The Environmental Consequences of Economic Inequalities: A Systematic Empirical Literature Review, 1998-2022

Supplementary Information (SI)

Contents

1 Constitution of the article pool

Figure 1 depicts the selection process of empirical articles following the PRISMA guidelines[1]. The constitution of the pool of articles depicted in Figure 1 started with the expansion of the studies identified by Berthe & Elie (2015)[2], who reviewed 14 studies and 41 empirical tests. We apply the following three-step process as in Berthe & Elie[2]:

First, the authors have reviewed all studies cited by at least one of the articles considered central to the theoretical part of the environmental consequences of inequalities[3–7] plus the article by Berthe & Elie (2025)[2], which offers an initial review of the literature on the present subject. We performed an Advanced Search on Scopus and extracted 1,218 records citing at least one of the aforementioned theories in January 2023. The search was limited to journal publications since the last literature review on this subject[2] and the languages "English", "French" and "Spanish". We did not have to exclude any records before screening. The search code is depicted below.

(REF ("Inequality as a cause of environmental degradation") OR REF ("The Environmental Kuznets Curve, environmental protection policy and income distribution") OR REF ("Political and economic inequality and the environment") OR REF ("The Spirit Level: Why Equality is Better for Everyone") OR REF ("Income inequality and the environment: aggregation bias in environmental Kuznets curves") OR REF ("Mechanisms explaining the impact of economic inequality on environmental deterioration")) AND PUBYEAR > 2014 AND (LIMIT-TO (SRC-TYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English") OR LIMIT-TO (LANGUAGE , "Spanish") OR LIMIT-TO (LANGUAGE , "French"))

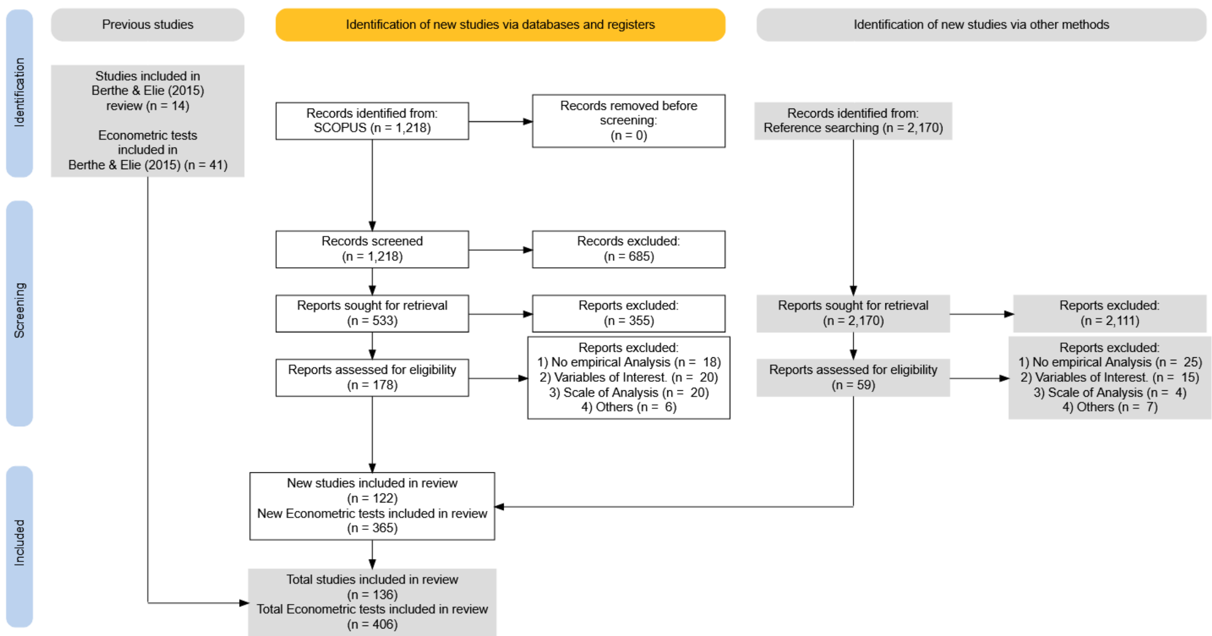

Fig. 1 | PRISMA flowdiagram: Description of the constitution of the final article pool.

Second, the authors have screened all the 1,218 selected records. We selected all articles whose title or abstract contained one of the following three terms "inequality", "distribution" and/or "income gap", leaving us with 533 entries. We further investigated all abstracts, excluding those articles that clearly did not address the inequality-environment nexus. Lastly, we assessed the eligibility of 178 full articles. Studies were included if they met the following pre-defined criteria: Firstly, the article must be published in a peer-reviewed scientific journal. Although, this was a pre-condition of our search, some articles suggested by SCOPUS did not apply to this criteria[8, 9]. In Figure 1 we list these articles in the category "Others" jointly with studies whose conceptual framework and / or methodology have been ambiguous, making an interpretation impossible[10]. Secondly, the paper must include an econometric study. This was not the case among others for Rao & Min[11], Ma et al.[12] and Millward-Hopkins& Oswald[13], whose analyses are either descriptive or based exclusively on theoretical models. Thirdly, the endogenous variables used must be measures of environmental pressure, policy or behavior & at least one independent variable must be a measure of inequality. Lastly, the central exogenous variables mobilized must be measures of economic inequality on regional or national scale. Multi-level analyses are added.

The last condition regarding the article selection excludes inequality measures at the micro or the meso-level. This decision has been taken with due to the fact, that primary theoretical frameworks[3, 5], which operate through individuals exerting their political power on governments to enforce their policy demands, are not considered in micro or meso analyses. These transmission channels can only be examined if the scale of the analyzes matches with national or regional political entities that shape environmental policies[14]. For this reason, the present research excludes among others the works of Sager[15] (US households) Zhao & Ren[16] (Chinese cities) and Michieka et al.[17] (US counties), which we consider to provide valuable insights about consumption patterns but do not capture systemic dynamics and aggregate environmental impacts that transcend individual or household behavior.

Finally, the authors have inspected the reference sections of the papers selected. We identified 2,170 entries (including double-entries) that contain the word "inequality". We screened these entries and excluded those that either did not concern the Inequality-Environment nexus or have been identified in the previous step of the article pool constitution. Subsequently, the 59 remaining articles have been assessed for their eligibility of which 51 have been excluded due to the reasons listed in step 2 above: No peer-reviewed journal publication and others[18], lack of empirical analysis[19], the analysis does not contain the variables of interest[20, 21] or the scale of the analysis is not adequate [22].

2 List of included articles[1]:

1. Agan, B. & Balcilar, M. On the Determinants of Green Technology Diffusion: An Empirical Analysis of Economic, Social, Political, and Environmental Factors. en. *Sustainability* **14,** 2008. doi:10.3390/su14042008 (Feb. 2022).
2. Ajide, K. B. & Ibrahim, R. L. Environmental impacts of income inequality: evidence from G7 economies. en. *Environmental Science and Pollution Research* **29,** 1887–1908. doi:10.1007/s11356-021-15720-6 (Jan. 2022).
3. Alataş, S. & Akın, T. The impact of income inequality on environmental quality: a sectoral-level analysis. en. *Journal of Environmental Planning and Management* **65,** 1949–1974. doi:10.1080/09640568.2022.2050684 (Aug. 2022).
4. Ali, I. M. A. Income inequality and environmental degradation in Egypt: evidence from dynamic ARDL approach. en. *Environmental Science and Pollution Research* **29,** 8408–8422. doi:10.1007/s11356-021-16275-2 (Feb. 2022).
5. Ali, H. S., Hassan, S. & Kofarmata, Y. I. Dynamic Impact of Income Inequality on Carbon Dioxide Emissions in Africa: New Evidence from Heterogeneous Panel Data Analysis. en. *International Journal of Energy Economics and Policy* **6** (2016).
6. Andersson, F. N. Income inequality and carbon emissions in the United States 1929–2019. en. *Ecological Economics* **204,** 107633. doi:10.1016/j.ecolecon.2022.107633 (Feb. 2023).
7. Aral, H. & López-Sintas, J. Is pro-environmentalism a privilege? Country development factors as moderators of socio-psychological drivers of pro-environmental behavior. en. *Environmental Sociology* **8,** 211–227. doi:10.1080/23251042.2021.2018123 (Apr. 2022).
8. Asongu, S. A. & Odhiambo, N. M. Inequality and renewable energy consumption in Sub-Saharan Africa: implication for high income countries. en. *Innovation: The European Journal of Social Science Research* **37,** 382–398. doi:10.1080/13511610.2020.1861442 (Apr. 2021).
9. Bae, J. H. Impacts of Income Inequality on CO2 Emission under Different Climate Change Mitigation Policies. en. *The Korean Economic Review* **34** (2018).
10. Baek, J. & Gweisah, G. Does income inequality harm the environment?: Empirical evidence from the United States. en. *Energy Policy* **62,** 1434–1437. doi:10.1016/j.enpol.2013.07.097 (Nov. 2013).

[1] We used the date of acceptance to depict the development of the literature in the main article while for this reference list the date of publication is used

11. Bai, C. *et al.* Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions? en. *Journal of Environmental Management* **264,** 110482. doi:10.1016/j.jenvman.2020.110482 (June 2020).

12. Bakaki, Z., Böhmelt, T. & Ward, H. Carbon Emission Performance and Regime Type: The Role of Inequality. en. *Global Environmental Politics* **22,** 156–179. doi:10.1162/glep_a_00656 (May 2022).

13. Baležentis, T., Liobikienė, G., Štreimikienė, D. & Sun, K. The impact of income inequality on consumption-based greenhouse gas emissions at the global level: A partially linear approach. en. *Journal of Environmental Management* **267,** 110635. doi:10.1016/j.jenvman.2020.110635 (Aug. 2020).

14. Baloch, M. A. & Danish. The nexus between renewable energy, income inequality, and consumption-based CO_2 emissions: An empirical investigation. en. *Sustainable Development* **30,** 1268–1277. doi:10.1002/sd.2315 (Oct. 2022).

15. Baloch, A., Shah, S. Z., Noor, Z. M. & Magsi, H. B. The nexus between income inequality, economic growth and environmental degradation in Pakistan. en. *GeoJournal* **83,** 207–222. doi:10.1007/s10708-016-9766-3 (Apr. 2018).

16. Baloch, M. A., Danish, Khan, S. U.-D., Ulucak, Z. & Ahmad, A. Analyzing the relationship between poverty, income inequality, and CO2 emission in Sub-Saharan African countries. en. *Science of The Total Environment* **740,** 139867. doi:10.1016/j.scitotenv.2020.139867 (Oct. 2020).

17. Bel, G. & Teixidó, J. J. The political economy of the Paris Agreement: Income inequality and climate policy. en. *Journal of Cleaner Production* **258,** 121002. doi:10.1016/j.jclepro.2020.121002 (June 2020).

18. Belaïd, F., Boubaker, S. & Kafrouni, R. Carbon emissions, income inequality and environmental degradation: the case of Mediterranean countries. en. *The European Journal of Comparative Economics.* doi:10.25428/1824-2979/202001-73-102 (2020).

19. Bhattacharya, H. Environmental and socio-economic sustainability in India: evidence from CO_2 emission and economic inequality relationship. en. *Journal of Environmental Economics and Policy* **9,** 57–76. doi:10.1080/21606544.2019.1604267 (Jan. 2020).

20. Bimonte, S. Information access, income distribution, and the Environmental Kuznets Curve. en. *Ecological Economics* **41,** 145–156. doi:10.1016/S0921-8009(02)00022-8 (Apr. 2002).

21. Bonnefond, C., Clement, M. & Yan, H. Income inequality and environmental quality in China: a semi-parametric analysis applied to provincial panel data. en. *Post-Communist Economies* **33,** 541–565. doi:10.1080/14631377.2020.1793604 (July 2021).

22. Bradshaw, C. J. A. & Di Minin, E. Socio-economic predictors of environmental performance among African nations. en. *Scientific Reports* **9,** 9306. doi:10.1038/s41598-019-45762-3 (June 2019).

23. Cepoi, C.-O., Bran, M. & Dinu, M. INVESTIGATING THE NEXUS BETWEEN FUEL ETHANOL AND CO2 EMISSIONS. A PANEL SMOOTH TRANSITION REGRESSION APPROACH. en. *Journal of Business Economics and Management* **21,** 1774–1792. doi:10.3846/jbem.2020.13695 (Oct. 2020).

24. Chen, J., Xian, Q., Zhou, J. & Li, D. Impact of income inequality on CO2 emissions in G20 countries. en. *Journal of Environmental Management* **271,** 110987. doi:10.1016/j.jenvman.2020.110987 (Oct. 2020).

25. Cheng, Y., Wang, Y., Chen, W., Wang, Q. & Zhao, G. Does income inequality affect direct and indirect household CO2 emissions? A quantile regression approach. en. *Clean Technologies and Environmental Policy* **23,** 1199–1213. doi:10.1007/s10098-020-01980-2 (May 2021).

26. Ching, S.-L., Lau, L.-S. & Choong, C.-K. Income inequality, educational attainment and environmental degradation: evidence from global panel. en. *Environmental Science and Pollution Research* **30,** 43056–43067. doi:10.1007/s11356-022-19256-1 (May 2022).

27. Cho, H. Determinants of the downward sloping segment of the EKC in high-income countries: The role of income inequality and institutional arrangement. en. *Cogent Economics & Finance* **9** (ed Ercolano, S.) 1954358. doi:10.1080/23322039.2021.1954358 (Jan. 2021).

28. Chu, L. K. & Hoang, D. P. The complementarity of income equalization and innovation for more effective emission reduction. en. *Journal of Environmental Management* **284,** 112007. doi:10.1016/j.jenvman.2021.112007 (Apr. 2021).

29. Awaworyi Churchill, S., Ivanovski, K. & Munyanyi, M. E. Income inequality and renewable energy consumption: Time-varying non-parametric evidence. en. *Journal of Cleaner Production* **296,** 126306. doi:10.1016/j.jclepro.2021.126306 (May 2021).

30. Clément, M. & Meunié, A. Inégalités, développement et qualité de l'environnement : mécanismes et application empirique: fr. *Mondes en développement* **n° 151,** 67–82. doi:10.3917/med.151.0067 (Oct. 2010).

31. Clement, M. & Meunie, A. Is Inequality Harmful for the Environment? An Empirical Analysis Applied to Developing and Transition Countries. en. *Review of Social Economy* **68,** 413–445. doi:10.1080/00346760903480590 (Dec. 2010).

32. Davidson, N., Mariev, O. & Turkanova, S. Does income inequality matter for CO2 emissions in Russian regions? en. *Equilibrium. Quarterly Journal of Economics and Economic Policy* **16,** 533–551. doi:10.24136/eq.2021.019 (Sept. 2021).

33. Demir, C., Cergibozan, R. & Gök, A. Income inequality and CO_2 emissions: Empirical evidence from Turkey. en. *Energy & Environment* **30,** 444–461. doi:10.1177/0958305X18793109 (May 2019).

34. Dorsch, M. T. & Kirkpatrick, B. Economic growth, inequality and environmental degradation. *International Journal of Sustainable Development* **24,** 124–140. doi:10.1504/IJSD.2021.118844 (2021).

35. Du, M. *et al.* Examining the relations of income inequality and carbon productivity: A panel data analysis. en. *Sustainable Production and Consumption* **31,** 249–262. doi:10.1016/j.spc.2022.01.027 (May 2022).

36. Ehigiamusoe, K. U., Majeed, M. T. & Dogan, E. The nexus between poverty, inequality and environmental pollution: Evidence across different income groups of countries. en. *Journal of Cleaner Production* **341,** 130863. doi:10.1016/j.jclepro.2022.130863 (Mar. 2022).

37. Ekeocha, D. O. Urbanization, inequality, economic development and ecological footprint: Searching for turning points and regional homogeneity in Africa. en. *Journal of Cleaner Production* **291,** 125244. doi:10.1016/j.jclepro.2020.125244 (Apr. 2021).

38. Franzen, A. & Vogl, D. Acquiescence and the Willingness to Pay for Environmental Protection: A Comparison of the ISSP, WVS, and EVS*. en. *Social Science Quarterly* **94,** 637–659. doi:10.1111/j.1540-6237.2012.00903.x (Sept. 2013).

39. Ghazouani, T. & Beldi, L. The Impact of Income Inequality on Carbon Emissions in Asian Countries: Non-Parametric Panel Data Analysis. en. *Environmental Modeling & Assessment* **27,** 441–459. doi:10.1007/s10666-021-09811-4 (June 2022).

40. Ghosh, S. Renewable energy and CO_2 emissions: the economics and geopolitical implications, experiences from the BRICS nations. en. *International Journal of Energy Sector Management* **16,** 1064–1090. doi:10.1108/IJESM-08-2021-0024 (Sept. 2022).

41. Grunewald, N., Klasen, S., Martínez-Zarzoso, I. & Muris, C. The Trade-off Between Income Inequality and Carbon Dioxide Emissions. en. *Ecological Economics* **142,** 249–256. doi:10.1016/j.ecolecon.2017.06.034 (Dec. 2017).

42. Guilhot, L., Meunié, A. & Pouyanne, G. Croissance, transition urbaine et pollutions atmosphériques en Chine: fr. *Mondes en développement* **n° 180,** 53–68. doi:10.3917/med.180.0053 (Dec. 2017).

43. Guo, L. INCOME INEQUALITY, HOUSEHOLD CONSUMPTION AND CO_2 EMISSIONS IN CHINA. en. *The Singapore Economic Review* **62,** 531–553. doi:10.1142/S0217590817400239 (June 2017).

44. Guo, Y., You, W. & Lee, C.-C. CO2 emissions, income inequality, and country risk: some international evidence. en. *Environmental Science and Pollution Research* **29,** 12756–12776. doi:10.1007/s11356-020-09501-w (Feb. 2022).

45. Hübler, M. The inequality-emissions nexus in the context of trade and development: A quantile regression approach. en. *Ecological Economics* **134,** 174–185. doi:10.1016/j.ecolecon.2016.12.015 (Apr. 2017).

46. Hailemariam, A., Dzhumashev, R. & Shahbaz, M. Carbon emissions, income inequality and economic development. en. *Empirical Economics* **59,** 1139–1159. doi:10.1007/s00181-019-01664-x (Sept. 2020).

47. Hao, Y., Chen, H. & Zhang, Q. Will income inequality affect environmental quality? Analysis based on China's provincial panel data. en. *Ecological Indicators* **67,** 533–542. doi:10.1016/j.ecolind.2016.03.025 (Aug. 2016).

48. Harring, N. Corruption, inequalities and the perceived effectiveness of economic pro-environmental policy instruments: A European cross-national study. en. *Environmental Science & Policy* **39,** 119–128. doi:10.1016/j.envsci.2013.08.011 (May 2014).

49. Hassan, S. A., Zaman, K. & Gul, S. The Relationship between Growth-Inequality-Poverty Triangle and Environmental Degradation: Unveiling the Reality. en. *Arab Economic and Business Journal* **10,** 57–71. doi:10.1016/j.aebj.2014.05.007 (June 2015).

50. Heerink, N., Mulatu, A. & Bulte, E. Income inequality and the environment: aggregation bias in environmental Kuznets curves. en. *Ecological Economics* **38,** 359–367. doi:10.1016/S0921-8009(01)00171-9 (Sept. 2001).

51. Holland, T. G., Peterson, G. D. & Gonzalez, A. A Cross-National Analysis of How Economic Inequality Predicts Biodiversity Loss. en. *Conservation Biology* **23,** 1304–1313. doi:10.1111/j.1523-1739.2009.01207.x (Oct. 2009).

52. Hundie, S. K. Income inequality, economic growth and carbon dioxide emissions nexus: empirical evidence from Ethiopia. en. *Environmental Science and Pollution Research* **28,** 43579–43598. doi:10.1007/s11356-021-13341-7 (Aug. 2021).

53. Huo, C. & Chen, L. The Impact of the Income Gap on Carbon Emissions: Evidence from China. en. *Energies* **15.** doi:10.3390/en15103771 (May 2022).

54. Idrees, M. & Majeed, M. T. Income inequality, financial development, and ecological footprint: fresh evidence from an asymmetric analysis. en. *Environmental Science and Pollution Research* **29,** 27924–27938. doi:10.1007/s11356-021-18288-3 (Apr. 2022).

55. Jain, M. & Kaur, S. Carbon emissions, inequalities and economic freedom: an empirical investigation in selected South Asian economies. en. *International Journal of Social Economics* **49,** 882–913. doi:10.1108/IJSE-02-2021-0108 (May 2022).

56. Jorgenson, A. K., Schor, J. B., Knight, K. W. & Huang, X. Domestic Inequality and Carbon Emissions in Comparative Perspective. en. *Sociological Forum* **31,** 770–786. doi:10.1111/socf.12272 (Sept. 2016).

57. Jorgenson, A., Schor, J. & Huang, X. Income Inequality and Carbon Emissions in the United States: A State-level Analysis, 1997–2012. en. *Ecological Economics* **134,** 40–48. doi:10.1016/j.ecolecon.2016.12.016 (Apr. 2017).

58. Jun, Y., Zhong-kui, Y. & Peng-fei, S. Income Distribution, Human Capital and Environmental Quality: Empirical Study in China. en. *Energy Procedia* **5,** 1689–1696. doi:10.1016/j.egypro.2011.03.288 (2011).

59. Kang, H. Impacts of Income Inequality and Economic Growth on CO2 Emissions: Comparing the Gini Coefficient and the Top Income Share in OECD Countries. en. *Energies* **15,** 6954. doi:10.3390/en15196954 (Sept. 2022).

60. Kashwan, P. Inequality, democracy, and the environment: A cross-national analysis. en. *Ecological Economics* **131,** 139–151. doi:10.1016/j.ecolecon.2016.08.018 (Jan. 2017).

61. Kazemzadeh, E., Fuinhas, J. A. & Koengkan, M. The impact of income inequality and economic complexity on ecological footprint: an analysis covering a long-time span. en. *Journal of Environmental Economics and Policy* **11,** 133–153. doi:10.1080/21606544.2021.1930188 (Apr. 2022).

62. Khan, A. Q., Saleem, N. & Fatima, S. T. Financial development, income inequality, and CO2 emissions in Asian countries using STIRPAT model. en. *Environmental Science and Pollution Research* **25,** 6308–6319. doi:10.1007/s11356-017-0719-2 (Mar. 2018).

63. Khan, H., Weili, L., Khan, I. & Han, L. The effect of income inequality and energy consumption on environmental degradation: the role of institutions and financial development in 180 countries of the world. en. *Environmental Science and Pollution Research* **29,** 20632–20649. doi:10.1007/s11356-021-17278-9 (Mar. 2022).

64. Khan, S. & Yahong, W. Symmetric and Asymmetric Impact of Poverty, Income Inequality, and Population on Carbon Emission in Pakistan: New Evidence From ARDL and NARDL Co-Integration. en. *Frontiers in Environmental Science* **9,** 666362. doi:10.3389/fenvs.2021.666362 (Apr. 2021).

65. Khan, S. & Yahong, W. Income inequality, ecological footprint, and carbon dioxide emissions in Asian developing economies: what effects what and how? en. *Environmental Science and Pollution Research* **29,** 24660–24671. doi:10.1007/s11356-021-17582-4 (Apr. 2022).

66. Khan, S., Yahong, W. & Zeeshan, A. Impact of poverty and income inequality on the ecological footprint in Asian developing economies: Assessment of Sustainable Development Goals. en. *Energy Reports* **8,** 670–679. doi:10.1016/j.egyr.2021.12.001 (Nov. 2022).

67. Knight, K. W., Schor, J. B. & Jorgenson, A. K. Wealth Inequality and Carbon Emissions in High-income Countries. en. *Social Currents* **4,** 403–412. doi:10.1177/2329496517704872 (Oct. 2017).

68. Kocak, E. & Baglitas, H. H. The path to sustainable municipal solid waste management: Do human development, energy efficiency, and income inequality matter? en. *Sustainable Development* **30,** 1947–1962. doi:10.1002/sd.2361 (Dec. 2022).

69. Kopp, T. & Nabernegg, M. Inequality and Environmental Impact – Can the Two Be Reduced Jointly? en. *Ecological Economics* **201,** 107589. doi:10.1016/j.ecolecon.2022.107589 (Nov. 2022).

70. Korkut Pata, U., Yilanci, V., Hussain, B. & Asif Ali Naqvi, S. Analyzing the role of income inequality and political stability in environmental degradation: Evidence from South Asia. en. *Gondwana Research* **107,** 13–29. doi:10.1016/j.gr.2022.02.009 (July 2022).

71. Kusumawardani, D. & Dewi, A. K. The effect of income inequality on carbon dioxide emissions: A case study of Indonesia. en. *Heliyon* **6,** e04772. doi:10.1016/j.heliyon.2020.e04772 (Aug. 2020).

72. Langnel, Z., Amegavi, G. B., Donkor, P. & Mensah, J. K. Income inequality, human capital, natural resource abundance, and ecological footprint in ECOWAS member countries. en. *Resources Policy* **74,** 102255. doi:10.1016/j.resourpol.2021.102255 (Dec. 2021).

73. Li, N., Ulucak, R. & Danish. Turning points for environmental sustainability: the potential role of income inequality, human capital, and globalization. en. *Environmental Science and Pollution Research* **29,** 40878–40892. doi:10.1007/s11356-021-18223-6 (June 2022).

74. Liobikienė, G. & Rimkuvienė, D. The role of income inequality on consumption-based greenhouse gas emissions under different stages of economic development. *Environmental Science and Pollution Research* **27,** 43067–43076. doi:10.1007/s11356-020-10244-x (Dec. 2020).

75. Liu, C., Jiang, Y. & Xie, R. Does income inequality facilitate carbon emission reduction in the US? en. *Journal of Cleaner Production* **217,** 380–387. doi:10.1016/j.jclepro.2019.01.242 (Apr. 2019).

76. Liu, Q., Wang, S., Zhang, W. & Li, J. Income distribution and environmental quality in China: A spatial econometric perspective. en. *Journal of Cleaner Production* **205,** 14–26. doi:10.1016/j.jclepro.2018.09.090 (Dec. 2018).

77. Liu, Q., Wang, S., Zhang, W., Li, J. & Kong, Y. Examining the effects of income inequality on CO2 emissions: Evidence from non-spatial and spatial perspectives. en. *Applied Energy* **236,** 163–171. doi:10.1016/j.apenergy.2018.11.082 (Feb. 2019).

78. Liu, Z., Zhang, H., Zhang, Y.-J. & Qin, C.-X. How does income inequality affect energy efficiency? Empirical evidence from 33 Belt and Road Initiative countries. en. *Journal of Cleaner Production* **269,** 122421. doi:10.1016/j.jclepro.2020.122421 (Oct. 2020).

79. Mader, S. The nexus between social inequality and CO2 emissions revisited: Challenging its empirical validity. en. *Environmental Science & Policy* **89,** 322–329. doi:10.1016/j.envsci.2018.08.009 (Nov. 2018).

80. Magnani, E. The Environmental Kuznets Curve, environmental protection policy and income distribution. en. *Ecological Economics* **32,** 431–443. doi:10.1016/S0921-8009(99)00115-9 (Mar. 2000).

81. Mahalik, M. K., Mallick, H., Padhan, H. & Sahoo, B. Is skewed income distribution good for environmental quality? A comparative analysis among selected BRICS countries. en. *Environmental Science and Pollution Research* **25,** 23170–23194. doi:10.1007/s11356-018-2401-8 (Aug. 2018).

82. Martínez-Zarzoso, I. & Phillips, J. Freedom of the press, inequality and environmental policy. en. *Environment and Development Economics* **25,** 537–560. doi:10.1017/S1355770X20000339 (Dec. 2020).

83. Masud, M. M., Kari, F. B., Banna, H. & Saifullah, M. K. Does income inequality affect environmental sustainability? Evidence from the ASEAN-5. en. *Journal of the Asia Pacific Economy* **23,** 213–228. doi:10.1080/13547860.2018.1442146 (Apr. 2018).

84. McGee, J. A. & Greiner, P. T. Can Reducing Income Inequality Decouple Economic Growth from CO_2 Emissions? en. *Socius: Sociological Research for a Dynamic World* **4.** doi:10.1177/2378023118772716 (Jan. 2018).

85. Mehmood, U. *et al.* Socio-Economic Drivers of Renewable Energy: Empirical Evidence from BRICS. en. *International Journal of Environmental Research and Public Health* **19,** 4614. doi:10.3390/ijerph19084614 (Apr. 2022).

86. Mikkelson, G. M., Gonzalez, A. & Peterson, G. D. Economic Inequality Predicts Biodiversity Loss. en. *PLoS ONE* **2** (ed Chave, J.) e444. doi:10.1371/journal.pone.0000444 (May 2007).

87. Mirza, M. U., Richter, A., Van Nes, E. H. & Scheffer, M. Institutions and inequality interplay shapes the impact of economic growth on biodiversity loss. en. *Ecology and Society* **25,** art39. doi:10.5751/ES-12078-250439 (2020).

88. Mittmann, Z. & De Mattos, E. J. INCOME INEQUALITY AND CARBON DIOXIDE EMISSIONS: EVIDENCE FROM LATIN AMERICA. en. *Journal of International Development* **32,** 389–407. doi:10.1002/jid.3459 (Apr. 2020).

89. Mohapatra, G. & Giri, A. K. The Economic Growth–Income Inequality–Poverty Nexus and Its Impact on Environmental Degradation: Empirical Evidence from India. en. *Millennial Asia* **13,** 470–490. doi:10.1177/09763996211023878 (Dec. 2022).

90. Mushtaq, A., Chen, Z., Ud Din, N., Ahmad, B. & Zhang, X. Income inequality, innovation and carbon emission: Perspectives on sustainable growth. en. *Economic Research-Ekonomska Istraživanja* **33,** 769–787. doi:10.1080/1331677X.2020.1734855 (Jan. 2020).

91. Odhiambo, N. M. Financial development, income inequality and carbon emissions in sub-Saharan African countries: A panel data analysis. en. *Energy Exploration & Exploitation* **38,** 1914–1931. doi:10.1177/0144598720941999 (Sept. 2020).

92. Ozturk, S., Cetin, M. & Demir, H. Income inequality and CO2 emissions: nonlinear evidence from Turkey. en. *Environment, Development and Sustainability* **24,** 11911–11928. doi:10.1007/s10668-021-01922-y (Oct. 2022).

93. Padhan, H., Haouas, I., Sahoo, B. & Heshmati, A. What matters for environmental quality in the Next Eleven Countries: economic growth or income inequality? en. *Environmental Science and Pollution Research* **26,** 23129–23148. doi:10.1007/s11356-019-05568-2 (Aug. 2019).

94. Pandit, R. & Laband, D. N. Economic well-being, the distribution of income and species imperilment. en. *Biodiversity and Conservation* **18,** 3219–3233. doi:10.1007/s10531-009-9638-y (Nov. 2009).

95. Rözer, J., Lancee, B. & Volker, B. Keeping Up or Giving Up? Income Inequality and Materialism in Europe and the United States. en. *Social Indicators Research* **159,** 647–666. doi:10.1007/s11205-021-02760-1 (Jan. 2022).

96. Rai, S. K. & Rawat, A. Exploring the nexus between environment quality, economic development and industrialization in BRICS nations: the role of technological innovation and income inequality. en. *Environmental Science and Pollution Research* **29,** 37842–37853. doi:10.1007/s11356-021-18181-z (May 2022).

97. Ravallion, M., Heil, M. & Jalan, J. Carbon Emissions and Income Inequality. en. *Oxford Economic Papers* **52,** 651–669 (2000).

98. Ridzuan, A. R., Ismail, N. A., Hamat, A. F. C., Nor, A. H. S. & Ahmed, E. M. Does Equitable Income Distribution Influence Environmental Quality? Evidence from Developing Countries of ASEAN-4. en. *SOCIAL SCIENCES HUMANITIES* (2017).

99. Ridzuan, S. Inequality and the environmental Kuznets curve. en. *Journal of Cleaner Production* **228,** 1472–1481. doi:10.1016/j.jclepro.2019.04.284 (Aug. 2019).

100. Ridzuan, S. Inequality and water pollution in India. en. *Water Policy* **23,** 985–999. doi:10.2166/wp.2021.057 (Aug. 2021).

101. Rojas-Vallejos, J. & Lastuka, A. The income inequality and carbon emissions trade-off revisited. en. *Energy Policy* **139,** 111302. doi:10.1016/j.enpol.2020.111302 (Apr. 2020).

102. Romuald, K. S. Democracy and Environmental Quality: Accounting for Transmission Channels. *Journal of Economic Development* **44,** 1–27 (2019).

103. Safar, W. Income inequality and C O 2 emissions in France: Does income inequality indicator matter? en. *Journal of Cleaner Production* **370,** 133457. doi:10.1016/j.jclepro.2022.133457 (Oct. 2022).

104. Scruggs, L. A. Political and economic inequality and the environment. en. *Ecological Economics* **26,** 259–275. doi:10.1016/S0921-8009(97)00118-3 (Sept. 1998).

105. Shahbaz, M., Abbas Rizvi, S. K., Dong, K. & Vo, X. V. Fiscal decentralization as new determinant of renewable energy demand in China: The role of income inequality and urbanization. en. *Renewable Energy* **187,** 68–80. doi:10.1016/j.renene.2022.01.064 (Mar. 2022).

106. Tan, Y. & Uprasen, U. Carbon neutrality potential of the ASEAN-5 countries: Implications from asymmetric effects of income inequality on renewable energy consumption. en. *Journal of Environmental Management* **299,** 113635. doi:10.1016/j.jenvman.2021.113635 (Dec. 2021).

107. Toigo, C. H. & De Mattos, E. J. Equality, freedom and democracy: how important are they for environmental performance? en. *Desenvolvimento e Meio Ambiente* **58.** doi:10.5380/dma.v58i0.73189 (Sept. 2021).

108. Torras, M. & Boyce, J. K. Income, inequality, and pollution: a reassessment of the environmental Kuznets Curve. en. *Ecological Economics* **25,** 147–160. doi:10.1016/S0921-8009(97)00177-8 (May 1998).

109. Torras, M., Moskalev, S. A., Hazy, J. K. & Ashley, A. S. An econometric analysis of ecological footprint determinants: implications for sustainability. en. *International Journal of Sustainable Society* **3,** 258. doi:10.1504/IJSSOC.2011.041267 (2011).

110. Uddin, M. M., Mishra, V. & Smyth, R. Income inequality and CO2 emissions in the G7, 1870–2014: Evidence from non-parametric modelling. en. *Energy Economics* **88,** 104780. doi:10.1016/j.eneco.2020.104780 (May 2020).

111. Ullah, S. & Awan, M. S. Environmental Kuznets Curve and Income Inequality: Pooled Mean Group Estimation for Asian Developing Countries. en. *Forman Journal of Economic Studies* **15,** 157–179. doi:10.32368/FJES.20191507 (Jan. 2020).

112. Uzar, U. & Eyuboglu, K. The nexus between income inequality and CO2 emissions in Turkey. en. *Journal of Cleaner Production* **227,** 149–157. doi:10.1016/j.jclepro.2019.04.169 (Aug. 2019).

113. Uzar, U. Is income inequality a driver for renewable energy consumption? en. *Journal of Cleaner Production* **255,** 120287. doi:10.1016/j.jclepro.2020.120287 (May 2020).

114. Valenzuela-Levi, N. Why do more unequal countries spend more on private vehicles? Evidence and implications for the future of cities. en. *Sustainable Cities and Society* **43,** 384–394. doi:10.1016/j.scs.2018.09.003 (Nov. 2018).

115. Valenzuela-Levi, N. & Abreu, M. The income equality dividend in 'green' infrastructure: Evidence from the transport and waste sectors in the OECD. en. *Journal of Cleaner Production* **315,** 128088. doi:10.1016/j.jclepro.2021.128088 (Sept. 2021).

116. Vona, F. & Patriarca, F. Income inequality and the development of environmental technologies. en. *Ecological Economics* **70,** 2201–2213. doi:10.1016/j.ecolecon.2011.06.027 (Sept. 2011).

117. Wan, G., Wang, C., Wang, J. & Zhang, X. The income inequality-CO2 emissions nexus: Transmission mechanisms. en. *Ecological Economics* **195,** 107360. doi:10.1016/j.ecolecon.2022.107360 (May 2022).

118. Wang, L. & Zhang, M. Exploring the impact of narrowing urban-rural income gap on carbon emission reduction and pollution control. en. *PLOS ONE* **16** (ed Xue, B.) e0259390. doi:10.1371/journal.pone.0259390 (Nov. 2021).

119. Wang, Y., Uddin, I. & Gong, Y. Nexus between Natural Resources and Environmental Degradation: Analysing the Role of Income Inequality and Renewable Energy. en. *Sustainability* **13,** 8364. doi:10.3390/su13158364 (July 2021).

120. Wolde-Rufael, Y. & Idowu, S. Income distribution and CO2 emission: A comparative analysis for China and India. en. *Renewable and Sustainable Energy Reviews* **74,** 1336–1345. doi:10.1016/j.rser.2016.11.149 (July 2017).

121. Wu, C., Zhang, Z., Elahi, E., Mu, G. & Zhao, P. Urban-rural income disparities and atmospheric contamination: Aggravating or restraining? en. *Frontiers in Environmental Science* **10,** 1015857. doi:10.3389/fenvs.2022.1015857 (Oct. 2022).

122. Wu, R. & Xie, Z. Identifying the impacts of income inequality on CO2 emissions: Empirical evidences from OECD countries and non-OECD countries. en. *Journal of Cleaner Production* **277,** 123858. doi:10.1016/j.jclepro.2020.123858 (Dec. 2020).

123. Xiao, D., Yu, F. & Yang, H. The Impact of Urban-Rural Income Inequality on Environmental Quality in China. en. *Complexity* **2022** (ed Zhang, W.) 4604467. doi:10.1155/2022/4604467 (Jan. 2022).

124. Yameogo, C. E. W. & Dauda, R. O. S. The effect of income inequality and economic growth on environmental quality: A comparative analysis between Burkina Faso and Nigeria. en. *Journal of Public Affairs* **22,** e2566. doi:10.1002/pa.2566 (Aug. 2022).

125. Yang, B., Ali, M., Hashmi, S. H. & Jahanger, A. Do Income Inequality and Institutional Quality affect CO2 Emissions in Developing Economies? en. *Environmental Science and Pollution Research* **29,** 42720–42741. doi:10.1007/s11356-021-18278-5 (June 2022).

126. Yang, B., Ali, M., Hashmi, S. H. & Shabir, M. Income Inequality and CO2 Emissions in Developing Countries: The Moderating Role of Financial Instability. en. *Sustainability* **12,** 6810. doi:10.3390/su12176810 (Aug. 2020).

127. Yang, Z. *et al.* The Emission-Inequality Nexus: Empirical Evidence From a Wavelet-Based Quantile-on-Quantile Regression Approach. en. *Frontiers in Environmental Science* **10,** 871846. doi:10.3389/fenvs.2022.871846 (Mar. 2022).

128. You, W., Li, Y., Guo, P. & Guo, Y. Income inequality and CO2 emissions in belt and road initiative countries: the role of democracy. en. *Environmental Science and Pollution Research* **27,** 6278–6299. doi:10.1007/s11356-019-07242-z (Feb. 2020).

129. Zecca, E. & Nicolli, F. Inequality, democracy and green technological change. en. *Journal of Cleaner Production* **306,** 127061. doi:10.1016/j.jclepro.2021.127061 (July 2021).

130. Zhang, C. & Hu, R. Does Fertilizer Use Intensity Respond to the Urban-Rural Income Gap? Evidence from a Dynamic Panel-Data Analysis in China. en. *Sustainability* **12,** 430. doi:10.3390/su12010430 (Jan. 2020).

131. Zhang, C. & Zhao, W. Panel estimation for income inequality and CO2 emissions: A regional analysis in China. en. *Applied Energy* **136,** 382–392. doi:10.1016/j.apenergy.2014.09.048 (Dec. 2014).

132. Zhang, M., Wang, L., Ma, P. & Wang, W. Urban-rural income gap and air pollution: A stumbling block or stepping stone. en. *Environmental Impact Assessment Review* **94,** 106758. doi:10.1016/j.eiar.2022.106758 (May 2022).

133. Zhao, W., Hafeez, M., Maqbool, A., Ullah, S. & Sohail, S. Analysis of income inequality and environmental pollution in BRICS using fresh asymmetric approach. en. *Environmental Science and Pollution Research* **28,** 51199–51209. doi:10.1007/s11356-021-14209-6 (Oct. 2021).

134. Zhong, K. Does the digital finance revolution validate the Environmental Kuznets Curve? Empirical findings from China. en. *PLOS ONE* **17** (ed Zhang, M.) doi:10.1371/journal.pone.0257498 (2022).

135. Zhou, A. & Li, J. Impact of income inequality and environmental regulation on environmental quality: Evidence from China. en. *Journal of Cleaner Production* **274,** 123008. doi:10.1016/j.jclepro.2020.123008 (Nov. 2020).

136. Zhu, H., Xia, H., Guo, Y. & Peng, C. The heterogeneous effects of urbanization and income inequality on CO2 emissions in BRICS economies: evidence from panel quantile regression. en. *Environmental Science and Pollution Research* **25,** 17176–17193. doi:10.1007/s11356-018-1900-y (June 2018).

3 Construction of the database

The information obtained from the articles was coded into a unique database. For each empirical test, we create a separate row/entry following the previous analysis of Berthe & Elie[2]. Author and year are provided as identifier (Table 6). We consider all empirical test that are 1) central to the study's results; 2) have a different empirical method; 3) utilize different measures of environmental degradation or inequality. We then obtain a total of 406 tests in the 136 papers with an average of ≈ 3 tests per paper. We coded various variables containing information about the sample characteristics, the estimations, the theories mobilized and the quality of publication. Table 6 - 17 provide a detailed description of all the variables constructed. The following section will provide an examination of the methodological decisions involved in the creation of the variables

3.1 Variables related to sample characteristics

General Indicators: Table 7 contains general indicators related to the sample characteristics of the empirical tests. This includes the number of observations, the number of geographical entities as well as a written description of the geographical entities.

Income level: The present article includes dummy variables as well as one summary variable for the level of income according to the World Bank Classification of income groups[23] (Table 8). We classify an analysis as focused on a single income group if more than 90% of the countries in the sample belong to the same income group. Analyses that do not align to this standard are classified as containing countries of "all income levels".

Development Level: Likewise we construct dummy variables and a respective summary variable to represent the levels of economic development of the countries included in the empirical tests (Table 9). The definition of economic development is inherently complex and hardly definable[24]. Nonetheless, we posit that certain groups of countries share comparable economic characteristics. These groups include mixed development samples, OECD countries[25], BRICS economies and developing countries not belonging to one of these groups. To classify the analyses, we apply as before a 90% rule: If an analysis is related predominantly (90% or more) to a single country group, it is classified accordingly. Analyses involving more than one country group are categorized as "all development levels".

Geographical Zones: We define dummy variables for studies focusing on the Americas, Europe, Asia and Africa. A summary variable is constructed as well. "Europe" includes former Soviet states and Turkey following the World Bank Classification[23]. The 90% rule applies likewise. Furthermore, we introduce the variable *scale*, indicating whether the analysis is conducted at a regional level and provide information of which country is subject of the regional analysis.

Our database encompasses multiple regional analyses for China and the United States, while only one regional analysis is conducted for Russia[26] and India[27]. A summary of the variables is provided in Table 10.

Time Frame : Lastly, we provide the start year, end year and length of the time frame used for the empirical test, which allows testing changes in the results over time (Table 11). Based on the end year of the employed data-frames, we construct two dummy variables related to the recentness of the data (df_time & df_time_2) The latter assumes the year 2000 as threshold while the first assumes 2014 (Table 11).

Overall, we deem the preceding information adequate to uncover dependencies within the literature on the Inequality-Environment nexus. The data has been carefully organized to allow for filtering specific groups of analyses, such as those concerning OECD countries in Europe[28] or low-income countries in Africa[29, 30].

3.2 Variables related to the empirical estimation

Inequality Indicators: We construct the variable *ineq_detail*, containing the abbreviation of the specific inequality indicator employed, *ineq_raw* classifying the inequality indicator by groups and *ineq_agg*, containing a more straight forward naming of the inequality indicators and an aggregation of distributional measures (Table 12). The vast majority of groups are determined based on the classification of Safar[31]. These include concentration, distributional and normative measures. Concentration measures refer to the Gini-coefficient while distributional measures refer to ratio-based measures (top 10%/ bottom 50%), bottom-end measures (bottom 20%) and top-end measures (top 10 %). The latter is utilized in the vast majority of studies employing distributional measures. Bottom-end measures are restricted to the studies of Kocak & Baglitas[32] & Wan et al.[33]. We additionally introduce the category "Spatial Measures", which predominantly encompasses the expanding body of research on Chinese urban–rural income inequality (spatial measures) and its environmental implications[34–37].

Results: Six indicators are developed to summarize the results of the empirical tests (Table 13). The variable *detailed_results* provides a brief description of the relationship between the environmental and inequality indicators. The variable *result_raw* is a coded indicator that represents the direction of the nexus with a single sign (U, $\cap$, $_{-}$NS, $^{+}$NS, NS^{+}, NS$_{-}$, $\sim$, $\backsim$, M, +, -, NS). Since the direction of results is reversed for response variables, we harmonize them in *result_adapt*. For example, higher inequalities decrease the response variable renewable energy consumption (signifying social-environmental complementarity). On the other hand, higher inequalities increase air pollution (signifying social-environmental complementarity). The direction of the result is different, but the environmental effect is the same. Thus, we solve this problem with *result_adapt*, where the result sign indicates social-environmental complementarity

ineq_agg	*ineq_raw*	*ineq_detail*	N
Concentration Measures			**274**
Gini-coefficient	1	Gini Index (Gini), Pre-tax Gini (Ginipretax), Post-tax Gini (Ginipost-tax), Urban Gini (Ugini), Rural Gini (Rgini)	274
Distributional Measures			**81**
Distributional	2 (ratio)	Ratio p80 to p20 (R80/20), Ratio p90 to p10 (R90/10), Palma-Index (Palma), decile dispersion	19
Distributional	5 (top %)	Income Top 20% (T20i), Income Top 10% (T10i), Income Top 5% (T5i), Income Top 1% (T1i), Wealth Top 10% (T10w)	56
Distributional	6 (bottom %)	Income Bottom 10% (B10i), Income Bottom 20% (B20i), Income second 20% (2nd20i), Income third 20% (3rd20i), Income fourth 20% (4th20i)	6
Normative Measures			**28**
Normative	3	Atkinson-Index (Atkinson), Theil-Index (Theil)	28
Spatial Measures			**23**
Spatial	4	Urban-Rural Income Gap (Urincgap), Urban-Rural Consumption Gap (Urconsgap)	23

Tab. 1 | Classification of inequality indicators.

with plus, a trade-offs with minus, etc. In addition, we simplify the results in *result_agg*, where we only distinguish between positive, negative, non-linear and non-significant results.Table 2 explains the coding of the results.

If an interaction effect is included in the analysis, the variable of interaction is captured in the variable *interact* (Table 13. Lastly, the *force* of the empirical test is assessed by calculating the ratio between the number of significant results and the total number of results for the same regression, but with varying control variables.

Environmental Dimensions: We construct information on the environmental dimension tested (*env_dim*), form groups of indicators utilized to assess the respective environmental dimension (e.g. production-based emissions (Pbco2)(*syntvar*) and provide information on the original variable utilized *detailed_variable* (Table 14). The methodological choices involved in the aggregation of environmental indicators are depicted in Table 3.

We construct eight environmental dimensions (5 environmental areas and 3 environmental responses). The environmental areas are based on Rockström et al.[38], which are Climate Change, Air Pollution, Water Pollution and Biodiversity loss. They respectively refer to the Planetary Boundaries (1) Climate Change and Ocean acidification (2), Atmospheric aerosol loading, (3) Global freshwater use and Biochemical flow boundary, (4), Biodiversity loss and Land-system change. The category General Environmental Indicators characterizes variables which include information on more than one planetary boundary in the same variable tested. The three types of environmental responses identified are Policies, Behaviors and Energy. The OECD differenti-

result_adapt	**meaning**	***result_agg***	**N**
+	Higher Inequalities increase environmental degradation (socio-environmental complementarity	+	159
-	Higher Inequalities decrease environmental degradation (socio-environmental trade-off)	-	68
U	U-shaped relationship: Higher inequalities decrease environmental degradation but the relationship is reversed at a certain threshold (e.g. income-level, time, inequality, democracy, etc.)	nl	33
$\cap$	Reversed U-shaped relationship. Higher inequalities increase environmental degradation. Reversion at a certain threshold (e.g. income-level, time, inequality, etc.)	nl	23
$_{-}$NS	Higher Inequalities decrease environmental degradation but the nexus turns non-significant at a certain threshold (e.g. income-level, democracy)	nl	2
$^{+}$NS	Higher Inequalities increase environmental degradation but the nexus turns non-significant at a certain threshold (e.g. income-level, time)	nl	11
NS^{+}	Higher inequalities do not affect environmental degradation below a certain threshold (e.g. income-level, time, democracy); positive effect beyond it	nl	6
NS$_{-}$	Higher inequalities do not affect environmental degradation below a certain threshold (e.g. time); negative effect beyond it	nl	3
$\sim$	Higher inequalities first increase, second decrease and third increase environmental degradation depending on two thresholds (e.g. income-level, inequality)	nl	3
$\backsim$	Higher inequalities first decrease, second increase and third decrease environmental degradation depending on two thresholds (e.g. income-level, inequality)	nl	2
M	Higher inequalities first increase, second decrease, third increase and fourth decrease environmental degradation depending on three thresholds (here, time)	nl	1
NS	No statistically significant relationship between inequalities and environmental degradation	NS	95

Tab. 2 | Summary of results.

ates between the same three types of environmental responses in their reports[39]. Environmental responses are more directly influenced by changes in inequalities/ political power[3, 5, 6].

The *syntvar* provides useful subcategories of these areas. For climate change, we distinguish between production-based (Pbco2) and consumption-based (Cbco2) emissions. Since the first is computed on the basis of consumption activities and the latter production activities, a differentiation is important to control for the outsourcing behavior of wealthier economies[40, 41]. If studies did not report the type of emissions (most of the studies), production-based emissions were assumed. Within the category "Air Pollution", we differentiate between local and regional pollutants[42]. The area of "Water Pollution" is further classified into organic pollution and chemical contamination, while that of "Biodiversity Loss" is divided into threats to overall biodiversity, vegetation diversity, and animal diversity. For the other general environmental indicators, we isolate the most common subgroup which is the "Environmental Footprint". Lastly, for "Policies," we differentiate between land protection policies, policy demand or ambitions, and public research and development expenditure. For behaviors, we create the subcategories:

env_dim	Var2: *syntvar*	Var3: *detailed_variable*	N
Environmental areas			
Climate Change	Pbco2, Cbco2	CO2 pc, Cons. GHG pc	215
Air Pollution	Airloc, Airreg	Soot emissions, SO2 emissions	37
Water Pollution	Orga, Wat	Biochemical oxygen demand (BOD), wastewater discharged	29
Biodiversity Loss	Bioani, Biodiv, Bioveg	birds/threat, species/threat, plants/threat	18
General Environmental Indicators	EF, GE,	EF (Environmental Footprint), EPI (Environmental Performance Index)	20
Environmental responses			
Policies	Landprot, Pol, Polclim, PubRD	Land protected (%), Demand for environmental policy, Climate policy ambition, Public green R&D pc	38
Behaviors	Behfirm, Behhous, Behval	green technology diffusion, % adoption of Recycling, post materialism	35
Energy	Nrjeff, Ren,	Energy efficiency, Renewable energy consumption	14

Tab. 3 | Summary of environmental dimensions.

"firm behavior (Behfirm)," "household behavior (Behhous)," and "values (Behval)," such as post-materialism. For energy-related indicators we distinguish between "renewable energies" and "energy efficiency".

Estimation Methods: Table 15 contains the list of variables constructed to systematize the estimation method used in the empirical tests on the Inequality-Environment nexus. We grouped the methods by eight subgroups contained in the variable *method_agg_2* while the respective written names are provided in *method_agg_name*. A detailed written description of the estimation method is provided in *method_detail* while a less aggregated level of subgroups is contained by *method_agg_1*.

Table 4 summarizes the classifications of the methodological approaches. The most prominent group of models are first generation panel (p1) models. This category includes traditional estimators such as Fixed Effects (FE), Random Effects (RE), and Grouped Fixed Effects (GFE) for panel data. They are static approaches that employ an Ordinary Least Squares (OLS) estimator, but offer the advantage of mitigating potential biases stemming from unobserved time-invariant factors such as cultural norms, institutional frameworks, and social infrastructure by employing individual effects[43, 44].

The second class of models are Ordinary Least Squares (OLS) models, which are quite frequently used in the current literature but do not employ individual effects. These models presume

method_agg_name	*method_agg_2*	*method_detail*	N
First Generation Panel	p1	Fixed Effects (FE), Random Effects (RE), Grouped Fixed Effects (GFE)	104
Ordinary Least Squares	ols	Pooled Model, OLS, two-stage least squares (2SLS)	66
Second Generation Panel	p2	D&K, Panel causality, panel coint, AMG, Granger, panel Pooled Mean Group (PMG), DOLS, FMOLS, DOLSMG, dynamic common correlated effects (DCCE), CCEMG	65
Non-Linear	nl	Non-para, Semi-para, Panel Smooth Transition, Quantile-on-quantile, Quantile, Threshold regression	53
Time Series Panel	tp	ARDL, NARDL, Cointegration, Granger	42
Generalized Method of Moments	gmm	GMM, SGMM	38
Special Econometrics	spe	BETA, Multilevel, SEM, StEM, Dynamic seemingly unrelated (SiEM), spatial panel regression model, GLS	22
Qualitative Analysis	qa	Count model, Tobit, Probit	16

Tab. 4 | Classes of methods utilized.

no biases from unobserved constant factors and do not account for cross-country heterogeneity. This approach is applicable to cross-sectional and panel data. Borghesi[18] highlighted that, when applied to panel data, this method can yield structurally opposite results compared to other fixed effects panel models.

The third group refers to Second Generation Panel (p2) models, which likewise utilize an OLS estimator, but employ heterogeneous panel regression techniques addressing in particular non-stationarity and cross-sectional dependence in panel data with cointegrated variables. Notable methods include the Mean Group (MG) estimator by Pesaran & Smith[45], the Common Correlated Effects Mean Group (CCEMG) method by Pesaran[46], and the Augmented Mean Group (AMG) estimator by Teal & Eberhardt[47].

The fourth class encompasses non-linear models including non-parametric and semi-parametric methods[48], as well as quantile regression techniques[49] and threshold regression estimations[50]. These approaches are especially suitable to address proposed nonlinearities within the relationship between inequality and environmental degradation without choosing a condition ex ante[51–53]. Furthermore, the fifth group contains time series models, such as the Autoregressive Distributed Lag (ARDL) models, along with associated time-series tests, including cointegration and Granger causality tests[54]. These models are useful for examining long-run and short-run dynamics between variables[55], but do not infer causal relationships[54].

Furthermore, we comprise (System) Generalized Method of Moments (GMM) estimators in the sixth group, which employ inherently different estimation techniques. These instrumental variable approaches are designed to address potential endogeneity issues arising from dynamic relationships within the data. GMM methods employ lags of the dependent variable as instruments to mitigate the correlation problem that introduces bias in standard models[56–58].

Lastly, the estimation classes seven and eight refer to "special methods" and qualitative analysis (Table 3), which are less frequently used in the present literature. The first captures Spatial Error Models (SEM) as well as Multilevel analyses[59–61], which include spatial components. These models are crucial if observations are influenced by their location and neighboring units. Furthermore, we also include models that work using the maximum likelihood method[62] and the STIRPAT model that allow spatial autocorrelation[60, 63] in this group. The last class "Qualitative Analysis" comprises models that are used for analyzing categorical or limited dependent variables. These models are appropriate for cases where the dependent variable is binary, ordinal, or censored, such as in studies of decision-making or event occurrences [64–67].

3.3 Variables related to the utilization of theories

Furthermore, we create dummy variables to indicate the theories mobilized in the articles. Dummy variables are constructed for each of the five central theories[3–7] and three novel transmission channels[68–70] (Table 16). A theory is considered mobilized if its theoretical mechanism is broadly articulated in the empirical article, even if it is not cited. Table 5 provides a short explanation of the mechanisms proposed by these theories and the percentage of the analytical framework created in this section to investigate the Inequality-Environment nexus ensures a holistic understanding of the inequality-environment nexus, offering insights into the broader implications for sustainability and equity.

Variables related to theoretical biases Lastly, our dataset contains two count variables for first, the number of theories mobilized proposing social-environmental complementarity and second, the number of theories mobilized proposing a trade-off between inequalities and environmental quality (Table 17). Based on these two count variables, we calculate the ratio between "positive" and "negative" theories and thus assess if either theories proposing social-environmental complementarity or a trade-off are dominant for each test.

3.4 Variables related to quality of publication

Lastly, Table 18 contains different indicators that are useful for evaluating the quality of the publication. First, we construct an index of statistical accuracy based on the number of observations. Second, we incorporate the full name of the journal, it's h-index according to the Scimago Journal & Country Rank[72] and the number of citations. (Table 18). We assume that journals with higher h-index have stricter review processes which allow only for the publication of high-quality research. The h-index is considered a robust measure for the qualification of journals[73]. Citations reflect the impact of each single paper but are only comparable with regard to the year of publication. Third, we also construct a count variable containing the number of theories mobilized per empirical test. We assume that studies considering a higher number of theories and transmission channels are of higher quality.

Authors	Env. Impact[1]	Mechanism	N
Boyce (1994)[3]	+	Reducing inequalities increases the power of those who bear the net costs of environmental degradation and vice versa → demand for environmental policies increases	82.27%
Scruggs (1998)[5]	-	The demand for environmental quality (superior good) increases with income. Reducing inequalities thus increases environmental degradation	47.04%
Magnani (2000)[6]	+	Marginalized households demand growth policies → Inequality reduction creates a wealthier median segment, opting for environmental protection.	21.42%
Heerink et al. (2001)[4] & Ravallion et al. [71]	-	Inverse U-shaped relationship between inequality and environmental degradation. Higher inequalities lead to a concentration of income among the affluent, whose consumption by dollar generates lower environmental degradation (marginal propensity to emit (MPE) is higher among low-income groups and vice versa)	61.82%
Wilkison & Pickett (2010)[7]	+	Inequality leads individuals to adopt consumerist and individualistic behaviors towards the environment. Reducing inequality reduces environmental degradation (more public goods and societal trust)	34.48%
Vona & Patriarca[68]	+	Higher inequality may imply that few consumers have access to eco-friendly goods, leading to fewer positive technological externalities → stagnation of prices at high levels	11.33%
Jones (2015)[69]	-	Higher inequality promotes the development of technology through capital accumulation	2.46%
Jorgenson et al. (2017)[70]	+	Inequality increases working hours, which drives energy consumption and CO2 emissions via both their impacts on economic growth and on households' consumption choices	11.08%

[1] + → Increasing inequality leads to higher environmental degradation; - → Increasing inequality leads to less environmental degradation

Tab. 5 | Main theories.

4 Database - Full Variable Description

Variable Name	Variable Description	Var. Type
author	Author's name written in citation format. Examples: single author = Mader (2018); Two authors = Franzen and Vogl (2013); More than two authors = Heerink et al. (2001)	string
year	Year of article publication as numerical variable.	numerical

Tab. 6 | Identification variables.

Variable Name	Variable Description	Var. Type
n	Number of observations	numerical
geo_entities_n	Number of geographical entities	numerical
geo_entities_descrip	Number and description of geographical entities	string

Tab. 7 | Sample characteristic variables: General indicators.

Variable Name	Variable Description	Var. Type
allinc	Dummy Variable: 0 if countries are from a single income group; 1 if the sample countries are from various income groups according to the World Bank classification of income groups[23]	binary
highinc	Dummy Variable: 0 if not only high income countries; 1 if high income countries according to the World Bank classification of income groups[23]	binary
medinc	Dummy Variable: 0 if not only middle income countries; 1 if middle income countries according to the World Bank classification of income groups[23]	binary
lowinc	Dummy Variable: 0 if not only low income countries; 1 if low income countries according to the World Bank classification of income groups[23]	binary
incomelvl	The variable contains the categories "Allincome", "High-Income", "Middle-Income" and "Low-Income" according to the World Bank classification of income groups[23]	ordinal

Tab. 8 | Sample characteristic variables: Income level.

Variable Name	Variable Description	Var. Type
alldvt	Dummy Variable: 0 if countries are from a single development level; 1 if countries have various development levels.	binary
oecd	Dummy Variable: 0 if not only OECD; 1 if OECD	binary
brics	Dummy Variable: 0 if not only BRICS; 1 if BRICS	binary
dc	Dummy Variable: 0 if not only Developing Countries; 1 if Developing Countries	binary
development	The variable contains the categories "alldvt", "OECD", "BRICS" and "DC"	ordinal

Tab. 9 | Sample characteristic variables: Development level.

Variable Name	Variable Description	Var. Type
allzone	Dummy Variable: 0 if specific geographical region; 1 if all geographical regions	binary
americ	Dummy Variable: 0 if not only Americas; 1 if Americas according to the World Bank[23]	binary
euro	Dummy Variable: 0 if not only Europe & Central Asia according to the World Bank[23]; 1 if Europe & Central Asia	binary
asia	Dummy Variable: 0 if not only Asia and Pacific; 1 if only Asia and Pacific	binary
africa	Dummy Variable: 0 if not only Africa; 1 if only Africa	binary
zone	The variable contains the categories "allzone", "Europe&CA", "Americas", "Asia" and "Africa"	nominal
scale	Modified dummy Variable: "national" if country scale analysis; "regional" if state/ province scale analysis	binary
russ_reg	Dummy Variable: 0 if not Russian Regions; 1 if Russian Regions	binary
india_stat	Dummy Variable: 0 if not Indian state-level analysis; 1 if Indian state-level analysis	binary
us_stat	Dummy Variable: 0 if not US state-level analysis; 1 if US state-level analysis	binary
chin_prov	Dummy Variable: 0 if not Chinese Provinces; 1 if Chinese Provinces	binary

Tab. 10 | Sample characteristic variables: Geographical zones.

Variable Name	Variable Description	Var. Type
tstart	Start year of the time frame	numerical
tend	End year of the time frame	numerical
length	Length of the time frame - Difference between end year and start year	numerical
df_time	Contains information on the recentness of the dataframe. Modified dummy variable: "2014 or before", "After 2014",	binary
df_time_2	Contains information on the recentness of the dataframe. Modified dummy variable: "2000 or before", "After 2000"	binary

Tab. 11 | Sample characteristic variables: Time-frame.

Variable Name	Variable Description	Var. Type
ineq_detail	Abbreviation of the inequality indicator utilized[1]. These are T20i, T10i, T5i, T1i, B10i, B20i, 2nd20i, 3rd20i, 4th20i, Gini, Ginipretax, Giniposttax, Ugini, Rgini, Atkinson, Theil, Urincgap, Urconsgap, Medinc	nominal
ineq_raw	Categorization of the inequality indicators based on Safar (2022)[31] into 7 groups depending on their nature[1]	nominal
ineq_agg	Contains the categories "Gini-Coefficient", "Distributional", "Spatial", "Normative" based on the categorization of ineq_raw.	nominal

[1] see Tab. 1 for a more detailed explanation of the variables.

Tab. 12 | Estimation related variables: Inequality indicators.

Variable Name	Variable Description	Var. Type
detailed_results	Written description of results	string
result_raw	Coded relationship between inequality and the environment. The utilized signs symbolize the nature of the relationship: + = positive, - = negative; U = negative, then positive; $\cap$ = positive, then negative; $\sim$ = positive, negative, positive; $\backsim$ = negative, positive, negative; $^{+}$NS = positive, then insignificant; $_{-}$NS = negative, then insignificant; NS^{+} = insignificant, then positive; NS$_{-}$ = insignificant, then negative; M = positive, negative, positive, negative; NS = non significant	nominal
result_adapt[1]	Coded relationship between inequality and the environment. The signs for environmental responses (Policies, Behaviors, Energy) have been reversed in contrast to *result_raw* in order to harmonize them with other environmental dimensions (same interpretation).	nominal
result_agg	Coded relationship between inequality and the environment. The utilized signs symbolize the nature of the relationship: + = positive, - = negative; nl = non-linear; NS = non-significant	nominal
interact	Indicates if an interaction effect is utilized. Interaction effects are: ineq (inequality), inco (income), Democ (democracy), Time (time), Patent (patents), Fin. Instit. (financial institutions), c_risk (country risk), innov & labor prod (Innovation and labor productivity), pesticides & non-agriculture output	nominal
force	The quotient between the the number of significant results and the total number of results for the same regression with different control variables.	numerical

[1] see Tab. 2 for a more detailed explanation.

Tab. 13 | Estimation related variables: Results.

Variable Name	Variable Description	Var. Type
env_dim	Environmental dimensions of inequalities[1]. We distinguish between Climate Change, Biodiversity Loss, Air Pollution, Water Pollution, General Indicators, Policies, Energy and Behaviors	nominal
syntvar	Subcategories of environmental dimensions[1]	nominal
detail_variable	Exact full name of the independent variable	nominal

[1] see Tab. 3 for a more detailed explanation of the variables.

Tab. 14 | Estimation-related variables: Env dimensions.

Variable Name	Variable Description	Var. Type
method_detail	detailed name of the estimation methods[1]	nominal
method_agg_1	Categories of estimation methods[1]	nominal
method_agg_2	Broad categories of estimation methods[1]	nominal
method_agg_name	Full names of the broad categories of estimation methods[1]	nominal

[1] see Tab. 4 for a more detailed explanation of the variables.

Tab. A15 | Estimation related variables: Estimation methods.

boyce	Refers to the theory of Boyce (1994)[3]. Dummy Variable: "not_boyce" if theory is not mobilized; "boyce" if theory is mobilized[1]	binary
scruggs	Refers to the theory of Scruggs (1998)[5]. Dummy Variable: "not_scruggs" if theory is not mobilized; "scruggs" if theory is mobilized[1]	binary
magnani	Refers to the theory of Magnani (2000)[6]. Dummy Variable: "not_magnani" if theory is not mobilized; "magnani" if theory is mobilized[1]	binary
heerink	Refers to the theory of Heerink et al (2001)[4] & Ravallion et al. (2000[71]. Dummy Variable: "not_heerink" if theory is not mobilized; "heerink" if theory is mobilized[1]	binary
wilkinson	Refers to the theory of Wilkinson & Pickett[7]. Dummy Variable: not_wilkinson" if theory is not mobilized; "wilkinson" if theory is mobilized[1]	binary
vona	Refers to the theory of Vona & Patriarca[68]. Dummy Variable: "not_vona" if theory is not mobilized; "vona" if theory is mobilized[1]	binary
jones	Refers to the theory of Jones (2015)[69]. Dummy Variable: "not_jones" if theory is not mobilized; "jones" if theory is mobilized[1]	binary
jorgenson	Refers to the theory of Jorgenson et al. (2017)[70]. Dummy Variable: "not_jorgenson" if theory is not mobilized; "jorgenson" if theory is mobilized[1]	binary

[1] see Tab. 5 for a more detailed explanation of the theories.

Tab. A16 | Variables related to the mobilization of theories.

theory_negative	Number of theories cited proposing a trade-off between inequality and the environment	numerical
theory_positive	Number of theories cited proposing a social-environmental complementarity	numerical
theory_ratio	Ratio between positive and negative theories cited	numerical
theory_dom	Dominant theoretical direction of the inequality-environment nexus. The categories are "more negative", "balanced", "more positive", "only positive"	ordinal

Tab. A17 | Variables related to theoretical biases.

sqrt_n	Square root of the number of observations	numerical
statistical_accuracy	Index between 1 and 5 based on the square root of the number of observations, where 5 signifies high statistical accuracy and vice versa.	ordinal
journal_name	Full name of the Journal	string
jhindex	H-Index of the Journal according to Scimago[72] on January 17^th, 2025	ordinal
jrnl_agg	Dummy Variable: containing information on the journal's rating: "h-index < 200" and "h-index > 200"	binary
citations	Number of citations according to SCOPUS on January 17^th	ordinal
mobilized_theories	Number of mobilized theories. Contains the Categories "1", "2", "3", "4", "5 & more"	ordinal

Tab. A18 | Variables related to the quality of publication.

5 Additional Results

5.1 Cartography of the literature

Figure 2 displays the evolution of tests by development level for each year since the first empirical study[74]. In addition, Figure 3 and 4 show the respective developments of geographical areas and income levels. In general, the graphs show similar developments. We observe that especially after 2015 the increase in the number of empirical tests has been accompanied by a greater focus on Asia and Africa. However, empirical tests on the latter remained limited. In addition, it seems that a significant portion of BRICS and developing countries studied are located in Asia, with China being the primary focus among the BRICS economies. Lastly, Figure 4 provides information on the income levels of the countries studied. Most studied developing countries seem to be middle-income countries while the poorest economies of the world still remain largely unexamined.

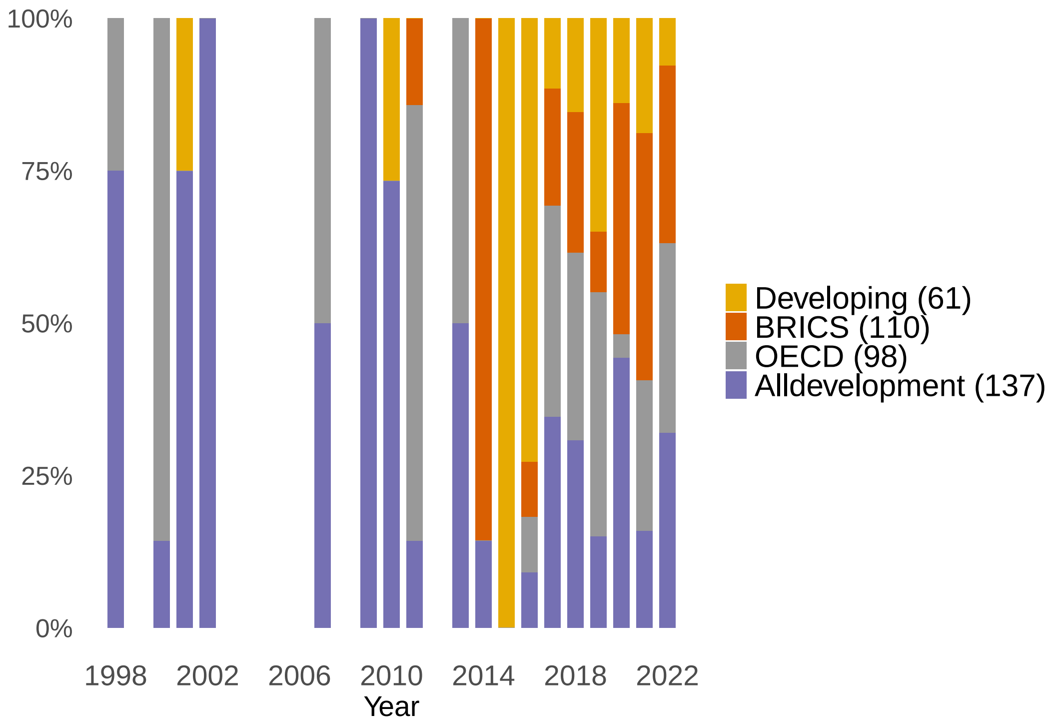

Fig. 2 | Evolution of tests by development level for each year.

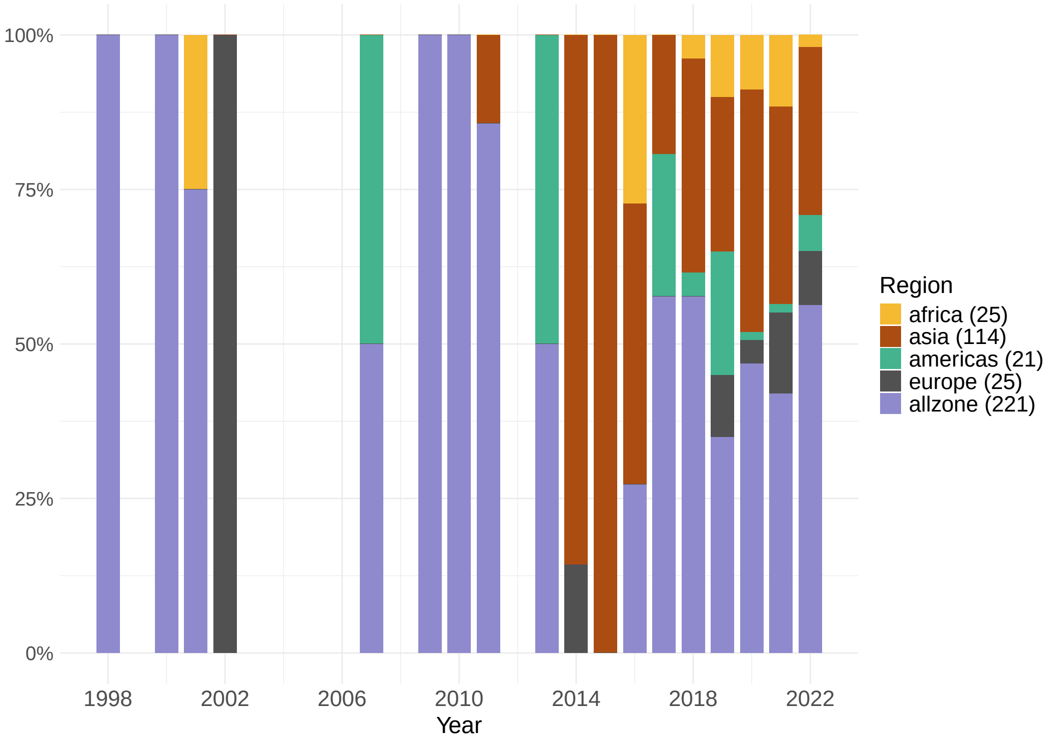

Fig. 3 | Evolution of tests by geographical zone for each year.

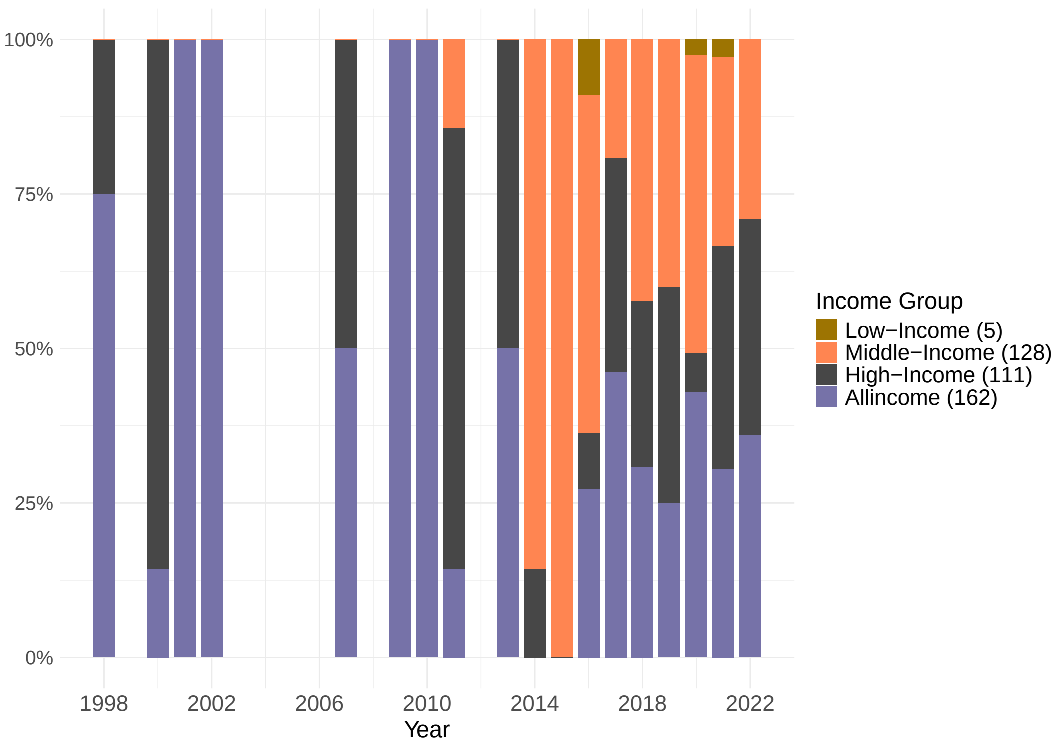

Fig. 4 | Evolution of tests by income group for each year.

5.2 The effect of test characteristics on the research outcome

5.2.1 Correlation tables/chi-squared tests

		result_agg			
		+	–	nl	NS
development	OECD	39.8%	11.2%	24.5%	24.5%
development	DC	36.1%	14.8%	23.0%	26.2%
development	BRICS	56.4%	20.0%	6.4%	17.3%
development	alldvt	21.9%	23.4%	28.5%	26.3%
zone	Europe&CA	40.0%	36.0%	12.0%	12.0%
zone	Asia	55.3%	14.0%	12.3%	18.4%
zone	Americas	42.9%	9.5%	33.3%	14.3%
zone	allzone	27.6%	18.6%	25.8%	28.1%
zone	Africa	40.0%	24.0%	12.0%	24.0%
scale	regional	57.6%	18.5%	6.5%	17.4%
scale	national	31.8%	18.2%	24.8%	25.2%
df_time	After 2014	41.1%	20.8%	21.9%	16.1%
df_time	2014 or before	34.6%	15.9%	19.6%	29.9%
method_agg_name	Time Series	40.5%	21.4%	14.3%	23.8%
method_agg_name	Special	63.6%	13.6%	18.2%	4.5%
method_agg_name	Qualitative	6.2%	0.0%	81.2%	12.5%
method_agg_name	Panel 2	55.4%	21.5%	13.8%	9.2%
method_agg_name	Panel 1	27.9%	17.3%	15.4%	39.4%
method_agg_name	Ols	43.9%	12.1%	16.7%	27.3%
method_agg_name	Non−linear	32.1%	24.5%	30.2%	13.2%
method_agg_name	GMM	26.3%	23.7%	23.7%	26.3%
env_dim	Water Pollution	44.8%	31.0%	3.4%	20.7%
env_dim	Policies	18.4%	2.6%	36.8%	42.1%
env_dim	General Ind.	60.0%	15.0%	15.0%	10.0%
env_dim	Energy	57.1%	0.0%	28.6%	14.3%
env_dim	Climate Change	31.2%	22.8%	23.7%	22.3%
env_dim	Biodiversity Loss	27.8%	16.7%	22.2%	33.3%
env_dim	Behaviors	74.3%	11.4%	5.7%	8.6%
env_dim	Air Pollution	40.5%	13.5%	13.5%	32.4%
ineq_agg	Spatial	43.5%	26.1%	8.7%	21.7%
ineq_agg	Normative	71.4%	7.1%	0.0%	21.4%
ineq_agg	Gini−Index	36.5%	15.7%	21.9%	25.9%
ineq_agg	Distributional	28.4%	28.4%	27.2%	16.0%
stat_accuracy	5	21.6%	33.3%	29.4%	15.7%
stat_accuracy	4	34.8%	24.6%	24.6%	15.9%
stat_accuracy	3	43.2%	18.2%	18.2%	20.5%
stat_accuracy	2	43.8%	11.4%	20.0%	24.8%
stat_accuracy	1	36.6%	12.9%	16.1%	34.4%
mobilized_theories	5	27.5%	32.5%	7.5%	32.5%
mobilized_theories	4	31.0%	19.0%	27.4%	22.6%
mobilized_theories	3	44.2%	16.3%	19.2%	20.2%
mobilized_theories	2	30.2%	10.5%	25.6%	33.7%
mobilized_theories	1	45.2%	21.0%	17.7%	16.1%
mobilized_theories	0	53.3%	20.0%	16.7%	10.0%
jrnl	h−index > 200	35.1%	16.7%	22.6%	25.6%
jrnl	h−index < 200	39.5%	19.3%	19.3%	21.8%
theory_dom	only positive	52.0%	12.0%	17.3%	18.7%
theory_dom	more positive	38.0%	20.4%	17.6%	24.1%
theory_dom	more negative	34.0%	32.1%	18.9%	15.1%
theory_dom	balanced	32.4%	15.3%	24.7%	27.6%

Chi² Residuals
3
2
−2
−3

Fig. 5 | Full sample - Correlation table/ chi-squared tests.

		result_agg			
		+	−	nl	NS
development	OECD	29.5%	14.8%	34.4%	21.3%
development	DC	27.0%	18.9%	27.0%	27.0%
development	BRICS	54.4%	19.3%	5.3%	21.1%
development	alldvt	13.3%	36.7%	28.3%	21.7%
zone	Europe&CA	35.0%	40.0%	15.0%	10.0%
zone	Asia	44.0%	10.0%	18.0%	28.0%
zone	Americas	33.3%	11.1%	38.9%	16.7%
zone	allzone	24.3%	27.0%	26.1%	22.5%
zone	Africa	31.2%	25.0%	18.8%	25.0%
scale	regional	56.4%	15.4%	5.1%	23.1%
scale	national	25.6%	24.4%	27.8%	22.2%
df_time	After 2014	30.2%	30.2%	21.6%	18.1%
df_time	2014 or before	32.3%	14.1%	26.3%	27.3%
method_agg_name	Time Series	34.2%	23.7%	15.8%	26.3%
method_agg_name	Special	71.4%	0.0%	28.6%	0.0%
method_agg_name	Panel 2	46.2%	26.9%	15.4%	11.5%
method_agg_name	Panel 1	16.4%	26.2%	21.3%	36.1%
method_agg_name	Ols	37.5%	6.2%	25.0%	31.2%
method_agg_name	Non−linear	19.2%	15.4%	46.2%	19.2%
method_agg_name	GMM	26.7%	33.3%	40.0%	0.0%
ineq_agg	Spatial	25.0%	25.0%	0.0%	50.0%
ineq_agg	Normative	53.8%	15.4%	0.0%	30.8%
ineq_agg	Gini−Index	30.8%	17.5%	29.4%	22.4%
ineq_agg	Distributional	27.3%	38.2%	16.4%	18.2%
stat_accuracy	5	15.6%	50.0%	25.0%	9.4%
stat_accuracy	4	30.0%	28.0%	24.0%	18.0%
stat_accuracy	3	38.2%	12.7%	23.6%	25.5%
stat_accuracy	2	37.9%	17.2%	20.7%	24.1%
stat_accuracy	1	30.6%	14.3%	24.5%	30.6%
mobilized_theories	5	16.7%	43.3%	10.0%	30.0%
mobilized_theories	4	37.1%	24.2%	19.4%	19.4%
mobilized_theories	3	38.1%	14.3%	23.8%	23.8%
mobilized_theories	2	27.3%	9.1%	34.1%	29.5%
mobilized_theories	1	37.5%	29.2%	29.2%	4.2%
mobilized_theories	0	15.4%	30.8%	30.8%	23.1%
jrnl	h−index > 200	23.0%	31.1%	20.3%	25.7%
jrnl	h−index < 200	35.5%	18.4%	25.5%	20.6%
theory_dom	only positive	36.4%	22.7%	31.8%	9.1%
theory_dom	more positive	36.6%	25.6%	14.6%	23.2%
theory_dom	more negative	13.3%	33.3%	46.7%	6.7%
theory_dom	balanced	28.1%	18.8%	26.0%	27.1%

Chi² Residuals: 3, 2, −2, −3

Fig. 6 | Climate change- Correlation table/ chi-squared tests.

		result_agg			
		+	−	nl	NS
development	OECD	75.0%	0.0%	0.0%	25.0%
development	DC	41.7%	16.7%	8.3%	33.3%
development	BRICS	57.5%	25.0%	10.0%	7.5%
development	alldvt	29.2%	16.7%	16.7%	37.5%
zone	Asia	62.5%	20.8%	10.4%	6.2%
zone	Americas	100.0%	0.0%	0.0%	0.0%
zone	allzone	23.5%	15.7%	15.7%	45.1%
zone	Africa	50.0%	50.0%	0.0%	0.0%
scale	regional	57.5%	25.0%	10.0%	7.5%
scale	national	34.4%	15.6%	14.1%	35.9%
df_time	After 2014	70.6%	2.9%	14.7%	11.8%
df_time	2014 or before	30.0%	27.1%	11.4%	31.4%
method_agg_name	Time Series	100.0%	0.0%	0.0%	0.0%
method_agg_name	Special	33.3%	33.3%	33.3%	0.0%
method_agg_name	Panel 2	85.7%	0.0%	14.3%	0.0%
method_agg_name	Panel 1	52.4%	9.5%	9.5%	28.6%
method_agg_name	Ols	37.5%	20.8%	8.3%	33.3%
method_agg_name	Non−linear	44.0%	36.0%	12.0%	8.0%
method_agg_name	GMM	16.7%	11.1%	16.7%	55.6%
env_dim	Water Pollution	44.8%	31.0%	3.4%	20.7%
env_dim	General Ind.	60.0%	15.0%	15.0%	10.0%
env_dim	Biodiversity Loss	27.8%	16.7%	22.2%	33.3%
env_dim	Air Pollution	40.5%	13.5%	13.5%	32.4%
ineq_agg	Spatial	50.0%	28.6%	14.3%	7.1%
ineq_agg	Normative	100.0%	0.0%	0.0%	0.0%
ineq_agg	Gini−Index	36.2%	20.0%	13.8%	30.0%
ineq_agg	Distributional	0.0%	0.0%	0.0%	100.0%
stat_accuracy	5	25.0%	8.3%	41.7%	25.0%
stat_accuracy	4	36.4%	18.2%	36.4%	9.1%
stat_accuracy	3	47.4%	31.6%	5.3%	15.8%
stat_accuracy	2	48.6%	20.0%	5.7%	25.7%
stat_accuracy	1	44.4%	14.8%	3.7%	37.0%
mobilized_theories	4	0.0%	14.3%	42.9%	42.9%
mobilized_theories	3	45.9%	27.0%	13.5%	13.5%
mobilized_theories	2	35.5%	12.9%	6.5%	45.2%
mobilized_theories	1	38.9%	27.8%	11.1%	22.2%
mobilized_theories	0	90.9%	0.0%	9.1%	0.0%
jrnl	h−index > 200	57.1%	11.4%	8.6%	22.9%
jrnl	h−index < 200	36.2%	23.2%	14.5%	26.1%
theory_dom	only positive	52.6%	15.8%	10.5%	21.1%
theory_dom	more positive	57.1%	14.3%	28.6%	0.0%
theory_dom	more negative	38.7%	35.5%	9.7%	16.1%
theory_dom	balanced	40.4%	10.6%	12.8%	36.2%

Chi² Residuals
2
−2
−3

Fig. 7 | Local and regional environmental pressures - Correlation table/ chi-squared tests.

		result_agg			
		+	−	nl	NS
development	OECD	54.5%	6.1%	9.1%	30.3%
development	DC	58.3%	0.0%	25.0%	16.7%
development	BRICS	61.5%	7.7%	0.0%	30.8%
development	alldvt	27.6%	6.9%	48.3%	17.2%
zone	Europe&CA	60.0%	20.0%	0.0%	20.0%
zone	Asia	68.8%	6.2%	0.0%	25.0%
zone	Americas	100.0%	0.0%	0.0%	0.0%
zone	allzone	37.3%	5.1%	33.9%	23.7%
zone	Africa	60.0%	0.0%	0.0%	40.0%
scale	regional	61.5%	7.7%	0.0%	30.8%
scale	national	44.6%	5.4%	27.0%	23.0%
df_time	After 2014	47.6%	9.5%	28.6%	14.3%
df_time	2014 or before	46.7%	2.2%	17.8%	33.3%
method_agg_name	Time Series	100.0%	0.0%	0.0%	0.0%
method_agg_name	Special	77.8%	11.1%	0.0%	11.1%
method_agg_name	Qualitative	6.2%	0.0%	81.2%	12.5%
method_agg_name	Panel 2	100.0%	0.0%	0.0%	0.0%
method_agg_name	Panel 1	36.4%	0.0%	4.5%	59.1%
method_agg_name	Ols	53.8%	7.7%	19.2%	19.2%
method_agg_name	Non−linear	50.0%	0.0%	50.0%	0.0%
method_agg_name	GMM	60.0%	40.0%	0.0%	0.0%
env_dim	Policies	18.4%	2.6%	36.8%	42.1%
env_dim	Energy	57.1%	0.0%	28.6%	14.3%
env_dim	Behaviors	74.3%	11.4%	5.7%	8.6%
ineq_agg	Spatial	40.0%	20.0%	0.0%	40.0%
ineq_agg	Normative	66.7%	0.0%	0.0%	33.3%
ineq_agg	Gini−Index	52.9%	3.9%	13.7%	29.4%
ineq_agg	Distributional	32.0%	8.0%	52.0%	8.0%
stat_accuracy	5	42.9%	0.0%	28.6%	28.6%
stat_accuracy	4	62.5%	12.5%	12.5%	12.5%
stat_accuracy	3	57.1%	21.4%	14.3%	7.1%
stat_accuracy	2	43.9%	0.0%	31.7%	24.4%
stat_accuracy	1	41.2%	5.9%	11.8%	41.2%
mobilized_theories	5	60.0%	0.0%	0.0%	40.0%
mobilized_theories	4	20.0%	0.0%	53.3%	26.7%
mobilized_theories	3	52.0%	4.0%	20.0%	24.0%
mobilized_theories	2	27.3%	9.1%	45.5%	18.2%
mobilized_theories	1	60.0%	5.0%	10.0%	25.0%
mobilized_theories	0	66.7%	33.3%	0.0%	0.0%
jrnl	h−index > 200	37.3%	1.7%	33.9%	27.1%
jrnl	h−index < 200	67.9%	14.3%	0.0%	17.9%
theory_dom	only positive	61.8%	2.9%	11.8%	23.5%
theory_dom	more positive	36.8%	0.0%	26.3%	36.8%
theory_dom	more negative	57.1%	14.3%	0.0%	28.6%
theory_dom	balanced	33.3%	11.1%	40.7%	14.8%

Chi² Residuals: 3, 2, −2

Fig. 8 | Environmental responses - Correlation table/ chi-squared tests.

5.2.2 Justification of separation into climate change, local and regional environmental pressures and responses

The environmental dimensions have been classified based on Rockström et al.[38]. Furthermore, we perform a separate analysis for climate change (the most investigated area), local and regional environmental pressures and environmental response variables motivated by theoretical considerations. Climate Change causes systemic process at planetary scale differentiating them from other environmental pressures, which are aggregated processes at local or regional scale[38]. This difference might cause a distortion of the political transmission channels[3, 5, 6, 42] since those who bear the costs of pollution are spatially separated from those who are responsible for the majority of global emissions[75–77]. In contrast, air, water and biodiversity pressures occur at local or regional level, making it possible for affected groups to demand environmental policies within their political entity. The transmission depends on the characteristics of the political system of each country. The general indicator includes composite rankings of environmental performance, mostly relying on local and regional environmental pressures. Thus, we consider this group jointly with the other local and regional pollutants. In addition, we examine all environmental responses (behaviors, policies and energy indicators) separately. For the latter, the political channels might apply directly[3, 5, 6, 78]

5.2.3 Results by variable modalities (without regional-level analysis)

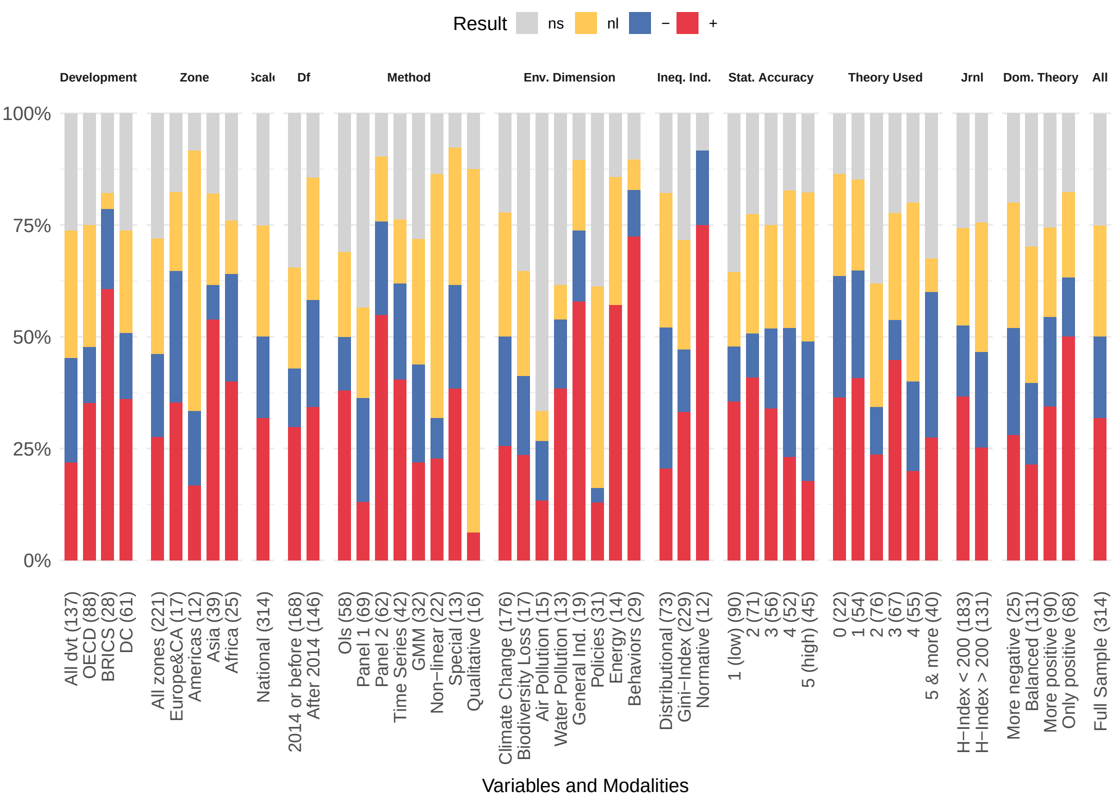

Fig. 9 | Full sample - Results by variable modalities (without regional).

result_agg

		+	−	nl	NS
development	OECD	35.2%	12.5%	27.3%	25.0%
development	DC	36.1%	14.8%	23.0%	26.2%
development	BRICS	60.7%	17.9%	3.6%	17.9%
development	alldvt	21.9%	23.4%	28.5%	26.3%
zone	Europe&CA	35.3%	29.4%	17.6%	17.6%
zone	Asia	53.8%	7.7%	20.5%	17.9%
zone	Americas	16.7%	16.7%	58.3%	8.3%
zone	allzone	27.6%	18.6%	25.8%	28.1%
zone	Africa	40.0%	24.0%	12.0%	24.0%
df_time	After 2014	34.2%	24.0%	27.4%	14.4%
df_time	2014 or before	29.8%	13.1%	22.6%	34.5%
method_agg_name	Time Series	40.5%	21.4%	14.3%	23.8%
method_agg_name	Special	38.5%	23.1%	30.8%	7.7%
method_agg_name	Qualitative	6.2%	0.0%	81.2%	12.5%
method_agg_name	Panel 2	54.8%	21.0%	14.5%	9.7%
method_agg_name	Panel 1	13.0%	23.2%	20.3%	43.5%
method_agg_name	Ols	37.9%	12.1%	19.0%	31.0%
method_agg_name	Non−linear	22.7%	9.1%	54.5%	13.6%
method_agg_name	GMM	21.9%	21.9%	28.1%	28.1%
env_dim	Water Pollution	38.5%	15.4%	7.7%	38.5%
env_dim	Policies	12.9%	3.2%	45.2%	38.7%
env_dim	General Ind.	57.9%	15.8%	15.8%	10.5%
env_dim	Energy	57.1%	0.0%	28.6%	14.3%
env_dim	Climate Change	25.6%	24.4%	27.8%	22.2%
env_dim	Biodiversity Loss	23.5%	17.6%	23.5%	35.3%
env_dim	Behaviors	72.4%	10.3%	6.9%	10.3%
env_dim	Air Pollution	13.3%	13.3%	6.7%	66.7%
ineq_agg	Normative	75.0%	16.7%	0.0%	8.3%
ineq_agg	Gini−Index	33.2%	14.0%	24.5%	28.4%
ineq_agg	Distributional	20.5%	31.5%	30.1%	17.8%
stat_accuracy	5	17.8%	31.1%	33.3%	17.8%
stat_accuracy	4	23.1%	28.8%	30.8%	17.3%
stat_accuracy	3	33.9%	17.9%	23.2%	25.0%
stat_accuracy	2	40.8%	9.9%	26.8%	22.5%
stat_accuracy	1	35.6%	12.2%	16.7%	35.6%
mobilized_theories	5	27.5%	32.5%	7.5%	32.5%
mobilized_theories	4	20.0%	20.0%	40.0%	20.0%
mobilized_theories	3	44.8%	9.0%	23.9%	22.4%
mobilized_theories	2	23.7%	10.5%	27.6%	38.2%
mobilized_theories	1	40.7%	24.1%	20.4%	14.8%
mobilized_theories	0	36.4%	27.3%	22.7%	13.6%
jrnl	h−index > 200	25.2%	21.4%	29.0%	24.4%
jrnl	h−index < 200	36.6%	15.8%	21.9%	25.7%
theory_dom	only positive	50.0%	13.2%	19.1%	17.6%
theory_dom	more positive	34.4%	20.0%	20.0%	25.6%
theory_dom	more negative	28.0%	24.0%	28.0%	20.0%
theory_dom	balanced	21.4%	18.3%	30.5%	29.8%

Chi² Residuals: 3, 2, −2, −3

Fig. 10 | Full sample - Correlation table/ chi-squared tests (without regional).

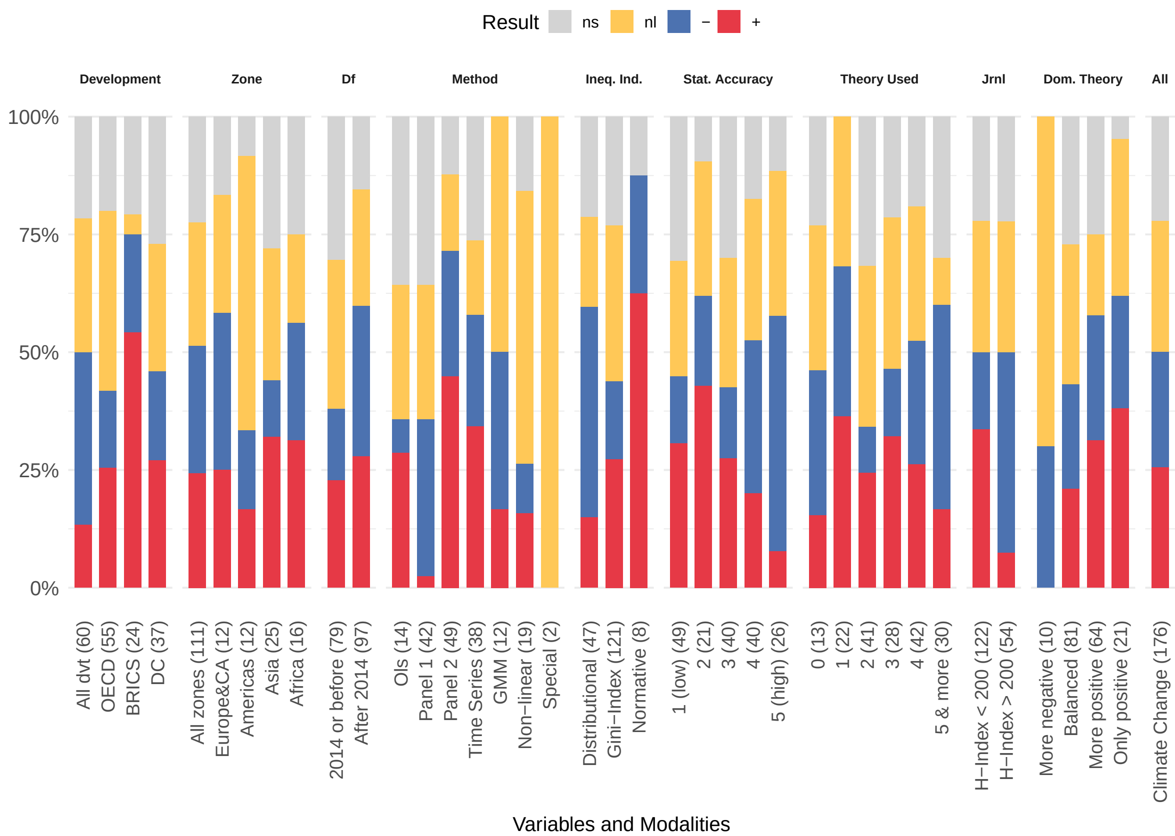

Fig. 11 | Climate change - Results by variable modalities (without regional).

		result_agg			
development	OECD	25.5%	16.4%	38.2%	20.0%
	DC	27.0%	18.9%	27.0%	27.0%
	BRICS	54.2%	20.8%	4.2%	20.8%
	alldvt	13.3%	36.7%	28.3%	21.7%
zone	Europe&CA	25.0%	33.3%	25.0%	16.7%
	Asia	32.0%	12.0%	28.0%	28.0%
	Americas	16.7%	16.7%	58.3%	8.3%
	allzone	24.3%	27.0%	26.1%	22.5%
	Africa	31.2%	25.0%	18.8%	25.0%
df_time	After 2014	27.8%	32.0%	24.7%	15.5%
	2014 or before	22.8%	15.2%	31.6%	30.4%
method_agg_name	Time Series	34.2%	23.7%	15.8%	26.3%
	Special	0.0%	0.0%	100.0%	0.0%
	Panel 2	44.9%	26.5%	16.3%	12.2%
	Panel 1	2.4%	33.3%	28.6%	35.7%
	Ols	28.6%	7.1%	28.6%	35.7%
	Non−linear	15.8%	10.5%	57.9%	15.8%
	GMM	16.7%	33.3%	50.0%	0.0%
ineq_agg	Normative	62.5%	25.0%	0.0%	12.5%
	Gini−Index	27.3%	16.5%	33.1%	23.1%
	Distributional	14.9%	44.7%	19.1%	21.3%
stat_accuracy	5	7.7%	50.0%	30.8%	11.5%
	4	20.0%	32.5%	30.0%	17.5%
	3	27.5%	15.0%	27.5%	30.0%
	2	42.9%	19.0%	28.6%	9.5%
	1	30.6%	14.3%	24.5%	30.6%
mobilized_theories	5	16.7%	43.3%	10.0%	30.0%
	4	26.2%	26.2%	28.6%	19.0%
	3	32.1%	14.3%	32.1%	21.4%
	2	24.4%	9.8%	34.1%	31.7%
	1	36.4%	31.8%	31.8%	0.0%
	0	15.4%	30.8%	30.8%	23.1%
jrnl	h−index > 200	7.4%	42.6%	27.8%	22.2%
	h−index < 200	33.6%	16.4%	27.9%	22.1%
theory_dom	only positive	38.1%	23.8%	33.3%	4.8%
	more positive	31.2%	26.6%	17.2%	25.0%
	more negative	0.0%	30.0%	70.0%	0.0%
	balanced	21.0%	22.2%	29.6%	27.2%
		+	−	nl	NS

Chi² Residuals
3
2
−2

Fig. 12 | Climate change - Correlation table/ chi-squared tests (without regional).

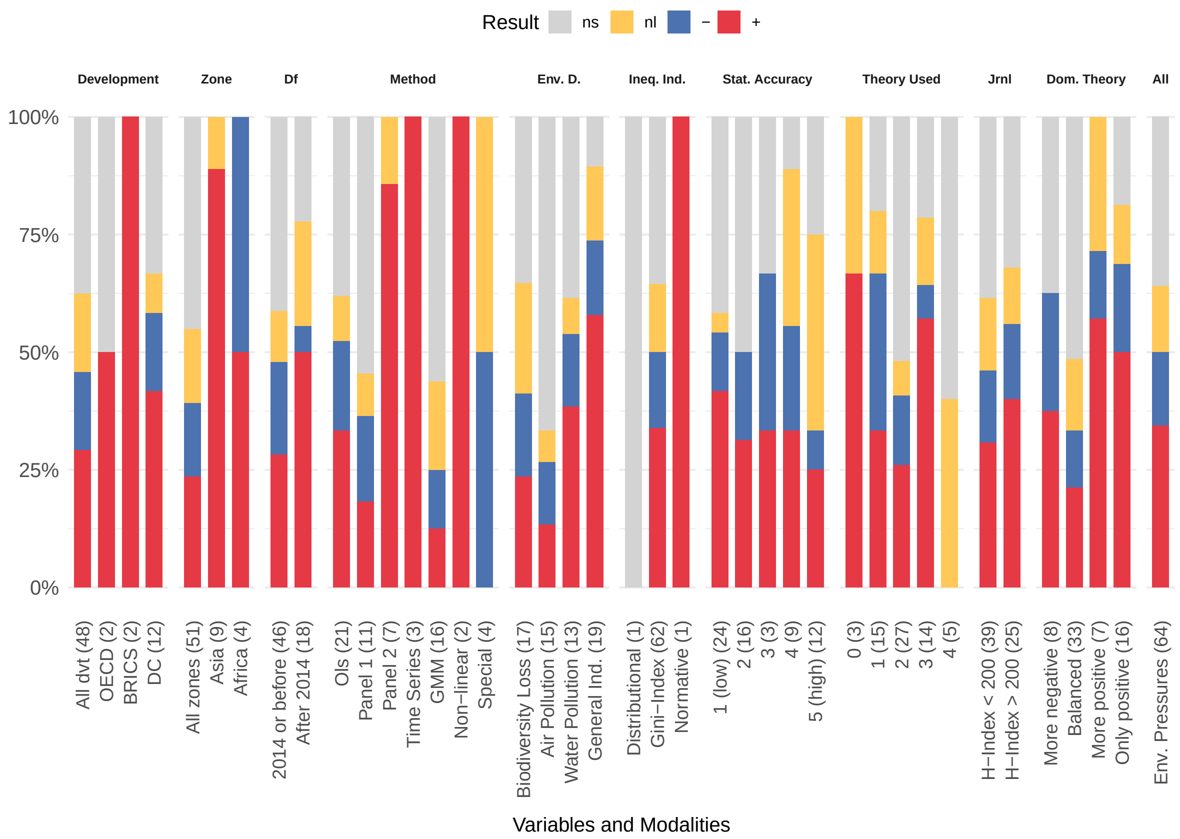

Fig. 13 | Local and regional environmental pressures - Results by variable modalities (without regional).

result_agg		+	−	nl	NS
development	OECD	50.0%	0.0%	0.0%	50.0%
	DC	41.7%	16.7%	8.3%	33.3%
	BRICS	100.0%	0.0%	0.0%	0.0%
	alldvt	29.2%	16.7%	16.7%	37.5%
zone	Asia	88.9%	0.0%	11.1%	0.0%
	allzone	23.5%	15.7%	15.7%	45.1%
	Africa	50.0%	50.0%	0.0%	0.0%
df_time	After 2014	50.0%	5.6%	22.2%	22.2%
	2014 or before	28.3%	19.6%	10.9%	41.3%
method_agg_name	Time Series	100.0%	0.0%	0.0%	0.0%
	Special	0.0%	50.0%	50.0%	0.0%
	Panel 2	85.7%	0.0%	14.3%	0.0%
	Panel 1	18.2%	18.2%	9.1%	54.5%
	Ols	33.3%	19.0%	9.5%	38.1%
	Non−linear	100.0%	0.0%	0.0%	0.0%
	GMM	12.5%	12.5%	18.8%	56.2%
env_dim	Water Pollution	38.5%	15.4%	7.7%	38.5%
	General Ind.	57.9%	15.8%	15.8%	10.5%
	Biodiversity Loss	23.5%	17.6%	23.5%	35.3%
	Air Pollution	13.3%	13.3%	6.7%	66.7%
ineq_agg	Normative	100.0%	0.0%	0.0%	0.0%
	Gini−Index	33.9%	16.1%	14.5%	35.5%
	Distributional	0.0%	0.0%	0.0%	100.0%
stat_accuracy	5	25.0%	8.3%	41.7%	25.0%
	4	33.3%	22.2%	33.3%	11.1%
	3	33.3%	33.3%	0.0%	33.3%
	2	31.2%	18.8%	0.0%	50.0%
	1	41.7%	12.5%	4.2%	41.7%
mobilized_theories	4	0.0%	0.0%	40.0%	60.0%
	3	57.1%	7.1%	14.3%	21.4%
	2	25.9%	14.8%	7.4%	51.9%
	1	33.3%	33.3%	13.3%	20.0%
	0	66.7%	0.0%	33.3%	0.0%
jrnl	h−index > 200	40.0%	16.0%	12.0%	32.0%
	h−index < 200	30.8%	15.4%	15.4%	38.5%
theory_dom	only positive	50.0%	18.8%	12.5%	18.8%
	more positive	57.1%	14.3%	28.6%	0.0%
	more negative	37.5%	25.0%	0.0%	37.5%
	balanced	21.2%	12.1%	15.2%	51.5%

Fig. 14 | Local and regional environmental pressures - Correlation table/ chi-squared tests (without regional).

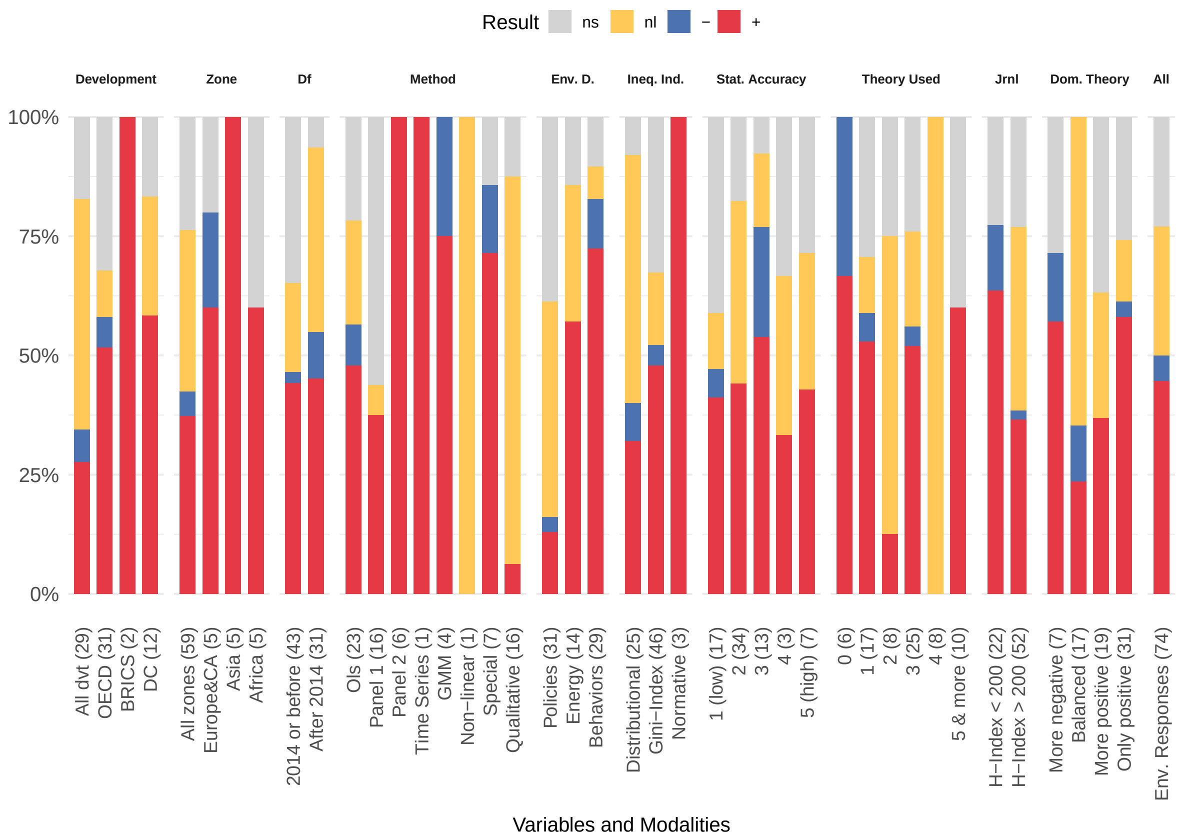

Fig. 15 | Environmental responses - Results by variable modalities (without regional).

		result_agg			
		+	–	nl	NS
development	OECD	51.6%	6.5%	9.7%	32.3%
development	DC	58.3%	0.0%	25.0%	16.7%
development	BRICS	100.0%	0.0%	0.0%	0.0%
development	alldvt	27.6%	6.9%	48.3%	17.2%
zone	Europe&CA	60.0%	20.0%	0.0%	20.0%
zone	Asia	100.0%	0.0%	0.0%	0.0%
zone	allzone	37.3%	5.1%	33.9%	23.7%
zone	Africa	60.0%	0.0%	0.0%	40.0%
df_time	After 2014	45.2%	9.7%	38.7%	6.5%
df_time	2014 or before	44.2%	2.3%	18.6%	34.9%
method_agg_name	Time Series	100.0%	0.0%	0.0%	0.0%
method_agg_name	Special	71.4%	14.3%	0.0%	14.3%
method_agg_name	Qualitative	6.2%	0.0%	81.2%	12.5%
method_agg_name	Panel 2	100.0%	0.0%	0.0%	0.0%
method_agg_name	Panel 1	37.5%	0.0%	6.2%	56.2%
method_agg_name	Ols	47.8%	8.7%	21.7%	21.7%
method_agg_name	Non–linear	0.0%	0.0%	100.0%	0.0%
method_agg_name	GMM	75.0%	25.0%	0.0%	0.0%
env_dim	Policies	12.9%	3.2%	45.2%	38.7%
env_dim	Energy	57.1%	0.0%	28.6%	14.3%
env_dim	Behaviors	72.4%	10.3%	6.9%	10.3%
ineq_agg	Normative	100.0%	0.0%	0.0%	0.0%
ineq_agg	Gini–Index	47.8%	4.3%	15.2%	32.6%
ineq_agg	Distributional	32.0%	8.0%	52.0%	8.0%
stat_accuracy	5	42.9%	0.0%	28.6%	28.6%
stat_accuracy	4	33.3%	0.0%	33.3%	33.3%
stat_accuracy	3	53.8%	23.1%	15.4%	7.7%
stat_accuracy	2	44.1%	0.0%	38.2%	17.6%
stat_accuracy	1	41.2%	5.9%	11.8%	41.2%
mobilized_theories	5	60.0%	0.0%	0.0%	40.0%
mobilized_theories	4	0.0%	0.0%	100.0%	0.0%
mobilized_theories	3	52.0%	4.0%	20.0%	24.0%
mobilized_theories	2	12.5%	0.0%	62.5%	25.0%
mobilized_theories	1	52.9%	5.9%	11.8%	29.4%
mobilized_theories	0	66.7%	33.3%	0.0%	0.0%
jrnl	h–index > 200	36.5%	1.9%	38.5%	23.1%
jrnl	h–index < 200	63.6%	13.6%	0.0%	22.7%
theory_dom	only positive	58.1%	3.2%	12.9%	25.8%
theory_dom	more positive	36.8%	0.0%	26.3%	36.8%
theory_dom	more negative	57.1%	14.3%	0.0%	28.6%
theory_dom	balanced	23.5%	11.8%	64.7%	0.0%

Chi² Residuals

3

2

−2

Fig. 16 | Environmental responses - Correlation table/ chi-squared tests (without regional).

5.2.4 Breakdown of non-linear results

Most of the time we summarize results suggesting dynamic relationships between inequalities and the environment under the term non-linear. Table 19 breaks down these non-linear results by the type of relationship as well as the interaction term employed. In general, studies have mainly suggested that the relationship between inequality and the environment depends on the country's income (37), time (short-run and long-run effects) (28), the initial level of inequality (17) and democracy (10). The latter is the only interaction term suitable to test the transmission channels if existing theories[2]. Eventually, the rest of the studies have tried to link the environmental consequences of inequalities to innovation and country risk indicators. A U-shaped and reverse-U shaped relationship is the most identified kind of non-linear relation for studies making the direction of the inequality effect dependent on income. These contrasting results can be partially explained by the country-groups studied: 8 of 11 studies that assess a reverse U-shaped relationship have been conducted on homogeneous country samples[79, 80]. In contrast, we find that for U-shaped relationships that most (8/13) have been find for heterogeneous samples[43, 44, 66, 81]. In addition, the turning points of the relationships are often not evaluated. Although investigated in a limited way, the probably most convincing result of an interaction effect is that of democracy. Nine out of ten empirical tests conclude that higher levels of democracy favor social-environmental complementarity[3, 6] while lower levels of democracy favor a trade-off between inequality reduction and environmental quality[5].

Interaction	U	$\cap$	$_{-}$NS	$^{+}$NS	NS^{+}	NS$_{-}$	$\sim$	$\backsim$	M	+	-	NS	Total
Income	13	11	1	9	1	0	0	0	0	0	1	3	39
Time	6	4	0	2	4	3	0	1	1	2	1	4	28
Inequality	4	7	0	0	0	0	1	1	0	1	2	1	17
Democracy	7	0	1	0	1	0	0	0	0	0	0	1	10
Fin. Dev.	0	0	0	0	0	0	0	0	0	0	3	0	3
Fin. Inst.	1	0	0	0	0	0	0	0	0	0	0	0	1
Patents	1	0	0	0	0	0	0	0	0	0	0	0	1
Rnew. Innov.	0	0	0	0	0	0	0	0	0	0	0	1	1
Country Risk	0	0	0	0	0	0	0	0	0	2	0	3	5
Income^2	0	0	0	0	0	0	2	0	0	0	0	1	3
Tech. Innov.	0	0	0	0	0	0	0	0	0	1	0	0	1
Indust.	0	0	0	0	0	0	0	0	0	1	0	0	1
NA	1	1	0	0	0	0	0	0	0	152	61	81	296
Total	33	23	2	11	6	3	3	2	1	159	68	95	406

Tab. 19 | Full sample - Detailed results table (harmonized)

Table 20 depicts the detailed non-linear results by interaction effect for climate change, local and regional environmental pressures and environmental responses separately. For climate change (Table 20a), an interaction effect with income point towards a U-shaped relationship for samples containing countries with various development levels. However, when applied to countries of similar development levels (OECD and China), a reverse-U shaped relationship is found, signifying that countries with higher income face a trade-off between equity and environmental quality (and vice versa). Studies on local and regional environmental pressures (Table 20c) test non-linearities and transmission mechanisms very limited, which is most likely related to the low number of novel studies in this field. Thus, we cannot draw conclusions about the dependencies and transmission mechanisms of local and regional environmental pressures. For environmental responses (Table 20b) the two most utilized interaction effects, income and democracy, point towards a U-shaped relationship.

Interaction	U	∩	$_{-}$NS	$^{+}$NS	NS^{+}	NS$_{-}$	∼	∽	+	-	NS	Total
Income	10	8[1]	0	1	1	0	0	0	0	1	3	24
Time	6	4	0	2	3	3	0	1	1	1	4	25
Inequality	1	4	0	0	0	0	1	0	1	2	1	10
Democracy	2	0	1	0	1	0	0	0	0	0	0	4
Fin. Dev.	0	0	0	0	0	0	0	0	0	3	0	3
Fin. Inst.	1	0	0	0	0	0	0	0	0	0	0	1
Patents	1	0	0	0	0	0	0	0	0	0	0	1
Rnew. Innov.	0	0	0	0	0	0	0	0	0	0	1	1
Country risk	0	0	0	0	0	0	0	0	2	0	3	5
Income^2	0	0	0	0	0	0	0	0	0	0	1	1
NA	0	0	0	0	0	0	0	0	67	38	35	140
Total	21	16	1	3	5	3	1	1	71	45	48	215

[1] The reverse U-shaped relationship is found only for studies of OECD countries and China.

(a) **Climate change - Detailed results table.**

Interaction	U	∩	$_{-}$NS	NS^{+}	∼	∽	+	-	NS	Total
Income	0	3	1	0	0	0	0	0	0	4
Time	0	0	0	1	0	0	1	0	0	2
Inequality	1	2	0	0	0	1	0	0	0	4
Income^2	0	0	0	0	2	0	0	0	0	2
Industrialization[1]	0	0	0	0	0	0	1	0	0	1
NA	1	1	0	0	0	0	43	20	26	91
Total	2	6	1	1	2	1	45	20	26	104

[1] Wu, Zhang, Elahi, Mu & Zhao 82 Share of non-agricultural output and Agrochemical Inputs

(b) **Local and regional env. pressures - Detailed results table.**

Interaction	U	∩	$_{-}$NS	M	+	-	NS	Total
Income	3	0	8	0	0	0	0	11
Time	0	0	0	1	0	0	0	1
Inequality	2	1	0	0	0	0	0	3
Democracy	5	0	0	0	0	0	1	6
Tech. Innov	0	0	0	0	1	0	0	1
NA	0	0	0	0	42	3	20	65
Total	10	1	8	1	43	3	21	87

(c) **Env. responses - Detailed results table.**

Tab. 20 | Detailed results of subgroups of environmental dimensions.

5.3 Inter-dependencies between test characteristics - full sample

In the following section we identify inter-dependencies between test characteristics via Multiple Component Analysis (MCA) and Hierarchical Cluster Analysis (HCA) and, separately, investigate the relationship of the identified clusters and the test results. We perform a MCA of the full database (Figure 17), including the following main modalities that might influence the test results: *development*, *zone*, *scale*, *df_time*, *method_agg_name*, *env_dim*, *ineq_agg* , and *statistical_accuracy*, *mobilized_theories* and *jrnl_agg*. We decided not to include the income level in the analysis due to its similarity with the development level, as well as the indicator *theory_dom*, since it might not directly influence the outcome of the empirical test.

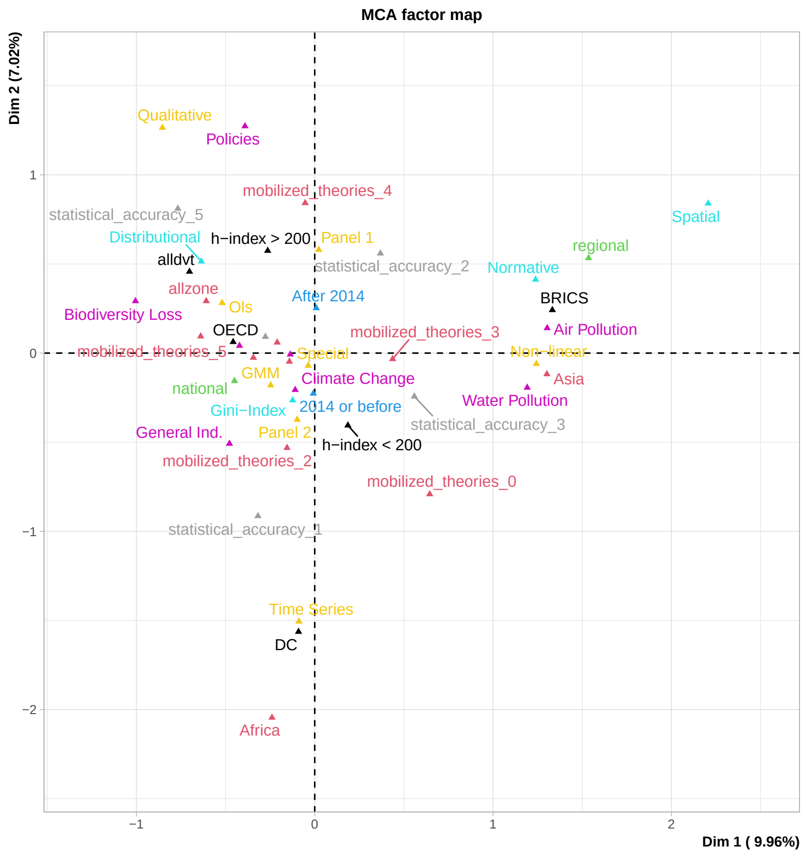

Fig. 17 | MCA of the full sample.

We interpret the first two dimensions of the MCA which jointly represent 16.98% of the overall variation in the dataset (the axis inertia rates are presented in Figure 19). Further, Table 23 contrasts the relative contributions of the variable modalities to the first two dimensions in descending order by influence. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 20 & 21. The scale of the analysis as well as sample characteristics primarily determine the first dimension of the MCA. However, inequality, the environmental dimension tested as well as modeling techniques have a distinctive impact as well.

The first dimension of Figure 17 highlights differences between tests conducted on global samples, which are associated with distributional inequality indicators and high statistical accuracy, and regional analyses of Asian and BRICS economies. The latter are affiliated with non-linear methods as well as spatial/normative inequality indicators.

In contrast, research quality (number of theories mobilized, statistical accuracy & journal's h-index), methodological approaches and environmental dimensions contribute more greatly to the second dimension of the MCA. The characteristics of the samples play a comparatively minor role, although developing countries are well represented. Analyses of the latter, especially in Africa, seem to heavily rely on time series modeling and are moreover associated with low statistical accuracy and a low number of mobilized theories. On the other hand, high-statistical accuracy, a high number of mobilized theories as well as a high journal h-index is associated with Panel 1 methods, tests on global samples and distributional inequality indicators. Outliers within this dimensions are qualitative analyses of policy indicators.

All in all, we identify three distinctive groups based on Figure 17 and Table 23. First, analyses of global samples associated with high-statistical accuracy, a high number of mobilized theories, distributional inequality measures, first generation panel modeling techniques and high-ranking journals. Second, regional-level analyses of China (BRICS, Asia) that utilize spatial and normative inequality measures and non-linear modeling techniques. Third, time series models of developing countries in Africa that exhibit low statistical and theoretical quality. Next, we perform a HCA based on the MCA to get more in-depth insights. Through the HCA we are able to consider more dimensions (based on the axis inertia rates) when identifying distinctive groups. Figure 22 & Figure 23 depict the respective cluster dendrogram and the factor map of the HCA. We can choose between 3 and 6 clusters. The 3-cluster solution confirms the clusters already identified in Figure 17. The six-cluster solution provides a more granular resolution of the groups and is described in Table 21.

Regional-level analyses of China as well as *developing country analyses* that utilize time series models form separate groups as evaluated in the previous MCA (Figure 17). The third group found in the MCA is disaggregated into *Old analyses*, *Global analyses*, *Qualitative analyses* (of energy-related environmental indicators) and *OECD analyses* (of climate change). Environmental dimensions such as policies and behaviors as well as biodiversity are primarily found among the cluster of old analyses, highlighting the need for intensified research on these categories. The clusters are divided along methods, quality of research and environmental dimensions, uncovering important biases in the research - specialization rather than diversification has taken place. Specific country groups are strongly associated with specific methods: most notably developing countries with time series models and global studies with first-generation panel and GMM models. In addition, the research quality for developing countries and China is on average lower than for tests conducted on global country samples.

Table 21 further depicts the results found for each cluster. Chi-squared tests and a graphical visualization are provided in Figure 24 and 25. Positive results dominate for *Old analyses* (mostly

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Old analyses*; Ols methods, high-ranking journals	OECD countries, main env. dim.: policies, behavior, biodiversity; low statistical accuracy; mixed number of theories mobilized	42.1%	8.8%	14%	35.1%	57
2	*Global analyses*; GMM and first-generation panel models	high statistical accuracy, high number of theories mobilized, Gini-coefficient as inequality ind.	19.6%	29%	24.3%	27.1%	107
3	*Qualitative analyses*; energy-related env. dim., high-ranking journals	medium statistical accuracy, env. dim.: energy & policies, distributional inequality ind., recent time-frame	31.6%	0%	57.9%	10.5%	19
4	*OECD analyses*; climate change	high-statistical accuracy, distributional inequality ind., recent time-frame, second-generation panel models, low-ranking journals	40.3%	18.2%	26%	15.6%	77
5	*Developing country analyses*; time-series models, low-ranking journals	studies in Africa and Asia, low theoretical and statistical quality, Gini-coefficient, env. dim.: climate change, second-generation panel models	41.7%	15.3%	18.1%	25%	72
6	*Regional-level analyses of China*	spatial & normative inequality ind., non-linear methods, env. dim.: air & water pollution, average statistical accuracy	55.4%	17.6%	8.1%	18.9%	74

Tab. 21 | Characterization of cluster obtained from the full sample.

on OECD countries), *OECD analyses* and *developing country analyses*. For *regional-level analyses of China* they even present the majority of findings (55.4%). In contrast, *global analyses* find significantly more negative results (29%) while *old analyses* report more non-significant results than other analyses (35.1%). Qualitative analyses on energy-related environmental indicators find mostly non-linear results. Although we cannot assess which factor is responsible for the differing research outcomes (method, country-group studied, or research quality), it is necessary to take these biases for future research into account.

The results of the MCA and HCA in Figure 17 might be consumed by regional analysis. Thus, we want to check the robustness of the results by excluding regional-level analyses (Figure 18).The first to dimension of the MCA represents 15.63% of the overall variation in the dataset (axis inertia rates in Figure 26). Table 24 contrasts the relative contributions of the variable modalities to the first two dimensions. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 27 & 28. .

Figure 18 highlights the contrast between, on one hand, global analyses characterized by a high number of mobilized theories and high statistical accuracy, often employing first-generation panel techniques, and on the other hand, time series analyses and second-generation panel models applied primarily to BRICS and developing economies. After excluding regional-level analyses, the characteristics of empirical assessments of BRICS and developing economies become similar. The recentness of the time-frame, the environmental dimensions as well as the methods contribute the most to the second dimension of the MCA (Figure 27). Analyses of biodiversity, air and water quality are associated with old time-frames and Ols methods. In contrast, analyses of energy-related indicators, the utilization of distributional inequality measures and qualitative as well as second-generation panel models are related to more recent time-frames.

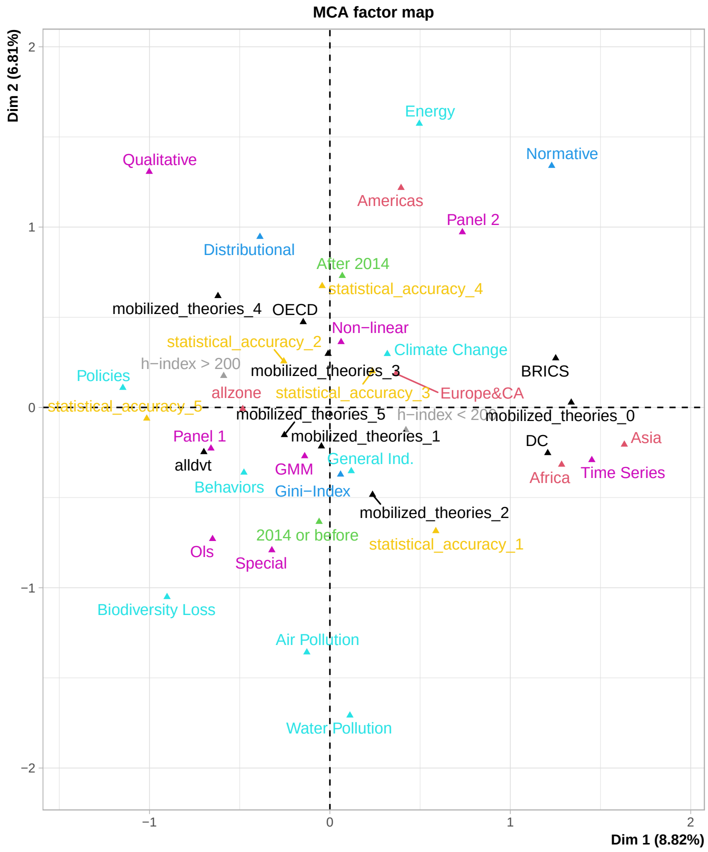

Fig. 18 | MCA of the full sample (without regional).

We perform again a hierarchical cluster analysis that assesses 7 clusters which allows us to obtain a higher degree of disaggregation. Figure 29 and 30 provide the respective cluster dendrogram and the factor map. Table 22 describes the 7 clusters and depicts their related results. Chi-squared tests and a graphical depiction of the results by cluster are illustrated in Figure 31 and 32.

We obtain 5 groups similar to the ones previously identified (except regional-level analyses) (Table 21). In addition, we identify two new clusters, which also influence the distribution of tests grouped within the five original clusters. First, the present hierarchical cluster analysis separates old analyses of local and regional environmental pressures and environmental responses (Clusters 3 & 2). Both of them obtain a high share of non-significant results, signifying the lack of recent studies on these topics. Second, we find a new cluster of second-generation panel models of BRICS economies that focus on general environmental indicators and exhibit a low-research quality (Cluster 6).

The results by cluster differ from the ones obtained in Table 21 in three aspects: First, positive results dominate only for analyses of environmental responses while they are similar to the share of negative results for old analyses on local and regional environmental pressures. Second, recent OECD analyses obtain a significantly higher share of negative results in contrast to the rest of the sample (Figure 31). However, positive results still dominate. Lastly, the newly identified

Cluster	Characterization	Details	+	-	nl	NS	N
3	*Old analyses of env. pressures*; OLS methods	global country samples, main env. dim.: air, water, biodiversity; Gini-coefficient as inequality ind., low number of theories mobilized, low statistical accuracy	22.7%	20.5%	13.6%	43.2%	44
1	*Global analyses*; recent time frame high-ranking journals	high number of theories utilized, high statistical accuracy, first-generation panel models;, GMM	16.3%	30.2%	27.9%	25.6%	43
4	*Qualitative analyses*; energy-related env. dim., high-ranking journals	medium statistical accuracy, high number of theories, env. dim.: energy & policies, distributional inequality ind., recent time-frame	30%	0%	60%	10%	20
5	*Recent OECD analyses*	second-generation panel models, high statistical accuracy, distributional inequality indicator, climate change, BRICS, low-ranking journals	38.7%	29%	24.2%	8.1%	62
7	*Time series analyses*; BRICS & DC, low-ranking journals	Asia, low statistical accuracy, climate change, Gini-coefficient	42.5%	15%	17.5%	25%	40
2	*Old OECD analyses of env. responses*	first-generation panel models, Ols, high number of theories mobilized, average statistical accuracy, env.ind.: policies & behaviors	31.6%	10.5%	23.7%	34.2%	76
6	*Second-generation panel models of developing countries*	very low number of theories mobilized, Africa and Asia, low-ranking journals, general env. indicators, Gini-Index	41.4%	10.3%	27.6%	20.7%	29

Tab. 22 | Characterization of cluster obtained from the full sample (without regional).

cluster of second-generation panel models of developing countries (and low research quality) find primarily positive results.

The MCAs and HCAs of the full sample shows that the increase in methods, country-groups studied and inequality indicators utilized can be rather described as a specialization than a diversification. The increase analyses specifically addressing the inequality-environment relationship in BRICS and developing countries has been associated with times series & second generation panel methods but on average low theoretical and statistical quality, which restricts this literature to less well-known scientific journals.

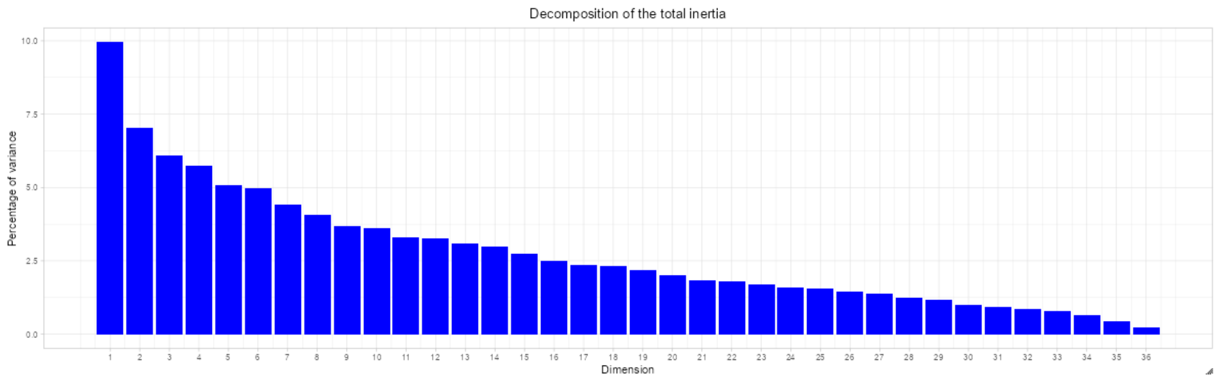

Fig. 19 | Decomposition of the total inertia full sample.

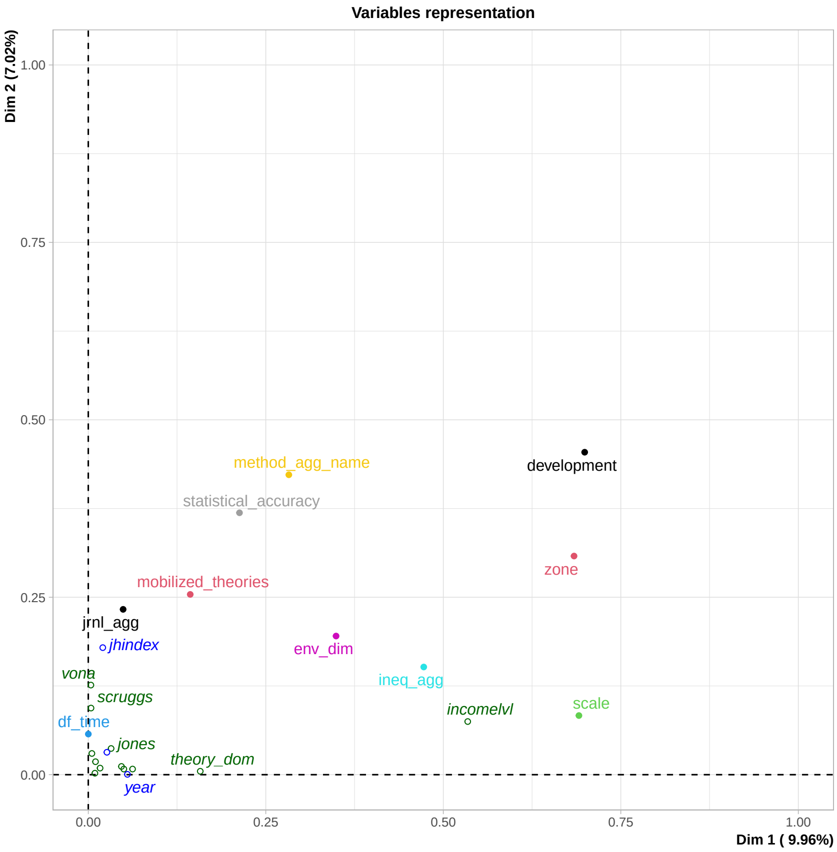

Fig. 20 | Variable representation full sample.

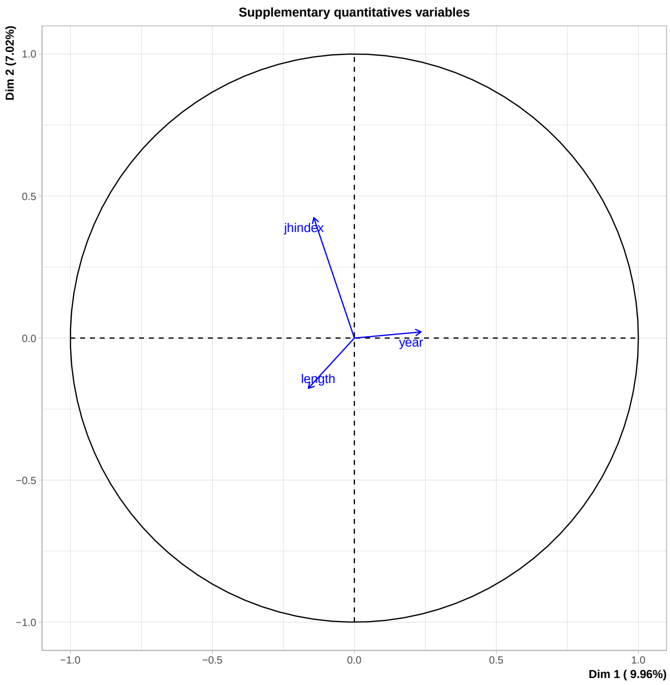

Fig. 21 | Quantitative supplementary variables full sample.

Negative Side	Positive Side
Axis 1	
allzone (5.618)	*regional* (14.912)
alldvt (4.642)	*BRICS* (13.421)
national (4.369)	*Asia* (13.273)
distributional (2.251	*Spatial* (7.693)
statistical_accurcay_5 (2.065)	*Non-linear* (5.625)
	Air (4.321)
	Normative (2.951)
	Water (2.829)
Axis 2	
DC (14.517)	*Policies* (5.999)
Africa (10.181)	*mobilized_theories_4* (5.800)
Time Series (9.274)	*h-index > 200* (5.400)
statistical_accuracy_1 (7.568)	*Panel 1* (3.403)
h-index < 200 (3.812)	*statistical_accuracy_5* (3.265)
mobilized_theories_2 (2.366)	*statistical_accuracy_2* (3.198)
	alldvt (2.788)
	Qualitative (2.492)
	regional (2.548)
	distributional (2.089)

Tab. 23 | Relative contributions of variables to axes: Full sample.

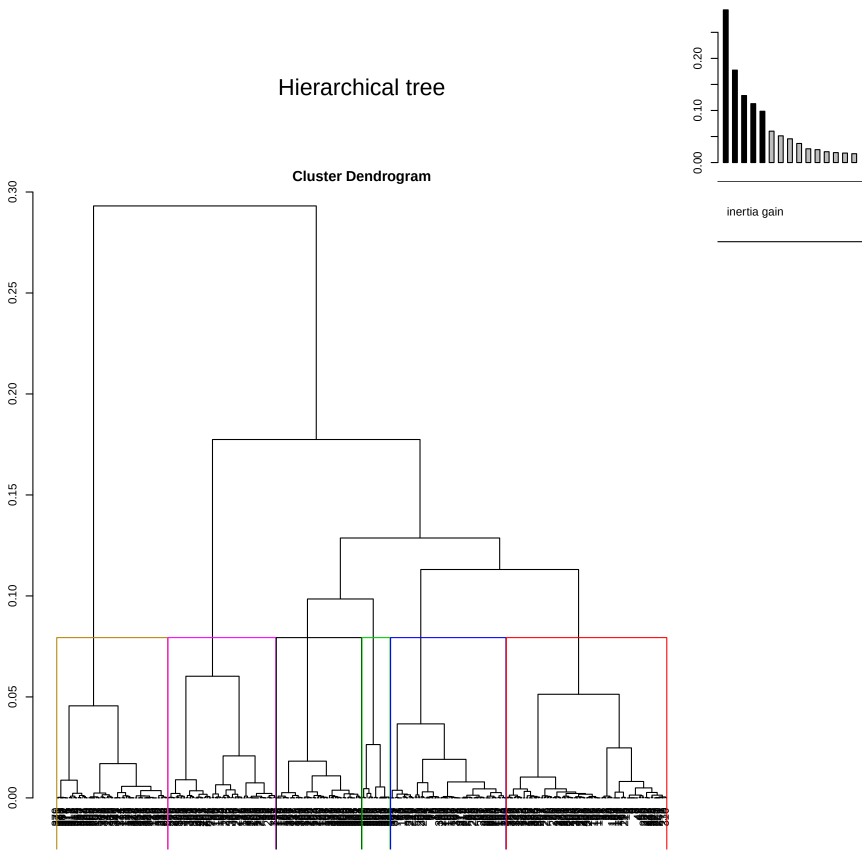

Fig. 22 | Cluster dendrogram of the full sample.

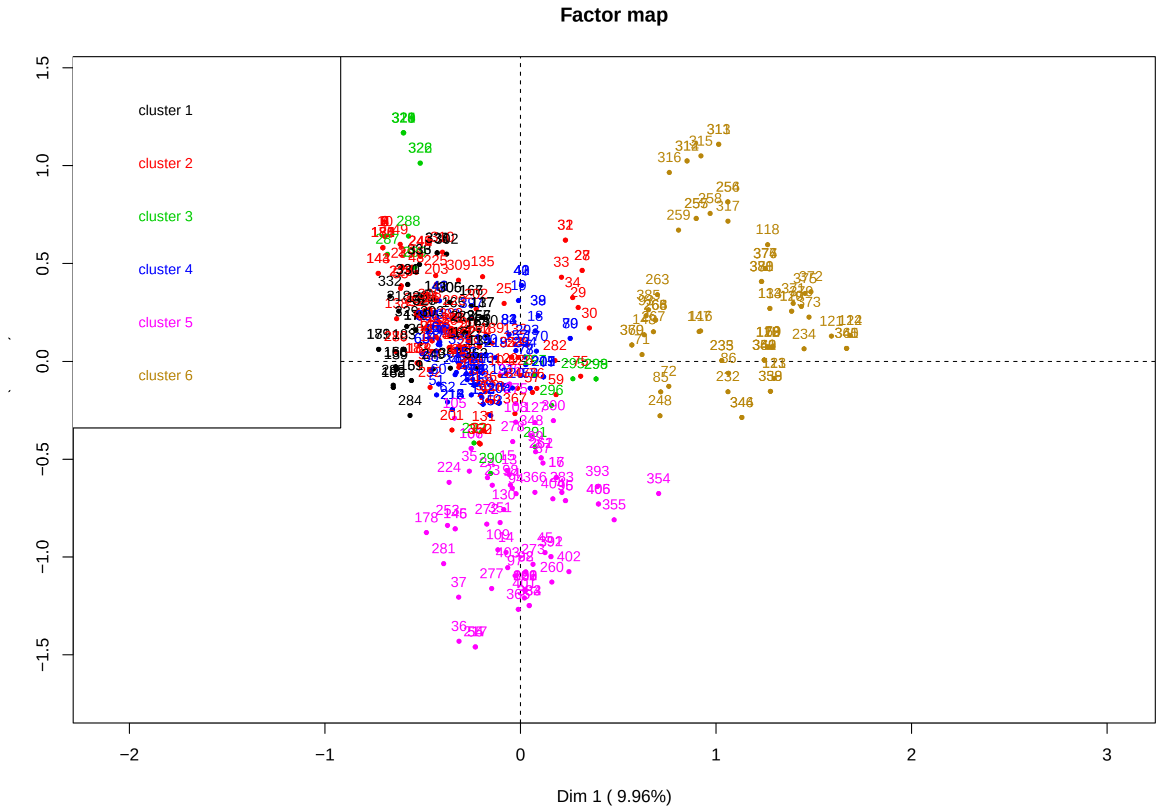

Fig. 23 | Factor map of HCA of the full sample.

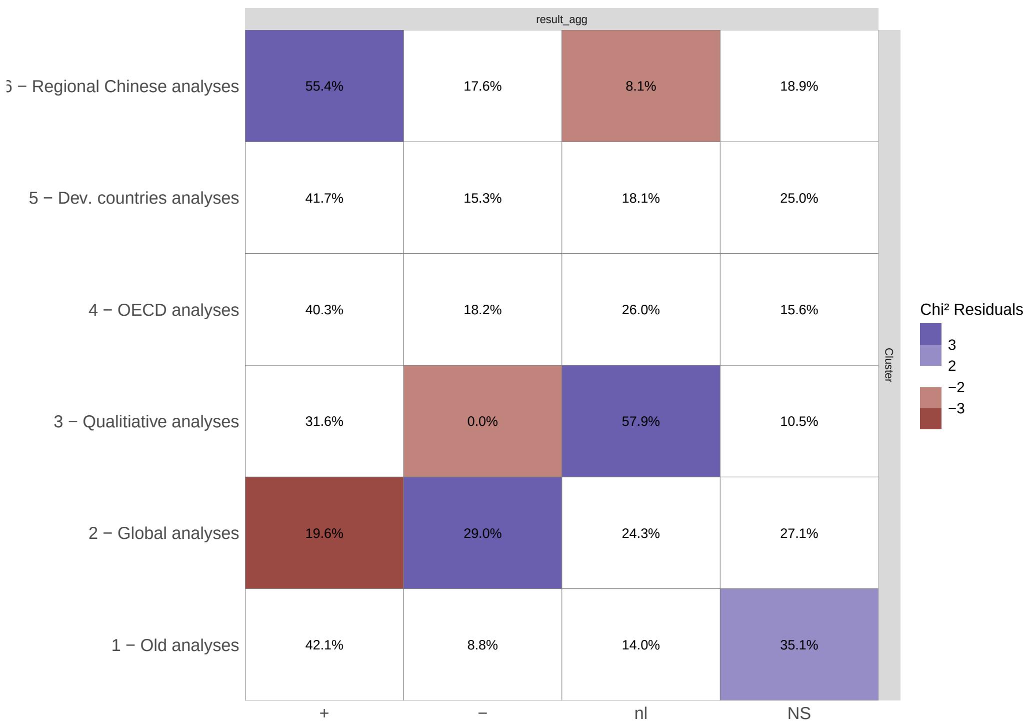

Fig. 24 | Correlation table - Clusters full sample.

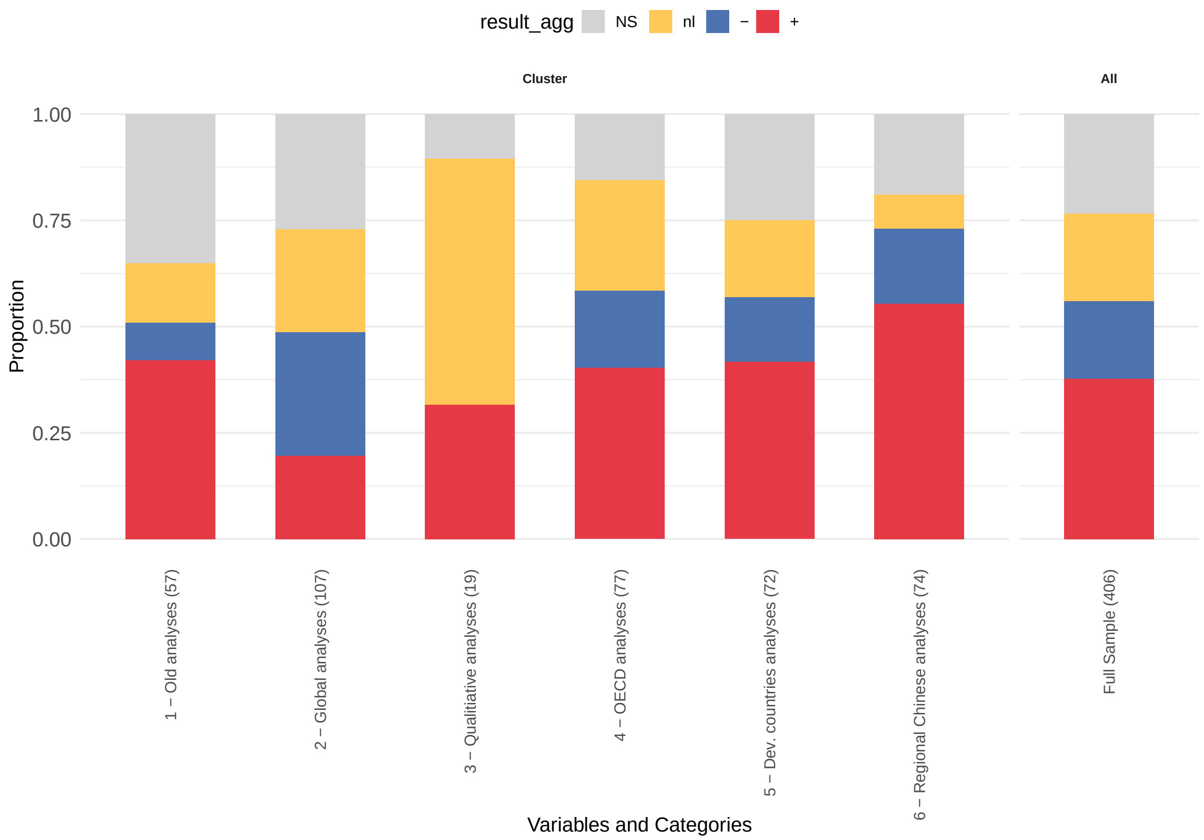

Fig. 25 | Cluster - Results full sample.

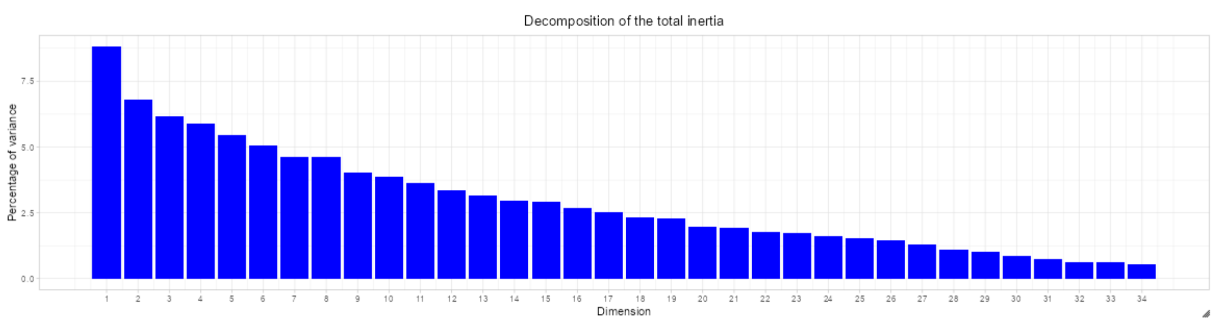

Fig. 26 | Decomposition of the total inertia full sample (without regional).

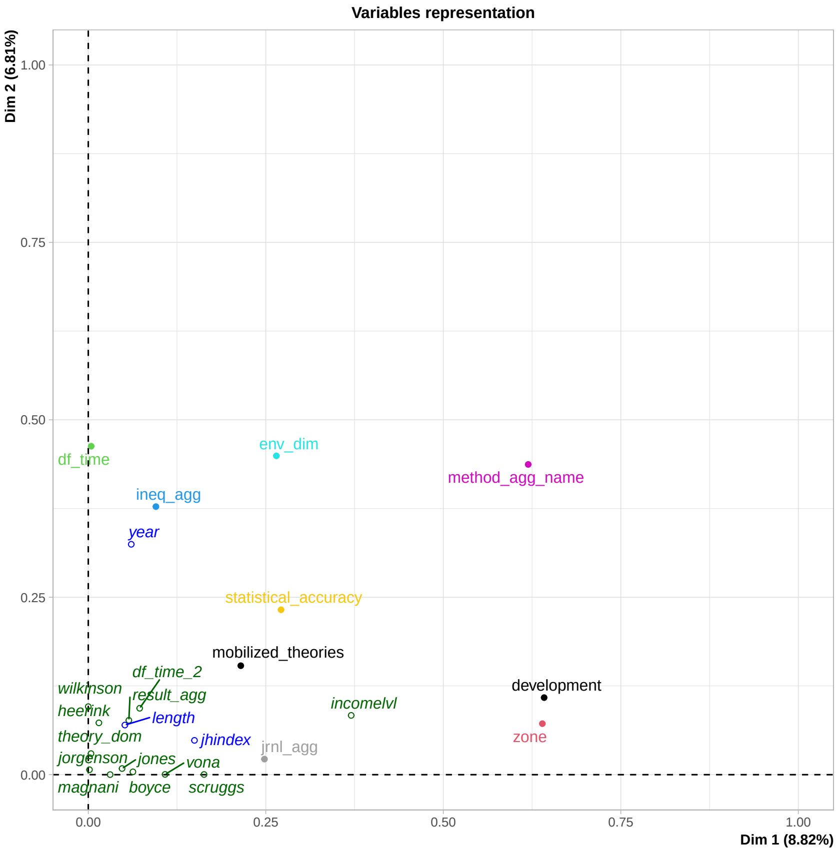

Fig. 27 | Variable representation full sample (without regional).

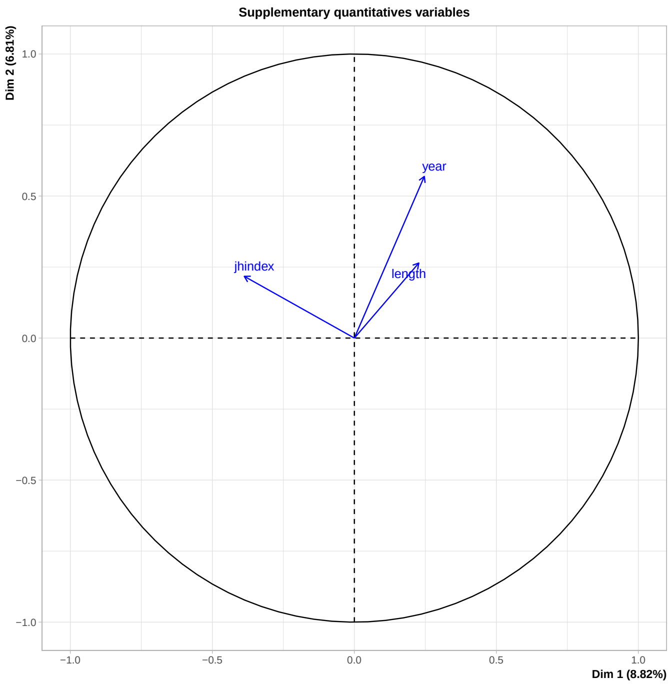

Fig. 28 | Quantitative supplementary variables full sample (without regional).

Negative Side	Positive Side
Axis 1	
alldvt (7.097)	*Asia* (11.028)
allzone (5.471)	*DC* (9.443)
statistical_accuracy_5 (4.923)	*Time Series* (9.399)
h-index > 200 (4.820)	*BRICS* (4.657)
Policies (4.333)	*Africa* (4.379)
Panel 1 (3.183)	*mobilized_theories_0* (4.179)
Ols (2.604)	*Panel 2* (3.549)
	h-index < 200 (3.451)
	statistical_accuracy_1 (3.295)
Axis 2	
2014 or before (9.294)	*After 2014* (10.694)
statistical_accuracy_1 (5.818)	*distributional* (8.993)
Water (5.218)	*Panel 2* (8.058)
Gini-Index (4.357)	*Energy* (4.770)
Ols (4.243)	*Qualitative* (3.760)
Air (3.805)	*statistical_accuracy_4* (3.244)
Biodiversity (2.584)	*Normative* (2.964)
mobilized_theories_2 (2.449)	*mobilized_theories_4* (2.891)
	OECD (2.714)
	Americas (2.448)

Tab. 24 | Relative contributions of variables to axes: Full sample (without regional).

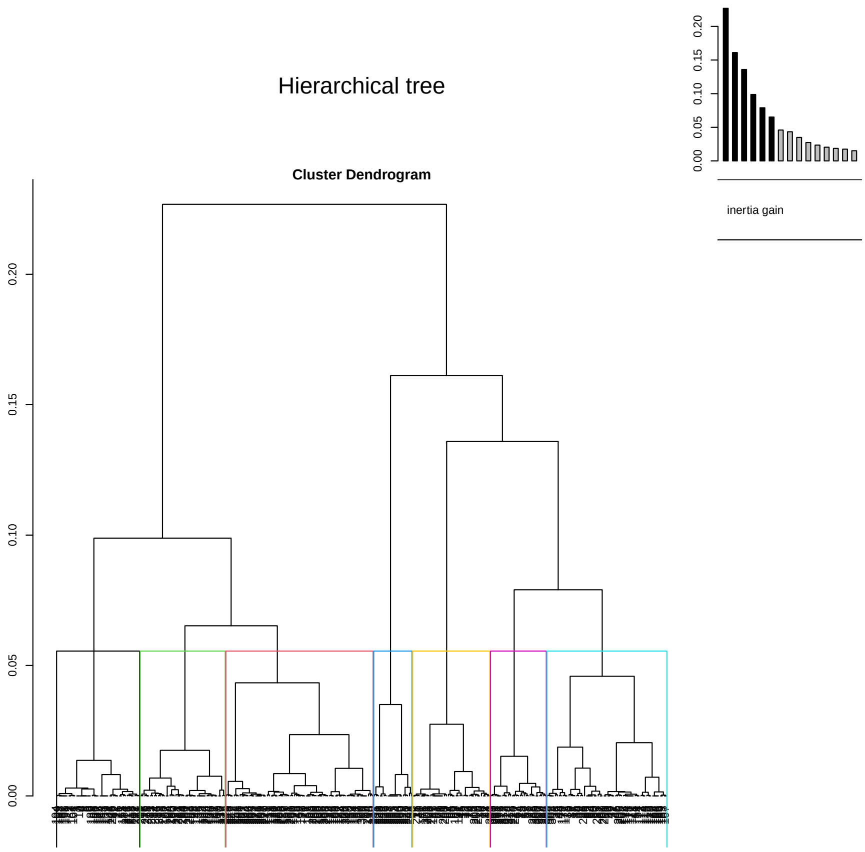

Fig. 29 | Cluster dendrogram of the full sample (without regional).

Fig. 30 | Factor map of HCA of the full sample (without regional).

Cluster	+	−	nl	NS
7−Time series, BRICS & DC	42.5%	15.0%	17.5%	25.0%
6−Panel 2 Dev. countries	41.4%	10.3%	27.6%	20.7%
5−Recent OECD analyses	38.7%	29.0%	24.2%	8.1%
4−Qualitative analyses	30.0%	0.0%	60.0%	10.0%
3−Old analyses, Pressures	22.7%	20.5%	13.6%	43.2%
2−Old OECD analyses, Responses	31.6%	10.5%	23.7%	34.2%
1−Global analyses, recent	16.3%	30.2%	27.9%	25.6%

result_agg

Chi² Residuals: 3, 2, −2, −3

Fig. 31 | Correlation table - Clusters full sample (without regional).

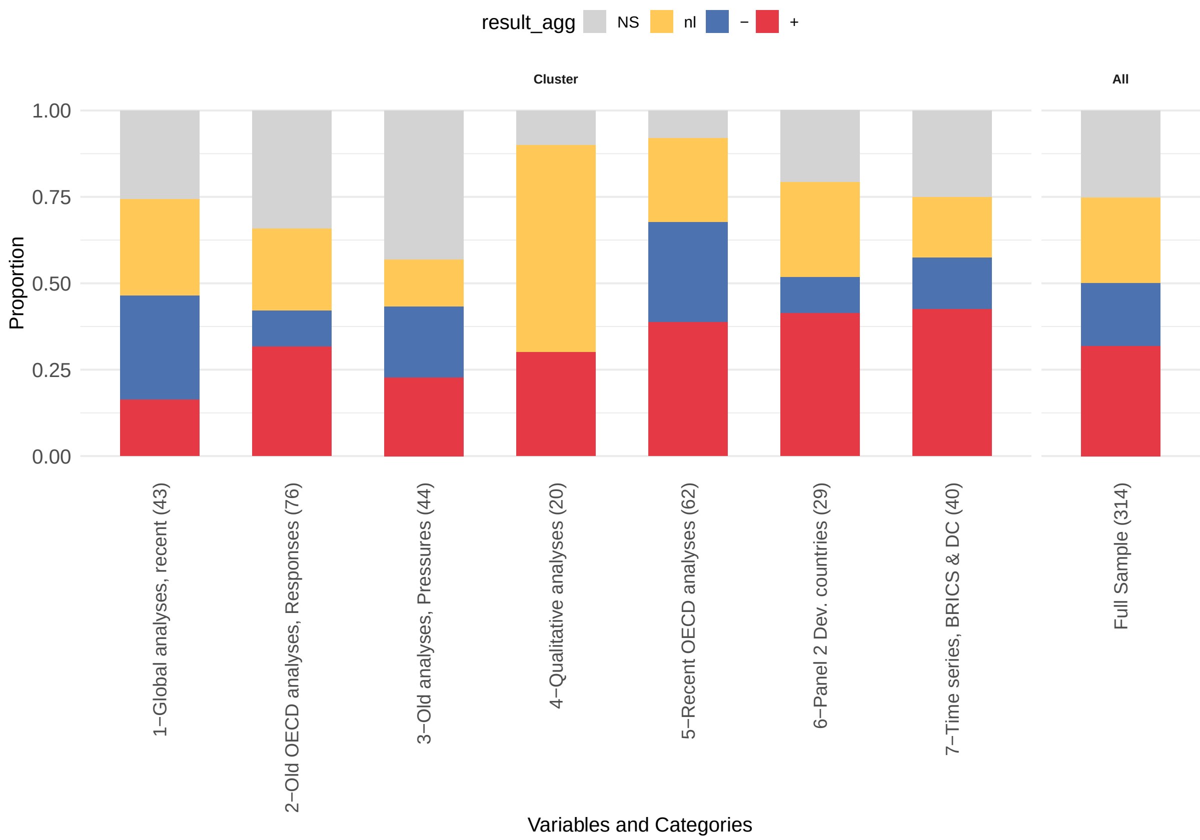

Fig. 32 | Cluster - Results full sample (without regional).

5.4 Inter-dependencies between test characteristics - climate change

The analysis of the full sample shows a difference in econometric specifications and research quality between empirical assessments of developing countries and global samples, which, in fact, lead to different results. These inter-dependencies might be as well different for tests on the environmental dimension climate change, local and regional environmental pressures and environmental responses. They exhibit different dominant results and different associations between research quality and results. In addition, a separate consideration allows us to isolate the effect of econometric specifications, country-group studied and research quality from those of the environmental dimensions. Thus, we perform separate MCAs and hierarchical cluster analyses of tests on climate change, local and regional environmental pressures (Air, Water, Biodiversity and General indicators) and environmental responses (Behavior, Policies, Energy).

Figure 33 shows the results of the MCA of empirical tests on climate change. The first two dimensions represent 20.51% of the overall variation in the dataset (axis inertia rates in Figure 37). Table 27 contrasts the relative contributions of the variable modalities. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 35 & 36. We assess a distinction between, on the one hand, global analyses using first-generation panel models & distributional inequality indicators that are associated with high research quality and, on the other hand, times series models of developing countries associated with low research quality. Furthermore, the second dimension highlights the difference between regional-level analyses of BRICS economies and other assessments on national-level. Although not significant (Table 27), these tests seem to be associated with second-generation panel and GMM methods.

Thus, we assess four groups partly similar to the ones in Figure 17. However, the distinction between these three groups and their division along countries, methods, theories and indicators utilized becomes even more evident.

We perform again a hierarchical cluster analysis, assessing 4 clusters similar to the ones already visible in the MCA. Figure 38 and 39 provide the respective cluster dendrogram and the factor map. Table 25 describes the 4 clusters and depicts their related results. Chi-squared tests and a graphical depiction of the results by cluster are illustrated in Figure 40. The division observed in Figure 33 is verified by the respective hierarchical cluster analysis.

The most notable difference between the four clusters identified for climate change (Table 25) and those based on the full sample (Table 21) is the emergence of a cluster of OECD countries (and other national-level analyses). Both the choice of empirical estimation methods and the sample composition determine the identified clusters. The four clusters can be characterized as follows. 1) *Global analyses* employing first-generation panel methods, 2) *OECD analyses* utilizing second-generation panel techniques and top% inequality indicators, 3) *Regional-level analyses on China*; and 4) *Time series models of developing countries*. Among global analyses (72), only 11.1% report a positive association between economic inequalities and climate change,

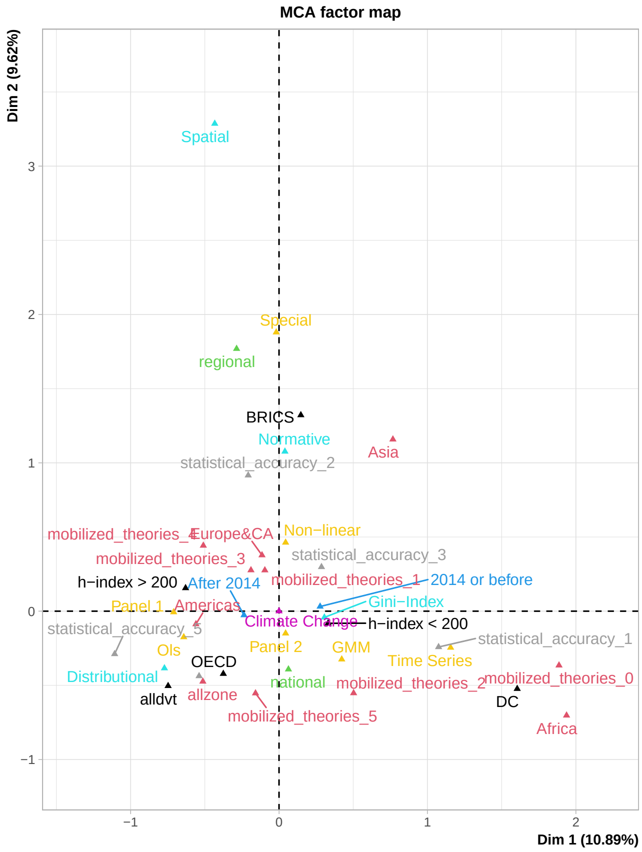

Fig. 33 | MCA of climate change.

whereas positive results are predominant in all other clusters. Figure 40 provides a correlation table with associated chi-squared tests for the clusters. In terms of our predefined research quality indicators, global studies rank highest, followed by OECD and regional studies, and lower quality for assessments of developing countries.

Consequently, we perform a MCA and cluster analysis without empirical tests of regional studies to control for a possible bias introduced by regional-level assessments. Figure 34 depicts the results of the MCA of tests on climate change excluding regional analyses. The first two dimensions represent 22.1% of the overall variation in the dataset (axis inertia rates in Figure 41). Table 28 again contrasts the relative contributions of the variable modalities to the axes. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 42 & 43.

We assess the same groups identified in the previous MCA and HCA, including their regional characteristics. The MCA reveals three groups: 1) high-quality global studies employing first-generation panel data and specialized modeling techniques, 2) low-quality time series analyses focused on developing countries, 3) more recent, mixed-quality studies targeting specific country groups. Compared to Figure 33, the MCA offers more detailed insights into methodological differences. In particular, time series models are associated with developing countries (low-quality). First-generation panel models and special methods are associated with global analyses

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Global analyses*, high statistical and theoretical accuracy, high-ranking journals	first-generation panel and OLS estimation techniques	11.1%	31.9%	29.2%	27.8%	72
2	*OECD analyses*, distributional inequality indicator	mixed statistical and theoretical accuracy, second-generation panel estimation techniques, recent time-frame	40.5%	11.9%	33.3%	14.3%	42
3	*Regional-level analyses of China*, spatial inequality indicator	Mixed number of theories utilized. mostly Asia as geographical zone but also Europe&CA, Normative and Spatial inequality indicators, Special and non-linear methods, recent time-frames	49%	23.5%	9.8%	17.6%	51
4	*Time Series models of developing countries*, low-ranking journals	Low statistical accuracy, low number of theories utilized, concentration inequality measure (Gini-coefficient), Africa & Asia	34%	18%	22%	26%	50

Tab. 25 | Characterization of cluster obtained from tests on climate change.

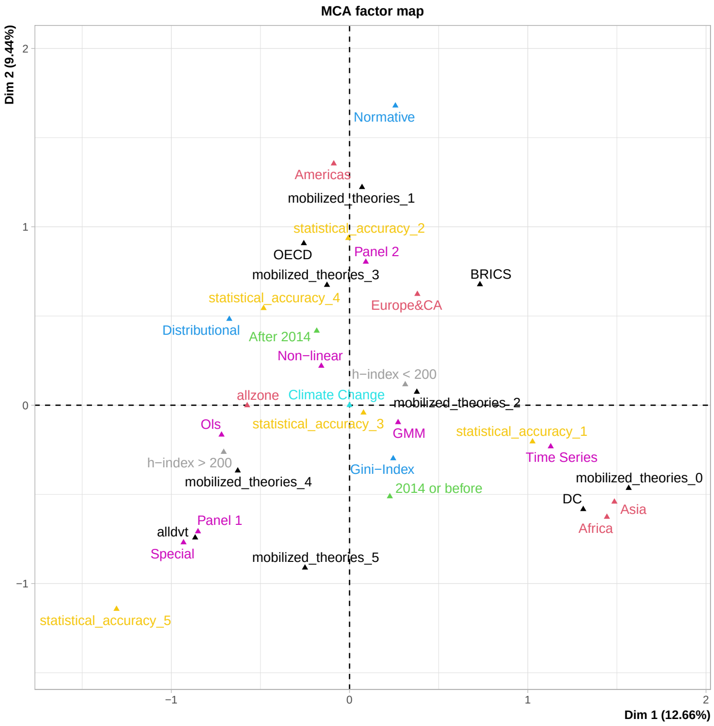

Fig. 34 | MCA of climate change (without regional).

(high quality) and second-generation panel approaches are related to recent analyses of BRICS and OECD countries.

The hierarchical cluster analyses suggest either a 3-cluster solution (same groups as the MCA) or a 6-cluster solution. Since we want to gain greater insights, we investigate the 6 clusters shown by the HCA. Figure 44 and 45 provide the respective cluster dendrogram and the factor map. Table 26 describes the 6 clusters and depicts their related results. Chi-squared tests and a graphical depiction of the results by cluster are illustrated in Figure 46.

Cluster 1 & 6, *Global analyses* and *Time series models*, have already been identified in the previous HCA. The differences between these two clusters in terms of results becomes even

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Global analyses,* high-ranking journals	first-generation panel estimation techniques high statistical and theoretical accuracy	3%	48.5%	30.3%	18.2%	33
2	*OECD analyses, Ols*	low-moderate statistical and theoretical quality, non-linear estimation techniques	18.3%	16.7%	35%	30%	60
3	*OECD analyses, top journals*	high-ranking journals, recent analyses, distributional inequality indicator, non-linear estimation methods	0%	46.6%	38.5%	15.4%	13
4	*BRICS, Panel 2*	low number of mobilized theories, recent analyses, low-ranking journals	60%	40%	0%	0%	10
5	*Panel 2, Africa*	moderate statistical and theoretical quality, GMM methods, normative inequality indicator, developing countries	52.4%	14.3%	14.3%	19%	21
6	*Time Series models, Asia,* low-ranking journals	low statistical accuracy, low number of theories utilized, concentration inequality measure (Gini-coefficient), developing countries and BRICS economies	41%	10.3%	25.6%	23.1%	39

Tab. 26 | Characterization of cluster obtained from tests on climate change (without regional).

stronger, with primarily negative results found for *Global analyses* and mostly positve results found for *Time series models*. However, both clusters decrease in size. In addition, we find new clusters of country-group specific studies. First, *OECD analyses* of low-moderate statistical accuracy that often use Ols estimation techniques. Second, *OECD studies published in high-ranking journals*[31, 53, 83, 84] that often use top% inequality indicator. These analyses primarily find negative and non-linear associations between inequalities and climate change. Third, empirical tests on *BRICS countries, using second-generation panel methods*[85, 86]. These assess with 60% the highest share of positive results found. Lastly, we find a cluster of *second-generation panel models containing a considerable amount of African countries*, primarily associated as well with positive findings. It is worth mentioning that clusters characterized with high research quality contain primarily OECD or global samples while empirical tests characterized by low research quality are often performed on BRICS economies or developing countries. Future research has to close this gap in research quality.

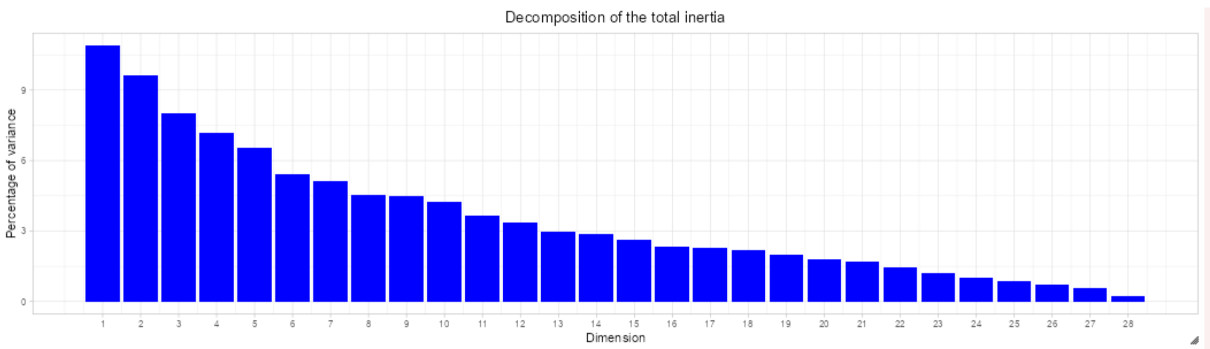

Fig. 35 | Decomposition of the total inertia climate change.

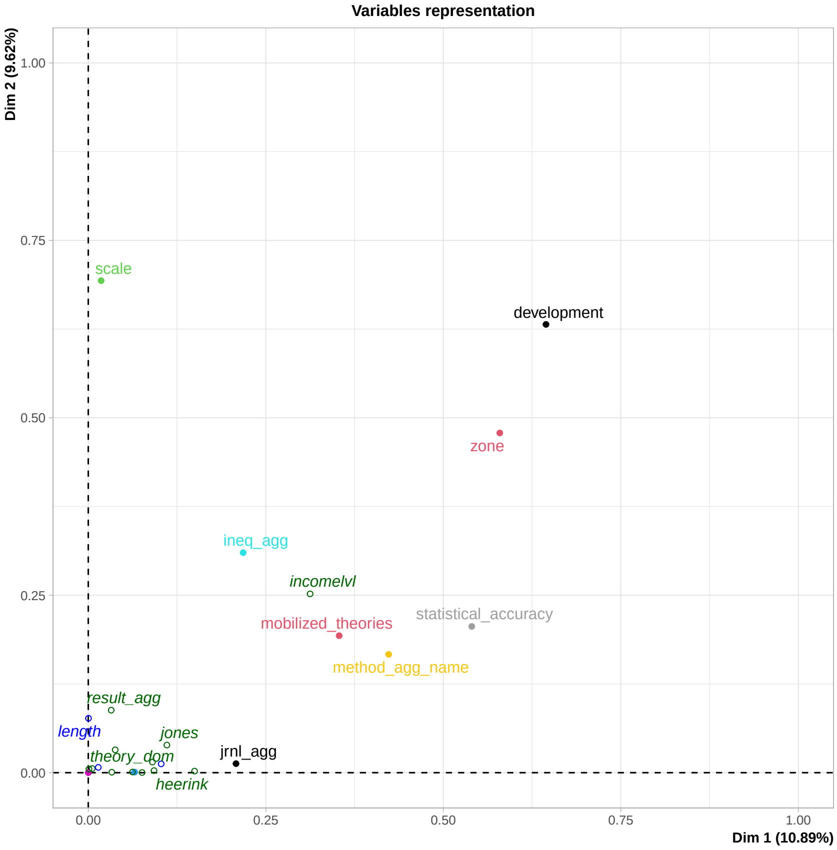

Fig. 36 | Variable representation climate change.

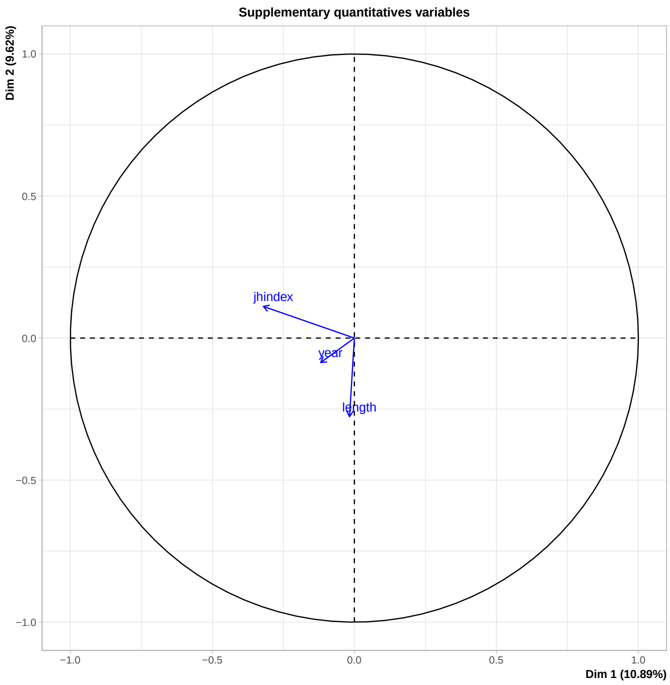

Fig. 37 | Quantitative supplementary variables climate change.

Negative Side	Positive Side
Axis 1	
statistical_accuracy_5 (5.986)	*DC* (14.525)
alldvt (5.110)	*Africa* (9.153)
distributional (5.000)	*statistical_accuracy_1* (8.632)
Panel 1 (4.690)	*Time Series* (7.743)
h-index > 200 (4.474)	*mobilized_theories_0* (7.052)
allzone (4.459)	*Asia* (4.487)
Axis 2	
national (4.670)	*regional* (21.075)
allzone (4.311)	*BRICS* (17.198)
	Asia (11.583)
	Spatial (7.462)
	Special (4.272)
	statistical_accuracy_2 (4.201)

Tab. 27 | Relative contributions of variables to axes: climate change.

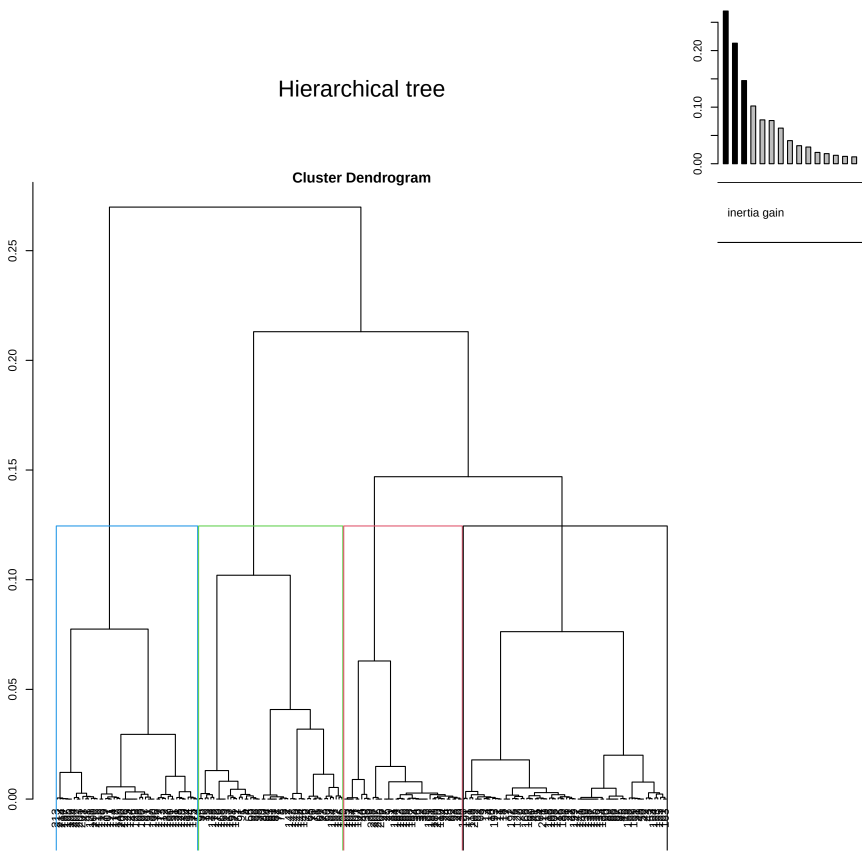

Fig. 38 | Cluster dendrogram of climate change.

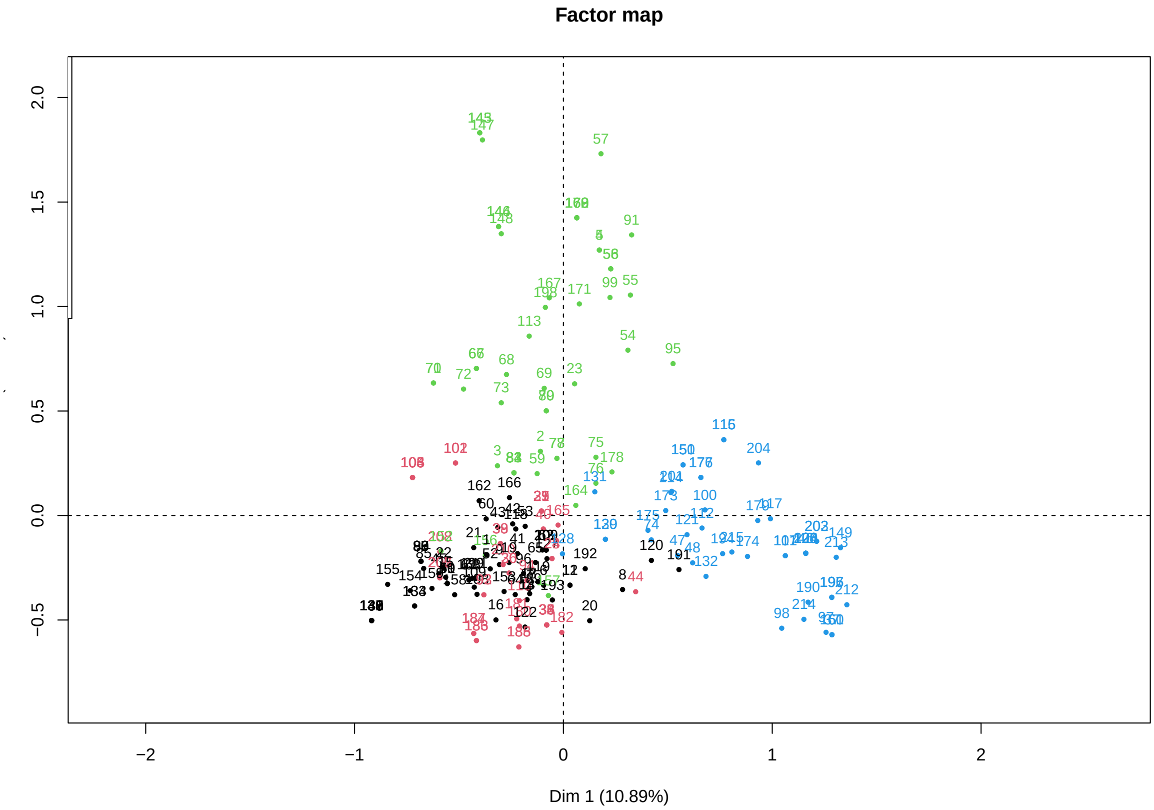

Fig. 39 | Factor map of HCA of climate change.

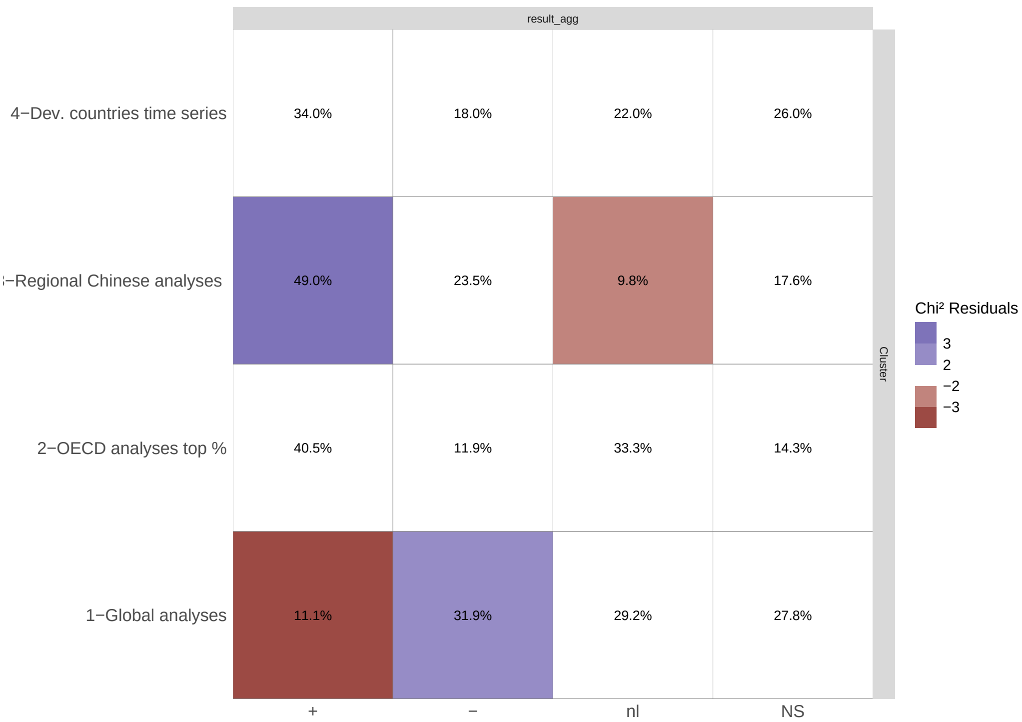

Fig. 40 | Correlation table - Clusters climate change.

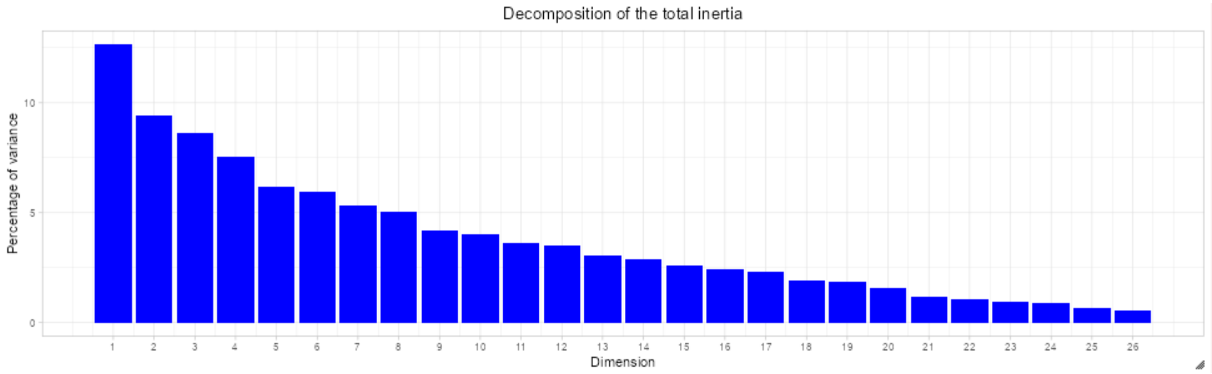

Fig. 41 | Decomposition of the total inertia climate change (without regional).

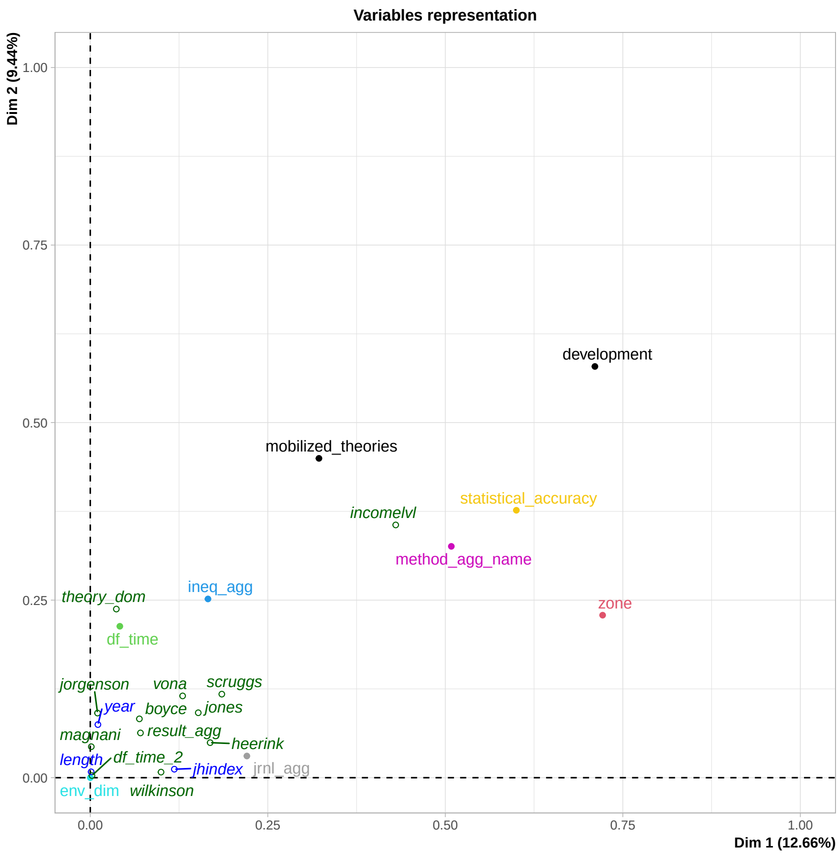

Fig. 42 | Variable representation climate change (without regional).

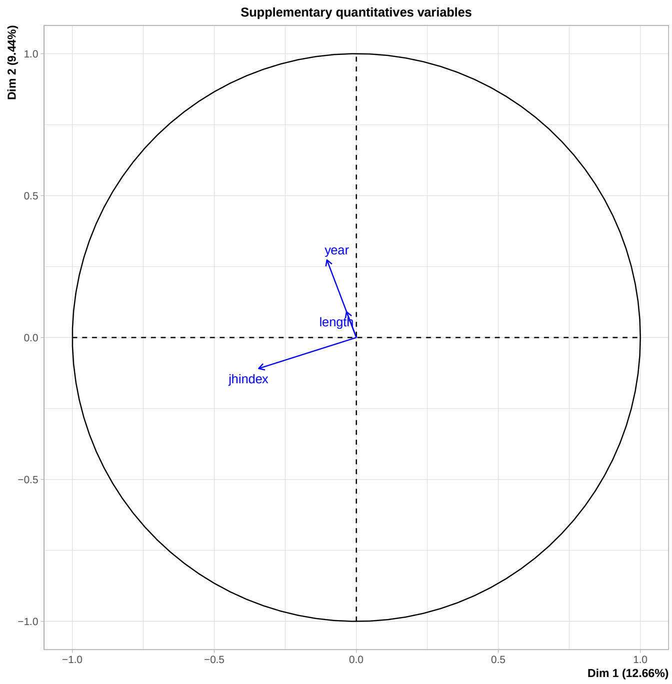

Fig. 43 | Quantitative supplementary variables climate change (without regional).

Negative Side	Positive Side
Axis 1	
alldvt (7.771)	*DC* (10.982)
statistical_accuracy_5 (7.672)	*Asia* (9.530)
allzone (6.322)	*statistical_accuracy_1* (8.914)
Panel 1 (5.240)	*Time Series* (8.359)
h-index > 200 (4.646)	*Africa* (5.759)
distributional (3.692)	*mobilized_theories_0* (5.505)
Axis 2	
statistical_accuracy_5 (7.856)	*OECD* (10.471)
alldvt (7.655)	*mobilized_theories_1* (7.599)
mobilized_theories_5 (5.763)	*Panel 2* (7.321)
Panel 1 (4.872)	*After 2014* (3.898)
2014 or before (4.786)	*mobilized_theories_3* (2.940)

Tab. 28 | Relative contributions of variables to axes: climate change (without regional).

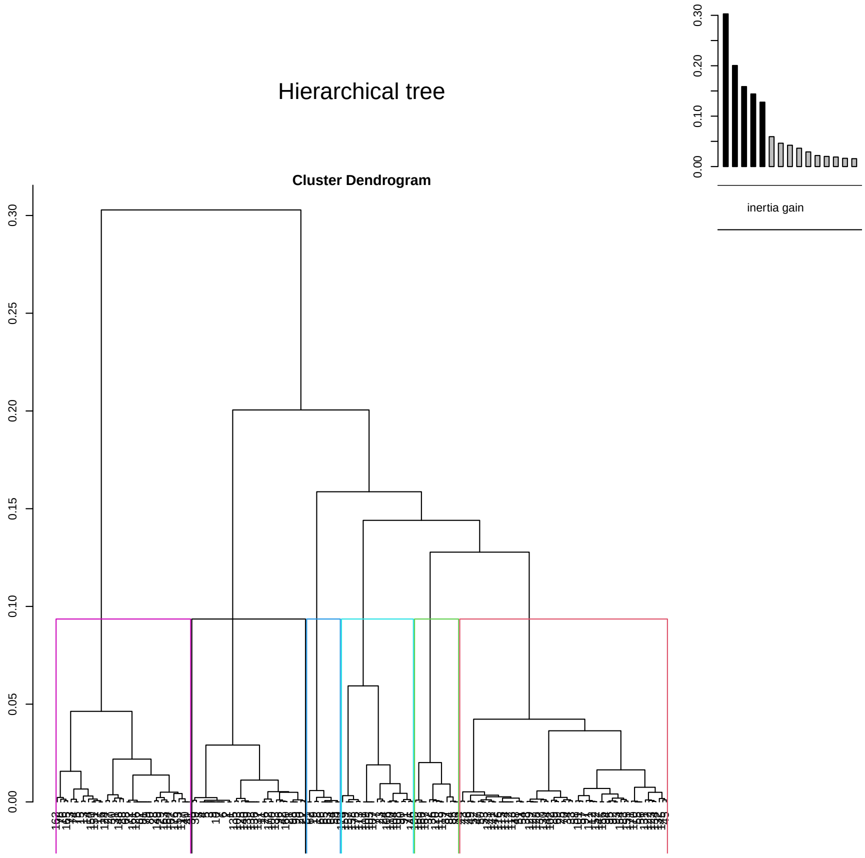

Fig. 44 | Cluster dendrogram of climate change (without regional).

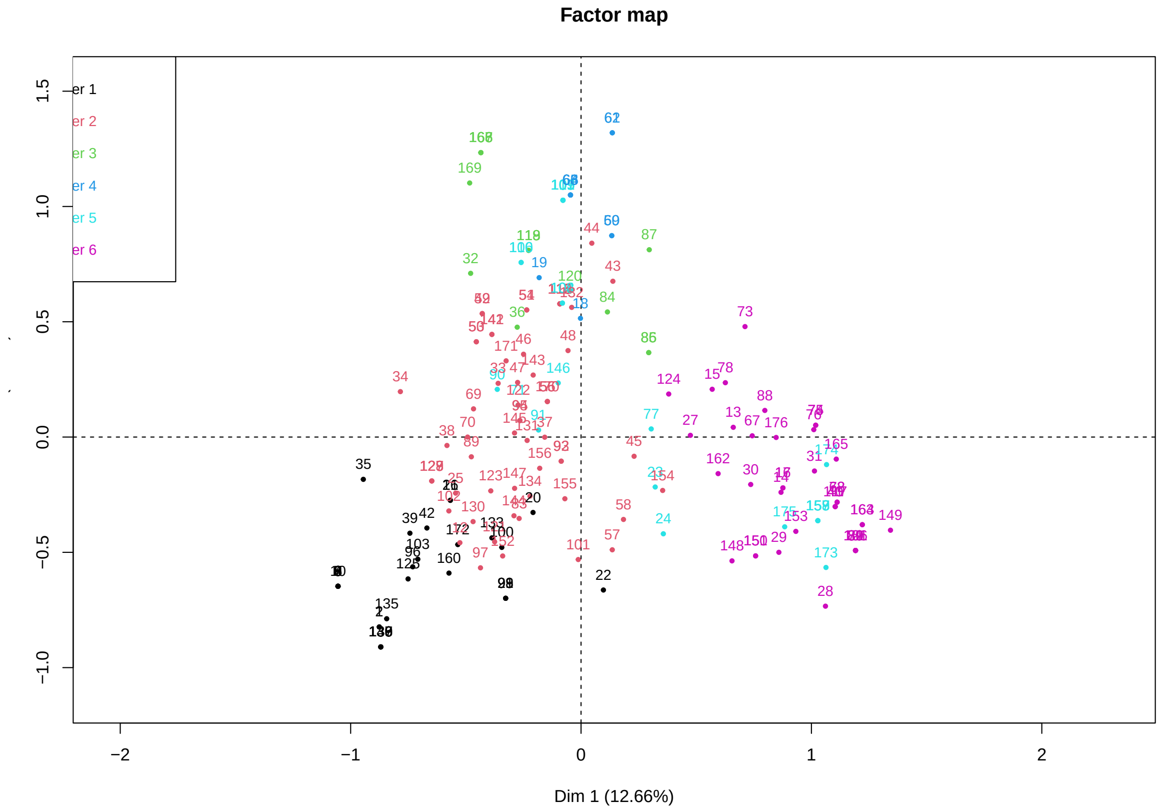

Fig. 45 | Factor map of HCA of climate change (without regional).

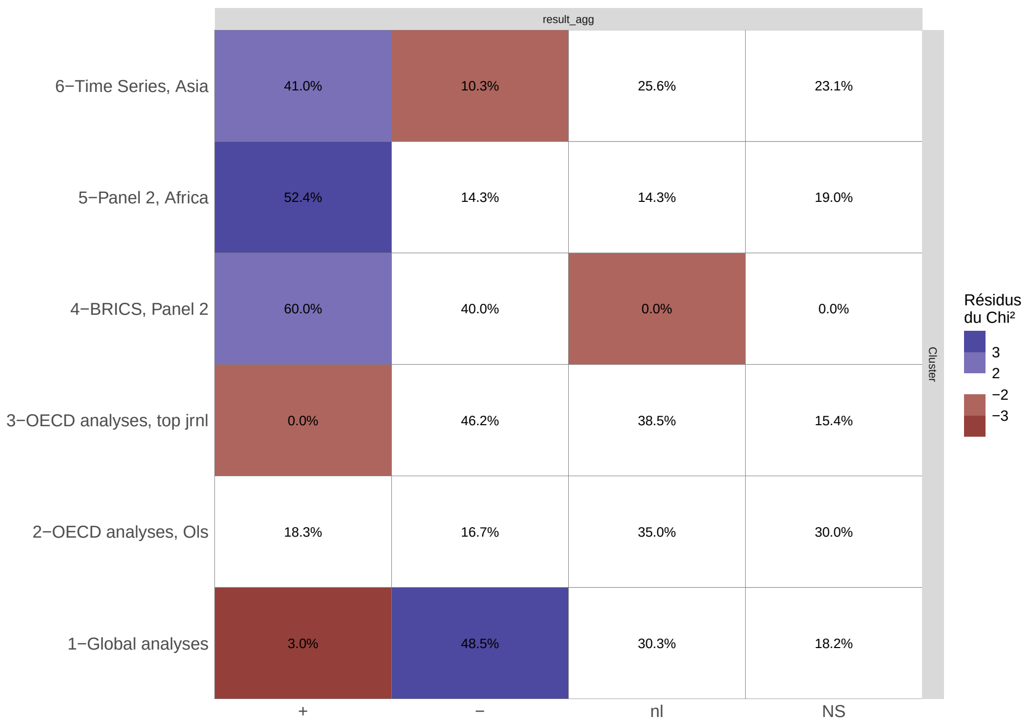

Fig. 46 | Correlation table - Clusters climate change (without regional).

5.5 Inter-dependencies between test characteristics - local and regional env. pressures

Figure 47 depicts the MCA for local and regional environmental pressures. The first two dimensions represent 26.77% of the overall variation in the dataset (axis inertia rates in Figure 49). Table 31 contrasts the relative contributions of the variable modalities to the axes. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 50 & 51.

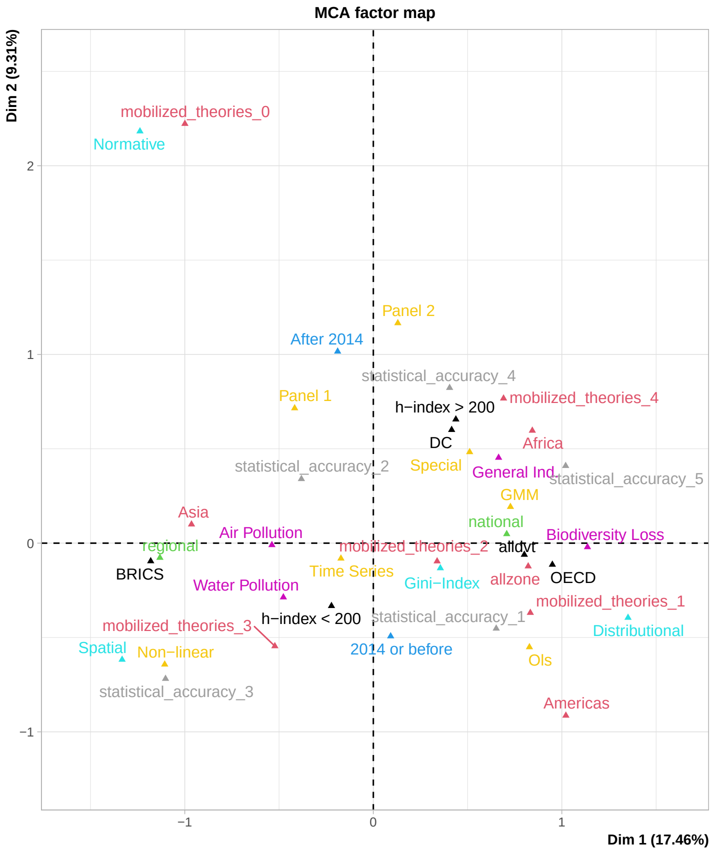

Fig. 47 | MCA of local and regional env. pressures.

The association between analyses employing normative inequality indicators and mobilizing no theories is considered an outlier. In contrast to the MCA of tests on climate change, Figure 47 does not suggest a systematic relationship between the quality of research (number of theories mobilized, statistical accuracy and the journal's h-index) and certain development levels or geographical zones for analyses of local or regional environmental pressures. In addition, methods appear to be rather linked to the age of the studied time-frame, whereas more recent time-frames are related to first- and second-generation panel modeling techniques. Furthermore, analyses on the impact of inequalities on biodiversity seem to be associated with OECD countries. Regional-level analyses are still conducted mainly in China.

The hierarchical cluster analysis is performed in order to better understand potential group structures. We assess 5 distinct clusters, which are relatively small due to the generally low number of empirical tests on local and regional environmental pressures. Figure 52 and 53 provide the respective cluster dendrogram and the factor map. Table 29 describes the 5 clusters and depicts their related results. Chi-squared tests and a graphical depiction of the results by cluster are illustrated in Figure 54.

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Analyses with Theil-Index*	low statisitcal accuracy and low number of theories mobilized, BRICS economies, recent time-frames first-generation panel methods, includes also regional-level analysis	100%	0%	0%	0%	8
2	*Regional-level studies on China*, non-linear methods, spatial inequality indicator	medium-high statistical and theoretical quality, published in low-ranking journals, often studies on air pollution	43.3%	33.3%	13.3%	10%	30
3	*Second-generation panel models of developing countries*	General Environmental Indicators, national-level studies in Africa with special methods, high-statistical accuracy	75%	16.7%	8.3%	0%	12
4	*Old global studies*, Ols methods	old time-frames, low statistical accuracy, concentration inequality measure, low number of theories	28.9%	15.8%	5.3%	50%	38
5	*Recent global studies*, GMM methods	recent time-frame, high statistical accuracy, high number of theories utilized, high-ranking journals	25%	12.5%	37.5%	25%	16

Tab. 29 | Characterization of cluster obtained from local and regional env. pressures.

The first cluster is the previously identified outlier of *Analyses employing the Theil-Index* as a measure of inequality[87]. However, it is remarkable that the choice of a normative inequality indicator plays a more decisive role in defining the cluster than a regional-level analysis[87]. The second cluster comprises *Regional-level analyses of China* while the third cluster contains *second-generation panel estimations of mostly developing countries*. The fourth and fifth cluster both contain global analyses, but one is associated with older time-frames and OLS methods while the other contains more recent analyses conducted with GMM estimation techniques.

The present MCA and HCA differ from the ones of climate change (Table 25 & 26) in three ways. First, methods and inequality indicators play a more decisive role in determining the groups than the sample composition. Second, the association between research quality and the development level of the investigated countries becomes weaker. Third, for none of the clusters, the negative results are dominant (Figure 54). Positive findings dominate for *Analyses with Theil-Index*, *Regional Chinese analyses* and *Second-generation panel models of developing countries* while *Old global studies* find mostly non-significant results and *Recent global studies* non-linear results.

We perform a MCA without regional-level analysis to account for the dominating effect of regional-level analyses of China (Figure 48). The first two dimensions represent 25.25% of the overall variation in the dataset (axis inertia rates in Figure 55). Table 32 again contrasts the relative contributions of the variable modalities to the axes. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 56 & 57.

The MCA of analyses on local and regional environmental pressures excluding regional analyses highlights a strong association between BRICS economies, time series modeling, and the use of normative inequality measures. This "outlier" is determined only by a single study[88], which assess a time series model for India using the Theil-Index. Otherwise, OECD countries are associated with water pollution, distributional measures, low statistical accuracy and an older time-frame. In contrast recent time frames investigate often developing countries with second-generation panel techniques and high statistical accuracy. Global studies are mostly associated with GMM methods and biodiversity indicators. The differences in the quality and methods of the empirical test appear to be mainly related to the age of the investigated sample, highlighting differences in regard to analyses on climate change(Figure 48).

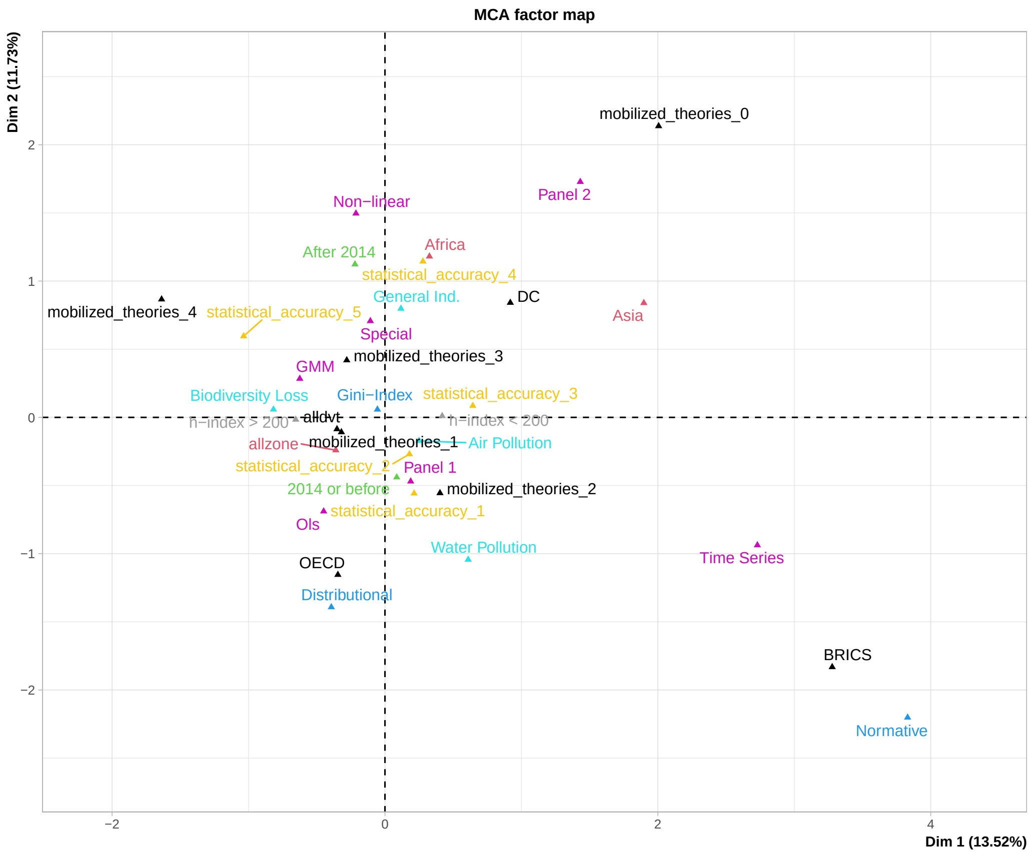

Fig. 48 | MCA of local and regional env. pressures (without regional).

We perform a HCA whose results are depicted in Table 30. Figure 58 and 59 provide the respective cluster dendrogram and the factor map. Table 30 describes the 5 clusters and depicts their related results. Chi-squared tests and a graphical depiction of the results by cluster are illustrated in Figure 60.

Table 30 presents a summary of the four identified clusters, which correspond to those depicted in Table 29, excluding the group of regional analyses. The results indicate as well that, for studies

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Recent global analyses, GMM methods*	recent time-frame, high statistical accuracy, high number of theories utilized, high journal ranking, global studies	30.8%	7.7%	30.8%	30.8%	13
2	*Old global analyses*, OLS methods	old time-frames, low statistical accuracy, concentration inequality measure, low number of theories	22%	22%	9.8%	46.3%	41
3	*Second-generation panel studies on developing countries*	General Environmental Indicators, Asia & Africa	87.5%	0%	12.5%	0%	8
4	*Ridzuan (2021)*[88]	time series model, BRICS, normative inequality measure	100%	0%	0%	0%	2

Tab. 30 | Characterization of cluster obtained from local and regional environmental pressures (without regional).

on local or regional environmental pressures, clusters are mainly determined by methods. Negative empirical findings are never dominant. *Old studies* find a high percentage of non-significant findings. The indicator of research quality appears to play a secondary role in distinguishing clusters. Thus, high- and low-ranking journals are not systematically associated with the development level of the countries studied. However, the amount of country-group speicic studies on local or regional environmental pressures is limited, especially after excluding regional analyses (Figure 13). Notably, the majority of studies focusing on local and regional environmental pressures are based on older time periods.

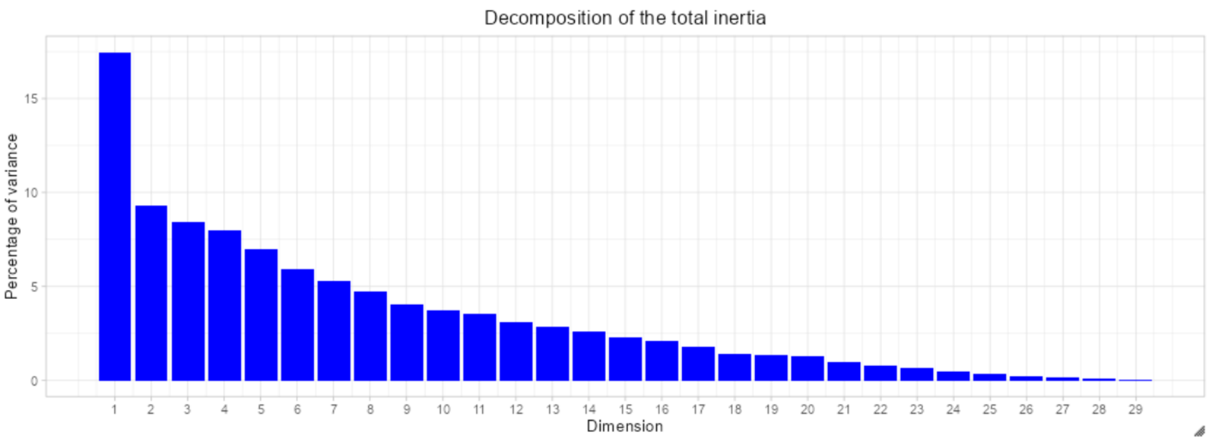

Fig. 49 | Decomposition of the total inertia rates env. pressures.

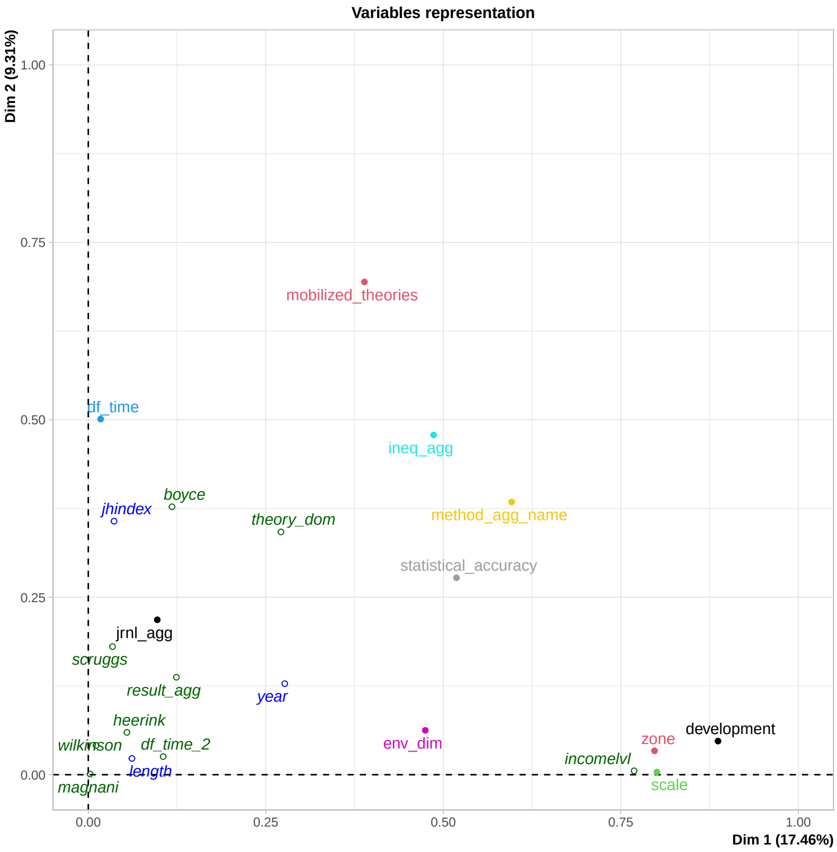

Fig. 50 | Variable representation env. pressures.

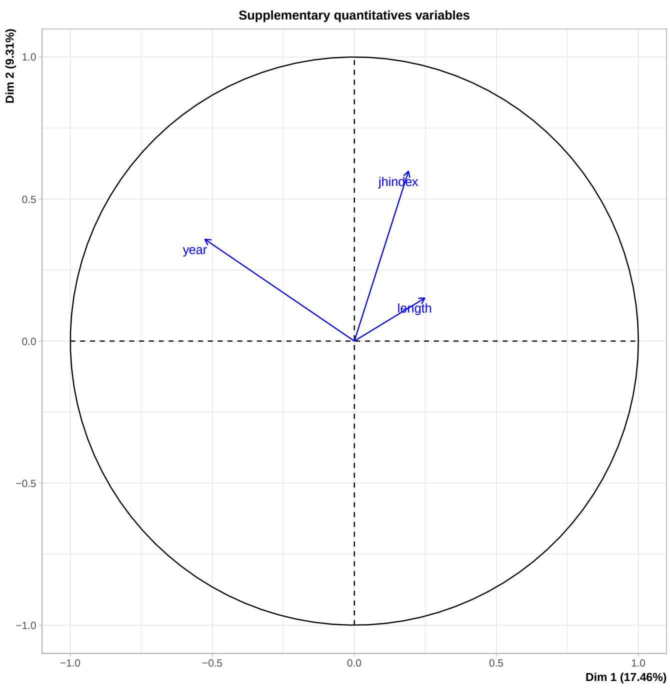

Fig. 51 | Quantitative supplementary variables env. pressures.

Negative Side	Positive Side
Axis 1	
BRICS (10.588) *regional* 9.731) *Asia* (8.475) *Non-linear* (5.811) *Spatial* (4.719) *statistical_accuracy_3* (4.381) *Normative* (2.618)	*allzone* (6.534) *national* (6.082) *alldvt* (5.846) *Biodiversity* (4.409) *Ols* (3.124)
Axis 2	
2014 or before (6.064) *mobilized_theories_3* (3.924) *Non-linear* (3.677) *statistical_accuracy_3* (3.494) *h-index < 200* (2.720)	*mobilized_theories_0 (19.339)* *Normative* (15.263) *After 2014* (12.485) *h-index > 200* (5.362) *Panel 1* (3.824) *Panel 2* (3.388) *statistical_accuracy_4* (2.653)

Tab. 31 | Relative contributions of variables to axes: Env. pressures.

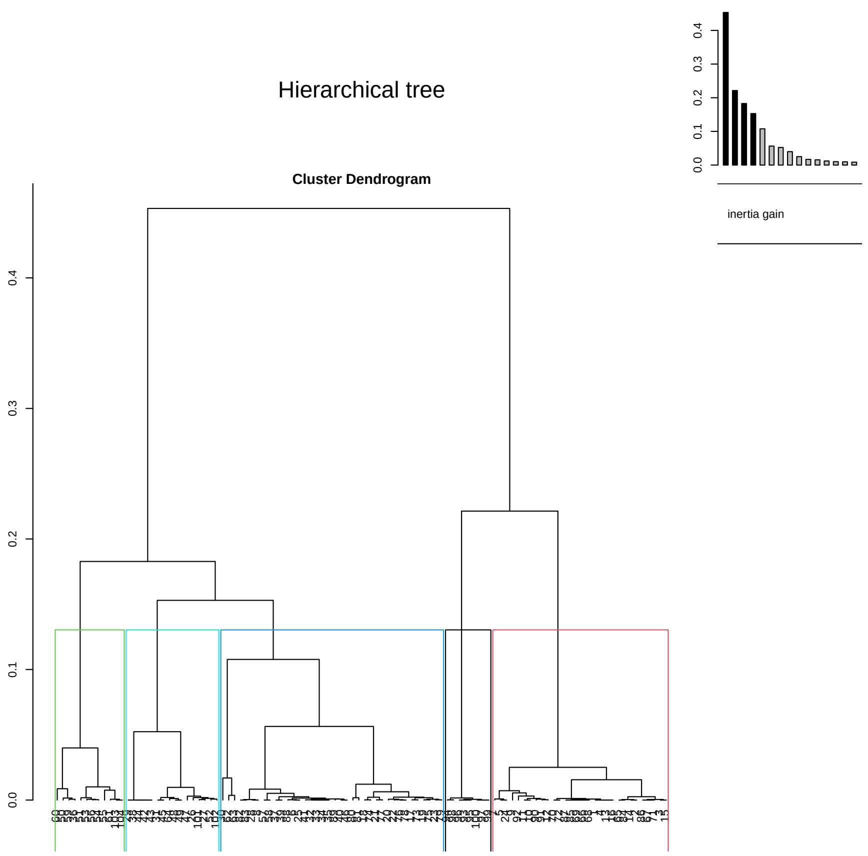

Fig. 52 | Cluster dendrogram of env. pressures.

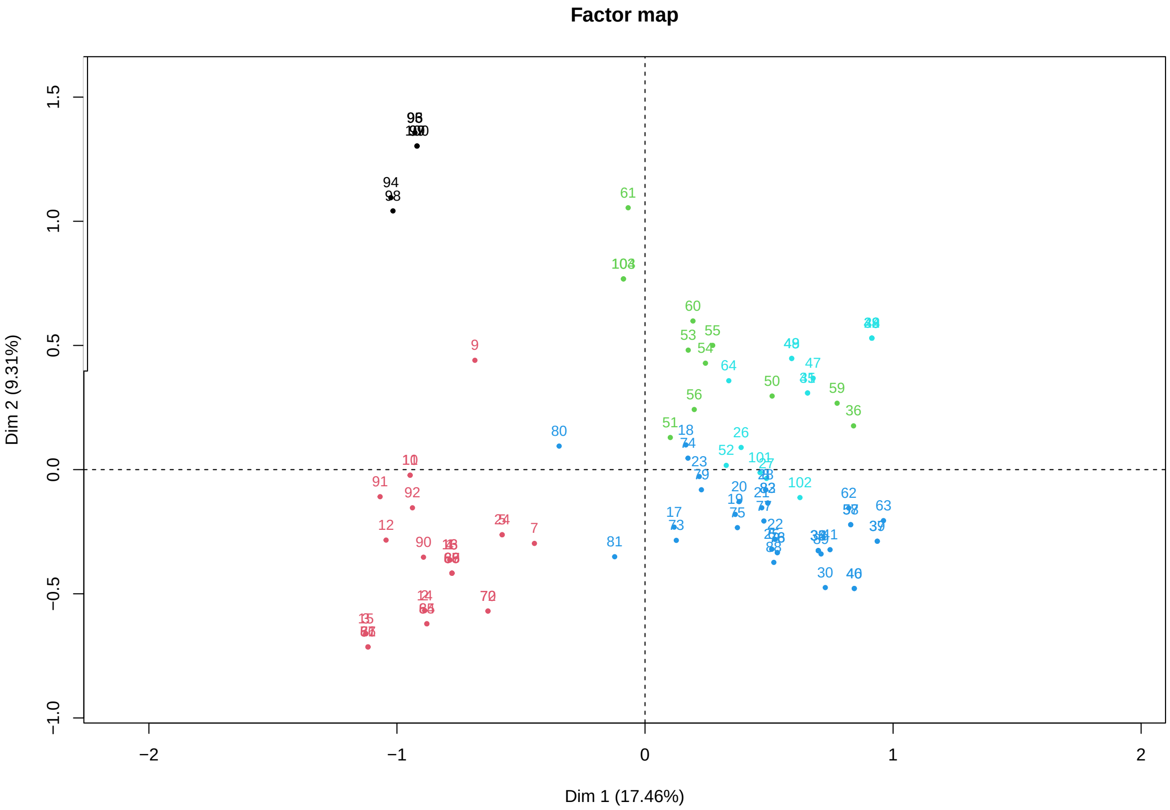

Fig. 53 | Factor map of HCA of env. pressures.

Fig. 54 | Correlation table - Clusters env. pressures.

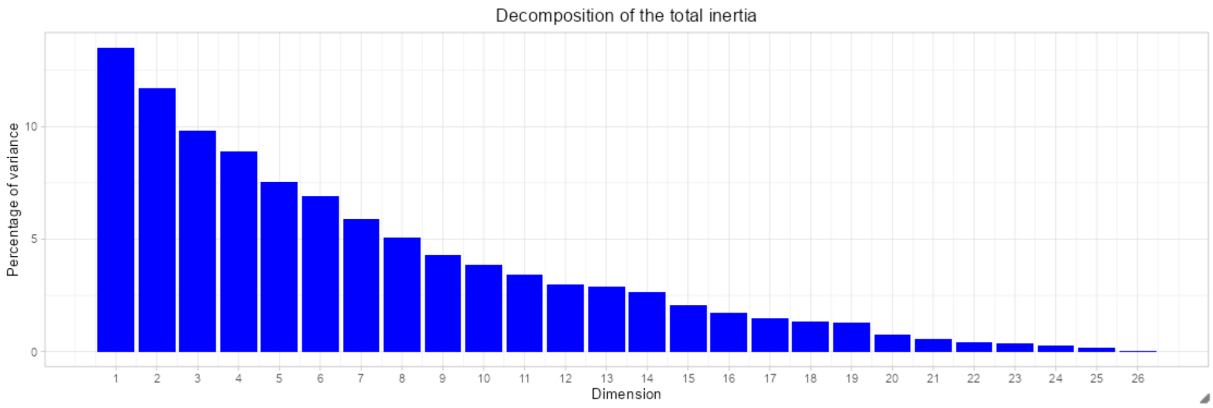

Fig. 55 | Decomposition of the total inertia other env. pressures (without regional).

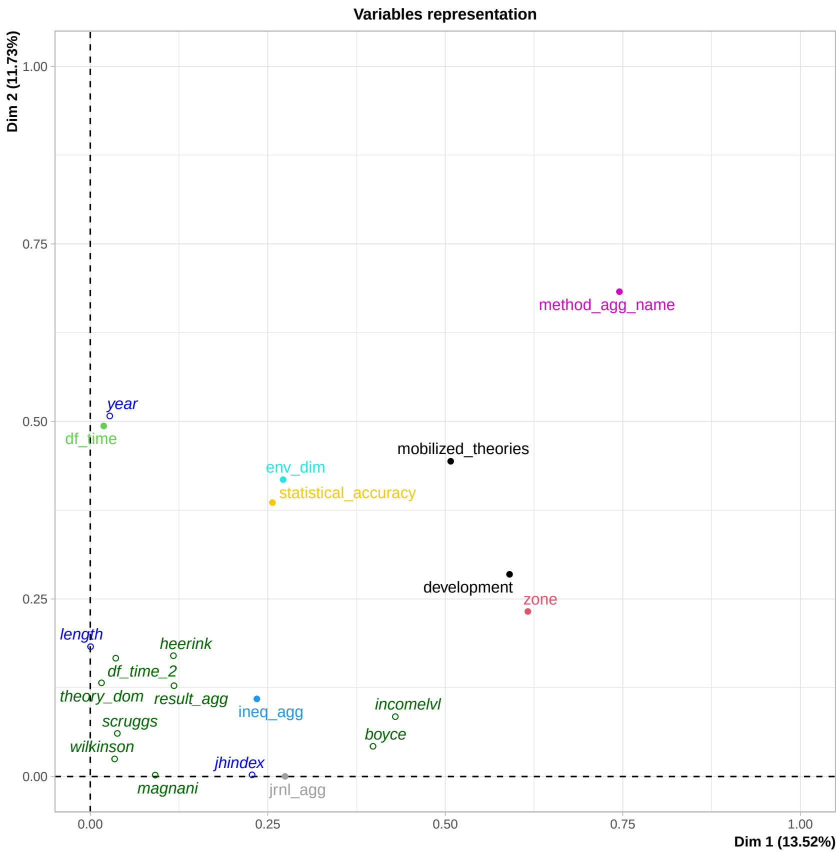

Fig. 56 | Variable representation env. pressures (without regional).

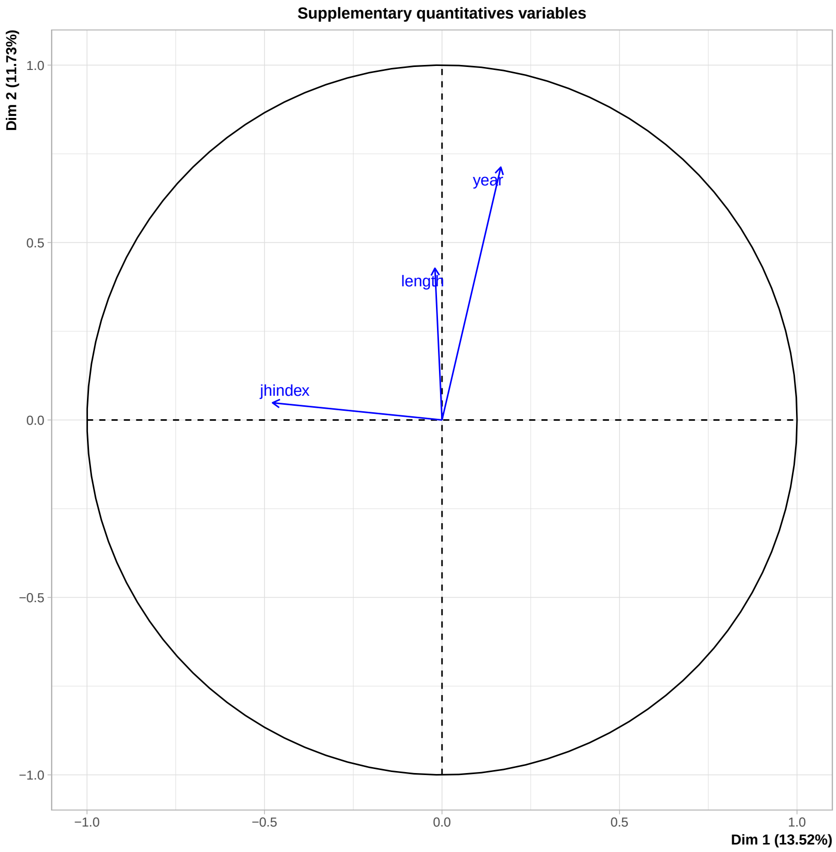

Fig. 57 | Supplementary quantitative variables env. pressures (without regional).

Negative Side	Positive Side
Axis 1	
mobilized_theories_4 (5.957) *statistical_accuracy_5* (5.721) *Biodiversity* (5.046) *h-index > 200* (4.754) *allzone* (2.943) *GMM* (2.773)	*Asia* (14.397) *Time Series* (9.932) *BRICS* (9.550) *DC (4.500)* *Normative* (6.521) *Panel 2* (6.374) *mobilized_theories_0* (5.363) *h-index < 200* (3.048)
Axis 2	
Water (7.253) *Ols* (5.108) *2014 or before* (4.551) *mobilized_theories_2* (4.263) *statistical_accuracy_1* (3.822) *BRICS* (3.436)	*After 2014* 11.631) *Panel 2* (10.702) *mobilized_theories_0* (7.016) *General* (6.194) *statistical_accuracy_4* (6.032) *DC* (4.350) *Asia* (3.248) *Africa* (2.857)

Tab. 32 | Relative contributions of variables to axes: Env. pressures (without regional).

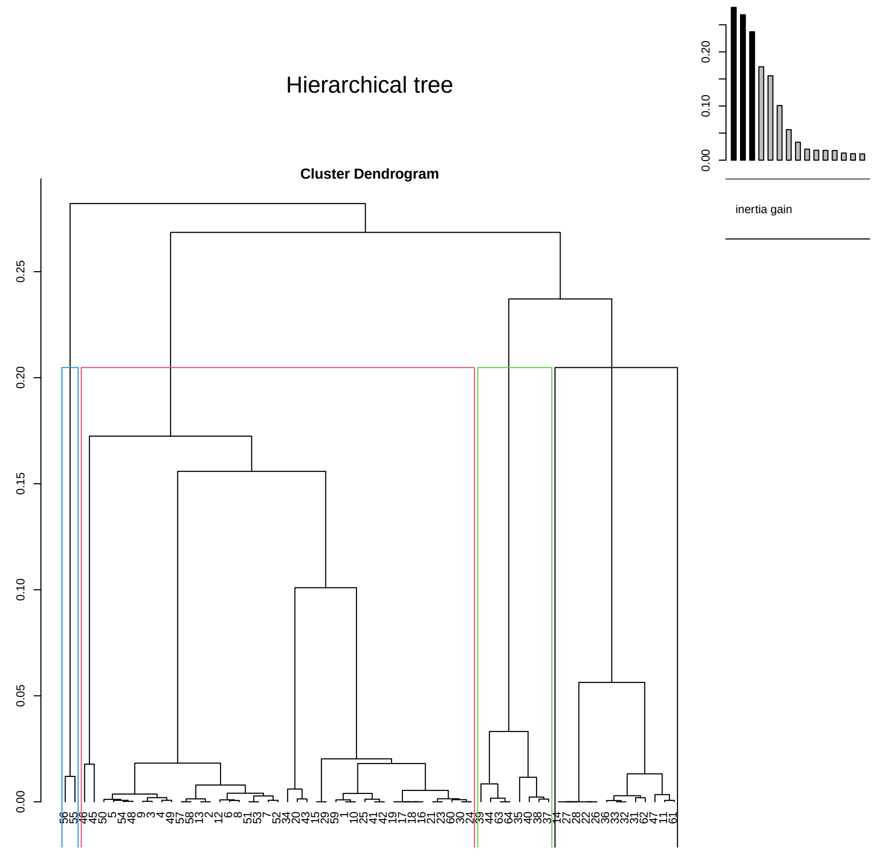

Fig. 58 | Cluster dendrogram of env. pressures (without regional).

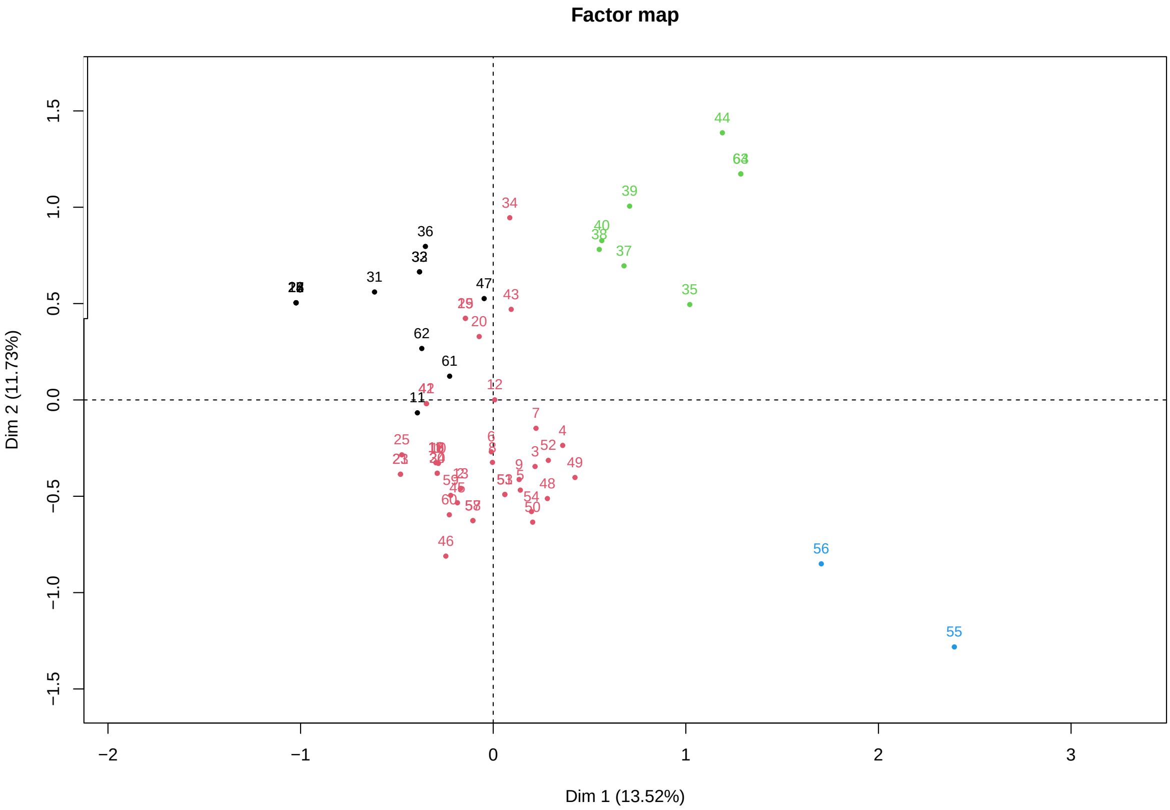

Fig. 59 | Factor map of HCA of env. pressures (without regional).

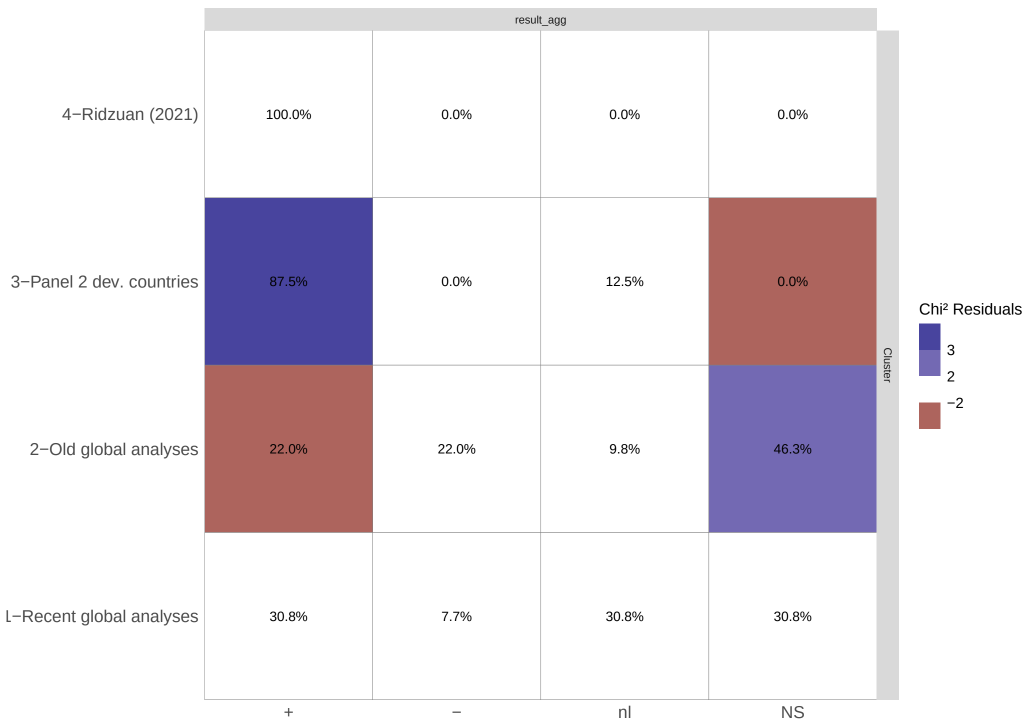

Fig. 60 | Correlation table - Clusters env. pressures (without regional).

5.6 Inter-dependencies between test characteristics - env. responses

The analysis of inter-dependencies between test characteristics for environmental responses is depicted in Figure 61. The first two dimensions represent 25.18% of the overall variation in the dataset (axis inertia rates in Figure 63). Table 35 contrasts the relative contributions of the variable modalities to the axes. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 64 & 65.

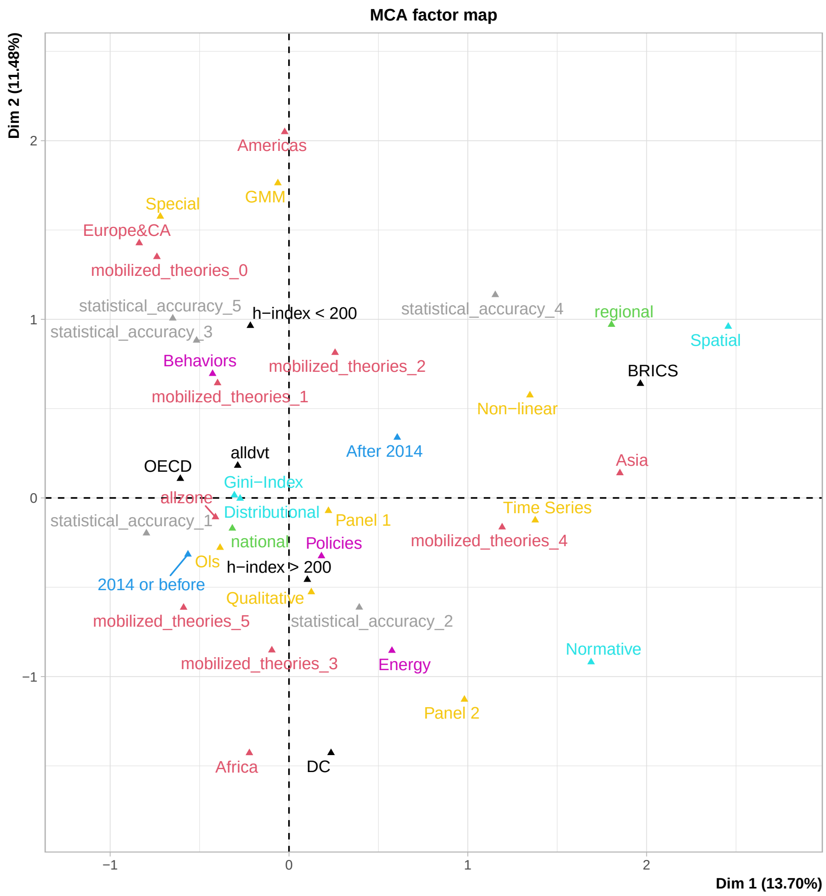

Fig. 61 | MCA of env. responses.

The MCA of tests on response indicators points out as well the unique group of regional analyses of China. These tests are associated with high statistical accuracy. In addition, time-series models of Asian countries are associated with a large number of theories mobilized. Analyses of energy-related indicators are primarily related to second-generation panel models and high-ranking journals. In contrast, studies of behavioral environmental response variables in Europe & Central Asia are associated with low-ranking journals, a low number of theories mobilized and high statistical accuracy. It seems that these studies utilize special or GMM methods. Lastly, we can identify a group of old studies affiliated with low statistical accuracy and Ols methods. The MCA of response indicators highlights the association of high-ranking journals with analyses of energy-related indicators while analyses on environmental behaviors are mostly limited to low-ranking journals. In contrast to analyses on climate change, we do not find adverse associations between research quality and country-group that would point towards less carefully conducted analyses of developing countries.

We perform a HCA based on the previously conducted MCA and identify six clusters which are described in Table 33. In addition, we depict the results found by cluster. Figure 66 and 67 provide the respective cluster dendrogram and the factor map. Chi-squared tests and a graphical depiction of the results by cluster are shown in Figure 68.

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Kocak&Baglitas (2022)*[32]	no theories mobilized, moderate statistical accuracy, low-ranking journal, GMM, OECD, Behavior, recent time-frame	66.7%	33.3%	0%	0%	6
2	*Special methods analyses*, behaviors	low-ranking journals, global samples, high statistical accuracy, little theories mobilized	56.2%	6.2%	12.5%	25%	16
3	*Old OECD analyses*, high-ranking journal	high number of theories mobilized, Gini-Index, Ols, low statistical accuracy, policies	40.6%%	3.1%	21.9%	34.4%	32
4	*Qualitative analyses*, global sample	distributional inequality indicator, morderate-high-number of theories mobilized, recent time-frame	8.3%	0%	91.7%		12
5	*Energy analyses in DC, second-generation panel model*	Africa & Asia, average number of theories and moderate statistical quality, normative inequality measures	80%	0%	0%	20%	10
6	*Regional analyses of China*	Spatial inequality indicators, recent time-frame, normative inequality Indicator, high number of theories, high statistical accuracy, first-generation panel methods	54.5%	9.1%	0%	36.4%	11

Tab. 33 | Characterization of cluster obtained from env. responses.

We obtain a high number of clusters considering the low number of observations (87). The first two studies separate, on the one hand, the analysis of *Kocak&Baglitas (2022)*[32] conducted on behaviors utilizing GMM methods and, on the other hand, *Special methods analyses* of behaviors. Both are performed on OECD/ global country-samples and are associated with low-ranking journals. We further identify the cluster of *Old OECD analyses*, utilizing OLS methods. It is the biggest cluster found for responses, highlighting the low number of new studies on this topic. The fourth cluster refers to recently conducted *Qualitative analyses* of global samples using distributional inequality indicators. This group is limited to analyses performed in only three studies[64, 67, 89]. The fifth cluster contains *Energy analyses in DC* conducted with second-generation panel modeling techniques[65, 90–93]. In particular, all analyses in this sample use renewable energy consumption as dependent variable. *Regional analyses of China* constitute a separate group, related to spatial inequality indicators, a high number of theories mobilized and high statistical accuracy. The HCA does not highlight a hierarchical structure between the country's development level and the quality of research. The clusters for environmental responses seem to be strongly determined by methods as well as the quality of research (especially for behaviors).

In contrast to analyses on climate change, negative results are comparatively rare across all clusters. The majority of analyses find positive results for *Special Methods analyes*, *Kocak&Baglitas*

(2022), *Energy analyses in DC* and *Regional analyses of China*. In addition, positive results are dominant across *Old OECD analyses* while *Qualitative analyses* find 91.7% of the time a non-linear association between inequality and environmental responses.

The MCA of environmental responses excluding regional-level analyses is depicted in Figure 62. The first two dimensions represent 26.35% of the overall variation in the dataset (axis inertia rates in Figure 69). Table 36 contrasts the relative contributions of the variable modalities to the axes. The variable representation in the first two dimensions as well as information of the supplementary quantitative variables is provided in Figure 70 & 71. The results are similar to the previously obtained ones. Energy-related indicators are investigated for developing and BRICS economies. They are associated with second-generation panel and time series models. Analyses using special and GMM methods are characterized by high statistical accuracy, but mobilize less theoretical mechanisms and are published in less renowned journals. Tests on older time-frames, especially regarding policies, are associated with high-ranking journals OECD, and to a certain extend African countries.

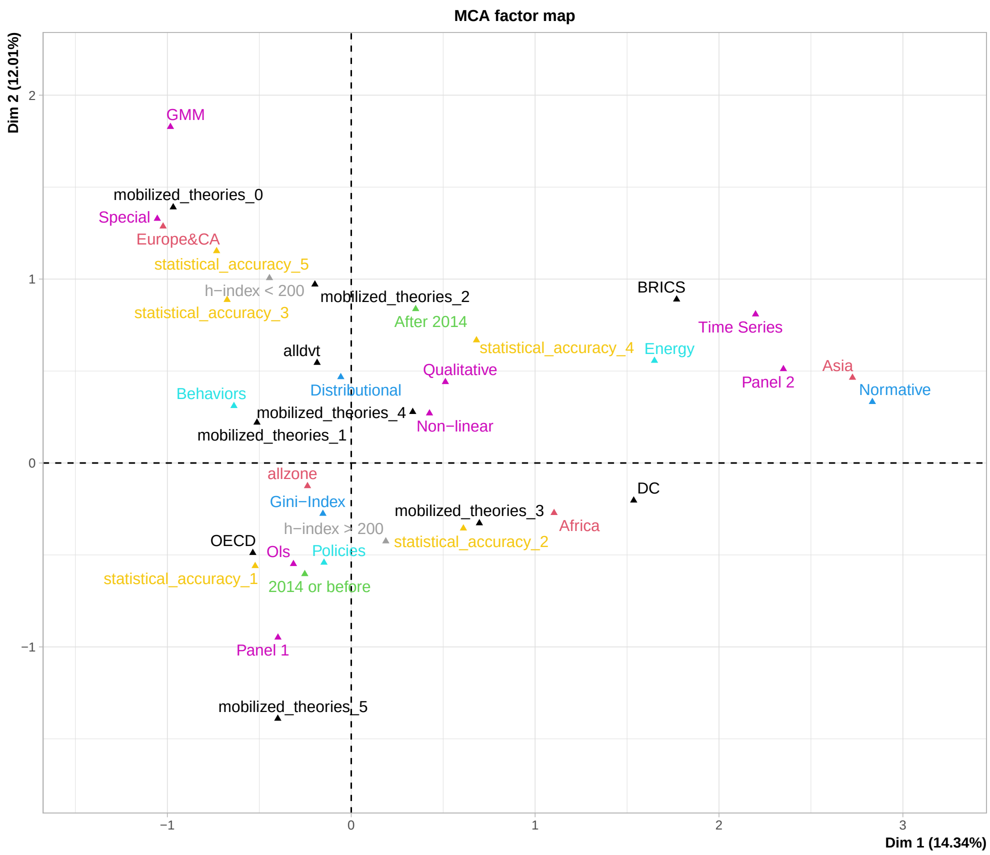

Fig. 62 | MCA of env. responses (without regional).

The respective HCA finding six clusters is described in Table 34. In addition, we depict the results by cluster. Figure 72 and 73 provide the respective cluster dendrogram and the factor map. Chi-squared tests and a graphical depiction of the results by cluster are shown in Figure 74.

Cluster	Characterization	Details	+	-	nl	NS	N
1	*Kocak&Baglitas (2022)*[32]	no theories mobilized, moderate statistical accuracy, low-ranking journal, GMM, OECD, Behavior, recent time-frame	66.7%	33.3%	0%	0%	6
2	*Special methods analyses*, behaviors	global samples, high statistical accuracy, low-ranking journals, little theories mobilized	53.3%	6.7%	13.3%	26.7%	15
3	*Old OECD analyses*, high-ranking journal	first-generation panel models, high number of theories mobilized, Gini-Index, policies, Ols	38.7%%	3.2%	22.6%	35.5%	31
4	*Qualitative analyses*, global sample	high number of mobilized theories, recent time-frame, distributional inequality indicator, moderate statistical accuracy, high-ranking journals	0%	0%	100%		11
5	*Time series models, BRICS*	Renewable Energy Consumption	100%	0%	0%	0 %	2
6	*Energy analyses in DC, second-generation panel model*	Africa & Asia, average number of theories and moderate statistical quality, normative inequality measures	77.8%	0%	0%	22.2%	9

Tab. 34 | Characterization of cluster obtained from env. responses (without regional)

Five of the six clusters found are similar to the ones in 33. The new cluster contains two recent *Time series models* of BRICS economies[Mehmood *et al.* 90 and Shahbaz, Abbas Rizvi, Dong & Vo 91] perfomed on renewable energy consumption. As previously, positive results dominate in all clusters except for *Qualitative analyses*, where non-linear findings make up 100% of the results.

All in all, we have performed numerous MCAs and HCAs on three groups of environmental dimensions, namely climate change, local and regional environmental pressures and environmental response indicators. The results by all clusters identified are depicted in Figure 75 and 76. For climate change, the MCAs and HCAs are strongly influenced by the development level of the country-group studied. Developing countries are primarily investigated via time series models and are characterized by a low research quality. In contrast analyses performed on global samples and certain OECD samples are characterized by high-research quality and first-generation panel techniques. The combination of these factors leads to inherently different research outcomes. In contrast, the research quality appears to play a secondary role for analyses of local and regional environmental pressures while especially the time of the analyses is related to the employed models. While the results vary in terms of statistical significance and non-linearity, they remain consistent. Furthermore, analyses of environmental responses do not exhibit a hierarchical structure between the country's development level and the quality of research. However, analyses of energy-related indicators (DCs) are performed with high research quality while analyses for environmental behaviors (OECD) are primarily limited to low-ranking journals.

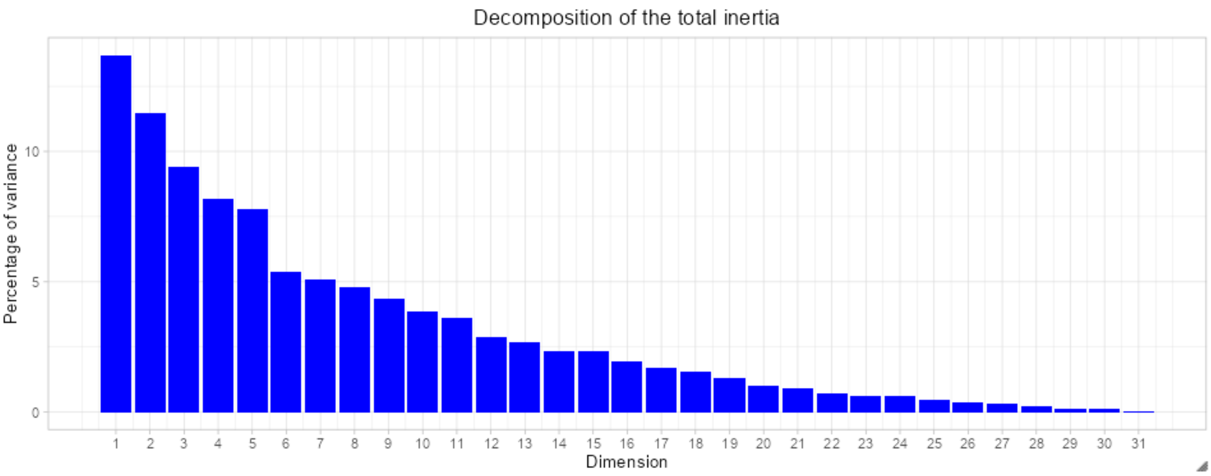

Fig. 63 | Decomposition of the total inertia env. responses.

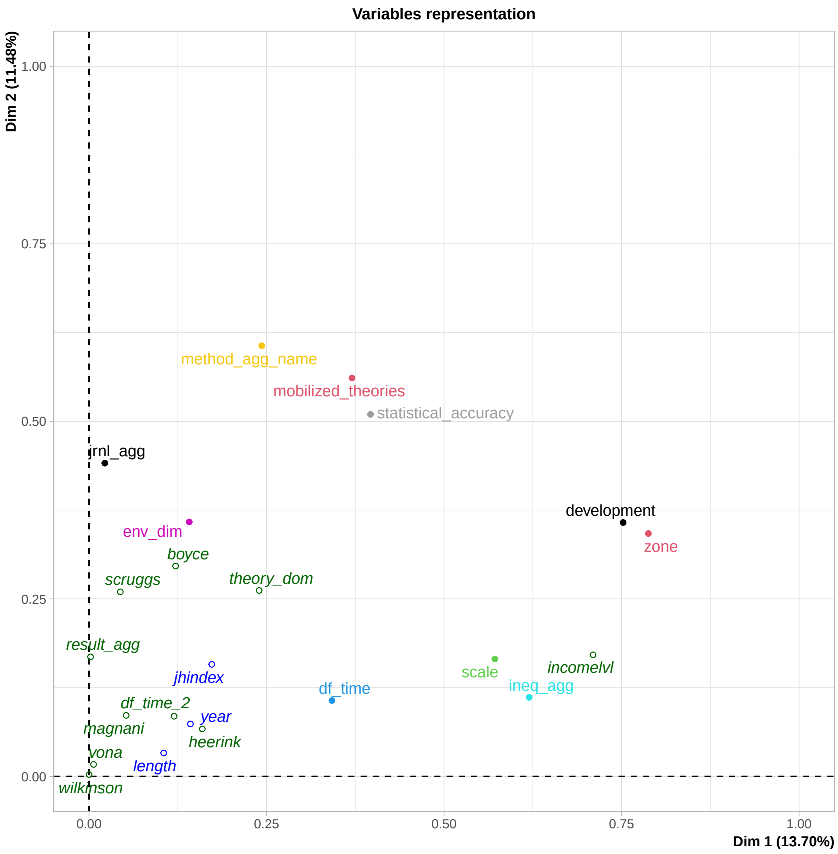

Fig. 64 | Variable representation env. responses.

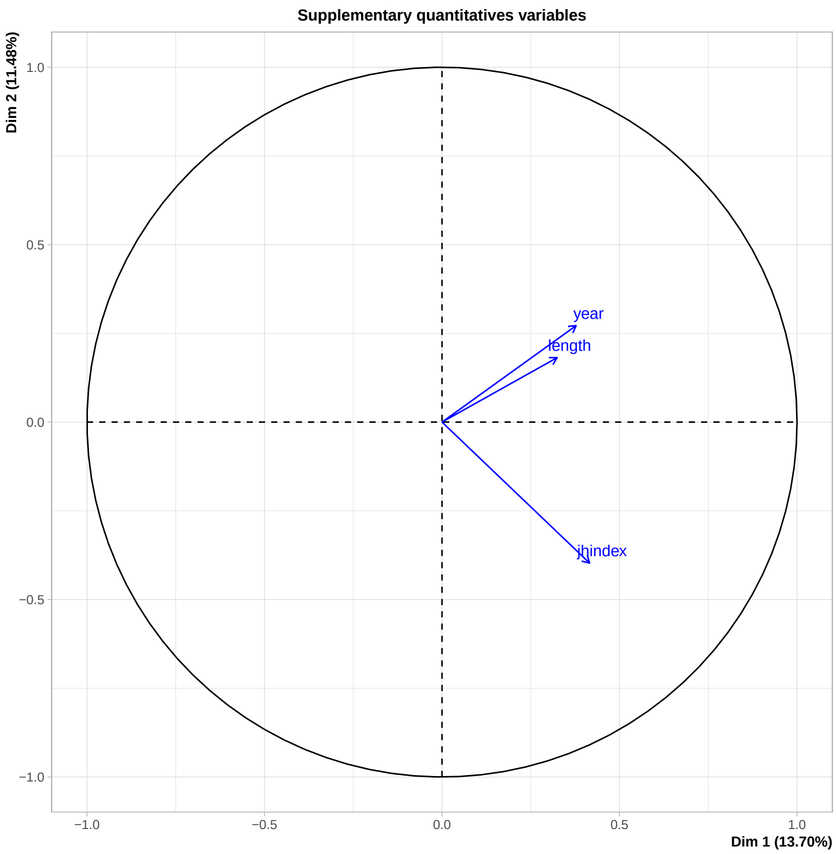

Fig. 65 | Supplementary quantitative variables env. responses.

Negative Side	Positive Side
Axis 1	
2014 or before (3.889)	*Asia* (14.832)
OECD (3.298)	*BRICS* (13.590)
statistical_accuracy_1 (2.926)	*regional* (11.446)
allzone (2.701)	*Spatial* (8.167)
	mobilized_theories_4 (5.769)
	Normative (4.635)
	After 2014 (4.167)
	statistical_accuracy_4 (2.882)
Axis 2	
DC (7.894)	*h-index < 200* (8.403)
mobilized_theories_3 (5.867)	*Special* (7.215)
statistical_accuracy_2 (4.969)	*Behavior* (5.463)
h-index > 200 (3.988)	*GMM* (5.016)
Africa (3.291)	*regional* (3.951)
Panel 2 (2.467)	*mobilized_theories_0* (3.529)
	statistical_accuracy_3 (3.515)
	statistical_accuracy_4 (3.338)
	Energy (3.303)
	Europe&CA (3.287)
	Americas (2.711)
	mobilized_theories_1 (2.672)

Tab. 35 | Relative contributions of variables to axes: Env. responses.

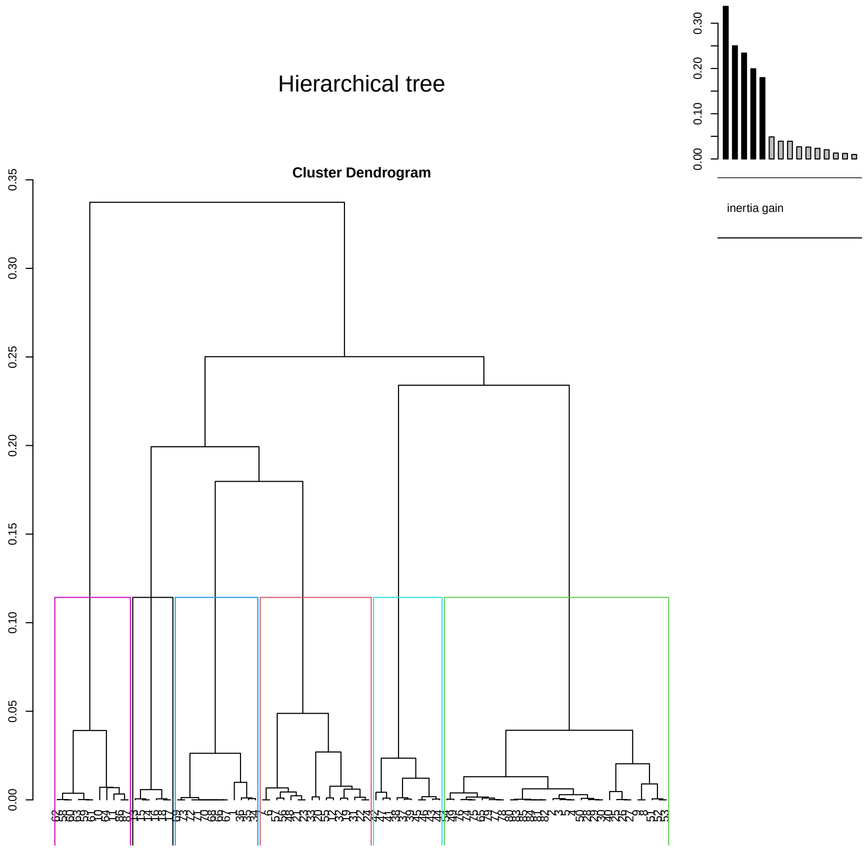

Fig. 66 | Cluster dendrogram of env. responses.

Negative Side	Positive Side
Axis 1	
Behavior (3.972) *OECD* (2.989)	*Energy* (12.819) *Asia* (12.509) *Panel 2* (11.159) *DC* (9.533) *Normative* (8.112) *statistical_accuracy_2* (4.259) *mobilized_theories_3* (4.087)
Axis 2	
mobilized_theories_5 (7.763) *2014 and before* (6.297) *Panel 1* (5.787) *Policies* (3.653) *h-index > 200* (3.784) *OECD* (2.974) *Ols* (2.785)	*h-index < 200* (8.944) *After 2014* (8.735) *GMM* (5.370) *Special* (4.963) *mobilized_theories_0* (4.663) *statistical_accuracy_3* (4.112) *statistical_accuracy_5*(3.736) *alldvt* (3.463) *Europe&CA* (3.325) *mobilized_theories_2* (3.032)

Tab. 36 | Relative contributions of variables to axes: Env. responses (without regional).

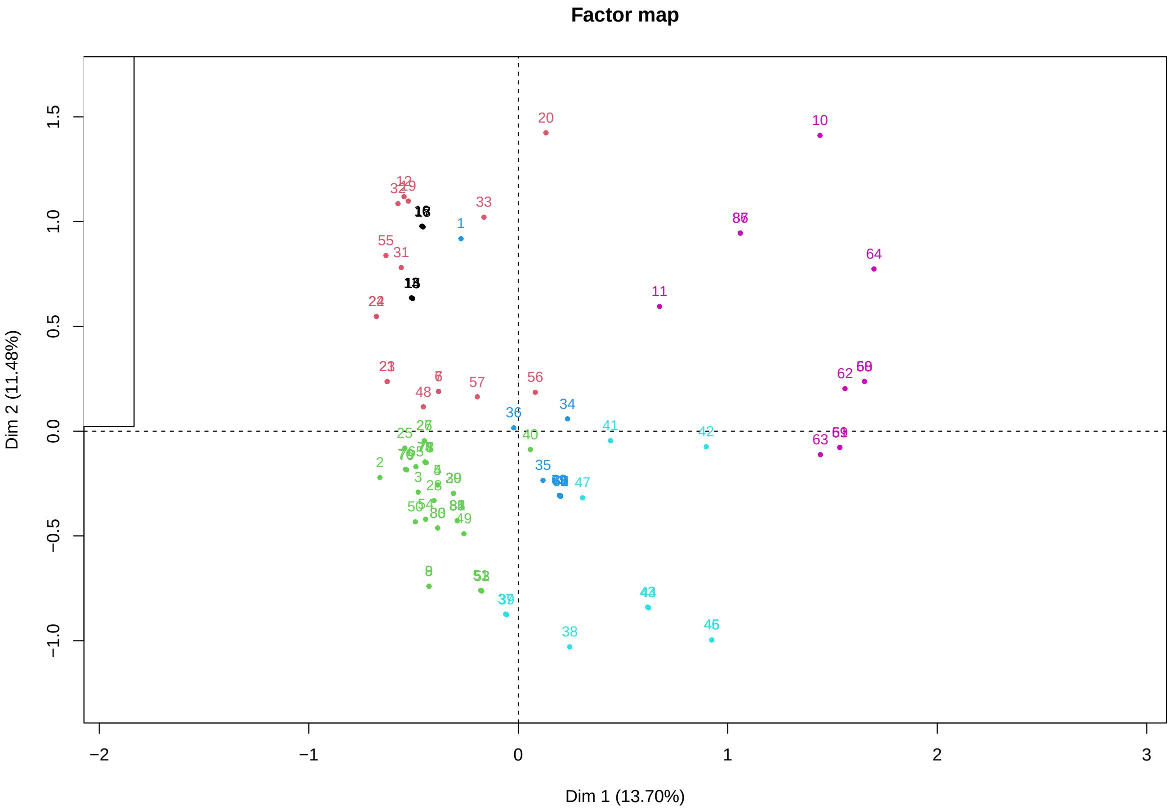

Fig. 67 | Factor map of HCA of env. responses.

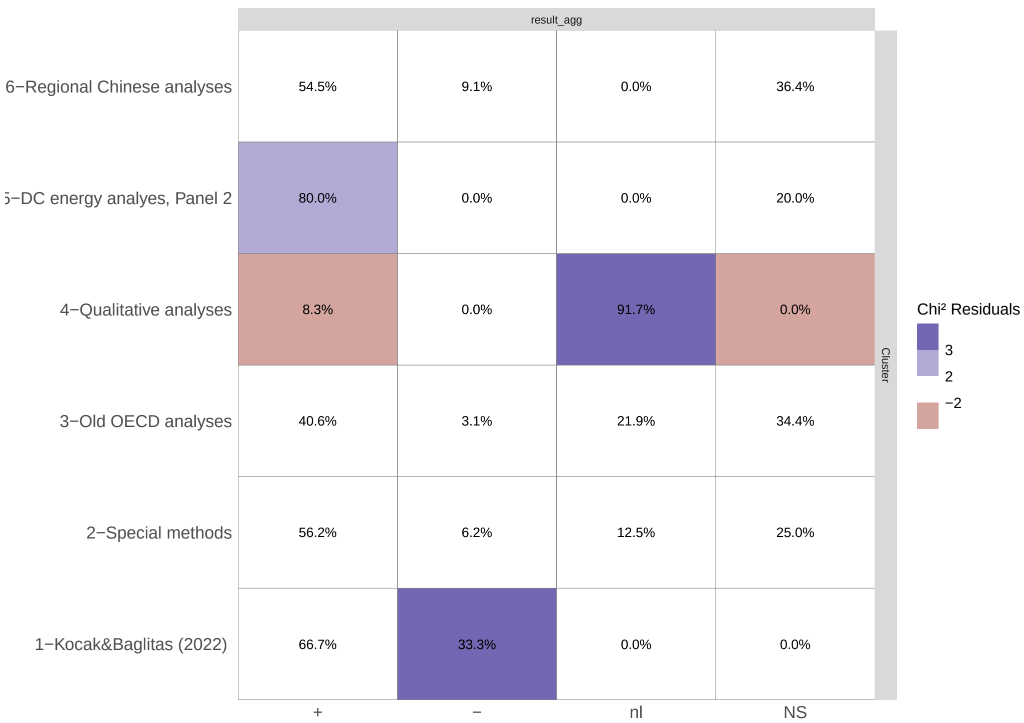

Fig. 68 | Correlation table - Clusters env. responses.

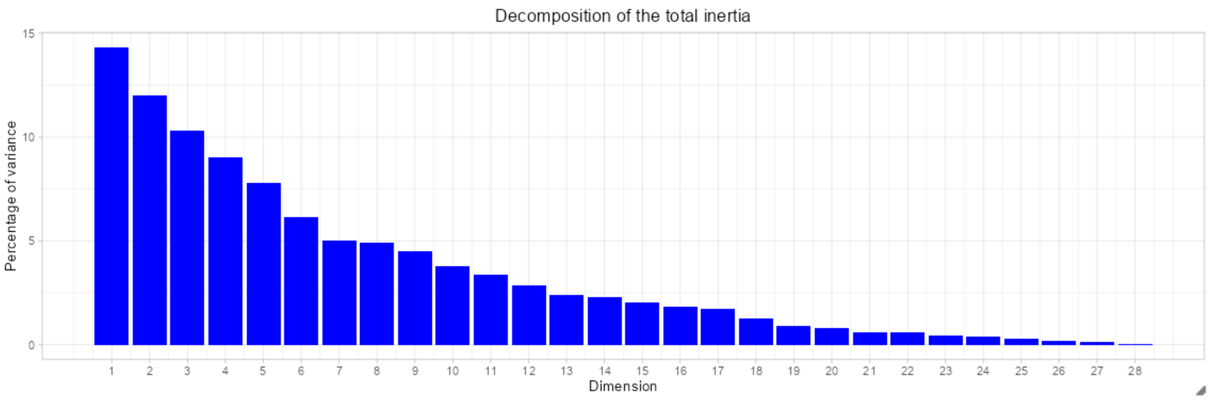

Fig. 69 | Decomposition of the total inertia env. responses (without regional).

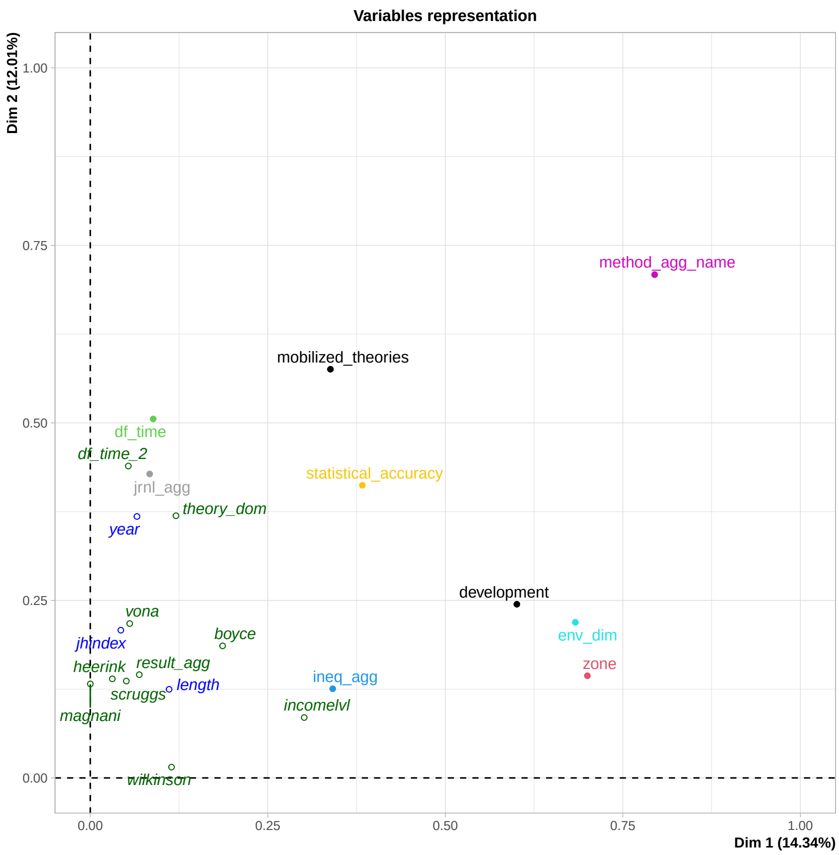

Fig. 70 | Variable representation env. responses (without regional).

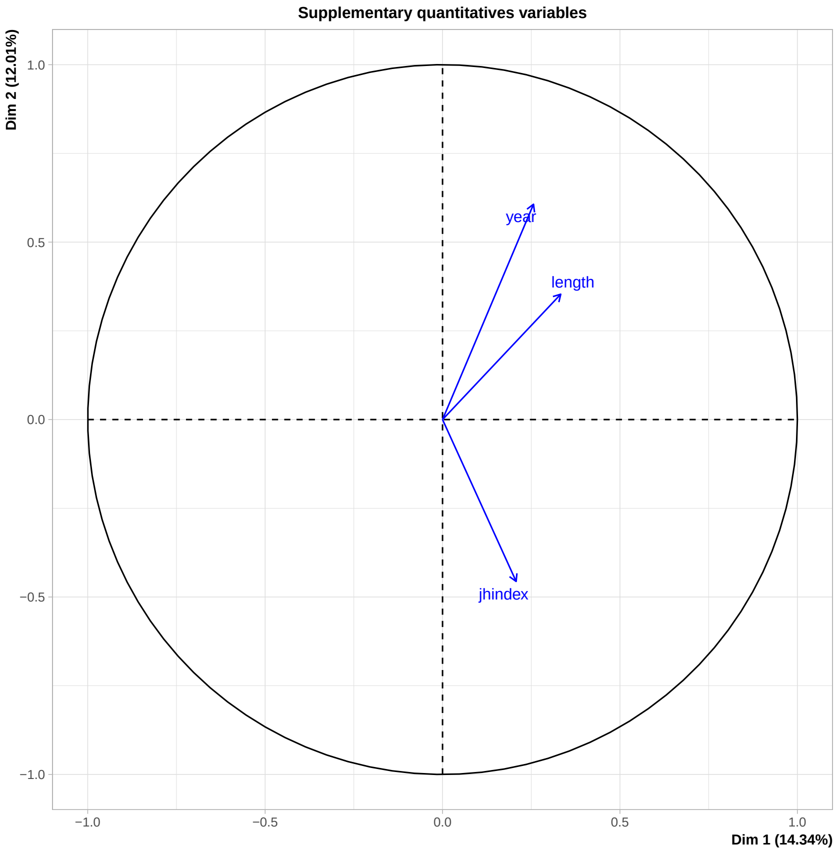

Fig. 71 | Supplementary quantitative variables env. responses (without regional).

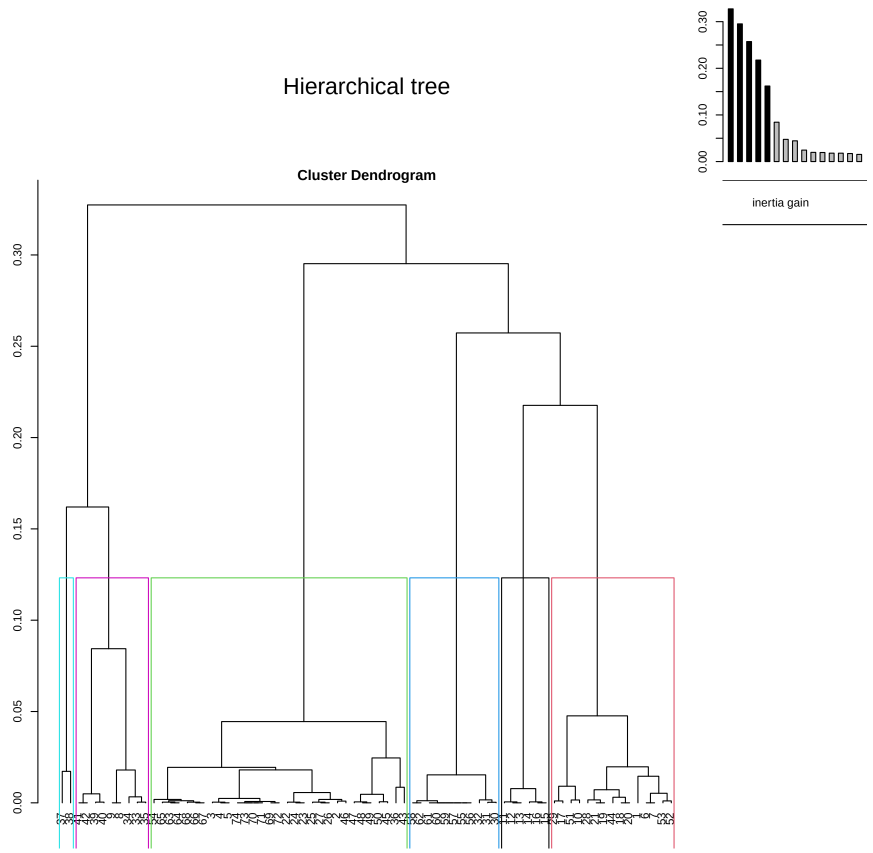

Fig. 72 | Cluster dendrogram of env. responses (without regional).

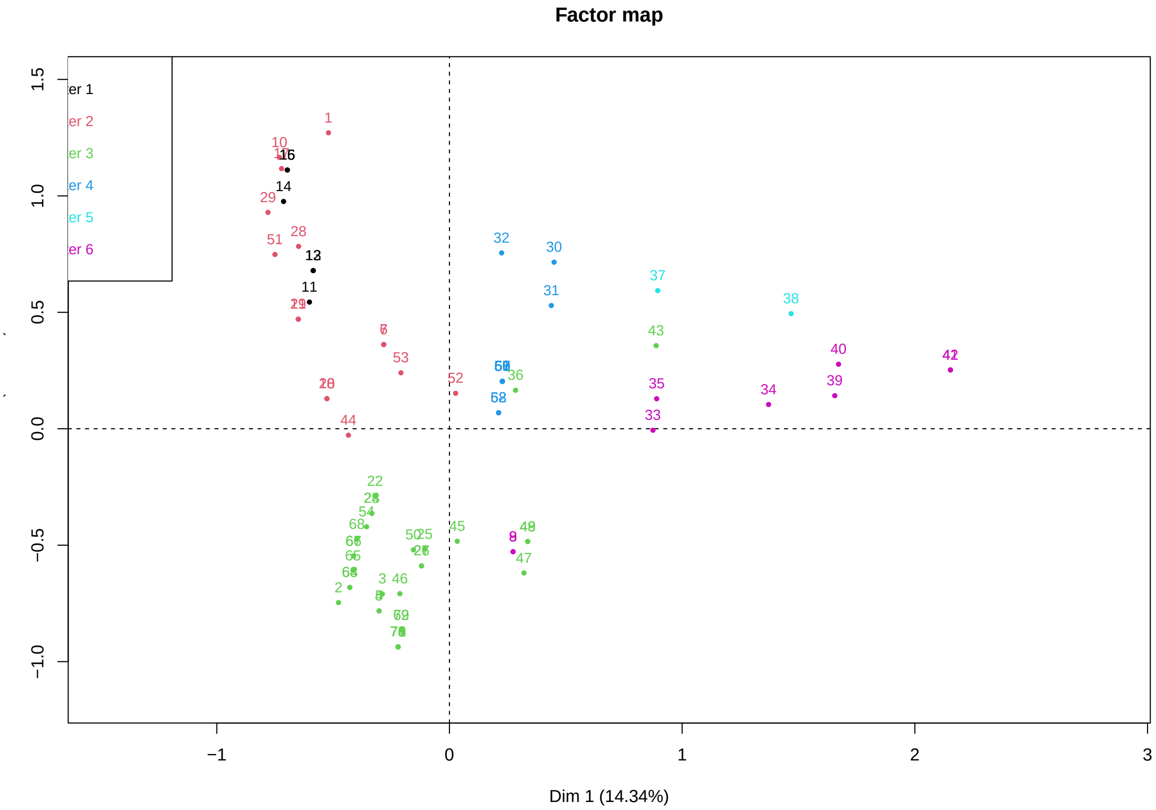

Fig. 73 | Factor map of HCA of env. responses (without regional).

Fig. 74 | Correlation table - Clusters env. responses (without regional).)

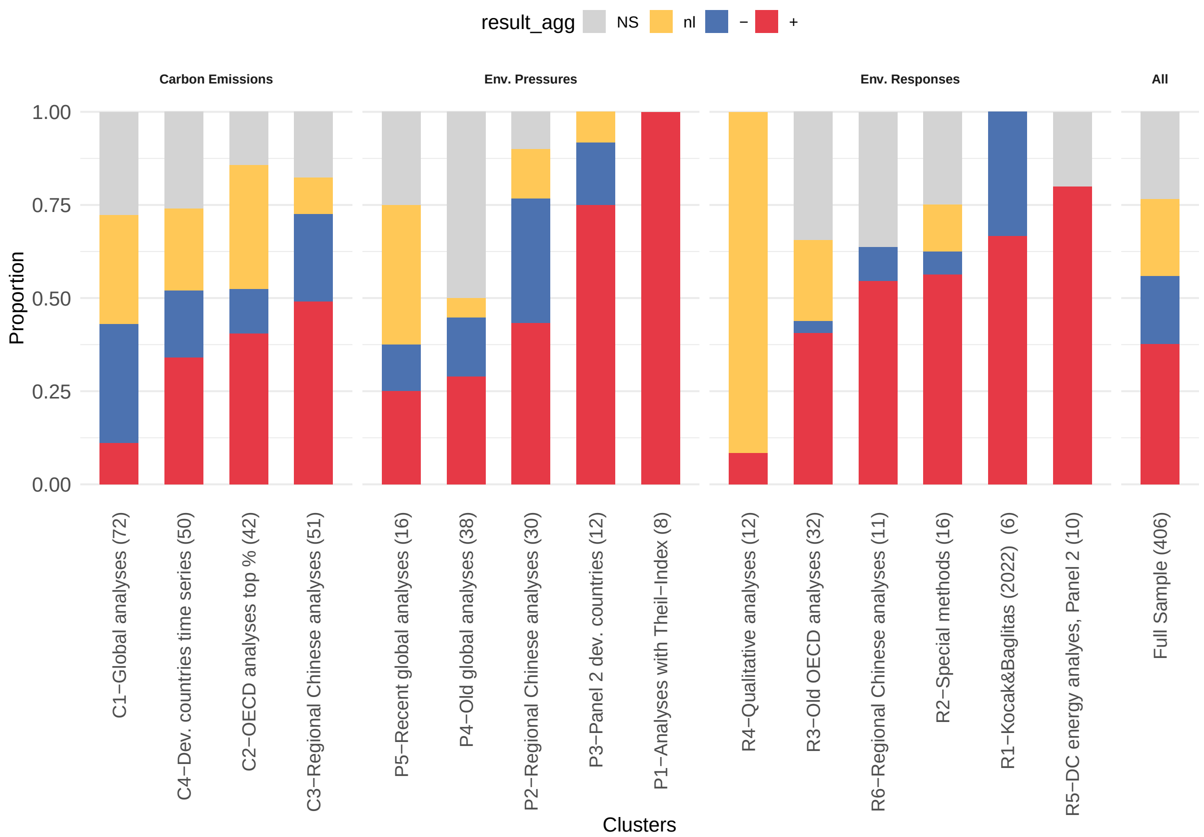

Fig. 75 | Results by clusters obtained from subgroups.

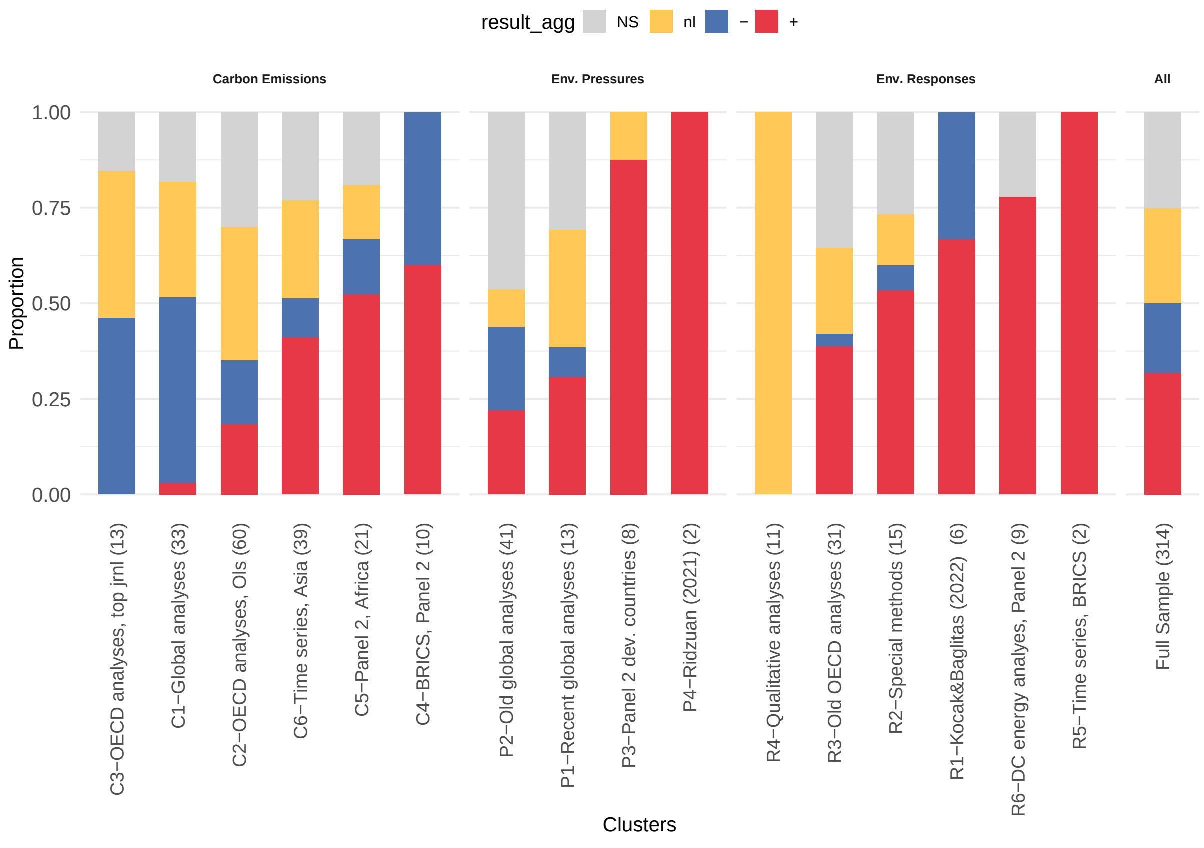

Fig. 76 | Results by clusters obtained from subgroups (without regional).

References

1. Haddaway, N. R., Page, M. J., Pritchard, C. C. & McGuinness, L. A. PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews* **18,** e1230. doi:https://doi.org/10.1002/cl2.1230. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/cl2.1230 (2022).
2. Berthe, A. & Elie, L. Mechanisms explaining the impact of economic inequality on environmental deterioration. *Ecological Economics* **116,** 191–200. doi:https://doi.org/10.1016/j.ecolecon.2015.04.026 (2015).
3. Boyce, J. Inequality as a Cause of Environmental Degradation. *Ecological Economics* **11,** 169–178. doi:10.1016/0921-8009(94)90198-8 (1994).
4. Heerink, N., Mulatu, A. & Bulte, E. Income inequality and the environment: aggregation bias in environmental Kuznets curves. en. *Ecological Economics* **38,** 359–367. doi:10.1016/S0921-8009(01)00171-9 (Sept. 2001).
5. Scruggs, L. A. Political and economic inequality and the environment. en. *Ecological Economics* **26,** 259–275. doi:10.1016/S0921-8009(97)00118-3 (Sept. 1998).
6. Magnani, E. The Environmental Kuznets Curve, environmental protection policy and income distribution. en. *Ecological Economics* **32,** 431–443. doi:10.1016/S0921-8009(99)00115-9 (Mar. 2000).
7. Wilkinson, R. & Pickett, K. *The spirit level: Why equality is better for everyone* (Penguin UK, 2010).
8. Granser Laura, L. *Analysis of the impact of income inequality on CO2 emissions* Journal Abbreviation: Analysis of the impact of Publication Title: Analysis of the impact of. doi:10.34726/hss.2021.86741 (Wien, Wien, 2021).
9. Chen, W., Chen, S. & Tang, Y. [Retracted] Does Income Inequality Harm Green Growth? The BRICS Experience. *Journal of Environmental and Public Health* **2022.** _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1155/2022/7046208, 7046208. doi:https://doi.org/10.1155/2022/7046208 (2022).
10. Vogel, J., Steinberger, J. K., O'Neill, D. W., Lamb, W. F. & Krishnakumar, J. Socio-economic conditions for satisfying human needs at low energy use: An international analysis of social provisioning. *Global Environmental Change* **69,** 102287. doi:https://doi.org/10.1016/j.gloenvcha.2021.102287 (2021).
11. Rao, N. D. & Min, J. Less global inequality can improve climate outcomes. *WIREs Climate Change* **9.** _eprint: https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/wcc.513, e513. doi:https://doi.org/10.1002/wcc.513 (2018).

12. Ma, X., Chen, D., Lan, J. & Li, C. The mathematical treatment for effect of income and urban-rural income gap on indirect carbon emissions from household consumption. *Environmental Science and Pollution Research* **27,** 36231–36241. doi:10.1007/s11356-020-09403-x (Oct. 2020).

13. Millward-Hopkins, J. & Oswald, Y. 'Fair' inequality, consumption and climate mitigation. en. *Environmental Research Letters* **16.** Publisher: IOP Publishing, 034007. doi:10.1088/1748-9326/abe14f (Feb. 2021).

14. Galaz, V. *et al.* 'Planetary boundaries'—exploring the challenges for global environmental governance. *Current Opinion in Environmental Sustainability* **4,** 80–87. doi:https://doi.org/10.1016/j.cosust.2012.01.006 (2012).

15. Sager, L. Income inequality and carbon consumption: Evidence from Environmental Engel curves. *Energy Economics* **84,** 104507. doi:https://doi.org/10.1016/j.eneco.2019.104507 (2019).

16. Zhao, J. & Ren, S. Urban Residential CO2 from Spatial and Non-Spatial Perspectives: Regional Difference between Northern and Southern China. *Atmosphere* **13.** doi:10.3390/atmos13081240 (2022).

17. Michieka, N. M., Deal, J. & Lahman, K. Air pollution and income inequality: a spatial econometric approach. *The Annals of Regional Science* **69,** 1–31. doi:10.1007/s00168-021-01105-7 (Aug. 2022).

18. Borghesi, S. *Income inequality and the environmental Kuznets curve* eng (Milano, 2000).

19. Baumgärtner, S., Drupp, M. A., Meya, J. N., Munz, J. M. & Quaas, M. F. Income inequality and willingness to pay for environmental public goods. *Journal of Environmental Economics and Management* **85,** 35–61. doi:https://doi.org/10.1016/j.jeem.2017.04.005 (2017).

20. Morse, S. Relating Environmental Performance of Nation States to Income and Income Inequality. en. *Sustainable Development* **26,** 99–115. doi:10.1002/sd.1693 (Jan. 2018).

21. Qu, B. & Zhang, Y. EFFECT OF INCOME DISTRIBUTION ON THE ENVIRONMENTAL KUZNETS CURVE. en. *Pacific Economic Review* **16,** 349–370. doi:10.1111/j.1468-0106.2011.00552.x (Aug. 2011).

22. Valenzuela-Levi, N. & Abreu, M. The income equality dividend in 'green' infrastructure: Evidence from the transport and waste sectors in the OECD. en. *Journal of Cleaner Production* **315,** 128088. doi:10.1016/j.jclepro.2021.128088 (Sept. 2021).

23. World Bank. *World Bank Country and Lending Groups.* 2023.

24. Furtado, C. *The myth of economic development* en. Trans. by Jones, J. B. (Polity Press, Medford, 2020).

25. OECD. *Members and partners* en. 2025.

26. Davidson, N., Mariev, O. & Turkanova, S. Does income inequality matter for CO2 emissions in Russian regions? en. *Equilibrium. Quarterly Journal of Economics and Economic Policy* **16,** 533–551. doi:10.24136/eq.2021.019 (Sept. 2021).

27. Bhattacharya, H. Environmental and socio-economic sustainability in India: evidence from CO_2 emission and economic inequality relationship. en. *Journal of Environmental Economics and Policy* **9,** 57–76. doi:10.1080/21606544.2019.1604267 (Jan. 2020).

28. Rözer, J., Lancee, B. & Volker, B. Keeping Up or Giving Up? Income Inequality and Materialism in Europe and the United States. en. *Social Indicators Research* **159,** 647–666. doi:10.1007/s11205-021-02760-1 (Jan. 2022).

29. Hundie, S. K. Income inequality, economic growth and carbon dioxide emissions nexus: empirical evidence from Ethiopia. en. *Environmental Science and Pollution Research* **28,** 43579–43598. doi:10.1007/s11356-021-13341-7 (Aug. 2021).

30. Yameogo, C. E. W. & Dauda, R. O. S. The effect of income inequality and economic growth on environmental quality: A comparative analysis between Burkina Faso and Nigeria. en. *Journal of Public Affairs* **22,** e2566. doi:10.1002/pa.2566 (Aug. 2022).

31. Safar, W. Income inequality and C O 2 emissions in France: Does income inequality indicator matter? en. *Journal of Cleaner Production* **370,** 133457. doi:10.1016/j.jclepro.2022.133457 (Oct. 2022).

32. Kocak, E. & Baglitas, H. H. The path to sustainable municipal solid waste management: Do human development, energy efficiency, and income inequality matter? en. *Sustainable Development* **30,** 1947–1962. doi:10.1002/sd.2361 (Dec. 2022).

33. Wan, G., Wang, C., Wang, J. & Zhang, X. The income inequality-CO2 emissions nexus: Transmission mechanisms. en. *Ecological Economics* **195,** 107360. doi:10.1016/j.ecolecon.2022.107360 (May 2022).

34. Bonnefond, C., Clement, M. & Yan, H. Income inequality and environmental quality in China: a semi-parametric analysis applied to provincial panel data. en. *Post-Communist Economies* **33,** 541–565. doi:10.1080/14631377.2020.1793604 (July 2021).

35. Guilhot, L., Meunié, A. & Pouyanne, G. Croissance, transition urbaine et pollutions atmosphériques en Chine: fr. *Mondes en développement* **n° 180,** 53–68. doi:10.3917/med.180.0053 (Dec. 2017).

36. Xiao, D., Yu, F. & Yang, H. The Impact of Urban-Rural Income Inequality on Environmental Quality in China. en. *Complexity* **2022** (ed Zhang, W.) 4604467. doi:10.1155/2022/4604467 (Jan. 2022).

37. Zhang, M., Wang, L., Ma, P. & Wang, W. Urban-rural income gap and air pollution: A stumbling block or stepping stone. en. *Environmental Impact Assessment Review* **94,** 106758. doi:10.1016/j.eiar.2022.106758 (May 2022).

38. Rockström, J. *et al.* Planetary boundaries: exploring the safe operating space for humanity. *Ecology and society* **14** (2009).

39. OECD. *How Green is Household Behaviour?: Sustainable Choices in a Time of Interlocking Crises* en. doi:10.1787/2bbbb663-en (OECD, June 2023).

40. Presberger, D. & Bernauer, T. Economic and political drivers of environmental impact shifting between countries. *Global Environmental Change* **79,** 102637. doi:https://doi.org/10.1016/j.gloenvcha.2023.102637 (2023).

41. Althouse, J., Cahen-Fourot, L., Carballa-Smichowski, B., Durand, C. & Knauss, S. Ecologically unequal exchange and uneven development patterns along global value chains. *World Development* **170,** 106308. doi:https://doi.org/10.1016/j.worlddev.2023.106308 (2023).

42. Roca, J. Do individual preferences explain the Environmental Kuznets curve? *Ecological Economics* **45,** 3–10. doi:https://doi.org/10.1016/S0921-8009(02)00263-X (2003).

43. Grunewald, N., Klasen, S., Martínez-Zarzoso, I. & Muris, C. The Trade-off Between Income Inequality and Carbon Dioxide Emissions. en. *Ecological Economics* **142,** 249–256. doi:10.1016/j.ecolecon.2017.06.034 (Dec. 2017).

44. Rojas-Vallejos, J. & Lastuka, A. The income inequality and carbon emissions trade-off revisited. en. *Energy Policy* **139,** 111302. doi:10.1016/j.enpol.2020.111302 (Apr. 2020).

45. Pesaran, M. H. & Smith, R. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* **68,** 79–113. doi:https://doi.org/10.1016/0304-4076(94)01644-F (1995).

46. Pesaran, M. H. Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica* **74.** doi:https://doi.org/10.1111/j.1468-0262.2006.00692.x (2006).

47. Teal, F. & Eberhardt, M. *Productivity Analysis in Global Manufacturing Production* Economics Series Working Papers 515 (University of Oxford, Department of Economics, 2010).

48. Baltagi, B. H., Li, D., *et al.* Series estimation of partially linear panel data models with fixed effects. *Annals of economics and finance* **3,** 103–116 (2002).

49. Koenker, R. & Bassett, G. Regression Quantiles. *Econometrica* **46.** Publisher: [Wiley, Econometric Society], 33–50. doi:10.2307/1913643 (1978).

50. Hansen, B. E. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics* **93,** 345–368. doi:https://doi.org/10.1016/S0304-4076(99)00025-1 (1999).

51. Hübler, M. The inequality-emissions nexus in the context of trade and development: A quantile regression approach. en. *Ecological Economics* **134,** 174–185. doi:10.1016/j.ecolecon.2016.12.015 (Apr. 2017).

52. Uddin, M. M., Mishra, V. & Smyth, R. Income inequality and CO2 emissions in the G7, 1870–2014: Evidence from non-parametric modelling. en. *Energy Economics* **88,** 104780. doi:10.1016/j.eneco.2020.104780 (May 2020).

53. Andersson, F. N. Income inequality and carbon emissions in the United States 1929–2019. en. *Ecological Economics* **204,** 107633. doi:10.1016/j.ecolecon.2022.107633 (Feb. 2023).

54. Pesaran, M. H., Shin, Y. & Smith, R. J. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* **16.** doi:https://doi.org/10.1002/jae.616 (2001).

55. Uzar, U. & Eyuboglu, K. The nexus between income inequality and CO2 emissions in Turkey. en. *Journal of Cleaner Production* **227,** 149–157. doi:10.1016/j.jclepro.2019.04.169 (Aug. 2019).

56. Arellano, M. & Bond, S. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies* **58.** _eprint: https://academic.oup.com/restud/article-pdf/58/2/277/4454458/58-2-277.pdf, 277–297. doi:10.2307/2297968 (Apr. 1991).

57. Arellano, M. & Bover, O. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* **68,** 29–51. doi:https://doi.org/10.1016/0304-4076(94)01642-D (1995).

58. Blundell, R. & Bond, S. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* **87,** 115–143. doi:https://doi.org/10.1016/S0304-4076(98)00009-8 (1998).

59. Mirza, M. U., Richter, A., Van Nes, E. H. & Scheffer, M. Institutions and inequality interplay shapes the impact of economic growth on biodiversity loss. en. *Ecology and Society* **25,** art39. doi:10.5751/ES-12078-250439 (2020).

60. You, W., Li, Y., Guo, P. & Guo, Y. Income inequality and CO2 emissions in belt and road initiative countries: the role of democracy. en. *Environmental Science and Pollution Research* **27,** 6278–6299. doi:10.1007/s11356-019-07242-z (Feb. 2020).

61. Harring, N. Corruption, inequalities and the perceived effectiveness of economic pro-environmental policy instruments: A European cross-national study. en. *Environmental Science & Policy* **39,** 119–128. doi:10.1016/j.envsci.2013.08.011 (May 2014).

62. Valenzuela-Levi, N. Why do more unequal countries spend more on private vehicles? Evidence and implications for the future of cities. en. *Sustainable Cities and Society* **43,** 384–394. doi:10.1016/j.scs.2018.09.003 (Nov. 2018).

63. York, R., Rosa, E. A. & Dietz, T. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics* **46,** 351–365. doi:https://doi.org/10.1016/S0921-8009(03)00188-5 (2003).

64. Liu, Z., Zhang, H., Zhang, Y.-J. & Qin, C.-X. How does income inequality affect energy efficiency? Empirical evidence from 33 Belt and Road Initiative countries. en. *Journal of Cleaner Production* **269,** 122421. doi:10.1016/j.jclepro.2020.122421 (Oct. 2020).

65. Asongu, S. A. & Odhiambo, N. M. Inequality and renewable energy consumption in Sub-Saharan Africa: implication for high income countries. en. *Innovation: The European Journal of Social Science Research* **37,** 382–398. doi:10.1080/13511610.2020.1861442 (Apr. 2021).

66. Zecca, E. & Nicolli, F. Inequality, democracy and green technological change. en. *Journal of Cleaner Production* **306,** 127061. doi:10.1016/j.jclepro.2021.127061 (July 2021).

67. Bel, G. & Teixidó, J. J. The political economy of the Paris Agreement: Income inequality and climate policy. en. *Journal of Cleaner Production* **258,** 121002. doi:10.1016/j.jclepro.2020.121002 (June 2020).

68. Vona, F. & Patriarca, F. Income inequality and the development of environmental technologies. en. *Ecological Economics* **70,** 2201–2213. doi:10.1016/j.ecolecon.2011.06.027 (Sept. 2011).

69. Jones, C. I. *The Facts of Economic Growth* Working Paper 21142 (National Bureau of Economic Research, 2015). doi:10.3386/w21142.

70. Jorgenson, A., Schor, J. & Huang, X. Income Inequality and Carbon Emissions in the United States: A State-level Analysis, 1997–2012. en. *Ecological Economics* **134,** 40–48. doi:10.1016/j.ecolecon.2016.12.016 (Apr. 2017).

71. Ravallion, M., Heil, M. & Jalan, J. Carbon Emissions and Income Inequality. en. *Oxford Economic Papers* **52,** 651–669 (2000).

72. Scimago (ed.) *Scimago Journal & Country Rank* 2025.

73. Malesios, C. Measuring the robustness of the journal h-index with respect to publication and citation values: A Bayesian sensitivity analysis. *Journal of Informetrics* **10,** 719–731. doi:https://doi.org/10.1016/j.joi.2016.03.002 (2016).

74. Torras, M. & Boyce, J. K. Income, inequality, and pollution: a reassessment of the environmental Kuznets Curve. en. *Ecological Economics* **25,** 147–160. doi:10.1016/S0921-8009(97)00177-8 (May 1998).

75. Althor, G., Watson, J. E. M. & Fuller, R. A. Global mismatch between greenhouse gas emissions and the burden of climate change. *Scientific Reports* **6,** 20281. doi:10.1038/srep20281 (Feb. 2016).

76. Cappelli, F., Costantini, V. & Consoli, D. The trap of climate change-induced "natural" disasters and inequality. *Global Environmental Change* **70,** 102329. doi:https://doi.org/10.1016/j.gloenvcha.2021.102329 (2021).

77. Chancel, L. Global carbon inequality over 1990–2019. *Nature Sustainability* **5,** 931–938. doi:10.1038/s41893-022-00955-z (Nov. 2022).

78. Roemer, J. E. Would Economic Democracy Decrease the Amount of Public Bads? *The Scandinavian Journal of Economics* **95,** 227–238 (1993).

79. Kang, H. Impacts of Income Inequality and Economic Growth on CO2 Emissions: Comparing the Gini Coefficient and the Top Income Share in OECD Countries. en. *Energies* **15,** 6954. doi:10.3390/en15196954 (Sept. 2022).

80. Huo, C. & Chen, L. The Impact of the Income Gap on Carbon Emissions: Evidence from China. en. *Energies* **15.** doi:10.3390/en15103771 (May 2022).

81. McGee, J. A. & Greiner, P. T. Can Reducing Income Inequality Decouple Economic Growth from CO_2 Emissions? en. *Socius: Sociological Research for a Dynamic World* **4.** doi:10.1177/2378023118772716 (Jan. 2018).

82. Wu, C., Zhang, Z., Elahi, E., Mu, G. & Zhao, P. Urban-rural income disparities and atmospheric contamination: Aggravating or restraining? en. *Frontiers in Environmental Science* **10,** 1015857. doi:10.3389/fenvs.2022.1015857 (Oct. 2022).

83. Wu, R. & Xie, Z. Identifying the impacts of income inequality on CO2 emissions: Empirical evidences from OECD countries and non-OECD countries. en. *Journal of Cleaner Production* **277,** 123858. doi:10.1016/j.jclepro.2020.123858 (Dec. 2020).

84. Liu, C., Jiang, Y. & Xie, R. Does income inequality facilitate carbon emission reduction in the US? en. *Journal of Cleaner Production* **217,** 380–387. doi:10.1016/j.jclepro.2019.01.242 (Apr. 2019).

85. Ghosh, S. Renewable energy and CO_2 emissions: the economics and geopolitical implications, experiences from the BRICS nations. en. *International Journal of Energy Sector Management* **16,** 1064–1090. doi:10.1108/IJESM-08-2021-0024 (Sept. 2022).

86. Baloch, M. A. & Danish. The nexus between renewable energy, income inequality, and consumption-based CO_2 emissions: An empirical investigation. en. *Sustainable Development* **30,** 1268–1277. doi:10.1002/sd.2315 (Oct. 2022).

87. Zhong, K. Does the digital finance revolution validate the Environmental Kuznets Curve? Empirical findings from China. en. *PLOS ONE* **17** (ed Zhang, M.) doi:10.1371/journal.pone.0257498 (2022).

88. Ridzuan, S. Inequality and water pollution in India. en. *Water Policy* **23,** 985–999. doi:10.2166/wp.2021.057 (Aug. 2021).

89. Agan, B. & Balcilar, M. On the Determinants of Green Technology Diffusion: An Empirical Analysis of Economic, Social, Political, and Environmental Factors. en. *Sustainability* **14,** 2008. doi:10.3390/su14042008 (Feb. 2022).

90. Mehmood, U. *et al.* Socio-Economic Drivers of Renewable Energy: Empirical Evidence from BRICS. en. *International Journal of Environmental Research and Public Health* **19,** 4614. doi:10.3390/ijerph19084614 (Apr. 2022).

91. Shahbaz, M., Abbas Rizvi, S. K., Dong, K. & Vo, X. V. Fiscal decentralization as new determinant of renewable energy demand in China: The role of income inequality and urbanization. en. *Renewable Energy* **187,** 68–80. doi:10.1016/j.renene.2022.01.064 (Mar. 2022).

92. Tan, Y. & Uprasen, U. Carbon neutrality potential of the ASEAN-5 countries: Implications from asymmetric effects of income inequality on renewable energy consumption. en. *Journal of Environmental Management* **299,** 113635. doi:10.1016/j.jenvman.2021.113635 (Dec. 2021).

93. Uzar, U. Is income inequality a driver for renewable energy consumption? en. *Journal of Cleaner Production* **255,** 120287. doi:10.1016/j.jclepro.2020.120287 (May 2020).