Advancing the Spatiotemporal Dimension of Wildlife–Pollution Interactions

Brand, Jack A.; Martin, Jake M.; Michelangeli, Marcus; Thoré, Eli S.J.; Sandoval-Herrera, Natalia; McCallum, Erin S.; Szabo, Drew; Callahan, Damien L.; Clark, Timothy D.; Bertram, Michael G.; Brodin, Tomas

Published in:
Environmental Science & Technology Letters

DOI:
10.1021/acs.estlett.5c00042

Publication date:
2025

Document Version
Publisher's PDF, also known as Version of record

Citation for pulished version (HARVARD):
Brand, JA, Martin, JM, Michelangeli, M, Thoré, ESJ, Sandoval-Herrera, N, McCallum, ES, Szabo, D, Callahan, DL, Clark, TD, Bertram, MG & Brodin, T 2025, 'Advancing the Spatiotemporal Dimension of Wildlife–Pollution Interactions', *Environmental Science & Technology Letters*, vol. 12, no. 4, pp. 358-370. https://doi.org/10.1021/acs.estlett.5c00042

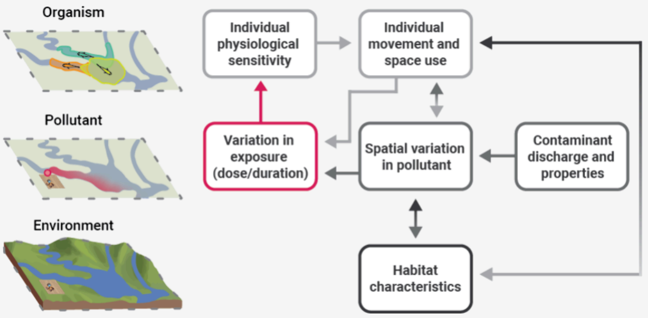
Environmental Science & Technology LETTERS

Advancing the Spatiotemporal Dimension of Wildlife–Pollution Interactions

Jack A. Brand,* Jake M. Martin,* Marcus Michelangeli, Eli S.J. Thoré, Natalia Sandoval-Herrera, Erin S. McCallum, Drew Szabo, Damien L. Callahan, Timothy D. Clark, Michael G. Bertram, and Tomas Brodin

Cite This: https://doi.org/10.1021/acs.estlett.5c00042

ABSTRACT: Chemical pollution is one of the fastest-growing agents of global change. Numerous pollutants are known to disrupt animal behavior, alter ecological interactions, and shift evolutionary trajectories. Crucially, both chemical pollutants and individual organisms are nonrandomly distributed throughout the environment. Despite this fact, the current evidence for chemical-induced impacts on wildlife largely stems from tests that restrict organism movement and force homogeneous exposures. While such approaches have provided pivotal ecotoxicological insights, they overlook the dynamic spatiotemporal interactions that shape wildlife–pollution relationships in nature. Indeed, the seemingly simple notion that pollutants and animals move nonrandomly in the environment creates a complex of dynamic interactions, many of which have never been theoretically modeled or experimentally tested. Here, we conceptualize dynamic interactions between spatiotemporal variation in pollutants and organisms and highlight their ecological and evolutionary implications. We propose a three-pronged approach—integrating *in silico* modeling, laboratory experiments that allow movement, and field-based tracking of free-ranging animals—to bridge the gap between controlled ecotoxicological studies and real-world wildlife exposures. Advances in telemetry, remote sensing, and computational models provide the necessary tools to quantify these interactions, paving the way for a new era of ecotoxicology that accounts for spatiotemporal complexity.



KEYWORDS: *behavioral 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 has exceeded the safe operating limits of the planetary boundary for novel entities in the environment.[1−3] To date, over 350000 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 behavior, 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 homogeneous 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

Received: January 16, 2025
Revised: March 13, 2025
Accepted: March 13, 2025

effects seen under these conditions would be reflective of exposures in the wild.[10]

Like pollutants, organisms are distributed nonrandomly 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 behavior 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, emphasizing recent advances in analytical chemistry, animal-tracking technologies, and computer-based modeling 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 localized 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., ref 21). For example, the concentration of point-source contaminants typically decreases with distance from the discharge site, as seen with higher zinc contamination in waterways near urbanized areas in Vietnam.[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, nonpoint 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 the 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] For example, research has shown that sediment type is associated with pollutant hotspots in lakes,[21] while soil pesticide concentrations can be influenced by physical soil characteristics[26] and local agricultural practices[27] in terrestrial systems. 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 be transferred and even biomagnify through trophic interactions between ecosystems.[28,29]

Temporal changes in 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 homogeneous 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.[30] Temporal changes can also occur on much shorter time scales. For example, concentrations of illicit drugs and their metabolites can increase in wastewater following public events.[31,32] In Lake Qingshan, China, organic pollutant concentrations spiked immediately following heavy rainfall events before eventually declining,[33] whereas daily variation 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.[34] 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 tire wear particle leachates in urban runoff.[35,36] 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 feed back 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 unfavorable 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,[37] while large marine predators like Atlantic bluefin tuna (*Thunnus thynnus*) are also known to migrate hundreds of meters of vertical distance each day, traversing stratified layers of water with remarkably different abiotic profiles.[38]

Individuals within populations also often differ in their space use and movement dynamics.[39] For instance, individual phenotypes (e.g., body size, body condition, sex, age) have been found to influence movement and space use in a variety of species.[40−45] Even when controlling for these factors, individuals within populations still often inherently differ from one another in their movement.[15,46] 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.[47] This intraspecific variation can have key effects on organismal ecology, with previous research showing relationships between individual movement rates, dietary niche, and habitat selection.[14,16,43] Collectively, this research demonstrates that individuals within populations exhibit significant variation in space use and movement, which are closely linked to niche specialization. Consequently, individual differences may lead to unique patterns of exposure to environmental challenges such as pollutants.[48−51]

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*),[50] Pacific bluefin tuna (*Thunnus orientalis*),[51] Pacific herring (*Clupea pallasi*),[49] and striped bass (*Morone saxatilis*).[48] In the wild, an individual's "realized 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 behaviors or by triggering avoidance, attraction, or conformity to polluted habitats.[20,52−57] Below, we conceptualize the dynamic feedback between the spatiotemporal distribution of contaminants and wildlife and discuss the likely ecological and evolutionary consequences (Figure 1).

4.1. Pollutants Impact the Spatiotemporal Distribution of Organisms and the Nature of Their Exposure.

4.1.1. Wildlife−Pollutant 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).[58,59] 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)[60−63] and can act as a chemical barrier preventing recolonization of suitable habitats and potentially isolating populations.[64] Organisms may also employ temporal avoidance strategies, especially when displacement is impossible, such as delaying colonization—exemplified by deterred oviposition in polluted habitats[65,66]—or entering dormant stages.[67] These avoidance behaviors have been demonstrated in laboratory-based, multicompartmental exposure systems[68,69] 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).[70] An important aspect to consider when evaluating risk is that the repellent nature of a substance

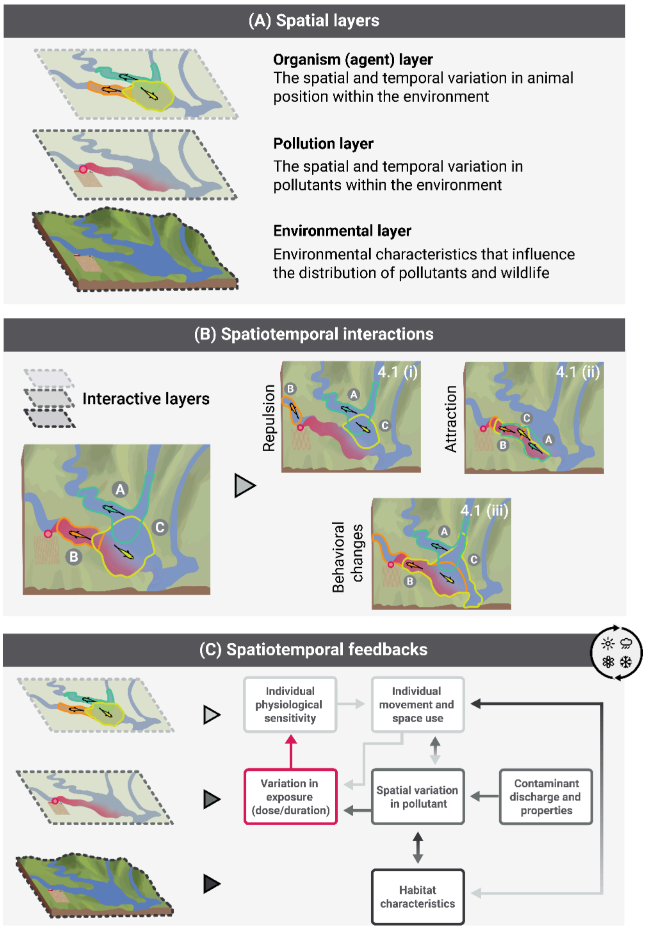


Figure 1. (A) Spatial layers that will influence the exposure risk and outcomes for wildlife. (B) Broad spatiotemporal wildlife−pollutant interactions and possible effects on the individual movement of fish from a hypothetical population. (C) Simple framework outlining potential pathways and dynamic feedback mechanisms between spatiotemporal variation in pollutants and animals that are described in this paper (the shading of the arrows helps represent the spatial layers that are influencing one another). The "seasonal" symbol in the top right-hand side of (C) represents the importance of changing environmental variables in determining spatiotemporal wildlife−pollutant interactions (e.g., via effects on habitat characteristics [ice versus free-flowing river], contaminant discharge rates [seasonal changes in agricultural practices or rainfall patterns], individual space use [seasonal differences in foraging areas or dispersal]).

https://doi.org/10.1021/acs.estlett.5c00042
Environ. Sci. Technol. Lett. XXXX, XXX, XXX−XXX

may not be directly correlated with its toxicity, meaning that a highly repellent contaminant could have low toxicity and *vice versa*.[71] Moreover, because pollutant-induced spatial avoidance occurs at sublethal 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).

4.1.2. 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.[72] 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.[73] Similarly, heavy metal pollutants can disrupt sensory system function, preventing organisms from detecting olfactory signals that might otherwise be avoided (e.g., predator cues).[74] 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.[75,76]

4.1.3. Pollutant-Induced Behavioral Shifts. 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 effects on organismal behavior (i.e., without a spatially explicit response to the contaminant itself). Small- and large-scale movement patterns are sensitive to contaminants that affect neurological function, metabolism, and endocrine regulation, such as psychoactive pharmaceutical pollutants,[52,55,56,77] endocrine-disrupting chemicals,[53,54,78,79] and pesticides.[54,80,81] As a small-scale example, chemicals can disrupt biological rhythms of exposed organisms, altering normal day–night activity cycles.[82,83] As a larger-scale example, contaminants can alter travel distances, migration dynamics, and stopover durations.[84−86] 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, contaminant-induced effects on other behavioral traits may also influence the spatial distribution of organisms and their probability of future exposures. As an example, risk landscapes[87] and social resistance (e.g., territoriality, within-group preferences)[88] are known to be major barriers to movement in many species, and there is evidence that many chemical contaminants can modify behaviors that generate these barriers, such as territoriality, risk-taking, aggression, and social behaviors.[54,79,89−91]

4.1.4. 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 behavior, sociality) and experience within populations can also mediate movement rates, space use, and habitat selection,[15,92,93] 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 behavioral response. For instance, exposure to environmental levels of an antidepressant over two years homogenized movement behavior among individual male guppies (*Poecilia reticulata*), but no shift in the variation of female movement phenotypes was observed.[94] 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.[95] 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 pollutant oxazepam and subsequent aggressive behavior in exposed brown trout (*Salmo trutta*).[96] 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 phenotypes 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, metapopulation, 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 the sake of simplicity, we have not specifically illustrated here. While we have focused on movement, space use, and behavior, we acknowledge that many pollutants can exert a variety of ecological and evolutionary effects via other mechanisms (e.g., mutagenesis, direct mortality, disrupted organismal development, reproductive changes),[97,98] which can also contribute to potentially adverse outcomes for wildlife populations.

4.2.1. 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., intraspecific interactions). For example, pollutants that act as repellents or attractants may decrease or increase intraspecific encounter rates 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 intrasexual

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;[68,120−122] pollutant positioning;[123−126] pollutant modeling;[127−129] modeling;[130] wildlife modeling;[131,132] wildlife positioning.[133−135] Approaches that can combine all of these different techniques (e.g., gray center of the Venn diagram)—such as agent-based models that incorporate empirical data from the spatiotemporal distribution of both wildlife and pollutants—may be particularly promising in predicting the outcomes of spatiotemporal dynamic wildlife–pollutant interactions.

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,[99] while also reducing individual movement[99,100] and increasing conspecific aggression,[101] 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,[102] pollination,[103] 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.[102]

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, as seen in killifish (*Fundulus* sp.)[104,105] and numerous other species that have evolved tolerance to pesticides.[98] 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.

4.2.2. (Meta)population-Level Outcomes. Pollutant-induced changes in movement and space use also have clear consequences for the ecoevolutionary dynamics of (meta)-populations. While avoiding exposure can be individually a more advantageous strategy than enduring the costs of chemical toxicity and depuration,[106] avoidance behavior also acts as a barrier to movement, resulting in habitat fragmentation, potentially affecting gene flow and population connectivity.[58,64] Even in the absence of direct avoidance, where pollutants alter dispersal-related traits—as seen in freshwater isopods (*Asellus aquaticus*) following sublethal insecticide exposure[107] —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 has been shown to act as a barrier to dispersal and gene flow, leading to reduced genetic diversity at highly contaminated sites.[108]

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[109] and copper pollution,[110] 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.[111] Conversely, shifts in space use due to preferences (either direct or indirect) for highly contaminated sites (e.g., refs 75 and 76) or avoidance of polluted areas (e.g., ref 8) could also increase interbreeding and hybridization between previously isolated groups, resulting in greater genetic diversity within populations.

4.2.3. 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.,refs 55 and 102) have been shown to restructure food webs.[112] Contaminants can also transfer through trophic interactions and even biomagnify, leading to complex exposure patterns for species across ecosystems.[113,114] Furthermore, species often exhibit varying sensitivities to chemical pollutants (e.g., ref 115), and in some cases, community composition may moderate responses to contaminant exposure.[115,116] For instance, zebrafish (*Danio rerio*) and freshwater shrimp (*Atyaephyra desmarestii*) demonstrated different spatial avoidance behaviors when tested independently versus together in response to copper pollution.[116]

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,[117−119] 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 behavioral and movement traits predicts an organism's 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, and animal tracking, as well as artificial intelligence and computational modeling, provide unprecedented opportunities to address these complexities (Figure 2). Using these recent advancements, we outline a three-pronged approach to guide future research in this area: *in silico* modeling, laboratory experiments, and semifield and field studies. It is important to highlight that such approaches may not be equally applicable to all environmental matrices. For example, *in silico* modeling and field-based experiments may be much more feasible in small freshwater lentic ecosystems (e.g., lakes) when compared to large marine systems (e.g., seas and oceans). Nevertheless, we believe that such approaches may provide insights into the nature of spatiotemporal interactions between organisms and pollutants across a range of habitat types.

5.1. *In Silico* Tools.

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

Agent-based modeling (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.[136] 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.[137] 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.[129] 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 behavior affects exposure to contaminants, providing insights into the potential long-term effects on population dynamics.

However, these ABMs need to be parametrized and validated based on empirical data, emphasizing a need for more research into the spatiotemporal variation of contaminants in natural systems. To this end, *in silico* tools, such as advanced data-driven computational models, supervised machine learning algorithms and artificial intelligence tools, molecular networking, and chromatographic retention time prediction, have been developed to help identify and predict the effects of thousands of potential contaminants that are detected in environmental and biological matrices using high-resolution mass spectrometry (HRMS).[138−141] With such approaches, concentration,[142] toxicity,[143] and endocrine-disrupting activity[144] can be derived from the chemical structure.[138,145] 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.[146] 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.

5.2. 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, 24−96 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 behaviors, 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.[147−149]

To overcome these limitations, multicompartmental arenas[69,117] and steep gradient assays[150] offer effective alternative designs. These designs incorporate ecological complexity into laboratory experiments while allowing for more spatial and temporal heterogeneity in exposure conditions.[151] 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 behaviors—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 contaminant scenarios, which are ideally informed by spatially explicit field sampling (Section 5.3).

To further refine these experiments, the integration of 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.[64] 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.[69,152] Further, incorporating mixture exposures based on observed environmental (co)occurrences and predicted biological interactions (e.g., via slow-release chemical mixture implants[153] or exposure to real-world wastewater effluents[154]) would more accurately reflect environmental conditions and could elucidate the potential interactive effects of different contaminants.

In all cases, it remains essential for future research in this area to adhere to fundamental principles of ecotoxicology wherever possible.[12] This includes aspects of sound experimental design and quality control such as adequate replication and standardization, the use of appropriate controls and study designs, accurate measures of exposure concentrations and relevant environmental parameters, and the use of appropriate statistical techniques. Incorporating such principles will be key in enhancing research credibility and reproducibility, which is particularly relevant for research that aims to inform chemical risk assessments and regulation.[12]

5.3. Field Studies. Laboratory studies are invaluable for understanding the underlying mechanisms of contaminant effects and 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.[155−157] Thus, spatially explicit water sampling and field studies are necessary for characterizing complex exposure scenarios and monitoring the spatial and temporal overlaps of chemical contaminants and animal populations.

Advancements in mass spectrometry libraries and computational tools, combined with spatially explicit sampling regimes, are improving the identification and characterization of contaminant distributions in the field.[127] These tools allow researchers to capture the fine-scale spatial and temporal variability of contamination in nature, 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 prioritization of chemicals that are predicted to have environmental implications are key to reducing these costs. As mentioned above, *in silico* modeling 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.[158]

Moreover, advances in remote-sensing technologies, such as acoustic telemetry and global positioning systems (GPS), have revolutionized our ability to quantify the behavior 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.[86,121,153] 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 homogeneously exposed while still moving freely) to disentangle complex wildlife−pollutant spatial interactions.[121] 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).[159−161]

Here, we categorize pollutant−animal spatial interactions and conceptualize a simple dynamic feedback model that may result from such interactions. We identify potential ecological and evolutionary consequences and highlight key areas of uncertainty. We recognize that incorporating these spatial interactions in experimental and observational work generates logistical challenges but emphasize that it is becoming ever more achievable, with advances in *in silico* modeling and prediction techniques, artificial intelligence, and 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.

■ ASSOCIATED CONTENT

Data Availability Statement

There are no new data associated with this article.

■ AUTHOR INFORMATION

Corresponding Authors

Jack A. Brand − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden; Institute of Zoology, Zoological Society of London, London NW1 4RY, United Kingdom;* orcid.org/0000-0003-3312-941X; Email: jack.brand@slu.se

Jake M. Martin − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden; Department of Zoology, Stockholm University, Stockholm 114 18, Sweden; School of Biological Sciences, Monash University, Melbourne 3800, Australia; School of Life and Environmental Sciences, Deakin University, Waurn Ponds 3216, Australia;* Email: jake.martin@deakin.edu.au

Authors

Marcus Michelangeli − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden; Australian Rivers Institute, Griffith University, Nathan 4111, Australia;* orcid.org/0000-0002-0053-6759

Eli S.J. Thoré − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden; TRANSfarm - Science, Engineering, & Technology Group, KU Leuven, Lovenjoel 3360, Belgium; Laboratory of Adaptive Biodynamics, Research Unit of Environmental and Evolutionary Biology, Institute of Life, Earth and Environment, University of Namur, Namur 5000, Belgium;* orcid.org/0000-0002-0029-8404

Natalia Sandoval-Herrera − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden*

Erin S. McCallum − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden;* orcid.org/0000-0001-5426-9652

Drew Szabo − *Centre of Excellence in Mass Spectrometry, Department of Chemistry, University of York, York YO10 5DD, United Kingdom; School of Chemistry, The University of Melbourne, Melbourne 3010, Australia;* orcid.org/0000-0002-0089-9218

Damien L. Callahan − *School of Life and Environmental Sciences, Deakin University, Waurn Ponds 3216, Australia*

Timothy D. Clark − *School of Life and Environmental Sciences, Deakin University, Waurn Ponds 3216, Australia*

Michael G. Bertram − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden; Department of Zoology, Stockholm University, Stockholm 114 18, Sweden; School of Biological Sciences, Monash University, Melbourne 3800, Australia*

Tomas Brodin − *Department of Wildlife, Fish, and Environmental Studies, Swedish University of Agricultural Sciences, Umeå 907 36, Sweden*

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.estlett.5c00042

Author Contributions

J.A.B. and J.M.M. should be considered joint first authors. J.A.B.: conceptualization (colead), project administration (colead), visualization (colead), writing − original draft preparation (colead), writing - review and editing (colead). J.M.M.: conceptualization (colead), project administration (colead), visualization (colead), writing - original draft preparation (colead), writing - review and editing (colead). M.M.: conceptualization, writing - original draft preparation, writing - review and editing. E.S.J.T.: conceptualization, writing - original draft preparation, writing - review and editing. N.S.-H.: conceptualization, writing - original draft preparation, writing - review and editing. E.S.M.: writing − review and editing. D.S.: writing − review and editing. D.C.: writing - review and editing. T.D.C.: writing − review and editing. M.G.B.: writing - review and editing. T.B.: funding acquisition, writing - review and editing.

Funding

This work was supported by funding from the Swedish Research Council Formas (J.A.B., 2024-00507; J.M.M., 2023-101801253 and 2022-02796; E.S.M., 2020-00981; T.B., 2018-00828; M.M., 2022-00503; M.G.B., 2020-02293), The Carl Tryggers Foundation (J.A.B., CTS 24:3381), the Kempe Foundations (T.B., JCK22-0037), the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska Curie grant agreement (M.M., 101061889), Deakin University (J.M.M., Alfred Deakin Postdoctoral Research Fellowship), Wenner-Gren Foundation (N.S., Foreign Postdoctoral Fellowship), and the Australian Research Council Future Fellowship program on behalf of the Australian Government (T.D.C., FT180100154).

Notes

This work previously appeared on a preprint server: Brand, J. A.; Martin, J. M.; Michelangeli, M.; Thoré, E.; Sandoval-Herrera, N.; McCallum, E. S.; Szabo, D.; Callahan, D. L.; Clark, T. D.; Bertram, M. G.; Brodin, T. Advancing the spatiotemporal dimension of wildlife−pollution interactions. 2024. *EcoEvoRxiv* DOI: 10.32942/X2Z63H (accessed March 13, 2025).

The authors declare no competing financial interest.

■ REFERENCES

(1) Sylvester, F.; et al. Better integration of chemical pollution research will further our understanding of biodiversity loss. *Nat. Ecol. Evol.* **2023**, *7*, 1552−1555, DOI: 10.1038/s41559-023-02117-6.

(2) Bernhardt, E. S.; Rosi, E. J.; Gessner, M. O. Synthetic chemicals as agents of global change. *Front. Ecol. Environ.* **2017**, *15*, 84−90, DOI: 10.1002/fee.1450.

(3) Persson, L.; et al. Outside the safe operating space of the planetary boundary for novel entities. *Environ. Sci. Technol.* **2022**, *56*, 1510−1521, DOI: 10.1021/acs.est.1c04158.

(4) Wang, Z.; Walker, G. W.; Muir, D. C. G.; Nagatani-Yoshida, K. Toward a global understanding of chemical pollution: a first comprehensive analysis of national and regional chemical inventories. *Environ. Sci. Technol.* **2020**, *54*, 2575−2584, DOI: 10.1021/acs.est.9b06379.

(5) Sigmund, G.; et al. Addressing chemical pollution in biodiversity research. *Glob. Chang. Biol.* **2023**, *29*, 3240−3255, DOI: 10.1111/gcb.16689.

(6) Saaristo, M.; et al. Direct and indirect effects of chemical contaminants on the behaviour, ecology and evolution of wildlife.

Proc. R Soc. B Biol. Sci. **2018**, *285*, 20181297 DOI: 10.1098/rspb.2018.1297.

(7) Richards, S.; Bidgood, L.; Watson, H.; Stutter, M. Biogeochemical impacts of sewage effluents in predominantly rural river catchments: are point source inputs distinct to background diffuse pollution? *J. Environ. Manage.* **2022**, *311*, 114891 DOI: 10.1016/j.jenvman.2022.114891.

(8) Bonvin, F.; Rutler, R.; Chèvre, N.; Halder, J.; Kohn, T. Spatial and temporal presence of a wastewater-derived micropollutant plume in Lake Geneva. *Environ. Sci. Technol.* **2011**, *45*, 4702−4709, DOI: 10.1021/es2003588.

(9) Cairns, J.; Niederlehner, B. R. Developing a field of landscape ecotoxicology. *Ecol Appl.* **1996**, *6*, 790−796, DOI: 10.2307/2269484.

(10) Schäfer, R. B. Why we need landscape ecotoxicology and how it could be advanced—an academic perspective. *Environ. Toxicol. Chem.* **2014**, *33*, 1193−1193, DOI: 10.1002/etc.2569.

(11) Johnson, A. R. Landscape ecotoxicology and assessment of risk at multiple scales. *Hum. Ecol. Risk Assess.* **2002**, *8*, 127−146, DOI: 10.1080/20028091056773.

(12) Bertram, M. G.; et al. Frontiers in quantifying wildlife behavioural responses to chemical pollution. *Biol. Rev.* **2022**, *97*, 1346−1364, DOI: 10.1111/brv.12844.

(13) Martin, J. M.; et al. Evidence of the impacts of pharmaceuticals on aquatic animal behaviour (EIPAAB): a systematic map and open access database. *EcoEvoRxiv* **2024**, DOI: 10.32942/X2NG9R.

(14) Harrison, P. M.; et al. Individual isotopic specializations predict subsequent inter-individual variation in movement in a freshwater fish. *Ecology* **2017**, *98*, 608−615, DOI: 10.1002/ecy.1681.

(15) Villegas-Ríos, D.; Réale, D.; Freitas, C.; Moland, E.; Olsen, E. M. Individual level consistency and correlations of fish spatial behaviour assessed from aquatic animal telemetry. *Anim. Behav.* **2017**, *124*, 83−94, DOI: 10.1016/j.anbehav.2016.12.002.

(16) Mawer, R.; et al. Individual variation in the habitat selection of upstream migrating fish near a barrier. *Mov. Ecol.* **2023**, *11*, 49 DOI: 10.1186/s40462-023-00414-0.

(17) Nathan, R.; et al. Big-data approaches lead to an increased understanding of the ecology of animal movement. *Science* **2022**, *375*, No. eabg1780, DOI: 10.1126/science.abg1780.

(18) McCallum, E. S.; et al. Investigating tissue bioconcentration and the behavioural effects of two pharmaceutical pollutants on sea trout (*Salmo trutta*) in the laboratory and field. *Aquat Toxicol* **2019**, *207*, 170−178, DOI: 10.1016/j.aquatox.2018.11.028.

(19) Michelangeli, M.; et al. Predicting the impacts of chemical pollutants on animal groups. *Trends Ecol. Evol.* **2022**, *37*, 789−802, DOI: 10.1016/j.tree.2022.05.009.

(20) Jacquin, L.; Petitjean, Q.; Côte, J.; Laffaille, P.; Jean, S. Effects of pollution on fish behavior, personality, and cognition: some research perspectives. *Front. Ecol .Evol.* **2020**, *8*, 86 DOI: 10.3389/fevo.2020.00086.

(21) Marvin, C.; et al. Spatial and temporal trends in surface water and sediment contamination in the Laurentian Great Lakes. *Environ. Pollut.* **2004**, *129*, 131−144, DOI: 10.1016/j.envpol.2003.09.029.

(22) Wilbers, G.-J.; Becker, M.; Nga, L. T.; Sebesvari, Z.; Renaud, F. G. Spatial and temporal variability of surface water pollution in the Mekong Delta, Vietnam. *Sci. Total Environ.* **2014**, *485−486*, 653−665, DOI: 10.1016/j.scitotenv.2014.03.049.

(23) Dereumeaux, C.; Fillol, C.; Quenel, P.; Denys, S. Pesticide exposures for residents living close to agricultural lands: a review. *Environ. Int.* **2020**, *134*, 105210 DOI: 10.1016/j.envint.2019.105210.

(24) Otto, S.; Lazzaro, L.; Finizio, A.; Zanin, G. Estimating ecotoxicological effects of pesticide drift on nontarget arthropods in field hedgerows. *Environ. Toxicol. Chem.* **2009**, *28*, 853−863, DOI: 10.1897/08-260R.1.

(25) Holt, M. S. Sources of chemical contaminants and routes into the freshwater environment. *Food Chem. Toxicol.* **2000**, *38*, S21−S27, DOI: 10.1016/S0278-6915(99)00136-2.

(26) Meftaul, I. M.; Venkateswarlu, K.; Annamalai, P.; Parven, A.; Megharaj, M. Degradation of four pesticides in five urban landscape soils: human and environmental health risk assessment. *Environ. Geochem. Health* **2023**, *45*, 1599−1614, DOI: 10.1007/s10653-022-01278-w.

(27) Humann-Guilleminot, S.; et al. A nation-wide survey of neonicotinoid insecticides in agricultural land with implications for agri-environment schemes. *J. Appl. Ecol.* **2019**, *56*, 1502−1514, DOI: 10.1111/1365-2664.13392.

(28) Hu, T.; et al. Bioaccumulation and trophic transfer of antibiotics in the aquatic and terrestrial food webs of the Yellow River Delta. *Chemosphere* **2023**, *323*, 138211 DOI: 10.1016/j.chemosphere.2023.138211.

(29) Schulz, R.; Bundschuh, M. Pathways of contaminant transport across the aquatic-terrestrial interface: implications for terrestrial consumers, ecosystems, and management. In *Contaminants and Ecological Subsidies*; Springer International Publishing: 2020; pp 35−57. DOI: 10.1007/978-3-030-49480-3_3.

(30) Gómez, M. J.; Herrera, S.; Solé, D.; García-Calvo, E.; Fernández-Alba, A. R. Spatio-temporal evaluation of organic contaminants and their transformation products along a river basin affected by urban, agricultural and industrial pollution. *Sci. Total Environ.* **2012**, *420*, 134−145, DOI: 10.1016/j.scitotenv.2012.01.029.

(31) da Silva, K. M.; et al. Assessing cocaine use patterns in the Brazilian capital by wastewater-based epidemiology. *Int. J. Environ. Anal. Chem.* **2018**, *98*, 1370−1387, DOI: 10.1080/03067319.2018.1554743.

(32) Gerrity, D.; Trenholm, R. A.; Snyder, S. A. Temporal variability of pharmaceuticals and illicit drugs in wastewater and the effects of a major sporting event. *Water Res.* **2011**, *45*, 5399−5411, DOI: 10.1016/j.watres.2011.07.020.

(33) Xu, J.; et al. Variations of concentration characteristics of rainfall runoff pollutants in typical urban living areas. *Bull. Environ. Contam. Toxicol.* **2021**, *106*, 608−613, DOI: 10.1007/s00128-021-03110-0.

(34) Eccles, K. M.; Pauli, B. D.; Chan, H. M. The use of geographic information systems for spatial ecological risk assessments: an example from the Athabasca oil sands area in Canada. *Environ. Toxicol. Chem.* **2019**, *38*, 2797−2810, DOI: 10.1002/etc.4577.

(35) Peter, K. T.; et al. Using high-resolution mass spectrometry to identify organic contaminants linked to urban stormwater mortality syndrome in coho salmon. *Environ. Sci. Technol.* **2018**, *52*, 10317−10327, DOI: 10.1021/acs.est.8b03287.

(36) Feist, B. E.; et al. Roads to ruin: conservation threats to a sentinel species across an urban gradient. *Ecol. Appl.* **2017**, *27*, 2382−2396, DOI: 10.1002/eap.1615.

(37) Nakayama, S.; et al. 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* **2018**, *27*, 798−812, DOI: 10.1111/eff.12393.

(38) Block, B. A.; et al. Migratory movements, depth preferences, and thermal biology of Atlantic bluefin tuna. *Science* **2001**, *293*, 1310−1314, DOI: 10.1126/science.1061197.

(39) Shaw, A. K. Causes and consequences of individual variation in animal movement. *Mov. Ecol.* **2020**, *8*, 12 DOI: 10.1186/s40462-020-0197-x.

(40) Dhellemmes, F.; et al. Body size scaling of space use in coastal pike (*Esox lucius*) in brackish lagoons of the southern Baltic Sea. *Fish. Res.* **2023**, *260*, 106560 DOI: 10.1016/j.fishres.2022.106560.

(41) Matich, P.; Heithaus, M. R. Individual variation in ontogenetic niche shifts in habitat use and movement patterns of a large estuarine predator (*Carcharhinus leucas*). *Oecologia* **2015**, *178*, 347−359, DOI: 10.1007/s00442-015-3253-2.

(42) Skerritt, D.; Robertson, P.; Mill, A.; Polunin, N.; Fitzsimmons, C. Fine-scale movement, activity patterns and home-ranges of European lobster *Homarus gammarus*. *Mar. Ecol. Prog. Ser.* **2015**, *536*, 203−219, DOI: 10.3354/meps11374.

(43) Nakayama, S.; Rapp, T.; Arlinghaus, R. Fast-slow life history is correlated with individual differences in movements and prey selection in an aquatic predator in the wild. *J. Anim. Ecol.* **2017**, *86*, 192−201, DOI: 10.1111/1365-2656.12603.

(44) Payne, E.; et al. Intrinsic traits, social context, and local environment shape home range size and fidelity of sleepy lizards. *Ecol. Monogr.* **2022**, *92*, e1519 DOI: 10.1002/ecm.1519.

(45) Gaynor, K. M.; McInturff, A.; Brashares, J. S. Contrasting patterns of risk from human and non-human predators shape temporal activity of prey. *J. Anim. Ecol.* **2022**, *91*, 46−60, DOI: 10.1111/1365-2656.13621.

(46) Nakayama, S.; Laskowski, K. L.; Klefoth, T.; Arlinghaus, R. Between- and within-individual variation in activity increases with water temperature in wild perch. *Behav. Ecol.* **2016**, *27*, 1676−1683, DOI: 10.1093/beheco/arw090.

(47) Harrison, P. M.; et al. Individual differences exceed species differences in the movements of a river fish community. *Behav. Ecol.* **2019**, *30*, 1289−1297, DOI: 10.1093/beheco/arz076.

(48) Zlokovitz, E. R.; Secor, D. H. Effect of habitat use on PCB body burden in Hudson River striped bass (*Morone saxatilis*). *Can. J. Fish. Aquat. Sci.* **1999**, *56*, 86−93, DOI: 10.1139/f99-209.

(49) West, J. E.; O'Neill, S. M.; Ylitalo, G. M. 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.* **2008**, *394*, 369−378, DOI: 10.1016/j.scitotenv.2007.12.027.

(50) O'Neill, S. M.; West, J. E. Marine distribution, life history traits, and the accumulation of polychlorinated biphenyls in chinook salmon from Puget Sound, Washington. *Trans Am. Fish. Soc.* **2009**, *138*, 616−632, DOI: 10.1577/T08-003.1.

(51) Colman, J. A.; Nogueira, J. I.; Pancorbo, O. C.; Batdorf, C. A.; Block, B. A. Mercury in Pacific bluefin tuna (*Thunnus orientalis*): bioaccumulation and trans-Pacific Ocean migration. *Can. J. Fish. Aquat. Sci.* **2015**, *72*, 1015−1023, DOI: 10.1139/cjfas-2014-0476.

(52) Brodin, T.; Fick, J.; Jonsson, M.; Klaminder, J. Dilute concentrations of a psychiatric drug alter behavior of fish from natural populations. *Science* **2013**, *339*, 814−815, DOI: 10.1126/science.1226850.

(53) Dzieweczynski, T. L.; Greaney, N. E. 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.* **2017**, *497*, 78−85, DOI: 10.1016/j.jembe.2017.09.013.

(54) Dzieweczynski, T. L.; Portrais, K. B.; Stevens, M. A.; Kane, J. L.; Lawrence, J. M. Risky business: changes in boldness behavior in male Siamese fighting fish, *Betta splendens*, following exposure to an antiandrogen. *Environ. Pollut.* **2018**, *235*, 1015−1021, DOI: 10.1016/j.envpol.2018.01.029.

(55) Bose, A. P. H.; et al. Pharmaceutical pollution disrupts the behavior and predator-prey interactions of two widespread aquatic insects. *iScience* **2022**, *25*, 105672 DOI: 10.1016/j.isci.2022.105672.

(56) Suryanto, M. E.; et al. Using crayfish behavior assay as a simple and sensitive model to evaluate potential adverse effects of water pollution: emphasis on antidepressants. *Ecotoxicol. Environ. Saf.* **2023**, *265*, 115507 DOI: 10.1016/j.ecoenv.2023.115507.

(57) Simmons, D. B. D.; et al. Reduced anxiety is associated with the accumulation of six serotonin reuptake inhibitors in wastewater treatment effluent exposed goldfish *Carassius auratus*. *Sci. Rep.* **2017**, *7*, 17001 DOI: 10.1038/s41598-017-15989-z.

(58) Moreira-Santos, M.; Ribeiro, R.; Araújo, C. V. M. What if aquatic animals move away from pesticide-contaminated habitats before suffering adverse physiological effects? A critical review. *Crit. Rev. Environ. Sci. Technol.* **2019**, *49*, 989−1025, DOI: 10.1080/10643389.2018.1564507.

(59) Araújo, C. V. M.; Moreira-Santos, M.; Ribeiro, R. Active and passive spatial avoidance by aquatic organisms from environmental stressors: a complementary perspective and a critical review. *Environ. Int.* **2016**, *92*−*93*, 405−415, DOI: 10.1016/j.envint.2016.04.031.

(60) Lefcort, H.; et al. Aquatic snails from mining sites have evolved to detect and avoid heavy metals. *Arch. Environ. Contam. Toxicol.* **2004**, *46*, 478−484, DOI: 10.1007/s00244-003-3029-2.

(61) Dornfeld, C. B.; Moreira-Santos, M.; Espíndola, E. L. G.; Ribeiro, R. Do larvae and ovipositing *Chironomus riparius* (Diptera: Chironomidae) females avoid copper-contaminated environments? *Hum. Ecol. Risk Assess.* **2009**, *15*, 63−75, DOI: 10.1080/10807030802615162.

(62) Araújo, C. V. M.; et al. Copper-driven avoidance and mortality in temperate and tropical tadpoles. *Aquat. Toxicol.* **2014**, *146*, 70−75, DOI: 10.1016/j.aquatox.2013.10.030.

(63) Fatima, R.; Briggs, R.; Dew, W. A. Avoidance of copper by fathead minnows (*Pimephales promelas*) requires an intact olfactory system. *PeerJ.* **2022**, *10*, No. e13988, DOI: 10.7717/peerj.13988.

(64) Islam, M. A.; Blasco, J.; Araújo, C. V. M. Spatial avoidance, inhibition of recolonization and population isolation in zebrafish (*Danio rerio*) caused by copper exposure under a non-forced approach. *Sci. Total Environ.* **2019**, *653*, 504−511, DOI: 10.1016/j.scitotenv.2018.10.375.

(65) Xue, R.-D.; Barnard, D. R.; Ali, A. Laboratory and field evaluation of insect repellents as larvicides against the mosquitoes *Aedes albopictus* and *Anopheles albimanus*. *Med. Vet. Entomol.* **2001**, *15*, 374−380, DOI: 10.1046/j.0269-283x.2001.00323.x.

(66) Takahashi, M. Oviposition site selection: pesticide avoidance by gray treefrogs. *Environ. Toxicol. Chem.* **2007**, *26*, 1476−1480, DOI: 10.1897/06-511R.1.

(67) Coelho, P. N.; Paes, T. A. S. V.; Maia-Barbosa, P. M.; dos Santos-Wisniewski, M. J. Effects of pollution on dormant-stage banks of cladocerans and rotifers in a large tropical reservoir. *Environ. Sci. Pollut. Res.* **2021**, *28*, 30887−30897, DOI: 10.1007/s11356-021-12751-x.

(68) Araújo, C. V. M.; Blasco, J. 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.* **2019**, *38*, 312−320, DOI: 10.1002/etc.4310.

(69) Araújo, C. V. M.; et al. Attractiveness of food and avoidance from contamination as conflicting stimuli to habitat selection by fish. *Chemosphere* **2016**, *163*, 177−183, DOI: 10.1016/j.chemosphere.2016.08.029.

(70) Araújo, C. V. M.; et al. 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* **2020**, *8*, 118 DOI: 10.3390/toxics8040118.

(71) Hill, C. E.; Myers, J. P.; Vandenberg, L. N. Nonmonotonic dose−response curves occur in dose ranges that are relevant to regulatory decision-making. *Dose-Response* **2018**, *16*, 1 DOI: 10.1177/1559325818798282.

(72) Dominoni, D. M.; et al. Why conservation biology can benefit from sensory ecology. *Nat. Ecol. Evol.* **2020**, *4*, 502−511, DOI: 10.1038/s41559-020-1135-4.

(73) Sánchez-Bayo, F. Indirect effect of pesticides on insects and other arthropods. *Toxics* **2021**, *9*, 177 DOI: 10.3390/toxics9080177.

(74) Tierney, K. B.; et al. Olfactory toxicity in fishes. *Aquat. Toxicol.* **2010**, *96*, 2−26, DOI: 10.1016/j.aquatox.2009.09.019.

(75) McCallum, E. S.; et al. Municipal wastewater effluent affects fish communities: a multi-year study involving two wastewater treatment plants. *Environ. Pollut.* **2019**, *252*, 1730−1741, DOI: 10.1016/j.envpol.2019.06.075.

(76) Mehdi, H.; et al. Municipal wastewater as an ecological trap: effects on fish communities across seasons. *Sci. Total Environ.* **2021**, *759*, 143430 DOI: 10.1016/j.scitotenv.2020.143430.

(77) Martin, J. M.; et al. The psychoactive pollutant fluoxetine compromises antipredator behaviour in fish. *Environ. Pollut.* **2017**, *222*, 592−599, DOI: 10.1016/j.envpol.2016.10.010.

(78) Bertram, M. G.; et al. Field-realistic exposure to the androgenic endocrine disruptor 17β-trenbolone alters ecologically important behaviours in female fish across multiple contexts. *Environ. Pollut.* **2018**, *243*, 900−911, DOI: 10.1016/j.envpol.2018.09.044.

(79) Lagesson, A.; et al. Fish on steroids: Temperature-dependent effects of 17β-trenbolone on predator escape, boldness, and exploratory behaviors. *Environ. Pollut.* **2019**, *245*, 243−252, DOI: 10.1016/j.envpol.2018.10.116.

(80) Denoël, M.; et al. Using sets of behavioral biomarkers to assess short-term effects of pesticide: a study case with endosulfan on frog

tadpoles. *Ecotoxicology* **2012**, *21*, 1240−1250, DOI: 10.1007/s10646-012-0878-3.

(81) Villa, S.; et al. Comparison of the behavioural effects of pharmaceuticals and pesticides on *Diamesa zernyi* larvae (Chironomidae). *Environ. Pollut.* **2018**, *238*, 130−139, DOI: 10.1016/j.envpol.2018.03.029.

(82) Tan, H.; Martin, J. M.; Alton, L. A.; Lesku, J. A.; Wong, B. B. M. Widespread psychoactive pollutant augments daytime restfulness and disrupts diurnal activity rhythms in fish. *Chemosphere* **2023**, *326*, 138446 DOI: 10.1016/j.chemosphere.2023.138446.

(83) Thoré, E. S. J.; et al. Time is of the essence: the importance of considering biological rhythms in an increasingly polluted world. *PLoS Biol.* **2024**, *22*, No. e3002478, DOI: 10.1371/journal.pbio.3002478.

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

(85) Eng, M. L.; Stutchbury, B. J. M.; Morrissey, C. A. Imidacloprid and chlorpyrifos insecticides impair migratory ability in a seed-eating songbird. *Sci. Rep.* **2017**, *7*, 15176 DOI: 10.1038/s41598-017-15446-x.

(86) Brand, J. A.; et al. Psychoactive pollutant alters movement dynamics of fish in a natural lake system. *Proc. R. Soc. B: Biol. Sci.* **2024**, *291*, 20241760 DOI: 10.1098/rspb.2024.1760.

(87) Gaynor, K. M.; Brown, J. S.; Middleton, A. D.; Power, M. E.; Brashares, J. S. Landscapes of fear: spatial patterns of risk perception and response. *Trends Ecol. Evol.* **2019**, *34*, 355−368, DOI: 10.1016/j.tree.2019.01.004.

(88) Armansin, N. C.; et al. Social barriers in ecological landscapes: the social resistance hypothesis. *Trends Ecol. Evol.* **2020**, *35*, 137−148, DOI: 10.1016/j.tree.2019.10.001.

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

(90) Dzieweczynski, T. L.; Hebert, O. L. Fluoxetine alters behavioral consistency of aggression and courtship in male Siamese fighting fish, *Betta splendens*. *Physiol. Behav.* **2012**, *107*, 92−97, DOI: 10.1016/j.physbeh.2012.06.007.

(91) Fisher, D. N.; et al. Anticipated effects of abiotic environmental change on intraspecific social interactions. *Biol. Rev.* **2021**, *96*, 2661−2693, DOI: 10.1111/brv.12772.

(92) Spiegel, O.; Leu, S. T.; Bull, C. M.; Sih, A. What's your move? Movement as a link between personality and spatial dynamics in animal populations. *Ecol. Lett.* **2017**, *20*, 3−18, DOI: 10.1111/ele.12708.

(93) Harrison, P. M.; et al. Personality-dependent spatial ecology occurs independently from dispersal in wild burbot (*Lota lota*). *Behav. Ecol.* **2015**, *26*, 483−492, DOI: 10.1093/beheco/aru216.

(94) Polverino, G.; et al. Sex-specific effects of psychoactive pollution on behavioral individuality and plasticity in fish. *Behav. Ecol.* **2023**, *34*, 969−978, DOI: 10.1093/beheco/arad065.

(95) Metcalfe, N. B.; Van Leeuwen, T. E.; Killen, S. S. Does individual variation in metabolic phenotype predict fish behaviour and performance? *J. Fish Biol.* **2016**, *88*, 298−321, DOI: 10.1111/jfb.12699.

(96) McCallum, E. S.; Dey, C. J.; Cerveny, D.; Bose, A. P. H.; Brodin, T. Social status modulates the behavioral and physiological consequences of a chemical pollutant in animal groups. *Ecol. Appl.* **2021**, *31*, No. e02454, DOI: 10.1002/eap.2454.

(97) Hamilton, P. B.; et al. Population-level consequences for wild fish exposed to sublethal concentrations of chemicals − a critical review. *Fish Fish.* **2016**, *17*, 545−566, DOI: 10.1111/faf.12125.

(98) Brady, S. P.; Monosson, E.; Matson, C. W.; Bickham, J. W. Evolutionary toxicology: toward a unified understanding of life's response to toxic chemicals. *Evol. Appl.* **2017**, *10*, 745−751, DOI: 10.1111/eva.12519.

(99) Horký, P.; et al. Methamphetamine pollution elicits addiction in wild fish. *J. Exp. Biol.* **2021**, *224*, jeb242145 DOI: 10.1242/jeb.242145.

(100) Sancho Santos, M. E.; et al. From metabolism to behaviour − multilevel effects of environmental methamphetamine concentrations on fish. *Sci. Total Environ.* **2023**, *878*, 163167 DOI: 10.1016/j.scitotenv.2023.163167.

(101) Hubená, P.; et al. Prescribed aggression of fishes: pharmaceuticals modify aggression in environmentally relevant concentrations. *Ecotoxicol. Environ. Saf.* **2021**, *227*, 112944 DOI: 10.1016/j.ecoenv.2021.112944.

(102) Weis, J. S.; Smith, G.; Santiago-Bass, C. 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* **2000**, *7*, 145−153, DOI: 10.1023/A:1009923414208.

(103) Ryalls, J. M. W.; et al. Anthropogenic air pollutants reduce insect-mediated pollination services. *Environ. Pollut.* **2022**, *297*, 118847 DOI: 10.1016/j.envpol.2022.118847.

(104) Oziolor, E. M.; et al. Adaptive introgression enables evolutionary rescue from extreme environmental pollution. *Science* **2019**, *364*, 455−457, DOI: 10.1126/science.aav4155.

(105) Reid, N. M.; et al. The genomic landscape of rapid repeated evolutionary adaptation to toxic pollution in wild fish. *Science* **2016**, *354*, 1305−1308, DOI: 10.1126/science.aah4993.

(106) De Lange, H. J.; Noordoven, W.; Murk, A. J.; Lürling, M.; Peeters, E. T. H. M. Behavioural responses of *Gammarus pulex* (Crustacea, Amphipoda) to low concentrations of pharmaceuticals. *Aquat. Toxicol.* **2006**, *78*, 209−216, DOI: 10.1016/j.aquatox.2006.03.002.

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

(108) Puritz, J. B.; Toonen, R. J. Coastal pollution limits pelagic larval dispersal. *Nat. Commun.* **2011**, *2*, 226 DOI: 10.1038/ncomms1238.

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

(110) Pease, C. J.; Johnston, E. L.; Poore, A. G. B. Genetic variability in tolerance to copper contamination in a herbivorous marine invertebrate. *Aquat. Toxicol.* **2010**, *99*, 10−16, DOI: 10.1016/j.aquatox.2010.03.014.

(111) Theodorakis, C. W.; Meyer, M.-A.; Okay, O.; Yakan, S. D.; Schramm, K.-W. Contamination acts as a genotype-dependent barrier to gene flow, causing genetic erosion and fine-grained population subdivision in Mussels from the Strait of Istanbul. *Ecotoxicology* **2024**, *33*, 47−65, DOI: 10.1007/s10646-023-02725-9.

(112) Kwan, C. K.; Sanford, E.; Long, J. Copper pollution increases the relative importance of predation risk in an aquatic food web. *PLoS One* **2015**, *10*, No. e0133329, DOI: 10.1371/journal.pone.0133329.

(113) Kelly, B. C.; Ikonomou, M. G.; Blair, J. D.; Morin, A. E.; Gobas, F. A. P. C. Food web-specific biomagnification of persistent organic pollutants. *Science* **2007**, *317*, 236−239, DOI: 10.1126/science.1138275.

(114) Richmond, E. K.; et al. A diverse suite of pharmaceuticals contaminates stream and riparian food webs. *Nat. Commun.* **2018**, *9*, 4491 DOI: 10.1038/s41467-018-06822-w.

(115) Redondo-López, S.; González-Ortegón, E.; Mena, F.; Araújo, C. V. M. Dissimilar behavioral and spatial avoidance responses by shrimps from tropical and temperate environments exposed to copper. *Environ. Sci. Pollut. Res.* **2023**, *30*, 28023−28034, DOI: 10.1007/s11356-022-23825-9.

(116) Araújo, C. V. M.; Pontes, J. R. S.; Blasco, J. Might the interspecies interaction between fish and shrimps change the pattern of their avoidance response to contamination? *Ecotoxicol. Environ. Saf.* **2019**, *186*, 109757 DOI: 10.1016/j.ecoenv.2019.109757.

(117) Lopes, I.; Baird, D. J.; Ribeiro, R. Avoidance of copper contamination by field populations of *Daphnia longispina*. *Environ. Toxicol. Chem.* **2004**, *23*, 1702−1708, DOI: 10.1897/03-231.

(118) Cherry, D. S.; Cairns, J. Biological monitoring part V—preference and avoidance studies. *Water Res.* **1982**, *16*, 263−301, DOI: 10.1016/0043-1354(82)90189-0.

(119) Hund-Rinke, K.; Wiechering, H. Earthworm avoidance test for soil assessments. *J. Soils Sediments* **2001**, *1*, 15−20, DOI: 10.1007/BF02986464.

(120) Williams, H. J.; et al. Optimizing the use of biologgers for movement ecology research. *J. Anim. Ecol.* **2020**, *89*, 186−206, DOI: 10.1111/1365-2656.13094.

(121) McCallum, E. S.; Cerveny, D.; Fick, J.; Brodin, T. Slow-release implants for manipulating contaminant exposures in aquatic wildlife: a new tool for field ecotoxicology. *Environ. Sci. Technol.* **2019**, *53*, 8282−8290, DOI: 10.1021/acs.est.9b01975.

(122) Brönmark, C.; et al. Ponds as experimental arenas for studying animal movement: current research and future prospects. *Mov. Ecol.* **2023**, *11*, 68 DOI: 10.1186/s40462-023-00419-9.

(123) Brack, W.; et al. High-resolution mass spectrometry to complement monitoring and track emerging chemicals and pollution trends in European water resources. *Environ. Sci. Eur.* **2019**, *31*, 62 DOI: 10.1186/s12302-019-0230-0.

(124) Ramírez, D. G.; et al. Occurrence, sources, and spatial variation of POPs in a mountainous tropical drinking water supply basin by passive sampling. *Environ. Pollut.* **2023**, *318*, 120904 DOI: 10.1016/j.envpol.2022.120904.

(125) Betti, M.; Boisson, F.; Eriksson, M.; Tolosa, I.; Vasileva, E. Isotope analysis for marine environmental studies. *Int. J. Mass Spectrom.* **2011**, *307*, 192−199, DOI: 10.1016/j.ijms.2011.03.008.

(126) Hollender, J.; et al. NORMAN guidance on suspect and non-target screening in environmental monitoring. *Environ. Sci. Eur.* **2023**, *35*, 75 DOI: 10.1186/s12302-023-00779-4.

(127) Arturi, K.; Hollender, J. Machine learning-based hazard-driven prioritization of features in nontarget screening of environmental high-resolution mass spectrometry data. *Environ. Sci. Technol.* **2023**, *57*, 18067−18079, DOI: 10.1021/acs.est.3c00304.

(128) *Chemometrics and Cheminformatics in Aquatic Toxicology*; Roy, K., Ed.; Wiley: 2021. DOI: 10.1002/9781119681397.

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

(130) Schadt, E. E.; Linderman, M. D.; Sorenson, J.; Lee, L.; Nolan, G. P. Computational solutions to large-scale data management and analysis. *Nat. Rev. Genet.* **2010**, *11*, 647−657, DOI: 10.1038/nrg2857.

(131) Joo, R.; et al. Navigating through the R packages for movement. *J. Anim. Ecol.* **2020**, *89*, 248−267, DOI: 10.1111/1365-2656.13116.

(132) Fleming, C. H.; et al. Rigorous home range estimation with movement data: a new autocorrelated kernel density estimator. *Ecology* **2015**, *96*, 1182−1188, DOI: 10.1890/14-2010.1.

(133) Romero-Ferrero, F.; Bergomi, M. G.; Hinz, R. C.; Heras, F. J. H.; de Polavieja, G. G. idtracker.ai: tracking all individuals in small or large collectives of unmarked animals. *Nat. Methods* **2019**, *16*, 179−182, DOI: 10.1038/s41592-018-0295-5.

(134) Raoult, V.; Tosetto, L.; Williamson, J. E. Drone-based high-resolution tracking of aquatic vertebrates. *Drones* **2018**, *2*, 37 DOI: 10.3390/drones2040037.

(135) Hussey, N. E.; et al. Aquatic animal telemetry: a panoramic window into the underwater world. *Science* **2015**, *348*, 1 DOI: 10.1126/science.1255642.

(136) McLane, A. J.; Semeniuk, C.; McDermid, G. J.; Marceau, D. J. The role of agent-based models in wildlife ecology and management. *Ecol. Modell.* **2011**, *222*, 1544−1556, DOI: 10.1016/j.ecolmodel.2011.01.020.

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

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

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

(140) Huber, C.; et al. In silico deconjugation of glucuronide conjugates enhances tandem mass spectra library annotation of human samples. *Anal. Bioanal. Chem.* **2022**, *414*, 2629−2640, DOI: 10.1007/s00216-022-03899-7.

(141) Ciallella, H. L.; Zhu, H. Advancing computational toxicology in the big data era by artificial intelligence: data-driven and mechanism-driven modeling for chemical toxicity. *Chem. Res. Toxicol.* **2019**, *32*, 536−547, DOI: 10.1021/acs.chemrestox.8b00393.

(142) Sepman, H.; et al. Bypassing the identification: MS2Quant for concentration estimations of chemicals detected with nontarget LC-HRMS from MS^2 data. *Anal. Chem.* **2023**, *95*, 12329−12338, DOI: 10.1021/acs.analchem.3c01744.

(143) Peets, P.; et al. MS2Tox machine learning tool for predicting the ecotoxicity of unidentified chemicals in water by nontarget LC-HRMS. *Environ. Sci. Technol.* **2022**, *56*, 15508−15517, DOI: 10.1021/acs.est.2c02536.

(144) Rahu, I.; Kull, M.; Kruve, A. Predicting the activity of unidentified chemicals in complementary bioassays from the HRMS data to pinpoint potential endocrine disruptors. *J. Chem. Inf. Model.* **2024**, *64*, 3093−3104, DOI: 10.1021/acs.jcim.3c02050.

(145) Dührkop, K.; et al. SIRIUS 4: a rapid tool for turning tandem mass spectra into metabolite structure information. *Nat. Methods* **2019**, *16*, 299−302, DOI: 10.1038/s41592-019-0344-8.

(146) Nothias, L.-F.; et al. Feature-based molecular networking in the GNPS analysis environment. *Nat. Methods* **2020**, *17*, 905−908, DOI: 10.1038/s41592-020-0933-6.

(147) Rosa, R.; Materatski, P.; Moreira-Santos, M.; Sousa, J. P.; Ribeiro, R. A scaled-up system to evaluate zooplankton spatial avoidance and the population immediate decline concentration. *Environ. Toxicol. Chem.* **2012**, *31*, 1301−1305, DOI: 10.1002/etc.1813.

(148) Grimmelpont, M.; et al. Avoidance behaviour and toxicological impact of sunscreens in the teleost *Chelon auratus*. *Mar. Pollut. Bull.* **2023**, *194*, 115245 DOI: 10.1016/j.marpolbul.2023.115245.

(149) Johns, M.; Deloe, K.; Beaty, L. E.; Simpson, A. M.; Nutile, S. A. Avoidance behavior of *Hyalella azteca* in response to three common-use insecticides. *Chemosphere* **2023**, *345*, 140492 DOI: 10.1016/j.chemosphere.2023.140492.

(150) Jutfelt, F.; Sundin, J.; Raby, G. D.; Krång, A.; Clark, T. D. Two-current choice flumes for testing avoidance and preference in aquatic animals. *Methods Ecol. Evol.* **2017**, *8*, 379−390, DOI: 10.1111/2041-210X.12668.

(151) Araújo, C. V. M.; Pereira, K. C.; Sparaventi, E.; González-Ortegón, E.; Blasco, J. Contamination may induce behavioural plasticity in the habitat selection by shrimps: a cost-benefits balance involving contamination, shelter and predation. *Environ. Pollut.* **2020**, *263*, 114545 DOI: 10.1016/j.envpol.2020.114545.

(152) Lopez, L. K.; et al. Integrating animal behaviour into research on multiple environmental stressors: a conceptual framework. *Biol. Rev.* **2023**, *98*, 1345−1364, DOI: 10.1111/brv.12956.

(153) Bertram, M. G.; et al. Slow-release pharmaceutical implants in ecotoxicology: validating functionality across exposure scenarios. *ACS Environ. Au* **2025**, *5*, 69−75, DOI: 10.1021/acsenvironau.4c00056.

(154) McCallum, E. S.; et al. Exposure to wastewater effluent affects fish behaviour and tissue-specific uptake of pharmaceuticals. *Sci. Total Environ.* **2017**, *605−606*, 578−588, DOI: 10.1016/j.scitotenv.2017.06.073.

(155) Niemelä, P. T.; Dingemanse, N. J. Artificial environments and the study of 'adaptive' personalities. *Trends Ecol. Evol.* **2014**, *29*, 245−247, DOI: 10.1016/j.tree.2014.02.007.

(156) Fisher, D. N.; James, A.; Rodríguez-Muñoz, R.; Tregenza, T. Behaviour in captivity predicts some aspects of natural behaviour, but not others, in a wild cricket population. *Proc. R. Soc. B: Biol. Sci.* **2015**, *282*, 20150708 DOI: 10.1098/rspb.2015.0708.

(157) Osborn, A.; Briffa, M. Does repeatable behaviour in the laboratory represent behaviour under natural conditions? A formal comparison in sea anemones. *Anim. Behav.* **2017**, *123*, 197−206, DOI: 10.1016/j.anbehav.2016.10.036.

(158) Brack, W. Effect-directed analysis: a promising tool for the identification of organic toxicants in complex mixtures? *Anal. Bioanal. Chem.* **2003**, *377*, 397−407, DOI: 10.1007/s00216-003-2139-z.

(159) Costa-Pereira, R.; Moll, R. J.; Jesmer, B. R.; Jetz, W. Animal tracking moves community ecology: opportunities and challenges. *J. Anim. Ecol.* **2022**, *91*, 1334−1344, DOI: 10.1111/1365-2656.13698.

(160) Michelangeli, M.; et al. Personality, spatiotemporal ecological variation and resident/explorer movement syndromes in the sleepy lizard. *J. Anim. Ecol.* **2022**, *91*, 210−223, DOI: 10.1111/1365-2656.13616.

(161) Besson, M.; et al. Towards the fully automated monitoring of ecological communities. *Ecol. Lett.* **2022**, *25*, 2753−2775, DOI: 10.1111/ele.14123.