats.trp.sn.lu),
+ subnational=nv(subnats.trp.lu),
+ driver=nv(drivers.lu)))
>
> # an alternative piece-meal example of the above one-liner for both:#
> # 1) using nv to create vectors from lookup tables: nv(<lookuptable.lu>, name='id')
> # 2) merging the main table to these three other lookup tables one at a time: nerge(list(df, vect))
> #tropical.loss.sn.ex <- nerge(list(tl=tropical.loss.sn, country= nv(nats.trp.sn.lu, 'id')), by.x='ids'
> #tropical.loss.sn.ex <- nerge(list(tl=tropical.loss.sn.ex, subnational=nv(subnats.trp.lu, 'id')), by.x='ids'
> #tropical.loss.sn.ex <- nerge(list(tl=tropical.loss.sn.ex, driver= nv(drivers.lu, 'id')), by.x='ids', al
>
> ## examples of recoding & conversions used in another script but in the context of the data.reconfig code b
> ## performed on the 'sub-national' dataset prior to saving as the above [GFW].csv file
> # drivers.df <- subset(drivers.df, driver!='Other natural disturbances')
> # drivers.df <- subset(drivers.df, driver!='Settlements & Infrastructure')
> # drivers.df$driver[drivers.df$driver=='Shifting cultivation'] <- 'Agriculture'
> # drivers.df$driver[drivers.df$driver=='Permanent agriculture'] <- 'Agriculture'
> # drivers.df$driver[drivers.df$driver=='Hard commodities'] <- 'Mining & Energy'
```

4 Methods

The *caroline* package contains several data cleaning [`m()`], conversion [`tab2df()`], and convenience functions [`eg, nv()`]—along-side many database-style merging [`nerge()`], aggregation [`groupBy()`, `bestBy()`], and reporting [`sstable()`] functions—that are routinely used throughout this vignette and the package itself. Here I use many of these to merge, reconfigure, regroup, and analyze the various tables of the Global Forest Watch data repository.

```
> #####
> ### NATIONAL level
> ##### ALL TREES #####
> alltrees.loss.n.C <- merge(x=alltrees.loss.n, y=C.df, by='country', all.x=T) # Merge tree loss data to conti
> alltrees.loss.n.C$years <- cut(x=alltrees.loss.n.C$year, breaks=2002+c(0:4*6)-1)
> alltrees.loss.n.C$continent <- factor(alltrees.loss.n.C$continent)
> alltrees.loss.n.C$driver <- factor(alltrees.loss.n.C$driver)
> all.nations.TOTs.by.C <- tapply(X=alltrees.loss.n.C[,tl.outcome.var], INDEX=list(alltrees.loss.n.C$continent
> all.nations.TOTs.by.c <- groupBy(df=alltrees.loss.n.C, by='country', aggregation=c('min', 'sum'),
+                                     clmns=c('country', tl.outcome.var))
> alltrees.loss.n.XTonCd <- tapply(X=alltrees.loss.n.C[,tl.outcome.var], FUN=sum,
+                                     INDEX=list(alltrees.loss.n.C$continent,
+                                     alltrees.loss.n.C$driver))
> ##### TROPICAL #####
> tropical.loss.n.C <- merge(x=tropical.loss.n, y=C.df, by='country', all.x=T) # Merge tree loss data to contin
> # Turn most predictors in to factors
> tropical.loss.n.C$years <- cut(x=tropical.loss.n.C$year, breaks=2002+c(0:4*6)-1)
> tropical.loss.n.C$continent <- factor(tropical.loss.n.C$continent)
> tropical.loss.n.C$driver <- factor(tropical.loss.n.C$driver)
> tropical.nations.TOTs.by.C <- tapply(X=tropical.loss.n.C[,tl.outcome.var], INDEX=list(tropical.loss.n.C$cont
> tropical.loss.n.XTonCYs <- tapply(X=tropical.loss.n.C[,tl.outcome.var], FUN=sum,
+                                     INDEX=list(tropical.loss.n.C$years,
+                                     tropical.loss.n.C$continent))
> tropical.loss.n.XTonCd <- tapply(X=tropical.loss.n.C[,tl.outcome.var], FUN=sum,
+                                     INDEX=list(tropical.loss.n.C$continent,
+                                     tropical.loss.n.C$driver))
> tropical.nations.TOTs.by.yr <- groupBy(tropical.loss.n.C, by='year', aggregation=c('max', 'sum'), clmns=c('y
> tropical.nations.TOTs.by.c <- groupBy(df=tropical.loss.n.C, by='country', aggregation=c('min', 'sum'),
+                                     clmns=c('country', tl.outcome.var))
> #####
> ### SUB-NATIONAL level*
> tropical.loss.sn.C <- merge(x=tropical.loss.sn, y=C.df, by='country', all.x=T) # Merge tree loss data to cont
> # Turn most predictors in to factors
> tropical.loss.sn.C$years <- cut(x=tropical.loss.sn.C$year, breaks=2002+c(0:4*6)-1) # factorized
> tropical.loss.sn.C$continent <- factor(tropical.loss.sn.C$continent)
> tropical.loss.sn.C$driver <- factor(tropical.loss.sn.C$driver)
> tropical.loss.sn.C$tc_loss_ha_log.f <- cut(tropical.loss.sn.C[,tl.outcome.var], breaks=c(0,3,6,9,12,15))
> tropical.subnats.TOTs.by.C <- tapply(X=tropical.loss.sn.C[,tl.outcome.var], INDEX=list(tropical.loss.sn.C$co
> tropical.subnats.XTbyc <- tab2df(table(tropical.loss.sn$country, tropical.loss.sn[,tl.outcome.var]), check.n
> tropical.subnats.XTbyc$total <- apply(tropical.subnats.XTbyc, 1, sum)
> tropical.subnats.TOTs.by.yr <- groupBy(tropical.loss.sn.C, by='year', aggregation=c('max', 'sum'), clmns=c('
> tropical.subnats.TOTs.by.c <- groupBy(tropical.loss.sn.C, by='country', aggregation=c('max', 'sum'), clmns=c
> tropical.subnats.TOTs.by.sn <- groupBy(tropical.loss.sn.C, by='subnational', aggregation=c('max', 'sum'), clm
> tropical.subnats.SST.by.yd <- sstable(x=tropical.loss.sn.C, idx.clmns=c('year', 'driver'), ct.clmns=tl.outcom
> tropical.subnats.SST.by.Cd <- sstable(x=tropical.loss.sn.C, idx.clmns=c('continent', 'driver'), ct.clmns=tl.o
> tropical.subnats.SST.by.yC <- sstable(x=tropical.loss.sn.C, idx.clmns=c('year', 'continent'), ct.clmns=tl.out
> ## Cross-tabulate the particular sub-national regions with the most de-forestation
> tropical.loss.sn.XTonCd <- tapply(X=tropical.loss.sn.C[,tl.outcome.var], FUN=sum,
+                                     INDEX=list(tropical.loss.sn.C$continent,
+                                     tropical.loss.sn.C$driver))
```

5 Results

Below are some examples of possible cross-tabulations and tabular regroupings as well as numerous plots that help extricate the primary factors influencing world-wide forest loss. Plots include a heatmap, a confound grid, (+corresponding [per-nation] line-series plots), and two different sparse plots—illustrating what the *caroline* package can do to help in untangling variable *confounding* ([16]). Most of the plots use the national ("country") level data (*which should have more realistic estimates of hectares) for tropical regions only, while the much higher-resolution "sub-national" level dataset is investigated supplementally, along-side the national level data, for independent (& relativistic) comparison purposes. (Note that the sparse plots have also been selectively generated here only for these smaller, national-level, datasets because of size constraints of [the vector-based plots, in this very PDF, shipped with such] a compact [~2MB] CRAN package)

```
> # Printing out some summaries of the key variables of interest for each dataset
> variables.of.primary.interest <- c('years', 'continent', 'driver', tl.outcome.var)
> summary(alltrees.loss.n.C[, variables.of.primary.interest])
```

years	continent	driver	tc_loss_ha_log
(2001,2007]:4502	Africa :4843	Agriculture :7111	Min. : 0.000
(2007,2013]:4568	Asia :4220	Logging :3947	1st Qu.: 2.830
(2013,2019]:4304	Europe :3827	Mining & Energy:3790	Median : 5.390
(2019,2025]:4404	North America:2688	Wildfire :3696	Mean : 5.565
NAs : 766	Oceania :1033		3rd Qu.: 8.060
	South America:1592		Max. :15.870
	NAs : 341		

```
> summary(tropical.loss.n.C[, variables.of.primary.interest])
```

years	continent	driver	tc_loss_ha_log
(2001,2007]:2128	Africa :2952	Agriculture :3832	Min. : 0.000
(2007,2013]:2152	Asia :1999	Logging :1676	1st Qu.: 2.080
(2013,2019]:2154	North America:1856	Mining & Energy:1522	Median : 4.960
(2019,2025]:2166	Oceania : 476	Wildfire :1570	Mean : 4.944
	South America:1314		3rd Qu.: 7.410
	NAs : 3		Max. :14.460

```
> summary(tropical.loss.sn.C[, variables.of.primary.interest])
```

years	continent	driver	tc_loss_ha_log
(2001,2007]:19025	Africa :19807	Agriculture :41761	Min. : 0.000
(2007,2013]:19732	Asia :27963	Logging :15250	1st Qu.: 1.100
(2013,2019]:19220	North America:11359	Mining & Energy:10346	Median : 2.830
(2019,2025]:19057	Oceania : 3456	Wildfire : 9677	Mean : 3.243
	South America:14446		3rd Qu.: 5.070
	NAs : 3		Max. :13.750

```
> ## ... also peek at the continent-level percentages for each
```

```
> pct(rev(sort( all.nations.TOTs.by.C)));
```

Africa	Asia	Europe	North America	South America	Oceania
"26%"	"23%"	"20%"	"13%"	"12%"	"5%"

```
> pct(rev(sort(tropical.nations.TOTs.by.C)));
```

Africa	Asia	South America	North America	Oceania
"32%"	"26%"	"22%"	"15%"	"4%"

```
> pct(rev(sort(tropical.subnats.TOTs.by.C)));
```

Asia	Africa	South America	North America	Oceania
"35%"	"26%"	"23%"	"11%"	"5%"

```

> fp.lines <- 50 # ()number of lines for printing a full page of tabular data)

> ## We can also look a the nations with the most losses per dataset by their individual outcome measures
> rev(sort(all.nations.TOTs.by.C))

      Africa      Asia      Europe North America South America      Oceania
26979.87    23514.15    20098.04    13541.55    12668.33    5327.04

> print(head(all.nations.TOTs.by.c[rev(order(all.nations.TOTs.by.c[,tl.outcome.var]))], fp.lines/4), row.name

      country tc_loss_ha_log
      India    1990.61
      Brazil    1499.93
      Indonesia 1452.68
      China     1289.18
Democratic Republic of the Congo 1243.07
      Malaysia 1221.49
      Russia    1200.80
      United States 1197.37
      Canada    1169.42
      Bolivia    1158.72
      Peru       1153.26
      México     1147.10

> rev(sort(tropical.nations.TOTs.by.C))

      Africa      Asia South America North America      Oceania
13410.19    11251.38    9565.00    6470.46    1818.05

> print(head(tropical.nations.TOTs.by.c[rev(order(tropical.nations.TOTs.by.c[,tl.outcome.var]))], fp.lines/4)

      country tc_loss_ha_log
      India    1455.86
      Brazil    1319.59
      Indonesia 1288.89
Democratic Republic of the Congo 1082.08
      Peru     1073.47
      Malaysia 1072.16
      Bolivia    1044.93
      Venezuela 914.82
      Papua New Guinea 914.59
      México     903.06
      Myanmar    899.64
      Colombia   893.82

> rev(sort(tropical.subnats.TOTs.by.C))

      Asia      Africa South America North America      Oceania
88658.99    64966.88    58057.32    26649.22    11485.50

> print(head(tropical.subnats.TOTs.by.c[rev(order(tropical.subnats.TOTs.by.c[,tl.outcome.var]))], fp.lines/4)

      country tc_loss_ha_log
      Indonesia 20311.82
Democratic Republic of the Congo 13683.06
      Brazil    12582.17
      Vietnam   12223.80
      Philippines 10221.51
      Colombia   9317.12
      Papua New Guinea 8807.41
      Laos       7837.11
      Peru       7499.82
      Thailand   7472.32
      México     6715.77
      Malaysia   6389.88

```

```

> ## Let's merge together all of the national totals for losses using the three different datasets'
> all3dfs <- list(a.n=all.nations.TOTs.by.c, t.n=tropical.nations.TOTs.by.c, t.sn=tropical.subnats.TOTs.by.c)
> ## We want to first just extract a single 'loss,ha' column and name it by country
> all3dfs.v1 <- lapply(all3dfs, nv, name=c(tl.outcome.var, 'country'))
> ## We can then "nerge()" them together using the so-named 'name-merge' function
> TOTs.by.c <- nerge(all3dfs.v1)#, method='rownames')
> ## We can now use the 'pct()' function to create column wise percentages to better compare across columns
> PTCs.by.c <- pct(TOTs.by.c, clmns=names(TOTs.by.c))
> PTCs.by.c <- PTCs.by.c[,grepl('pct',names(PTCs.by.c))] *100
> PTCs.by.c$avg <- apply(PTCs.by.c[,1:2], 1, mean) # avg of just the first two 'national' level columns
> ## merge the finished percentage table back with the continents
> PTCs.by.cC<- nerge(list(pcts=round(PTCs.by.c,1), continents=continents)) #conts=C.df))
> head(PTCs.by.cC[rev(order(PTCs.by.cC$avg)),], fp.lines*3/4)

```

	a.n.pct	t.n.pct	t.sn.pct	avg	continents
India	3.0	3.4	2.3	3.2	Asia
Brazil	2.3	3.1	5.0	2.7	South America
Indonesia	2.2	3.0	8.1	2.6	Asia
Malaysia	1.9	2.5	2.6	2.2	Asia
Democratic Republic of the Congo	1.9	2.6	5.5	2.2	Africa
Peru	1.8	2.5	3.0	2.1	South America
Bolivia	1.8	2.5	1.8	2.1	South America
Venezuela	1.7	2.2	2.1	1.9	South America
Papua New Guinea	1.6	2.2	3.5	1.9	Oceania
Myanmar	1.7	2.1	2.3	1.9	Asia
México	1.8	2.1	2.7	1.9	North America
Colombia	1.6	2.1	3.7	1.9	South America
Vietnam	1.7	2.0	4.9	1.8	Asia
Republic of the Congo	1.5	2.1	1.9	1.8	Africa
Madagascar	1.7	2.0	1.3	1.8	Africa
Laos	1.6	2.0	3.1	1.8	Asia
China	2.0	1.6	0.6	1.8	Asia
Cameroon	1.5	2.1	1.6	1.8	Africa
Guyana	1.4	1.9	1.7	1.7	South America
Cambodia	1.5	1.9	2.5	1.7	Asia
Suriname	1.3	1.8	1.1	1.6	South America
Philippines	1.5	1.8	4.1	1.6	Asia
Guatemala	1.5	1.8	1.4	1.6	North America
Gabon	1.3	1.8	1.7	1.6	Africa
Argentina	1.6	1.7	1.0	1.6	South America
Angola	1.6	1.5	1.2	1.6	Africa
Paraguay	1.4	1.6	1.7	1.5	South America
Liberia	1.3	1.7	2.1	1.5	Africa
Ecuador	1.4	1.7	1.6	1.5	South America
Central African Republic	1.4	1.7	1.7	1.5	Africa
Thailand	1.4	1.4	3.0	1.4	Asia
Tanzania	1.6	1.2	0.9	1.4	Africa
Nigeria	1.2	1.5	1.1	1.4	Africa
Ghana	1.3	1.5	1.0	1.4	Africa
Nicaragua	1.2	1.4	0.8	1.3	North America
Honduras	1.3	1.3	1.3	1.3	North America
Belize	1.1	1.5	0.8	1.3	North America

```

> ## Above is a table of column-wise percentages of loss ordered by the "avg" column,
> ## which is merely an average of the first two *national*level* columns. The third
> ## *sub-national percentage column is merely here for informational/comparison reasons.

```

```
> # Now just look at the top best(inverse=T)->[worst] 5 countries in each continent
> PTCs.by.cC$country <- rownames(PTCs.by.cC)
> BB.PTC.cC <- bestBy(df=PTCs.by.cC, by='continents', best='avg', top=6, rebind=F, inverse=T)
> print(BB.PTC.cC, row.names=F)
```

\$Africa

a.n.pct	t.n.pct	t.sn.pct	avg	continents	country
1.9	2.6	5.5	2.2	Africa	Democratic Republic of the Congo
1.5	2.1	1.6	1.8	Africa	Cameroon
1.7	2.0	1.3	1.8	Africa	Madagascar
1.5	2.1	1.9	1.8	Africa	Republic of the Congo
1.6	1.5	1.2	1.6	Africa	Angola
1.3	1.8	1.7	1.6	Africa	Gabon

\$Asia

a.n.pct	t.n.pct	t.sn.pct	avg	continents	country
3.0	3.4	2.3	3.2	Asia	India
2.2	3.0	8.1	2.6	Asia	Indonesia
1.9	2.5	2.6	2.2	Asia	Malaysia
1.7	2.1	2.3	1.9	Asia	Myanmar
2.0	1.6	0.6	1.8	Asia	China
1.6	2.0	3.1	1.8	Asia	Laos

\$`North America`

a.n.pct	t.n.pct	t.sn.pct	avg	continents	country
1.8	2.1	2.7	1.9	North America	México
1.5	1.8	1.4	1.6	North America	Guatemala
1.1	1.5	0.8	1.3	North America	Belize
1.3	1.3	1.3	1.3	North America	Honduras
1.2	1.4	0.8	1.3	North America	Nicaragua
1.1	1.4	1.1	1.2	North America	Panama

\$Oceania

a.n.pct	t.n.pct	t.sn.pct	avg	continents	country
1.6	2.2	3.5	1.9	Oceania	Papua New Guinea
1.0	1.2	0.8	1.1	Oceania	Solomon Islands
1.6	0.0	0.0	0.8	Oceania	Australia
0.6	0.4	0.1	0.5	Oceania	Fiji
0.5	0.4	0.1	0.4	Oceania	Vanuatu
0.2	0.1	0.0	0.1	Oceania	Palau

\$`South America`

a.n.pct	t.n.pct	t.sn.pct	avg	continents	country
2.3	3.1	5.0	2.7	South America	Brazil
1.8	2.5	1.8	2.1	South America	Bolivia
1.8	2.5	3.0	2.1	South America	Peru
1.6	2.1	3.7	1.9	South America	Colombia
1.7	2.2	2.1	1.9	South America	Venezuela
1.4	1.9	1.7	1.7	South America	Guyana

```
> ## Above is a version of of the forest loss percentage table that has been broken down by
> ## each continent, ranked within each sub section (using bestBy()) to highlight the top
> ## six highest forest losses for each country within in each continent separately.
```

```
> ## Now let's look at how forest loss happens (for TROPICAL NATIONS ONLY) over time'
> # we've already created a cross-tabulation of loss by continent over the years
> tropical.loss.n.XTonCYs
```

	Africa	Asia	North America	Oceania	South America
(2001,2007]	2760.50	2674.00	1467.73	398.18	2216.15
(2007,2013]	3066.71	2840.22	1563.66	457.48	2335.12
(2013,2019]	3722.59	2855.01	1712.22	509.87	2441.57
(2019,2025]	3860.39	2882.15	1726.85	452.52	2572.16

```
> # let's modify this to a finer level of partitioning so that the drivers are included split by continents
> tropical.loss.n.XTonYsdC <- tapply(X=tropical.loss.n.C[,tl.outcome.var], FUN=sum,
+                                     INDEX=list(tropical.loss.n.C$years,
+                                     tropical.loss.n.C$driver,
+                                     tropical.loss.n.C$continent))
> tropical.loss.n.XTonYsdC
```

, , Africa

	Agriculture	Logging	Mining & Energy	Wildfire
(2001,2007]	1711.84	556.72	249.98	241.96
(2007,2013]	1841.99	603.00	336.80	284.92
(2013,2019]	2082.53	738.81	463.76	437.49
(2019,2025]	2074.81	691.08	551.12	543.38

, , Asia

	Agriculture	Logging	Mining & Energy	Wildfire
(2001,2007]	1373.83	616.65	376.58	306.94
(2007,2013]	1409.35	643.30	460.11	327.46
(2013,2019]	1375.26	633.91	489.58	356.26
(2019,2025]	1363.36	623.39	523.71	371.69

, , North America

	Agriculture	Logging	Mining & Energy	Wildfire
(2001,2007]	954.38	160.38	111.45	241.52
(2007,2013]	998.77	187.61	128.85	248.43
(2013,2019]	1029.80	185.50	160.12	336.80
(2019,2025]	990.01	193.11	171.30	372.43

, , Oceania

	Agriculture	Logging	Mining & Energy	Wildfire
(2001,2007]	177.87	150.44	31.34	38.53
(2007,2013]	210.38	158.16	39.17	49.77
(2013,2019]	217.39	166.58	46.49	79.41
(2019,2025]	192.08	154.89	52.24	53.31

, , South America

	Agriculture	Logging	Mining & Energy	Wildfire
(2001,2007]	1070.70	417.97	362.03	365.45
(2007,2013]	1096.41	436.53	399.29	402.89
(2013,2019]	1104.49	463.70	439.02	434.36
(2019,2025]	1119.21	480.33	465.52	507.10

```
> ## the loss driver by years grouped by continent (tabular) format above can also be realized as
> ## a sparge plot showing all underlying datapoints (see the last plot [Fig.3] below for an example)
```

```

> ## PLOT DEFAULTS
> # axis limits
> axis.limit.outcome.an <- c(1, max(alltrees.loss.n[,tl.outcome.var])) # log(treeeloss, ha)
> axis.limit.outcome.tn <- c(1, max(tropical.loss.n[,tl.outcome.var])) # log(treeeloss, ha)
> axis.limit.outcome.sn <- c(1, max(tropical.loss.sn[,tl.outcome.var])) # log(treeeloss, ha)
> ## last minue outcome and plot setup
> driver.cols <- nv(c('green','brown','purple','red'), levels(tropical.loss.sn.C$driver))
> # main titles for the heat matrix plots
> main.forest <- nv(c('All Trees (Worldwide)','Humid Tropical Primary Forest'), c('all', 'trp'))
> main.level <- nv(c("@ national level"),'(@ sub-national level)'), c('ntnl','subn'))
> main.unit <- "loss in log(ha)"

> ## We might want to take a quick peek and see if what appears to be flat loss over these decades
> ## ... isn't actually confounded by driver of the loss: plot.confound.grid() should do the trick
> plot.confound.grid(x=tropical.loss.n, f='tc_loss_ha_log ~ year | driver' )
> ## This plot (below) should give us a general idea of which drivers have the highest positive trends

> ## LINE PLOTS CROSS TABULATION set-up
> ## The breakdown of the previous page has inspired looking into trending losses for such leading countries
> ## Note that this is a much higher resolution (sub-national level) breakdown (eg, islands detail)
> tropical.loss.sn.XTon.ydc <- with(tropical.loss.sn, tapply(X=get(tl.outcome.var), FUN=sum,
+ INDEX=list(driver,country,year)))
> ## Such a breakdown is line-plotted below to gauge which of these countries might continue in hosting losses

> ## LINE PLOTS results defaults
> trop.majors <- c('India','Brazil','Democratic Republic of the Congo')
> trop.africa <- c('Madagascar','Cameroon','Angola','Gabon', 'Republic of the Congo')
> trop.samerca <- c('Colombia','Venezuela','Peru','Bolivia')
> trop.centrl <- c('México','Guatemala','Honduras','Panama')
> trop.S.E.A.MAINLAND <- c('Malaysia','Laos','Vietnam','Thailand','Cambodia','Myanmar')
> trop.S.E.A.ISLANDS <- c('Indonesia','Papua New Guinea','Philippines')
> trop.CONGO <- jungle.DF[jungle.DF$jungle=='Congo','nation']
> trop.AMAZON <- jungle.DF[jungle.DF$jungle=='Amazon','nation']
> ## colors for countries
> t.mj.cols <- nv(c('orange3','forestgreen','blue'), trop.majors)
> t.af.cols <- nv(c(paste('deepskyblue', 4:1), 'navyblue'), trop.africa)
> t.sa.cols <- nv(paste('olivedrab',1:4,sep=''),trop.samerca)
> t.ca.cols <- nv(paste('gold',1:4), trop.centrl)
> t.sea.cls <- nv(c(paste('salmon',1:3),paste('tomato',1:3)), trop.S.E.A.MAINLAND)
> t.so.cols <- nv(c('red','orangered3','orange'), trop.S.E.A.ISLANDS)
> cntry.cols <- c(t.mj.cols, t.af.cols, t.sa.cols, t.ca.cols, t.sea.cls, t.so.cols)
> jungles <- c('CONGO','AMAZON',"S.E.A.MAINLAND","S.E.A.ISLANDS")
> jung.cols <- nv(c('blue','green','deeppink3','orangered'), jungles)
> fun <- nv(c('mean',rep('sum',3)), drivers.lu$driver) # Agg is MEAN rest are SUM (to use extra space)
> j.lty <- nv(c(3,rep(2,3)), drivers.lu$driver)
> xs <- 2002:2025 ; ylims <- c(0,max(tropical.loss.sn.XTon.ydc,na.rm=T))
> par(mfrow=c(2,2), mar=c(2.5,2.5,3,1), mgp=c(1.5,.5,0))
> for(driver in drivers.lu$driver){
+ plot(x=xs+c(0,5),y=1:(26-2), pch='', ylim=ylims, ylab='log(loss)', xlab='year', main=driver)
+ for(country in names(cntry.cols)){
+ losses <- tropical.loss.sn.XTon.ydc[driver,,][country,]
+ lines(x=names(losses),y=losses, col=cntry.cols[country])
+ text(x=2025.5, y=losses['2025'], country, adj=0, cex=.4)
+ }
+ for(jungle in jungles){
+ j.losses <- apply(tropical.loss.sn.XTon.ydc[driver,,][get(paste('trop', jungle ,sep='.')),],2, fun[driver])
+ lines(x=names(j.losses),y=j.losses, col=jung.cols[jungle], lwd=4, lty=j.lty[driver])
+ text(x=2025.5, y=j.losses['2025'], jungle, adj=0, cex=.4)
+ }
+ }

```

```

> ### HEATMATRIX PLOTS FOR ALL THREE DATASETS: [SUB-]NATIONAL & ALL/TROPICAL
> par(mfrow=c(3,1), mar=c(3,6,3,1), mgp=c(2.5,2,.5) )
> heatmap(round(alltrees.loss.n.XTonCd ), text.col='chartreuse', cex=1.1,
+   main=paste(main.forest['all'], "\n", main.unit, main.level['ntnl']))
> heatmap(round(tropical.loss.n.XTonCd ), text.col='chartreuse', cex=1.1,
+   main=paste(main.forest['trp'], "\n", main.unit, main.level['ntnl']))
> heatmap(round(tropical.loss.sn.XTonCd), text.col='chartreuse', cex=1.1,
+   main=paste(main.forest['trp'], "\n", main.unit, main.level['subn']))

> ### SPARGE PLOTS FOR THE *NATIONAL* LEVEL
> ## NATIONAL LEVEL DATASET ##
> # sparge plot: forest loss (@ national level): vs continent grouped by loss driver
> par(las=1, cex=.7, mar=c(3,6,1,1), mgp=c(1.6,.7,0))
> model.4 <- paste(tl.outcome.var, 'continent | driver', sep='~')
> pds.4 <- plot.sparge(x=tropical.loss.n.C, f=model.4, xlim=axis.limit.outcome.tn,
+   xlab='log(forest loss, ha)', ylab='', pt.cols=driver.cols, main='tropical nations',
+   legend.cex=.6, legend.inset=.008, legend.title='loss driver',
+   boxplot.notch=TRUE, boxplot.lwd=1.5, boxplot.col=rgb(0,0,1,.2))
> lines.sparge(x=tropical.loss.n.C, f=model.4, pds=pds.4, cat.order=2:1, lwd=1.5, pt.cex=2,col=gray(.5))

> # sparge plot: forest loss (@ national level): vs years grouped by loss driver
> par(las=1, cex=.6, mar=c(2.5,2.5,1,.2), mgp=c(1.6,.7,0)); horiz.5 <- FALSE
> model.5 <- paste(tl.outcome.var, 'years | driver', sep='~');
> pds.5 <- plot.sparge(x=tropical.loss.n.C, f=model.5, horiz=horiz.5, ylim=axis.limit.outcome.tn,
+   pt.cols=driver.cols, xlab='years', ylab='log(forest loss, ha)', las=1,
+   legend.cex=.7 , legend.inset=.112, legend.title='loss driver', main='tropical nations'
+   boxplot.notch=TRUE, boxplot.lwd=1.5, boxplot.col=rgb(0,0,1,.2))
> ## add some per-group median trendline overlays (using the returned p[oosition]d[odge]s above)
> lines.sparge(x=tropical.loss.n.C, f=model.5, pds=pds.5, rb=driver.cols, lty=1, lwd=.8, horiz=horiz.5)
> lines.sparge(x=tropical.loss.n.C, f=model.5, pds=pds.5, cat.order=2:1, horiz=horiz.5, lwd=1.7, col=gray(.5))

```

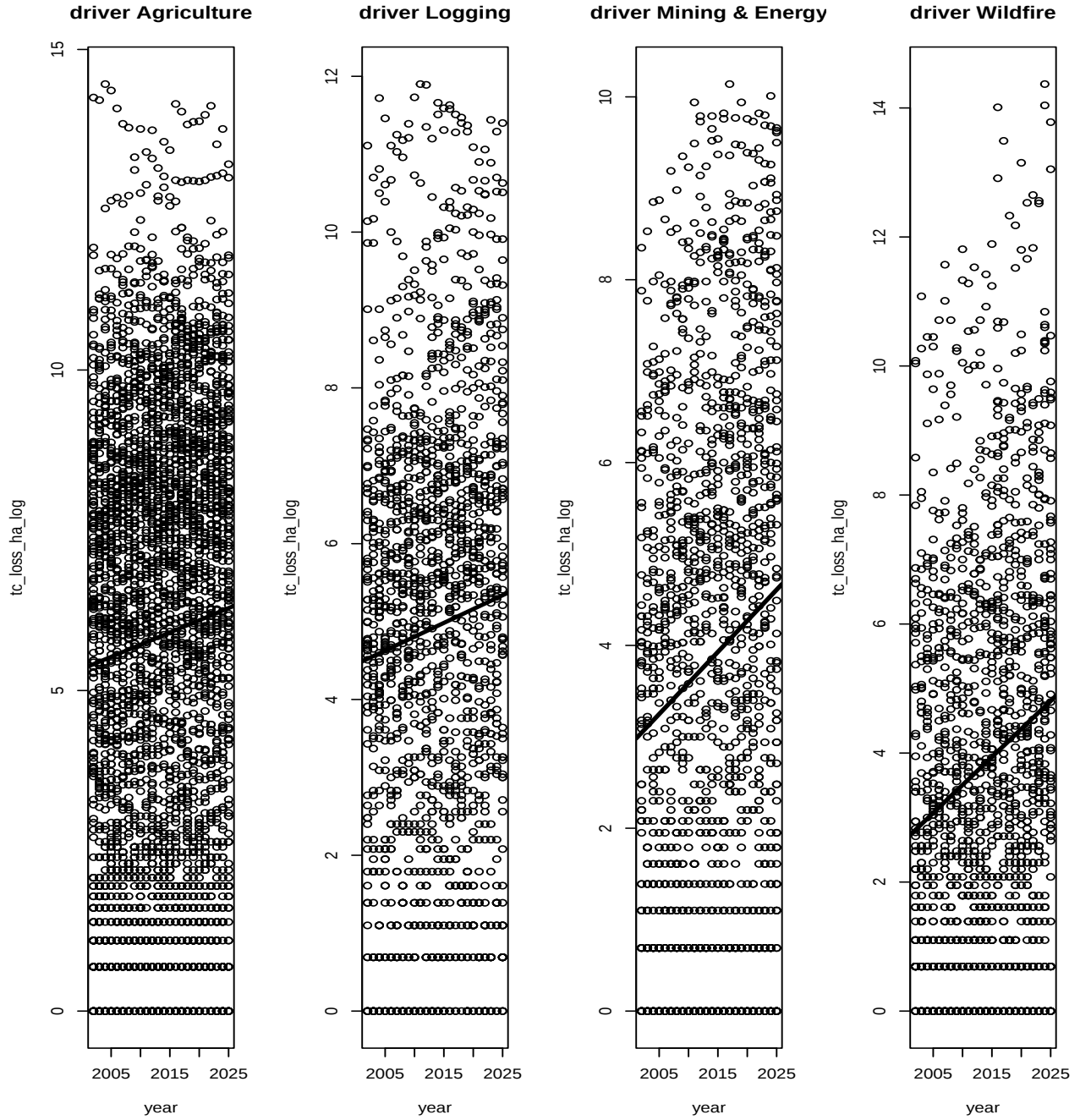


Figure 1: While losses have been gradually increasing over the years, we see that the slope is higher in both mining/energy as well as in wildfire. We'll take another look at this for the top loss countries on a line-by line basis next. (Note: the above plot [confound-grid] series illustrates only a very mild [concordant slopes] verison of "Simpson's paradox" for confounded variables [16] [17])

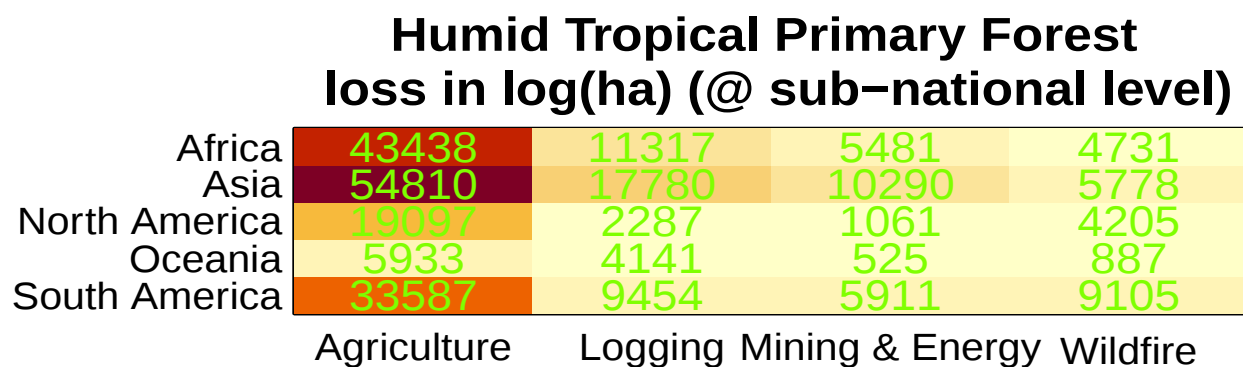
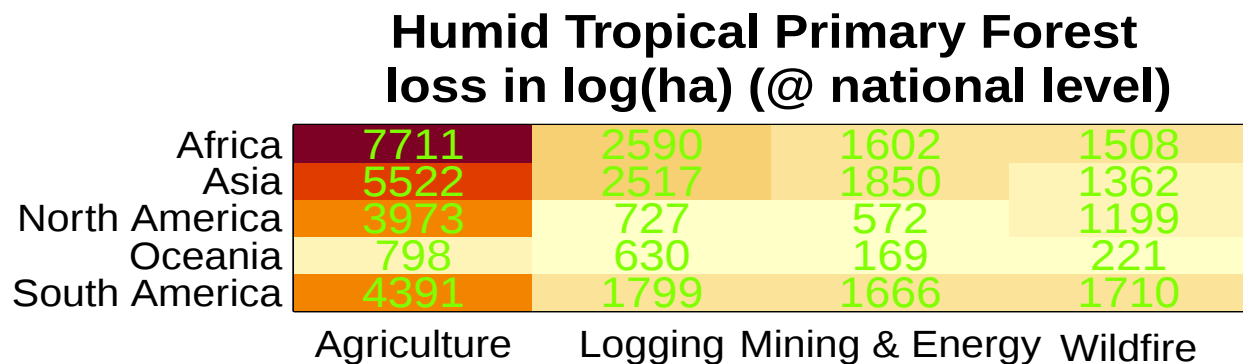
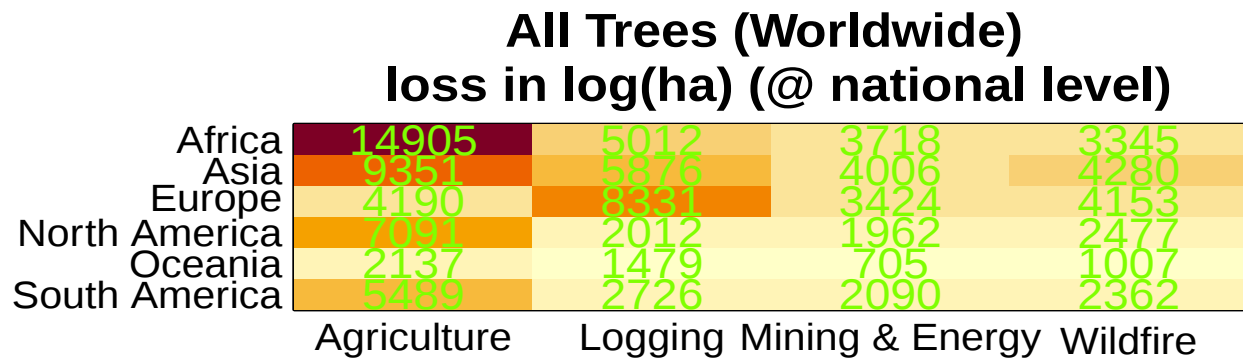


Figure 3: Three 'heatmatrix()' plots showing the (intersection of continent by drivers of) types of tree cover loss for each continent. Note that Agriculture dominates all other forms, with African (and possibly also Asian*) agriculture typically ranking highest among world-wide forest loss. The continent of Europe (eg, in Finland and Sweden) non-tropical forestry also registers as a not insignificant manifestation of planetary-scale losses.

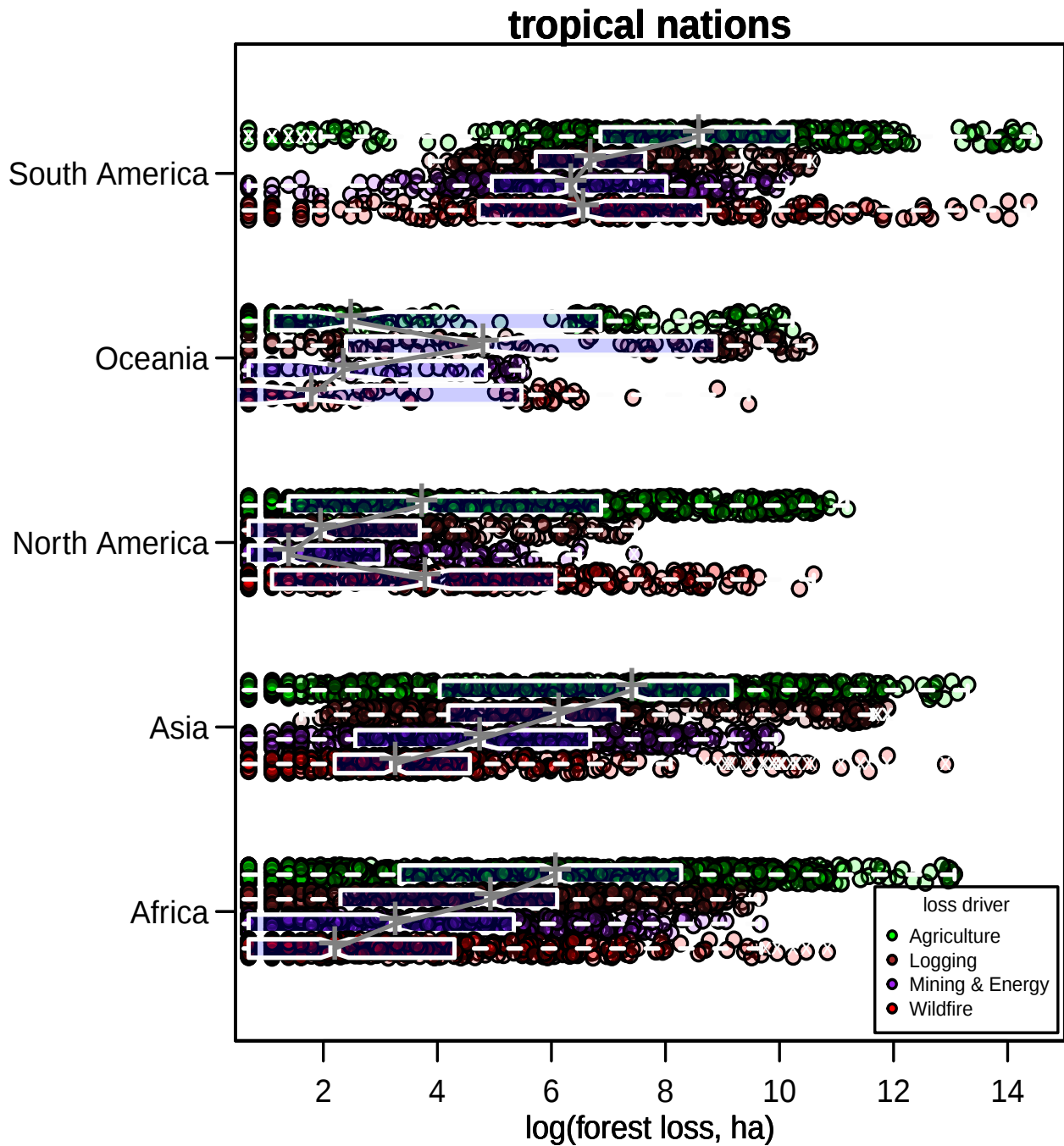


Figure 4: A sparge plot of forest loss (at the national level): vs continent grouped by loss driver. Despite the relatively low loss numbers for North America, do note the unusual trending of logging in Oceania whose inter-quartile range is outstripping all forms of loss in [tropical!] N. America. (Note that these point represent [$\sim 200 \times 24 =$] thousands of individual nation-year records)

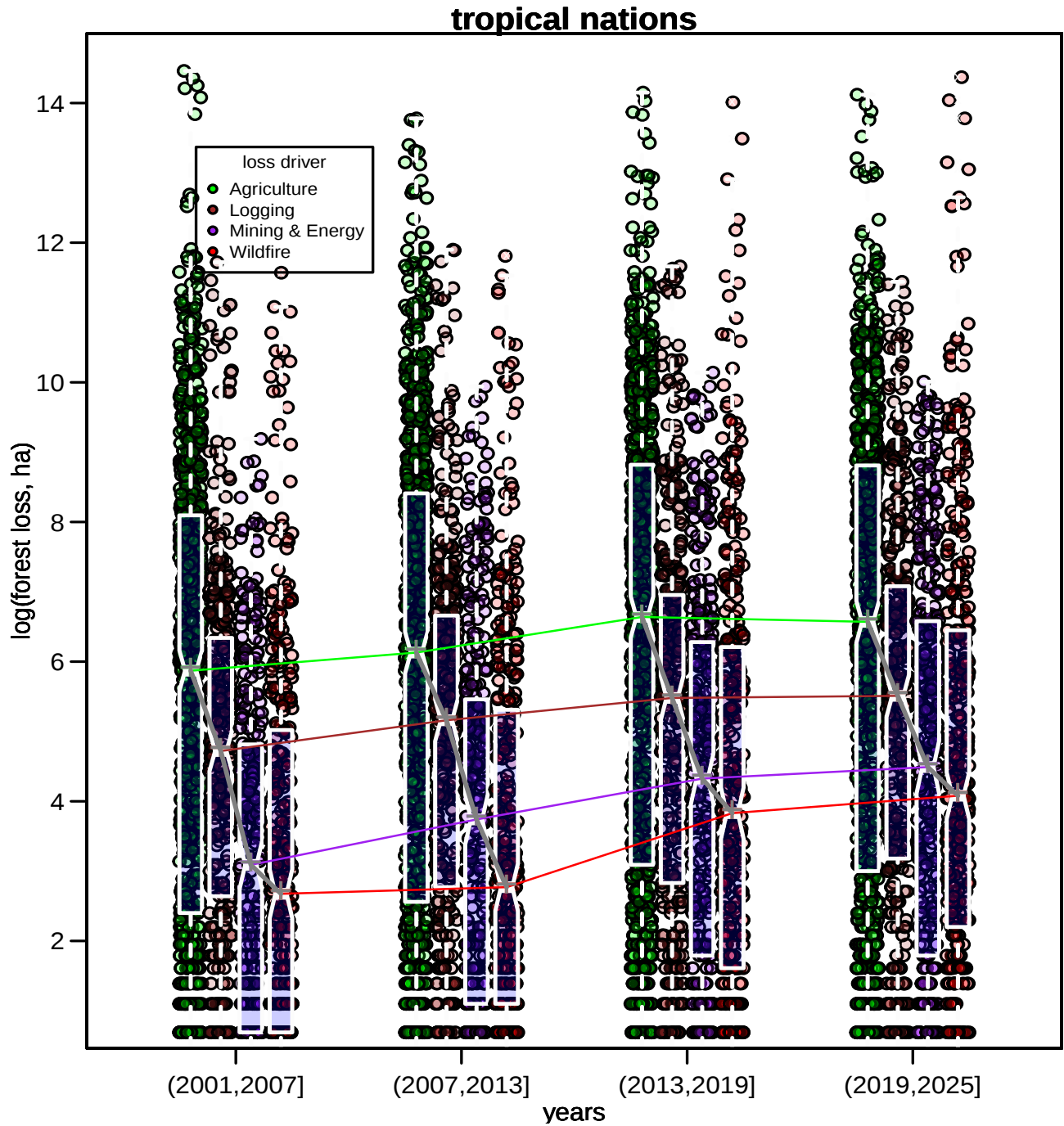


Figure 5: A [vertical] sparge plot of forest loss (at the national level): vs years grouped by loss driver. The medians ("+") of each box plot for each subgroup have been externally joined together via dashed lines showing increasing trends for our four primary drivers of tree loss. (Note that these points represent [$\sim 200 \times 24 =$] thousands of individual nation-year records)

6 Conclusions

In addition to showcasing several of the *caroline* package functions [eg, `m()`, `nv()`, `pct()`, `tab2df()`, `nerge()`, `groupBy()`, `bestBy()`, `sstable()`, `heatmap()`, `plot.confound.grid()`], I have also introduced the `sparge` plot anew [18], as a possible apotheosis of visual-analytics, which promises to facilitate the untangling of deeply confounding data. Using relatively simple formula-based calls to `plot.sparge()`, in conjunction with appropriate merges to (eg, continent) lookup table(s) (via `nerge()`), I have shown the capabilities of this statistical software package to import, clean, re-configure, analyze, and plot larger datasets.

En route, I have re-confirmed what other forestry researchers have observed: that while the dual quandary of the Congo and Amazon rain-forests are of predominate environmental concern [19], many other regions—including developing tropical countries (India, Mexico, & Panama) as well as more temperate behemoths (China, Russia, & U.S.)—also rank among the world’s worst in hosting forest losses. This research has also uncovered which tropical forests have been most heavily depleted recently—not only in the countries of Africa ([Democratic &] Republic of Congo, Cameroon, & Madagascar), South America (esp. Brazil, Columbia, Peru, Venezuela, & Bolivia), as well as more populous countries in Asia (China & India)—but also many many smaller ones in South East Asia (incl. Laos, Vietnam, Malaysia, Thailand, Myanmar, & Cambodia). And a possibly even more distressing form of distributed depletion (esp. logging) has manifested in more remote island-based countries (eg, Oceania [& S.E. Asian island nations]) that may have been previously prohibitively difficult to efficiently explore, develop, survey, appraise, harvest/mine, and ship-from internationally—notably in Indonesia, Papua New Guinea, and the Philippines.

The primary drivers of world-wide losses may be shifting from agriculture and logging [both plateauing (except in the Congo & Papua)] to minerals/energy, and wildfires [gaining (especially in the Congo, Brazil, & Mexico)] over this past decade. And the logging of islands circa-Oceania (in Papua & Indonesia) appears to be out-pacing all other forms of loss there—topping all countries [for *both* extractive drivers] especially when these two adjacent countries’ losses are considered together. And, less surprisingly, the high levels of forest loss due to [rice] agriculture in [south-east] Asia remains overshadowed only by the undeniable environmental discordance afflicted by South American [ranching] agriculture—both often deploying *slash-and-burn* methods to clear land of native trees [20] [22] [21]. Hopefully with continued support for high-resolution datasets (as sourced here in the Global Forest Watch data repository)—along with further democratization of telecommunication and computer access—such reporting of these trends may be reflected back to citizens of these countries to raise a counter-balanced awareness of the potentially predestinate concomitants of such loss—that of persistent climate alteration and biome degradation.

To conclude this brief report on a more uplifting note, it should be added that there are momentous strides being taken recently in mitigating, reversing, and preventing [the negative consequences of] these forest losses. Some nations have made efforts to promote new growth—in China, for example, where an astounding number of trees (~ 80 billion) have been planted, as part of their "Great Green Wall" endeavor—in order to mitigate the desertification of their northern provinces [23] and reach carbon neutrality goals in the coming decades [24]. Other countries, like Columbia, plan to institute laws that will require [beef] ranchers to prove that no forests are cleared in order to support grazing by any cattle raised for commerce [25]. Malaysia is discouraging illegal logging and re-amalgamating previously partitioned jungles by re-connecting protected areas (eg, national parks) by means of re-wilded forest corridors, which should allow declining faunal census numbers to rebound [26]. Indonesia, likewise, is preventing deforestation by both addressing the scourge of bribery and graft in government sectors involved in resource regulation [28], revoking licenses for resource companies that are not doing enough to prevent deforestation-exacerbated flooding [27], and otherwise taking action toward protection (eg, via ranger forest patrols) for fauna such as the orangutan [29], an endangered primate—notably also a member of our own primate family, the Great Apes.

7 Licensing

The *caroline* package is licensed under the Artistic License v2.0: it is therefore free to use and redistribute, however, we, the copyright holders, wish to maintain primary control over any further development. Please be sure to cite *caroline* if you use the package in presentations or work leading to publication (see the appropriate entry in the bibliography on the next page).

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