

Global Drivers of Natural Forest Loss: a visual workflow for functions in the *caroline* R-package (Version 1.1.1)

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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 sober work of protecting fauna, preventing erosion, buffering the water-table, and performing many other ecosystem services, importantly including the production of oxygen we breathe from carbon-dioxide (normally a net-CO₂ sink in forests) [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, **lumber**), powering our increasingly technology [machine & computer] driven industries (eg, **mining**), and indirectly as an result of ([anthropogenic] global-warming fueled) **wildfires**.

Here I showcase some of the statistical (especially plotting) tools in the *caroline* (R [9]) package (version 1.1.1) [11] that serve to highlight these biodiversity-imperiling threats which have done little but increase in severity—not only throughout the Anthropocene, but notably also over the past few decades, as illustrated here by way of analyzing the Global Forest Watch dataset ([6] [7] [8]). In the following vignette, I highlight these evolving problems while expounding upon the principal findings prevised above. Further notable, while African (The Republic of Congo) and South American countries (Brazil & Columbia) 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) are rapidly over-taking them just this past decade. Furthermore, mining and (especially) wildfire are catching-up to logging and agriculture, both of which appear to be plateauing over the past few decades. These findings and more are previewed below via demonstration of the many useful functions built into the package.

My featured analysis tool, introduced here as the ‘sparge plot’, combines modern plotting technology features (translucent over-plotting) with the simplicity of one the oldest forms of distributional representation: the boxplot [10]. Additional plots, innovated since, have improved upon mere boxplots, including the `stripchart()` [12], the `forestplot()` [14], but these functions, like boxplots themselves, have the drawback of abstracting away too much detail. The even more rudimentary `rug()`, `stem()` & `leaf` plot functions attempted to show more unadulterated detail, but these remain rather limited when simultaneously representing any potentially superimposed univariate plot points. There are many plotting functions currently, however, that do a fine job of succinctly showing more distributional detail, including `sinaplot` [15], `beanplot()` [13], and `vioplot` (note that an instantiation here as `violins()` was withdrawn from *caroline* for greater perspicuity). And some packages can now even showcase both individual points and distributional smoothing summary-shapes simultaneously, as in `raincloud()` [16] and `beeswarm()` plots, although these tend to occupy more plotting space than their predecessors.

My hybrid innovation, presented in the form of the `plot.sparge()`, goes even further by revealing the myriad possible underlying nuances of distributional conformation, for even the largest of datasets, in an efficiently compact way—thanks primarily to the broad continuum of possible shades of overlapping translucent points—all while managing to circumvent engineering complexities of external smoothing, density, or positioning algorithms. The added essentialistic scaffolding of a boxplot (with auto-adjusting grayscale-shaded outlines) overlaid atop the underlying data, empowers quantitative visual undergirding in alleviation of any residual coordinate opacity, especially within the most congested areas (of the narrow rectangular strips of point-nebula) within the plot—importantly demarcating the median, quartiles, whiskers (and [thus] possible outliers) of the many point-values so routinely generated by automated systems that typify our modern, data-fertile era.

2 Software

```
> # wget https://cran.r-project.org/src/contrib/Archive/caroline/caroline_1.0.1.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: *forestplot()*, *sinaplot*, *stripchart()*, *beeswarm()*, *raincloud()*) is efficiently coded and lightweight, by depending on no 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 recoding (eg, consolidation of some loss 'driver' levels), merging, and regrouping. Below I read in the tree cover data and continents lookup list and merge them together.

```
> 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)
> ## 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 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 has several data cleaning (`m()`), conversion `tab2df()`, and convenience functions (eg, `nv()`)—alongside several database-style merging (`merge()`), 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 contin
> # turn most predictors in to factors
> 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$driver))
> ##### TROPICAL #####
> tropical.loss.n.C <- merge(x=tropical.loss.n, y=C.df, by='country', all.x=T) ##merge tree loss data to conti
> # turn most predictors in to factors
> tropical.loss.n.C$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 con
> # 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 five different sparge plots illustrating what the *caroline* package can do to untangle confounding—using such an essentialistic implementation, less-reliant on many other packages. The first three plots use the national ("country") level data, while the much higher-resolution "sub-national" level dataset is investigated somewhat along-side for independent comparison purposes. (Note that the sparge plots have only been generated here for these smaller, national-level, datasets due to size constraints of the vector based plots in a PDF shipped in a compact 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
Republic of the Congo    2227.67
      India    1990.61
      Brazil    1499.93
Indonesia    1452.68
      China    1289.18
      Malaysia    1221.49
      Russia    1200.80
United States    1197.37
      Canada    1169.42
      Bolivia    1158.72
      Peru    1153.26
      México    1147.10

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

      country tc_loss_ha_log
Republic of the Congo    1958.96
      India    1455.86
      Brazil    1319.59
Indonesia    1288.89
      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(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(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
Republic of the Congo    18362.78
      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 my 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
Republic of the Congo	3.4	4.6	7.4	4.0	Africa
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
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
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
Zambia	1.6	0.8	0.2	1.2	Africa

```

> ## 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
3.4	4.6	7.4	4.0	Africa	Republic of the Congo
1.5	2.1	1.6	1.8	Africa	Cameroon
1.7	2.0	1.3	1.8	Africa	Madagascar
1.6	1.5	1.2	1.6	Africa	Angola
1.3	1.8	1.7	1.6	Africa	Gabon
1.4	1.7	1.7	1.5	Africa	Central African Republic

\$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)
```

```

> ## plotting results defaults
> axis.limit.outcome.an <- c(1, max(alltrees.loss.n[,tl.outcome.var])) # log(treeloss, ha)
> axis.limit.outcome.tn <- c(1, max(tropical.loss.n[,tl.outcome.var])) # log(treeloss, ha)
> axis.limit.outcome.sn <- c(1, max(tropical.loss.sn[,tl.outcome.var])) # log(treeloss, 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)"

> ### 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(3,3,1,1), 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))

```

All Trees (Worldwide) loss in log(ha) (@ national level)

Africa	14905	5012	3718	3345
Asia	9351	5876	4006	4280
Europe	4190	8331	3424	4153
North America	7091	2012	1962	2477
Oceania	2137	1479	705	1007
South America	5489	2726	2090	2362
	Agriculture	Logging	Mining & Energy	Wildfire

Humid Tropical Primary Forest loss in log(ha) (@ national level)

Africa	7711	2590	1602	1508
Asia	5522	2517	1850	1362
North America	3973	727	572	1199
Oceania	798	630	169	221
South America	4391	1799	1666	1710
	Agriculture	Logging	Mining & Energy	Wildfire

Humid Tropical Primary Forest loss in log(ha) (@ sub-national level)

Africa	43438	11317	5481	4731
Asia	54810	17780	10290	5778
North America	19097	2287	1061	4205
Oceania	5933	4141	525	887
South America	33587	9454	5911	9105
	Agriculture	Logging	Mining & Energy	Wildfire

Figure 1: 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.

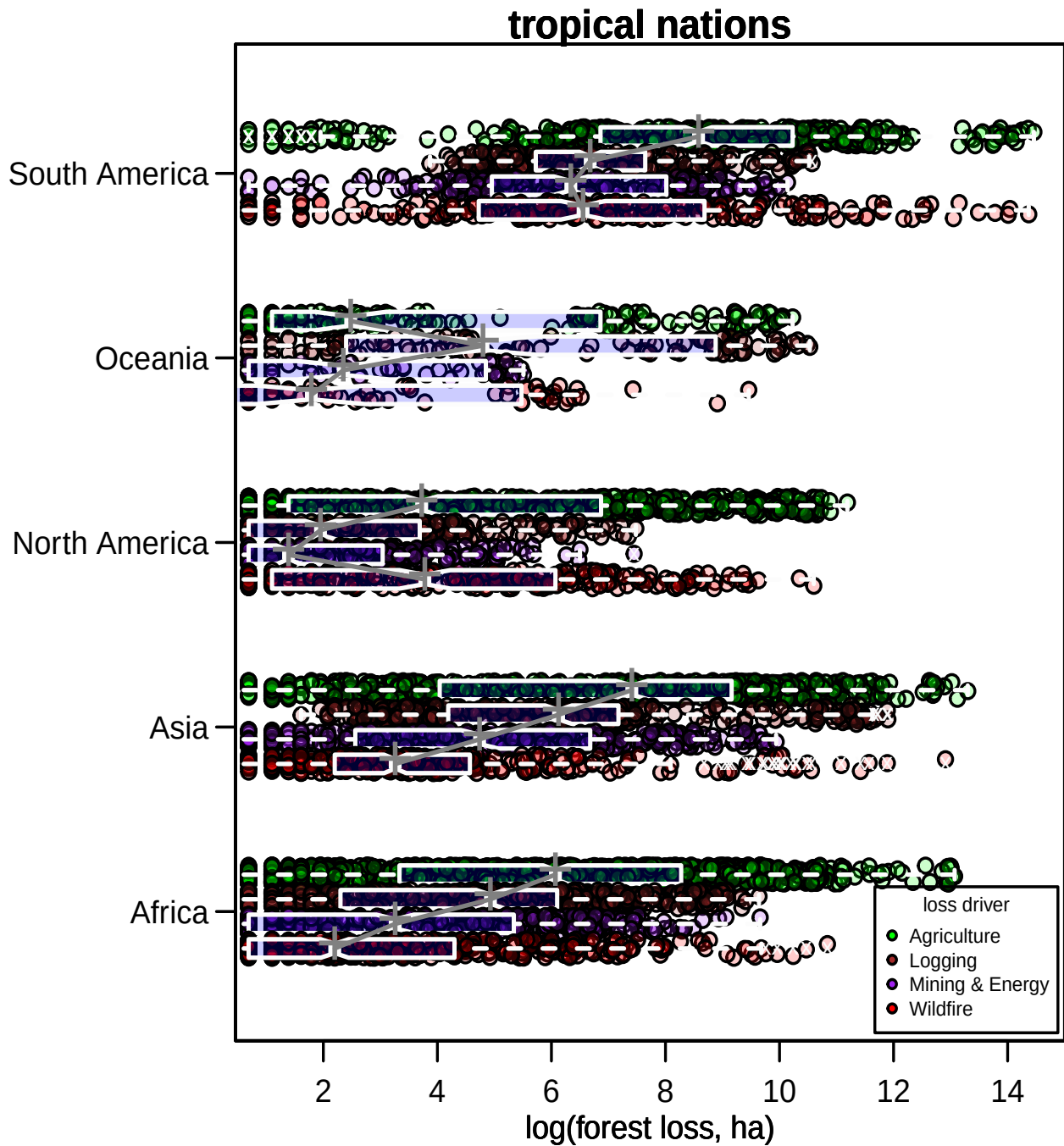


Figure 2: A sparge plot of forest loss (at the national level): vs continent grouped by loss driver. Despite the relatively low loss numbers for North America, do observe the unusual trending of logging in Oceania whose inter-quartile range is apparently outstripping all forms of loss in N. America. (Note that these point represent [$\sim 200 \times 24 =$] thousands of individual nation-year records)

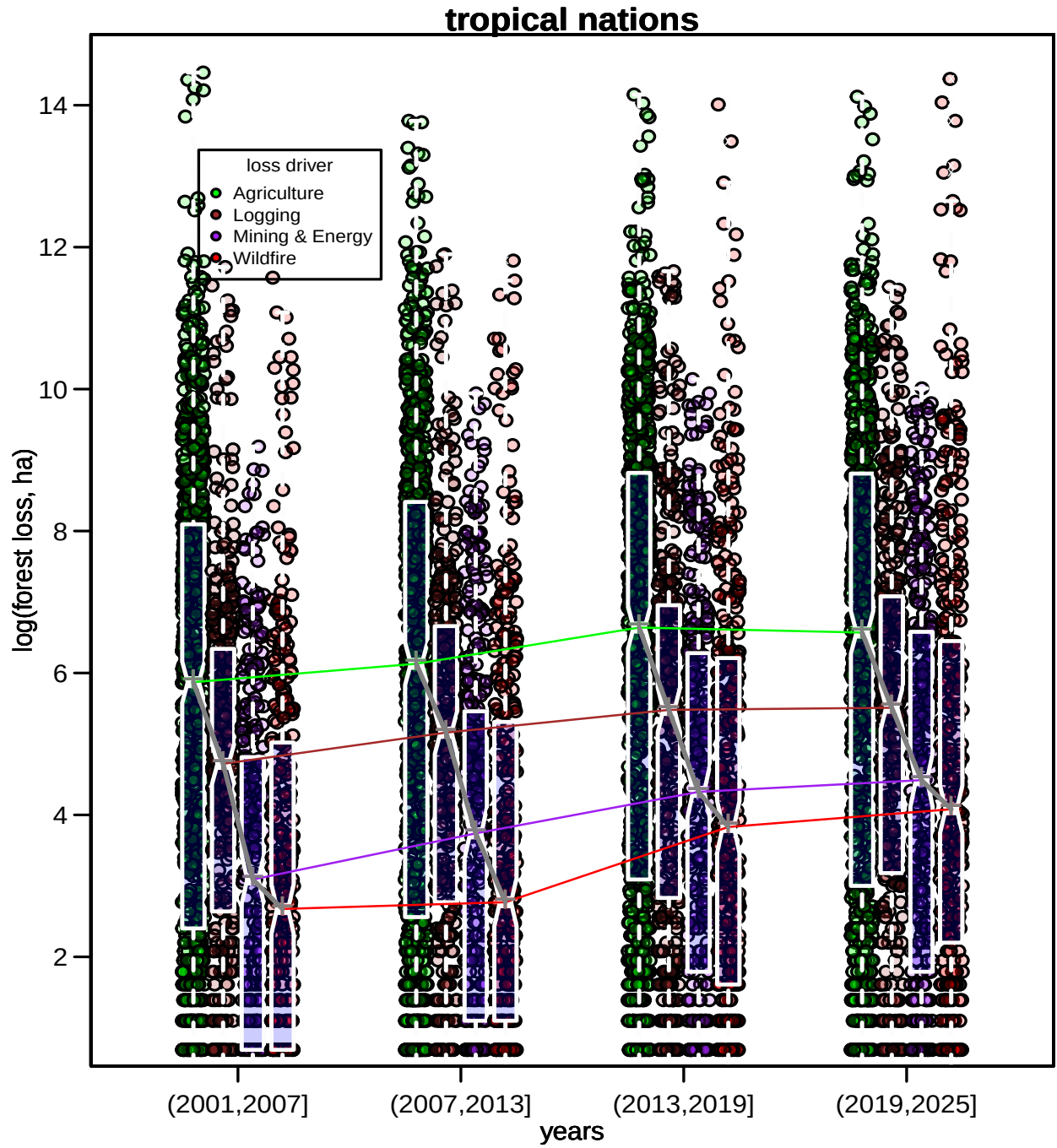


Figure 3: A [vertical] sparge plot of forest loss (at the national level): vs years grouped by loss driver. The medians ("+") of each box plot for each subgroup have been externally joined together via dashed lines showing increasing trends for our four primary drivers of tree loss. (Note that these 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()`, `heatmapmatrix()`), I have also introduced the `sparge` plot anew [17], 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 [18], many other nations—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 discovered that—the world’s (tropical) trees may have been most heavily depleted, over the past several decades, not only in the countries of Africa (Republic of Congo & 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. Malaysia, Laos, Vietnam, Philippines, Thailand, Cambodia, & Myanmar). And a possibly even more distressing form of distributed depletion is increasingly appearing in more remote island-based countries (eg, of Oceania) that presumably have been previously prohibitively difficult to explore, develop, survey, appraise, harvest/mine, and ship-from internationally—most especially Indonesia and Papua New Guinea.

Furthermore, while the primary drivers of world-wide losses have shifted from agriculture and logging (which both seem to be plateauing) to wildfires and minerals & energy (both still increasing) over this past decade, logging in Oceania appears to be out-pacing all other forms of loss (in Oceania) and, for comparison, even beyond all drivers in [tropical] North America. And, less surprisingly, forest loss due to [rice] agriculture in [south-east] Asia only remains overshadowed by the persistently undeniable environmental-discordance inherent to much of South American [ranching] agriculture—both often deploying slash-and-burn methods to clear land of native trees. Hopefully with increased (internet-based) access to larger higher-resolution datasets (such as the Global Forest Watch data repository, utilized extensively in this report) along with further democratization of computational access and globally-open communication, such remote reporting of these trends, can be reflected back to citizens of these countries so as to raise a counter-balanced awareness toward the potentially predestinate concomitants in such loss—that of persistent climate alteration and biome degradation.

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.

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