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APPLICATION

# *allodb*: An R package for biomass estimation at globally distributed extratropical forest plots

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## Abstract

1. Allometric equations for calculation of tree above-ground biomass (*AGB*) form the basis for estimates of forest carbon storage and exchange with the atmosphere. While standard models exist to calculate forest biomass across the tropics, we lack a standardized tool for computing *AGB* across boreal and temperate regions that comprise the global extratropics.
2. Here we present an integrated R package, *allodb*, containing systematically selected published allometric equations and proposed functions to compute *AGB*. The data component of the package is based on 701 woody species identified at 24 large Forest Global Earth Observatory (ForestGEO) forest dynamics plots representing a wide diversity of extratropical forests.

3. A total of 570 parsed allometric equations to estimate individual tree biomass were retrieved, checked and combined using a weighting function designed to ensure optimal equation selection over the full tree size range with smooth transitions across equations. The equation dataset can be customized with built-in functions that subset the original dataset and add new equations.
4. Although equations were curated based on a limited set of forest communities and number of species, this resource is appropriate for large portions of the global extratropics and can easily be expanded to cover novel forest types.

**KEYWORDS**

above-ground biomass, extratropics, forest carbon storage, Forest Global Earth Observatory (ForestGEO), R, temperate forest, tree allometry, tree biomass

## 1 | INTRODUCTION

Forest trees account for 70%–90% of the land biomass of earth (Houghton, 2008). The quantification of forest above-ground biomass (*AGB*) is an essential step to understand the sources, sinks and flow of carbon world-wide and, more importantly, how carbon storage and fluxes are changing through time (Houghton, 2005). Changes in forest carbon storage will strongly influence the course of climate change (Friedlingstein et al., 2006), and forest conservation, management and restoration are among the most cost-effective tools for climate change mitigation (Griscom et al., 2017). Indeed, changes in forest carbon are emphasized in the guidelines for national greenhouse gas inventories by the Intergovernmental Panel on Climate Change (IPCC, Buendia et al., 2019), and account for approximately one-quarter of national emission reductions planned by countries under the Paris Climate Agreement (Grassi et al., 2017). Thus, accurate estimates of tree biomass are critical to understanding forest carbon dynamics and managing forests for climate change mitigation.

Despite rapidly developing technology focusing on remote sensing to estimate forest biomass over large areas (Knapp et al., 2020; Zolkos et al., 2013), ground-based assessments that combine tree census data and allometric equations remain the most widely applied indirect method to estimate forest biomass and are still required to calibrate remote sensing data (Chave et al., 2014, 2019). These models are based on common biomass predictors including *DBH* and height (*H*) (e.g. Feldpausch et al., 2012), sometimes incorporating wood density and crown structure (Chave et al., 2005, 2014; Goodman et al., 2014). Although ground-based LiDAR is emerging as a promising technique for non-destructive allometry development (Stovall et al., 2018), the vast majority of biomass allometries have been created through destructive tree harvest. Yet, the development of reliable allometric equations requires large sample sizes (Duncanson et al., 2015), particularly for large trees that are the most problematic to sample (Stovall et al., 2018) and usually underrepresented (Burt et al., 2020). Moreover, allometric relationships vary across species (Poorter et al., 2015; but see Paul et al., 2016) and with environmental factors such as climate and nutrient availability (Duncanson et al., 2015; Lines et al., 2012), stand age (Fatemi et al., 2011) and stand density (Gower et al., 1992). Whereas tropical biomass data have been pooled to form the basis of a standardized approach to biomass estimation across the tropics (Chave et al., 2005, 2014; Réjou-Méchain et al., 2017), no such standardized approach currently exists for extratropical regions (above 23.5° latitude N or S). Rather, a wide variety of allometries developed for various levels of taxonomic and geographic organization, and of variable quality, are scattered throughout the literature (Chojnacky et al., 2014; Conti et al., 2019; Jenkins et al., 2004; Luo et al., 2018, 2020; Muukkonen, 2007; Návar, 2009; Paul et al., 2016; Rojas-García et al., 2015). These equations differ in functional form, input and output variables, units and size range across which they can be applied. This makes identification and application of appropriate allometries a time-consuming and error-prone process (van Breugel et al., 2011) with low reproducibility and little standardization across studies (Somogyi et al., 2007). While challenging for studies at individual sites, this becomes particularly problematic for studies aiming to apply an approach that is both locally optimized and standardized across multiple forest types and regions (e.g. Lutz et al., 2017).

Several key principles should guide the development of temperate and boreal allometries. First, larger sample sizes of trees used to develop allometric equations greatly reduce biases and systematic errors (Duncanson, Rourke, et al., 2015), and are particularly important in constraining the uncertainty in *AGB* estimates of large trees (Chave et al., 2004; Stovall et al., 2018; Sullivan et al., 2018). For example, pantropical models based on large datasets (Chave et al., 2005; Feldpausch et al., 2011) give reliable results with smaller errors compared to regional models (Rutishauser et al., 2013). Second, the precision of predictions can be improved by using equations calibrated with trees from a similar taxonomic group, and that grew in similar climatic conditions (Daba & Soromessa, 2019; Ngomanda et al., 2014; Roxburgh et al., 2015). In practice, these two principles are in conflict, in that taxa- or location-specific allometries are usually constructed based on a much lower sample size than generic allometries. Furthermore, specific allometries are often limited in the size range over which they were calibrated and are largely driven by a very small number of large trees, leading to potentially large errors if extrapolated beyond their size range, or to discontinuous functions if an alternative equation is applied beyond the calibrated range. Lastly, biomass allometries should be continuous functions of tree size. This is especially critical for applications using records of tree diameter growth to estimate woody productivity (e.g. Anderson-Teixeira et al., 2021; Helcoski et al., 2019) or to compare carbon stocks or fluxes across tree size classes (e.g. Lutz et al., 2018; Meakem et al., 2018; Piponiot, C. unpubl. data). Ideally, continuous functions based on sufficient sample sizes would be derived from re-analysis of data collected to produce existing sets of allometric equations, as has been done for the tropics (Chave et al., 2014), but unfortunately original data are often difficult to access, lack proper documentation or are unavailable. Although there has been some progress in developing comprehensive databases to support the development of allometries (Falster et al., 2015; Henry et al., 2013; Schepaschenko et al., 2017), these are not yet comparable in coverage to the existing set of allometric models. Thus, for now, a standardized process for applying biomass allometries across extratropical forests must draw upon existing sets of allometric equations.

Here we present a framework aimed at facilitating tree biomass estimation across globally distributed extratropical forests. To standardize and simplify the biomass estimation process, we developed *allodb* (Table 1, https://docs.ropensci.org/allodb/) as an open-source application aiming to: (a) compile relevant published and unpublished allometric equations, focusing on *AGB* but structured to handle other variables (e.g. height and biomass components); (b) objectively select and integrate appropriate available equations across the full range of tree sizes; and (c) serve as a platform for future updates and expansion to other research sites globally.

## 2 | SOFTWARE DEVELOPMENT AND WORKFLOW

### 2.1 | Focal sites and species

We focus on multiple sites within the Forest Global Earth Observatory (ForestGEO), the largest world-wide network of long-term forest monitoring sites using standardized methods (Anderson-Teixeira et al., 2015; Davies et al., 2021). As such, it is a good model for assembling and applying allometric equations across a wide range of species, forest environments and to understand associated challenges in calculating biomass. ForestGEO currently includes 33 extratropical forests across North America ($n$ = 17), Europe ($n$ = 4) and Asia ($n$ = 12), ranging in latitude from 23 to 61 degrees N. At each site, all stems ≥1 cm *DBH* within 5–50 ha plots are censused following standardized protocols, including identification to species level (Condit, 1998). From the 24 participant sites included in *allodb* (Table S1), there are 1109 species-location combinations, 701 woody species, 248 genera and 86 plant families represented (see *site-species* table in *allodb*).

### 2.2 | Systematic search for biomass allometries

We compiled 570 allometric equations from the literature, focusing on retrieving equations to estimate *AGB* based on *DBH* and

TABLE 1 Description of data and functions in allodb. A detailed explanation of functions and data can be found in the *allodb* R package documentation (https://docs.ropensci.org/allodb/reference/index.html)

| Name | Description |
|---|---|
| Data | |
| equations | A dataframe with retrieved equations from literature and auxiliary data |
| references | A dataframe listing all references by reference ID used in equation table |
| site-species | A dataframe listing focal sites in this study and the identified family, genus and species per site |
| Metadata | |
| equations_metadata | A dataframe explaining fields in the equation table |
| missing_values | A dataframe describing the use of codes for missing values used in the equation table |
| reference_metadata | A dataframe explaining fields in the reference table |
| site-species_metadata | A dataframe explaining fields in the site-species table |
| Functions | |
| est_params | Estimates the parameters (slope, intercept, sigma) of the recalibrated allometric equations |
| get_biomass | Executes the AGB calculation per stem (kg) |
| illustrate_allodb | Produces illustrative graphs of the recalibration process |
| new_equations | Customizes the original set of allometric equations by subsetting it and/or by adding new equations |
| resample_agb | Resamples the original equations |
| weight_allom | Combines multiple variables (taxa, climate and sample size) to attribute a weight to each equation |

developed primarily in extratropical regions (Chojnacky et al., 2014; Forrester et al., 2017; Jenkins et al., 2004; Luo et al., 2018), and drew upon these and local expertise to help identify original, species-specific and location-specific allometries (Figure S1). Three of our focal sites have local biomass allometries (SCBI: Stovall et al., 2018; Wytham Woods: Fenn et al., 2015; and Yosemite: Lutz et al., 2014). For eighteen species found at the University of California Santa Cruz ForestGEO site (UCSC, Table S1), we include new local allometric equations to estimate *H*, which is an independent variable in some allometric models. In some cases, equations were only available for separate tree components (stem, bark, branches, foliage); these were summed to obtain *AGB*. For each equation, we retrieved standard information including location, taxa, units, *DBH* ranges, sample size (see *allodb* equations table for other categories), which are used in the proposed weighting scheme. We assigned Köppen climate zones to each equation using the R package *kgc* (Bryant et al., 2017; Köppen, 2011). When equations were calibrated for broad regions (e.g. North America, Northern Germany) or vaguely defined locations, we estimated their location from brief descriptions or regional maps in the original publication and included all possible Köppen zones. Details on all equations are available in the *equations.csv* file within *allodb*.

## 2.3 | Inputs for calculating biomass

Prior to calculating tree biomass using *allodb*, users need to provide: (a) *DBH* (cm), (b) parsed species Latin names and (c) site coordinates (Figure 1).

a. *DBH*: *allodb* makes consistent calculations of *AGB* (kg) based on *DBH* (cm) as the primary predictor. In some instances, available allometric equations include *H* as an additional predictor (e.g. Jansen et al., 1996), for these cases, inputs of *H* (m) refine predictions. We structured *allodb* expecting that the input *DBH* from plot inventories is checked in advance. For sites where trees are commonly measured at heights other than the standard 1.3 m (e.g. buttresses, trunk irregularities, differing census protocols), we recommend users to apply a taper correction function to improve the estimates of biomass changes (see Cushman et al., 2014) before using *allodb*. As many forest census protocols recommend measuring stems at 1.3 m (including shrubs), we provided additional equations to convert *DBH* into diameter at base (*dba*, i.e. diameter conversion models by Lutz, 2005; Paul et al., 2016) for those allometries that use *dba* or diameter at stump height (20–30 cm above the ground) to predict biomass.
b. *Latin species names*: Species identification is critical for selecting appropriate allometric equations. To standardize spelling and nomenclature, plant names for all sites were checked using the function *correctTaxo* from the *BIOMASS* package (Réjou-Méchain et al., 2017). Accepted family names (used in the weighting scheme) were retrieved using the function *tax_name* from the package *taxize* (Chamberlain et al., 2020). We recommend the use of such a function to homogenize and correct taxonomic information prior to using *allodb*.
c. *Site coordinates*: These are needed to account for climate zones. The Köppen classification scheme (Köppen, 2011) provides an efficient way to describe climatic conditions defined by multiple variables with a single and ecologically relevant metric (Chen & Chen, 2013) and allows the assignment to a particular climate based on site coordinates. *allodb* obtains the Köppen climate zone of a given site using the *kgc* R package (Bryant et al., 2017). The obtained climate is then compared to the allometric equations' Köppen zone(s) and used in the weighting scheme. By including a climate input, we are able to represent bioclimatic variables otherwise not included in original publications.

A user constructs a table with *DBH*, species and site coordinates, as in the example provided in the *allodb* package:

```
install.packages("remotes")
remotes::install_github("ropensci/allodb")
library(allodb)
data(scbi_stem1)
scbi_stem1$agb =
 get_biomass(
dbh = scbi_stem1$dbh,
 genus = scbi_stem1$genus,
 species = scbi_stem1$species,
 coords = c(−78.2, 38.9)
 )
```

## 2.4 | *AGB* estimation in *allodb*

*allodb* estimates *AGB* (or any other dependent variable) by calibrating a new allometric equation for each taxon and location in the user-provided census data. The new allometric equation is based on a set of allometric equations that can be customized using the *new_equations()* function. Each equation is then given a weight by the function *weight_allom()* based on: (1) its original sample size (numbers of trees used to develop a given allometry), (2) its climatic similarity with the target location and (3) its taxonomic similarity with the target taxon (see weighting scheme below). The final weight attributed to each equation is the product of those three weights. Equations are then resampled with the function *resample_agb()*: the number of samples per equation is proportional to its weight, and the total number of samples is $10^4$ by default. The resampling is done by drawing *DBH* values from a uniform distribution on the *DBH* range of the equation, and estimating the *AGB* with the equation. The pairs of values (*DBH*, *AGB*) obtained are then used in the function *est_params()* to recalibrate a new allometric equation: this is done by applying a linear regression to the log-transformed data (see example in Figure 1). The parameters of the new allometric equations are then used in the *get_biomass()*

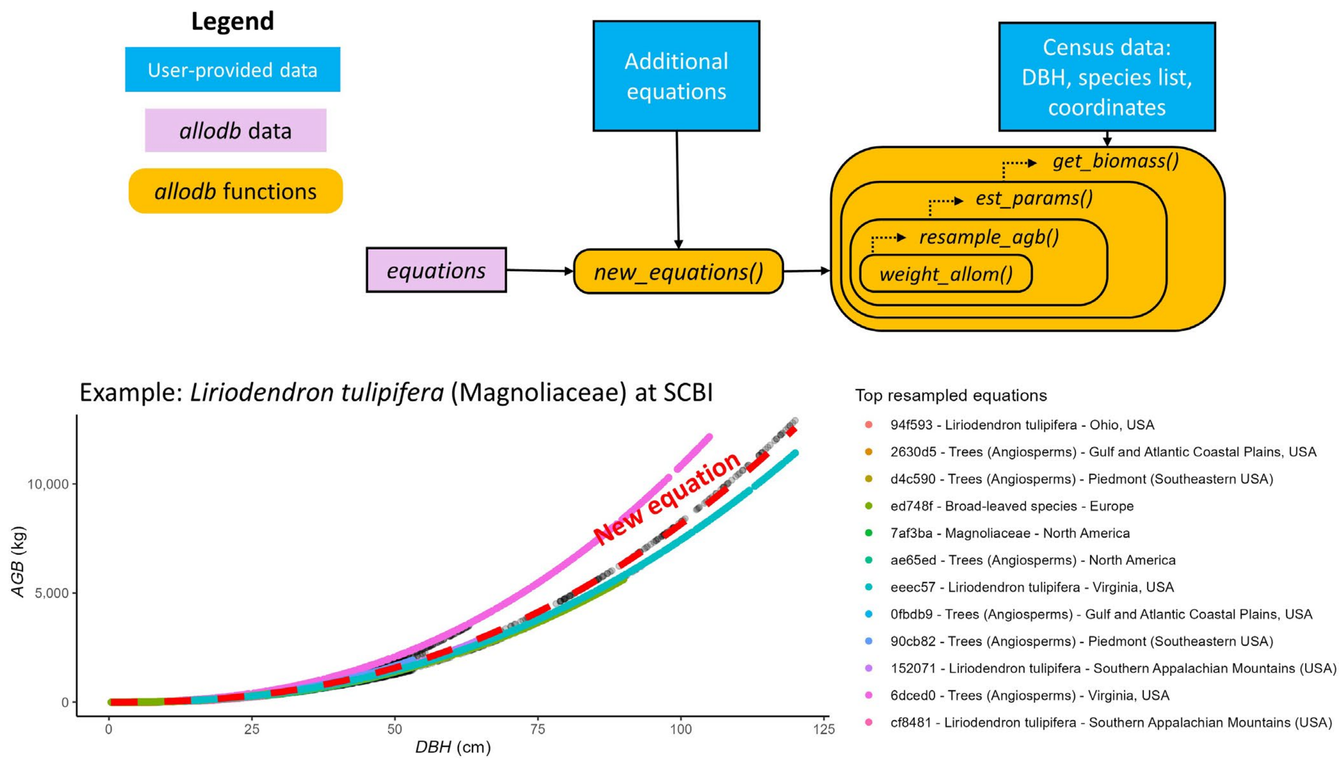


**FIGURE 1** Illustration of *allodb* workflow and predictions. User provides a dataframe with *DBH* (cm), parsed species Latin names and site coordinates. *allodb* estimates *AGB* by calibrating a new allometric equation for each taxon in the user-provided data. The equations table in *allodb* can be customized using the *new_equations()* function. Each equation is given a weight by the *weight_allom()* function and then resampled with the function *resample_agb()*. The values obtained are used in the function *est_params()* to recalibrate a new allometric equation and then used in the *get_biomass()* function. *illustrate_allodb()* is used to visualize the top resampled equations (details for each equation can be found in the equations table within *allodb*) and the final fitted equation

function by back-transforming the *AGB* predictions based on the user-provided *DBHs*. By using the function *illustrate_allodb()*, the user can visualize in a plot the top 10 resampled equations and the final fitted equation (e.g. Figure 1; Figure S3).

## 2.5 | Weighting scheme of allometric equations

Each equation is given a weight by the function *weight_allom()*, calculated as the product of the following components:

1. **Sample-size weight**: because larger sample sizes greatly reduce biases and systematic errors (Duncanson, Rourke, et al., 2015), we attribute a larger weight to equations calibrated with a larger number of trees. This weight is calculated as an asymptotic function of the sample size *n*: $1 - e^{-n\cdot\left(\frac{\log(20)}{w95}\right)}$. The sample-size weight increases sharply at low sample sizes and gets close to 1 (its asymptotic value) for sample sizes >*w*95. *w*95 is 500 by default, and may be adjusted by the user. Equations with no sample size information are given a sample-size weight of 0.1 by default: this value can be adjusted by the user using the argument wna.
2. **Climatic weight**: equations calibrated in similar climatic conditions as the target location are given a higher weight, using the three-letter system of Köppen climate scheme (Köppen, 2011). This weight is calculated in three steps: (1) if the main climate group (first letter) is the same, the climate weight starts at 0.4; if one of the groups is 'C' (temperate climate) and the other is 'D' (continental climate), the climate weight starts at 0.2 because the two groups are considered similar enough; otherwise, the weight is 1e-6; (2) if the equation and site belong to the same group, the weight is incremented by an additional value between 1e-6 and 0.3 based on precipitation pattern similarity (second letter of the Köppen zone); and (3) if the equation and site belong to the same group, the weight is incremented by an additional value between 1e-6 and 0.3 based on temperature pattern similarity (third letter of the Köppen zone). The resulting weight has a value between 1e-6 (different climate groups) and 1 (exactly the same climate classification). When an equation was calibrated with trees from several locations with different Köppen climates, the maximum value out of all pairwise equation-site climate weights is used.
3. **Taxonomic weight**: equations calibrated with trees from a similar taxonomic group as the target taxon are given a higher weight (Figure S2). The taxonomic weight is equal to 1 for same species equations, 0.8 for same genus equations and 0.5 for same family equations and for equations calibrated for the same broad functional or taxonomic group (e.g. shrubs, conifers, angiosperms). All other equations are given a low taxonomic weight of $10^{-6}$: these

equations will have a significant relative weight in the final prediction only when no other more specific equation is available.

The choices of weighting functions and parameter values are selected based on our current understanding of the principles of allometric equations and experimentation with various options, and weightings may be adjusted based on user discretion. However, adjusting these values can result in unsatisfactory predictions: alternative weighting schemes should be checked before being used for predictions.

In particular, we use taxonomic similarity as an easily measurable proxy of expected similarity among species' allometries, but the assumption that related species have similar allometries does not always hold. For example, the North American high-elevation five-needle pines (*Pinus longaeva*, *P. aristata*, *P. albicaulis* and *P. balfouriana*) are morphologically similar to one another but extremely different from the more common *Pinus* species (e.g. *Pinus strobus*). Because generic genus-level equations are usually based on the more common species (e.g. Chojnacky et al., 2014), biased predictions can result where the target species has vastly different morphology or wood density from the genus-level mean, particularly if they grow in similar climate zones. The resulting errors can be especially important when dealing with large trees. Using species' phylogenetic or morphological similarity and wood density could help reduce such biases, but this information is not always available for all species and equations. We recommend that researchers working with species that do not conform to generalized allometric models for their taxa and climate zone (i.e. ~8% of species in analysis of Paul et al., 2016) carefully evaluate the weighting of *allodb* equations and apply alternative allometric models if needed.

## 2.6 | Evaluation and validation of methods

To validate and evaluate *allodb*, we (a) screened for equation errors; (b) evaluated against widely used regional allometric models; and (c) compared *allodb* predictions against raw data.

As a preliminary test to detect preventable equation errors (e.g. unit conversion issues, typos when transcribing, errors within original publications), we manually evaluated each equation in R (R Core Team, 2018) as it was entered into our dataset to ensure that predictions were within reasonable range. We identified outliers through plotting of each species per focal ForestGEO site to compare biomass values predicted by the different equations on a hypothetical *DBH* range between 1 and 200 cm (e.g. Figure S3). Through this process, equation errors were corrected when possible, and problematic equations removed.

Next, we evaluated how *AGB* estimates using *allodb* compare to those obtained from the widely used regional equations for North America of Chojnacky et al. (2014). Using the SCBI ForestGEO plot as a test case, we found that *allodb* predictions aligned reasonably with those of the Chojnacky et al. (2014) equations (Figure S4), but with differences that can be meaningful. The most notable departure occurred for the largest *DBH* trees in the plot, for which absolute differences could be large (>3,000 kg) for a couple of species (e.g. *Quercus velutina*), with the Chojnacky et al. (2014) allometries predicting higher *AGB*. Across smaller and intermediate tree sizes, *allodb* predictions could be higher or lower depending on the species, with an overall tendency for *allodb* predictions to be higher. Both of these differences align with the findings of a terrestrial LiDAR study at this site (Stovall et al., 2018), which found that the Chojnacky et al. (2014) equations underestimated biomass overall while overestimating biomass of the largest individuals. Summing across all trees in the SCBI plot, *allodb* predicted a total AGB of ss307.6 Mg/ha, which is 19% higher than a published estimate of 258.9 Mg/ha that applies Chojnacky et al. (2014) equations to the same data (Lutz et al., 2018).

Finally, we tested the accuracy of *allodb* predictions against a comprehensive compilation on destructive sampling by Schepaschenko et al. (2017). A subset ($n = 6266$ trees) from the original dataset was used providing *DBH* (>1 cm), *H* (m) and measured *AGB* (kg) at 176 sites distributed in Eurasia (Figure S5). The *allodb* predictions were reasonable across the tree size range, with root-mean-square error (RMSE) of 87.02 kg on a linear scale (and a mean relative error [MRE] of 72%) and 0.71 kg on a logarithmic scale.

# 3 | CONCLUSIONS AND FUTURE IMPROVEMENTS

The calculation of tree biomass has multiple challenges that we tried to overcome when designing *allodb*. The *allodb* package makes it possible to obtain consistent, reproducible *AGB* estimates for extratropical forests, noting that careful attention to versioning (i.e. citation of package version) will be necessary to ensure reproducibility. We believe that these estimates are as accurate as possible given the issues that currently plague the field (e.g. limited diameter ranges, allometries based on low sample sizes, lack of harvested data; Burt et al., 2020). In addition, the *allodb* platform and scope can be expanded to include more equations and thereby represent more species and sites. It can also be expanded to cover more response variables (e.g. roots, foliage, heights and crown dimensions) so that we can better predict *AGB* (or below ground biomass) on an ecosystem scale, characterize forest structure and potentially link it with LiDAR applications and more general remote sensing methods. With appropriate accounting for snags and down wood (Janik et al., 2017) and appropriate reduction factors (e.g. Harmon et al., 2011), *allodb* can also form the basis for calculating dead woody biomass. We encourage the user community to contribute to building *allodb* into an increasingly useful resource for estimating extratropical forest biomass, thereby better meeting the challenge of characterizing and managing forest carbon stocks and fluxes in an era of climate change.

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## CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

## AUTHORS' CONTRIBUTIONS

E.G.-A. and K.J.A.-T. conceived the idea; C.P., M.L., E.G.-A. and K.J.A.-T. designed the software; V.H. contributed with workflow improvements; K.J.A.-T., E.G.-A. and C.P. led the writing of the manuscript. And all other authors contributed critically and approved for publication.

## PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/2041-210X.13756.

## DATA AVAILABILITY STATEMENT

The *allodb* source code and data are published under the GNU General Public License 3. The version described in this paper (version 0.0.0.9000) can be accessed at https://docs.ropensci.org/allodb/.

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