TEXT

Doug McNeall[1], Jonny Williams[2], Ben Booth[1], Richard Betts[1], Peter Challenor[3], Andrew Wiltshire[1], and David Sexton[1]

[1]Met Office Hadley Centre, FitzRoy Road, Exeter, EX1 3PB UK
[2]NIWA, New Zealand
[3]University of Exeter, North Park Road, Exeter EX4 4QE UK

Correspondence to: Doug McNeall (doug.mcneall@metoffice.gov.uk)

Abstract. We use observations of forest fraction to constrain carbon cycle and land surface input parameters of the reduced resolution global climate model, FAMOUS. Using a history matching approach along with a computationally cheap statistical proxy (emulator) of the climate model, we compare an ensemble of simulations of forest fraction with observations, and rule out parameter settings where the forests are poorly simulated.

Regions of parameter space where FAMOUS best simulates the Amazon forest fraction are incompatible with the regions where FAMOUS best simulates other forests. Previous studies using climate models have used similar methods to find previously untried candidate input parameter sets that remove what was assumed an underlying structural error. We offer a counter example, arguing that we have found a true structural discrepancy. This has implications for the calibration of FAMOUS: using observations of different forest regions to calibrate the model leads to very different conclusions about the best values, the corresponding uncertainty of input parameters, and potentially, predictions of future forest cover. Dealing with this structural discrepancy is vital when choosing a set of "best" parameters for the land surface - failure to do so could lead to poor parameter selection.

We characterise the structural model discrepancy, and explore the consequences of ignoring it in a history matching exercise. We perform a sensitivity analysis to find the parameters most responsible for simulator error and therefore most promising for tuning. We use the emulator to simulate the forest fraction at the best set of parameters implied by matching the model to the Amazon, and to other major forests in turn. We can find parameters that lead to a realistic forest fraction in the Amazon, but using the Amazon alone to tune the simulator would result in a significant overestimate of forest fraction in the other forests. Conversely, using the other forests to calibrate the model leads to a larger underestimate of the Amazon forest fraction.

Finally, we perform a history matching exercise using credible estimates for simulator discrepancy and observational uncertainty terms. We find that we are unable to constrain the parameters individually, but that just under half of joint parameter space is ruled out as being incompatible with forest observations. We discuss the possible sources of the discrepancy in the simulated Amazon, including missing processes in the land surface component, and a bias in the climatology of the Amazon.

1 Introduction

(Craig et al., 1997) (Booth et al., 2012) (Booth et al., 2013) (Huntingford et al., 2009) (Sellers et al., 1996) (Abramowitz, 2012) (Luo et al., 2012) (Williamson et al., 2014) (Kennedy and O'Hagan, 2001) (Brynjarsdóttir and O'Hagan, 2014) (Higdon et al., 2008) (Jones et al., 2005) (Smith et al., 2008) (Gordon et al., 2000) (Pope et al., 2000) (Cox, 2001) (Smith, 2012) (Williams et al., 2013) (Williams et al., 2014) (Gnanadesikan and Stouffer, 2006) (McKay et al., 1979) (Urban and Fricker, 2010) (Gregoire et al., 2010) (Loveland et al., 2000) (Roustant et al., 2012) (R Core Team, 2016) (Vernon et al., 2010) (Lee et al., 2016) (Williamson et al., 2013) (Ritz et al., 2015) (McNeall et al., 2013) (Pukelsheim, 1994) (Carslaw et al., 2013) (Saltelli et al., 1999) (Pujol et al., 2015) (Cox et al., 2004) (Good et al., 2008) (Joetzjer et al., 2013) (Staver et al., 2011) (Malhi et al., 2009) (Yin et al., 2012)

2 HEADING

TEXT

2.1 HEADING

TEXT

2.1.1 HEADING

TEXT

3 Conclusions

TEXT

Appendix A

A1

Author contributions. TEXT

Acknowledgements. TEXT

References

Abramowitz, G.: Towards a public, standardized, diagnostic benchmarking system for land surface models, Geoscientific Model Development, 5, 819–827, doi:10.5194/gmd-5-819-2012, http://www.geosci-model-dev.net/5/819/2012/, 2012.

Booth, B. B. B., Jones, C. D., Collins, M., Totterdell, I. J., Cox, P. M., Sitch, S., Huntingford, C., Betts, R. A., Harris, G. R., and Lloyd, J.: High sensitivity of future global warming to land carbon cycle processes, Environmental Research Letters, 7, 024 002, http://stacks.iop.org/1748-9326/7/i=2/a=024002, 2012.

Booth, B. B. B., Bernie, D., McNeall, D., Hawkins, E., Caesar, J., Boulton, C., Friedlingstein, P., and Sexton, D. M. H.: Scenario and modelling uncertainty in global mean temperature change derived from emission-driven global climate models, Earth System Dynamics, 4, 95–108, doi:10.5194/esd-4-95-2013, http://www.earth-syst-dynam.net/4/95/2013/, 2013.

Brynjarsdóttir, J. and O'Hagan, A.: Learning about physical parameters: the importance of model discrepancy, Inverse Problems, 30, 114 007, http://stacks.iop.org/0266-5611/30/i=11/a=114007, 2014.

Carslaw, K., Lee, L., Reddington, C., Pringle, K., Rap, A., Forster, P., Mann, G., Spracklen, D., Woodhouse, M., Regayre, L., et al.: Large contribution of natural aerosols to uncertainty in indirect forcing, Nature, 503, 67–71, 2013.

Cox, M. P., Betts, A. R., Collins, M., Harris, P. P., Huntingford, C., and Jones, D. C.: Amazonian forest dieback under climate-carbon cycle projections for the 21st century, Theoretical and Applied Climatology, 78, 137–156, doi:10.1007/s00704-004-0049-4, http://dx.doi.org/10.1007/s00704-004-0049-4, 2004.

Cox, P. M.: Description of the TRIFFID dynamic global vegetation model, Tech. rep., Technical Note 24, Hadley Centre, United Kingdom Meteorological Office, Bracknell, UK, 2001.

Craig, P., Goldstein, M., Seheult, A., and Smith, J.: Pressure matching for hydrocarbon reservoirs: a case study in the use of Bayes linear strategies for large computer experiments, in: Case studies in Bayesian statistics, edited by Gatsonis, C., Hodges, J., Kass, R., McCulloch, R., Rossi, P., and Singpurwalla, N., vol. 3, pp. 36–93, Springer-Verlag, New York, USA, 1997.

Gnanadesikan, A. and Stouffer, R. J.: Diagnosing atmosphere-ocean general circulation model errors relevant to the terrestrial biosphere using the Koppen climate classification, Geophysical Research Letters, 33, n/a–n/a, doi:10.1029/2006GL028098, http://dx.doi.org/10.1029/2006GL028098, l22701, 2006.

Good, P., Lowe, J. A., Collins, M., and Moufouma-Okia, W.: An objective tropical Atlantic sea surface temperature gradient index for studies of south Amazon dry-season climate variability and change, Philosophical Transactions of the Royal Society of London B: Biological Sciences, 363, 1761–1766, doi:10.1098/rstb.2007.0024, http://rstb.royalsocietypublishing.org/content/363/1498/1761, 2008.

Gordon, C., Cooper, C., Senior, A. C., Banks, H., Gregory, M. J., Johns, C. T., Mitchell, B. J. F., and Wood, A. R.: The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments, Climate Dynamics, 16, 147–168, doi:10.1007/s003820050010, http://dx.doi.org/10.1007/s003820050010, 2000.

Gregoire, L. J., Valdes, P. J., Payne, A. J., and Kahana, R.: Optimal tuning of a GCM using modern and glacial constraints, Climate Dynamics, 37, 705–719, doi:10.1007/s00382-010-0934-8, http://dx.doi.org/10.1007/s00382-010-0934-8, 2010.

Higdon, D., Gattiker, J., Williams, B., and Rightley, M.: Computer Model Calibration Using High-Dimensional Output, Journal of the American Statistical Association, 103, 570–583, doi:10.1198/016214507000000888, http://dx.doi.org/10.1198/016214507000000888, 2008.

Huntingford, C., Lowe, J. A., Booth, B. B. B., Jones, C. D., Harris, G. R., Gohar, L. K., and Meir, P.: Contributions of carbon cycle uncertainty to future climate projection spread, Tellus B, 61, 355–360, doi:10.1111/j.1600-0889.2009.00414.x, http://dx.doi.org/10.1111/j.1600-0889.2009.00414.x, 2009.

Joetzjer, E., Douville, H., Delire, C., and Ciais, P.: Present-day and future Amazonian precipitation in global climate models: CMIP5 versus CMIP3, Climate Dynamics, 41, 2921–2936, doi:10.1007/s00382-012-1644-1, http://dx.doi.org/10.1007/s00382-012-1644-1, 2013.

Jones, C., Gregory, J., Thorpe, R., Cox, P., Murphy, J., Sexton, D., and Valdes, P.: Systematic optimisation and climate simulation of FAMOUS, a fast version of HadCM3, Climate Dynamics, 25, 189–204, doi:10.1007/s00382-005-0027-2, http://dx.doi.org/10.1007/s00382-005-0027-2, 2005.

Kennedy, M. and O'Hagan, A.: Bayesian calibration of computer models, Journal of the Royal Statistical Society: Series B (Statistical Methodology), 63, 425–464, 2001.

Lee, L. A., Reddington, C. L., and Carslaw, K. S.: On the relationship between aerosol model uncertainty and radiative forcing uncertainty, Proceedings of the National Academy of Sciences, doi:10.1073/pnas.1507050113, http://www.pnas.org/content/early/2016/02/04/1507050113.abstract, 2016.

Loveland, T. R., Reed, B. C., Brown, J. F., Ohlen, D. O., Zhu, Z., Yang, L., and Merchant, J. W.: Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data, International Journal of Remote Sensing, 21, 1303–1330, doi:10.1080/014311600210191, http://dx.doi.org/10.1080/014311600210191, 2000.

Luo, Y. Q., Randerson, J. T., Abramowitz, G., Bacour, C., Blyth, E., Carvalhais, N., Ciais, P., Dalmonech, D., Fisher, J. B., Fisher, R., Friedlingstein, P., Hibbard, K., Hoffman, F., Huntzinger, D., Jones, C. D., Koven, C., Lawrence, D., Li, D. J., Mahecha, M., Niu, S. L., Norby, R., Piao, S. L., Qi, X., Peylin, P., Prentice, I. C., Riley, W., Reichstein, M., Schwalm, C., Wang, Y. P., Xia, J. Y., Zaehle, S., and Zhou, X. H.: A framework for benchmarking land models, Biogeosciences, 9, 3857–3874, doi:10.5194/bg-9-3857-2012, http://www.biogeosciences.net/9/3857/2012/, 2012.

Malhi, Y., Aragão, L. E. O. C., Galbraith, D., Huntingford, C., Fisher, R., Zelazowski, P., Sitch, S., McSweeney, C., and Meir, P.: Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest, Proceedings of the National Academy of Sciences, 106, 20 610–20 615, doi:10.1073/pnas.0804619106, http://www.pnas.org/content/106/49/20610.abstract, 2009.

McKay, M., Beckman, R., and Conover, W.: A comparison of three methods for selecting values of input variables in the analysis of output from a computer code, Technometrics, pp. 239–245, 1979.

McNeall, D. J., Challenor, P. G., Gattiker, J. R., and Stone, E. J.: The potential of an observational data set for calibration of a computationally expensive computer model, Geoscientific Model Development, 6, 1715–1728, doi:10.5194/gmd-6-1715-2013, http://www.geosci-model-dev.net/6/1715/2013/, 2013.

Pope, D. V., Gallani, L. M., Rowntree, R. P., and Stratton, A. R.: The impact of new physical parametrizations in the Hadley Centre climate model: HadAM3, Climate Dynamics, 16, 123–146, doi:10.1007/s003820050009, http://dx.doi.org/10.1007/s003820050009, 2000.

Pujol, G., Iooss, B., with contributions from Sebastien Da Veiga, A. J., Fruth, J., Gilquin, L., Guillaume, J., Gratiet, L. L., Lemaitre, P., Ramos, B., and Touati, T.: sensitivity: Sensitivity Analysis, https://CRAN.R-project.org/package=sensitivity, r package version 1.11.1, 2015.

Pukelsheim, F.: The three sigma rule, The American Statistician, 48, 88–91, 1994.

R Core Team: R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, https://www.R-project.org/, 2016.

Ritz, C., Edwards, T. L., Durand, G., Payne, A. J., Peyaud, V., and Hindmarsh, R. C.: Potential sea-level rise from Antarctic ice-sheet instability constrained by observations, Nature, 528, 115–118, 2015.

Roustant, O., Ginsbourger, D., and Deville, Y.: DiceKriging, DiceOptim: Two R Packages for the Analysis of Computer Experiments by Kriging-Based Metamodeling and Optimization, Journal of Statistical Software, 51, 1–55, doi:10.18637/jss.v051.i01, https://www.jstatsoft.org/index.php/jss/article/view/v051i01, 2012.

Saltelli, A., Tarantola, S., and Chan, K. P.-S.: A Quantitative Model-Independent Method for Global Sensitivity Analysis of Model Output, Technometrics, 41, 39–56, doi:10.1080/00401706.1999.10485594, http://amstat.tandfonline.com/doi/abs/10.1080/00401706.1999.10485594, 1999.

Sellers, P., Randall, D., Collatz, G., Berry, J., Field, C., Dazlich, D., Zhang, C., Collelo, G., and Bounoua, L.: A Revised Land Surface Parameterization (SiB2) for Atmospheric GCMS. Part I: Model Formulation, Journal of Climate, 9, 676–705, doi:10.1175/1520-0442(1996)009<0676:ARLSPF>2.0.CO;2, http://dx.doi.org/10.1175/1520-0442(1996)009<0676:ARLSPF>2.0.CO;2, 1996.

Smith, R. S.: The FAMOUS climate model (versions XFXWB and XFHCC): description update to version XDBUA, Geoscientific Model Development, 5, 269–276, doi:10.5194/gmd-5-269-2012, http://www.geosci-model-dev.net/5/269/2012/, 2012.

Smith, R. S., Gregory, J. M., and Osprey, A.: A description of the FAMOUS (version XDBUA) climate model and control run, Geoscientific Model Development, 1, 53–68, doi:10.5194/gmd-1-53-2008, http://www.geosci-model-dev.net/1/53/2008/, 2008.

Staver, A. C., Archibald, S., and Levin, S. A.: The Global Extent and Determinants of Savanna and Forest as Alternative Biome States, Science, 334, 230–232, doi:10.1126/science.1210465, http://science.sciencemag.org/content/334/6053/230, 2011.

Urban, N. M. and Fricker, T. E.: A comparison of Latin hypercube and grid ensemble designs for the multivariate emulation of an Earth system model, Computers & Geosciences, 36, 746–755, 2010.

Vernon, I., Goldstein, M., and Bower, R.: Galaxy formation: a Bayesian uncertainty analysis, Bayesian Analysis, 5, 619–669, 2010.

Williams, J. H. T., Smith, R. S., Valdes, P. J., Booth, B. B. B., and Osprey, A.: Optimising the FAMOUS climate model: inclusion of global carbon cycling, Geoscientific Model Development, 6, 141–160, doi:10.5194/gmd-6-141-2013, http://www.geosci-model-dev.net/6/141/2013/, 2013.

Williams, J. H. T., Totterdell, I. J., Halloran, P. R., and Valdes, P. J.: Numerical simulations of oceanic oxygen cycling in the FAMOUS Earth-System model: FAMOUS-ES, version 1.0, Geoscientific Model Development, 7, 1419–1431, doi:10.5194/gmd-7-1419-2014, http://www.geosci-model-dev.net/7/1419/2014/, 2014.

Williamson, D., Goldstein, M., Allison, L., Blaker, A., Challenor, P., Jackson, L., and Yamazaki, K.: History matching for exploring and reducing climate model parameter space using observations and a large perturbed physics ensemble, Climate dynamics, 41, 1703–1729, 2013.

Williamson, D., Blaker, A. T., Hampton, C., and Salter, J.: Identifying and removing structural biases in climate models with history matching, Climate Dynamics, 45, 1299–1324, doi:10.1007/s00382-014-2378-z, http://dx.doi.org/10.1007/s00382-014-2378-z, 2014.

Yin, L., Fu, R., Shevliakova, E., and Dickinson, R. E.: How well can CMIP5 simulate precipitation and its controlling processes over tropical South America?, Climate Dynamics, 41, 3127–3143, doi:10.1007/s00382-012-1582-y, http://dx.doi.org/10.1007/s00382-012-1582-y, 2012.

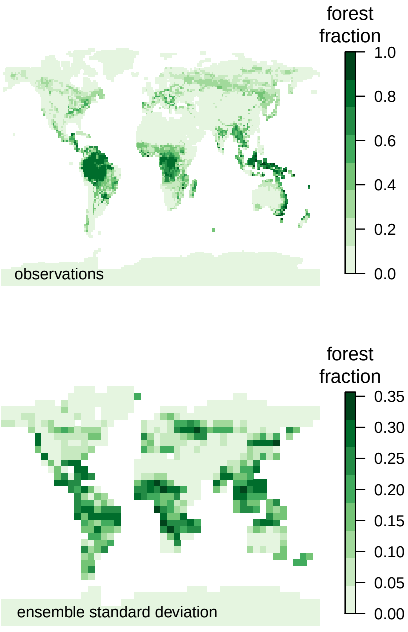

Figure 1. TEXT

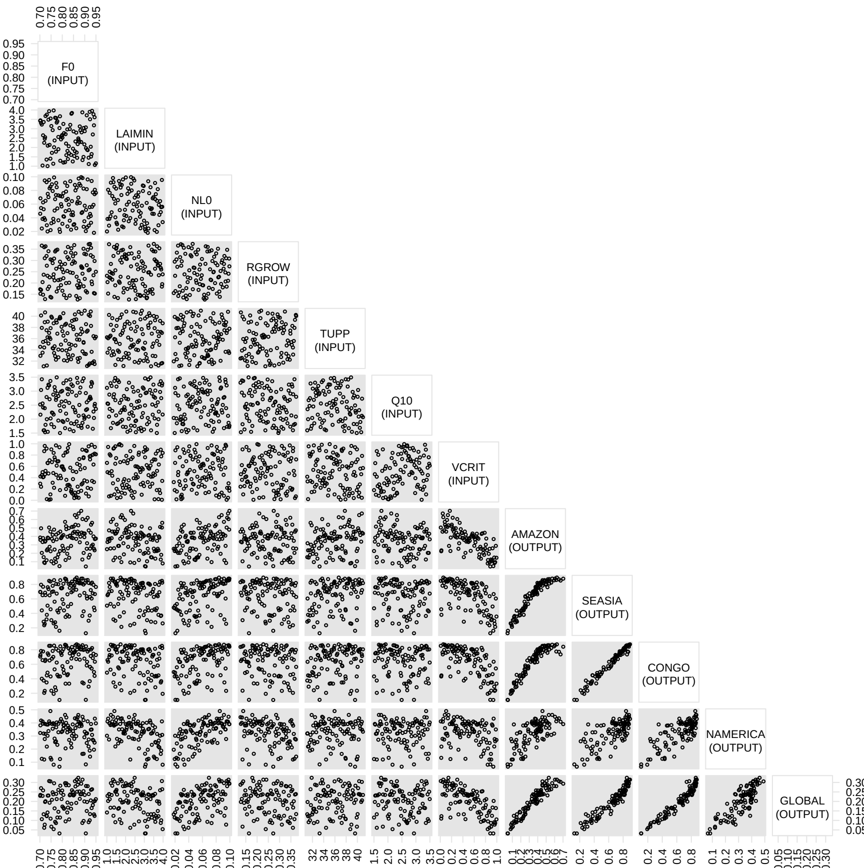

Figure 2. TEXT

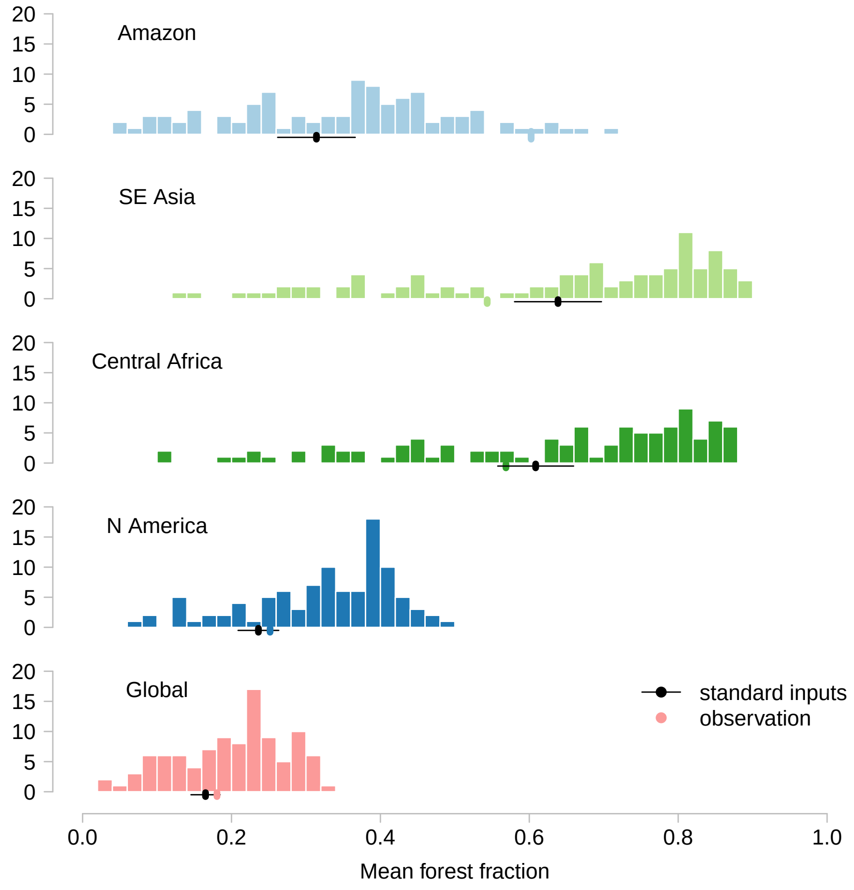

Figure 3. TEXT

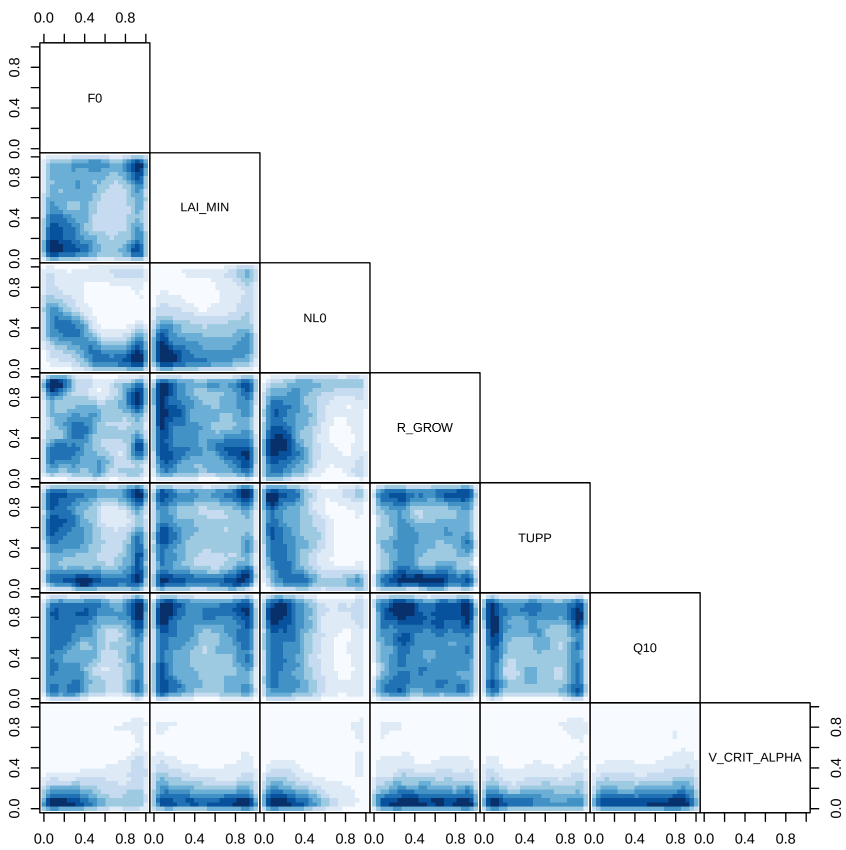

Figure 4. TEXT

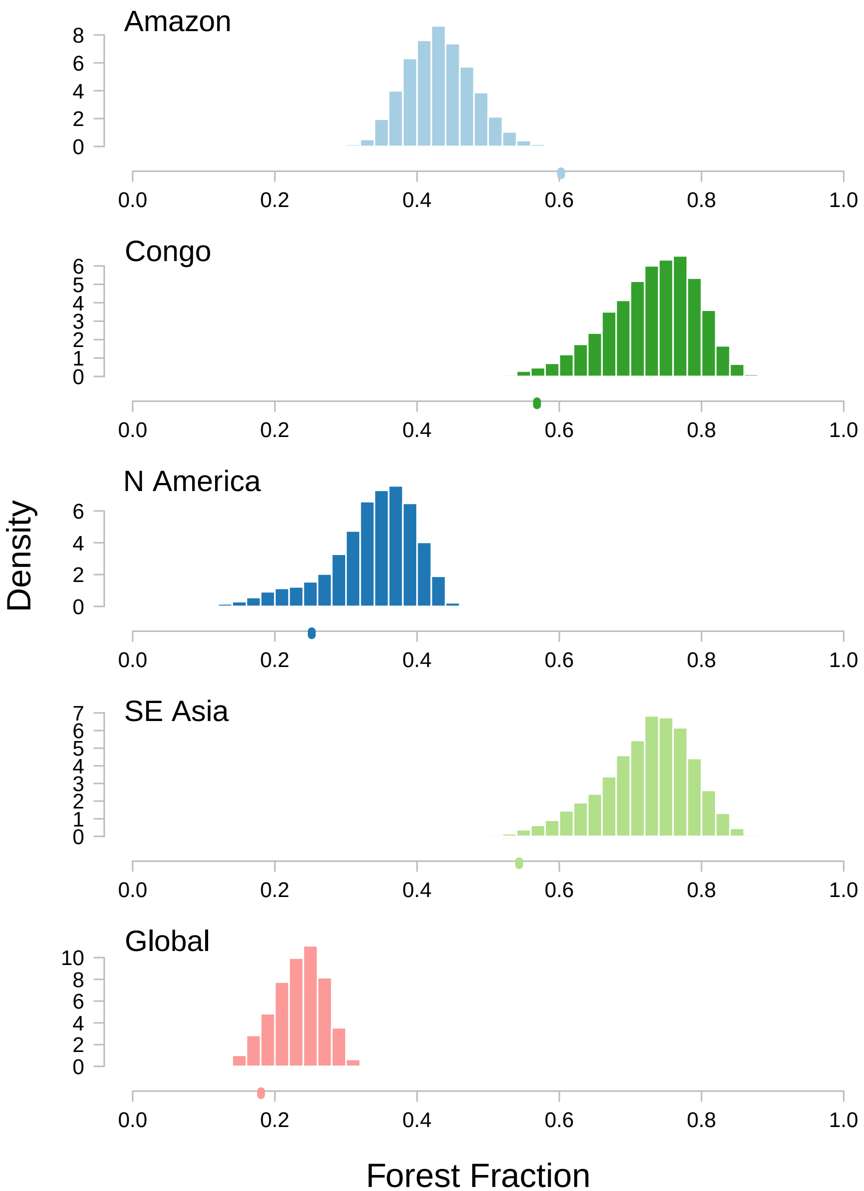

Figure 5. TEXT

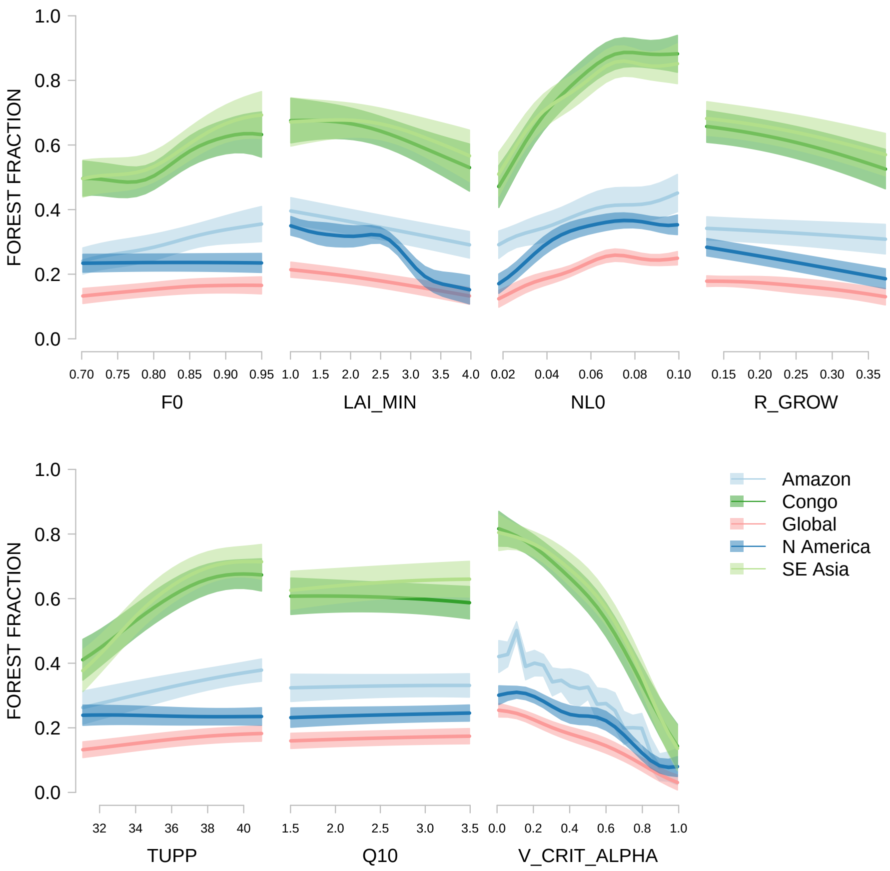

Figure 6. TEXT

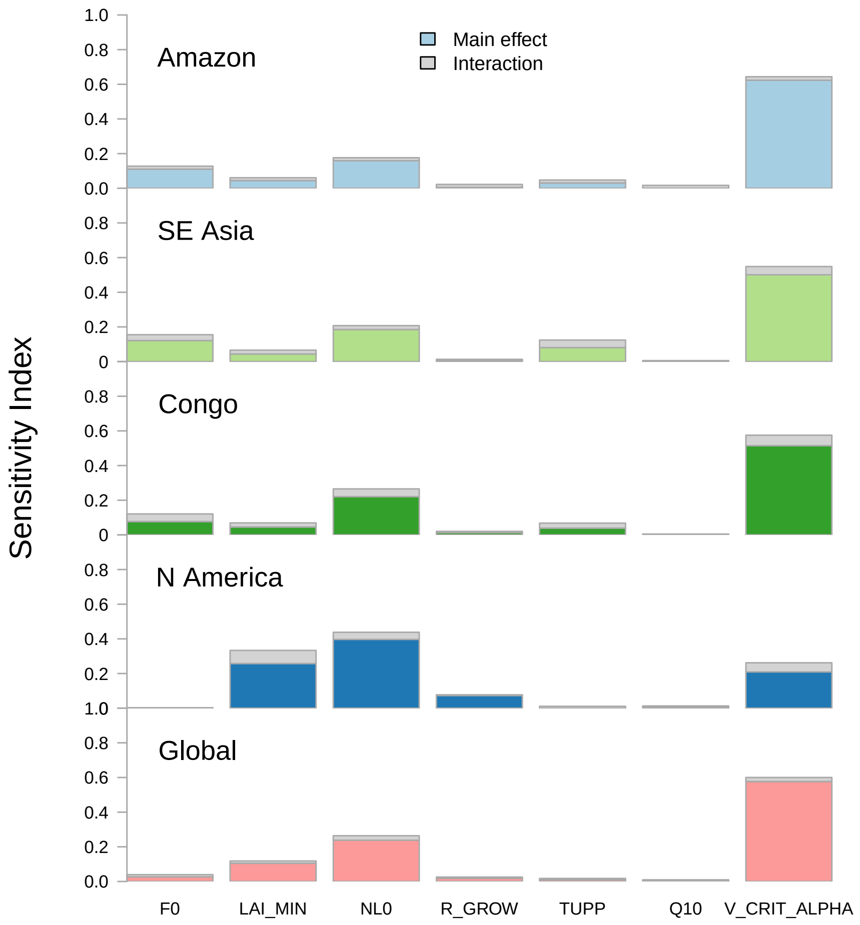

Figure 7. TEXT

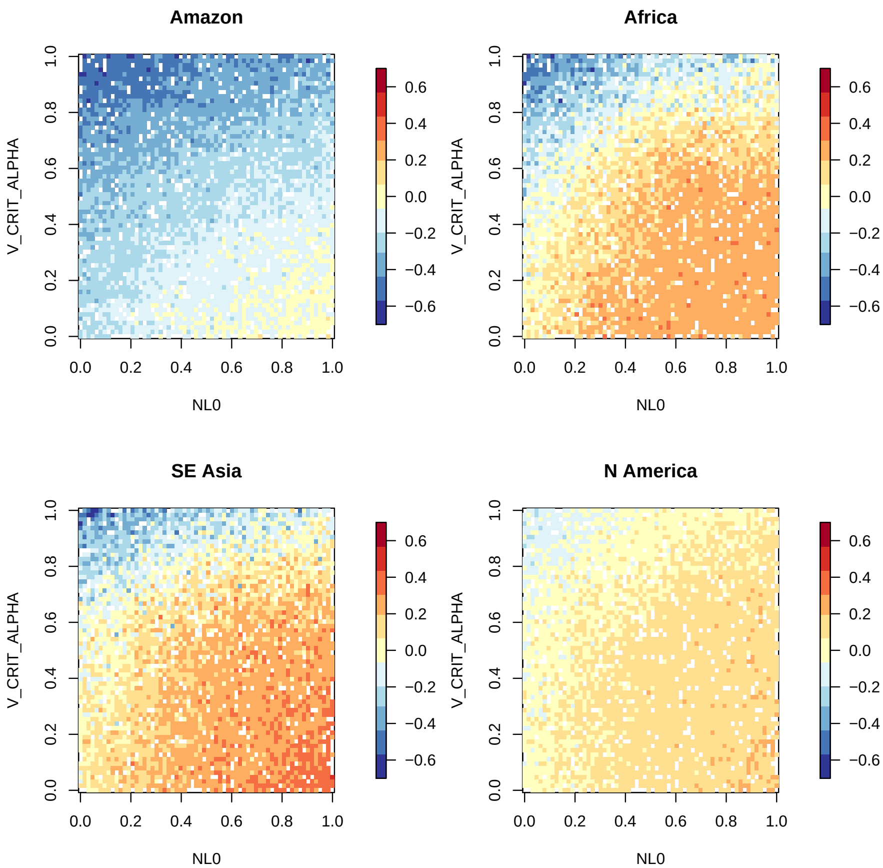

Figure 8. TEXT

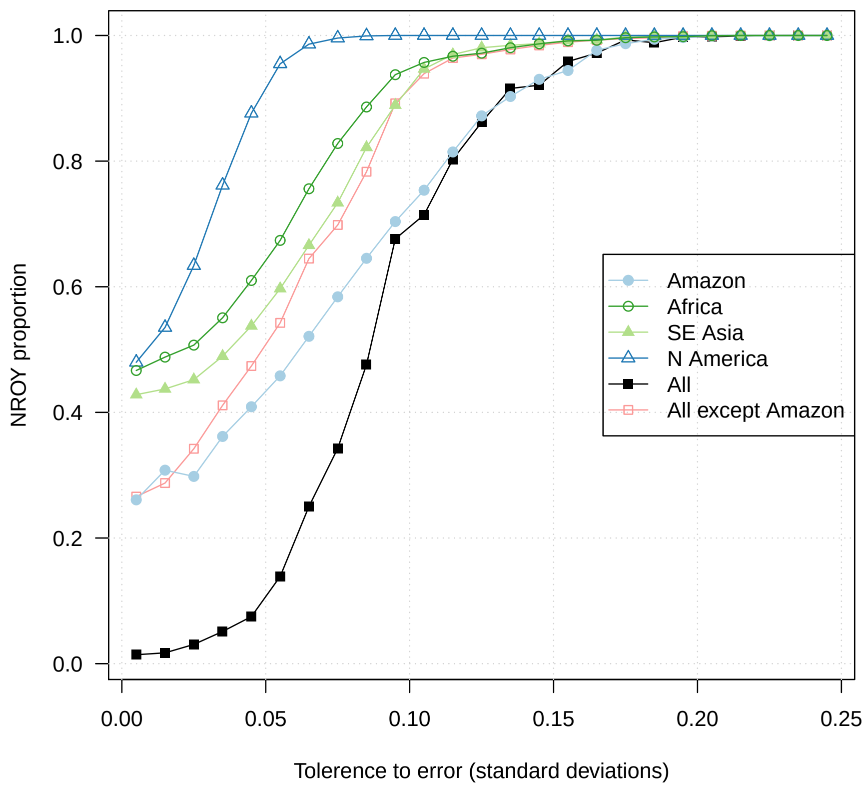

Figure 9. TEXT

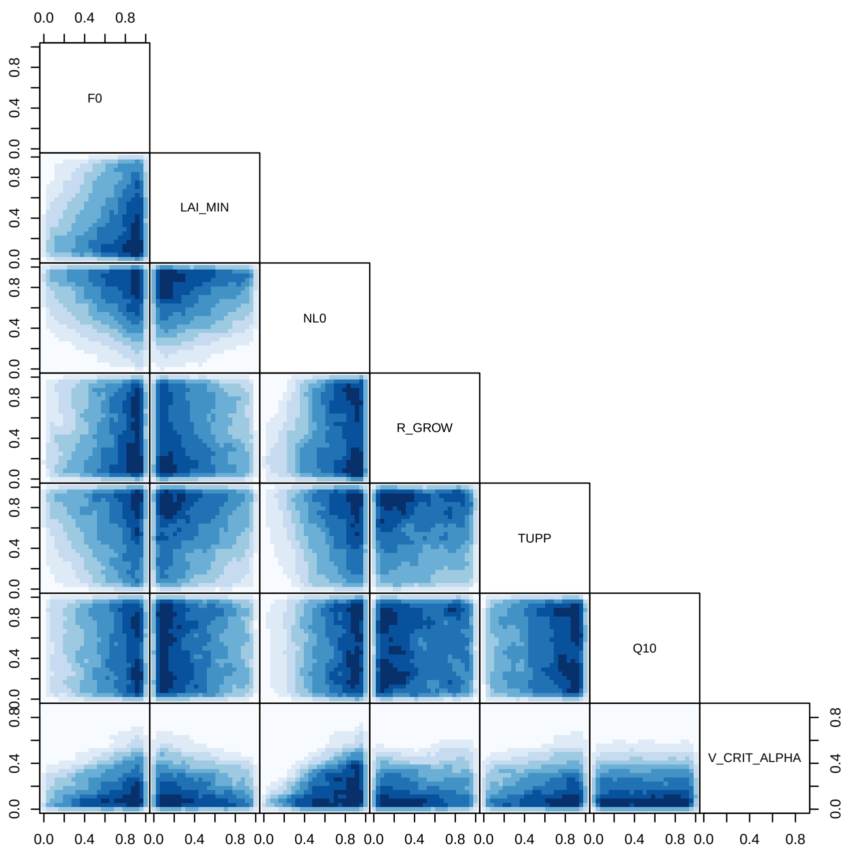

Figure 10. TEXT

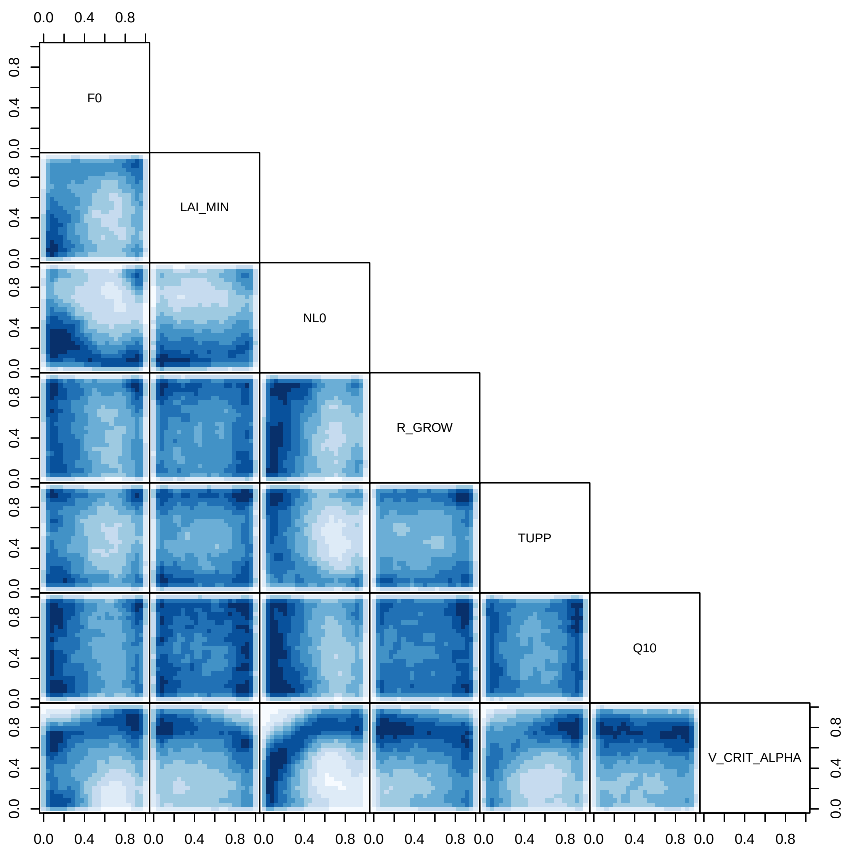

Figure 11. TEXT

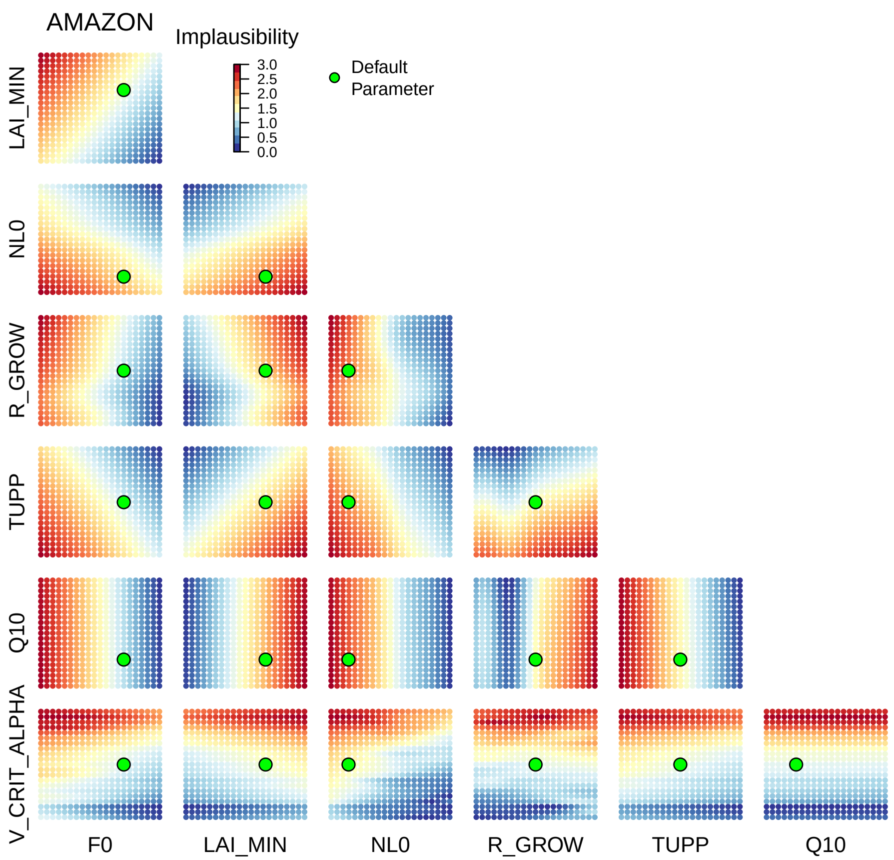

Figure 12. TEXT

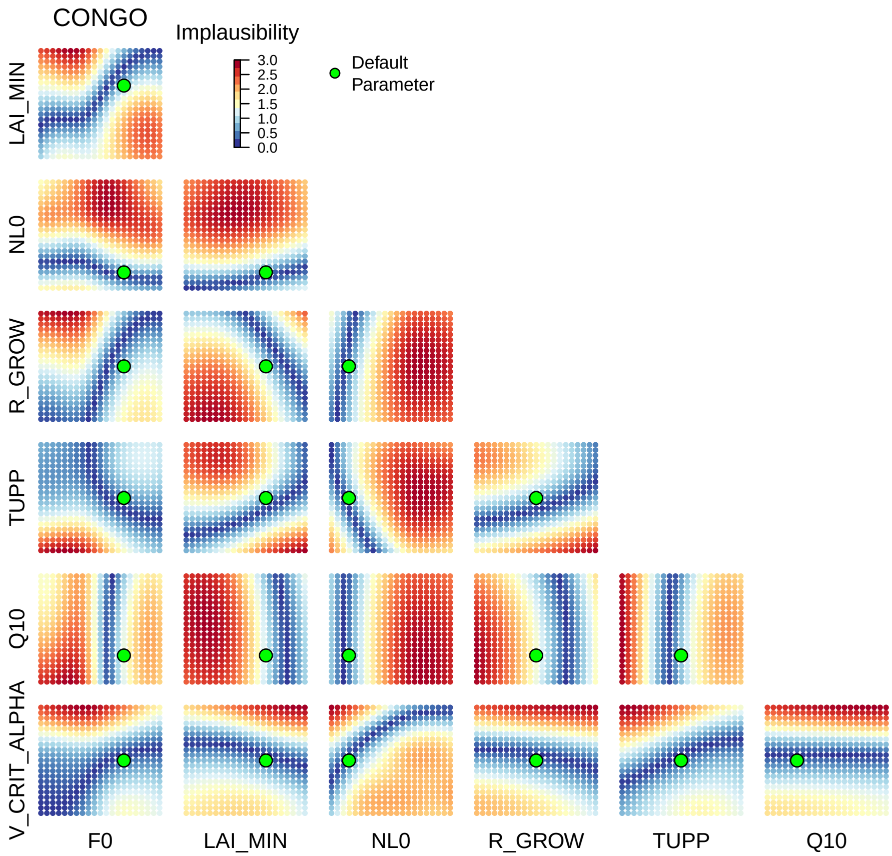

Figure 13. TEXT

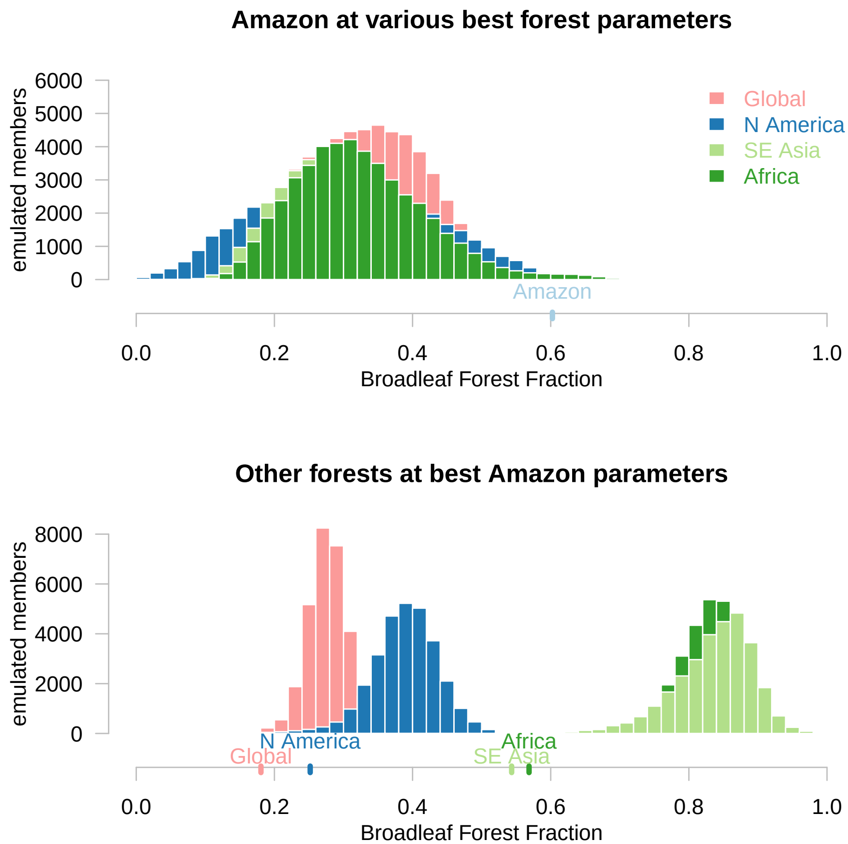

Figure 14. TEXT

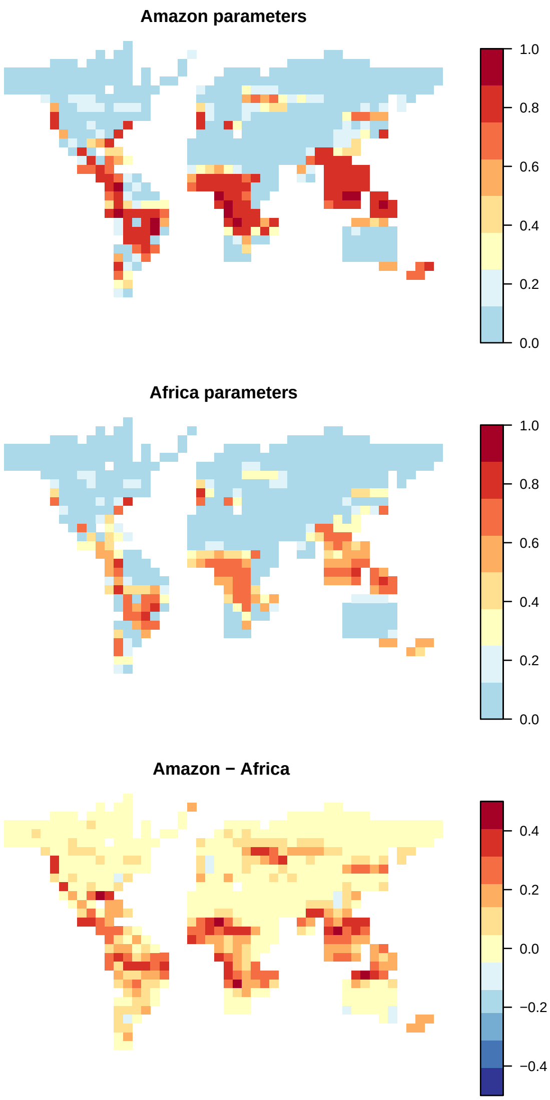

Figure 15. TEXT

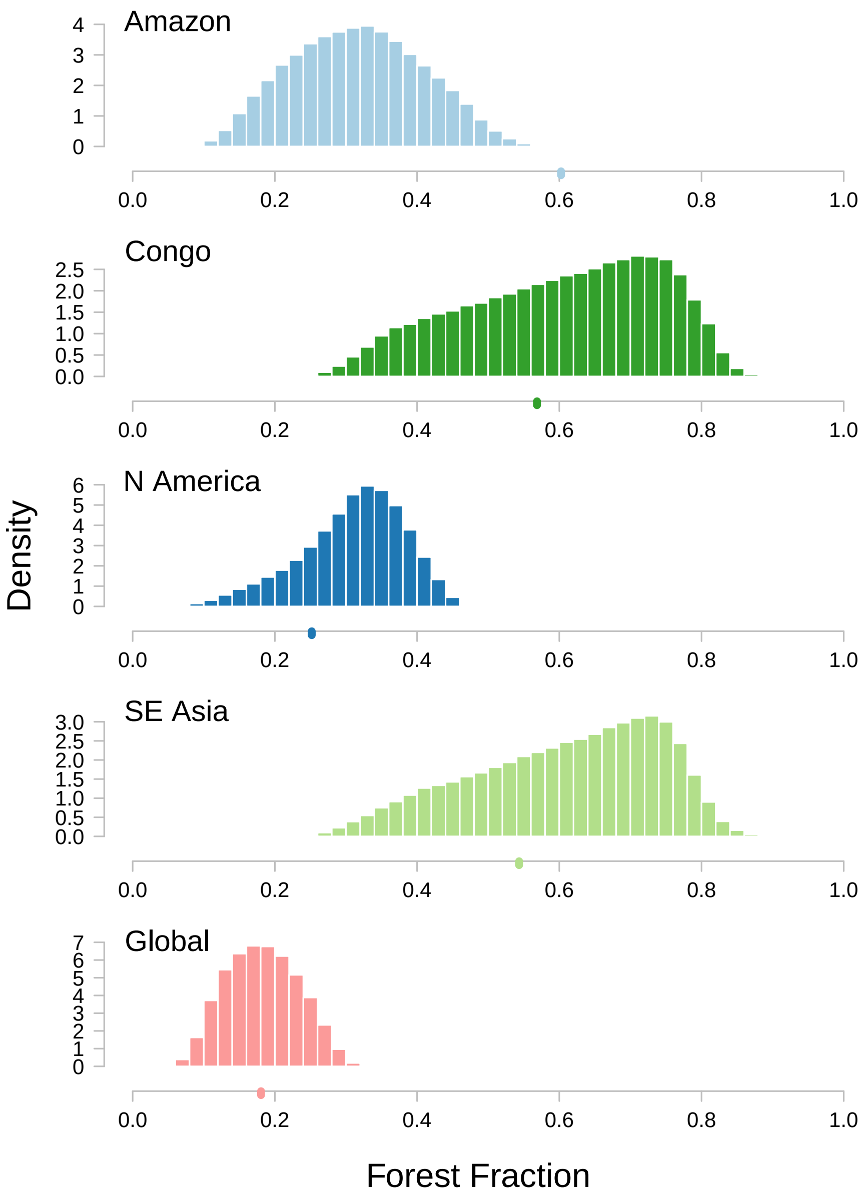

Figure 16. TEXT

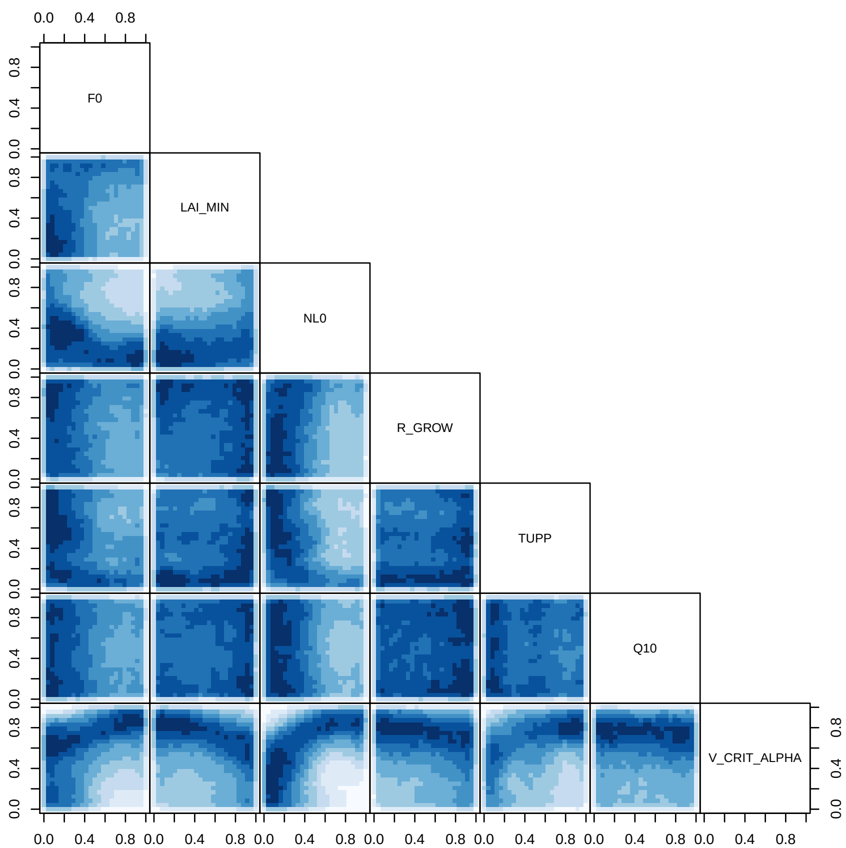

Figure 17. TEXT

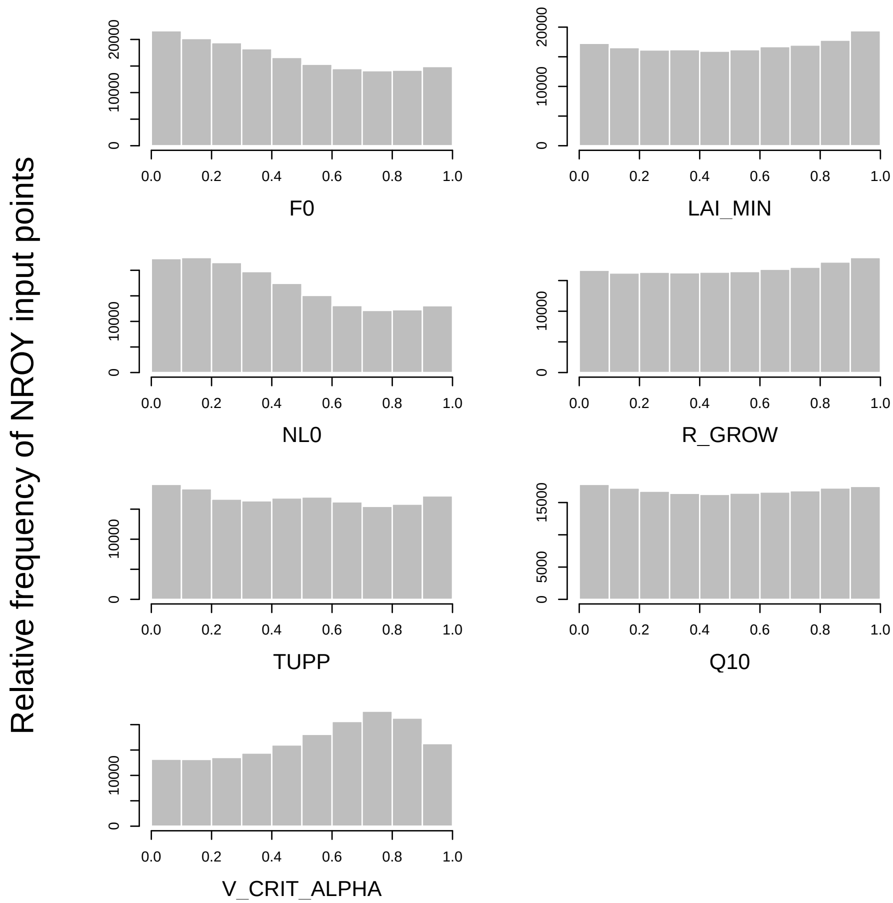

Figure 18. TEXT