

# Journal Pre-proof

Beyond Linear Thinking: Redefining Chemical Pollution Impacts on Biodiversity

Yingying Liu, Xiaowei Jin, Aibin Zhan, Jinbao Liao, Andrew C. Johnson, Jian Xu



PII: S2666-4984(25)00067-5

DOI: <https://doi.org/10.1016/j.ese.2025.100589>

Reference: ESE 100589

To appear in: *Environmental Science and Ecotechnology*

Received Date: 1 April 2025

Revised Date: 13 June 2025

Accepted Date: 14 June 2025

Please cite this article as: Y. Liu, X. Jin, A. Zhan, J. Liao, A.C. Johnson, J. Xu, Beyond Linear Thinking: Redefining Chemical Pollution Impacts on Biodiversity, *Environmental Science and Ecotechnology*, <https://doi.org/10.1016/j.ese.2025.100589>.

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1 **Beyond Linear Thinking: Redefining Chemical Pollution Impacts on**  
2 **Biodiversity**

3 **Yingying Liu<sup>a, b</sup>, Xiaowei Jin<sup>c\*</sup>, Aibin Zhan<sup>d</sup>, Jinbao Liao<sup>e</sup>, Andrew C. Johnson<sup>f</sup>, Jian Xu<sup>a, b\*</sup>**

4 <sup>a</sup> State Key Laboratory of Environmental Criteria and Risk Assessment, Chinese Research  
5 Academy of Environmental Sciences, Beijing 100012, China

6 <sup>b</sup> College of Water Sciences, Beijing Normal University, Beijing 100875, China

7 <sup>c</sup> China National Environmental Monitoring Centre, Beijing 100012, China

8 <sup>d</sup> Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing  
9 100085, China

10 <sup>e</sup> State Key Laboratory for Vegetation Structure, Function and Construction (VegLab), Ministry of  
11 Education Key Laboratory for Transboundary Ecoscience of Southwest China, Institute of  
12 Biodiversity, School of Ecology and Environmental Science, Yunnan University, Kunming  
13 650091, China

14 <sup>f</sup> UK Centre for Ecology and Hydrology, Wallingford, Oxfordshire OX10 8BB, UK

15

16 \*Corresponding authors:

17 **Xiaowei Jin**

18 China National Environmental Monitoring Centre, Beijing 100012, China

19 E-mail: [jinxw@cnemc.cn](mailto:jinxw@cnemc.cn)

20

21 **Jian Xu**

22 Chinese Research Academy of Environmental Sciences, Beijing 100012, China

23 E-mail: [xujian@craes.org.cn](mailto:xujian@craes.org.cn)

24 Since the onset of the Anthropocene, chemical pollution has emerged as a primary  
25 global threat to biodiversity across all biogeographical realms. This planetary-scale  
26 challenge affects ecosystem functionality from local to global scales, contributing  
27 significantly to biodiversity loss worldwide [1]. Traditional ecological risk assessments  
28 have predominantly relied on chemical-by-chemical dose–response linear models,  
29 presuming that incremental increases in harmful chemical pollutant concentrations lead  
30 to proportional declines in species abundance (Fig. 1a). However, this linear paradigm,  
31 which forms the foundation of environmental regulations across diverse geopolitical  
32 contexts—critically oversimplifies the intricate interactions within ecosystems. Such  
33 simplification fails to capture the multifaceted responses elicited by chemical pollutants  
34 interacting with other global change drivers across different biomes, ecoregions, and  
35 latitudinal gradients. Emerging evidence from cross-continental studies highlights that  
36 pollutant impacts on ecosystems often exhibit significant nonlinear characteristics,  
37 including thresholds, hysteresis, and potentially irreversible regime shifts [2]. These  
38 nonlinearities are shaped by ecological phenomena, including baseline stress levels,  
39 species sensitivity, and habitat connectivity. For example, pollutants that seem benign  
40 in isolation may cause severe disruption when associated with thermal stress or habitat  
41 loss [1]. Such nonlinear responses could be linked to delays in population recovery,  
42 spatial heterogeneity, adaptive traits, and reinforcing loops. For instance, in coral reef  
43 ecosystems, functional groups of herbivores, such as grazers and scrapers, play a critical  
44 role in mediating algal-coral dynamics and influencing ecosystem recovery trajectories  
45 [3]. These complex dynamics challenge traditional predictive frameworks and  
46 underscore the need for monitoring systems capable of detecting indirect, delayed, and  
47 context-dependent effects.

48 Biodiversity across global ecosystems experiences nonlinear impacts from  
49 chemical pollutants. At sublethal levels prevalent in human-dominated landscapes, they  
50 subtly disrupt physiology, metabolism, and gene expression, thereby reducing  
51 individual fitness, reproduction, and population resilience, while also heightening  
52 susceptibility to co-stressors across diverse taxa. These effects accumulate through  
53 trophic levels and regions, gradually compromising ecosystem integrity without

54 necessarily triggering detectable population declines. As concentrations rise, sensitive  
55 species may exhibit non-monotonic population dynamics, potentially triggering  
56 cascading disruptions via altered competition interactions, predation pressures, and  
57 ecosystem engineering processes [4]. Such threshold-driven responses, as emphasized  
58 by Folke et al. [3], reveal that minor increases in pollutant levels can precipitate  
59 disproportionate ecological disruptions, necessitating a review of context-specific  
60 safety thresholds to avert irreversible tipping points.

61 Chemical contaminants persist and bioaccumulate across interconnected  
62 ecosystems, posing significant threats to global biodiversity and ecosystem stability [5].  
63 These pollutants interact with ecological drivers across spatial scales, including habitat  
64 structure, resource availability, disturbance regimes, and biotic interactions, shaping  
65 complex, multi-peaked biodiversity patterns that challenge linear and unimodal models  
66 across biomes [6]. This complexity demands a shift from simplistic risk assessments as  
67 we become aware of nonlinear interactions between pollutants and global change  
68 drivers across terrestrial, freshwater, and marine ecosystems. For instance, Rockström  
69 et al. [1] demonstrated that an agricultural nitrogen surplus of 61 Tg N per year,  
70 combined with land-use change and a tightened boundary of 57 Tg N per year due to  
71 groundwater nitrate, disrupted soil microbial communities and plant species richness in  
72 temperate grasslands. This case underscores how nutrient pollution and land  
73 degradation can interact through altered nutrient cycling and habitat loss, amplifying  
74 ecological impacts beyond those predicted by single-stressor models. Similarly,  
75 Schartup et al. [4] revealed non-additive interactions among climate warming,  
76 overfishing, and methylmercury (MeHg) bioaccumulation in the Gulf of Maine over  
77 three decades. A 1 °C rise in seawater temperature increased MeHg concentrations in  
78 Atlantic cod by 32%, whereas overfishing-induced trophic shifts reduced them by 12%,  
79 resulting in a net 10% decrease. However, warming and herring depletion drove a 70%  
80 surge in MeHg in spiny dogfish through physiological and dietary changes, highlighting  
81 the unpredictable nature of multiple interacting stressors over decades of environmental  
82 change in marine ecosystems. At a broader landscape scale, Johnson et al. [7] employed  
83 a machine learning model incorporating 41 environmental variables to explain 73% of

84 macroinvertebrate family richness variation in English rivers. Their findings revealed  
85 that elevated zinc and copper levels, particularly when combined with high wastewater  
86 exposure, disproportionately drove biodiversity declines, even after adjusting for  
87 habitat quality and hydromorphology, emphasizing the dominant influence of chemical  
88 stressors in freshwater ecosystems worldwide. These cases collectively demonstrate  
89 that the ecological risks of chemical pollution cannot be solely predicted by  
90 contaminant concentrations but must account for interactions with environmental  
91 context and co-occurring stressors. In stressed or degraded ecosystems, ranging from  
92 tropical to temperate zones, such synergies can amplify toxicological impacts, driving  
93 severe and potentially irreversible biodiversity and functional losses across multiple  
94 scales [3]. Addressing these global challenges, identifying and quantifying these  
95 nonlinear relationships, alongside defining ecological safety thresholds for pollutants,  
96 could be vital for advancing environmental science in the Anthropocene [1].

97 The intrinsic complexity and interconnectedness of ecological networks amplify  
98 the nonlinear effects of chemical pollutants, extending their impacts far beyond direct  
99 toxicological interactions across ecosystem boundaries. Pollutants influence  
100 ecosystems through multiple pathways, including bioaccumulation, biomagnification,  
101 food web restructuring, altered competitive dynamics, and delayed demographic  
102 responses, resulting in complex, nonlinear patterns at both community and ecosystem  
103 scales [3]. For example, biomagnification of persistent organic pollutants within food  
104 webs can exert selective pressure on apex predators through reproductive impairment  
105 or immune suppression. These disruptions cascade through trophic networks,  
106 potentially triggering alternative stable states characterized by fundamentally different  
107 community structures and ecosystem functions [9]. Additionally, ecosystems under  
108 multiple anthropogenic stressors become increasingly vulnerable to ecological tipping  
109 points, which are thresholds that trigger rapid, nonlinear shifts to alternate states with  
110 reduced biodiversity and ecosystem services [1,10]. These transitions, such as shallow  
111 lakes transitioning to phytoplankton-dominated systems or coral reefs collapsing into  
112 algal dominance, occur when interacting stressors disrupt feedback mechanisms [2,3].  
113 Such disruptions arise from interactions between chemical pollution and other global

114 environmental pressures, such as climate change and habitat fragmentation, which  
115 erode resilience by weakening negative feedback and amplifying positive ones, thereby  
116 accelerating shifts while hindering recovery. The combined effects of various  
117 environmental stressors, including chemical pollutants, climate change, and land-use  
118 change, heighten the probability of crossing these tipping points across ecosystems  
119 worldwide. For instance, the accumulation of persistent pollutants can undermine coral  
120 reef resilience, diminishing their capacity to withstand ocean acidification and  
121 accelerating their transition to degraded states [3]. These global cases underscore the  
122 urgent need for a shift from single-stressor assessments to integrated frameworks that  
123 capture complex, nonlinear dynamics in real-world ecosystems under multiple  
124 pressures.

125 **Fig.1.** Frameworks of ecological risk assessments. **a**, Traditional dose–response  
126 linear models for conventional approaches. **b**, Nonlinear response patterns framework  
127 for natural ecosystems under multiple stressors.

128 Addressing these complex global challenges requires a fundamental paradigm  
129 shift toward a comprehensive framework centered on “nonlinear response patterns  
130 under multiple stressors” (Fig. 1b). We propose an innovative and integrated framework  
131 that consolidates multiple approaches to tackle the complex, multi-peaked nonlinear  
132 behaviors arising from interactions between chemical pollutants and biodiversity across  
133 ecosystems worldwide. Unlike traditional approaches, which often treat stressors in  
134 isolation, this framework considers the combined effects of multiple environmental  
135 stressors, providing a more holistic and predictive tool for ecosystem management in  
136 diverse geographical contexts [4,8]. It aims to overcome the limitations of conventional  
137 monitoring by integrating real-time data, advanced data analysis, predictive modeling,  
138 and technology development. To tackle chemical pollution’s biodiversity impact across  
139 global ecosystems, this approach requires recognizing the complexity of anthropogenic  
140 chemicals and leveraging expertise from ecotoxicology, community ecology,  
141 biogeochemistry, and environmental informatics. Transdisciplinary collaboration  
142 strengthens predictive power and supports targeted, context-specific mitigation [1,2].

143 The framework comprises four interconnected components. First, a hierarchically

144 structured, integrated monitoring system should be developed, combining chemical,  
145 biological, and ecological data to track pollutant effects across ecosystems [5]. Tools  
146 such as non-target screening (NTS), molecular biomarkers, and environmental  
147 deoxyribonucleic acid metabarcoding can detect emerging contaminants, shifts in  
148 community structure and function, and early warning signals of ecological transitions.  
149 In Chebei Stream, Guangzhou, NTS-based chemical fingerprints effectively traced  
150 pollutant sources in complex mixtures, illustrating its potential in ecosystem monitoring  
151 [8]. A multi-source data fusion platform can synthesize such data to identify tipping  
152 points and guide proactive management across environmental gradients. Second, multi-  
153 stressor assessments require advanced methods to quantify interactive effects across  
154 ecosystems. Tools such as mixture toxicity testing, food web metrics, and functional  
155 redundancy analysis help identify the impacts and thresholds of compounds. Machine  
156 learning enhances early warning capabilities by detecting signals such as critical  
157 slowing. At the global level, the Safe and Just Earth System Boundaries framework  
158 applies similar principles, revealing that multiple thresholds have been exceeded in  
159 densely populated regions [1]. Third, environmental management policies must  
160 integrate multi-stressor frameworks into chemical management decisions to boost  
161 adaptive capacity and ecological relevance. For instance, the European Union's  
162 Registration, Evaluation, Authorisation, and Restriction of Chemicals requires  
163 manufacturers to provide safety data before market approval, creating a strategic point  
164 for integrating nonlinear, multi-stressor monitoring [9]. Embedding real-time early  
165 warning systems based on remote sensing and biosensors into such frameworks can  
166 enable timely responses near ecological thresholds and improve resilience under  
167 multiple pressures. Finally, advancing supportive technologies is essential for nonlinear  
168 ecological risk assessment. Smart biosensors enable the real-time detection of stress in  
169 sentinel species, while remote sensing facilitates large-scale resilience monitoring. In  
170 the Amazon Basin, satellite vegetation indices showed increasing autocorrelation and  
171 slower recovery after droughts, indicating a decline in ecosystem resilience [10].  
172 Combined with machine learning, these tools enhance the early detection of ecological  
173 tipping points and support timely interventions in response to multiple stressors. This

174 framework lays a foundation for assessing the impacts of complex pollutants and setting  
175 science-based safety boundaries, thereby strengthening environmental decision-making  
176 amid interacting global change drivers.

177 The implementation of nonlinear ecological risk assessment at scale may face  
178 practical challenges, including high costs, data heterogeneity, and limited infrastructure,  
179 particularly in resource-constrained settings. These obstacles can be addressed through  
180 modular monitoring, standardized protocols, and cross-sector collaboration. While  
181 nonlinear models offer valuable insights, they are sensitive to data quality, structural  
182 assumptions, and system complexity, often producing outputs that are difficult to  
183 interpret or validate. Therefore, they are most effective when used as adaptive decision-  
184 support tools, supported by empirical validation and transparent communication of  
185 uncertainties. By integrating multidimensional monitoring with nonlinear analyses,  
186 environmental management can enhance the early detection of ecosystem instability  
187 and facilitate timely interventions. Ultimately, this framework fosters adaptive, context-  
188 specific risk models that identify ecological tipping points and pollution thresholds,  
189 thereby enhancing policy responses, safeguarding biodiversity, and sustaining  
190 ecosystem resilience in the face of global change.

#### 191 **CRedit authorship contribution statement**

192 **Yingying Liu:** Conceptualization, Visualization, Writing - Original Draft, Writing -  
193 Review & Editing. **Xiaowei Jin:** Conceptualization, Funding Acquisition,  
194 Methodology, Project Administration, Writing - Original Draft, Writing - Review &  
195 Editing. **Aibin Zhan:** Conceptualization, Writing - Review & Editing. **Jinbao Liao:**  
196 Conceptualization, Writing - Review & Editing. **Andrew C. Johnson:**  
197 Conceptualization, Writing - Review & Editing. **Jian Xu:** Conceptualization, Funding  
198 Acquisition, Methodology, Project Administration, Writing - Original Draft, Writing -  
199 Review & Editing.

#### 200 **Declaration of competing interest**

201 The authors declare that they have no known competing financial interests or personal  
202 relationships that could have appeared to influence the work reported in this paper.  
203 Dr. Jian Xu, the Associate Editor for *Environmental Science and Ecotechnology*, was  
204 not involved in the editorial review or the decision to publish this article.

#### 205 **Acknowledgments**

206 This work was funded by the National Natural Science Foundation of China (42322710,  
207 42477299) and the National Science Fund for Distinguished Young Scholars  
208 (42325706).

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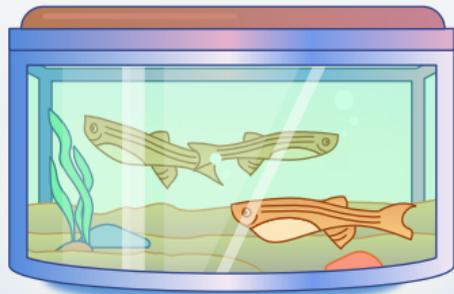
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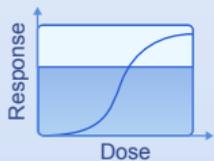
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**a**

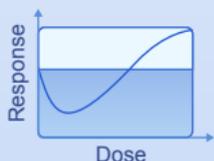
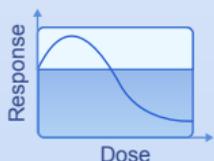
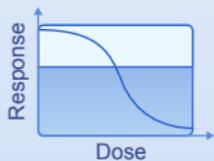
## Linear dose–effect relationships under a single stressor



Laboratory simulation



Single pollutant



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**1**

**1**  
Establish layered integrated monitoring system

**2**

**2**  
Improve multi-stressor assessment methods

**3**

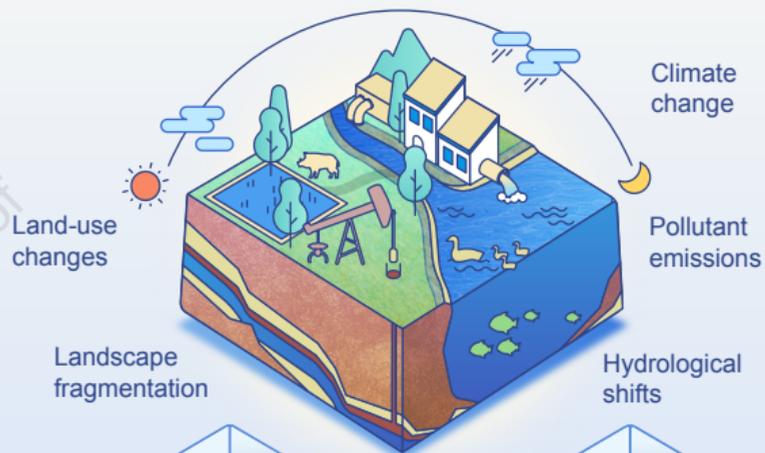
**3**  
Innovate environmental management policies

**4**

**4**  
Develop supportive technologies and tools

**b**

## Nonlinear pressure–response relationships under multiple stressors



Landscape fragmentation

Species richness

Pressure

Time

Species diversity

Pressure

Time

Functional diversity

Pressure

Time

Ecosystem function

Pressure

Time

**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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