Analysing economic costs of invasive alien species with the invacost R package

Running title: Analysing economic costs of invasions in R

Boris Leroy[1*], Andrew M. Kramer[2], Anne-Charlotte Vaissière[3], Franck Courchamp[3] & Christophe Diagne[3]

[1] Unité Biologie des Organismes et Ecosystèmes Aquatiques (BOREA, UMR 7208), Muséum national d'Histoire naturelle, Sorbonne Université, Université de Caen Normandie, CNRS, IRD, Université des Antilles, Paris, France.

[2] University of South Florida, Department of Integrative Biology. Tampa Fl, 33620, USA

[3] Université Paris-Saclay, CNRS, AgroParisTech, Ecologie Systématique Evolution, 91405, Orsay, France

***Corresponding author:** Boris Leroy, leroy.boris@gmail.com

Acknowledgements:

We thank Anna Turbelin and Phillip J Haubrock for their assistance in proofreading and beta-testing the invacost R package. We thank Nicolas Dubos for discussions on statistics. BL, ACV and FC were funded by their salaries as French public agents. The post-doctoral contract of CD was funded by the BiodivERsA-Belmont Forum Project "Alien Scenarios" (BMBF/PT DLR 01LC1807C).

Abstract

1. Multi-disciplinary datasets are becoming increasingly available for ecological research, but can be difficult to grasp for non-specialists. This is the case for the global database on reported economic costs of invasive alien species (InvaCost). Indeed, while this is an instrumental resource for invasion ecological research and expertise, the nature of the data makes it difficult for primary users (e.g. ecologists, biodiversity managers) to use it.

2. We introduce here the invacost R package, an open-source software designed to query and analyse the InvaCost database. We illustrate this package and its framework with cost data associated with invasive alien invertebrates.

3. First, the invacost package provides updates of this dynamic database directly in the analytical environment R. Second, it helps understand the heteregoneous nature of economic cost data for invasive species, their harmonisation process, and the inherent biases associated with such data. Third, it readily provides complementary methods to investigate the costs of invasive species at different scales, all the while accounting for econometric statistical issues.

4. This tool will be useful for scientists working on invasive alien species, by (i) facilitating access to and use of this multi-disciplinary data resource and (ii) providing a standard procedure which will facilitate reproducibility and comparability among studies, one of the major critics of this topic until now.

Key-words: biological invasions, drivers of change in biodiversity, economic costs, economic impacts, ecosystem services, invasive alien species

Introduction

Many datasets could be useful for ecological research but lack accessibility, or have specific nature and jargon difficult to grasp for non-specialists. A promising solution lies in open-source software providing frameworks to openly share data and methods altogether (e.g., Michener & Jones, 2012). Here we focus on *InvaCost*, a freely available database of the economic costs of invasive alien species worldwide (Diagne, Leroy, et al., 2020a). This database is global in extent and covers many taxonomic groups, ecosystem types, activity sectors, and temporal and spatial scales. The barriers to accessing and using economic data can prevent primary users – e.g., ecologists or biodiversity managers – from readily using and analysing it. To address this, we present here the invacost R package.

The economic costs of invasive alien species are a case of heterogeneous data with different spatio-temporal scales that pose issues for global or comparative studies (Diagne, Catford, Essl, Nuñez, & Courchamp, 2020; Diagne, Leroy, et al., 2020b). Yet such studies is needed because biological invasions are a major threat to biodiversity which have insufficient attention from decision makers and the general public. Adequately addressing the costs of biological invasions requires being able to respond to a large array of questions, such as: how are costs distributed across space, time, taxonomic groups, and economic sectors? How have these costs evolved over the last decades and will evolve for the decades to come? How do damage and loss costs compare to management expenditures?

To properly answer these questions, we need to make sure it is straightforward for the users who have not been trained as economists to extract and use information from this database. Furthermore, the absence of a standard procedure to derive cost values for invasive species may lead to the development of idiosyncratic and heterogenous methods, resulting in a lost opportunity for the repeatability and comparativeness of studies. Therefore, we developed the invacost R package as a tool to query and investigate the *InvaCost* database. The package and its framework have already been used in 21 publications to describe the economic costs

of biological invasions at multiple spatial scales (e.g., Diagne et al., 2021; Haubrock et al., 2021).

We developed the invacost R package with three objectives. First was to provide the up-to-date database directly into R, to relieve users from the burdens of compatibility issues and errors associated with loading such a large dataset in R. Second, to help users understand the nature of economic cost data for invasive species and the inherent biases associated with such data with a step-by-step tutorial provided with the package. The third objective was to provide two complementary ways to analyse these data. One is a standard method to derive cumulative and average cost values over different periods of time, with relevant visualisation methods. The other derives the trend of costs over time with different modelling techniques accounting for the statistical issues of such econometric datasets, such as non-linearities, heteroskedasticity, temporal autocorrelation and outliers. In the following sections, we describe the rationale and methods implemented for these objectives along with relevant literature. We do so with the illustration of a simple case study on the global economic costs caused by invertebrates (i.e., all non-chordata animals).

The invacost R package

The package requires a standard installation of R (version≥4.0.0) and is available on the Comprehensive R Archive Network (see Appendix A.1 for a code example). Upon installation eight dependencies will be automatically installed: dplyr (Wickham, François, Henry, & Müller, 2020), earth (Milborrow, Derived from mda:mars by Hastie T and Tibshirani R, & Uses Alan Miller's Fortran utilities with Thomas Lumley's leaps wrapper, 2019), ggplot2 (Wickham, 2016), lmtest (Zeileis & Hothorn, 2002), mgcv (Wood, Pya, & B, 2016), quantreg (Koenker, 2020), robustbase (Maechler et al., 2020), sandwich (Zeileis, 2004) and scales (Wickham & Seidel, 2020). All the package code is open-source, available on the GitHub repository, where users can also contribute or submit issues: https://github.com/Farewe/invacost. All objects created in the package have associated generic functions, meaning that if users want to see their object in the console or plot it, they

will get a user-friendly output with useful information or see appropriate graphical representation of their results (figure 1), designed on the basis of recommended practices for data presentation, especially at small sample sizes (e.g., Weissgerber et al. 2015). In addition, output objects are lists composed of the necessary elements for reproducing the results: input data, chosen arguments, and analysis results. These objects can be stored (e.g. with `saveRDS`) and used as electronic supplementary material to ensure replicability.

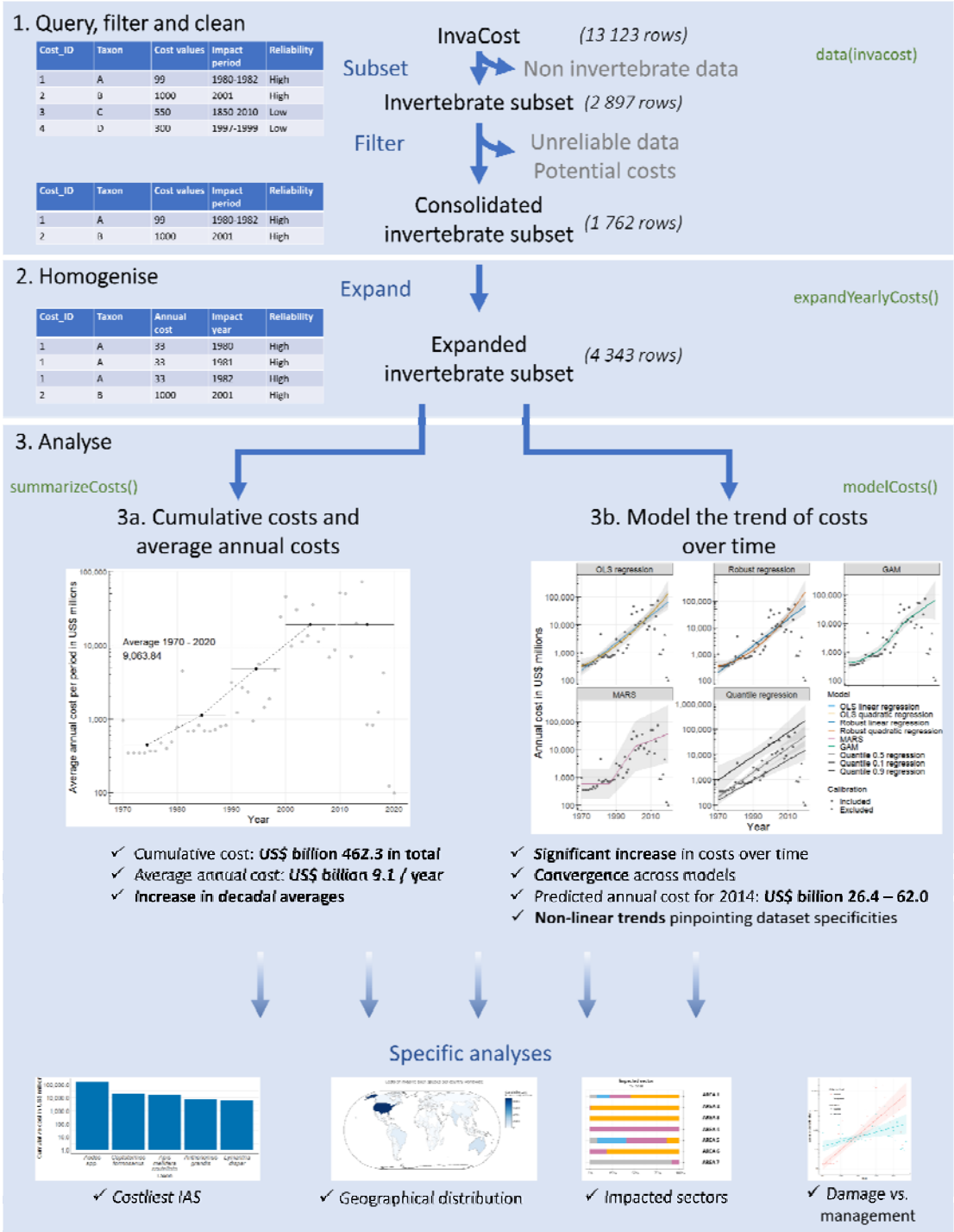

Figure 1. Conceptual framework of analysing economic costs of biological invasions within the invacost R package. We illustrate this framework with the example of a subset of the database (invertebrates, i.e., all non-chordata animals). The framework depicts the three objectives detailed in the manuscript. Within each objective, functions used in the invacost R package are written in green. In 1 and 2, we illustrate with simplified tables how the structure of the database changes as the database is subsetted, filtered and then expanded. The cost over time graphs in 3a and 3b illustrate the native graphical outputs implemented in the package.

Objective 1 – Querying, cleaning and filtering the InvaCost database

The *InvaCost* database is a dynamic database where existing information can be corrected and new data regularly added. The latest version of the *InvaCost* database (accessible at https://doi.org/10.6084/m9.figshare.12668570) is shipped with every release of the R package. The database can be accessed with the command `data(invacost)`. To make sure that users understand the database and the package, we provide a step-by-step tutorial with thorough explanations on the GitHub repository (https://github.com/Farewe/invacost).

The database loaded in R contains over 60 fields (see here for a full description https://doi.org/10.6084/m9.figshare.12668570 and here for frequently asked questions https://gihtub.com/Farewe/invacost_FAQ, such as *(i)* how to collate data from the literature to the database, *(ii)* how double-counting is managed, or *(iii)* caveats and avenues for further improvement). These fields include, for example taxonomic information on the focal invasive taxa or geographic information on the impacted area, which enable convenient filtering within R (using '`subset()`' for example) to refine the database into a subset relevant to specific research questions. To facilitate reproducibility of published analyses, we provide the function `getInvaCostVersion` to rollback the database to previous major releases (this function currently includes five releases: 1.0, 2.0, 2.1, 3.0 and 4.0).

The diversity of sources, cases and methods included in *InvaCost* will typically require users to make methodological choices about filters to apply to the database (e.g., reliable vs. unreliable sources, potential vs. observed costs) and about the costs to use (e.g., standardized on the basis of exchange rates or purchase power parity, spatial scale of the study). We provide recommendations in Appendix B on these necessary choices, and we detailed everything step-by-step in the online tutorial of the invacost R package (https://github.com/Farewe/invacost).

In our example on the global costs of invertebrates, we chose to filter out less reliable cost estimates and potential costs, to focus only on observed costs, which yielded a consolidated invertebrate subset of 1 762 cost estimates (Fig. 1.1, see Appendix A.2 for code).

142 **Objective 2 – homogenization of costs: expression in annual costs and**
143 **expansion to their relevant time periods**

144 Once the relevant filters have been applied to the database, extracting meaningful cost
145 estimations from the resulting subset of cost records requires accounting for the fact that cost
146 entries in the database have different temporal coverages: entries can be one-time costs,
147 annual costs with repetitions over multiple years, or total costs of impacts which spread over
148 multiple years. Therefore, to be comparable, cost estimates must be homogenized with a two-
149 step process. First, they must be expressed with the same temporal unit, where the most
150 relevant choice is annual costs. This step is already accounted for in the database with fields
151 containing "cost_estimate_per_year" in their names. Second, once they have been
152 homogenized on an annual basis, costs must be applied to their relevant time periods, i.e.
153 repeated for each year over which the monetary impact was reported. This step is performed
154 with the `expandYearlyCosts` function. This function relies on the fields indicating the
155 starting and ending years of the annual costs. For example, reference ID 1619 reports a
156 cumulative eradication budget of € 550,000 for *Anoplophora glabripennis* in France
157 between 2003 and 2008. A preliminary step, already included in the *InvaCost* database
158 allows to standardize the costs into a common currency (conversion and inflation into 2017
159 US Dollars (USD), see Diagne et al. 2020 for details) - it yields an annual cost of 2017
160 USD 136,437 for that period. The expansion step implemented in our package replicates this
161 standard annual cost over each year of the impact period (2003-2008, Fig. 1.2). The costs are
162 not expanded for the database by default because the database is easier to distribute in the
163 compact form and because expanding the costs requires decisions which should be assessed
164 by the user.

165 The expansion step requires adequate information with respect to the beginning and ending
166 years of cost impacts. However, information on the beginning and ending years was not
167 directly provided in the literature sources of economic costs for 23% of entries in the
168 database (2,166 rows of data). Therefore, for each source for which it was not available, we

169 made educated guesses (Diagne, Leroy, et al., 2020b) on the probable starting and ending
170 years, and included these guesses in the columns "*Probable_starting_year_adjusted*" and
171 "*Probable_ending_year_adjusted*" columns. Because these columns are based on
172 conservative assumptions (e.g., the ending year of costs does not extend beyond the
173 publication year), they should limit over-estimation; hence, we recommend using these
174 columns (see discussion and Extended Data Fig. 6 in Diagne et al., 2021). Consequently, this
175 process requires removing any cost entry for which the period impact could not be extracted
176 from the source material. Once the homogenization step has been performed on all cost
177 entries in the user's consolidated subset of the database, extractions and analyses can be
178 performed to explore the patterns of costs of invasive alien species. In our example, after
179 expansion the data on invertebrate costs contained 4,343 rows (Fig. 1.2, code in Appendix
180 A.3), each representing a single year of costs for a specific species/group.

181

182 **Objective 3a – Estimating the cumulative and average reported costs of**
183 **invasions**

184 The first method to analyse economic costs of invasive species consists of calculating the
185 cumulative and average costs over time using cost estimates, as they appear in the filtered
186 and homogenized material. These costs can be investigated on an annual basis, over the
187 entire period covered by the database, or over a series of time intervals to account for the
188 evolution of costs over time. All these options are performed simultaneously with the
189 function `summarizeCosts`. First, this function calculates the sum of costs for each year of
190 the time period requested by the user (by default, from 1960 - first year with available
191 exchange rates/inflation rates in the official websites, e.g. www.worldbank.org, to the last
192 year of the dataset). Note that exchange rates are not readily available on an annual basis for
193 all countries in the world, so the standard currency currently available in InvaCost is US
194 dollar for 2017. Second, it computes the cumulative total costs and average annual costs over

195 the requested period. Last, it computes cumulative and average annual costs for user-defined
196 time intervals (by default, 10 years) in the requested period.

197 A typical usage of this function is to automatically derive cumulative or average costs for
198 specific subsets of the database, such as for specific geographical areas, type of cost, or on a
199 per-species basis (see the detailed example on how to derive per-species cumulative cost
200 estimates in the online tutorial https://github.com/Farewe/invacost#example-on-many-
201 subsets-all-taxaspecies-in-the-database). In our example on the costs of invasive
202 invertebrates, the function yielded a cumulative cost of 2017 USD billion 462.3 for the 1970-
203 2020 time period, which corresponded to an annual cost of 2017 USD billion 9.1 per year
204 (Figure 1.3a, code in Appendix A4).

205 **Objective 3b – Modelling the trend of economic costs of invasive species over**
206 **time**

207 The second analytical method implemented in the package consists of modelling the long-
208 term trend in economic impacts of invasive alien species by fitting models of annual costs as
209 a function of time. Such a modelling approach is appealing because it accounts for the
210 dynamic nature of costs, and can reliably estimate the evolution of the reported costs of
211 invasive alien species over time, along with estimations of uncertainty. The package
212 implements such a modelling procedure in the `modelCosts` function, which includes four
213 different modelling techniques with specific parameterisation resulting in a total of nine
214 models fitted. We chose these different statistical methods because they are complementary
215 in their description of the trend of costs over time, and robust to the statistical issues of
216 econometrics data: heteroskedasticity, temporal autocorrelation and outliers. We expect one
217 or more will fulfil the general needs of most users. Below we briefly describe each modelling
218 technique.

219 - **Ordinary Least Square regression** (OLS). These simple regression models are
220 well understood by users which make them good candidates to illustrate the linear or
221 log-linear trend of costs over time. While the estimation of coefficients is robust to the

issues mentioned above, error estimations are not. Therefore, we implemented the covariance matrix with Heteroskedasticity and Autocorrelation Consistent estimators as described in (Andrews, 1991), using the `vcovHAC` function in R package `sandwich`. On the basis of these robust covariance matrices, the function derives 95% confidence intervals and estimates whether the regression coefficients significantly differ from zero with partial t test as described in Zeileis (2004), using the function `coeftest` from package `lmtest`. The function fits two OLS models, with linear vs. quadratic terms.

- **Robust regressions**. Because the econometrics data in *InvaCost* are likely to include outliers, which may significantly bias the estimates of linear regression, particularly when the time period of costs is unclear, we also implemented MM-type regression (hereafter called "robust regressions"). This type of regression model is based on iteratively reweighted least squares which makes them less sensitive to the effect of outliers than OLS regressions (Yohai, Stahel, & R, 1991; Koller & Stahel, 2011). This method estimates standard errors robust to heteroskedasticity and autocorrelation as described in Croux et al., (2003). We implemented the `lmrob` function from the `robustbase` R package. Like OLS regressions, the function fits two robust models, with linear vs. quadratic terms.
- **Multivariate adaptive regression splines** (MARS). We expect nonlinearities in the cost trends over time to be common, so we implemented the non-parametric MARS model which automatically models nonlinearities, using Generalized Cross-Validation to avoid overfitting (Friedman, 1991; Hastie, Tibshirani, & Friedman, 2009). We implemented MARS with the `earth` function of the `earth` R package, with the default parameters in order to follow Friedman's parameters, as described in Milborrow (2020a) – these default parameters minimize the risk of overfitting. The function provides prediction intervals which account for heteroskedasticity by fitting a linear model on the residuals, fitted with Iteratively Reweighting Least Squares (Milborrow, 2020b). Note, however, that the temporal range of *InvaCost* limits the

number of data points such that we can only approximately model the variance, as explained in Milborrow (2020b). Therefore, there is greater uncertainty in the prediction intervals than in the predictions themselves.

- **Generalized additive models** (GAM). GAM models are automatic flexible statistical methods used to identify and characterize nonlinear regression effects (Hastie & Tibshirani, 1990; Hastie et al., 2009). Like MARS, the GAM model was chosen to show non-linear patterns in cost trends over time. To account for heteroskedasticity, we used a location-scale method which consists in fitting two GAMs, one for the average trend and one for the standard deviation. We implemented the `gam` methods from the `mgcv` R package, including the smoothing function `s` therein (Wood et al., 2016). We used a simple Gaussian location scale family (function `gaulss`) because, like MARS, the limited number of data points allows only for an approximate variance model.
- **Quantile regressions**. Contrary to the previous models which estimate the average trend in costs over time, quantile regressions estimate specific quantiles of the distribution of costs over time. To describe the evolution of the distribution of costs over time, we implemented three quantile regression models, to estimate the conditional median, 0.1 and 0.9 quantiles. We implemented the `qt` function from the `quantreg` R package with default parameters (Koenker, 2020).

The fitting of these different models provides a description of the linear (with or without outlier correction) and non-linear patterns in the average trend of costs over time, as well as linear trends in the distribution of costs over time. The output of the `modelCosts` function includes all the fitted models with their parameters, a table with predicted values per model over the temporal range chosen by the user, as well as diagnostic tools, such as the summary statistics specific to each model and the root mean square error between observations and predictions. The object also includes the formatted input data and parameters for reproducibility. Several parameters can be modified, including the temporal range of data to

use; transformations to apply to cost values beforehand (e.g. by default, costs are log10-transformed); weights or a threshold to reduce the impact of years with incomplete data. For example, there is a lag between the occurrence of a cost and its reporting and publication in the literature. This time lag impacts the most recent years, which consequently constitute obvious outliers with the latest annual costs significantly lower than the rest of the data, a pattern pervasive to all subsets of *InvaCost*. Users can account for this incompleteness of data either by investigating results of models robust to outliers (e.g., robust regressions), by defining an optional threshold to exclude the most recent years from calibration, or by applying optional weights to reduce the influence of incomplete years on model calibration (as illustrated in examples of the online tutorial). When users are satisfied with their models and want to export results to prepare a manuscript, we provide the function `prettySummary` to export the main statistics for each model into a conveniently formatted table.

In our example on invertebrates, we excluded from model calibration all cost values from 2015 onwards, because they constituted obvious outliers with a sudden drop of two orders of magnitude (Fig. 1.3b, code in Appendix A.5). We confirmed these outliers by investigating robust regressions which had set the weights of years above 2015 to zero (see also discussion in Supplementary Methods 1 in Diagne et al., 2021). We found significant increases in costs over time, with convergent predictions among modelling methods suggesting annual costs in 2014 of 2017 USD billion 26.4 to 62.0. Models MARS, GAM, and quadratic regressions identified non-linear patterns in costs, pinpointing an acceleration in cost increase from the mid-1980s onwards. Quantile regressions for 0.1 and 0.9 quantiles had slightly distinct slopes suggesting an increase in between-year cost amplitude over time.

Conclusion

Tackling all these aspects with the invacost R package was likely key in enabling the rapid emergence of new research pertaining to the costs of biological invasions over the past year (e.g., it has been used in all 19 articles of the NeoBiota special issue on the economic costs of

biological invasions around the world (Zenni, Essl, García-Berthou, & McDermott, 2021)). Hopefully, this R package will establish as a powerful tool to complement assessments of the diversity of impacts of biological invasions, and better inform decision-makers from sub-national scales (e.g., Manfrini et al., 2021) to international assessments (e.g., the Intergovernmental Science-Policy Platform on Biodiversity & Ecosystem Services).

Supplementary material

Appendix A. Code used for the analyses.

Appendix B. Additional recommendations on data filtering.

Data availability

All data is freely available in the invacost R package, and the R package code is open-source and available here: https://github.com/Farewe/invacost.

References

Andrews, D. W. K. (1991). Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica*. doi:10.2307/2938229

Croux, C., Dhaene, G., & Hoorelbeke, D. (2003). Robust Standard Errors for Robust Estimators. *Katholieke Universiteit Leuven*, (December), Working Paper.

Diagne, C., Catford, J. A., Essl, F., Nuñez, M. A., & Courchamp, F. (2020). What are the economic costs of biological invasions? A complex topic requiring international and interdisciplinary expertise. *NeoBiota*, *63*(November 2019), 25–37. doi:10.3897/neobiota.63.55260

Diagne, C., Leroy, B., Gozlan, R. E., Vaissière, A. C., Assailly, C., Nuninger, L., … Courchamp, F. (2020a). InvaCost, a public database of the economic costs of biological invasions worldwide. *Scientific Data*, *7*(1), 1–12. doi:10.1038/s41597-020-00586-z

Diagne, C., Leroy, B., Gozlan, R. E., Vaissière, A. C., Assailly, C., Nuninger, L., … Courchamp, F. (2020b). InvaCost: References and description of economic cost estimates associated with biological invasions worldwide. doi:https://doi.org/10.6084/m9.figshare.12668570.v3

Diagne, C., Leroy, B., Vaissière, A. C., Gozlan, R. E., Roiz, D., Jarić, I., … Courchamp, F. (2021). High and rising economic costs of biological invasions worldwide. *Nature*, *592*(7855), 571–576. doi:10.1038/s41586-021-03405-6

Friedman, J. H. (1991). Multivariate adaptive regression splines. *Annals of Statistics*, *19*(1), 1–141. doi:10.1214/aos/1176347963

Hastie, T., & Tibshirani, R. (1990). Exploring the Nature of Covariate Effects in the Proportional Hazards Model. *Biometrics*, *46*(4), 1005–1016. doi:10.2307/2532444

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning - Data Mining, Inference, and Prediction*. New York: Springer.

Haubrock, P. J., Turbelin, A. J., Cuthbert, R. N., Novoa, A., Taylor, N. G., Angulo, E., … Courchamp, F. (2021). Economic costs of invasive alien species across Europe. *NeoBiota*, *67*, 153–190. doi:10.3897/neobiota.67.58196

Koenker, R. (2020). quantreg: Quantile Regression. Retrieved from http://cran.r-project.org/package=quantreg

Koller, M., & Stahel, W. A. (2011). Sharpening Wald-type inference in robust regression for small samples. *Computational Statistics & Data Analysis*, *55*(8), 2504–2515.

Maechler, M., Rousseeuw, P., Croux, C., Todorov, V., Ruckstuhl, A., Salibian-barrera, M., … di Palma, M. A. (2020). robustbase: Basic Robust Statistics. *R Package*.

Manfrini, E., Leroy, B., Diagne, C., Soubeyran, Y., Sarat, E., & Courchamp, F. (2021). *Les coûts économiques des invasions biologiques en France. Synthèse à l'intention des décideurs*. Paris, France. Retrieved from https://hal.inrae.fr/hal-03349020

Michener, W. K., & Jones, M. B. (2012). Ecoinformatics: Supporting ecology as a data-intensive science. *Trends in Ecology and Evolution*, *27*(2), 85–93. doi:10.1016/j.tree.2011.11.016

Milborrow, S. (2020a). Notes on the earth package, 1–68. Retrieved from http://www.milbo.org/doc/earth-notes.pdf

Milborrow, S. (2020b). Variance models in earth, 1–29.

Milborrow, S., Derived from mda:mars by Hastie T and Tibshirani R, & Uses Alan Miller's Fortran utilities with Thomas Lumley's leaps wrapper. (2019). earth: Multivariate Adaptive Regression Splines. Retrieved from https://cran.r-project.org/package=earth

Weissgerber, T. L., Milic, N. M., Winham, S. J., & Garovic, V. D. (2015). Beyond Bar and Line Graphs: Time for a New Data Presentation Paradigm. *PLOS Biology*, *13*(4), e1002128. doi:10.1371/journal.pbio.1002128

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-

Verlag.

Wickham, H., François, R., Henry, L., & Müller, K. (2020). dplyr: A Grammar of Data Manipulation. Retrieved from https://cran.r-project.org/package=dplyr

Wickham, H., & Seidel, D. (2020). scales: Scale Functions for Visualization.

Wood, S., Pya, N., & B, S. (2016). Smoothing parameter and model selection for general smooth models. *Journal of the American Statistical Association*, *111*, 1548–1575.

Yohai, V., Stahel, W. A., & R, Z. (1991). A procedure for robust estimation and inference in linear regression. In Stahel & Weisberg (Eds.), *Directions in Robust Statistics and Diagnostics, Part II* (pp. 365–374). New York: Springer. doi:doi: 10.1007/978-1-4612-4444-8_20

Zeileis, A. (2004). Econometric Computing with HC and HAC Covariance Matrix Estimators. *Journal of Statistical Software*, *11*(10), 1–17. doi:https://doi.org/10.18637/jss.v011.i10

Zeileis, A., & Hothorn, T. (2002). Diagnostic testing in Regression Relationships. *R News*, *2/3*, 7–10. Retrieved from https://cran.r-project.org/doc/Rnews/Rnews_2002-3.pdf

Zenni, R. D., Essl, F., García-Berthou, E., & McDermott, S. M. (2021). The economic costs of biological invasions around the world. *NeoBiota*, *67*, 1–9. doi:10.3897/neobiota.67.69971