



From Signals to Smells: Integrating Microbial Ecology and Environmental Drivers to Predict Taste and Odour Events

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Received: 10 March 2026 / Accepted: 12 October 2026
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Abstract

Taste and odour (T&O) issues caused by geosmin and 2-MIB persist worldwide in drinking water. Though posing minimal health risks, their low odour thresholds lead to customer complaints and costly treatments. These compounds in freshwater reservoirs mainly stem from cyanobacterial activity, influenced by interactions among microbes, nutrients, and physical processes like stratification and redox cycling. Conventional prediction methods rely on environmental factors or cyanobacterial biomass but don't fully capture the biological mechanisms behind T&O production.

This review synthesises current understanding of the environmental drivers of geosmin and 2-MIB and evaluates existing modelling approaches. A case study introduces an environmental DNA (eDNA)-informed modelling framework integrating biological indicators, chemical variables, and physical drivers within Generalised Additive Models (GAMs) to forecast geosmin concentrations in three UK drinking-water reservoirs.

Integrating biological indicators into predictive models provides a promising pathway toward operational early-warning systems for proactive T&O management.

Keywords Geosmin · Taste and odour · Drinking water quality · Forecasting water quality risk · Modelling · Environmental DNA

Introduction

Customers' perception of drinking water quality is largely governed by the aesthetic properties, of which taste and odour (T&O) are among the most influential [1]. Unpleasant T&O is frequently assumed by customers to indicate

contamination and remains a primary driver of complaints to Water Companies worldwide [2–5]. The occurrence of T&O events in drinking water reservoirs is increasing in both frequency and magnitude globally, posing a growing operational challenge for Water Companies [6]. These events are predominantly driven by biological processes, with the volatile secondary metabolites, geosmin (trans-1-10 dimethyl-trans-9-decalol) and 2-MIB (2-methylisoborneol) most implicated in customer complaints worldwide [3, 7–9].

Geosmin and 2-MIB

The molecular basis of cyanobacterial geosmin production is governed by the presence of the *geoA* gene, which encodes the bifunctional enzyme geosmin synthase [10]. Geosmin is a sesquiterpene produced from the conversion of the precursor farnesyl diphosphate (FPP), occurring through two steps catalysed by a bifunctional geosmin synthase encoded by *geoA* in the presence of Mg²⁺ [10]. The enzyme first catalyses the conversion of FPP to germacadienol via its N-terminal domain, and subsequently

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to geosmin via its C-terminal domain [10]. The organisation of the geosmin gene cluster in Cyanobacteria is highly conserved, except for *Phormidium* sp., and includes two global transcriptional regulator genes that have previously been described as modulating cellular signals related to responses to environmental stress [11, 12].

Wang, Xu [13] demonstrated that cyanobacterial 2-MIB production originates from two adjacent genes, the S-adenosyl-L-methionine-dependent methyltransferase (*mtf*) gene and the 2-MIB cyclase (*mic*) gene. These genes are responsible for the methylation of geranyl diphosphate (GPP) and its subsequent cyclisation to 2-MIB. Located between two homologous cyclic nucleotide-binding protein genes, the *mtf* and *mic* genes collectively form a putative operon. The neighbouring cyclic nucleotide-binding proteins are predicted to belong to the Crp-Fnr family, a widespread regulatory family involved in processes such as photosynthesis and nitrogen fixation in microorganisms [13, 14]. The synthesis of 2-MIB involves two key reactions: *mtf*-catalysed methylation of GPP to produce 2-methyl-GPP, followed by *mic*-catalysed cyclisation of 2-methyl-GPP to form 2-MIB.

From an operational perspective, geosmin and 2-MIB are especially problematic because they can be detected by consumers at very low concentrations, with events in reservoirs classified as concentrations $> 5 \text{ ng L}^{-1}$ for 2-MIB and $> 10 \text{ ng L}^{-1}$ for geosmin [15]. These compounds are also difficult to remove through conventional drinking-water treatment processes, often requiring additional methods such as activated carbon adsorption, which raises operational costs [6, 8]. Their presence is also likely to become more problematic due to climate-driven changes in reservoir ecology, including higher temperatures, stronger stratification, and altered nutrient cycling, all of which may promote conditions favourable to T&O production [16–18]. Therefore, geosmin and 2-MIB pose not only an aesthetic water-quality concern but also an increasingly significant operational and economic challenge for drinking-water utilities worldwide.

Operational Challenges for Water Companies

For water companies, T&O events are operationally significant because they are highly visible to consumers but challenging to manage once compounds have entered the treatment plant. Although geosmin and 2-MIB are generally not considered major toxicological hazards at concentrations typically found in drinking water, their presence heavily influences consumer perception of water quality and often triggers complaints, loss of confidence, and reputational damage [3, 5]. In practice, consumers often interpret earthy or musty tastes and odours as signs of contamination, regardless of the actual health risk, which puts pressure on water companies to respond swiftly and effectively.

The challenge is intensified by the low odour thresholds of these compounds and their resistance to conventional treatment methods. When geosmin or 2-MIB concentrations increase in source waters, utilities may need to adopt costly measures such as powdered or granular activated carbon dosing, modified abstraction strategies, blending, or other immediate operational responses to prevent these compounds from reaching treatment facilities and distribution systems [6, 8, 19–21]. These responses are often reactive, costly, and logistically limited, particularly when T&O events escalate rapidly or when source-water choices are scarce. Another challenge is that T&O events are often episodic and specific to particular reservoirs. They are driven by interacting biological, chemical, and physical processes that can change quickly over time and vary significantly between water bodies [2, 22]. Routine monitoring programmes, usually aimed at general compliance and surveillance, can miss brief precursor changes in nutrient concentrations, microbial community makeup, or redox conditions that occur before noticeable rises in geosmin or 2-MIB. As a result, operational responses are often only initiated after concentrations have already increased.

These constraints emphasise the need for forecasting frameworks that can provide earlier warnings of T&O risk. Instead of relying solely on chemical detection of compounds after events have begun, water companies would benefit from predictive tools that identify environmental and biological conditions likely to precede metabolite production. Such an approach would enable earlier intervention, lessen dependence on emergency treatment responses, and enhance the resilience of drinking-water management amid increasingly variable reservoir conditions [6, 15, 23].

What Influences T&O Production?

To forecast future T&O events, you first need to understand the environmental triggers that regulate the biological production of geosmin and 2-MIB. The distribution of T&O biosynthetic genes (*geoA* and *mic* – subsection “[Geosmin and 2-MIB](#)”) within *Cyanobacteria* is not uniform across all taxa. Among the eight orders described by Churro, Semedo-Aguiar [24], *Oscillatoriales*, *Nostocales*, and *Synechococcales* contain the majority of known geosmin producers, highlighting the importance of taxonomic composition when assessing T&O risk in drinking water reservoirs. However, the presence of potential producers alone does not necessarily translate into detectable T&O compounds. Evidence from reservoir monitoring indicates that T&O production is often productivity-driven rather than biomass-related, with studies failing to establish a correlation between T&O concentrations and cyanobacterial biomass [16, 25–28].

Productivity-driven T&O events would explain why heightened 2-MIB concentrations occur during times of high ATP synthesis [29].

Understanding how environmental factors affect the biological production of geosmin and 2-MIB involves considering three interrelated components: community composition (biology), nutrient dynamics (chemistry), and the redox potential of reservoirs (physical).

Bacterial and Algal Community Composition

The biological composition of a reservoir is a key factor in evaluating T&O risk, as biological shifts in communities can capture environmental changes, such as chemical spikes, which are often missed by routine sampling. Ordination analysis of bacterial (16 S rRNA) and algal (*rbcL*) communities in reservoirs experiencing T&O revealed that both domains clustered according to low, medium, and high concentration categories for geosmin and 2-MIB, highlighting T&O signature communities [30]. The community composition of reservoir water can infer T&O risk and is more than just a background factor in reservoir ecology; it is a mechanistically informative element of T&O risk. Although the presence of *Cyanobacteria* capable of producing geosmin and 2-MIB is crucial, the broader bacterial and algal communities are highly informative because of their ecological functions and potential influences on cyanobacterial T&O production.

T&O indicator taxa have previously been described and grouped by functional traits: T&O degraders, nutrient-enrichment indicators, nutrient-exchange and recycling taxa, and cyanobacterial benefactors [30]. These functional groups comprise taxa that affect cyanobacterial productivity, in turn influencing metabolite production through ecological processes such as nutrient cycling, competition, and the biodegradation of T&O compounds. These taxa could serve as useful early indicators of environmental shifts that promote or are indicative of T&O production. However, most studies on geosmin and 2-MIB indicator taxa have mainly focused on identifying the specific biological producers of these compounds, rather than exploring the broader microbial communities [31–34].

Microbial communities respond rapidly to environmental change and can thus serve as informative indicators of conditions that promote cyanobacterial T&O production. For example, Reynolds' trait-based phytoplankton classification (algae and *Cyanobacteria*) groups species based on common ecological traits and environmental tolerances instead of strict taxonomy [35, 36]. The Reynolds Functional Groups (RFG) framework enhances the prediction of phytoplankton community responses to environmental change by condensing species-level complexity into functional ecological

groups, while retaining core ecological mechanisms driving those responses [37]. Implementing an RFG approach and broadening communities to encompass all bacterial taxa, as well as *Cyanobacteria*, could serve as indicators of underlying chemical and physical pressures in aquatic ecosystems that influence cyanobacterial T&O production. For example, some diatoms associated with eutrophic conditions, such as *Asterionella* and *Aulacoseira*, quickly respond to nutrient enrichment and can affect nutrient dynamics in the water by absorbing major anions, such as NO_3^- [35, 36]. Rapid proliferation of these taxa can therefore alter nutrient availability and ratios within the water column, potentially creating conditions that favour cyanobacterial productivity [15, 38]. Consequently, communities that indicate nutrient enrichment or altered nutrient ratios may serve as ecological precursors to T&O production.

Nutrients and Nutrient Ratios

Triggers, such as NH_4^+ (23) stimulate the metabolic production of T&O compounds even when cyanobacterial abundance remains relatively low. This reinforces the notion that T&O production is more directly related to cyanobacterial productivity rather than simply biomass, especially during periods of rapid growth when environmental conditions are favourable [39]. Historically, phosphorus was considered the primary nutrient limiting cyanobacterial growth in freshwater ecosystems [40, 41]. However, later research has shown that nitrogen limitation is common in lakes and reservoirs [42]. Anthropogenic activities such as the use of nitrogen fertilisers and the application of agricultural slurry have altered nitrogen and phosphorus inputs in many freshwater systems, thereby affecting nutrient ratios in already nutrient-rich waters [43, 44]. Such alterations in nutrient stoichiometry can substantially influence microbial community compositions.

Cyanobacterial growth and dominance are often linked to the ratio of total nitrogen to total phosphorus (TN: TP). *Cyanobacteria* tend to become increasingly dominant when TN: TP ratios decrease, especially below around 29:1 by mass [45]. However, nutrient ratios may affect not only cyanobacterial proliferation but also the metabolic conditions that promote T&O production. For instance, geosmin production has been linked to heightened phosphorus limitation, with studies reporting negative correlations between geosmin concentrations and orthophosphate availability [46]. Orthophosphate is the most bioavailable form of phosphorus for *Cyanobacteria*, and uptake is instantaneous, promoting higher productivity rates [47] – although due to rapid uptake, routine sampling often misses spikes. In highly eutrophic systems, however, where nutrients are rarely limiting, the TN: TP ratio may become less reliable in predicting cyanobacterial dominance or T&O risk [48].

Besides overall nutrient availability, the form of nitrogen in the water appears to significantly influence T&O production. Several studies have highlighted ammonium (NH_4^+), the most reduced form of nitrogen in aquatic environments, as a key factor linked to increased geosmin and 2-MIB concentrations [23, 49–52]. Reductions in the ratio of oxidised to reduced nitrogen species ($\text{NO}_3^-:\text{NH}_4^+$ or $\text{NO}_3^-:\text{NH}_4^+$) may create favourable conditions for cyanobacteria to produce T&O compounds [49, 53]. One reason is that assimilating oxidised nitrogen sources such as nitrate (NO_3^-) requires extra cellular energy for reduction before being incorporated into biomass. When reduced nitrogen sources like NH_4^+ are present, *Cyanobacteria* can bypass these energy-intensive reduction steps, potentially allowing energy to be redirected towards synthesising carbon-rich secondary metabolites, such as geosmin and 2-MIB [54]. Therefore, conditions with low TN: TP and $\text{NO}_3^-:\text{NH}_4^+$ ratios may provide ideal conditions for T&O formation by promoting cyanobacterial growth and enabling metabolite synthesis [23, 49, 54].

Beyond nitrogen and phosphorus, other nutrients and trace elements can influence cyanobacterial dominance and potentially affect T&O production. Iron, for example, plays a crucial role in cyanobacterial physiology, especially for nitrogen-fixing species that depend on iron-rich enzymes involved in nitrogen fixation [55, 56]. Iron availability is closely linked to redox reactions within stratified reservoirs. Under oxygenated conditions, iron is typically present as ferric iron (Fe^{3+}), which is relatively insoluble and subsequently less accessible to phytoplankton. However, under anoxic conditions in sediments or bottom waters, Fe^{3+} can be reduced to ferrous iron (Fe^{2+}), a more soluble form that can diffuse into the water column and become available [57]. According to the conceptual model proposed by Molot, Watson [58], phosphorus controls cyanobacterial biomass and productivity until nutrient enrichment reaches a point where the water body becomes either nitrogen- or light-limited. Under these conditions, the availability of Fe^{2+} becomes a crucial factor in determining whether *Cyanobacteria* can outcompete their eukaryotic phytoplankton counterparts. In addition, certain *Cyanobacteria* enhance iron uptake by secreting siderophores (specialised molecules that chelate and ferry iron when nutrients are scarce) [59–63].

Stratification and Redox Potential

Physical processes within reservoirs significantly affect the chemical conditions that regulate T&O production. In particular, thermal stratification and associated redox gradients govern the release and cycling of nutrients, thereby promoting cyanobacterial productivity and secondary metabolite production.

Redox potential reflects a system's overall tendency to undergo oxidation (loss of electrons) or reduction (gain of electrons). In waters with ample oxygen, the redox potential stays high, and oxidised chemicals are prevalent. When oxygen levels drop, the redox potential decreases, resulting in more reduced chemical reactions [64]. This shift from oxygen-rich (oxic) to oxygen-poor (anoxic) follows a well-known sequence of microbial redox reactions, often called the redox cascade or ladder ($\text{O}_2 \rightarrow \text{NO}_3^- \rightarrow \text{Mn(IV)} \rightarrow \text{Fe(III)} \rightarrow \text{SO}_4^{2-} \rightarrow \text{CO}_2$). This progression leads to processes such as denitrification, manganese reduction, iron reduction, sulphate reduction, and methanogenesis, each of which gradually releases reduced species into the water column.

In reservoirs, redox dynamics are closely linked to thermal stratification, as surface waters warm during spring and summer, density decreases and a warm, well-mixed epilimnion forms above a colder, denser hypolimnion. These layers are separated by a sharp temperature gradient known as the thermocline, which restricts vertical mixing [65]. Because the hypolimnion receives little light and becomes isolated from atmospheric oxygen, dissolved oxygen levels gradually decrease due to microbial respiration and the oxidation of reduced compounds within sediments [66]. As oxygen levels decline, the hypolimnion can become anoxic. Anoxia development at the sediment-water interface greatly influences nutrient cycling. In oxic conditions, oxidised iron and manganese (Fe^{3+} and Mn^{4+}) effectively bind phosphorus and other nutrients in sediments. When redox potential drops under anoxic conditions, these metal oxides are reduced to more soluble forms (Fe^{2+} and Mn^{2+}), releasing nutrients previously stored in sediments into the hypolimnion. This process, known as internal nutrient loading, can mobilise significant amounts of nitrogen, phosphorus, iron, and manganese into the water column [64].

Consequently, stratified reservoirs often develop strong chemical gradients between surface and bottom waters. While the epilimnion typically remains oxygenated and nutrient-poor, the hypolimnion may accumulate reduced nutrients and metals released from sediments. When stratification breaks down during seasonal turnover, these nutrient-rich bottom waters can mix into the epilimnion, increasing nutrient availability in surface waters and stimulating phytoplankton productivity [67]. Such mixing events can quickly alter nutrient ratios and nitrogen forms in the water column, potentially creating conditions favourable for cyanobacterial T&O production. Importantly, stratification not only affects nutrient availability but also controls the chemical forms of nutrients in the water. The release of reduced nitrogen species like NH_4^+ under anoxic conditions can lead to low $\text{NO}_3^-:\text{NH}_4^+$ ratios previously linked with T&O events [2, 15, 23, 68]. In addition, the release of reduced iron (Fe^{2+})

from sediments under low redox conditions can give *Cyanobacteria* an extra edge in stratified reservoirs [56, 58, 61, 62, 69]. These interactions emphasise the strong connection between physical stratification, redox chemistry, and nutrient cycling in creating environmental conditions that promote T&O production.

Understanding how stratification influences redox potential and internal nutrient loading is vital for predicting reservoir vulnerability to T&O events. Seasonal transitions between stratified and mixed states can rapidly alter nutrient concentrations/ ratios, nitrogen forms, and microbial activity in the water column, setting the stage for conditions that favour the cyanobacterial production of geosmin and 2-MIB.

Current Approaches to T&O Prediction

Predicting T&O events in drinking water reservoirs remains a significant challenge despite advances in environmental monitoring and modelling. Recent studies demonstrate promising improvements through the use of long-term monitoring, multivariate statistics, and machine learning-assisted surveillance, but robust early-warning capability remains limited because T&O events emerge from interacting biological, chemical and physical processes that vary between reservoirs and across seasons [18, 70–72]. Consequently, most predictive frameworks still rely on empirical relationships between environmental parameters and measured concentrations of geosmin or 2-MIB rather than on mechanistic representations of the processes underlying metabolite production.

Statistical Approaches to Identify T&O Drivers

Early predictive approaches primarily relied on traditional statistical modelling techniques to identify environmental factors associated with T&O events. These studies commonly employed regression-based models to connect geosmin or 2-MIB concentrations to environmental variables such as nutrient concentrations, temperature, and cyanobacterial biomass [73–76]. Although such models have been helpful in finding associations between environmental conditions and T&O concentrations, their ability to predict outcomes has often been inconsistent because cyanobacterial biomass does not often align with geosmin production [25, 28].

Recent research has attempted to overcome these limitations by incorporating molecular or community-level data into statistical analyses. For example, Qiu, Zhang [71] combined Quantile Regression (QR) with metagenomic sequencing to identify the main drivers and producers of

geosmin and 2-MIB concentrations in a reservoir over a four-year monitoring period. By analysing functional gene predictions from metagenomic data, the authors identified potential T&O producers and examined the environmental factors associated with their metabolic pathways. Their findings showed that the permanganate index (COD_{Mn}), a measure of organic matter content, was significantly and positively linked to pathways involved in secondary metabolite biosynthesis and terpenoid backbone biosynthesis. QR is particularly useful for highly variable environmental datasets because it allows covariate effects to vary across the distribution of the response variable, rather than assuming a single linear relationship for all observations [77].

Although approaches such as QR offer valuable insights into the environmental factors linked to T&O production, their use has primarily focused on identifying these factors rather than on producing accurate forecasts. In most cases, these statistical methods remain descriptive, explaining variability in observed T&O levels rather than predicting future occurrences. An additional limitation of QR for prediction is that estimates at individual quantiles are typically associated with greater uncertainty than predictions based on the central tendency of the data. The reliable estimation of conditional quantiles generally requires relatively large sample sizes, particularly for extreme quantiles.

Machine Learning Approaches

Recent advances in environmental data science have increased interest in applying machine learning techniques to predict T&O concentrations. These models excel at identifying intricate, nonlinear patterns within large environmental datasets and frequently outperform conventional statistical approaches in ecological forecasting. For instance, Zengin, Koker [72] employed machine-learning techniques in combination with long-term reservoir monitoring to identify environmental variables associated with geosmin occurrence. Similarly, Yue, Chen [18] showed that stratification dynamics and phytoplankton community composition were significant predictors of T&O variability in subtropical reservoirs. Machine learning models have also been used in riverine systems supplying drinking water treatment plants, where they identify potential geosmin and 2-MIB producers and the environmental conditions related to their activity [70].

Despite their predictive potential, machine learning methods often lack interpretability, making it hard to understand the ecological mechanisms underlying the predicted outcomes. Harris and Graham [78] assessed various modelling approaches for predicting cyanobacterial metabolites and found that Cubist modelling achieved moderate success in predicting geosmin concentrations, although, none of the

models reliably forecasted maximum microcystin concentrations. These findings emphasise the inherent challenge of predicting episodic ecological events such as cyanobacterial metabolite production.

Limitations of Current Approaches

Despite advances in statistical modelling and machine learning, reliable forecasting of T&O events remains limited. One of the main challenges is that most predictive models depend heavily on environmental variables and microscopy-derived cyanobacterial abundance data, which may not accurately reflect the biological processes responsible for metabolite production. Many early predictive models used total cyanobacterial biomass as a predictor variable. However, cyanobacterial blooms often consist of multiple taxa, not all of which produce geosmin or 2-MIB. Consequently, models based on total cyanobacterial biomass can introduce substantial estimation error. For example, Chong, Lee [79] demonstrated that geosmin concentrations were overestimated when blooms of *Microcystis*, a non-geosmin-producing cyanobacterium, dominated the phytoplankton community. Similarly, several studies have reported weak or inconsistent correlations between cyanobacterial biomass and measured geosmin concentrations [16, 25, 28].

Another significant limitation of current modelling approaches is the lack of biological integration. Most predictive models rely mainly on physical and chemical parameters, while overlooking the microbial communities responsible for both producing and degrading T&O compounds. However, microbial processes are vital to the fluctuations of geosmin concentrations in reservoirs, as both cyanobacterial production and bacterial biodegradation affect T&O concentrations [80]. Furthermore, predictive models developed for one reservoir often perform poorly when applied to other systems. This limited transferability reflects that T&O events arise from complex interactions among microbial communities, nutrient dynamics, and physical processes such as stratification and mixing, all of which vary among reservoirs.

Earlier modelling approaches, such as Generalised Linear Models (GLMs), were limited in their ability to capture complex ecological responses [81, 82]. By contrast, Generalised Additive Models (GAMs) use non-parametric smoothing functions that allow relationships between predictors and response variables to vary across the environmental gradient, enabling a more realistic representation of ecological processes. This flexibility makes GAMs particularly suitable for modelling geosmin dynamics, which often exhibit threshold responses to environmental drivers such as nutrient availability,

stratification dynamics, and microbial community composition. More recently, advances in molecular ecology have enabled the direct detection of geosmin-producing *Cyanobacteria* through the *geoA* gene [24]. Incorporating gene-based indicators into predictive models may provide a more biologically meaningful variable than total cyanobacterial biomass. For example, Hooper, Kille [15] demonstrated that *geoA* gene copy numbers were directly associated with geosmin concentrations exceeding detection thresholds in drinking water reservoirs. Integrating environmental DNA (eDNA) data into predictive frameworks, therefore, offers a promising opportunity to improve forecasting capabilities by linking environmental conditions directly to the organisms responsible for T&O production.

Despite these advances, dependable early-warning systems for T&O events are still uncommon. Building predictive frameworks that combine biological indicators, environmental monitoring, and adaptable modelling methods are crucial for enhancing forecasting accuracy and enabling proactive management of drinking water reservoirs.

Bridging the Gap Between Events and Prediction

Considering the environmental factors from Section “[What Influences T&O Production?](#)” and the modelling approaches from Section “[Current Approaches to T&O Prediction](#)”, a key question is why T&O events remain difficult to predict reliably in drinking-water systems? The explanation involves a gap between the biological origins of T&O production, the structure of routine monitoring programmes, and the typical variables used in predictive models. Most current methods tend to detect the outcomes of T&O rather than the biological processes that cause them. Consequently, many models are reactive, designed for specific reservoirs, and lack the sensitivity required to detect subtle changes in reservoir conditions that could lead to T&O events.

Why Current Monitoring Fails to Capture T&O Onset

Routine monitoring of drinking-water reservoirs is typically carried out at relatively low temporal resolution, often every two weeks or monthly. While this method is suitable for broad water-quality surveillance, it does not effectively capture the dynamics of T&O production and limits the sample size available for downstream analyses. Important precursor changes, such as transient increased concentrations of NH_4^+ , can occur between sampling intervals and may therefore be missed entirely [23, 30, 49, 83, 84]. Another limitation is

that routine chemical monitoring mainly detects state variables rather than process variables. Measured geosmin or 2-MIB concentrations result from multiple interacting processes, including cyanobacterial production, microbial degradation, dilution, stratification, and internal loading. Since chemical data only give a partial and delayed view of T&O dynamics, this issue is worsened by the fact that key drivers of T&O production, especially nutrient pulses and redox changes, are often short-lived and vary across different parts of reservoirs.

Routine biological monitoring remains limited. Microscopy-based phytoplankton counts are commonly used as biological indicators, yet they cannot distinguish T&O producers from non-producers and seldom include non-photosynthetic bacteria relevant to T&O dynamics. This is particularly problematic because T&O production is not a general property of cyanobacterial biomass, but specific to certain taxa and biosynthetic traits. As shown earlier, total cyanobacterial abundance can be a poor proxy for T&O risk when non-producing taxa dominate or when T&O production is decoupled from biomass [15, 25, 79].

Why Conventional Biological Indicators are Insufficient

Taxonomic presence alone does not adequately reflect T&O risk because it fails to distinguish between taxa with different ecological roles, nor does it determine whether taxa in a sample can produce or break down T&O compounds. Operationally, simply knowing that *Cyanobacteria* are present is not enough; what matters is whether the community includes functionally relevant producers, if environmental conditions favour metabolite synthesis, and whether degraders are likely to suppress or mask the resulting concentrations [80]. This distinction is critical because T&O events are best understood as community-mediated outcomes of cyanobacterial productivity, not simply as the presence of *Cyanobacteria* in a reservoir. As discussed in Section “[Bacterial and Algal Community Composition](#)”, bacterial and algal communities cluster according to assigned T&O concentration categories [30]. These community-level features are likely to shift before detectable chemical increases in geosmin or 2-MIB, making them potentially more useful as early-warning indicators than conventional biomass metrics.

Thus, the issue is not only that biological data are underused in T&O prediction, but also that the incorrect biological metrics are often employed. Models based on total cyanobacterial biomass or broad phytoplankton counts are fundamentally limited because they lack the functional biological specificity needed to mechanistically forecast T&O production.

Case Study: An eDNA-Informed Framework for Forecasting Geosmin Risk

To demonstrate how functional biological indicators can be integrated into predictive models, we present a case study applying an eDNA-informed modelling framework to forecast geosmin concentrations. This approach integrates biological, chemical, and physical datasets to capture biologically mediated production and degradation of geosmin that precede observable chemical changes, while accounting for climatic influences. Collating datasets supports a holistic understanding of geosmin dynamics in the studied reservoir, which can be used to model geosmin concentrations for future forecasts – enabling early warning of T&O risk.

Study Overview

Three UK drinking-water reservoirs with varying severities of geosmin concentrations were investigated: Reservoir 1 (mild $\leq 16 \text{ ng L}^{-1}$), Reservoir 2 (moderate $\leq 29 \text{ ng L}^{-1}$), and Reservoir 3 (severe $\leq 520 \text{ ng L}^{-1}$) (based on maximum geosmin readings per reservoir; Supplementary Table [S11](#)). The categories for mild, moderate and severe were chosen following this process as they are based upon Water Company response (i.e. Treatment response). Details on study sites and sampling strategies for Reservoirs 1–3 are provided in Supplementary Information [SI2](#). Reservoir water samples were processed for both 16 S rRNA gene-based environmental DNA (eDNA) sequencing and chemical analysis, with corresponding atmospheric temperature data incorporated to represent seasonal structure within modelled data (Supplementary Information, [SI3-5](#)).

Temperature was included as a linear covariate in each model to capture seasonal variation, reduce temporal dependence in model residuals, and serve as a proxy for stratification dynamics and associated redox processes (subsection “[Stratification and Redox Potential](#)”) within each reservoir – processes which can influence internal nutrient cycling.

Generalised Additive Models (GAMs) were developed for each reservoir to model geosmin concentration as a function of reservoir-specific covariates. This semi-parametric framework accommodates both linear (parametric) and non-linear (smooth) effects, allowing monotonic relationships to be estimated alongside flexible, data-driven responses. Smooth terms characterise non-linear patterns, including thresholds and ranges along the covariate scale associated with increases or decreases in predicted geosmin concentration. Linear terms quantify consistent directional effects and provide interpretable effect estimates, while interaction terms capture combined effects between covariates (e.g.,

NH_4^+ and NO_3^-), thereby enabling the identification of conditional relationships that drive variability in geosmin concentrations.

Here, we present reservoir-specific models for all three reservoirs, enabling direct comparison of predictive performance across reservoirs with different sampling frequencies and geosmin concentration severity. Reservoir 1 (mild; training $n=92$; withheld $n=6$) provides a high-resolution example of model development and forecasting performance on unseen data, while Reservoir 2 (moderate; training $n=19$; withheld $n=1$) and Reservoir 3 (severe; training $n=28$; withheld $n=3$) demonstrate model behaviour under more limited sampling regimes.

This case study provides a blueprint for a proof-of-concept framework to forecast geosmin risk. We demonstrate that integrating chemical, physical, and biological datasets improves predictive capability by capturing the environmental drivers of geosmin production and degradation. All variables included in each reservoir-specific model are presented in Table 1.

Utilising Biologically Meaningful Predictors from eDNA Data

Key limitations of biological covariates in traditional predictive models (Section “[Bridging the Gap Between Events and Prediction](#)”) arise from reliance on bulk community metrics (e.g., total cyanobacterial biomass), which do not resolve taxonomic or functional differences within the community. Such metrics fail to distinguish between taxa capable and incapable of producing geosmin, reducing predictive accuracy, particularly when non-producing taxa dominate [79]. Furthermore, geosmin production is not directly proportional to producer biomass; it is driven by metabolic activity and environmental regulation of geosmin biosynthetic pathways [15, 24, 85], decoupling biomass/ bloom-formation from T&O production. Traditional approaches overlook the functional capacity and community compositional structure in biological data that could be indicative of T&O risk [30].

In addition, routine biological monitoring is predominantly based on microscopy; subjective judgement can lead to misidentifications of taxa [86]. Microscopy-generated community data are restricted to morphologically visible taxa, thereby biasing the data toward algae and *Cyanobacteria* whilst excluding additional bacterial communities of interest, e.g., geosmin degraders. Consequently, metrics derived from conventional biological data do not adequately capture the biotic processes influencing geosmin concentrations, limiting their application in predictive models.

To address constraints in conventional biological data, we present a novel alternative approach to deriving biologically

Table 1 Summary of reservoir-specific model variables, including units and dataset-type (chemistry, eDNA and weather) used in GAM development for geosmin forecasting

Reservoir 1 (Mild Geosmin)			Reservoir 2 (Moderate Geosmin)			Reservoir 3 (Severe Geosmin)		
Model variable name	Units	Dataset Type	Model Variable Name	Units	Dataset Type	Model Variable Name	Units	Dataset Type
Ammonium	mg L ⁻¹	Chemistry	Ammonium	mg L ⁻¹	Chemistry	Ammonium	mg L ⁻¹	Chemistry
Nitrate	mg L ⁻¹	Chemistry	Nitrate	mg L ⁻¹	Chemistry	Nitrate	mg L ⁻¹	Chemistry
Total <i>geoA</i> relative abundance	%	eDNA	Atmospheric Temperature	°C	Weather	Atmospheric Temperature	°C	Weather
Total geosmin degrading relative abundance	%	eDNA	Dissolved Manganese	mg L ⁻¹	Chemistry	Total Phosphorus	mg L ⁻¹	Chemistry
Season	NA	NA	Total <i>geoA</i> Relative Abundance	%	eDNA	Iron	mg L ⁻¹	Chemistry
Total phosphorus	mg L ⁻¹	Chemistry	Total Geosmin Degrading Relative Abundance	%	eDNA	Dissolved Manganese	mg L ⁻¹	Chemistry
Iron	mg L ⁻¹	Chemistry						
Atmospheric temperature	°C	Weather				Total <i>geoA</i> Relative Abundance	%	eDNA
Manganese	mg L ⁻¹	Chemistry				Total Geosmin Degrading Relative Abundance	%	eDNA

meaningful variables from eDNA data, enabling models to account for the production and degradation of geosmin and its associated concentration variability.

Targeting Geosmin-Producers Using the *geoA* Gene.

The *geoA* gene encodes for the enzymatic conversion of farnesyl diphosphate to geosmin (Section “[What Influences T&O Production?](#)”). By identifying *Cyanobacteria* that possess *geoA*, it is possible to derive a functional proxy for geosmin production potential [15]. In this model framework, the relative abundances of *geoA*-containing *Cyanobacteria* were derived from the eDNA datasets for Reservoirs 1–3, totalled, and incorporated as a predictor variable in each model (methods and taxa list in Supplementary Information, [SI16](#) and [SI17](#)). This targeted approach focuses on taxa capable of producing geosmin, avoiding overestimation associated with total cyanobacterial abundance, which includes both producers and non-producers. Incorporating the total abundance of *Cyanobacteria* capable of producing geosmin as a smooth term into each reservoir’s GAM structure allows the model to capture the non-linear relationship between producers and geosmin concentrations.

Accounting for Microbial Degradation Potential of Geosmin

In addition to biological production, microbial degradation can potentially affect geosmin concentrations, leading to temporal variability in recorded values. Many heterotrophic bacteria have been identified as capable of utilising geosmin as a carbon source, resulting in the biotic removal of geosmin [80, 87, 88]. To account for the potential degradation in Reservoirs 1–3, the total relative abundances of geosmin-degrading bacteria were integrated as a smooth term in each model (see methods and taxa list in Supplementary Information, [SI18](#) and [SI19](#)). Inclusion of this smooth term enables the model to account for both the production and degradation of geosmin, thereby improving the representation of the biological mechanisms driving fluctuations in recorded concentrations.

Model Performance and Forecasting Geosmin Risk

Model Performance

Across the three studied reservoirs, models performed strongly, with adjusted R^2 values ranging from 0.694 to 0.974 and deviance explained ranging from 79.6 to 98.5% (Table 2). Performance was highest in the mild reservoir (Reservoir 1), which benefited from higher-frequency sampling (training $n=92$; Supplementary Table [SI1](#)), thereby improving the representation of geosmin concentrations in this reservoir. Full model specifications and diagnostic plots for each model (Q-Q, residuals versus fitted, residual distributions, and response versus fitted) are provided in Supplementary Information [SI10–11](#).

Predictive Capability and Practical Limitations

Beyond assessing model fit on the training data, the reservoir-specific GAMs were tested in an operational setting using withheld (“unseen”) observations that were excluded from the model fitting process. This stage of model development evaluates whether the models can support out-of-sample forecasting, which is crucial for early warning systems rather than just retrospective analysis. Across reservoirs, predictions on withheld data remained within acceptable bounds relative to the overall model error distributions (Figs. 1, 2 and 3), indicating that the models maintain predictive skill when applied to new observations collected after the training period.

Model performance varied across systems in a way that aligns with known limits when modelling environmental data (Supplementary Information [SI12](#)). Reservoir 1 achieved the highest overall performance (Table 2), likely due to its higher temporal resolution and larger training dataset (training $n = 92$), which enhances the model’s ability to capture short-term variability and minimise uncertainty around non-linear responses. Conversely, Reservoir 2 (training $n = 19$) and Reservoir 3 (training $n = 28$) were modelled with more limited sampling schemes (Supplementary Table [SI1](#)), which can restrict the stability of estimated relationships and the reliability of event-scale predictions.

Table 2 Summary of reservoir-specific GAM performance, including significant parametric terms and smooth terms are shown for each model ($p < 0.05$)

Reservoir (severity)	Adjusted R^2	Deviance explained	REML	Scale estimate	Key significant parametric terms ($p < 0.05$)	Key significant smooth terms ($p < 0.05$)
1 (Mild)	0.974	98.50%	124.53	0.007	Winter; TP; Fe	$s(\text{NH}_4^+)$; $s(\text{NO}_3^-)$; $s(\text{Total } geoA)$; $s(\text{Total geosmin degrader})$
2 (Moderate)	0.774	89.20%	14.02	0.196	Temperature; DMn; $\text{NH}_4^+ \times \text{DMn}$	NA
3 (Severe)	0.694	79.60%	27.79	0.786	Temperature; DMn; $\text{NH}_4^+ \times \text{Total } geoA$	$s(\text{Total } geoA)$

Fig. 1 Time series plot of actual geosmin (grey markers) and predicted geosmin concentrations ng L^{-1} (black markers) using the Reservoir 1 (mild geosmin) GAM model. Black bars on the predicted geosmin concentrations indicate the error rate for that sample. The red box highlights predictions made on unseen data ($n=6$)

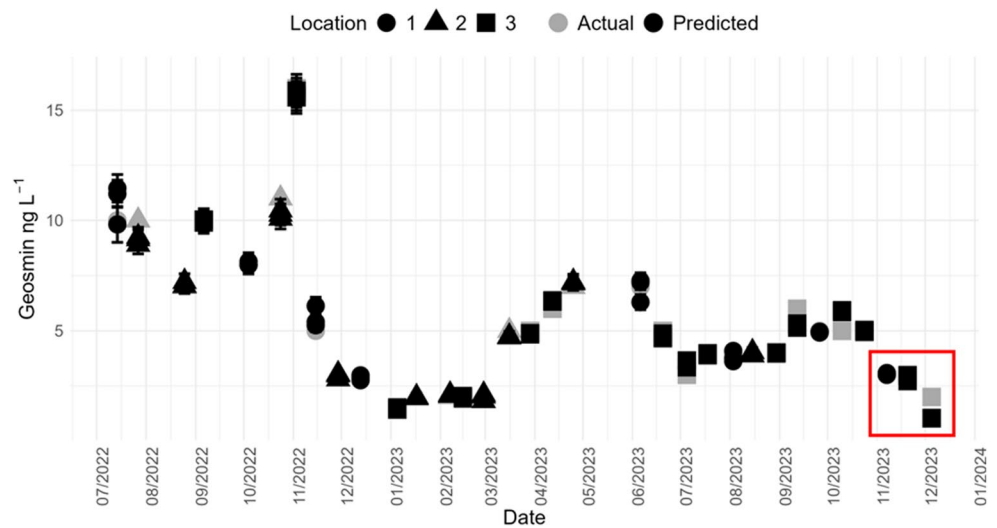


Fig. 2 Time series plot of actual geosmin (grey markers) and predicted geosmin concentrations ng L^{-1} (black markers) using the Reservoir 2 (moderate geosmin) GAM model. Black bars on the predicted geosmin concentrations indicate the error rate for that sample. The red box highlights predictions made on unseen data ($n=1$)

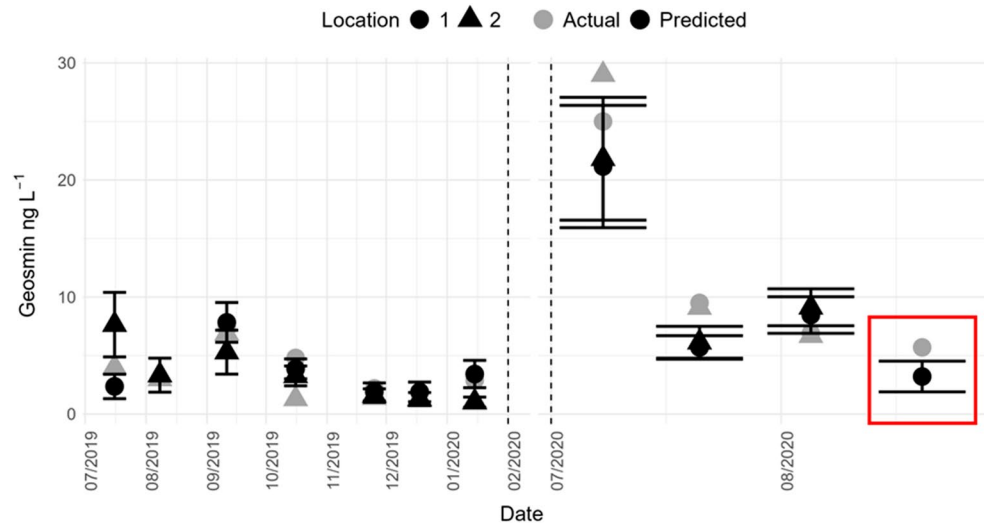
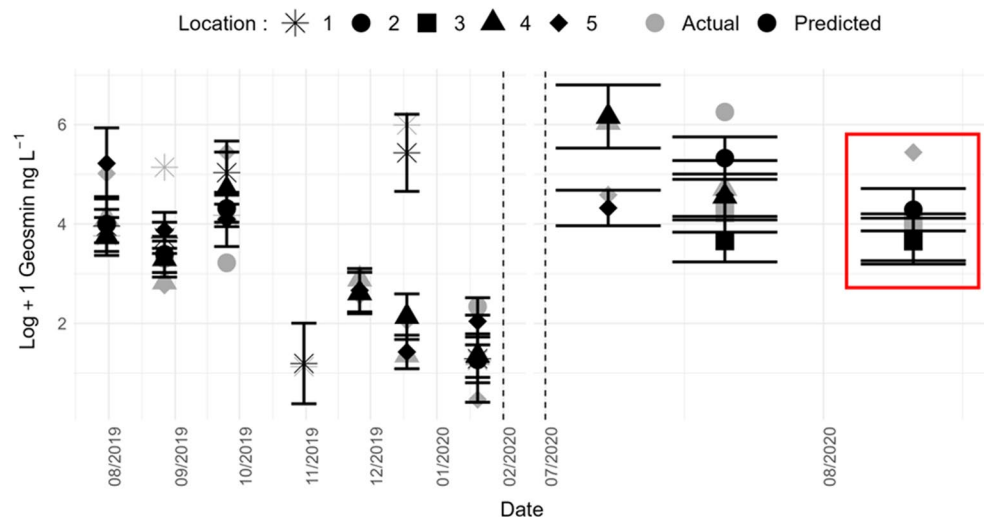


Fig. 3 Time series plot of actual $\log(+1)$ geosmin (grey markers) and predicted $\log(+1)$ geosmin concentrations ng L^{-1} (black markers) using the Reservoir 3 (severe geosmin) GAM model. Black bars on the predicted geosmin concentrations indicate the error rate for that sample. The red box highlights predictions made on unseen data ($n=3$)



This is a well-known limitation when modelling environmental data: predictive performance generally declines as sample size decreases, and model behaviour can become sensitive to the specific set of observations used for training, especially when $n < 30$ [89–93]. As highlighted by Wisz, Hijmans [93]; no modelling approach consistently performs well when the sample size is small, reinforcing the need for cautious interpretation when predictive models are trained on sparse datasets.

The choice of modelling framework also influences predictive utility. GAMs offer a practical balance between flexibility and interpretability, enabling the representation of non-linear responses and thresholds while maintaining transparent relationships between predictors and geosmin concentration. This is a significant advantage over purely linear approaches, which often struggle to capture threshold-like responses expected in biologically mediated metabolite production [15, 94–96]. However, even with a flexible framework, forecasting performance fundamentally depends on data quantity, sampling frequency, and the extent to which key drivers are observed across their relevant ranges. Therefore, the moderate and severe reservoirs demonstrate the typical trade-off in operational monitoring: lower sampling frequency reduces the ability to characterise reservoir geosmin dynamics, especially during rapid nutrient transitions related to stratification and redox shifts.

To our knowledge, predictive models incorporating eDNA-derived biological indicators have not previously been documented. The framework presented here combines proxies for both geosmin production potential (Total *geoA*-containing *Cyanobacteria*) and biodegradation capacity (Total geosmin-degrading bacteria), along with chemical and redox-related covariates (Table 1). Although the statistical significance of biological predictors varied between reservoirs (Table 2), this likely reflects differences in sampling resolution and event representation rather than a lack of biological control.

Overall, the results demonstrate that GAMs integrating chemical, physical, and functionally derived biological indicators can provide a robust and interpretable framework for forecasting geosmin risk. However, model performance remains fundamentally dependent on the availability, resolution, and quality of monitoring data. Increasing sampling frequency and incorporating biologically meaningful indicators will therefore be critical for improving predictive capability and enabling operational early-warning systems for T&O events in drinking-water reservoirs.

Environmental Drivers Underlying Geosmin Forecasts

The environmental variables retained within each reservoir-specific model reflect known biogeochemical controls on

geosmin production. In stratified drinking-water reservoirs, internal nutrient cycling is strongly influenced by interactions between temperature, redox conditions, and nutrient availability [64]. Previous studies have identified ammonium (NH_4^+) as a key trigger for cyanobacterial geosmin production, particularly when nitrate (NO_3^-) concentrations are low [23, 84]. Under warm conditions, thermal stratification promotes oxygen depletion in bottom waters, creating reducing conditions that favour the mobilisation of redox-sensitive elements such as dissolved manganese and iron from sediments [97]. Elevated dissolved manganese can therefore serve as an indicator of suboxic conditions that support anaerobic microbial pathways, such as dissimilatory nitrate reduction to ammonium (DNRA), which converts nitrate to ammonium and contributes to internal nitrogen loading [98].

These processes offer a plausible mechanism that links redox conditions to geosmin production. Under stratified conditions, increased microbial regeneration of NH_4^+ in sediments may raise the availability of reduced nitrogen in the water column, potentially stimulating the activity of geosmin-producing *Cyanobacteria*. Warmer temperatures can further amplify these processes by speeding up microbial metabolism and enhancing stratification. Consequently, interactions between temperature, nutrient availability, and redox-sensitive elements are likely to play a role in the non-linear responses observed between geosmin concentrations and nitrogen species within the GAM framework – for example, in Reservoir 1 (Supplementary Information S11).

Importantly, these relationships varied among reservoirs, highlighting that geosmin dynamics are highly specific to each reservoir. Variations in hydrology, nutrient regimes, and microbial community composition can influence both the magnitude and nature of environmental factors affecting geosmin production. As a result, reservoir-specific models are essential to accurately represent the unique ecological and biogeochemical conditions that drive geosmin variability within individual systems. This underscores the value of adaptable modelling approaches such as GAMs, which allow environmental responses to vary non-linearly across systems while preserving biological interpretability.

Toward Operational Early-Warning Frameworks

The case study in Section “[Case Study: An eDNA-Informed Framework for Forecasting Geosmin Risk](#)” shows that combining biological, chemical, and physical data can enhance predictive models for geosmin behaviour in drinking-water reservoirs. However, turning these research-based frameworks into operational early-warning systems requires more than just good model performance. It also involves changes

to routine monitoring, standardising biologically meaningful indicators, and fostering greater collaboration among water companies. Moving from reactive management to predictive reservoir surveillance will therefore depend on both developing new methods and implementing them in practice.

It should be noted, however, that the above modifications to “business as usual” is effectively business critical, with increasing customer complaints related to the increasing frequency of T&O events driven, in part, by climate change favouring cyanobacterial T&O metabolite producers. The case study described, enables a Water Company to predict 28 days in advance of a potential T&O event, therefore providing ample time to switch to PAC within a treatment works or optimise other aspects of treatment. This will reduce customer complaints, increase customer confidence in the quality of the water supply, as well as reducing treatment costs to the water company.

Standardising Monitoring Workflows

A key requirement for operational forecasting is the integration of functional biological indicators into routine monitoring programmes. Traditional monitoring methods focus heavily on physicochemical variables and microscopy-based phytoplankton counts, but these metrics do not differentiate T&O producers from non-producers and rarely include microbial degraders important for metabolite removal [30, 79]. Including eDNA in routine reservoir sampling would offer a more direct way to monitor taxa capable of producing geosmin and 2-MIB, as well as bacteria involved in biodegradation processes [30, 80].

In parallel, monitoring strategies should better detect the fleeting environmental changes that lead to T&O events. Infrequent sampling risks missing short-lived nutrient pulses, quick shifts in nitrogen forms, and redox transitions linked to stratification breakdown or internal loading [15, 23, 30, 49]. Increasing sampling frequency during high-risk periods, especially during summer stratification and seasonal turnover, would improve the ability to detect early warning signs before T&O concentrations exceed operational thresholds. However, it should be noted that fortnightly sampling as utilised in this study provided adequate model sensitivity to fulfil Water Company operational needs based upon the model accuracy presented in this study. There is also a need to standardise the range of predictors used in forecasting frameworks. Combining biological indicators such as total *geoA*-containing cyanobacteria and geosmin-degrading bacteria with redox-sensitive chemical variables, including dissolved manganese, iron, ammonium, and nitrate, would enhance the alignment between monitoring data and the underlying ecological mechanisms of T&O production [15, 30, 58, 97]. These integrated datasets would also support the development of operational trigger thresholds to flag increasing T&O risk

before compounds reach treatment works. In practice, such thresholds could be based on combinations of elevated *geoA* signal, falling $\text{NO}_3^-:\text{NH}_4^+$ ratios, and increasing dissolved manganese or iron, reflecting the coupling between community shifts, nutrient availability, and redox change [15, 23, 49].

Scaling Across Water Companies

Although reservoir-specific models are likely to remain the most accurate because T&O dynamics are strongly system-dependent, predictive capability can still be enhanced through cross-company collaboration. Expanding training datasets across multiple reservoirs would help identify which predictors are widely transferable and which require site-specific calibration. This is especially important because reservoir morphology, trophic state, nutrient regime, hydrology, and microbial community structure all influence geosmin dynamics differently across systems [16, 18, 70]. Collaborative monitoring frameworks would also facilitate the harmonisation of sampling protocols, molecular workflows, and metadata collection. Currently, the limited size and fragmentation of environmental datasets remain significant barriers to robust predictive modelling, especially for event-scale forecasting [89, 90, 93]. Sharing datasets among water companies could therefore enhance model training, external validation, and the creation of more generalisable forecasting tools.

A practical long-term goal would be to develop hybrid frameworks that combine reservoir-specific models with a common set of standardised biological and physicochemical indicators. Such an approach would maintain local ecological relevance while enabling broader comparisons across reservoirs. In this context, eDNA-derived functional indicators might be especially useful because they are more mechanistically informative than traditional biomass metrics and could provide greater consistency across reservoirs than microscopy-based counts alone [15, 30]. Taken together, these developments suggest a future where T&O forecasting becomes part of routine reservoir management. Combining biologically informed monitoring with high-resolution environmental data and adaptable modelling frameworks offers the best way to develop operational early-warning systems that enable proactive intervention.

Conclusions

T&O events caused by geosmin and 2-MIB continue to pose a recurring challenge for drinking-water management because their occurrence is influenced by complex biological, chemical, and physical processes that are often hard to resolve using conventional monitoring alone [15, 16, 22].

Although considerable progress has been made in identifying environmental factors associated with T&O production, predicting the onset of these events remains limited by infrequent monitoring, insufficient biological understanding, and the continued reliance on broad biological proxies such as total cyanobacterial biomass [15, 25, 79]. This review highlights that T&O production is best understood as a biologically mediated process influenced by nutrient ratios, redox dynamics, and microbial community structure rather than simply a consequence of cyanobacterial abundance. The production of geosmin and 2-MIB is shaped by community-level ecological interactions, nutrient speciation, and stratification-driven internal loading, all of which affect cyanobacterial productivity and secondary metabolite biosynthesis [30, 49, 58]. As such, prediction frameworks that do not account for these biological and biogeochemical linkages are unlikely to perform reliably across reservoirs.

The case study shown here illustrates that integrating eDNA-derived biological indicators with chemical and physical covariates within a flexible modelling framework can significantly enhance the prediction of geosmin concentrations. By directly including proxies for geosmin production potential and biodegradation capacity, it becomes possible to go beyond mere descriptive correlations and develop a more mechanistic understanding of T&O dynamics [15, 30, 80]. GAMs are especially suitable for this purpose because they enable the representation of nonlinear ecological responses and thresholds while maintaining interpretability [94, 96].

Enhancing T&O forecasting will depend on integrating functional biological indicators into routine monitoring, increasing temporal resolution during high-risk periods, and developing collaborative datasets across water companies. These advances are vital for shifting T&O management from reactive detection to proactive early warning. More broadly, linking microbial ecology with reservoir biogeochemistry offers a promising route to more resilient drinking-water systems capable of anticipating and mitigating T&O events before they affect treatment works and consumers.

Key References

Foundational T&O Understanding

- Mustapha, Tijani (19)
 - Comprehensive modern review of sources, impacts, and treatment of T&O compounds, geosmin and 2-MIB.

Molecular Foundation and Biosynthesis of T&O Compounds

- Jiang, He (10)
 - Landmark paper elucidating the biochemical mechanism of geosmin formation and identifying and characterising the responsible enzyme.
- Wang, Xu (13)
 - Core reference on the genetic basis of 2-MIB formation; identifying and characterising the core genes responsible for 2-MIB production in Cyanobacteria.
- Hooper, Kille (15)
 - An emerging modelling framework for predictive, gene-informed management of geosmin and 2-MIB events in drinking water reservoirs.

Environmental Drivers of T&O Events

Key Nutrients and Nutrient Ratios

- Perkins, Slavin (23)
 - Demonstration of ammonium, specifically the ammonium:nitrate ratio, is a critical trigger for cyanobacterial production of T&O metabolites geosmin and 2-MIB.
- Harris, Smith (49)
 - Combined effects of nitrogen-to-phosphorus ratios and nitrogen speciation on cyanobacterial metabolite concentrations in eutrophic reservoirs.

Redox and Stratification

- Elçi (65)
 - Effects of thermal stratification on reservoir water quality, employing modelling approaches to assess how temperature-driven density gradients influence the distribution of oxygen and nutrients in reservoir systems.

- Yue, Chen (18)
 - Linking physical lake stratification to phytoplankton dynamics and to the production of T&O compounds that give rise to drinking water complaints.

Microbial Community Ecology and Functional Indicators

- Hooper, Christofides (30)
 - Data-driven evidence that links algal-bacterial community composition in drinking water reservoirs to the risk of cyanobacterial production of T&O metabolites, geosmin and 2-MIB, proposing community-based T&O risk categories as an early-warning tool for drinking Water Companies.
- Kruk, Devercelli (37)
 - Synthesised Reynolds Functional Groups (RFGs) framework for freshwater phytoplankton. Positioning RFGs as a trait-based tool for describing, explaining and ultimately predicting phytoplankton community responses along environmental gradients.
- Clercin, Druschel (80)
 - Investigation into naturally occurring bacteria capable of the degradation of T&O compounds, geosmin and 2-MIB, in a drinking water reservoir, and how much of these compounds are cell-bound versus dissolved.

Prediction and Modelling T&O

Limitations of Traditional Approaches

- Harris and Graham (78)
 - Models showed that cyanobacterial composition, along with nutrient conditions, could predict geosmin events with reasonable accuracy, enabling utilities to implement early-warning systems and make targeted treatment adjustments.
- Chong, Lee (79)
 - Modelling cyanobacterial biomass as a linear term provides evidence of a weak relationship between biomass and T&O metabolite concentrations.

- Graham, Loftin (25)
 - Results reveal that periods of heightened cyanobacterial biomass (i.e., cyanobacterial blooms) do not necessarily predict toxin or T&O presence, supporting the notion that T&O is productivity-driven rather than biomass-related.

Machine Learning and Statistical Advances

- Qiu, Zhang (71)
 - Integrating quantile regression with shotgun metagenomics to identify biological producers and environmental drivers of T&O compounds in a drinking-water reservoir.
- Franklin, Podduturi (70)
 - Identification of riverine geosmin and 2-MIB producers and interpreting them using molecular tools and statistical/ML-style analyses.
- Pedersen, Miller (96)
 - This paper introduces hierarchical generalised additive models (HGAMs) to combine GAMs with a hierarchical (mixed-effects) structure. A widely used tutorial-style reference for ecologists working with complex, grouped, nonlinear data.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s44481-026-00001-w>.

Acknowledgements The authors are extremely grateful to the Water Companies who co-funded aspects of the case study included in this work and who contributed staff time and costs for reservoir sampling as well as guidance for stakeholder use of our collaborative work on Taste and Odour: Dŵr Cymru Welsh Water, United Utilities, Yorkshire Water, Scottish Water, Jersey Water and Bristol Water.

Author Contributions A.S.H.: Conceptualisation; Methodology; Formal analysis; Data acquisition; Data curation; Visualisation; Writing – original draft, review, and editing. S.C.: Methodology; Interpretation of results; Writing – review & editing. S.W.: Writing – review. P.K.: Conceptualisation; Resources; Supervision; Writing – review. R.P.: Conceptualisation; Resources; Supervision; Funding acquisition; Writing – review.

Funding Funding for this work was received from the Water industry partners named in the acknowledgements.

Data Availability Data will be made available on request. Data will be stored in an online depository.

Declarations

Competing Interests The authors declare no competing interests.

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