Advancing the spatiotemporal dimension of wildlife–pollution interactions

Jack A. Brand[1,2,†,*], Jake M. Martin[1,3,4,5,*], Marcus Michelangeli[1,6], Eli S.J. Thoré[1,7,8], Natalia Sandoval-Herrera[1], Erin S. McCallum[1], Drew Szabo[9], Damien L. Callahan[5], Timothy D. Clark[5], Michael G. Bertram[1,3,4], Tomas Brodin[1]

[1] Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå, Sweden

[2] Institute of Zoology, Zoological Society of London, London, United Kingdom

[3] Department of Zoology, Stockholm University, Stockholm, Sweden

[4] School of Biological Sciences, Monash University, Melbourne, Australia

[5] School of Life and Environmental Sciences, Deakin University, Geelong, Australia

[6] Australian Rivers Institute, Griffith University, Nathan, Queensland, Australia

[7] TRANSfarm - Science, Engineering, & Technology Group, KU Leuven, Lovenjoel, Belgium

[8] Laboratory of Adaptive Biodynamics, Research Unit of Environmental and Evolutionary Biology, Institute of Life, Earth and Environment, University of Namur, Namur, Belgium

[9] Centre of Excellence in Mass Spectrometry, Department of Chemistry, University of York, York, United Kingdom.

* Brand JA and Martin JM should be considered joint first author

***Correspondence**:

Jack A. Brand, Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå, Sweden

Email: jackbrand.work@gmail.com

Jake M. Martin, School of Life and Environmental Sciences, Deakin University, Geelong, Australia

Email: jake.martin@deakin.edu.au

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Abstract

Chemical pollution is a pervasive problem and is now considered the fastest-growing agent of global environmental change. Numerous pollutants are known to disrupt animal behaviour, alter ecological interactions, and shift evolutionary trajectories. Crucially, both chemical pollutants and individual organisms are non-randomly distributed throughout the environment. Despite this, the current evidence for chemical-induced impacts largely stems from tests that restrict organism movement and force homogenous exposures. While such approaches have provided pivotal ecotoxicological insights, they ignore the spatiotemporal dimension of wildlife–pollution interactions, which are key to accurately predicting the impacts of chemical pollutants on free-roaming wildlife. Indeed, the seemingly simple notion that pollutants and animals move non-randomly in the environment creates a complex of dynamic interactions, many of which have never been theoretically modelled or experimentally tested. Here, we conceptualise potential dynamic interactions between spatiotemporal variation in pollutants and individual organisms, and highlight how these processes could scale up to have substantial ecological and evolutionary impacts across populations, communities, and whole ecosystems. We conclude by outlining technological advancements and approaches that will facilitate the necessary spatiotemporal integration in ecotoxicology, and a three-pronged approach—*in silico* modelling, laboratory approaches, and field approaches—to guide future research.

Keywords

Behavioural ecotoxicology, Ethology, Field toxicology, Landscape ecotoxicology, Movement ecology

1. Introduction

Chemical pollution is a globally pervasive problem. The contamination of ecosystems with synthetic chemicals is now considered the fastest-growing agent of global environmental change, with fears that humanity is currently outside the safe operating space for the planetary boundary for novel entities in the environment [1–3]. To date, over 350,000 chemicals (e.g. plastics, pesticides, pharmaceuticals) are registered for use worldwide [4], with an increasing number of these substances being routinely detected in the environment [5]. Importantly, many of these contaminants have been shown to disrupt wildlife behaviour, alter ecological interactions, and shift evolutionary trajectories [5,6]. Given their widespread presence and capacity to disturb key ecological processes, understanding how pollutants affect wildlife populations remains a critical topic of research.

Over the last several decades, increased environmental monitoring of contaminants has demonstrated that chemicals are often spatially and temporally structured within the environment [7,8]. In light of this, it has long been acknowledged that spatiotemporal information must be better integrated into ecotoxicology in order to accurately predict a species' local exposure risk (e.g. 'landscape ecotoxicology'; [9–11]). However, our current knowledge of chemical pollution-induced effects on wildlife is largely based on tests performed under simplified laboratory conditions, where the potential impacts of a contaminant are often assessed using a single isolated individual, at one or more set dosages [12,13]. In most cases, these studies aim to achieve homogenous exposure conditions—both spatially and temporally—and restrict the physical space in which the study organisms can move. Consequently, there is an underlying assumption that the effects seen under these conditions would be reflective of exposures in the wild [10].

Like pollutants, organisms are distributed non-randomly throughout their environment and their distribution can change over time. Recent high-resolution tracking studies on wild organisms have demonstrated that seemingly similar species, populations, and even individuals within those populations, often consistently differ in their movement, space use, and habitat selection [14–17], suggesting that organisms differ from one another in their likelihood of encountering pollutants. Furthermore, exposure to chemical pollutants has itself been shown to alter organismal behaviour and movement rates [6,12,18,19], generating the potential for dynamic feedback loops between spatiotemporally structured chemical pollutants and variation in animal movement [20]. Given that spatiotemporal dynamics are fundamental to all ecological and evolutionary processes, understanding how the spatial and temporal structuring of contaminants and organisms affects variation in exposure rates, subsequent organismal movement and how this may scale up to population-level processes is a vitally important area for future research.

We contend that accurately measuring and forecasting the risk of environmental contaminants on wildlife populations depends on (I) the spatiotemporal variation of pollutants, (II) the spatiotemporal variation of organisms, and (III) the relationship between the two. Here, we briefly examine how spatiotemporal variation in pollutants and individual organisms may result in differential exposure risk within populations. We then propose a series of dynamic interactions that could arise from these spatiotemporal processes and discuss how they may scale up to have substantial ecological and evolutionary effects. Finally, we outline promising directions for future research, emphasising recent advances in analytical chemistry, animal-tracking technologies, and computer-based modelling as a much-needed window into the spatiotemporal elements of environmental ecotoxicology.

2. Pollutants are spatially and temporally structured within environments

Chemical pollutants are not evenly distributed in the environment across space or time. First, the source of contamination plays a significant role in the spatial distribution of a pollutant. Some pollutants originate from localised point sources, such as wastewater or stormwater outflows, while others result from diffuse sources, such as large-scale agriculture spray-drift. In aquatic systems, factors like water flow patterns, river discharge, and precipitation levels can dilute/concentrate and transport these contaminants once they enter the environment (e.g. [21]). For example, the concentration of point-source contaminants typically decreases with distance from the discharge site [22]. Similar patterns are evident in terrestrial systems, with prior studies showing that contamination of dust and air with pesticides is highest near agricultural lands and is diluted further from the source [23]. However, it is important to note that this is not always the case, particularly when complex contaminant drift dynamics are involved [23,24]. Indeed, non-point source contaminants, such as agricultural runoff and atmospheric deposition, often show more varied spatial distributions [25].

The matrix through which contaminants move (e.g. soil, water, or gas), as well as their physical, structural, and molecular properties of chemicals—such as hydrophobicity, functional groups, reactivity, and volatility—also determine their mobility, transformation, persistence, and subsequent distribution in the environment [25]. Additionally, habitat and environmental characteristics like UV exposure, temperature, precipitation, soil-sediment composition, prevailing wind direction, and ocean currents can influence the degradation and dispersal of contaminants [8,21,26]. Plants, microbes, and animals can further alter contaminant breakdown and distribution through uptake, biomagnification, and biotransformation. These processes can occur across the aquatic–terrestrial interface, where pollutants may transfer and even bio-magnify through trophic interactions between ecosystems [27,28].

Temporal changes to the spatial distribution of chemical contaminants are also common. For example, a known hotspot of wastewater-derived pharmaceuticals and other pollutants in Lake Geneva, Switzerland, dissipated with a change in thermal stratification in colder months, resulting in a more homogenous vertical distribution in the water column [8]. Similarly, seasonal variation in the concentration of pesticides and polycyclic aromatic hydrocarbons (PAHs) has been documented in the Henares River basin in central Spain, likely due to seasonality in agricultural practices and changes in sunlight intensity affecting chemical degradation [29]. Temporal changes can also occur on much shorter timescales. For example, concentrations of illicit drugs and their metabolites can increase in wastewater following public events [30,31]. In Lake Qingshan, China, organic pollutant concentrations spiked immediately following heavy rainfall events before eventually declining [32], whereas daily variations in the concentrations of organic and heavy metal pollutants in surface waters of the Mekong Delta, Vietnam, were linked to water mixing caused by tidal activity [22].

The spatiotemporal variation in exposure to chemical pollutants has gained increasing attention [9,10]. For example, in the Athabasca Oil Sands Region of Canada, recent research integrating spatial geographic information systems with mercury bioaccumulation data—including from amphibians, bird eggs, plants, and terrestrial and aquatic mammals—has identified spatial 'hotspots' of mercury contamination near industrial facilities [33]. Further, in the Puget Sound Basin (Pacific Northwest of the United States), coho salmon (*Oncorhynchus kisutch*) mortality has been linked to nearby road density and traffic intensity, a finding attributed to tyre wear particle leachates in urban runoff [34,35]. However, much of this research has focused on relatively large spatial scales to identify how contaminant exposure varies between species or populations in different locations across time, with little attention paid to how the spatial structuring of these chemicals affects within-population differences in exposure rates, how exposure can subsequently feedback to alter animal movement and space use, and how this may influence broader ecological and evolutionary processes.

3. Individuals are spatially and temporally distributed within environments

It is well known that the distribution of organisms varies across both space and time. The movement of animals within their environment, for example, allows species to track changes in resources (e.g. food, breeding sites) and avoid unfavourable environmental conditions. This can occur at large spatial scales over long timeframes (e.g. seasonal shifts in distribution during long-distance migrations), as well as much smaller scales where organisms vary their within-environment space use over shorter timeframes. For example, Eurasian perch (*Perca fluviatilis*) displayed the highest activity rates and increased space use during the day [36], while large marine predators like Atlantic bluefin tuna (*Thunnus thynnus*) are also known to migrate hundreds of metres of vertical distance each day, traversing stratified layers of water with remarkably different abiotic profiles [37].

Individuals within populations also often differ in their space use and movement dynamics [38]. For instance, individual phenotypic traits (e.g. body size, body condition, sex, age) have been found to influence movement and space use in a variety of species [39–44]. Even when controlling for these factors, individuals within populations still often inherently differ from one another in their movement [15,45]. Indeed, a long-term (8-year) radio telemetry study tracking over 500 individual fish from 5 different species showed that inherent individual differences within populations accounted for more variation in movement dynamics than differences between the tested species [46]. This intraspecific variation can have key effects on organismal ecology, with previous research showing relationships between individual movement rates, dietary niche, and habitat selection [14,16,42]. Collectively, this research demonstrates that individuals within populations exhibit significant variation in space use and movement, which are closely linked to niche specialisation. Consequently, individual differences may lead to unique patterns of exposure to environmental challenges such as pollutants [47–50].

4. Wildlife–pollution interactions in a spatiotemporal context

Given that both pollutants and animals vary in their spatial and temporal distribution within the environment, an individual's movement patterns, habitat preference, and space use will directly influence its exposure to chemical pollutants. This has been demonstrated in species such as Chinook salmon (*Oncorhynchus tshawytscha*) [49], Pacific Bluefin tuna (*Thunnus orientalis*) [50], Pacific herring (*Clupea pallasi*) [48], and Striped bass (*Morone saxatilis*) [47]. In the wild, an individual’s ‘realised exposure’ is determined by the alignment between its spatiotemporal distribution and that of a pollutant, combined with individual bioaccumulation processes (i.e. the balance of uptake and loss). Importantly, pollutant exposure can also create feedback effects that influence future movement and decision-making, either by disrupting normal behaviours or by triggering avoidance, attraction, or conformity to polluted habitats [20,51–56]. Below, we conceptualise the dynamic feedback between the spatiotemporal distribution of contaminants and wildlife and discuss likely ecological and evolutionary consequences (Fig. 1).

4.1 Pollutants impact the spatiotemporal distribution of organisms and the nature of their exposure

i) Wildlife–pollutants repulsion-like interactions

Organisms may actively avoid contaminated areas, with contaminants directly triggering sensorial repellence or by making environments less suitable for occupation (i.e. acting as habitat disrupters) [57,58]. Such effects can alter the duration and extent of individual exposure. For example, even at low concentrations, copper pollution has been shown to induce spatial repellence in numerous taxa (including invertebrates, fish, and amphibians) [59–62], and can act as a chemical barrier preventing recolonisation of suitable habitats and potentially isolating populations [63]. Organisms may also employ temporal avoidance strategies, especially when displacement is impossible, such as delaying colonisation—exemplified by deterred oviposition in polluted habitats [64,65]—or entering dormant stages [66]. These avoidance behaviours have been demonstrated in laboratory-based, multicompartmental exposure systems [67,68], and are influenced by the organism's ability to detect the pollutant (sensory physiology), its capacity to escape (e.g. sessile *versus* mobile stage, pollutant-induced locomotion impairment), and also environmental features such as resource availability, interspecific interactions, and the characteristics of the chemical exposure (e.g. chemical properties, concentration, and duration) [69]. An important aspect to consider when evaluating risk is that the repellent nature of a substance may not be directly correlated with its toxicity, meaning that a highly repellent contaminant could have low toxicity and *vice versa* [70]. Moreover, because pollutant-induced spatial avoidance occurs at sub-lethal concentrations or concentrations too low to produce detectable physiological effects, environmental risk assessments based solely on these measures may overlook important shifts in population and community dynamics (see Section 4.2).

ii) Wildlife–pollutant attraction-like interactions

While many chemical contaminants are expected to be repellents, some compounds can attract wildlife by interfering with sensory systems or by altering environmental cues used for habitat selection [71]. This can result in 'sink habitats' or even 'ecological traps', whereby organisms select suboptimal habitats where their exposure to harmful substances is heightened, and their fitness is consequently reduced. Some pesticides, for example, resemble insect pheromones, leading insects to mistake these chemicals for mating signals [72]. Similarly, heavy metal pollutants can disrupt sensory system function, preventing organisms from detecting olfactory signals that might otherwise be avoided (e.g. predator cues) [73]. Furthermore, contaminated areas can be associated with modified local habitat characteristics (e.g. temperature, nutrient availability, sediment type), inadvertently making them more attractive to certain species. Wastewater effluents, for example, may attract fish due to nutrient-rich discharge and warmer temperatures, increasing their exposure to harmful contaminants [74,75].

iii) Wildlife–pollutant indirect interactions

In addition to repulsion from, or attraction to contaminated sites, chemical pollutants may also alter the spatial distribution of organisms and their subsequent exposure via indirect effects on organismal behaviour (i.e. without a spatially explicit response to the contaminant). Small- and large-scale movement patterns are sensitive to contaminants that affect neurological function, metabolism and endocrine regulation, such as psychoactive pharmaceutical pollutants [51,54,55,76], endocrine-disrupting chemicals [52,53,77,78], and pesticides [53,79,80]. As a small-scale example, chemicals can disrupt biological rhythms of exposed organisms, altering normal day-night activity cycles [81,82]. As a larger-scale example, contaminants can alter travel distances, migration timing, and stopover durations [83,84]. Contaminant-induced shifts in movement can, in turn, lead to altered subsequent exposures to the same or other pollutants (i.e. positive or negative feedback loops), by affecting the likelihood of encountering pollutants as well as the duration of exposure. Further, contaminants-induced effects on other behavioural traits may also indirectly influence the spatial distribution of organisms and their probability of future exposures. As an example, risk landscapes [85] and social resistance (e.g. territoriality, within-group preferences) [86] are known to be major barriers to movement in many species, and there is evidence that many chemical contaminants can modify behaviours that generate these barriers, such as territoriality, risk-taking, aggression, and social behaviours [53,78,87–89].

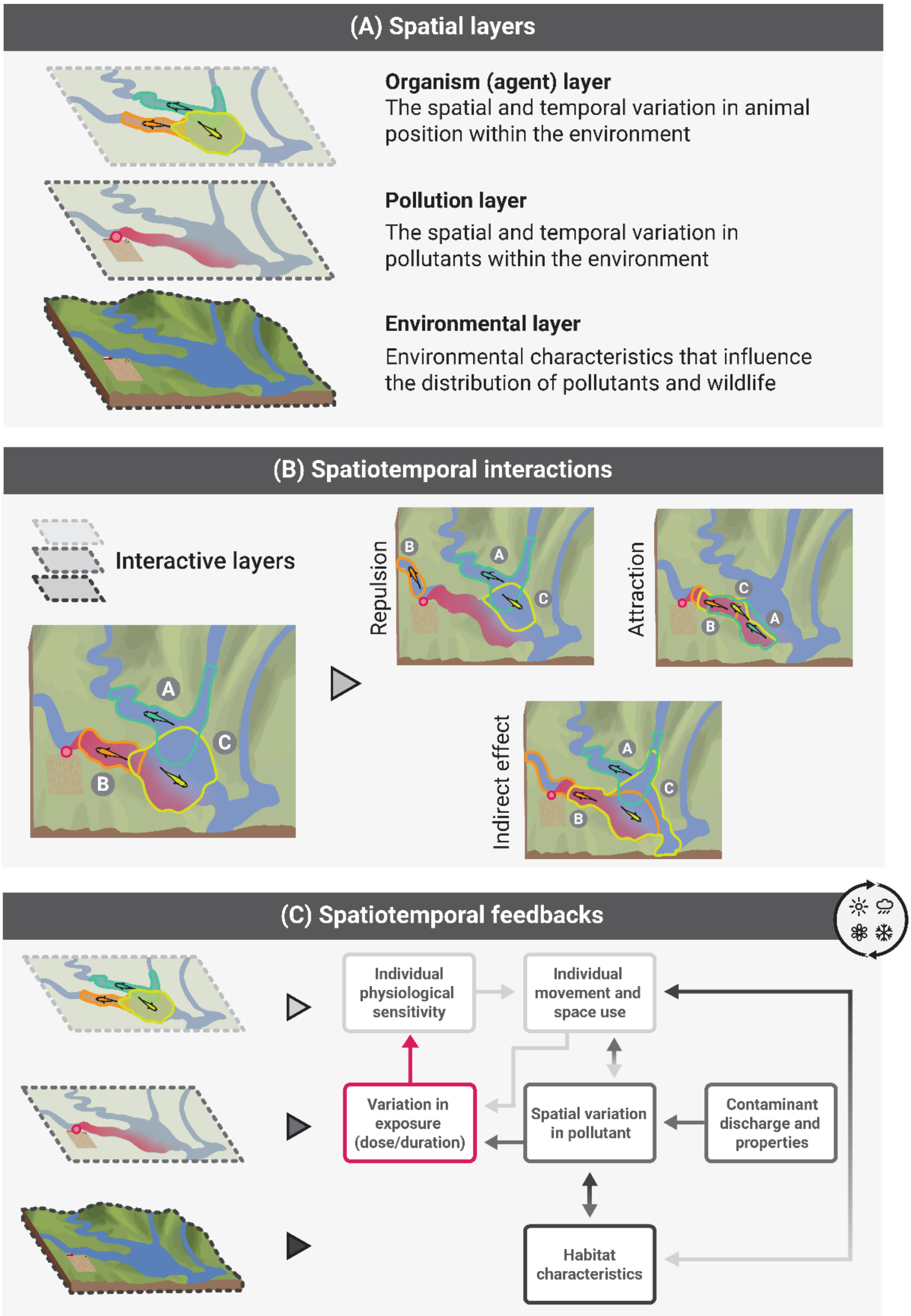

Fig. 1 | (A) Spatial layers that will influence the exposure risk and outcomes for wildlife. (B) Broad spatiotemporal wildlife-pollutant interactions and possible effects on the individual movement of fish from a hypothetical population. (C) Dynamic feedback between spatiotemporal variation in pollutants and animals.

iv) Individual-specific effects

Trait variation among individuals within a population may also determine the nature of individual exposure. For instance, several demographic characteristics (e.g. age, sex, body condition, reproductive status) are known to influence the spatial distribution of organisms in the environment (see section 3). Similarly, individual differences in personality (e.g. foraging propensity, risk-taking behaviour, sociality) and experience within populations can also mediate movement rates, space use, and habitat selection [15,90,91], suggesting that some individuals may be more likely to encounter contaminants than other individuals in the population.

Moreover, even when organisms are exposed to the same contaminant concentrations for the same duration, individual responses may still differ. Genetic and physiological differences can influence individual sensitivity to pollutants and their subsequent behavioural response. For instance, exposure to environmental levels of an antidepressant over two years homogenised movement behaviour among individual male guppies (*Poecilia reticulata*), but no shift in the variation of female movement phenotypes was observed [92]. Variation in metabolic rate, enzyme activity, and hormone regulation can also affect how contaminants are processed and detoxified, influencing the stress signals perceived by organisms and leading to the avoidance of, or attraction to, certain areas [93]. Other traits have also been shown to influence the sensitivity of organisms to pollutants. Indeed, independent of body mass, social status influenced the bioaccumulation of the psychoactive pharmaceutical oxazepam and subsequent aggressive behaviour in exposed brown trout (*Salmo trutta*) [94]. Taken together, this research highlights that where pollutants are spatially structured within an environment, individual differences in phenotypic traits (e.g. body condition, physiology, personality) likely mediate the nature and extent of exposure in the wild, and that this exposure can subsequently feedback to affect these same phenotypic traits. To our knowledge, the potential for individual phenotypic traits to influence exposure risk, moderate individual sensitivities, and feedback to influence those same phylotypic traits has not been empirically assessed.

4.2 Ecological and evolutionary consequences

Below, we illustrate several potential ecological and evolutionary consequences of spatiotemporal interactions between pollutants and organismal movement at the individual, meta-population, and community levels. This overview is not intended to be exhaustive but instead highlights several key outcomes of spatiotemporal wildlife–pollution interactions that are seldom considered in ecotoxicology. It is also worth noting that many of the highlighted consequences likely have effects across multiple biological and spatial scales, which, for simplicity, we have not specifically illustrated here. While we have focused on movement, space use, and behaviour, we acknowledge that many pollutants may exert a variety of ecological and evolutionary effects via other mechanisms (e.g. direct mortality, disrupted organismal development, reproductive changes) [95], which can also contribute to potentially adverse outcomes for wildlife populations.

i) Individual-level outcomes:

Likely consequences of pollution-induced changes in animal movement and space use are alterations in the rate and nature of conspecific encounters (i.e. intra-specific interactions). For example, pollutants that act as repellents or attractants may decrease or increase intraspecific encounter rates, respectively, via changes in local population density. Likewise, pollutants that increase movement rates may similarly heighten the likelihood of encountering conspecifics (and *vice versa*). Changes in encounter rates and local population densities could lead to shifts in the strength/direction of both natural and sexual selection within the population via changes in resource (e.g. food and shelter) competition, disease, and social information transmission, as well as altered mating dynamics (e.g. inter- and intra-sexual competition). For example, in brown trout, methamphetamine (a common psychoactive pollutant) has been reported to cause a spatial attraction of individuals to methamphetamine-polluted zones [96], while also reducing individual movement [96,97] and increasing conspecific aggression [98], in combination creating conditions that would likely disrupt the local ecological interactions of brown trout populations. In addition, pollution-induced changes in wildlife movement and space use could alter interspecific interactions, including changes in predation [99], pollination [100], and parasitism. For example, mummichog killifish (*Fundulus heteroclitus*) from metal-contaminated environments exhibit slower movement rates, resulting in a decreased ability to capture prey and an increased susceptibility to predation themselves [99].

These interactions may be further complicated where individuals differ in their response to the pollutant, thus altering the distribution of movement phenotypes within the population. Where such traits are associated with fitness (e.g. via predation susceptibility), this will reduce the variation available for selection to act upon within the population. However, variation in pollutant sensitivity is not necessarily fixed; selection on toxicity-mediating genes can result in populations evolving tolerance (or resistance) to chemical pollutants [101,102]. It may seem like an overwhelming challenge for ecotoxicology to incorporate these complex interactions between individual physiological sensitivity, pollution-induced changes in movement traits, organismal fitness, and adaptive tolerance in spatially and temporally dynamic environments; but in many ways, it is necessary if we are to accurately predict and assess the impacts of pollution on wildlife.

ii) (Meta)population-level outcomes:

Pollutant-induced changes in movement and space use also have clear consequences for the eco-evolutionary dynamics of (meta)populations. While avoiding exposure can be individually a more advantageous strategy than enduring the costs of chemical toxicity and depuration [103], avoidance behaviour also acts as a barrier to movement, resulting in habitat fragmentation, potentially affecting gene flow and population connectivity [57,63]. Even in the absence of direct avoidance, where pollutants alter dispersal-related traits—as seen in freshwater isopods (*Asellus aquaticus*) following sub-lethal insecticide exposure [104]—there are likely changes in population growth rates via emigration and immigration and subsequent gene flow. For several bat star (*Patiria miniate*) populations, pollution from stormwater runoff and wastewater effluent have been shown to act as barriers to dispersal and gene flow, leading to reduced genetic diversity at highly contaminated sites [105].

Differential sensitivity to pollutants may also influence gene flow between populations via specific changes in allele frequencies, rather than changes in the absolute number of migrants. Research in alpine whitefish (*Coregonus* sp.) and marine invertebrates (*Peramphithoe parmerong*) has demonstrated genetic variation in tolerance to pollution for endocrine-disrupting pollutants [106] and copper pollution [107], respectively. In cases where tolerance and avoidance of pollutants are genotype-dependent, this may lead to pollutant-induced spatial sorting of genotypes (and phenotypes). For instance, chemical pollutants were found to serve as genotype-dependent dispersal barriers in Mediterranean mussels (*Mytilus galloprovincialis*), leading to substantial population genetic differences over short distances. Conversely, shifts in space use due to preferences (either direct or indirect) for highly contaminated sites (e.g. [74,75]) or avoidance of polluted areas (e.g. [8]) could also increase interbreeding and hybridisation between previously isolated groups, resulting in greater genetic diversity within populations.

iii) Community-level outcomes:

Pollutant-induced changes in movement and space use at the individual level can scale up to impact community and ecosystem dynamics. For example, shifts in predator–prey interactions caused by chemical pollutants (e.g. [54,99]) have been shown to restructure food webs [108]. Contaminants can also transfer through trophic interactions and even biomagnify, leading to complex exposure patterns for species across ecosystems [109,110]. Furthermore, species often exhibit varying sensitivities to chemical pollutants (e.g. [111]), and in some cases, community composition may moderate responses to contaminant exposure [111,112]. For instance, zebrafish (*Danio rerio*) and freshwater shrimp (*Atyaephyra desmarestii*) demonstrated different spatial avoidance behaviours when tested independently *versus* together in response to copper pollution [112].

5. Ways forward

Predicting the outcome of dynamic interactions between pollutants and organisms across different scales of biological complexity is inherently challenging and requires detailed knowledge of both organism- and environment-specific factors. Nevertheless, it is imperative to advance research on spatiotemporal exposure risks to accurately predict the ecological and evolutionary impacts of chemical pollution. While ecotoxicology has a relatively long history of conducting laboratory-based contaminant attraction/avoidance studies [113–115], spatial and temporal variation are still not widely incorporated, and the scope of these studies has often been limited. For instance, few studies have investigated whether individual variation within populations in behavioural and movement traits predicts an organisms' level of attraction to, or avoidance of, contamination.

To advance this field, it is necessary to incorporate the spatiotemporal variability of pollutants and the movement patterns of wildlife into existing research frameworks, as well as increasing crosstalk between related disciplines. In this regard, recent methodological and technological advancements in ecotoxicology, analytical chemistry, animal tracking, and computational modelling provide unprecedented opportunities to address these complexities (Fig. 2). Using these recent advancements, we outline a three-pronged approach to guide future research in this area: *in silico* modelling, laboratory experiments, and semi-field and field studies.

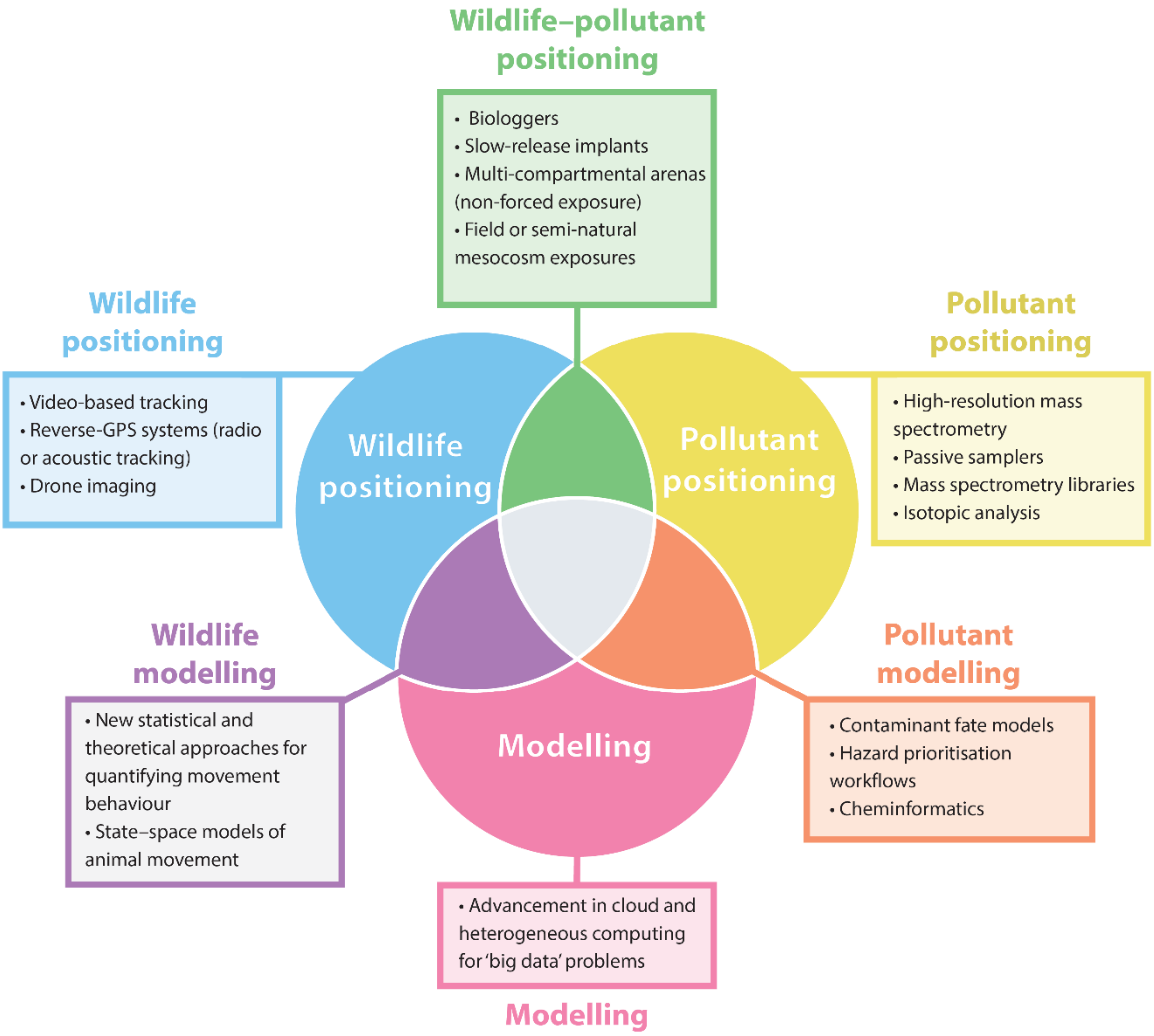

Figure 2. Recently developed and established methodological and technological approaches that can facilitate the study of the spatiotemporal dynamics of wildlife–pollution interactions. Wildlife–pollutant positioning [67,116–118]; Pollutant positioning [119–122]; Pollutant modelling [123–125]; Modelling [126]; Wildlife modelling [127,128]; Wildlife positioning [129–131].

i) *In silico* tools

While verbal and conceptual models are a key first step in describing dynamic interactions between contaminants and organisms (Fig. 1), computational approaches are required to predict the outcomes of such interactions over time.

Agent-based modelling (ABM) is a key tool to investigate how wildlife will respond to changing environmental conditions—including contaminants—given that these models are able to incorporate the adaptive movement ecology of animals inhabiting a changing landscape [132]. As an example, ABM approaches incorporating individual movement and life-history traits in combination with pesticide application schedules have been used to predict spatial patterns of pesticide exposure, as well as subsequent population dynamics [133]. Despite their utility, ABMs have rarely been applied to understand complex interactions and feedback between spatiotemporally dynamic contaminants and animal movement, particularly in terms of within-population variation in movement. Such approaches are increasingly feasible given the increase in modern computing power and the development and refinement of contaminant fate models [125]. Integrating spatial and temporal information on contaminant concentrations at a local scale into ABM approaches will be critical in predicting how individual variability in movement and behaviour affects exposure to contaminants, providing insights into the potential long-term effects on population dynamics.

However, these ABMs need to be parametrised and validated based on empirical data, emphasising a need for more research into the spatiotemporal variation of contaminants in natural systems. To this end, *in silico* tools, such as supervised machine learning algorithms, molecular networking, chromatographic retention time prediction have been developed to help identify thousands of potential contaminants that are detected in environmental and biological matrices using high-resolution mass spectrometry (HRMS) [134–136]. With such approaches, concentration [137], toxicity [138], and endocrine-disrupting activity [139] can be derived from the chemical structure [134,140]. Feature-based molecular networking (FBMN) is a high-throughput tool that can identify related chemicals in a sample, indicating potential transformation or degradation pathways of labile substances [141]. These *in silico* analytical chemistry tools, coupled with high sensitivity profiling methods, will be essential if we wish to determine the spatial and temporal scale of pollution at a high resolution.

ii) Laboratory experiments

Conventional studies in ecotoxicology typically expose organisms to contaminants within spatially restricted compartments (e.g. containers, aquaria) and/or under temporally consistent exposure conditions (acute exposure: 24 to 96 h; chronic exposure: several days to months [12,13]). While useful for testing the toxicity and concentration thresholds of different chemicals, this approach limits the organisms' ability to exhibit their full range of behaviours, such as the capacity to move away from contaminated areas. Many laboratory studies have demonstrated that animals actively avoid contaminated habitats when given the option [142–144].

To overcome these limitations, multi-compartmental arenas [68,113] and steep gradient assays [145] offer effective alternative designs. These designs incorporate ecological complexity into laboratory experiments while allowing for more spatial and temporal heterogeneity in exposure conditions [146]. By combining these experimental designs with consumer-grade video cameras and freely available animal tracking software, researchers can obtain high-resolution (spatial and temporal) measurements of individual and group behaviours—see Bertram et al. [12] for a list of tracking software options. This approach also allows for the quantification of individual variation in movement and within-population variation in exposure risks under different ecological and chemical contaminants scenarios, which are ideally informed by spatially explicit field sampling (see Section 5 iii).

To further refine these experiments, integrating environmental variables that mimic real-world conditions is crucial. For example, creating gradient-based exposure scenarios that simulate the gradual increase or decrease of contaminant concentrations across a landscape can reveal how animals detect and respond to changing contamination levels [63]. Similarly, incorporating dynamic elements such as fluctuating contaminant levels or introducing other ecological pressures (e.g. predation risk) can offer insights into how animals balance their responses to multiple stressors, providing a more realistic prediction of their responses in natural environments [68,147]. Further, incorporating mixture exposures based on observed environmental (co)occurrences would more accurately reflect environmental conditions and could elucidate the potential interactive effects of different contaminants.

iii) Field studies

Laboratory studies are invaluable for understanding the underlying mechanisms of contaminant effects and for rapidly generating predictions that can be applied to real-world scenarios. However, the outcomes of laboratory experiments often diverge from field observations due to the inherent limitations of replicating the complexity of natural systems within controlled environments [148–150]. Thus, spatially explicit water sampling and field studies are necessary for characterising complex exposure scenarios and monitoring the spatial and temporal overlap of chemical contaminants and animal populations.

Continually expanding mass spectrometry libraries and improving computational tools enhance the identification of these compounds, facilitating more accurate and comprehensive environmental monitoring [123]. These tools allow researchers to capture the intricate variability of contamination across spatial and temporal scales, offering a more precise and comprehensive understanding of the true exposure risks to wildlife populations. With that being said, the process of field-validated ecotoxicological experiments is costly, in terms of financial commitment and personnel time. Therefore, the careful selection and prioritisation of chemicals that are predicted to have environmental implications is key to reducing these costs. As mentioned above, *in silico* modelling can be used to help select chemicals with predicted toxicity and to highlight transformation products that may also contribute to the overall risk to environmental health. To elucidate potentially harmful substances from complex environmental matrices, effects-directed analysis is a powerful technique that has benefited by improved HRMS techniques to simultaneously identify chemicals and perform *in vitro* toxicity tests [151].

Moreover, advances in remote-sensing technologies, such as acoustic telemetry and global positioning systems (GPS), have revolutionised our ability to quantify the behaviour and movement of animals in their natural habitats [17]. These tools, when combined with spatially explicit field sampling, enable researchers to map the spatial distribution of animal populations, track their movements, and assess their potential exposure to contaminants. Targeted exposure devices, such as slow-release implants, are another emerging tool that can be used to study exposure under field-realistic settings [117]. Targeted exposure devices can be used to isolate chemical exposure to specific individuals in the field, while holding spatial exposure elements constant (i.e. the animal remains homogenously exposed while still moving freely) to disentangle complex wildlife–pollutant spatial interactions [117]. In combination, such an approach offers unprecedented opportunities to understand the impacts of contaminants on (meta)populations and community-level processes by delivering near-continuous data on individual movements and ecological interactions (e.g. social dynamics, predator–prey relationships) [152–154].

6. Conclusion

Here, we categorise pollutant–animal spatial interactions and conceptualise a simple dynamic feedback model that may result from such interactions. We identify potential ecological and evolutionary consequences and highlighted key areas of uncertainty. We recognise that incorporating these spatial interactions in experimental and observational work generates logistical challenges but highlight that it is becoming ever more achievable, with advances in *in silico* modelling and prediction techniques, laboratory- and field-based animal-tracking technologies, as well as the rapid advances in high-throughput and sensitive analytical chemistry approaches. We contend that considering and incorporating wildlife–pollutant spatiotemporal interactions in ecotoxicology will improve our ability to assess and predict the risk of contaminants to wildlife.

Author Contributions Statement

Jack A. Brand: Conceptualization (co-lead), Project Administration (co-lead), Visualization (co-lead), Writing – Original Draft Preparation (co-lead), Writing – Review & Editing (co-lead). **Jake M. Martin:** Conceptualization (co-lead), Project Administration (co-lead), Visualization (co-lead), Writing – Original Draft Preparation (co-lead), Writing – Review & Editing (co-lead). **Marcus Michelangeli:** Conceptualization, Writing - Original Draft Preparation, Writing - Review & Editing. **Eli S.J. Thoré:** Conceptualization, Writing - Original Draft Preparation, Writing - Review & Editing. **Natalia Sandoval-Herrera:** Conceptualization, Writing - Original Draft Preparation, Writing - Review & Editing. **Erin S. McCallum:** Writing – Review & Editing**. Drew Szabo:** Writing – Review & Editing. **Damien Callahan:** Writing – Review & Editing. **Timothy D. Clark:** Writing – Review & Editing. **Michael G. Bertram:** Writing – Review & Editing. **Tomas Brodin:** Funding acquisition, Writing – Review & Editing.

Conflict of Interest Statement

The authors declare no competing interests.

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Data availability

There are no new data associated with this article.

References

1. Sylvester F *et al.* 2023 Better integration of chemical pollution research will further our understanding of biodiversity loss. *Nat Ecol Evol* **7**, 1552–1555. (doi:10.1038/s41559-023-02117-6)
2. Bernhardt ES, Rosi EJ, Gessner MO. 2017 Synthetic chemicals as agents of global change. *Front Ecol Environ* **15**, 84–90. (doi:10.1002/fee.1450)

3. Persson L *et al.* 2022 Outside the safe operating space of the planetary boundary for novel entities. *Environ Sci Technol* **56**, 1510–1521. (doi:10.1021/acs.est.1c04158)
4. Wang Z, Walker GW, Muir DCG, Nagatani-Yoshida K. 2020 Toward a global understanding of chemical pollution: a first comprehensive analysis of national and regional chemical inventories. *Environ Sci Technol* **54**, 2575–2584. (doi:10.1021/acs.est.9b06379)
5. Sigmund G *et al.* 2023 Addressing chemical pollution in biodiversity research. *Glob Chang Biol* **29**, 3240–3255. (doi:10.1111/gcb.16689)
6. Saaristo M *et al.* 2018 Direct and indirect effects of chemical contaminants on the behaviour, ecology and evolution of wildlife. *Proc R Soc B* **285**, 20181297. (doi:10.1098/rspb.2018.1297)
7. Richards S, Bidgood L, Watson H, Stutter M. 2022 Biogeochemical impacts of sewage effluents in predominantly rural river catchments: Are point source inputs distinct to background diffuse pollution? *J Environ Manage* **311**, 114891. (doi:10.1016/j.jenvman.2022.114891)
8. Bonvin F, Rutler R, Chèvre N, Halder J, Kohn T. 2011 Spatial and temporal presence of a wastewater-derived micropollutant plume in Lake Geneva. *Environ Sci Technol* **45**, 4702–4709. (doi:10.1021/es2003588)
9. Cairns J, Niederlehner BR. 1996 Developing a field of landscape ecotoxicology. *Ecol Appl* **6**, 790–796. (doi:10.2307/2269484)
10. Schäfer RB. 2014 Why we need landscape ecotoxicology and how it could be advanced—An academic perspective. *Environ Toxicol Chem* **33**, 1193–1193. (doi:10.1002/etc.2568)
11. Johnson AR. 2002 Landscape ecotoxicology and assessment of risk at multiple scales. *Hum ecol risk assess* **8**, 127–146. (doi:10.1080/20028091056773)
12. Bertram MG *et al.* 2022 Frontiers in quantifying wildlife behavioural responses to chemical pollution. *Biol Rev* **97**, 1346–1364. (doi:10.1111/brv.12844)
13. Martin JM *et al.* 2024 Evidence of the impacts of pharmaceuticals on aquatic animal behaviour (EIPAAB): a systematic map and open access database. *EcoEvoRxiv* (doi:10.32942/X2NG9R)
14. Harrison PM, Gutowsky LFG, Martins EG, Ward TD, Patterson DA, Cooke SJ, Power M. 2017 Individual isotopic specializations predict subsequent inter-individual variation in movement in a freshwater fish. *Ecology* **98**, 608–615. (doi:10.1002/ecy.1681)
15. Villegas-Ríos D, Réale D, Freitas C, Moland E, Olsen EM. 2017 Individual level consistency and correlations of fish spatial behaviour assessed from aquatic animal telemetry. *Anim Behav* **124**, 83–94. (doi:10.1016/j.anbehav.2016.12.002)
16. Mawer R, Bruneel SP, Pauwels IS, Elings J, Pickholtz E, Pickholtz R, Schneider M, Coeck J, Goethals PLM. 2023 Individual variation in the habitat selection of upstream migrating fish near a barrier. *Mov Ecol* **11**, 49. (doi:10.1186/s40462-023-00414-0)
17. Nathan R *et al.* 2022 Big-data approaches lead to an increased understanding of the ecology of animal movement. *Science* **375**. (doi:10.1126/science.abg1780)
18. McCallum ES, Sundelin A, Fick J, Alanärä A, Klaminder J, Hellström G, Brodin T. 2019 Investigating tissue bioconcentration and the behavioural effects of two pharmaceutical pollutants on sea trout (*Salmo trutta*) in the laboratory and field. *Aquat Toxicol* **207**, 170–178. (doi:10.1016/j.aquatox.2018.11.028)
19. Michelangeli M, Martin JM, Pinter-Wollman N, Ioannou CC, McCallum ES, Bertram MG, Brodin T. 2022 Predicting the impacts of chemical pollutants on animal groups. *Trends Ecol Evol* **37**, 789–802. (doi:10.1016/j.tree.2022.05.009)

20. Jacquin L, Petitjean Q, Côte J, Laffaille P, Jean S. 2020 Effects of pollution on fish behavior, personality, and cognition: some research Perspectives. *Front Ecol Evol* **8**. (doi:10.3389/fevo.2020.00086)
21. Marvin C, Painter S, Williams D, Richardson V, Rossmann R, Van Hoof P. 2004 Spatial and temporal trends in surface water and sediment contamination in the Laurentian Great Lakes. *Environ Pollut* **129**, 131–144. (doi:10.1016/j.envpol.2003.09.029)
22. Wilbers G-J, Becker M, Nga LT, Sebesvari Z, Renaud FG. 2014 Spatial and temporal variability of surface water pollution in the Mekong Delta, Vietnam. *Science of The Total Environment* **485–486**, 653–665. (doi:10.1016/j.scitotenv.2014.03.049)
23. Dereumeaux C, Fillol C, Quenel P, Denys S. 2020 Pesticide exposures for residents living close to agricultural lands: a review. *Environ Int* **134**, 105210. (doi:10.1016/j.envint.2019.105210)
24. Otto S, Lazzaro L, Finizio A, Zanin G. 2009 Estimating ecotoxicological effects of pesticide drift on nontarget arthropods in field hedgerows. *Environ Toxicol Chem* **28**, 853–863. (doi:10.1897/08-260R.1)
25. Holt MS. 2000 Sources of chemical contaminants and routes into the freshwater environment. *Food Chem Toxicol* **38**, S21–S27. (doi:10.1016/S0278-6915(99)00136-2)
26. Meftaul IM, Venkateswarlu K, Annamalai P, Parven A, Megharaj M. 2023 Degradation of four pesticides in five urban landscape soils: human and environmental health risk assessment. *Environ Geochem Health* **45**, 1599–1614. (doi:10.1007/s10653-022-01278-w)
27. Hu T, Zhang J, Xu X, Wang X, Yang C, Song C, Wang S, Zhao S. 2023 Bioaccumulation and trophic transfer of antibiotics in the aquatic and terrestrial food webs of the Yellow River Delta. *Chemosphere* **323**, 138211. (doi:10.1016/j.chemosphere.2023.138211)
28. Schulz R, Bundschuh M. 2020 Pathways of contaminant transport across the aquatic-terrestrial interface: implications for terrestrial consumers, ecosystems, and management. In *Contaminants and Ecological Subsidies*, pp. 35–57. Cham: Springer International Publishing. (doi:10.1007/978-3-030-49480-3_3)
29. Gómez MJ, Herrera S, Solé D, García-Calvo E, Fernández-Alba AR. 2012 Spatio-temporal evaluation of organic contaminants and their transformation products along a river basin affected by urban, agricultural and industrial pollution. *Sci Total Environ* **420**, 134–145. (doi:10.1016/j.scitotenv.2012.01.029)
30. da Silva KM, Quintana JB, González-Mariño I, Rodil R, Gallassi AD, Arantes LC, Sodré FF. 2018 Assessing cocaine use patterns in the Brazilian Capital by wastewater-based epidemiology. *Int J Environ Anal Chem* **98**, 1370–1387. (doi:10.1080/03067319.2018.1554743)
31. Gerrity D, Trenholm RA, Snyder SA. 2011 Temporal variability of pharmaceuticals and illicit drugs in wastewater and the effects of a major sporting event. *Water Res* **45**, 5399–5411. (doi:10.1016/j.watres.2011.07.020)
32. Xu J, Wu X, Ge X, Tian Y, Ma X, Li Y, Xu X, Li Z. 2021 Variations of concentration characteristics of rainfall runoff pollutants in typical urban living areas. *Bull Environ Contam Toxicol* **106**, 608–613. (doi:10.1007/s00128-021-03110-0)
33. Eccles KM, Pauli BD, Chan HM. 2019 The use of geographic information systems for spatial ecological risk assessments: an example from the Athabasca oil sands area in Canada. *Environ Toxicol Chem* **38**, 2797–2810. (doi:10.1002/etc.4577)
34. Peter KT, Tian Z, Wu C, Lin P, White S, Du B, McIntyre JK, Scholz NL, Kolodziej EP. 2018 Using high-resolution mass spectrometry to identify organic contaminants linked to urban

stormwater mortality syndrome in coho salmon. *Environ Sci Technol* **52**, 10317–10327. (doi:10.1021/acs.est.8b03287)

35. Feist BE, Buhle ER, Baldwin DH, Spromberg JA, Damm SE, Davis JW, Scholz NL. 2017 Roads to ruin: conservation threats to a sentinel species across an urban gradient. *Ecol Appl* **27**, 2382–2396. (doi:10.1002/eap.1615)
36. Nakayama S, Doering-Arjes P, Linzmaier S, Briege J, Klefoth T, Pieterek T, Arlinghaus R. 2018 Fine-scale movement ecology of a freshwater top predator, Eurasian perch (*Perca fluviatilis*), in response to the abiotic environment over the course of a year. *Ecol Freshw Fish* **27**, 798–812. (doi:10.1111/eff.12393)
37. Block BA *et al.* 2001 Migratory movements, depth preferences, and thermal biology of Atlantic bluefin tuna. *Science* **293**, 1310–1314. (doi:10.1126/science.1061197)
38. Shaw AK. 2020 Causes and consequences of individual variation in animal movement. *Mov Ecol* **8**, 12. (doi:10.1186/s40462-020-0197-x)
39. Dhellemmes F, Aspillaga E, Rittweg T, Alós J, Möller P, Arlinghaus R. 2023 Body size scaling of space use in coastal pike (*Esox lucius*) in brackish lagoons of the southern Baltic Sea. *Fish Res* **260**, 106560. (doi:10.1016/j.fishres.2022.106560)
40. Matich P, Heithaus MR. 2015 Individual variation in ontogenetic niche shifts in habitat use and movement patterns of a large estuarine predator (*Carcharhinus leucas*). *Oecologia* **178**, 347–359. (doi:10.1007/s00442-015-3253-2)
41. Skerritt D, Robertson P, Mill A, Polunin N, Fitzsimmons C. 2015 Fine-scale movement, activity patterns and home-ranges of European lobster *Homarus gammarus*. *Mar Ecol Prog Ser* **536**, 203–219. (doi:10.3354/meps11374)
42. Nakayama S, Rapp T, Arlinghaus R. 2017 Fast-slow life history is correlated with individual differences in movements and prey selection in an aquatic predator in the wild. *J Anim Ecol* **86**, 192–201. (doi:10.1111/1365-2656.12603)
43. Payne E, Spiegel O, Sinn DL, Leu ST, Gardner MG, Godfrey SS, Wohlfeil C, Sih A. 2022 Intrinsic traits, social context, and local environment shape home range size and fidelity of sleepy lizards. *Ecol Monogr* **92**. (doi:10.1002/ecm.1519)
44. Gaynor KM, McInturff A, Brashares JS. 2022 Contrasting patterns of risk from human and non-human predators shape temporal activity of prey. *J Anim Ecol* **91**, 46–60. (doi:10.1111/1365-2656.13621)
45. Nakayama S, Laskowski KL, Klefoth T, Arlinghaus R. 2016 Between- and within-individual variation in activity increases with water temperature in wild perch. *Behav Ecol* **27**, 1676–1683. (doi:10.1093/beheco/arw090)
46. Harrison PM, Keeler RA, Robichaud D, Mossop B, Power M, Cooke SJ. 2019 Individual differences exceed species differences in the movements of a river fish community. *Behav Ecol* **30**, 1289–1297. (doi:10.1093/beheco/arz076)
47. Zlokovitz ER, Secor DH. 1999 Effect of habitat use on PCB body burden in Hudson River striped bass (*Morone saxatilis*). *Can J Fish Aquat Sci* **56**, 86–93. (doi:10.1139/f99-209)
48. West JE, O'Neill SM, Ylitalo GM. 2008 Spatial extent, magnitude, and patterns of persistent organochlorine pollutants in Pacific herring (*Clupea pallasi*) populations in the Puget Sound (USA) and Strait of Georgia (Canada). *Sci Total Environ* **394**, 369–378. (doi:10.1016/j.scitotenv.2007.12.027)

49. O'Neill SM, West JE. 2009 Marine distribution, life history traits, and the accumulation of polychlorinated biphenyls in chinook salmon from Puget Sound, Washington. *Trans Am Fish Soc* **138**, 616–632. (doi:10.1577/T08-003.1)
50. Colman JA, Nogueira JI, Pancorbo OC, Batdorf CA, Block BA. 2015 Mercury in Pacific bluefin tuna (*Thunnus orientalis*): bioaccumulation and trans-Pacific Ocean migration. *Can J Fish Aquat Sci* **72**, 1015–1023. (doi:10.1139/cjfas-2014-0476)
51. Brodin T, Fick J, Jonsson M, Klaminder J. 2013 Dilute concentrations of a psychiatric drug alter behavior of fish from natural populations. *Science* **339**, 814–815. (doi:10.1126/science.1226850)
52. Dzieweczynski TL, Greaney NE. 2017 Sex and dose-dependent effects of an estrogen mimic on boldness in threespine stickleback, *Gasterosteus aculeatus*, from an anadromous population. *J Exp Mar Biol Ecol* **497**, 78–85. (doi:10.1016/j.jembe.2017.09.013)
53. Dzieweczynski TL, Portrais KB, Stevens MA, Kane JL, Lawrence JM. 2018 Risky business: Changes in boldness behavior in male Siamese fighting fish, *Betta splendens*, following exposure to an antiandrogen. *Environ Pollut* **235**, 1015–1021. (doi:10.1016/j.envpol.2018.01.029)
54. Bose APH *et al.* 2022 Pharmaceutical pollution disrupts the behavior and predator-prey interactions of two widespread aquatic insects. *iScience* **25**, 105672. (doi:10.1016/j.isci.2022.105672)
55. Suryanto ME, Luong CT, Vasquez RD, Roldan MJM, Hung C-H, Ger T-R, Hsiao C-D. 2023 Using crayfish behavior assay as a simple and sensitive model to evaluate potential adverse effects of water pollution: Emphasis on antidepressants. *Ecotoxicol Environ Saf* **265**, 115507. (doi:10.1016/j.ecoenv.2023.115507)
56. Simmons DBD, McCallum ES, Balshine S, Chandramouli B, Cosgrove J, Sherry JP. 2017 Reduced anxiety is associated with the accumulation of six serotonin reuptake inhibitors in wastewater treatment effluent exposed goldfish *Carassius auratus*. *Sci Rep* **7**, 17001. (doi:10.1038/s41598-017-15989-z)
57. Moreira-Santos M, Ribeiro R, Araújo CVM. 2019 What if aquatic animals move away from pesticide-contaminated habitats before suffering adverse physiological effects? A critical review. *Crit Rev Environ Sci Technol* **49**, 989–1025. (doi:10.1080/10643389.2018.1564507)
58. Araújo CVM, Moreira-Santos M, Ribeiro R. 2016 Active and passive spatial avoidance by aquatic organisms from environmental stressors: a complementary perspective and a critical review. *Environ Int* **92–93**, 405–415. (doi:10.1016/j.envint.2016.04.031)
59. Lefcort H, Abbott DP, Cleary DA, Howell E, Keller NC, Smith MM. 2004 Aquatic snails from mining sites have evolved to detect and avoid heavy metals. *Arch Environ Contam Toxicol* **46**, 478–484. (doi:10.1007/s00244-003-3029-2)
60. Dornfeld CB, Moreira-Santos M, Espíndola ELG, Ribeiro R. 2009 Do larvae and ovipositing *Chironomus riparius* (Diptera: Chironomidae) females avoid copper-contaminated environments? *Hum ecol risk assess* **15**, 63–75. (doi:10.1080/10807030802615162)
61. Araújo CVM, Shinn C, Moreira-Santos M, Lopes I, Espíndola ELG, Ribeiro R. 2014 Copper-driven avoidance and mortality in temperate and tropical tadpoles. *Aquat Toxicol* **146**, 70–75. (doi:10.1016/j.aquatox.2013.10.030)
62. Fatima R, Briggs R, Dew WA. 2022 Avoidance of copper by fathead minnows (*Pimephales promelas*) requires an intact olfactory system. *PeerJ* **10**, e13988. (doi:10.7717/peerj.13988)

63. Islam MA, Blasco J, Araújo CVM. 2019 Spatial avoidance, inhibition of recolonization and population isolation in zebrafish (*Danio rerio*) caused by copper exposure under a non-forced approach. *Scie Total Environ* **653**, 504–511. (doi:10.1016/j.scitotenv.2018.10.375)
64. Xue R -D., Barnard DR, Ali A. 2001 Laboratory and field evaluation of insect repellents as larvicides against the mosquitoes *Aedes albopictus* and *Anopheles albimanus*. *Med Vet Entomol* **15**, 374–380. (doi:10.1046/j.0269-283x.2001.00323.x)
65. Takahashi M. 2007 Oviposition site selection: pesticide avoidance by gray treefrogs. *Environ Toxicol Chem* **26**, 1476–1480. (doi:10.1897/06-511R.1)
66. Coelho PN, Paes TASV, Maia-Barbosa PM, dos Santos-Wisniewski MJ. 2021 Effects of pollution on dormant-stage banks of cladocerans and rotifers in a large tropical reservoir. *Environ Sci Pollut Res* **28**, 30887–30897. (doi:10.1007/s11356-021-12751-x)
67. Araújo CVM, Blasco J. 2019 Spatial avoidance as a response to contamination by aquatic organisms in nonforced, multicompartmented exposure systems: a complementary approach to the behavioral response. *Environ Toxicol Chem* **38**, 312–320. (doi:10.1002/etc.4310)
68. Araújo CVM, Rodríguez ENV, Salvatierra D, Cedeño-Macias LA, Vera-Vera VC, Moreira-Santos M, Ribeiro R. 2016 Attractiveness of food and avoidance from contamination as conflicting stimuli to habitat selection by fish. *Chemosphere* **163**, 177–183. (doi:10.1016/j.chemosphere.2016.08.029)
69. Araújo CVM *et al.* 2020 Not only toxic but repellent: what can organisms' responses tell us about contamination and what are the ecological consequences when they flee from an environment? *Toxics* **8**, 118. (doi:10.3390/toxics8040118)
70. Hill CE, Myers JP, Vandenberg LN. 2018 Nonmonotonic dose–response curves occur in dose ranges that are relevant to regulatory decision-making. *Dose-Response* **16**, 155932581879828. (doi:10.1177/1559325818798282)
71. Dominoni DM *et al.* 2020 Why conservation biology can benefit from sensory ecology. *Nat Ecol Evol* **4**, 502–511. (doi:10.1038/s41559-020-1135-4)
72. Sánchez-Bayo F. 2021 Indirect effect of pesticides on insects and other arthropods. *Toxics* **9**, 177. (doi:10.3390/toxics9080177)
73. Tierney KB, Baldwin DH, Hara TJ, Ross PS, Scholz NL, Kennedy CJ. 2010 Olfactory toxicity in fishes. *Aquat Toxicol* **96**, 2–26. (doi:10.1016/j.aquatox.2009.09.019)
74. McCallum ES, Nikel KE, Mehdi H, Du SNN, Bowman JE, Midwood JD, Kidd KA, Scott GR, Balshine S. 2019 Municipal wastewater effluent affects fish communities: a multi-year study involving two wastewater treatment plants. *Environ Pollut* **252**, 1730–1741. (doi:10.1016/j.envpol.2019.06.075)
75. Mehdi H *et al.* 2021 Municipal wastewater as an ecological trap: effects on fish communities across seasons. *Scie Total Environ* **759**, 143430. (doi:10.1016/j.scitotenv.2020.143430)
76. Martin JM, Saaristo M, Bertram MG, Lewis PJ, Coggan TL, Clarke BO, Wong BBM. 2017 The psychoactive pollutant fluoxetine compromises antipredator behaviour in fish. *Environ Pollut* **222**, 592–599. (doi:10.1016/j.envpol.2016.10.010)
77. Bertram MG, Saaristo M, Martin JM, Ecker TE, Michelangeli M, Johnstone CP, Wong BBM. 2018 Field-realistic exposure to the androgenic endocrine disruptor 17β-trenbolone alters ecologically important behaviours in female fish across multiple contexts. *Environ Pollut* **243**, 900–911. (doi:10.1016/j.envpol.2018.09.044)

78. Lagesson A, Saaristo M, Brodin T, Fick J, Klaminder J, Martin JM, Wong BBM. 2019 Fish on steroids: Temperature-dependent effects of 17β-trenbolone on predator escape, boldness, and exploratory behaviors. *Environ Pollut* **245**, 243–252. (doi:10.1016/j.envpol.2018.10.116)

79. Denoël M, D'Hooghe B, Ficetola GF, Brasseur C, De Pauw E, Thomé J-P, Kestemont P. 2012 Using sets of behavioral biomarkers to assess short-term effects of pesticide: a study case with endosulfan on frog tadpoles. *Ecotoxicology* **21**, 1240–1250. (doi:10.1007/s10646-012-0878-3)

80. Villa S, Di Nica V, Pescatore T, Bellamoli F, Miari F, Finizio A, Lencioni V. 2018 Comparison of the behavioural effects of pharmaceuticals and pesticides on *Diamesa zernyi* larvae (Chironomidae). *Environ Pollut* **238**, 130–139. (doi:10.1016/j.envpol.2018.03.029)

81. Tan H, Martin JM, Alton LA, Lesku JA, Wong BBM. 2023 Widespread psychoactive pollutant augments daytime restfulness and disrupts diurnal activity rhythms in fish. *Chemosphere* **326**, 138446. (doi:10.1016/j.chemosphere.2023.138446)

82. Thoré ESJ, Aulsebrook AE, Brand JA, Almeida RA, Brodin T, Bertram MG. 2024 Time is of the essence: the importance of considering biological rhythms in an increasingly polluted world. *PLoS Biol* **22**, e3002478. (doi:10.1371/journal.pbio.3002478)

83. Ecke F *et al.* 2017 Sublethal lead exposure alters movement behavior in free-ranging golden eagles. *Environ Sci Technol* **51**, 5729–5736. (doi:10.1021/acs.est.6b06024)

84. Eng ML, Stutchbury BJM, Morrissey CA. 2017 Imidacloprid and chlorpyrifos insecticides impair migratory ability in a seed-eating songbird. *Sci Rep* **7**, 15176. (doi:10.1038/s41598-017-15446-x)

85. Gaynor KM, Brown JS, Middleton AD, Power ME, Brashares JS. 2019 Landscapes of fear: spatial patterns of risk perception and response. *Trends Ecol Evol* **34**, 355–368. (doi:10.1016/j.tree.2019.01.004)

86. Armansin NC, Stow AJ, Cantor M, Leu ST, Klarevas-Irby JA, Chariton AA, Farine DR. 2020 Social barriers in ecological landscapes: the social resistance hypothesis. *Trends Ecol Evol* **35**, 137–148. (doi:10.1016/j.tree.2019.10.001)

87. Chen T-H, Hsieh C-Y. 2017 Fighting Nemo: Effect of 17α-ethinylestradiol (EE2) on aggressive behavior and social hierarchy of the false clown anemonefish *Amphiprion ocellaris*. *Mar Pollut Bull* **124**, 760–766. (doi:10.1016/j.marpolbul.2016.12.042)

88. Dzieweczynski TL, Hebert OL. 2012 Fluoxetine alters behavioral consistency of aggression and courtship in male Siamese fighting fish, *Betta splendens*. *Physiol Behav* **107**, 92–97. (doi:10.1016/j.physbeh.2012.06.007)

89. Fisher DN, Kilgour RJ, Siracusa ER, Foote JR, Hobson EA, Montiglio P, Saltz JB, Wey TW, Wice EW. 2021 Anticipated effects of abiotic environmental change on intraspecific social interactions. *Biol Rev* **96**, 2661–2693. (doi:10.1111/brv.12772)

90. Spiegel O, Leu ST, Bull CM, Sih A. 2017 What's your move? Movement as a link between personality and spatial dynamics in animal populations. *Ecol Lett* **20**, 3–18. (doi:10.1111/ele.12708)

91. Harrison PM, Gutowsky LFG, Martins EG, Patterson DA, Cooke SJ, Power M. 2015 Personality-dependent spatial ecology occurs independently from dispersal in wild burbot (*Lota lota*). *Behav Ecol* **26**, 483–492. (doi:10.1093/beheco/aru216)

92. Polverino G, Aich U, Brand JA, Bertram MG, Martin JM, Tan H, Soman VR, Mason RT, Wong BBM. 2023 Sex-specific effects of psychoactive pollution on behavioral individuality and plasticity in fish. *Behav Ecol* **34**, 969–978. (doi:10.1093/beheco/arad065)

93. Metcalfe NB, Van Leeuwen TE, Killen SS. 2016 Does individual variation in metabolic phenotype predict fish behaviour and performance? *J Fish Biol* **88**, 298–321. (doi:10.1111/jfb.12699)

94. McCallum ES, Dey CJ, Cerveny D, Bose APH, Brodin T. 2021 Social status modulates the behavioral and physiological consequences of a chemical pollutant in animal groups. *Ecol Appl* **31**, e02454. (doi:10.1002/eap.2454)

95. Hamilton PB, Cowx IG, Oleksiak MF, Griffiths AM, Grahn M, Stevens JR, Carvalho GR, Nicol E, Tyler CR. 2016 Population-level consequences for wild fish exposed to sublethal concentrations of chemicals – a critical review. *Fish Fish* **17**, 545–566. (doi:10.1111/faf.12125)

96. Horký P, Grabic R, Grabicová K, Brooks BW, Douda K, Slavík O, Hubená P, Sancho Santos EM, Randák T. 2021 Methamphetamine pollution elicits addiction in wild fish. *J Exp Biol* **224**. (doi:10.1242/jeb.242145)

97. Sancho Santos ME, Horký P, Grabicová K, Steinbach C, Hubená P, Šálková E, Slavík O, Grabic R, Randák T. 2023 From metabolism to behaviour – multilevel effects of environmental methamphetamine concentrations on fish. *Sci Total Environ* **878**, 163167. (doi:10.1016/j.scitotenv.2023.163167)

98. Hubená P, Horký P, Grabic R, Grabicová K, Douda K, Slavík O, Randák T. 2021 Prescribed aggression of fishes: Pharmaceuticals modify aggression in environmentally relevant concentrations. *Ecotoxicol Environ Saf* **227**, 112944. (doi:10.1016/j.ecoenv.2021.112944)

99. Weis JS, Smith G, Santiago-Bass C. 2000 Predator/prey interactions: a link between the individual level and both higher and lower level effects of toxicants in aquatic ecosystems. *J Aquat Ecosyst Stress Recovery* **7**, 145–153. (doi:10.1023/A:1009923414208)

100. Ryalls JMW, Langford B, Mullinger NJ, Bromfield LM, Nemitz E, Pfrang C, Girling RD. 2022 Anthropogenic air pollutants reduce insect-mediated pollination services. *Environ Pollut* **297**, 118847. (doi:10.1016/j.envpol.2022.118847)

101. Oziolor EM, Reid NM, Yair S, Lee KM, Guberman VerPloeg S, Bruns PC, Shaw JR, Whitehead A, Matson CW. 2019 Adaptive introgression enables evolutionary rescue from extreme environmental pollution. *Science* **364**, 455–457. (doi:10.1126/science.aav4155)

102. Reid NM *et al.* 2016 The genomic landscape of rapid repeated evolutionary adaptation to toxic pollution in wild fish. *Science* **354**, 1305–1308. (doi:10.1126/science.aah4993)

103. De Lange HJ, Noordoven W, Murk AJ, Lürling M, Peeters ETHM. 2006 Behavioural responses of *Gammarus pulex* (Crustacea, Amphipoda) to low concentrations of pharmaceuticals. *Aquat Toxicol* **78**, 209–216. (doi:10.1016/j.aquatox.2006.03.002)

104. Augusiak J, Van den Brink PJ. 2016 The influence of insecticide exposure and environmental stimuli on the movement behaviour and dispersal of a freshwater isopod. *Ecotoxicology* **25**, 1338–1352. (doi:10.1007/s10646-016-1686-y)

105. Puritz JB, Toonen RJ. 2011 Coastal pollution limits pelagic larval dispersal. *Nat Commun* **2**, 226. (doi:10.1038/ncomms1238)

106. Brazzola G, Chèvre N, Wedekind C. 2014 Additive genetic variation for tolerance to estrogen pollution in natural populations of Alpine whitefish (*Coregonus* sp., Salmonidae). *Evol Appl* **7**, 1084–1093. (doi:10.1111/eva.12216)

107. Pease CJ, Johnston EL, Poore AGB. 2010 Genetic variability in tolerance to copper contamination in a herbivorous marine invertebrate. *Aquat Toxicol* **99**, 10–16. (doi:10.1016/j.aquatox.2010.03.014)

108. Kwan CK, Sanford E, Long J. 2015 Copper pollution increases the relative importance of predation risk in an aquatic food web. *PLoS One* **10**, e0133329. (doi:10.1371/journal.pone.0133329)
109. Kelly BC, Ikonomou MG, Blair JD, Morin AE, Gobas FAPC. 2007 Food web-specific biomagnification of persistent organic pollutants. *Science* **317**, 236–239. (doi:10.1126/science.1138275)
110. Richmond EK, Rosi EJ, Walters DM, Fick J, Hamilton SK, Brodin T, Sundelin A, Grace MR. 2018 A diverse suite of pharmaceuticals contaminates stream and riparian food webs. *Nat Commun* **9**, 4491. (doi:10.1038/s41467-018-06822-w)
111. Redondo-López S, González-Ortegón E, Mena F, Araújo CVM. 2022 Dissimilar behavioral and spatial avoidance responses by shrimps from tropical and temperate environments exposed to copper. *Environ Sci Pollut Res* **30**, 28023–28034. (doi:10.1007/s11356-022-23825-9)
112. Araújo CVM, Pontes JRS, Blasco J. 2019 Might the interspecies interaction between fish and shrimps change the pattern of their avoidance response to contamination? *Ecotoxicol Environ Saf* **186**, 109757. (doi:10.1016/j.ecoenv.2019.109757)
113. Lopes I, Baird DJ, Ribeiro R. 2004 Avoidance of copper contamination by field populations of *Daphnia longispina*. *Environ Toxicol Chem* **23**, 1702–1708. (doi:10.1897/03-231)
114. Cherry DS, Cairns J. 1982 Biological monitoring part V—preference and avoidance studies. *Water Res* **16**, 263–301. (doi:10.1016/0043-1354(82)90189-0)
115. Hund-Rinke K, Wiechering H. 2001 Earthworm avoidance test for soil assessments. *J Soils Sediments* **1**, 15–20. (doi:10.1007/BF02986464)
116. Williams HJ *et al.* 2020 Optimizing the use of biologgers for movement ecology research. *J Anim Ecol* **89**, 186–206. (doi:10.1111/1365-2656.13094)
117. McCallum ES, Cerveny D, Fick J, Brodin T. 2019 Slow-release implants for manipulating contaminant exposures in aquatic wildlife: a new tool for field ecotoxicology. *Environ Sci Technol* **53**, 8282–8290. (doi:10.1021/acs.est.9b01975)
118. Brönmark C, Hellström G, Baktoft H, Hansson L-A, McCallum ES, Nilsson PA, Skov C, Brodin T, Hulthén K. 2023 Ponds as experimental arenas for studying animal movement: current research and future prospects. *Mov Ecol* **11**, 68. (doi:10.1186/s40462-023-00419-9)
119. Brack W, Hollender J, de Alda ML, Müller C, Schulze T, Schymanski E, Slobodnik J, Krauss M. 2019 High-resolution mass spectrometry to complement monitoring and track emerging chemicals and pollution trends in European water resources. *Environ Sci Eur* **31**, 62. (doi:10.1186/s12302-019-0230-0)
120. Ramírez DG, Narváez Valderrama JF, Palacio Tobón CA, García JJ, Echeverri JD, Sobotka J, Vrana B. 2023 Occurrence, sources, and spatial variation of POPs in a mountainous tropical drinking water supply basin by passive sampling. *Environ Pollut* **318**, 120904. (doi:10.1016/j.envpol.2022.120904)
121. Betti M, Boisson F, Eriksson M, Tolosa I, Vasileva E. 2011 Isotope analysis for marine environmental studies. *Int J Mass Spectrom* **307**, 192–199. (doi:10.1016/j.ijms.2011.03.008)
122. Hollender J *et al.* 2023 NORMAN guidance on suspect and non-target screening in environmental monitoring. *Environ Sci Eur* **35**, 75. (doi:10.1186/s12302-023-00779-4)
123. Arturi K, Hollender J. 2023 Machine learning-based hazard-driven prioritization of features in nontarget screening of environmental high-resolution mass spectrometry data. *Environ Sci Technol* **57**, 18067–18079. (doi:10.1021/acs.est.3c00304)

124. Roy K. 2021 *Chemometrics and Cheminformatics in Aquatic Toxicology*. Wiley. (doi:10.1002/9781119681397)

125. Ehalt Macedo H, Lehner B, Nicell J, Grill G. 2024 HydroFATE (v1): a high-resolution contaminant fate model for the global river system. *Geosci Model Dev* **17**, 2877–2899. (doi:10.5194/gmd-17-2877-2024)

126. Schadt EE, Linderman MD, Sorenson J, Lee L, Nolan GP. 2010 Computational solutions to large-scale data management and analysis. *Nat Rev Genet* **11**, 647–657. (doi:10.1038/nrg2857)

127. Joo R, Boone ME, Clay TA, Patrick SC, Clusella-Trullas S, Basille M. 2020 Navigating through the r packages for movement. *J Anim Ecol* **89**, 248–267. (doi:10.1111/1365-2656.13116)

128. Fleming CH, Fagan WF, Mueller T, Olson KA, Leimgruber P, Calabrese JM. 2015 Rigorous home range estimation with movement data: a new autocorrelated kernel density estimator. *Ecology* **96**, 1182–1188. (doi:10.1890/14-2010.1)

129. Romero-Ferrero F, Bergomi MG, Hinz RC, Heras FJH, de Polavieja GG. 2019 idtracker.ai: tracking all individuals in small or large collectives of unmarked animals. *Nat Methods* **16**, 179–182. (doi:10.1038/s41592-018-0295-5)

130. Raoult V, Tosetto L, Williamson JE. 2018 Drone-based high-resolution tracking of aquatic vertebrates. *Drones* **2**, 37. (doi:10.3390/drones2040037)

131. Hussey NE *et al.* 2015 Aquatic animal telemetry: a panoramic window into the underwater world. *Science* **348**. (doi:10.1126/science.1255642)

132. McLane AJ, Semeniuk C, McDermid GJ, Marceau DJ. 2011 The role of agent-based models in wildlife ecology and management. *Ecol Modell* **222**, 1544–1556. (doi:10.1016/j.ecolmodel.2011.01.020)

133. Liu C, Sibly RM, Grimm V, Thorbek P. 2013 Linking pesticide exposure and spatial dynamics: an individual-based model of wood mouse (*Apodemus sylvaticus*) populations in agricultural landscapes. *Ecol Modell* **248**, 92–102. (doi:10.1016/j.ecolmodel.2012.09.016)

134. Aalizadeh R *et al.* 2021 Development and application of liquid chromatographic retention time indices in HRMS-based suspect and nontarget screening. *Anal Chem* **93**, 11601–11611. (doi:10.1021/acs.analchem.1c02348)

135. Oberleitner D, Schmid R, Schulz W, Bergmann A, Achten C. 2021 Feature-based molecular networking for identification of organic micropollutants including metabolites by non-target analysis applied to riverbank filtration. *Anal Bioanal Chem* **413**, 5291–5300. (doi:10.1007/s00216-021-03500-7)

136. Huber C, Krauss M, Reinstadler V, Denicolò S, Mayer G, Schulze T, Brack W, Oberacher H. 2022 In silico deconjugation of glucuronide conjugates enhances tandem mass spectra library annotation of human samples. *Anal Bioanal Chem* **414**, 2629–2640. (doi:10.1007/s00216-022-03899-7)

137. Sepman H, Malm L, Peets P, MacLeod M, Martin J, Breitholtz M, Kruve A. 2023 Bypassing the identification: MS2Quant for concentration estimations of chemicals detected with nontarget LC-HRMS from MS ^{2} data. *Anal Chem* **95**, 12329–12338. (doi:10.1021/acs.analchem.3c01744)

138. Peets P, Wang W-C, MacLeod M, Breitholtz M, Martin JW, Kruve A. 2022 MS2Tox machine learning tool for predicting the ecotoxicity of unidentified chemicals in water by nontarget LC-HRMS. *Environ Sci Technol* **56**, 15508–15517. (doi:10.1021/acs.est.2c02536)

139. Rahu I, Kull M, Kruve A. 2024 Predicting the activity of unidentified chemicals in complementary bioassays from the HRMS data to pinpoint potential endocrine disruptors. *J Chem Inf Model* **64**, 3093–3104. (doi:10.1021/acs.jcim.3c02050)
140. Dührkop K, Fleischauer M, Ludwig M, Aksenov AA, Melnik A V., Meusel M, Dorrestein PC, Rousu J, Böcker S. 2019 SIRIUS 4: a rapid tool for turning tandem mass spectra into metabolite structure information. *Nat Methods* **16**, 299–302. (doi:10.1038/s41592-019-0344-8)
141. Nothias L-F *et al.* 2020 Feature-based molecular networking in the GNPS analysis environment. *Nat Methods* **17**, 905–908. (doi:10.1038/s41592-020-0933-6)
142. Rosa R, Materatski P, Moreira-Santos M, Sousa JP, Ribeiro R. 2012 A scaled-up system to evaluate zooplankton spatial avoidance and the population immediate decline concentration. *Environ Toxicol Chem* **31**, 1301–1305. (doi:10.1002/etc.1813)
143. Grimmelpont M, Lefrançois C, Panisset Y, Jourdon G, Receveur J, Le Floch S, Boudenne J-L, Labille J, Milinkovitch T. 2023 Avoidance behaviour and toxicological impact of sunscreens in the teleost *Chelon auratus*. *Mar Pollut Bull* **194**, 115245. (doi:10.1016/j.marpolbul.2023.115245)
144. Johns M, Deloe K, Beaty LE, Simpson AM, Nutile SA. 2023 Avoidance behavior of *Hyalella azteca* in response to three common-use insecticides. *Chemosphere* **345**, 140492. (doi:10.1016/j.chemosphere.2023.140492)
145. Jutfelt F, Sundin J, Raby GD, Krång A, Clark TD. 2017 Two-current choice flumes for testing avoidance and preference in aquatic animals. *Methods Ecol Evol* **8**, 379–390. (doi:10.1111/2041-210X.12668)
146. Araújo CVM, Pereira KC, Sparaventi E, González-Ortegón E, Blasco J. 2020 Contamination may induce behavioural plasticity in the habitat selection by shrimps: a cost-benefits balance involving contamination, shelter and predation. *Environ Pollut* **263**, 114545. (doi:10.1016/j.envpol.2020.114545)
147. Lopez LK, Gil MA, Crowley PH, Trimmer PC, Munson A, Ligocki IY, Michelangeli M, Sih A. 2023 Integrating animal behaviour into research on multiple environmental stressors: a conceptual framework. *Biol Rev* **98**, 1345–1364. (doi:10.1111/brv.12956)
148. Niemelä PT, Dingemanse NJ. 2014 Artificial environments and the study of ‘adaptive’ personalities. *Trends Ecol Evol* **29**, 245–247. (doi:10.1016/j.tree.2014.02.007)
149. Fisher DN, James A, Rodríguez-Muñoz R, Tregenza T. 2015 Behaviour in captivity predicts some aspects of natural behaviour, but not others, in a wild cricket population. *Proc R Soc B* **282**, 20150708. (doi:10.1098/rspb.2015.0708)
150. Osborn A, Briffa M. 2017 Does repeatable behaviour in the laboratory represent behaviour under natural conditions? A formal comparison in sea anemones. *Anim Behav* **123**, 197–206. (doi:10.1016/j.anbehav.2016.10.036)
151. Brack W. 2003 Effect-directed analysis: a promising tool for the identification of organic toxicants in complex mixtures? *Anal Bioanal Chem* **377**, 397–407. (doi:10.1007/s00216-003-2139-z)
152. Costa-Pereira R, Moll RJ, Jesmer BR, Jetz W. 2022 Animal tracking moves community ecology: opportunities and challenges. *J Anim Ecol* **91**, 1334–1344. (doi:10.1111/1365-2656.13698)
153. Michelangeli M, Payne E, Spiegel O, Sinn DL, Leu ST, Gardner MG, Sih A. 2022 Personality, spatiotemporal ecological variation and resident/explorer movement syndromes in the sleepy lizard. *J Anim Ecol* **91**, 210–223. (doi:10.1111/1365-2656.13616)

154. Besson M, Alison J, Bjerge K, Gorochowski TE, Høye TT, Jucker T, Mann HMR, Clements CF. 2022 Towards the fully automated monitoring of ecological communities. *Ecol Lett* **25**, 2753–2775. (doi:10.1111/ele.14123)