

# 1 LazyModeler: An R package for automatic 2 simplification, check, and visualization of regression 3 models

4 **Lara M. Kösters** <sup>1,2\*</sup> and **Kevin Karbstein** <sup>1,2\*</sup>




5 <sup>1</sup> Max-Planck-Institute for Biogeochemistry, Department of Biogeochemical Integration, Jena, Germany

6 <sup>2</sup> Technical University Ilmenau, Data-Intensive Systems and Visualization Group (dAI.SY), Ilmenau,

7 Germany \* These authors contributed equally.

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

## Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

## License

Authors of papers retain copyright  
and release the work under a  
Creative Commons Attribution 4.0  
International License ([CC BY 4.0](#))

## 8 Summary

9 Setting up, simplifying, checking, and visualizing regression models continues to be a time-  
10 consuming task involving multiple, sometimes concurrent, workflows and software packages.  
11 This particularly applies to big data research where several models need to be set up and  
12 optimized. To tackle this problem, we present LazyModeler - a statistical package for the  
13 programming language R that allows to easily perform regression modeling. It includes removal  
14 of autocorrelated variables, choice between several types of (non)linear regression models,  
15 standard stepwise model simplification, various model quality checks, plotting of coefficient  
16 estimates and relationships, and output generation. LazyModeler will significantly speed up  
17 regression modeling, enabling people to analyze and illustrate their data in a statistically  
18 reliable and standardized manner.

## 19 Statement of need

20 Statistical modeling describes the process of finding a mathematical function with specific  
21 statistical assumptions that best fits the observed data ([Crawley, 2007, 2015](#); [Henley et al., 2020](#)).  
22 This process attempts, in practice, to find a (causal) relationship between a dependent  
23 response variable  $y$  and an independent predictor variable  $x$  for any postulated hypothesis. For  
24 statistical inference and graphics in science, the programming environment R ([R Core Team, 2024](#))  
25 has become highly popular.

26 Linear regression models, as one of the most basic and powerful tools, have been frequently  
27 applied in this context ([Crawley, 2007, 2015](#); [Li, 2023](#); [Schielzeth et al., 2020](#)). Because of  
28 their flexibility, they also allow for non-normally distributed response variables (e.g., in the  
29 case of binomial, proportional, or count data), and any kind of transformation for numerical  
30 (e.g., polynomial or logarithmic) and categorical (e.g., centered or one-hot/fractional encoded)  
31 predictor variables, as well as interactions among them ([Cai et al., 2023](#); [Henley et al., 2020](#);  
32 [Karbstein et al., 2019, 2020, 2021](#); [Liaw et al., 2021](#); [Römermann et al., 2016](#); [Schielzeth, 2010](#)).  
33 Regression models also provide the ability to control for random effects that may  
34 influence the variables of interest (e.g., [Bauer & Albrecht, 2020](#); [Schielzeth et al., 2020](#);  
35 [Wicke et al., 2016](#)). Although other statistical technologies can outperform them in highly  
36 complex, non-linear scenarios, regression models allow for detailed variable transformation  
37 and interaction, mathematical formula specification, calculation of effect sizes, determination  
38 of variable significance, and thus hypothesis testing and explanation ([Benjamin et al., 2018](#);  
39 [Bzdok & Ioannidis, 2019](#); [Cai et al., 2023](#); [Karbstein et al., 2023](#); [Li, 2023](#); [Schulz et al., 2020](#)).  
40 Recent developments make regression models also applicable to nonlinear scenarios

(e.g., Bates et al., 2024; Hastie, 2023). Consequently, they are of high practical value in finding and interpreting significant relationships.

In statistical modeling, and especially in real-world applications, multiple predictors are assumed for a given response variable. As a consequence, people strive to exclude the irrelevant from the relevant (statistically significant) information, which is called model simplification (Crawley, 2007, 2015; Forstmeier & Schielzeth, 2011). One of the most widely used optimization workflows is stepwise model simplification. For example, starting from a full/saturated model, the least significant variable ( $p > 0.05$ ) is excluded until the final minimal adequate model is attained ['backward simplification'; Crawley (2007); Forstmeier & Schielzeth (2011); Crawley (2015)]. Each model simplification step will be justified with certain metrics (e.g., SSE, AIC, or BIC) (Henley et al., 2020). Given the number of models, variables of interest, and their data characteristics, this task can be extraordinarily time consuming. Currently, only AIC/BIC-based automated simplification is available (e.g., 'stepAIC,' Venables & Ripley, 2002). Nevertheless, model simplification continues to be a rather manual process [on Google Scholar, only ca. 5,000 "stepAIC" entries despite ca. 5,000,000 "linear regression model" studies (0.1%); e.g., Römermann et al. (2016); Karbstein et al. (2019); Henley et al. (2020); Karbstein et al. (2020); Cai et al. (2023); Li (2023)]. In addition, simplification and other aspects such as data cleaning, model comparison and quality control, and output visualization have not been automated. An easy-to-use, all-in-one function for the entire modeling process within a single software package is missing.

Our R package LazyModeler addresses these issues by automating variable selection, model optimization, and output illustration and generation. In detail, users will be enabled to automatically remove autocorrelated variables, choose between several types of (non)linear regression models (e.g., LM, GLM, LMER, GLMER, GAM, or NLMER), perform stepwise model simplification, check model quality, plot coefficient estimates and relationships, and generate the output of the final model.

## Overview and major functions

LazyModeler automatizes all necessary steps needed for use of (non)linear regression models. It comprises three major functions that are included within the main function `optimize_model`.

The first major function `remove_autocorrelations` checks for any autocorrelations ( $|r| > 0.7$ ) (Dormann et al., 2013) given a list of variables sorted by relevance. Automatic removal of these autocorrelations is possible through the use of a function parameter. Removal will follow the order of the list of variables, ensuring that the user's expertise on the importance of features is respected. A named list is returned with a) a vector containing all removed predictors, and b) a dataframe listing autocorrelations and information on deleted variables.

The main function provides the model formula to the second major function `simplify_model`. If autocorrelations were detected, the formula is updated accordingly. The regression model is then calculated. Options for the models are: `lm`, `glm`, `lmer`, `glmer`, `gam`, or `nlmer`, with all possible distributions of the response variable being allowed. Stepwise backward simplification or forward model selection takes place using an iterative process where each time the metric(s) specified by the user are applied on the model to check whether further simplification/selection is needed. Main variables are kept when they are involved in interactions. Options for the metrics are: `aov`, `aic`, `aicc`, or `bic`. The final model is returned to the main function alongside its metadata as well as simplification history if requested by the user.

Using the third major function `plot_model_features`, the final model then undergoes multiple visualization steps. Plots to assess model quality are created using the standard plot function available through base R, or model check included in the performance R package (Lüdtke et al., 2021). Furthermore, the script produces regression, box, or violin plots for each numerical or categorical coefficient as well as plots depicting effects sizes and estimates. All generated

90 plots are returned to the user within a named list. The main function additionally returns the  
91 output of both the model simplification/selection and autocorrelation functions as well as the  
92 summary of the final model.

93 LazyModeler makes use of the R package corrrplot (Wei & Simko, 2021) to calculate  
94 correlations between variables, lme4 (Bates et al., 2024) and lmerTest (Kuznetsova et al.,  
95 2017) for regression modeling, tidyverse (Wickham et al., 2019) for data handling, and MuMIn  
96 (Bartoń, 2024) for calculation of AICc scores. For generation of plots visualizing regression,  
97 effect size, and estimates, the script further leverages tidyverse and color palettes included in  
98 the colorspace (Zeileis et al., 2020) and viridis (Garnier et al., 2024) R packages.

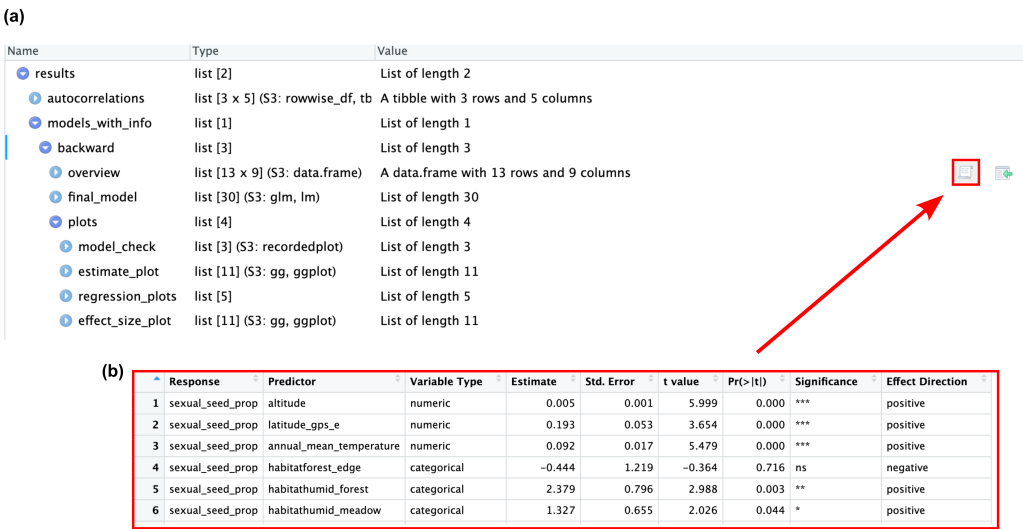
## 99 Example

```
# import example data
data(plants)

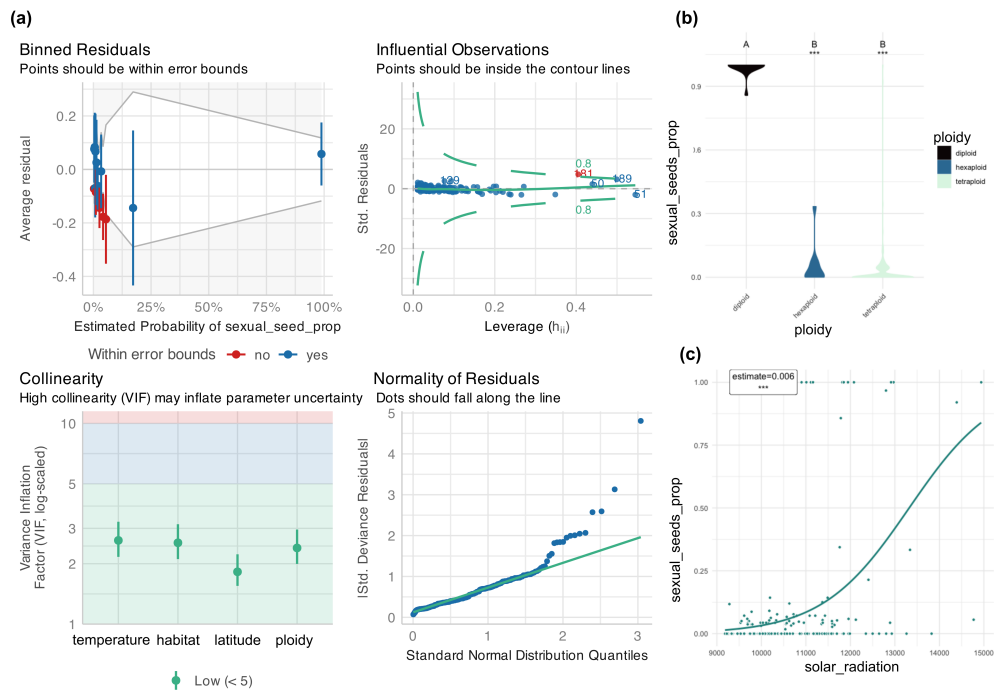
# check data structure
str(plants)
summary(plants)

# testing dataset (subset) based on Karbstein et al. 2021
#(https://onlinelibrary.wiley.com/doi/10.1111/mec.15919)

results_example <- optimize_model(plants, quote(sexual_seed_prop ~
altitude + latitude_gps_n + longitude_gps_e + (solar_radiation +
annual_mean_temperature + isothermality)^2 + I(isothermality^2) +
habitat + ploidy), autocorrelation_cols = c("solar_radiation",
"annual_mean_temperature", "isothermality", "altitude",
"latitude_gps_n", "longitude_gps_e"), automatic_removal=TRUE,
autocorrelation_threshold = 0.8, correlation_method="spearman",
model_type = "glm", model_family = "quasibinomial",
assessment_methods=c("anova"), simplification_direction="backward",
omit.na="overall", scale_predictor=TRUE,
plot_quality_assessment="performance", round_p=3,
cor_use="complete.obs", plot_relationships=TRUE, jitter_plots=TRUE,
plot_type="violinplot", stat_test="wilcox",
backward_simplify_model=TRUE, trace=TRUE)
```



**Figure 1:** Navigating through the output. For example, (a) simply click on dataframe button highlighted with a red arrow to (b) illustrate the final model output.



**Figure 2:** (a) Model quality check and (b,c) exemplary output plots of significant relationships.

**Conclusions**

In summary, LazyModeler streamlines the process of building, simplifying, and visualizing regression models in R. By automating key steps such as autocorrelation removal, model selection, quality assessment, and output generation, it significantly reduces manual effort. The package is especially valuable for researchers dealing with large and complex datasets who seek a reproducible and statistically sound regression modeling workflow. We anticipate that

<sup>106</sup> LazyModeler will serve as a practical and accessible tool for both novice and experienced users  
<sup>107</sup> in the scientific community.

DRAFT

## Code Availability

The code including basic documentation and an exemplary testing dataset will be made available upon publication on [Github](#) and on [Comprehensive R Archive Network \(CRAN\)](#).

## Acknowledgements

We acknowledge financial support from the German Federal Ministry of Education and Research (BMBF) grant 01IS20062.

## References

- Bartoń, K. (2024). *MuMIn: Multi-model inference*. <https://doi.org/10.32614/cran.package.mumin>
- Bates, D., Maechler, M., Bolker, B., & Walker, S. (2024). *lme4 - Linear mixed-effects models using Eigen and S4*. <https://github.com/lme4/lme4/>
- Bauer, M., & Albrecht, H. (2020). Vegetation monitoring in a 100-year-old calcareous grassland reserve in Germany. *Basic and Applied Ecology*, 42, 15–26. <https://doi.org/10.1016/j.baae.2019.11.003>
- Benjamin, A. S., Fernandes, H. L., Tomlinson, T., Ramkumar, P., VerSteeg, C., Chowdhury, R. H., Miller, L. E., & Kording, K. P. (2018). Modern machine learning as a benchmark for fitting neural responses. *Frontiers in Computational Neuroscience*, 12(July), 1–13. <https://doi.org/10.3389/fncom.2018.00056>
- Bzdok, D., & Ioannidis, J. P. A. (2019). Exploration, Inference, and Prediction in Neuroscience and Biomedicine. *Trends in Neurosciences*, 42(4), 251–262. <https://doi.org/10.1016/j.tins.2019.02.001>
- Cai, L., Kreft, H., Taylor, A., Denelle, P., Schrader, J., Essl, F., Kleunen, M. van, Pergl, J., Pyšek, P., Stein, A., Winter, M., Barcelona, J. F., Fuentes, N., Inderjit, Karger, D. N., Kartesz, J., Kuprijanov, A., Nishino, M., Nickrent, D., ... Weigelt, P. (2023). Global models and predictions of plant diversity based on advanced machine learning techniques. *New Phytologist*, 237(4), 1432–1445. <https://doi.org/10.1111/nph.18533>
- Crawley, M. J. (2007). *The R Book* (p. 942). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9780470515075>
- Crawley, M. J. (2015). *Statistics: an introduction using R* (sec. ed., p. 339). John Wiley & Sons. ISBN: 1118448960
- Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., & Lautenbach, S. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1), 27–46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>
- Forstmeier, W., & Schielzeth, H. (2011). Cryptic multiple hypotheses testing in linear models: overestimated effect sizes and the winner's curse. *Behavioral Ecology and Sociobiology*, 65(1), 47–55. <https://doi.org/10.1007/s00265-010-1038-5>
- Garnier, Simon, Ross, Noam, Rudis, Robert, Camargo, Pedro, A., Sciaini, Marco, Scherer, & Cédric. (2024). *viridis(Lite) - colorblind-friendly color maps for r*. <https://doi.org/10.5281/zenodo.4679423>
- Hastie, T. (2023). *gam: Generalized Additive Models*. <https://cran.r-project.org/web/>



- 151 [packages/gam/index.html](#)
- 152 Henley, S. S., Golden, R. M., & Kashner, T. M. (2020). Statistical modeling methods:  
153 challenges and strategies. *Biostatistics & Epidemiology*, 4(1), 105–139. <https://doi.org/10.1080/24709360.2019.1618653>  
154
- 155 Karbstein, K., Prinz, K., Hellwig, F., & Römermann, C. (2020). Plant intraspecific functional  
156 trait variation is related to within-habitat heterogeneity and genetic diversity in *Trifolium*  
157 *montanum* L. *Ecology and Evolution*, 10(11), 5015–5033. <https://doi.org/10.1002/ece3.6255>  
158
- 159 Karbstein, K., Römermann, C., Hellwig, F., & Prinz, K. (2023). Population size affected  
160 by environmental variability impacts genetics, traits, and plant performance in *Trifolium*  
161 *montanum* L. *Ecology and Evolution*, 13(8), 1–19. <https://doi.org/10.1002/ece3.10376>
- 162 Karbstein, K., Tomasello, S., Hodač, L., Lorberg, E., Daubert, M., & Hörandl, E. (2021).  
163 Moving beyond assumptions: Polyploidy and environmental effects explain a geographical  
164 parthenogenesis scenario in European plants. *Molecular Ecology*, 30(11), 2659–2675.  
165 <https://doi.org/10.1111/mec.15919>
- 166 Karbstein, K., Tomasello, S., & Prinz, K. (2019). Desert-like badlands and surrounding  
167 (semi-)dry grasslands of Central Germany promote small-scale phenotypic and genetic  
168 differentiation in *Thymus praecox*. *Ecology and Evolution*, 9(24), 14066–14084. <https://doi.org/10.1002/ece3.5844>  
169
- 170 Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests  
171 in linear mixed effects models. *Journal of Statistical Software*, 82(13), 1–26. <https://doi.org/10.18637/jss.v082.i13>  
172
- 173 Li, J. (2023). Overview of high dimensional linear regression models. *Theoretical and Natural*  
174 *Science*, 5(1), 656–661. <https://doi.org/10.54254/2753-8818/5/20230427>
- 175 Liaw, K., Khomik, M., & Arain, M. A. (2021). Explaining the shortcomings of log-transforming  
176 the dependent variable in regression models and recommending a better alternative:  
177 Evidence from soil CO<sub>2</sub> emission studies. *Journal of Geophysical Research: Biogeosciences*,  
178 126(5), 1–18. <https://doi.org/10.1029/2021JG006238>
- 179 Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). Performance:  
180 An r package for assessment, comparison and testing of statistical models. *Journal of Open*  
181 *Source Software*, 6(60), 3139. <https://doi.org/10.21105/joss.03139>
- 182 R Core Team. (2024). *R: a language and environment for statistical computing*. R Foundation  
183 for Statistical Computing. <http://www.r-project.org/>
- 184 Römermann, C., Bucher, S. F., Hahn, M., & Bernhardt-Römermann, M. (2016). Plant  
185 functional traits – fixed facts or variable depending on the season? *Folia Geobotanica*,  
186 51(2), 143–159. <https://doi.org/10.1007/s12224-016-9250-3>
- 187 Schielzeth, H. (2010). Simple means to improve the interpretability of regression coefficients.  
188 *Methods in Ecology and Evolution*, 1(2), 103–113. <https://doi.org/10.1111/j.2041-210X.2010.00012.x>  
189
- 190 Schielzeth, H., Dingemanse, N. J., Nakagawa, S., Westneat, D. F., Allogue, H., Teplitsky, C.,  
191 Réale, D., Dochtermann, N. A., Garamszegi, L. Z., & Araya-Ajoy, Y. G. (2020). Robustness  
192 of linear mixed-effects models to violations of distributional assumptions. *Methods in*  
193 *Ecology and Evolution*, 11(9), 1141–1152. <https://doi.org/10.1111/2041-210X.13434>
- 194 Schulz, M.-A., Yeo, B. T. T., Vogelstein, J. T., Mourao-Miranada, J., Kather, J. N., Kording,  
195 K., Richards, B., & Bzdok, D. (2020). Different scaling of linear models and deep learning  
196 in UKBiobank brain images versus machine-learning datasets. *Nature Communications*,  
197 11(1), 4238. <https://doi.org/10.1038/s41467-020-18037-z>

- 198 Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S* (Fourth). Springer.  
199 ISBN: 0-387-95457-0
- 200 Wei, T., & Simko, V. (2021). *R package 'corrplot': Visualization of a correlation matrix*.  
201 <https://github.com/taiyun/corrplot>
- 202 Wicke, S., Müller, K. F., DePamphilis, C. W., Quandt, D., Bellot, S., & Schneeweiss, G. M.  
203 (2016). Mechanistic model of evolutionary rate variation en route to a nonphotosynthetic  
204 lifestyle in plants. *Proceedings of the National Academy of Sciences of the United States*  
205 *of America*, 113(32), 9045–9050. <https://doi.org/10.1073/pnas.1607576113>
- 206 Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Golemund,  
207 G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M.,  
208 Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome  
209 to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. [https://doi.org/10.21105/](https://doi.org/10.21105/joss.01686)  
210 [joss.01686](https://doi.org/10.21105/joss.01686)
- 211 Zeileis, A., Fisher, J. C., Hornik, K., Ihaka, R., McWhite, C. D., Murrell, P., Stauffer, R.,  
212 & Wilke, C. O. (2020). colorspace: A toolbox for manipulating and assessing colors and  
213 palettes. *Journal of Statistical Software*, 96(1), 1–49. [https://doi.org/10.18637/jss.v096.](https://doi.org/10.18637/jss.v096.i01)  
214 [i01](https://doi.org/10.18637/jss.v096.i01)

DRAFT