Received: 12 December 2020 | Revised: 17 February 2021 | Accepted: 28 February 2021

DOI: 10.1111/gcb.15577

OPINION

Global Change Biology WILEY

Classifying human influences on terrestrial ecosystems

Matthias C. Rillig[1,2] | **Masahiro Ryo**[3,4] | **Anika Lehmann**[1,2]

[1]Institut für Biologie, Freie Universität Berlin, Berlin, Germany

[2]Berlin-Brandenburg Institute of Advanced Biodiversity Research (BBIB), Berlin, Germany

[3]Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany

[4]Brandenburg University of Technology Cottbus–Senftenberg, Cottbus, Germany

Correspondence
Matthias C. Rillig, Institut für Biologie, Freie Universität Berlin, 14195 Berlin, Germany.
Email: matthias.rillig@fu-berlin.de

Funding information
H2020 European Research Council, Grant/Award Number: 694368; Freie Universitat Berlin; Projekt DEAL

Abstract

Human activity is affecting every ecosystem on Earth, with terrestrial biodiversity decreasing rapidly. Human influences materialize in the form of numerous, jointly acting factors, yet the experimental study of such joint impacts is not well developed. We identify the absence of a systematic ordering system of factors according to their properties (traits) as an impediment to progress and offer an a priori trait-based factor classification to illustrate this point, starting at the coarsest level with the physical, biological or chemical nature of factors. Such factor classifications can serve in communication of science, but also can be used as heuristic tools to develop questions and formulate new hypotheses, or as predictors of effects, which we explore here. We hope that classifications such as the one proposed here can help shift the spotlight on the multitude of anthropogenic changes affecting ecosystems, and that such classifications can be used to help unravel joint impacts of a great number of factors.

KEYWORDS
classification, factors, global change, multiple factors, research synthesis, science communication, trait-based factor classification

Human activity is affecting every ecosystem on Earth, with terrestrial biodiversity decreasing rapidly (Diaz et al., 2019; Tilman et al., 2017). A major amount of research in ecology is dedicated to uncovering the effects of various anthropogenic influences on biota, communities and ecosystems to understand the mechanisms underpinning biodiversity decline and functional change (Sala et al., 2000; Vitousek, 1994).

The empirical arsenal of ecologists includes observational studies, where no intervention is applied to assess the influence of factors, and experiments, where factors are applied and responses observed using replication, controlling for other influences. Experiments are our best tools for demonstrating causality and as such they occupy a central role in the canon of approaches, including when studying impacts of environmental drivers. While observational studies routinely include many explanatory variables, the number of factors applied in experiments is typically much more limited. For example, in a recent systematic mapping of the existing literature on global change and soil, over 98% of papers reported on experiments dealing with just one or two factors simultaneously (Rillig, Ryo, et al., 2019). This is a sobering result considering the multifactor nature of anthropogenic change: effects are due to a wide range of factors (Sage, 2020) and their effects on systems are often concurrent (Bowler et al., 2020; Crain et al., 2008; Gunderson et al., 2016; Orr et al., 2020).

There are probably a number of reasons for this limitation in data on joint impacts of a large number of factors, chiefly among which the combinatorial explosion problem (Katzir et al., 2019; Lundstedt et al., 1998). Most experiments are factorial experiments (meaning that different levels of factors are combined, typically all levels of one factor with all levels of other factors, i.e. a complete factorial design). The combinatorial explosion problem means that it becomes increasingly difficult to factorially combine a larger number of factors, because combinations increase rapidly with factor number (e.g. for 10 factors it would be 2^{10} combinations if there are just two levels of each factor). But another issue is research compartmentalization (Orr et al., 2020), that is research labs are increasingly specialized in dealing with just one or a few factors, because the literature output is enormous and because some factors present logistical challenges in terms of gearing up for experimental study (e.g. gas exposure systems). This has led to the current situation where we know little about the joint impacts of multiple environmental factors, yet understanding the effects of multiple, concurrently acting factors on ecological systems is of paramount importance. This insight is not new (Paine et al., 1998); about two decades ago, Paine et al. concluded that multiple compounded perturbations 'will be basic to environmental management decisions of the 21st century'.

We believe another reason for the lack of progress in studying joint impacts of multiple factors is not having an ordering system for such environmental factors. Such an ordering system could offer several advantages, which we describe below in greater detail, including: (i) serving as a teaching and communication tool; (ii) informing about new factors of global change by systematically embedding them among the known factors; (iii) defining what an individual factor actually is; and (iv) helping with experimental design and in making predictions for experimental outcomes (similar factors might have similar effects). There currently are no ordering systems or classifications capturing the range of anthropogenic factors potentially influencing terrestrial ecosystems. Coarse level categorizations recognize whether a factor is globally mixed or of local origin scaling up to a global issue (Sage, 2020), but most frequently, global environmental factors are listed without implying an underlying ordering system. Classifications based on relatedness of items have a long tradition in biology and other disciplines, and serve to organize knowledge and to offer opportunities for prediction; for example, a phylogeny of species can be used to predict traits (Aguilar-Trigueros et al., 2015; Goberna & Verdu, 2016). Classifications are available for certain groups of factors, especially chemical pollutants (Eisenberg & McKone, 1998; Verhaar et al., 2000), but not for a broader range of environmental drivers. We argue here that such a classification is an important ingredient to advancing the field.

1 | AN A PRIORI TRAIT-BASED FACTOR CLASSIFICATION

To illustrate the potential advantage of a factor classification, we here offer such an a priori trait-based factor classification for 30 factors of human influence on terrestrial ecosystems and soils (Figure 1). We focus on plants and soil, as soils are particularly affected by many human factors; with their high biodiversity density and key contributions to terrestrial ecosystem functioning, they are a high priority study subject (Rillig, Ryo, et al., 2019; Thakur et al., 2020).

We classified these 30 factors on the very nature of the factors themselves, their basic modes of action and key properties (none of the traits were chosen with particular research questions in mind, aiming for broadest possible applicability of this classification in plant–soil systems). We first array the factors according to their physical, chemical or biological nature. Physical factors are further divided into particles, energy and mechanical; chemical factors are either organic or inorganic, and biological factors entail the removal and addition of species. We then ask questions about the proximate effect direction (nominally positive or negative), separately for plants, soil microbes or soil animals (using biomass effects as the currency, which for example does not include effects on diversity within a group of biota). We include different general effect modes (resource, toxicant, rhythm changer: Bennie et al., 2016; soil physical habitat modifier: Machado et al., 2018; osmotic, general metabolic rate regulator). We did not distinguish among organism groups when effects were deemed not to differ in principle. Additionally, we include several other key properties: are effects directly on soil, or indirectly via plants (Kardol et al., 2010); do effects unfold in a simultaneous fashion on all soil biota, or are they cascade-like effects initially only affecting one type of biota; do they affect the movement of soil biota or not (Erktan et al., 2020); are they pulse versus press perturbations (Bender et al., 1984); are the factors atmospheric/mixed or local (Sage, 2020).

The resulting classification results in a complete matrix of 30 anthropogenic factors and all traits (Figure 1). Many factors were chemical in nature, followed by physical, and few factors were biological in nature; some particles are classified as both chemical and physical agents.

2 | ADVANTAGES OF FACTOR CLASSIFICATION AND APPLICATION

Classifying such factors of influence could have a number of advantages. First, our ordering system captures and illustrates the diversity of factors affecting ecosystems better than simply listing a range of factors could achieve. As such, classifications such as this could be useful for teaching and communicating the nature of global change to a broader audience (Corner et al., 2018). Along these lines, integrating the range of factors in one common system highlights the fact that these are all different manifestations of anthropogenic influence and global change; this helps abate unhelpful debates about whether one global change factor is given more public attention than another, 'stealing' attention from more important factors. Perhaps shifting the focus to the diversity of factors and their traits also helps overcome research compartmentalization.

Importantly, we are unlikely to have already experienced and discovered all global change factors: microplastic is a recent addition to this group, and also the realization that chemical pollutants should be a part of global change is rapidly increasing. This means that existing classifications also serve another important function: additional factors, as they are discovered or manifest themselves, can be added to the classification, and we can then fairly rapidly gauge how to best study their effects or how different or similar they are to existing factors. For example, should sound pollution become recognized as a factor of importance for soils (Rillig et al., 2019), then we could start systematically comparing it with existing factors to ascertain

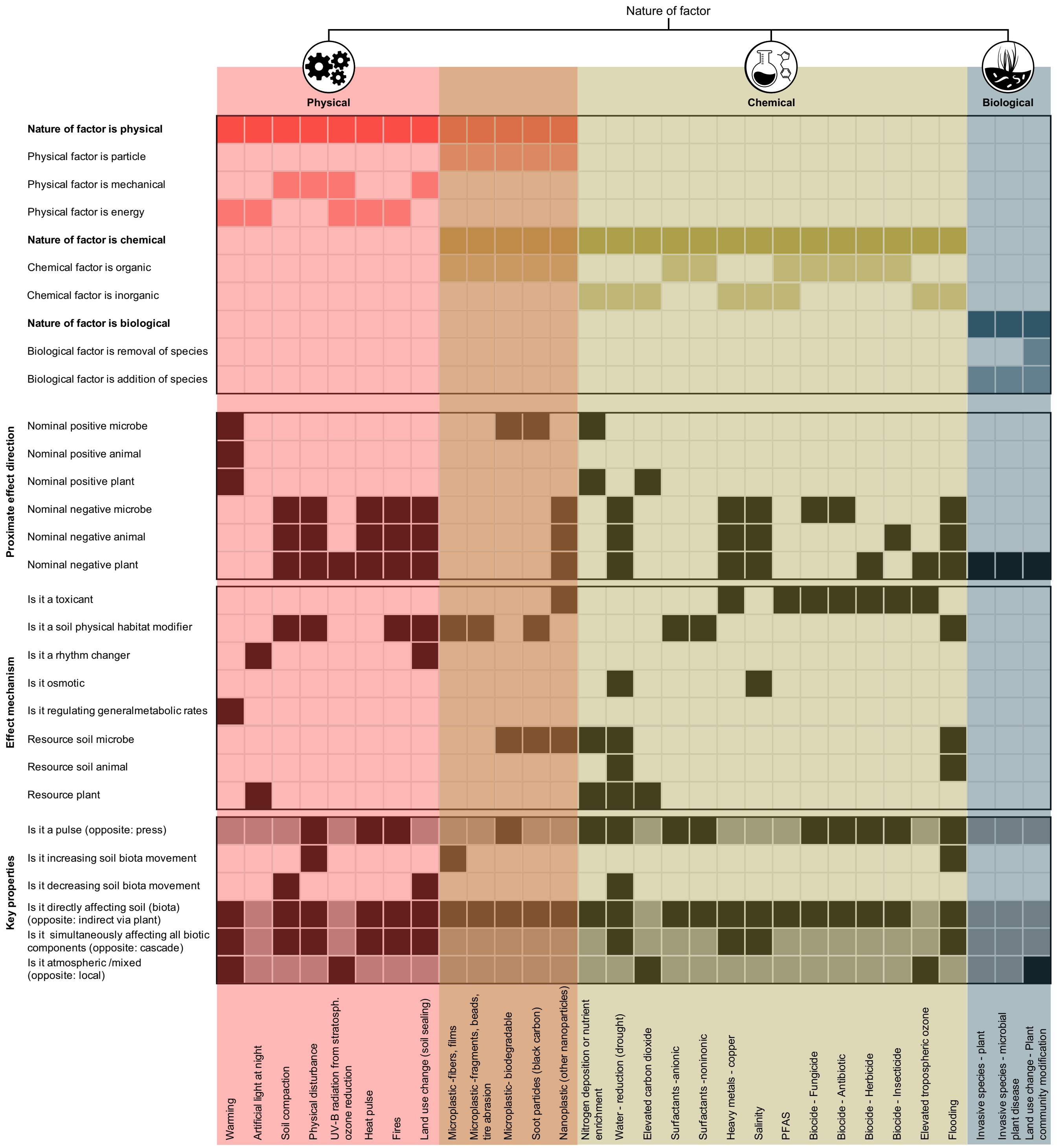

FIGURE 1 An a priori trait-based classification of 30 anthropogenic influences on terrestrial ecosystems and soils. Factors are first divided by their nature (physical, chemical, biological), and then subcategories of these criteria. Some factors are both physical and chemical in nature, as indicated by the overlap. The additional criteria (divided into proximate effect direction, effect mode and key properties) are presented in a non-hierarchical fashion. Grey bars signify the opposite of the trait (indicated in brackets in the criteria questions) in cases where responses are mutually exclusive. PFAS, per- and polyfluoroalkyl substances

how novel it is compared to the existing group of environmental factors.

Third, we believe that classifications can also provide an answer to the question of factor individuation, that is what is an individual factor? This question seems trivial at first, since we all work with factors in experiments, but it is not so easy to answer when considering a broad range of factors. For example, is 'pollution' a factor, or should it be specified to 'microplastic pollution', or to certain types of polymers, or forms of particles? A classification can help address this individuation question: if two candidate factors cannot be separated by criteria that are applicable to the entire population of factors, they should be merged and become one factor.

A fourth point is that such classifications, as the source of dissimilarity among factors, could be helpful in designing experiments and for predicting outcomes of factors. For example, one could postulate that more similar factors would similarly affect ecosystems, or that more dissimilar factors would have a higher probability to produce joint impacts deviating from additivity, that is that they could produce synergistic or antagonistic effects. Such applications necessitate transforming the qualitative classification into a quantifiable tree or cluster analysis. As a case study, we did this here by coding all answers to the criteria used for classification (in Figure 1) as either zeros or ones. We then calculated a dendrogram of a hierarchical clustering of the 30 factors based on the traits in Figure 1, resulting in a tree in which factors with more similar traits are positioned closer in the tree structure (Figure 2a). Then, making use of the dendrogram, we examined whether factors with similar traits have more similar effects on soil microbial biodiversity and ecosystem functioning parameters, by re-analysing an experimental dataset that examined effects of 10 factors of global change on soils (Rillig, Ryo, et al., 2019). This experiment assessed the effects of 10 global change factors on three biodiversity measures (fungal community richness [based on amplified sequence variants], community composition and community dispersion) and four soil structure and functioning measures (water repellency, soil aggregation stability, decomposition rate and soil respiration; see details in Rillig, Ryo, et al., 2019). Using the effects on these measures, we quantified the dissimilarities among the 10 factors and calculated a dendrogram. In addition, we built another dendrogram of just the 10 factors based on the classification scheme for the 30 factors (Figure 1). The structures of these dendrograms are more similar to each other than expected by chance (cophenetic correlation coefficient: mean = 0.29 [95% CI: 0.07–0.48]), suggesting that similar factors have similar effect characteristics. The similarity can be also seen (Figure 2b), as salinity, copper and drought are positioned closely in both dendrograms, and also biocides (fungicide, insecticide and antibiotic) show the same trend.

To explore if fewer traits than the entire set could also be informative, we carried out a subset analysis, in which we removed one of the four main trait groups (see Figure 1) in turn. When dropping the traits representing 'effect mechanism' for building the dendrogram, the mean correlation coefficient decreases from

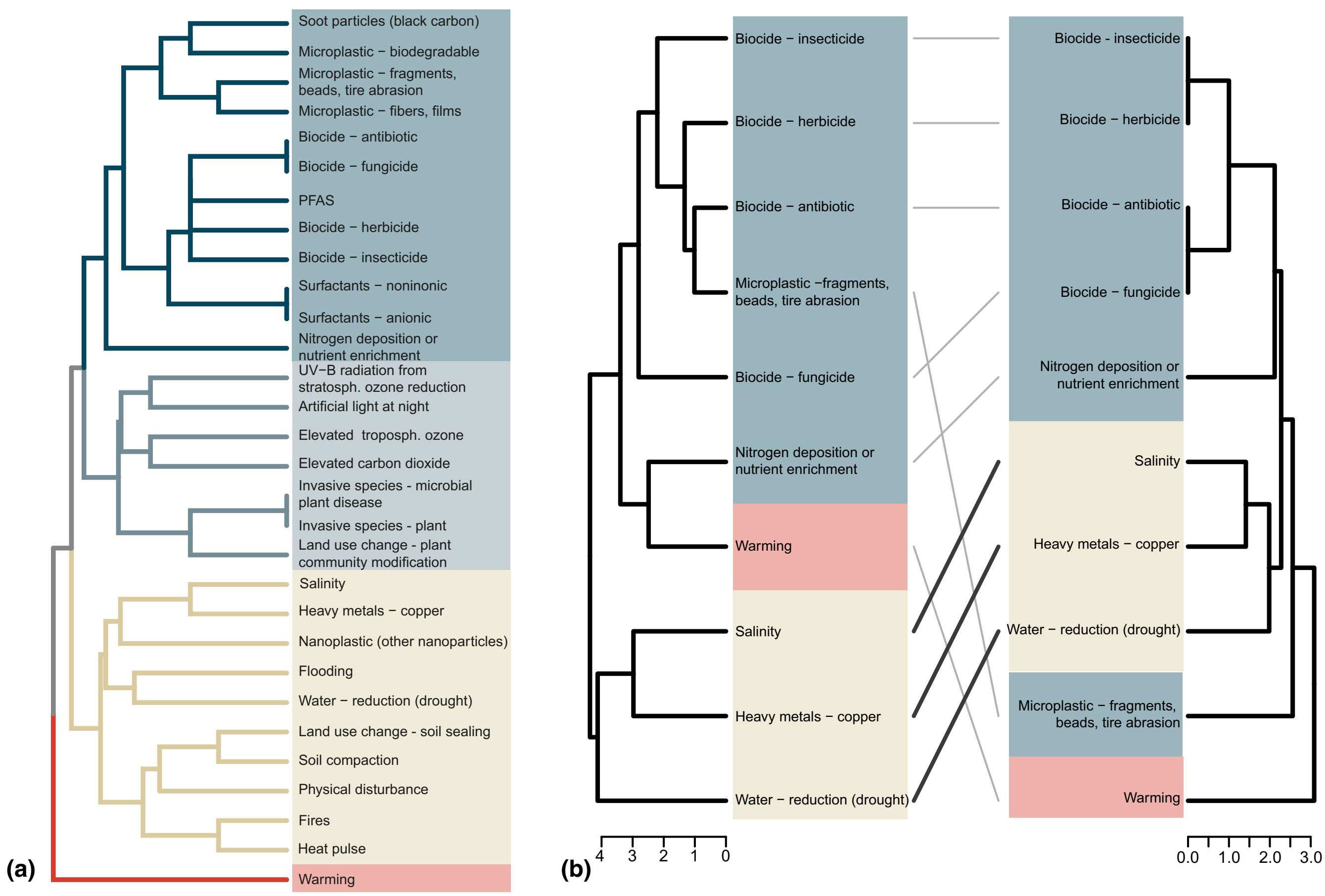

FIGURE 2 (a) Dendrogram from a hierarchical clustering of 30 anthropogenic influences on terrestrial ecosystems and soils according to the similarity of an a priori trait-based classification in Figure 1. All traits are equally scaled. (b) A comparison of dendrograms of a subset of 10 global change factors based on the similarity in their traits and in the effects on soil microbial biodiversity and functions of these 10 factors (measured in a soil global change experiment [5]). The two dendrograms have structures more similar to each other than expected by chance (cophenetic correlation coefficient: mean = 0.29 [95% CI: 0.07–0.48]), indicating that factors having similar traits affect soil microbial biodiversity and functions similarly

0.29 to 0.21 and the 95% CI includes zero, suggesting that this set of traits is key for predicting the effect similarity among factors in our soil experiment. On the contrary, dropping the traits of 'nature of factor' increases the coefficient from 0.29 to 0.42, indicating that this set of traits is likely not important for prediction here. The other sets, 'proximate effect direction' and 'key properties', do not change the correlation coefficient (mean: 0.32 and 0.28 respectively). These findings indicate that, starting with a comprehensive list, it may be possible to identify a narrower core set of traits important for representing the major effects of factors. Data and R script for these analyses are available here: https://masahiroryo.github.io/Classifying-human-influences/Rillig_etal_2020_Appendix_Final.html.

3 | OTHER CLASSIFICATION APPROACHES AND THE WAY FORWARD

Our proposed ordering system should be understood as a starting point: other classification approaches are possible and should be explored. Notably, our approach is focused on local effects on a given plant–soil system. Ordering systems could also more explicitly focus on scale issues. For example, invasive species operate on a broad biogeographical scale, land use on a more regional/landscape scale, whereas salinity would be a much more locally acting factor. Additional information can also come from more detailed knowledge of precise effect mechanisms, if available; our classification uses general information on mode of action rather than precise mechanisms. Other ordering concepts could be used or added, for example traits could focus on concepts related to biogeochemistry or trophic interactions. Further work should extend classifications also to the aquatic realm, including freshwater systems and the oceans, where other factors will come into play (e.g. acidification), as well as other classification criteria. Finally, the classification approach, in addition to being useful in generating hypotheses and informing experimental designs, can also become a powerful tool in data synthesis, such as in meta-analyses: here, similar factors could be grouped (e.g. different fertilization treatments) and their general effects compared with other factors or factor groups.

4 | CONCLUSION

We hope that classifications such as the one introduced here can help shift the spotlight on the multitude of anthropogenic changes affecting ecosystems, and that such classifications can even be used, as an analytical tool, to help unravel joint impacts of a great number of concurrently acting factors.

ACKNOWLEDGEMENT

Matthias C. Rillig acknowledges funding from an ERC Advanced grant (no. 694368). Open access funding enabled and organized by ProjektDEAL.

AUTHOR CONTRIBUTIONS

Matthias C. Rillig carried out the factor classification and wrote the paper; Masahiro Ryo conducted statistical analyses; Anika Lehmann designed figures. All authors contributed to the manuscript text.

DATA AVAILABILITY STATEMENT

The data are directly displayed in Figure 1 and data and code are available at https://masahiroryo.github.io/Classifying-human-influences/Rillig_etal_2020_Appendix_Final.html.

ORCID

Matthias C. Rillig https://orcid.org/0000-0003-3541-7853

REFERENCES

Aguilar-Trigueros, C. A., Hempel, S., Powell, J. R., Anderson, I. C., Antonovics, J., Bergmann, J., Cavagnaro, T. R., Chen, B. D., Hart, M. M., Klironomos, J., Petermann, J. S., Verbruggen, E., Veresoglou, S. D., & Rillig, M. C. (2015). Branching out: Towards a trait-based understanding of fungal ecology. *Fungal Biology Reviews*, *29*(1), 34–41. https://doi.org/10.1016/j.fbr.2015.03.001

Bender, E. A., Case, T. J., & Gilpin, M. E. (1984). Perturbation experiments in community ecology – Theory and practice. *Ecology*, *65*(1), 1–13. https://doi.org/10.2307/1939452

Bennie, J., Davies, T. W., Cruse, D., & Gaston, K. J. (2016). Ecological effects of artificial light at night on wild plants. *Journal of Ecology*, *104*(3), 611–620. https://doi.org/10.1111/1365-2745.12551

Bowler, D. E., Bjorkman, A. D., Dornelas, M., Myers-Smith, I. H., Navarro, L. M., Niamir, A., Supp, S. R., Waldock, C., Winter, M., Vellend, M., Blowes, S. A., Böhning-Gaese, K., Bruelheide, H., Elahi, R., Antão, L. H., Hines, J., Isbell, F., Jones, H. P., Magurran, A. E., … Bates, A. E. (2020). Mapping human pressures on biodiversity across the planet uncovers anthropogenic threat complexes. *People and Nature*, *2*(2), 380–394. https://doi.org/10.1002/pan3.10071

Corner, A., Shaw, C., & Clarke, J. (2018). *Principles for effective communication and public engagement on climate change. A Handbook for IPCC authors*. Climate Outreach.

Crain, C. M., Kroeker, K., & Halpern, B. S. (2008). Interactive and cumulative effects of multiple human stressors in marine systems. *Ecology Letters*, *11*(12), 1304–1315. https://doi.org/10.1111/j.1461-0248.2008.01253.x

Diaz, S., Settele, J., Brondizio, E. S., Ngo, H. T., Agard, J., Arneth, A., Balvanera, P., Brauman, K. A., Butchart, S. H. M., Chan, K. M. A., Garibaldi, L. A., Ichii, K., Liu, J. G., Subramanian, S. M., Midgley, G. F., Miloslavich, P., Molnar, Z., Obura, D., Pfaff, A., … Zayas, C. N. (2019). Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science*, *366*(6471), eaax3100. https://doi.org/10.1126/science.aax3100

Eisenberg, J. N. S., & McKone, T. E. (1998). Decision tree method for the classification of chemical pollutants: Incorporation of across-chemical variability and within-chemical uncertainty. *Environmental Science & Technology*, *32*(21), 3396–3404. https://doi.org/10.1021/es970975s

Erktan, A., Or, D., & Scheu, S. (2020). The physical structure of soil: Determinant and consequence of trophic interactions. *Soil Biology & Biochemistry*, *148*, 107876. https://doi.org/10.1016/j.soilbio.2020.107876

Goberna, M., & Verdu, M. (2016). Predicting microbial traits with phylogenies. *The ISME Journal*, *10*(4), 959–967. https://doi.org/10.1038/ismej.2015.171

Gunderson, A. R., Armstrong, E. J., & Stillman, J. H. (2016). Multiple stressors in a changing world: The need for an improved perspective on physiological responses to the dynamic marine environment. *Annual Review of Marine Science*, *8*(1), 357–378. https://doi.org/10.1146/annurev-marine-122414-033953

Kardol, P., Cregger, M. A., Campany, C. E., & Classen, A. T. (2010). Soil ecosystem functioning under climate change: Plant species and community effects. *Ecology*, *91*(3), 767–781. https://doi.org/10.1890/09-0135.1

Katzir, I., Cokol, M., Aldridge, B. B., & Alon, U. (2019). Prediction of ultra-high-order antibiotic combinations based on pairwise interactions. *PLOS Computational Biology*, *15*(1), 1–15. https://doi.org/10.1371/journal.pcbi.1006774

Lundstedt, T., Seifert, E., Abramo, L., Thelin, B., Nystrom, A., Pettersen, J., & Bergman, R. (1998). Experimental design and optimization. *Chemometrics and Intelligent Laboratory Systems*, *42*(1–2), 3–40. https://doi.org/10.1016/s0169-7439(98)00065-3

Machado, A. A. D., Lau, C. W., Till, J., Kloas, W., Lehmann, A., Becker, R., & Rillig, M. C. (2018). Impacts of microplastics on the soil biophysical environment. *Environmental Science & Technology*, *52*(17), 9656–9665. https://doi.org/10.1021/acs.est.8b02212

Orr, J. A., Vinebrooke, R. D., Jackson, M. C., Kroeker, K. J., Kordas, R. L., Mantyka-Pringle, C., Van den Brink, P. J., De Laender, F., Stoks, R., Holmstrup, M., Matthaei, C. D., Monk, W. A., Penk, M. R., Leuzinger, S., Schafer, R. B., & Piggott, J. J. (2020). Towards a unified study of multiple stressors: Divisions and common goals across research disciplines. *Proceedings of the Royal Society B: Biological Sciences*, *287*(1926), 1–10. https://doi.org/10.1098/rspb.2020.0421

Paine, R. T., Tegner, M. J., & Johnson, E. A. (1998). Compounded perturbations yield ecological surprises. *Ecosystems*, *1*(6), 535–545. https://doi.org/10.1007/s100219900049

Rillig, M. C., Bonneval, K., & Lehmann, J. (2019). Sounds of soil: A new world of interactions under our feet? *Soil Systems*, *3*(3), 1–5. https://doi.org/10.3390/soilsystems3030045

Rillig, M. C., Ryo, M., Lehmann, A., Aguilar-Trigueros, C. A., Buchert, S., Wulf, A., Iwasaki, A., Roy, J., & Yang, G. W. (2019). The role of multiple global change factors in driving soil functions and microbial biodiversity. *Science*, *366*(6467), 886–890. https://doi.org/10.1126/science.aay2832

Sage, R. F. (2020). Global change biology: A primer. *Global Change Biology*, *26*(1), 3–30. https://doi.org/10.1111/gcb.14893

Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L. F., Jackson, R. B., Kinzig, A., Leemans, R., Lodge, D. M., Mooney, H. A., Oesterheld, M., Poff, N. L., Sykes, M. T., Walker, B. H., Walker, M., & Wall, D. H. (2000). Biodiversity – Global biodiversity scenarios for the year 2100. *Science*, *287*(5459), 1770–1774. https://doi.org/10.1126/science.287.5459.1770

Thakur, M. P., Phillips, H. R. P., Brose, U., De Vries, F. T., Lavelle, P., Loreau, M., Mathieu, J., Mulder, C., Van der Putten, W. H., Rillig, M. C., Wardle, D. A., Bach, E. M., Bartz, M. L. C., Bennett, J. M., Briones, M. J. I., Brown, G., Decaens, T., Eisenhauer, N., Ferlian, O., … Cameron, E. K. (2020). Towards an integrative understanding of soil biodiversity. *Biological Reviews*, *95*(2), 350–364. https://doi.org/10.1111/brv.12567

Tilman, D., Clark, M., Williams, D. R., Kimmel, K., Polasky, S., & Packer, C. (2017). Future threats to biodiversity and pathways to their prevention. *Nature*, *546*(7656), 73–81. https://doi.org/10.1038/nature22900

Verhaar, H. J. M., Solbe, J., Speksnijder, J., van Leeuwen, C. J., & Hermens, J. L. M. (2000). Classifying environmental pollutants: Part 3. External validation of the classification system. *Chemosphere*, *40*(8), 875–883. https://doi.org/10.1016/s0045-6535(99)00317-3

Vitousek, P. M. (1994). Beyond global warming – Ecology and global change. *Ecology*, *75*(7), 1861–1876. https://doi.org/10.2307/1941591

How to cite this article: Rillig MC, Ryo M, Lehmann A. Classifying human influences on terrestrial ecosystems. *Glob Change Biol*. 2021;27:2273–2278. https://doi.org/10.1111/gcb.15577