Monte Carlo Simulation Tools for REDD+ Uncertainty Estimates

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Objective

When preparing for Monte Carlo simulations, it is best practice to start by examining descriptive statistics to characterize the empirical distributions of input variables. This preliminary analysis typically includes statistical tests for normality and visualizations of univariate distributions, such as histograms, kernel density plots, and Q-Q plots. Together, these tools provide critical insights into the shape, spread, symmetry, skewness, and presence of potential outliers in the data. Although this preliminary step may seem minor, it substantially influences uncertainty estimates, which can directly translate into increased financial returns, particularly within forest project landscapes exhibiting non-normal data distributions.

Accurately characterizing data distributions also helps in identifying and addressing biases, thereby ensuring high data quality and increasing confidence in subsequent estimations of biomass and carbon emissions. Selecting appropriate statistical distributions, informed by exploratory analyses, significantly enhances the reliability and precision of Monte Carlo simulations. Consequently, such careful statistical characterizations reduce overall uncertainty in forest biomass and emissions estimates. In turn, this strengthens the credibility of jurisdictional claims made under REDD+ programs and maximizes potential financial returns for Guyana from carbon financing initiatives.

Univariate distribution visualizations additionally provide auditors with useful diagnostic resources, enabling rapid identification and characterization of biases commonly encountered in biomass data. These diagrams help auditors efficiently assess the technical rigor and statistical approaches implemented by the project to monitor and manage uncertainty (ART, 2021: 8). Winrock strongly recommends incorporating distribution analyses early in a project's quantitative planning and throughout its technical standard operating procedures (SOPs). Such early integration represents a low hanging fruit with cost-effective strategy and significant potential in reducing audit findings, lowering uncertainty, and enhancing financial outcomes for Guyana's REDD+ activities. Specifically, early attention to data distributions directly informs appropriate simulation selection from the available options in SimVoi.

To effectively guide practitioners and stakeholders in selecting appropriate statistical distributions for Monte Carlo methods within forestry and REDD+ contexts, the following two tables present findings from a rapid review of relevant literature. The review identified and summarized statistical distributions frequently encountered in forestry, biomass estimation, and emissions analysis, which are dis-aggregated below between discrete and continuous types and according to their inherent statistical characteristics.

Table 1: Continuous data distributions, and example use cases of Monte Carlo simulations.

Distribution	Statistical Use Cases	PDF
Normal	Symmetric, bell-shaped distribution used for modeling continuous variables: biomass/ha	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$
Lognormal	Right-skewed distribution suitable for variables constrained to positive values (e.g., emission rates).	$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right)$
Exponential	Models waiting times between independent events, such as forest fire occurrences or logging events.	$f(x) = \lambda e^{-\lambda x},\; x \geq 0$
Cont. Uniform	Assumes all values in an interval [a, b] are equally likely; useful for random spatial sampling in forests.	$f(x) = \frac{1}{b-a},\; a \leq x \leq b$
Chi-Square	Often used in goodness-of-fit tests to evaluate model accuracy in biomass estimation.	$f(x) = \frac{1}{2^{k/2}\Gamma(k/2)} x^{\frac{k}{2}-1} e^{-x/2}, \quad x > 0$
t-Distribution	Suitable for small sample sizes with unknown population stdev (e.g., limited forest carbon data).	$f(x) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)}\left(1+\frac{x^2}{v}\right)^{-\frac{v+1}{2}}$
Gamma	Models positively skewed data, such as biomass growth rates or carbon accumulation over time.	$f(x) = \frac{x^{k-1}e^{-x/\theta}}{\theta^k\Gamma(k)}$
Weibull	Flexible distribution used in reliability analysis, e.g., modeling tree mortality.	$f(x) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$

Table 2: Discrete data distributions, and example use cases of Monte Carlo simulations.

Distribution	Statistical Use Cases	PMF
Bernoulli	Binary outcome probability, e.g., presence/absence of deforestation in an area.	$P(X=x) = p^x(1-p)^{1-x},\; x \in \{0,1\}$
Binomial	Probability of fixed #no. of successes over n Bernoulli trials, e.g., no. of heads in ten coin flips.	$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k},\; k = 0,1,\ldots,n$
Poisson	Models counts of independent events within an interval, e.g., number of wildfire incidents per year.	$P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!},\; k = 0,1,2,\ldots$
Geometric	Models #no. of trials until the first success, e.g., number of inspections until detecting deforestation.	$P(X=k) = (1-p)^{k-1}p,\; k = 1,2,\ldots$
Negative Binomial	Counts #no. failures until r successes occur, treats overdispersed or repeated deforestation detections.	$P(X=k) = \binom{k+r-1}{k}(1-p)^r p^k,\; k = 0,1,2,\ldots$
Discrete Uniform	Assumes outcome in a finite set is equally likely, e.g., random sampling of inventory across a forest.	$P(X=x) = \frac{1}{n},\; x = 1,2,\ldots,n$

Discrete distributions describe forestry monitoring scenarios where data outcomes are countable and finite. Common examples include the number of deforestation events, occurrences of wildfires, or counts of logged trees within a defined monitoring interval. Accurate representation of discrete events using appropriate distributions such as Binomial, Poisson, or Negative Binomial significantly enhances the accuracy of model predictions and uncertainty assessments. For instance, employing a Poisson distribution to model occurrences of illegal logging events can improve the precision of estimated deforestation emissions and reduce uncertainty around compliance risks.

In contrast, continuous distributions capture variables capable of taking any value within a specified range and are particularly relevant in forestry when modeling measurements such as tree heights, carbon stock densities, or biomass values. Continuous distributions like the Normal (Gaussian), Lognormal, Weibull, and Gamma distributions frequently arise in ecological modeling and biomass estimations due to their ability to realistically represent ecological variability and complex environmental factors. For example, using a Lognormal distribution for tree biomass data often provides more reliable estimates, particularly when the dataset is right-skewed due to natural variability in tree growth and forest conditions.

Central to these distributions are two mathematical concepts: Probability Mass Functions (PMFs) for discrete data and Probability Density Functions (PDFs) for continuous data. PMFs allocate specific probabilities to discrete outcomes, essential for accurately simulating events such as species occurrences or forest disturbances. PDFs describe the relative likelihood of continuous data points, enabling the robust estimation of variables like forest carbon content or annual biomass increment.

In Monte Carlo simulations, precise definition and utilization of PMFs and PDFs are crucial. These functions underpin random sampling processes that directly influence the reliability, precision, and credibility of uncertainty estimates. Given that forestry data is known to exhibit non-normal distributions due to inherent ecological heterogeneity that, informed selection and rigorous application of these functions are vital. Accurate modeling of the underlying data distribution enhances biomass and emissions estimates, significantly reduces uncertainty, and bolsters the financial and ecological credibility of REDD+ reporting initiatives (Morgan & Henrion, 1990; IPCC, 2019; ART, 2021).

Practitioners are encouraged to conduct exploratory data analysis early in their project planning stages, integrating statistical tests of normality and visual assessments (histograms, kernel density plots, Q-Q plots). Such preliminary analyses assist in diagnosing data distributions accurately, improving model selection, reducing potential auditor findings, and ultimately enhancing the financial and environmental outcomes of national REDD+ monitoring programs.

Method

Import

```r
# Point this to the correct path where your file is located:
workbook = "./data/art/GuyanaARTWorkbookMC-thru2022-April2024_values.xlsx"
CarbonStocks = readxl::read_excel(workbook, "CarbonStocks") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
CarbonStocks_MC = readxl::read_excel(workbook, "CarbonStocks (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

DeforestationEF = readxl::read_excel(workbook, "Deforestation EFs") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
DeforestationEF_MC = readxl::read_excel(workbook, "Deforestation EFs (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

DegradationEF = readxl::read_excel(workbook, "Degradation EFs") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
DegradationEF_MC = readxl::read_excel(workbook, "Degradation EFs (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

ActivityData = readxl::read_excel(workbook, "Activity Data") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
ActivityData_MC = readxl::read_excel(workbook, "Activity Data (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

Emissions = readxl::read_excel(workbook, "Emissions") |>
    janitor::clean_names() |>
```

```r
    mutate(across(where(is.numeric), ~round(.x, 1)))
Emissions_MC = readxl::read_excel(workbook, "Emissions (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

Crediting = readxl::read_excel(workbook, "ART Crediting Period") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
Crediting_MC = readxl::read_excel(workbook, "ART Crediting Period") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

EmissionsReductions = readxl::read_excel(workbook, "Emission Reductions") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))
EmissionsReductions_MC = readxl::read_excel(workbook, "Emission Reductions (MC)") |>
    janitor::clean_names() |>
    mutate(across(where(is.numeric), ~round(.x, 1)))

# Vislualize
flextable(head(CarbonStocks_MC[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

x1	ag_tree_t_c_ha	bg_tree_t_c_ha	saplings_t_c_ha	standing_dead_wood_t_c_ha	lying_dead_wood_t_c_ha	sum_carbon_pools	litter_t_c_ha
tC/ha	181.1	65.0	3.5	7.3	17.1		3.7
tCO2/ha	664.2	238.2	12.8	26.9	62.6		13.7

```r
flextable(head(CarbonStocks[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

statistic	ag_tree_t_c_ha	bg_tree_t_c_ha	saplings_t_c_ha	standing_dead_wood_t_c_ha	lying_dead_wood_t_c_ha	sum_carbon_pools	litter_t_c_ha
mean	205.8	48.3	3.7	2.6	8.6	269.0	3.3
std_dev	60.4	14.3	2.0	4.0	8.1	75.2	1.3
minimum	91.6	21.2	0.5	0.0	0.0		1.2
maximum	353.7	83.1	18.8	13.7	42.3		8.7
90%_CI	9.2	2.2	0.3	0.6	1.2	11.5	0.2
CI_%_of_mean	0.0	0.0	0.1	0.2	0.1	0.0	

```r
flextable(head(DeforestationEF_MC[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

stratum	drivers	emission_factors	x4	x5	x6	x7	x8
		tC/ha	t CO2/ha				
Combined - all forest	Forestry infrastructure	292.6299433864[illegible]	[illegible]9764590836501				
	Agriculture	309.2683633316[illegible]	[illegible]98399888266				

stratum	drivers	emission_factors	x4	x5	x6	x7	x8
	Mining (medium and large scale)	292.629943386414879229764590836501					
	Mining infrastructure	292.629943386414879229764590836501					
	Infrastructure	292.629943386414879229764590836501					

```r
flextable(head(DeforestationEF[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

stratum	drivers	emission_factors	x4	x5	x6	x7	x8
		tC/ha	t CO2/ha	uncertainty (IPCC approach 1)	uncertainty (IPCC approach 1)		
Combined - all forest	Forestry infrastructure	286.72598083121105916328596381107		4.8281339665925099E-2	35.368573711171344		
	Agriculture	302.8353793496721107.3963909487979		4.8281339665925099E-2	35.368573711171344		
	Mining (medium and large scale)	286.72598083121105916328596381107		4.8281339665925099E-2	35.368573711171344		
	Mining infrastructure	286.72598083121105916328596381107		4.8281339665925099E-2	35.368573711171344		
	Infrastructure	286.72598083121105916328596381107		4.8281339665925099E-2	35.368573711171344		

```r
flextable(head(ActivityData[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

x1	x2	x3	change_data_from_wall_to_wall_mapping_by_gfoi	x5	x6	x7	x8
	Drivers	units	2011	2,012	2,013	2014	2,015
	Deforestation						
Deforestation	Forestry infrastructure	ha	186	240	330	204	313
	Agriculture		41	440	424	817	379
	Mining (medium and large scale)		7340	13,664	11,518	10434	6,782
	Mining infrastructure						

```r
flextable(head(ActivityData_MC[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

x1	x2	x3	change	x5	x6	x7	x8
	Drivers	units	2,011.0	2,012.0	2,013.0	2014	2,015.0
Deforestation	Forestry infrastructure	ha	225.2	194.4	269.9	229.322762617862	325.1
	Agriculture		36.2	384.1	462.7	881.60601412734502	436.2
	Mining (medium and large scale)		8,835.0	13,156.9	7,686.7	12583.070934203801	7,673.2
	Mining infrastructure		0.0	0.0	0.0	0	0.0
	Infrastructure		116.8	121.1	330.8	142.54724233274399	182.1

```
flextable(head(Emissions[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

drivers	units	x2011	x2012	x2013	x2014	x2015	x2016
Forestry infrastructure	tCO2	195,547.1	252,318.9	346,938.4	214,471.0	329065.85066728649	329,065.9
Agriculture		45,526.3	488,574.4	470,808.1	907,193.9	420840.2321695944	420,840.2
Mining (medium and large scale)		7,716,751.9	14,365,353.9	12,109,202.8	10,969,562.6	7130110.540656667	7,130,110.5
Infrastructure		124,477.3	133,518.7	359,554.4	148,237.3	228138.30541470021	228,138.3
Settlements		0.0	0.0	24,180.6	74,644.3	8410.6287710488559	8,410.6
Fire-Biomass burning		48,436.9	193,747.7	101,085.8	272,721.0	1588942.112251644	1,588,942.1

```
flextable(head(Emissions_MC[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

drivers	units	x2011	x2012	x2013	x2014	x2015	x2016
Forestry infrastructure	tCO2	241,594.0	208,610.9	289,633.3	246,057.9	348,853.5	308,654.5
Agriculture		41,036.5	435,510.7	524,713.8	999,727.1	494,631.4	454,779.0
Mining (medium and large scale)		9,479,796.2	14,117,045.3	8,247,621.5	13,501,338.9	8,233,167.9	7,599,187.4
Infrastructure		125,287.5	129,973.5	354,898.9	152,949.8	195,363.9	253,644.8
Settlements		0.0	0.0	26,317.3	78,166.4	8,033.6	7,630.6
Fire-Biomass burning		55,974.3	199,540.4	94,090.4	319,448.8	1,946,314.3	1,649,411.3

```
flextable(head(DegradationEF[, 1:8])) |>
    fontsize(size = 8, part = "all")
```

logging_emission_factors	x2	x3	x4	x5	x6	x7	x8
Component	Unit	Factor (tC)	Std Dev (tC)	90% CI (tC)	t CO2	Std Dev (tCO2)	90% CI (tCO2)
LDF	per m3	1.05	0.68	0.08	3.85	2.4933333333333	0.2963333333333333
Wood Density of timber harvested	per m3	0.4	0.03	3.0000000000000001E-3	1.4666666666666	0.10999999999999999	1.0999999999999999E-2
LIF (Skid Trails)	per km	46.865095626648	8.288	1.6	171.83868396432	29.626666666666	5.8666666666666671

```
# flextable(head(DegradationEF_MC[, 1:8])) |> fontsize(size = 8, part = 'all')
# dplyr::glimpse(CarbonStocks)
```

Tidy

Data cleaning tasks often needed for dataframes imported with `readxl::read_exel()` function, as variables, labels and dataframes are corrupted in the process. This especially likely with summary statistics in non-standard formats, such as in Guyana's workbook data. Re-installing and applying the function `janitor::clean_names()` may sometimes solve this, but more often not. For future debugging, I added notes in this Tidy section on the steps identified to complete data cleaning.

We begin by identifying the relevant rows and columns for each pool, specifically those containing mean, standard deviation, minimum, maximum, and confidence interval values. Assuming rows in the "CarbonStocks_MC" tab maintain the same order, these cleaning operations can hopefully be repeated quickly. A common approach involves reshaping the data so that each row represents a "Statistic," such as mean or standard deviation, and each column corresponds to a carbon pool, like "AG Tree" or "BG Tree."

In the chunk below we select columns pertinent to carbon pools, including "AG Tree (tC/ha)", "BG Tree (tC/ha)," and rename them to match the "SimVoi" workbook. Subsequently, we extract the rows containing the summary statistics, and reshape the data to our preferred layout. To effectively transpose the data and transition between wide and long formats, utilize the `tidyr` package's `pivot_longer()` and `pivot_wider()` functions, which essentially flip rows and columns. Finally, you must pivot back from long to wide layout to ensure that "Statistic" becomes a distinct column and the carbon pools, such as "AG_Tree" and "BG_Tree," are represented as separate variable columns. Happy to walk you through this again if you need.

Distribution Analysis

```
# Descriptive statistics
psych::describe(CarbonStocks)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
statistic*	1	8	4.5000	2.449490	4.50	4.5000	2.96520	1.0	8.0	7.0	0.0000000	-1.6510417	0.8660254
ag_tree_t_c_ha	2	8	163.8375	169.68320	104.80	163.8375	145.7395	8.0	472.0	472.0	0.6781874	-1.2269063	59.9920945
bg_tree_t_c_ha	3	8	94.8875	157.9223	30.075	94.8875	49.8894	0.0	472.0	472.0	1.617563	1.111153	55.8339644
saplings_t_c_ha	4	8	76.9250	164.63802	2.685	76.9250	3.92889	0.1	472.0	471.9	1.663116	1.175109	58.2083442
standing_dead_wood_t_c_ha	5	8	76.3875	164.85423	3.430	76.3875	4.74432	0.0	472.0	472.0	1.663932	1.175453	58.2847764
lying_dead_wood_t_c_ha	6	8	81.2875	162.90978	2.255	81.2875	12.30558	0.0	472.0	472.0	1.655839	1.169258	57.5972855

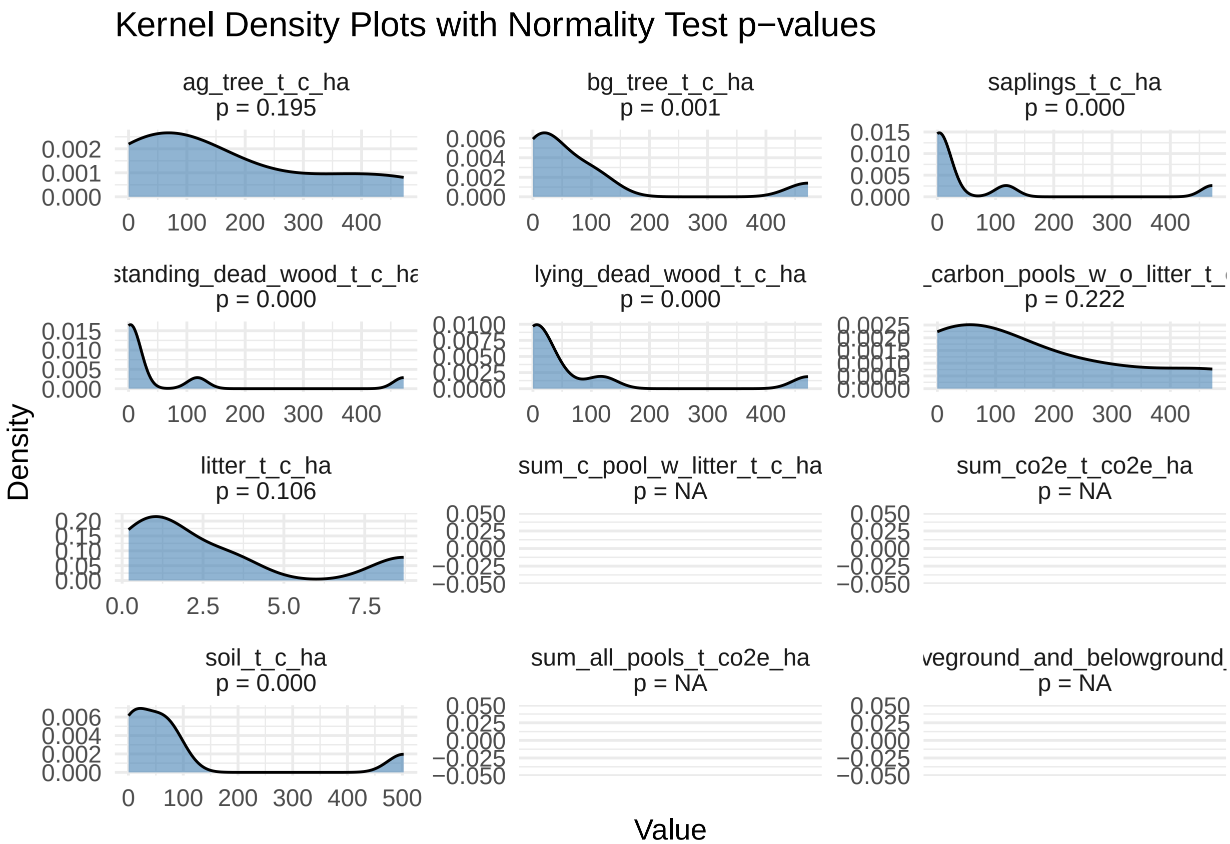
	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
sum_carbon_pools_w_o_litter_t_c_ha	7	6	157.6167	182.0978	99.60	157.6167	134.69420	0.0	472.0	472.0	0.6844433	-1.3259625	74.3411524
litter_t_c_ha	8	5	2.9400	3.410718	1.30	2.9400	1.63086	0.2	8.7	8.5	0.8110507	-1.2656277	1.5253196
sum_c_pool_w_litter_t_c_ha	9	1	272.3000	NA	272.30	272.3000	0.00000	272.3	272.3	0.0	NA	NA	NA
sum_co2e_t_co2e_ha	10	1	998.5000	NA	998.50	998.5000	0.00000	998.5	998.5	0.0	NA	NA	NA
soil_t_c_ha	11	7	104.4143	178.4700	58.70	104.4143	70.72002	0.2	502.4	502.2	1.5096601	0.5723096	67.4553377
sum_all_pools_t_co2e_ha	12	1	1213.7000	NA	1213.70	1213.7000	0.00000	1213.7	1213.7	0.0	NA	NA	NA
sum_aboveground_and_belowground_live_tree	13	1	931.9000	NA	931.90	931.9000	0.00000	931.9	931.9	0.0	NA	NA	NA

```
psych::describe(Emissions)
psych::describe(DeforestationEF)
psych::describe(DegradationEF)
psych::describe(ActivityData)
psych::describe(EmissionsReductions)
psych::describe(Crediting)

MASS::truehist(CarbonStocks$ag_tree_t_c_ha, nbins = 30, xlab = "ag_tree_t_c_ha",
    main = paste("Distribution of", "ag_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$bg_tree_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$saplings_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$standing_dead_wood_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$lying_dead_wood_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$sum_carbon_pools_w_o_litter_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$litter_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha", main = paste("Distribut
    "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$sum_c_pool_w_litter_t_c_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$sum_co2e_t_co2e_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$x11, nbins = 30, xlab = "bg_tree_t_c_ha", main = paste("Distribution of",
    "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$sum_co2e_t_co2e_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")
MASS::truehist(CarbonStocks$sum_co2e_t_co2e_ha, nbins = 30, xlab = "bg_tree_t_c_ha",
    main = paste("Distribution of", "bg_tree_t_c_ha"), col = "gray")

truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
```

```r
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")
truehist(CarbonStocks, nbins = nbins, xlab = var_name, main = paste("Distribution of",
    var_name), col = "gray")

# Shapiro-Wilk normality test
normalityTests <- function(data) {
    numericData <- data[sapply(data, is.numeric)]
    results <- sapply(numericData, function(x) {
        x_clean <- na.omit(x)
        if (length(x_clean) >= 3 && length(x_clean) <= 5000) {
            test <- shapiro.test(x_clean)
            c(W = test$statistic, p.value = test$p.value)
        } else {
            c(W = NA, p.value = NA)
        }
    })
    results_df <- as.data.frame(t(results))
    return(results_df)
}

# Function to plot kernel density plots with p-values annotated in facet labels
plotKernelDensitiesWithNormality <- function(data) {
    numericData <- data[sapply(data, is.numeric)]
    meltedData <- melt(numericData, variable.name = "Variable", value.name = "Value")
    norm_results <- normalityTests(data)
    norm_results$Variable <- rownames(norm_results)
    norm_results$p.value.formatted <- sprintf("p = %.3f", norm_results$p.value)
    facet_labels <- setNames(paste0(norm_results$Variable, "\n", norm_results$p.value.formatted),
        norm_results$Variable)
    ggplot(meltedData, aes(x = Value)) + geom_density(fill = "steelblue", alpha = 0.6) +
        facet_wrap(~Variable, scales = "free", ncol = 3, labeller = as_labeller(facet_labels)) +
        theme_minimal() + labs(title = "Kernel Density Plots with Normality Test p-values",
        x = "Value", y = "Density")
}

# Deploy:
norm_results <- normalityTests(CarbonStocks)
print(norm_results)
```

```
                                              W.W      p.value
ag_tree_t_c_ha                          0.8815235 1.947395e-01
bg_tree_t_c_ha                          0.6458968 5.427110e-04
saplings_t_c_ha                         0.5603122 5.424425e-05
standing_dead_wood_t_c_ha               0.5559837 4.820435e-05
lying_dead_wood_t_c_ha                  0.5865634 1.106360e-04
sum_carbon_pools_w_o_litter_t_c_ha      0.8688451 2.216401e-01
litter_t_c_ha                           0.8144912 1.058007e-01
sum_c_pool_w_litter_t_c_ha                     NA           NA
sum_co2e_t_co2e_ha                             NA           NA
soil_t_c_ha                             0.6168788 4.287387e-04
sum_all_pools_t_co2e_ha                        NA           NA
sum_aboveground_and_belowground_live_tree      NA           NA
```

```r
plotKernelDensitiesWithNormality(CarbonStocks)
```



The Coefficient of Variation `CV` is a standardized, unit-less measure of dispersion defined as the ratio of the standard deviation to the mean, typically expressed as a percentage. This standardization enables comparison of variability across datasets or scales, regardless of the underlying units, offering helpful tool for assessing novel data from periodic field inventories or mapping updates.

$$\mathrm{CV} = \frac{\sigma}{\mu} \times 100\%$$

$$\mathrm{CV}_{\%} = 100 \times \frac{\text{std. dev}}{\text{mean of all plots (calculated)}}$$

For these carbon stocks, a higher CV indicates greater relative variability or "scatter" in the data. While the CV is a useful indicator of dispersion and can signal potential non-normality, it does not provide any information on the direction of skew in the distribution.

In the following, the CV variable was computed from within the larger helper function `calc_derived_stats`. This helper function was designed as an aggregated relational estimate, which calculates CV while also comparing the reported 90% confidence interval with the standard deviation, which, under assumed normality, should approximate to $\pm 1.645 \times$ SD. This iterative scoring helps assess the internal consistency of the reported descriptive statistics.

```
# Helper function of derived descriptive statistics:
calc_derived_stats <- function(df) {
    df %>%
        mutate(CV_percent = 100 * (std_dev/`mean of all plots (calculated)`), sd_implied_by_90CI = `90%
            SDs_below_mean = (`mean of all plots (calculated)` - minimum)/`std. dev`,
            SDs_above_mean = (maximum - `mean of all plots (calculated)`)/`std. dev`)
}
```

```
# CarbonStocks_stats <- calc_derived_stats(CarbonStocks)
```

Replicating SimVoi

We utilize the replicate function to repeat a simulation following a randomized normally truncated multiple times with `replicate(n=10000`, while determining the size of the sampled subset with `rnorm(n=100`. The first model explores sample size parameters only, replication parameters are tested below this in comparisons.

Compare simulations

```
MEAN = CarbonStocks$`AG Tree (tC/ha)`[1]
SD = CarbonStocks$`AG Tree (tC/ha)`[2]

randtruncnormal_sim_10000 <- rnorm(n = 10000, mean = MEAN, sd = SD)
hist(randtruncnormal_sim_10000, freq = F)
AG_Tree_tC_ha = mean(randtruncnormal_sim_10000)
AG_Tree_tCO2_ha = AG_Tree_tC_ha * (44/12)
AG_Tree_tC_ha
AG_Tree_tCO2_ha
# curve(dnorm(x, mean=MEAN, sd=SD), from=0, to=450, add=T, col='red')

# 10,000 simulations sampling 10 observations
randtruncnormal_sim_10000_10 = replicate(n = 10000, rnorm(n = 10, mean = MEAN, sd = SD))
hist(apply(X = randtruncnormal_sim_10000_10, MARGIN = 2, FUN = mean))
sd(apply(X = randtruncnormal_sim_10000_10, MARGIN = 2, FUN = mean))
mean(apply(X = randtruncnormal_sim_10000_10, MARGIN = 2, FUN = mean))
(mean(apply(X = randtruncnormal_sim_10000_10, MARGIN = 2, FUN = mean))) * (44/12)

# 10,000 simulations sampling 100 observations
randtruncnormal_sim_10000_100 = replicate(n = 10000, rnorm(n = 100, mean = MEAN,
    sd = SD))
hist(apply(X = randtruncnormal_sim_10000_100, MARGIN = 2, FUN = mean))
sd(apply(X = randtruncnormal_sim_10000_100, MARGIN = 2, FUN = mean))
mean(apply(X = randtruncnormal_sim_10000_100, MARGIN = 2, FUN = mean))
(mean(apply(X = randtruncnormal_sim_10000_100, MARGIN = 2, FUN = mean))) * (44/12)

# 10,000 simulations sampling 1,000 observations
randtruncnormal_sim_10000_1000 = replicate(n = 10000, rnorm(n = 1000, mean = MEAN,
    sd = SD))
hist(apply(X = randtruncnormal_sim_10000_1000, MARGIN = 2, FUN = mean))
sd(apply(X = randtruncnormal_sim_10000_1000, MARGIN = 2, FUN = mean))
mean(apply(X = randtruncnormal_sim_10000_1000, MARGIN = 2, FUN = mean))
(mean(apply(X = randtruncnormal_sim_10000_1000, MARGIN = 2, FUN = mean))) * (44/12)

# 10,000 simulations sampling 10,000 observations
randtruncnormal_sim_10000_10000 = replicate(n = 10000, rnorm(n = 10000, mean = MEAN,
    sd = SD))
hist(apply(X = randtruncnormal_sim_10000_10000, MARGIN = 2, FUN = mean))
sd(apply(X = randtruncnormal_sim_10000_10000, MARGIN = 2, FUN = mean))
mean(apply(X = randtruncnormal_sim_10000_10000, MARGIN = 2, FUN = mean))
(mean(apply(X = randtruncnormal_sim_10000_10000, MARGIN = 2, FUN = mean))) * (44/12)
```

Annex I: SimVoi Functions & Syntax

SimVoi adds seventeen random number generator functions defined with the following syntax:

- `RandBeta(alpha,beta,,[MinValue],[MaxValue])`
- `RandBinomial(trials,probability_s)`
- `RandBiVarNormal(mean1,stdev1,mean2,stdev2,correl12)`
- `RandCumulative(value_cumulative_table)`
- `RandDiscrete(value_discrete_table)`
- `RandExponential(lambda)`
- `RandInteger(bottom,top)`
- `RandLogNormal(Mean,StDev)`
- `RandNormal(mean,standard_dev)`
- `RandPoisson(mean)`
- `RandSample(population)`
- `RandTriangular(minimum,most_likely,maximum)`
- `RandTriBeta(minimum,most_likely,maximum,[shape])`
- `RandTruncBiVarNormal(mean1,stdev1,mean2,stdev2,correl12, [min1],[max1],[min2],[max2])`
- `RandTruncLogNormal(Mean,StDev,[MinValue],[MaxValue])`
- `RandTruncNormal(Mean,StDev,[MinValue],[MaxValue])`
- `RandUniform(minimum,maximum)`

In the following, we attempt to match the SimVoi Excel formula of

```
=[1]!randtruncnormal(CarbonStocks.B2,CarbonStocks.B3,0)
```

function, as closely as random seeding allows. According to package documentation, the `RandTruncNormal()` function "*Returns a random value from a truncated normal probability density function. This function can model an uncertain quantity with a bell-shaped density function where extreme values in the tails of the distribution are not desired.*"

In terms of simulation parameters, *"RandTruncNormal(Mean,StDev,MinValue,MaxValue)) uses values of RandNormal until a value is found between MinValue and MaxValue or until it has made 10,000 attempts."* The above formula provides a minimum value of `0`, passing to the default number of simulations of 10,000.

Annex II: Rapid literature review or Monte Carlo methods in REDD+

Table A.2: Search parameters, resource scope, and objectives informing search

REDD+[1]	**MC Application**	**Region**	**Key Findings**
ADD	Uncertainty of SAAB estimate	Rondônia, Brazil	Estimated ± 20% measurement error in SAAB using Monte Carlo simulations; emphasized large trees' role in biomass.
ADD	AGB Uncertainty	Kenya, Mozambique	Assessed mixed-effects models in estimating mangrove biomass.
ADD	Blanket uncertainty propagation	Ghana	AGB prediction error >20%; addressed error propagation from trees to pixels in remote sensing.
ADD	Plot-based uncertainty	New Zealand	Cross-plot variance greatest magnitude of uncertainty

[1]1. ADD: Avoided deforestation degradation, IFM: Improved forest management, JNR: Jurisdictional nested REDD+

JNR	Multi-scale AGB uncertainty modeling	Minnesota, USA	Cross-scale tests showing effects of spatial resolution on AGB uncertainty.
N/A	Allometric uncertainty modeling	Panama	Allometric models identified as largest source of biomass estimation error.
ADD	Sampling and allometric uncertainty	Tapajos Nat Forest, Brazil	Significance of allometric models on uncertainty of root biomass, 95% CI, 21 plots.
ADD	Uncertainty of volume estimates	Santa Catarina, Brazil	Negligible effects of residual uncertainty on large-area estimates
N/A	Uncertainty metrics in model selection	Oregon, USA	Uncertainty estimates call for local validation or new local model development
ADD	AGB model uncertainty	French Guiana	AGB sub-model errors dominate uncertainty; height and wood-specific gravity errors are minor but can cause bias.
IFM	Emission factor uncertainty	Central Africa	Model selection is the largest error source (40%); weighting models reduces uncertainty in emission factors.
NA	Uncertainty in ecosystem nutrient estimate	New Hampshire, USA	Identified 8% uncertainty in nitrogen budgets, mainly from plot variability (6%) and allometric errors (5%).

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```r
devtools::session_info()
```

```
- Session info ---------------------------------------------------------------
 setting  value
 version  R version 4.3.0 (2023-04-21)
 os       macOS 15.3.2
 system   aarch64, darwin20
 ui       X11
 language (EN)
 collate  en_US.UTF-8
 ctype    en_US.UTF-8
 tz       America/Vancouver
 date     2025-03-23
 pandoc   3.6.1 @ /usr/local/bin/ (via rmarkdown)

- Packages -------------------------------------------------------------------
 package           * version    date (UTC) lib source
 animation         * 2.7        2021-10-07 [1] CRAN (R 4.3.3)
 askpass             1.2.1      2024-10-04 [1] CRAN (R 4.3.3)
```

```
 assertthat          0.2.1      2019-03-21 [1] CRAN (R 4.3.0)
 backports           1.5.0      2024-05-23 [1] CRAN (R 4.3.3)
 BIOMASS           * 2.2.3      2025-02-24 [1] CRAN (R 4.3.3)
 boot                1.3-31     2024-08-28 [1] CRAN (R 4.3.3)
 broom             * 1.0.7      2024-09-26 [1] CRAN (R 4.3.3)
 c2z               * 0.2.0      2023-08-10 [1] CRAN (R 4.3.0)
 cachem              1.1.0      2024-05-16 [1] CRAN (R 4.3.3)
 caret             * 7.0-1      2024-12-10 [1] CRAN (R 4.3.3)
 cellranger          1.1.0      2016-07-27 [1] CRAN (R 4.3.0)
 chromote            0.4.0      2025-01-25 [1] CRAN (R 4.3.3)
 class               7.3-23     2025-01-01 [1] CRAN (R 4.3.3)
 classInt            0.4-11     2025-01-08 [1] CRAN (R 4.3.3)
 cli                 3.6.3      2024-06-21 [1] CRAN (R 4.3.3)
 codetools           0.2-20     2024-03-31 [1] CRAN (R 4.3.1)
 colorspace          2.1-1      2024-07-26 [1] CRAN (R 4.3.3)
 data.table          1.16.4     2024-12-06 [1] CRAN (R 4.3.3)
 dataMaid          * 1.4.1      2021-10-08 [1] CRAN (R 4.3.0)
 DBI                 1.2.3      2024-06-02 [1] CRAN (R 4.3.3)
 DEoptimR            1.1-3-1    2024-11-23 [1] CRAN (R 4.3.3)
 DescTools         * 0.99.59    2025-01-26 [1] CRAN (R 4.3.3)
 devtools            2.4.5      2022-10-11 [1] CRAN (R 4.3.0)
 dials             * 1.3.0      2024-07-30 [1] CRAN (R 4.3.3)
 DiceDesign          1.10       2023-12-07 [1] CRAN (R 4.3.1)
 digest              0.6.37     2024-08-19 [1] CRAN (R 4.3.3)
 dplyr             * 1.1.4      2023-11-17 [1] CRAN (R 4.3.1)
 e1071               1.7-16     2024-09-16 [1] CRAN (R 4.3.3)
 easypackages        0.1.0      2016-12-05 [1] CRAN (R 4.3.0)
 ellipsis            0.3.2      2021-04-29 [1] CRAN (R 4.3.0)
 evaluate            1.0.3      2025-01-10 [1] CRAN (R 4.3.3)
 Exact               3.3        2024-07-21 [1] CRAN (R 4.3.3)
 expm                1.0-0      2024-08-19 [1] CRAN (R 4.3.3)
 extrafont         * 0.19       2023-01-18 [1] CRAN (R 4.3.3)
 extrafontdb         1.0        2012-06-11 [1] CRAN (R 4.3.3)
 farver              2.1.2      2024-05-13 [1] CRAN (R 4.3.3)
 fastmap             1.2.0      2024-05-15 [1] CRAN (R 4.3.3)
 flextable         * 0.9.7      2024-10-27 [1] CRAN (R 4.3.3)
 fontBitstreamVera   0.1.1      2017-02-01 [1] CRAN (R 4.3.3)
 fontLiberation      0.1.0      2016-10-15 [1] CRAN (R 4.3.3)
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 ggplot2           * 3.5.1      2024-04-23 [1] CRAN (R 4.3.1)
 gld                 2.6.7      2025-01-17 [1] CRAN (R 4.3.3)
 globals             0.16.3     2024-03-08 [1] CRAN (R 4.3.1)
 glue                1.8.0      2024-09-30 [1] CRAN (R 4.3.3)
 gower               1.0.2      2024-12-17 [1] CRAN (R 4.3.3)
 GPfit               1.0-8      2019-02-08 [1] CRAN (R 4.3.0)
```

```
gridExtra           2.3        2017-09-09 [1] CRAN (R 4.3.0)
gtable              0.3.6      2024-10-25 [1] CRAN (R 4.3.3)
hardhat             1.4.0      2024-06-02 [1] CRAN (R 4.3.3)
haven               2.5.4      2023-11-30 [1] CRAN (R 4.3.1)
hms                 1.1.3      2023-03-21 [1] CRAN (R 4.3.0)
htmltools         * 0.5.8.1    2024-04-04 [1] CRAN (R 4.3.1)
htmlwidgets         1.6.4      2023-12-06 [1] CRAN (R 4.3.1)
httpuv              1.6.15     2024-03-26 [1] CRAN (R 4.3.1)
httr                1.4.7      2023-08-15 [1] CRAN (R 4.3.0)
infer             * 1.0.7      2024-03-25 [1] CRAN (R 4.3.1)
ipred               0.9-15     2024-07-18 [1] CRAN (R 4.3.3)
iterators           1.0.14     2022-02-05 [1] CRAN (R 4.3.0)
janitor           * 2.2.1      2024-12-22 [1] CRAN (R 4.3.3)
jsonlite          * 1.8.9      2024-09-20 [1] CRAN (R 4.3.3)
kableExtra        * 1.4.0      2024-01-24 [1] CRAN (R 4.3.1)
kernlab           * 0.9-33     2024-08-13 [1] CRAN (R 4.3.3)
KernSmooth          2.23-26    2025-01-01 [1] CRAN (R 4.3.3)
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later               1.4.1      2024-11-27 [1] CRAN (R 4.3.3)
latex2exp         * 0.9.6      2022-11-28 [1] CRAN (R 4.3.0)
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lattice           * 0.22-6     2024-03-20 [1] CRAN (R 4.3.1)
lava                1.8.1      2025-01-12 [1] CRAN (R 4.3.3)
lhs                 1.2.0      2024-06-30 [1] CRAN (R 4.3.3)
lifecycle           1.0.4      2023-11-07 [1] CRAN (R 4.3.1)
listenv             0.9.1      2024-01-29 [1] CRAN (R 4.3.1)
lmom                3.2        2024-09-30 [1] CRAN (R 4.3.3)
lubridate         * 1.9.4      2024-12-08 [1] CRAN (R 4.3.3)
magrittr            2.0.3      2022-03-30 [1] CRAN (R 4.3.0)
MASS              * 7.3-58.4   2023-03-07 [2] CRAN (R 4.3.0)
Matrix              1.6-5      2024-01-11 [1] CRAN (R 4.3.1)
memoise             2.0.1      2021-11-26 [1] CRAN (R 4.3.0)
mime                0.12       2021-09-28 [1] CRAN (R 4.3.0)
miniUI              0.1.1.1    2018-05-18 [1] CRAN (R 4.3.0)
minpack.lm          1.2-4      2023-09-11 [1] CRAN (R 4.3.3)
mnormt              2.1.1      2022-09-26 [1] CRAN (R 4.3.0)
modeldata         * 1.4.0      2024-06-19 [1] CRAN (R 4.3.3)
ModelMetrics        1.2.2.2    2020-03-17 [1] CRAN (R 4.3.0)
munsell             0.5.1      2024-04-01 [1] CRAN (R 4.3.1)
mvtnorm             1.3-3      2025-01-10 [1] CRAN (R 4.3.3)
nlme                3.1-166    2024-08-14 [1] CRAN (R 4.3.3)
nnet                7.3-20     2025-01-01 [1] CRAN (R 4.3.3)
officer             0.6.7      2024-10-09 [1] CRAN (R 4.3.3)
openssl             2.3.1      2025-01-09 [1] CRAN (R 4.3.3)
pander              0.6.6      2025-03-01 [1] CRAN (R 4.3.3)
parallelly          1.41.0     2024-12-18 [1] CRAN (R 4.3.3)
parsnip           * 1.2.1      2024-03-22 [1] CRAN (R 4.3.1)
pillar              1.10.1     2025-01-07 [1] CRAN (R 4.3.3)
pkgbuild            1.4.6      2025-01-16 [1] CRAN (R 4.3.3)
pkgconfig           2.0.3      2019-09-22 [1] CRAN (R 4.3.0)
pkgload             1.4.0      2024-06-28 [1] CRAN (R 4.3.3)
plyr                1.8.9      2023-10-02 [1] CRAN (R 4.3.1)
pROC                1.18.5     2023-11-01 [1] CRAN (R 4.3.1)
```

```
processx        3.8.5      2025-01-08 [1] CRAN (R 4.3.3)
prodlim         2024.06.25 2024-06-24 [1] CRAN (R 4.3.3)
profvis         0.4.0      2024-09-20 [1] CRAN (R 4.3.3)
promises        1.3.2      2024-11-28 [1] CRAN (R 4.3.3)
proxy           0.4-27     2022-06-09 [1] CRAN (R 4.3.0)
ps              1.8.1      2024-10-28 [1] CRAN (R 4.3.3)
psych           2.4.12     2024-12-23 [1] CRAN (R 4.3.3)
purrr         * 1.0.2      2023-08-10 [1] CRAN (R 4.3.0)
R6              2.5.1      2021-08-19 [1] CRAN (R 4.3.0)
ragg            1.3.3      2024-09-11 [1] CRAN (R 4.3.3)
rappdirs        0.3.3      2021-01-31 [1] CRAN (R 4.3.0)
Rcpp            1.0.14     2025-01-12 [1] CRAN (R 4.3.3)
readr         * 2.1.5      2024-01-10 [1] CRAN (R 4.3.1)
readxl        * 1.4.3      2023-07-06 [1] CRAN (R 4.3.0)
recipes       * 1.1.0      2024-07-04 [1] CRAN (R 4.3.3)
remotes         2.5.0      2024-03-17 [1] CRAN (R 4.3.1)
reshape2      * 1.4.4      2020-04-09 [1] CRAN (R 4.3.0)
rlang           1.1.4      2024-06-04 [1] CRAN (R 4.3.3)
rmarkdown     * 2.29       2024-11-04 [1] CRAN (R 4.3.3)
robustbase      0.99-4-1   2024-09-27 [1] CRAN (R 4.3.3)
rootSolve       1.8.2.4    2023-09-21 [1] CRAN (R 4.3.3)
rpart           4.1.24     2025-01-07 [1] CRAN (R 4.3.3)
rsample       * 1.2.1      2024-03-25 [1] CRAN (R 4.3.1)
rstudioapi      0.17.1     2024-10-22 [1] CRAN (R 4.3.3)
Rttf2pt1        1.3.12     2023-01-22 [1] CRAN (R 4.3.3)
rvest           1.0.4      2024-02-12 [1] CRAN (R 4.3.1)
scales        * 1.3.0      2023-11-28 [1] CRAN (R 4.3.1)
sessioninfo     1.2.2      2021-12-06 [1] CRAN (R 4.3.0)
sf              1.0-19     2024-11-05 [1] CRAN (R 4.3.3)
shiny           1.10.0     2024-12-14 [1] CRAN (R 4.3.3)
snakecase       0.11.1     2023-08-27 [1] CRAN (R 4.3.0)
stringi         1.8.4      2024-05-06 [1] CRAN (R 4.3.1)
stringr       * 1.5.1      2023-11-14 [1] CRAN (R 4.3.1)
survival        3.8-3      2024-12-17 [1] CRAN (R 4.3.3)
svglite         2.1.3      2023-12-08 [1] CRAN (R 4.3.1)
systemfonts     1.1.0      2024-05-15 [1] CRAN (R 4.3.3)
terra           1.8-29     2025-02-26 [1] CRAN (R 4.3.3)
textshaping     0.4.1      2024-12-06 [1] CRAN (R 4.3.3)
tibble        * 3.2.1      2023-03-20 [1] CRAN (R 4.3.0)
tidymodels    * 1.2.0      2024-03-25 [1] CRAN (R 4.3.1)
tidyr         * 1.3.1      2024-01-24 [1] CRAN (R 4.3.1)
tidyselect      1.2.1      2024-03-11 [1] CRAN (R 4.3.1)
tidyverse     * 2.0.0      2023-02-22 [1] CRAN (R 4.3.0)
timechange      0.3.0      2024-01-18 [1] CRAN (R 4.3.1)
timeDate        4041.110   2024-09-22 [1] CRAN (R 4.3.3)
tinytex       * 0.54       2024-11-01 [1] CRAN (R 4.3.3)
truncnorm     * 1.0-9      2023-03-20 [1] CRAN (R 4.3.3)
tune          * 1.2.1      2024-04-18 [1] CRAN (R 4.3.1)
tzdb            0.4.0      2023-05-12 [1] CRAN (R 4.3.0)
units           0.8-5      2023-11-28 [1] CRAN (R 4.3.1)
urlchecker      1.0.1      2021-11-30 [1] CRAN (R 4.3.0)
useful        * 1.2.6.1    2023-10-24 [1] CRAN (R 4.3.1)
usethis         3.1.0      2024-11-26 [1] CRAN (R 4.3.3)
uuid            1.2-1      2024-07-29 [1] CRAN (R 4.3.3)
```

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 vctrs              0.6.5      2023-12-01 [1] CRAN (R 4.3.1)
 viridisLite        0.4.2      2023-05-02 [1] CRAN (R 4.3.0)
 webshot          * 0.5.5      2023-06-26 [1] CRAN (R 4.3.0)
 webshot2         * 0.1.1      2023-08-11 [1] CRAN (R 4.3.0)
 websocket          1.4.2      2024-07-22 [1] CRAN (R 4.3.3)
 withr              3.0.2      2024-10-28 [1] CRAN (R 4.3.3)
 workflows        * 1.1.4      2024-02-19 [1] CRAN (R 4.3.1)
 workflowsets     * 1.1.0      2024-03-21 [1] CRAN (R 4.3.1)
 xfun               0.50       2025-01-07 [1] CRAN (R 4.3.3)
 xml2               1.3.6      2023-12-04 [1] CRAN (R 4.3.1)
 xtable             1.8-4      2019-04-21 [1] CRAN (R 4.3.0)
 yaml               2.3.10     2024-07-26 [1] CRAN (R 4.3.3)
 yardstick        * 1.3.1      2024-03-21 [1] CRAN (R 4.3.1)
 zip                2.3.1      2024-01-27 [1] CRAN (R 4.3.1)

 [1] /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library
 [2] /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library

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```
# Sys.getenv() .libPaths()
```