Science of the Total Environment 921 (2024) 171074

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Eliciting expert judgements to underpin our understanding of faecal indicator organism loss from septic tank systems

Chisha Chongo Mzyece [a,*], Miriam Glendell [b], Zisis Gagkas [b], Richard S. Quilliam [a], Ian Jones [a], Eulyn Pagaling [b], Ioanna Akoumianaki [b], Claire Newman [b], David M. Oliver [a]

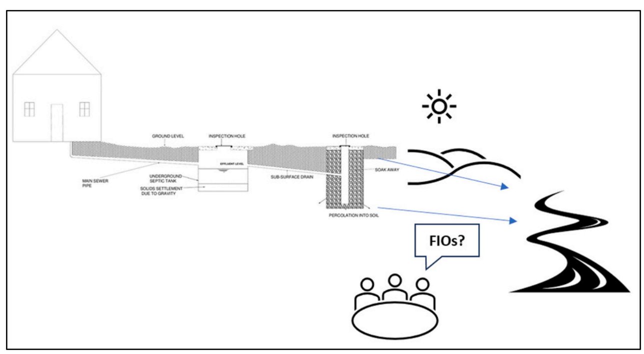
[a] Biological and Environmental Sciences, Faculty of Natural Sciences, University of Stirling, Stirling FK9 4LA, Scotland, United Kingdom of Great Britain and Northern Ireland

[b] Environmental and Biochemical Sciences Group, The James Hutton Institute, Craigiebuckler, Aberdeen AB15 8QH, Scotland, United Kingdom of Great Britain and Northern Ireland

HIGHLIGHTS

- Elicitation is used to derive probabilities of septic tank faecal organism losses.
- Expert consensus is strong that high risk conditions yield 93 % loss to watercourses.
- Likelihood of faecal organism losses drops to 5 % for low-risk conditions.
- Soil properties are critical in driving losses; slope and distance are secondary.
- Septic tanks with intermediate risk conditions are priority for empirical research.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Kyle Bibby

Keywords:
E. coli
Expert elicitation
Sheffield Elicitation Framework
Water quality
Environmental pollution
Hydrological connectivity
Faecal bacteria

ABSTRACT

Septic tank systems (STS) in rural catchments represent a potential source of microbial pollution to watercourses; however, data concerning the risk of faecal indicator organism (FIO) export from STS to surface waters are scarce. In the absence of empirical data, elicitation of expert judgements can provide an alternative approach to aid understanding of FIO pollution risk from STS. Our study employed a structured elicitation process using the Sheffield Elicitation Framework to obtain expert judgements on the proportion of FIOs likely to be delivered from STS to watercourses, based on 36 scenarios combining: (i) septic tank effluent movement risk, driven by soil hydro-morphological characteristics; (ii) distance of septic tank to watercourse; and (iii) degree of slope. Experts used the tertile method to elicit a range of values representing their beliefs of the proportion of FIOs likely to be delivered to a watercourse for each scenario. The experts judged that 93 % of FIOs would likely be delivered from an STS to a watercourse under the highest risk scenario that combined (i) very high STS effluent movement risk, (ii) STS distance to watercourse <10 m, and (iii) a location on a steep slope with gradient >25 %. Under the lowest risk scenario, the proportion of FIOs reaching a watercourse would likely reduce to 5 %. Expert confidence was high for scenarios that represented extremes of risk, while uncertainty increased for scenarios depicting intermediate risk conditions. The behavioural aggregation process employed to obtain a consensus among the

* Corresponding author.
E-mail address: c.c.mzyece@stir.ac.uk (C.C. Mzyece).

https://doi.org/10.1016/j.scitotenv.2024.171074
Received 15 November 2023; Received in revised form 5 February 2024; Accepted 16 February 2024
Available online 18 February 2024

experts proved to be useful for highlighting both areas of strong consensus and high uncertainty. The latter therefore represent priorities for future empirical research to further improve our understanding of potential pollution risk from septic tanks and in turn enable better assessments of potential threats to water quality in rural catchments throughout the world where decentralised wastewater systems are common.

1. Introduction

Managing faecal pollution of watercourses is complex due to a variety of potential catchment sources that include agricultural management, urban wastewater discharges and wildlife contributions (Afolabi et al., 2020; Neill et al., 2018; Oliver et al., 2016). Human sources of faecal pollution are often associated with sewage overflows; however, there are potential losses from other rural sources, including septic tanks (Humphrey et al., 2018; Iverson et al., 2020; Richards et al., 2016). Catchment characteristics, e.g., population size, land use, topography and soil type, will influence the composition and magnitude of faecal loading to receiving waters (D'Arcy et al., 2022), and in large mixed catchments, streams and rivers can be impacted by a combination of multiple faecal sources and a diversity of hydrological pathways delivering pollutants from land to water. This often makes understanding pollution signals in catchments challenging due to their integration of multiple upstream influences.

The relative importance of STS as a contributor of microbial pollution to watercourses, as measured via faecal indicator organisms (FIOs), is relatively unknown. Although much research has investigated diffuse FIO pollution from agriculture (e.g., Neill et al., 2020; Oliver et al., 2010; Porter et al., 2019) and point source inputs from wastewater discharges (Igere et al., 2020; Li et al., 2015; Naidoo and Olaniran, 2013), decentralised wastewater treatment has received limited investigation as a source of FIOs to water (Beal et al., 2005; Murphy et al., 2020). This is likely due to several factors, including: a lack of data on septic tank locations in catchments (Withers et al., 2012); poor records of tank maintenance (Akoumianaki and Ibiyemi, 2022), uncertainties regarding tank condition, age, and treatment levels (Richards et al., 2016). Additionally, sampling from intricate diffuse septic tank effluent pathways is complex (Tamang et al., 2022) and generally, there is uncertainty associated with FIO fate and transfer dynamics in response to a suite of varying and interacting environmental variables (Afolabi et al., 2020; Buckerfield et al., 2019b). The lack of quantitative evidence on the contribution of STS to FIO pollution in receiving waters under a range of hydrological and environmental scenarios, especially in rural areas, presents a challenge for regulators and environmental decision-makers who have a responsibility for managing catchment water quality (Beal et al., 2005; Schwetschenau et al., 2022).

In contrast to the limited quantitative data on FIO export from STS, there is a growing body of evidence that documents the risk posed to downstream ecological water quality from nitrogen (N) and phosphorus (P) loss from septic tanks (Brewton et al., 2022; Iverson et al., 2018). The lack of FIO data in the UK and much of Europe reflects the historical focus on nutrient losses, from which FIO losses have been inferred rather than directly measured (Gill and Mockler, 2016; Glendell et al., 2022; Withers et al., 2014). Spatially targeted management and mitigation measures within catchments can help to reduce FIO loading to receiving waters and alleviate subsequent downstream impacts at end-point receptors such as bathing zones and shellfish harvesting waters (Oliver et al., 2016). Effective prioritisation of mitigation, however, first requires an understanding of the spatial distribution of FIO sources within a catchment, and in rural catchments STS may represent localised hotspots of FIO pollution risk to nearby watercourses.

An improved understanding of which factors influence the transport and delivery of FIOs discharged from STS to receiving waters is therefore crucial to assist catchment risk assessment. Anecdotally, factors such as the angle of slope of soakaway fields, distance to watercourse, and soil characteristics can govern the risk of effluent movement in different soil types (Gagkas and Lilly, 2019; Glendell et al., 2018). Together these factors can influence the transfer of FIOs from STS to receiving waters, but quantitative evidence to support this is still lacking (Gill and Mockler, 2016). One approach to better understand the relative risks of FIOs discharged from STS is through the elicitation of judgements from experts in water and environmental management, which would provide an opportunity to assess the likelihood of lesser-known risks when quantitative evidence is scarce (e.g., Fish et al., 2009; Glendell et al., 2022; Oliver et al., 2010).

Expert elicitation involves knowledge acquisition from a group of experts about one or more uncertain quantities, which can then inform decision-making or can be used as prior information to augment limited data in statistical models, for example, in the Bayesian approach to statistics (O'Hagan, 2006). In this approach, formal elicitation of prior distributions is only used in situations where prior information is appreciable and empirical data is limited. Therefore, elicitation of expert knowledge is regarded as complementary to, rather than a substitute for, primary research (Best et al., 2020). Elicitation of expert knowledge is not only a practical aid when data are limited in complex environmental systems, but also helps to reveal areas of agreement as well as uncertainties surrounding the quantity of interest (QoI) for which the knowledge is being elicited (Krueger et al., 2012). Despite having benefits, there are concerns over expert-elicited data, such as: accuracy relative to typical values derived from experiments (O'Hagan, 2006); performance over an ensemble of cases (Kahneman et al., 2021) and reproducibility across different expert groups. It is therefore important that approaches to expert elicitation follow a structured methodology to address these concerns and ensure efficiency (Courtney Jones et al., 2023). Several structured methods exist for quantifying expert knowledge over an unknown QoI. These include, among others: Delphi (von der Gracht, 2012), the Classical Method (Quigley et al., 2018), the 'Investigate, Discuss, Estimate, Aggregate' (IDEA) protocol (Hanea et al., 2018a); and the Sheffield Elicitation Framework (SHELF) (Gosling, 2018). All approaches begin with an individual elicitation stage allowing experts to give individual judgements followed by a group consensus stage that employs mathematical aggregation (in the case of Delphi and the Classical method) or behavioural aggregation (SHELF) or a mix of both approaches (IDEA).

In this study, the SHELF methodology was used to elicit expert judgements on the proportion of FIOs likely to be delivered to surface waters from STS based on a pre-defined set of 36 scenarios of STS soil effluent movement risk, distance to watercourse and slope. The specific objectives of the elicitation were to: (i) determine individual judgements, (ii) employ a deliberative approach to derive consensus judgements across a range of experts for the 36 scenarios under investigation and (iii) provide an alternative approach to understating FIO pollution from STS.

2. Materials and methods

SHELF is a package of documents, templates and software designed to carry out elicitation of probability distributions over an unknown QoI from a group of experts. Detailed steps and processes in the SHELF methodology are given in Gosling (2018). Here, we describe how this process was implemented.

2.1. Defining the Quantity of Interest (QoI)

The unknown QoI was defined as the proportion of FIOs (*p*FIO) that could be transferred to a surface water body on an annual time step from STS depending on STS effluent movement risk, STS distance to watercourse and slope. The *p*FIO was specified as percentage where values close to 0 % represented a low likelihood of delivery and those close to 100 % represented a high likelihood of delivery. For the purposes of the elicitation, it was assumed that all STS were associated with a soakaway. Some inappropriate ad-hoc systems may exist, including STS that directly discharge to watercourses; however, to constrain uncertainties such STS were not considered. Therefore, our focus was on FIOs that could be delivered via surface, sub-surface and groundwater pathways.

STS effluent movement through these three pathways is characterised using the Hydrology of Soil Types (HOST) (Boorman et al., 1995) conceptual models (Fig. 1), which were deployed to guide the elicitation. HOST is a UK soil classification scheme devised to predict river flows at ungauged catchments, by linking soil morphology (presence of a gleyed layer, a slowly permeable layer or peaty topsoil) and hydrology (soil infiltration and percolation) to conceptual models of surface/sub-surface flow pathways through the soil profile (Gagkas and Lilly, 2019). To guide this elicitation, experts used HOST classes (Table 1) grouped based on their conceptual soil and hydrological pathways and translated into STS effluent movement risk, and pathways driving risk (Glendell et al., 2018). This classification was informed by previous assessment of the role of soils in determining water quality risks (Lilly and Baggaley, 2014).

The distance from STS to watercourse was specified as Euclidean distance between the STS discharge point and nearest receiving water. Distances (in metres) of <10, 10–50 and > 50 were selected for the elicitation scenarios based on a range of STS distances to watercourse determined from a national-scale dataset of modelled STS locations and associated stream network data (Glendell et al., 2022). Although specific evidence of the influence of STS distance to watercourse on FIO delivery is scarce, experts were guided by the assumption that for low permeability soils, STS located <50 m to a surface water body will deliver 100 % of their effluent to the surface water body while for those located >200 m, the amount of effluent reaching the water is reduced to negligible levels (0 %) (Gill and Mockler, 2016). Slope represented the angle of inclined land associated with the STS distance to a receiving water. Steeper slopes (25 %) are generally associated with high surface water FIO contamination risk because they promote more rapid water flow compared to gentle slopes (5 %) (Glendell et al., 2022). These three

Table 1
STS effluent movement risk factors based on HOST classes and pathways driving risk.

Risk factor	HOST class groupings	Characteristics of HOST class groupings	Pathways driving risk
Very high	HOST4, HOST7, HOST8, HOST9, HOST10, HOST12, HOST26, HOST28, HOST29	Free draining (sandy) soil & deep groundwater (GW)	Leaching to GW
		Poorly draining soil or soil with peaty topsoil & shallow GW or basin peat	Surface runoff & leaching to GW
		Soil with peaty topsoil & no GW or Upland blanket peat	Surface runoff
High	HOST5, HOST14, HOST18, HOST24 HOST15	Relatively free draining soil & deep GW	Leaching to GW, some runoff
	HOST27	Relatively poor draining soil & deep GW	Surface runoff, some leaching to GW
		Poor draining soil & no GW	Surface runoff
		Soil with peaty topsoil & deep GW	Surface runoff, some leaching to GW
		Soil with thin peaty topsoil & no GW	Surface runoff
Medium	HOST6, HOST13, HOST17, HOST19, HOST22	Free draining soil & deep GW	Leaching to GW
		Relatively free draining soil & no GW	Surface runoff
Low	HOST16	Free draining soil & no GW	Some surface runoff

factors, STS effluent movement risk, STS distance to watercourse, and slope, were used to generate 36 Scenarios (Table 2) for which experts gave a range of values characterising the QoI.

2.2. SHELF Expert Elicitation Workshop

The recruitment of an appropriate number of experts (4–8) with relevant expertise or knowledge of the QoI is key to the workshop element of the SHELF elicitation process (O'Hagan, 2006). Criteria for expert selection are primarily expertise in a field of relevance to the defined quantity of interest. Potential experts were identified and

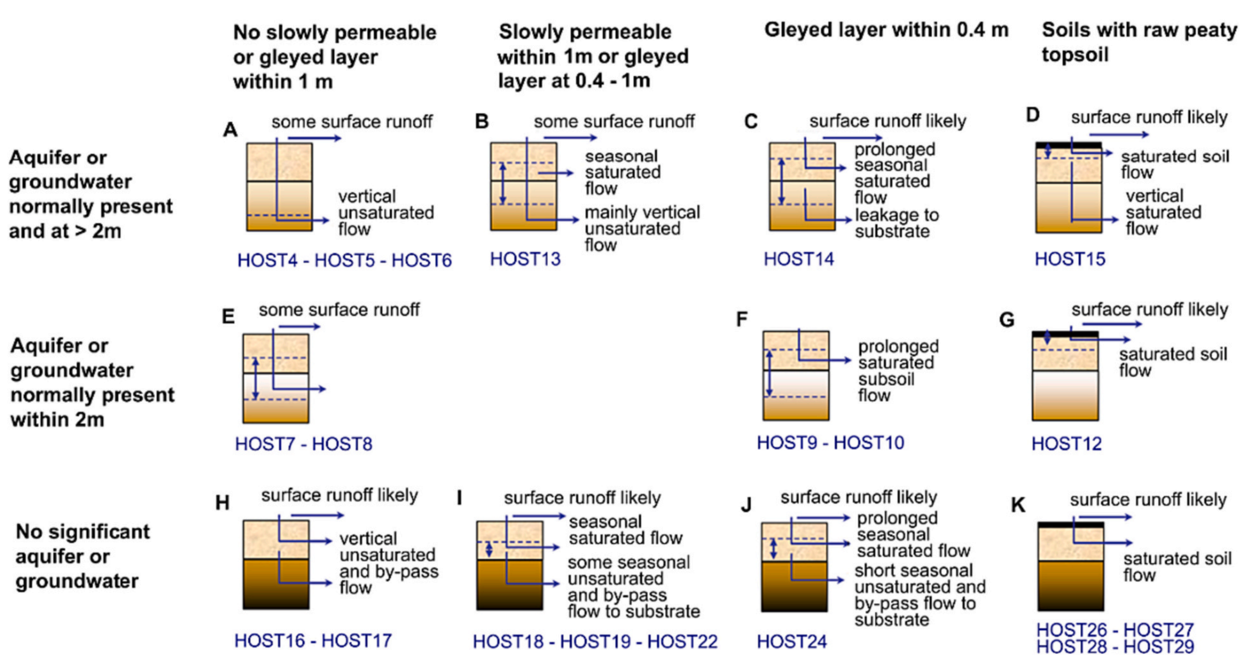


Fig. 1. HOST conceptual models of water movement and respective HOST classes present in Scotland (Gagkas et al., 2021).

Table 2
Elicitation scenarios, consensus values and summary statistics[a] of the consensus plots and linear aggregation plots[b] of expert judgements.

Elicitation scenarios				Consensus values			Summary statistics of consensus beta distributions					
Number	*STS effluent movement risk*	*STS distance to watercourse (m)*	*Slope (%)*	*Tertile 1*	*Median*	*Tertile 2*	*x*	*y*	*Mean x/(x + y)*	*Variance xy/((x + y)^2*(x + y + 1))*	*Credible intervals*	
				P(X < x) = 0.33	*P(X < x) = 0.5*	*P(X < x) = 0.66*					*5 %*	*95 %*
1			>25	90	93	95	17.7	1.65	0.915	0.004	79.4	98.8
2		< 10	5 to 25	75	82	87	6.24	1.63	0.793	0.019	53.1	96.7
3			0–5	66*	73*	78*	7.42	2.99	0.713	0.018	47	90.7
4			>25	65	70	75	10.8	4.77	0.694	0.013	49.3	86.5
5	Very High	10 to 50	5 to 25	70	75	80	10.2	3.59	0.740	0.013	53.4	90.6
6			0–5	57	66	72	4.91	2.75	0.641	0.027	35.1	88.6
7			>25	65	67	72	19	9.07	0.677	0.008	52.7	81.2
8		>50	5 to 25	46*	56*	65*	2.96	2.39	0.553	0.039	21.7	86.4
9			0–5	40*	50*	63*	1.91	1.84	0.509	0.053	13.3	88
10			>25	65	78	81	3.54	1.37	0.721	0.034	37.1	96.4
11		< 10	5 to 25	68	75	78	9.91	3.7	0.728	0.014	51.8	89.9
12			0–5	55	60	64	13.1	8.88	0.596	0.010	42.1	75.9
13			>25	60*	65*	70*	10.9	5.98	0.646	0.013	45	82.2
14	High	10 to 50	5 to 25	50*	59	68	3.37	2.41	0.583	0.036	25.5	87.6
15			0–5	43	54	63	2.6	2.29	0.532	0.042	18.7	86.1
16			>25	40	50	58	2.95	3	0.496	0.036	18.5	80.8
17		>50	5 to 25	39*	47*	56*	3.16	3.47	0.477	0.033	18.4	77.9
18			0–5	32*	41*	49*	2.67	3.74	0.417	0.033	13.5	73
19			>25	55	60	64	13.1	8.88	0.596	0.010	42.1	75.9
20		< 10	5 to 25	42*	48*	55*	5.37	5.7	0.485	0.021	25	72.4
21			0–5	35	40	45	7.2	10.6	0.404	0.013	22.4	59.7
22			>25	36*	43*	52*	3.23	4.07	0.442	0.030	16.8	73.6
23	Moderate	10 to 50	5 to 25	33*	40*	46*	4.28	6.32	0.404	0.021	17.7	65.2
24			0–5	25*	33*	40*	2.51	4.85	0.341	0.027	9.89	63.6
25			>25	25	30	40	2.32	4.66	0.332	0.028	8.86	63.3
26		>50	5 to 25	22	29	36	2.42	5.49	0.306	0.024	8.34	58.8
27			0–5	15	21	26	2.2	7.57	0.225	0.016	5.22	46.4
28			>25	27	33	40	3.4	6.49	0.344	0.021	12.6	59.9
29		< 10	5 to 25	19	26	36	1.54	3.68	0.295	0.033	4.68	63.8
30			0–5	15	21	28	1.75	5.66	0.236	0.021	4.21	51.4
31			>25	13*	19*	28*	1.23	4.1	0.231	0.028	2.37	55.8
32	Low	10 to 50	5 to 25	15	20	25	2.52	9.19	0.215	0.013	5.72	43.1
33			0–5	8	10	12	4.28	36.1	0.106	0.002	3.99	19.5
34			>25	4.5	8	13.5	0.77	5.61	0.121	0.014	0.33	36.9
35		>50	5 to 25	5	7	9	2.25	26.2	0.079	0.002	1.7	17.4
36			0–5	3	5	7	1.23	18.4	0.063	0.003	0.55	17

[a] x and y are shape parameters specifying the beta distribution and used to calculate the mean and variance.
[b] Consensus mean and tertile judgements marked by an asterisk (*) were automatically generated in SHELF, by linear aggregation for Scenarios where experts could not reach consensus.

recruited based on knowledge of the transfer dynamics of FIOs in the environment, experience in STS-related work and broad knowledge of the management of catchment-scale diffuse pollution sources of FIOs. Invitations were sent by email to eight experts in research/academia and environmental regulation. Five experts from research and academia were available to participate in the workshop; however, the regulators declined the invitation. The expertise of the team spanned the fields of environmental microbiology, soil and catchment science and water resource management. The experts were furnished with an evidence dossier (available in the Supplementary materials), which gave a concise summary of existing information in the literature linked to the factors that influence FIO transfer from STS and subsequent delivery to watercourses. The dossier together with the scenarios of STS effluent movement risk, distance to watercourse, and slope were shared two weeks prior to the workshop to allow experts enough time to read the documents and provide additional evidence. To enable experts to understand how to make probability judgements, one week before the workshop all the experts took a self-paced SHELF e-learning course accessed through the SHELF website (https://shelf.sites.sheffield.ac.uk/e-learning-course). The elicitation workshop was held in-person over a single day (total of 7 h), starting with an information sharing session to discuss any issues from the evidence dossier and the e-learning course.

2.2.1. *Individual elicitation*

The tertile method (generates two tertiles-T1 and T2, which divide the plausible range of values elicited for the unknown QoI, into three intervals each with a 0.33 probability) was used at the individual elicitation stage. To eliminate potential bias from over-confidence and anchoring, experts began by defining a plausible range (i.e., between 0, denoting the lower limit (L), and 100, denoting the upper limit (U)) within which a value of *p*FIO was likely to lie for all scenarios. For each scenario, experts individually elicited a median value at which they judged it equally likely for *p*FIO to be below or above. Experts then elicited a lower tertile 1 (T1) and an upper tertile 2 (T2) by giving values that divided the plausible range into three equiprobable regions meaning that T1 was a value between L and M and T2 was a value between M and U. A further rule guiding the elicitation at this stage was that the tertiles had to be elicited in such a way that the interval between T1 and T2 (t) was less than the interval between L and T1 (l) and between M and T2 (u). The values were recorded in real-time on online excel spreadsheets.

2.2.2. *Fitting probability distribution curves*

Beta distributions were fitted and plotted in the SHELF R package, version 1.9.0, using pre-prepared code in R markdown scripts and feedback was generated in real time for the consensus group discussion. Beta distributions were used as the best fitting distribution to constrain the experts' judgements within the 0–1 range (Gosling, 2018).

2.2.3. Group consensus

The experts used the tertile method where they agreed to consensus median and tertile values. In cases where the experts could not reach consensus, they agreed to use a linear pool automatically generated in the SHELF R package representing a weighted average of the individual distributions summing to 1 (O'Hagan, 2006). Although desirable, experts are not expected to reach a consensus that represents all their views but might be asked to give the perspective of a Rational Impartial Observer (RIO) who has seen their judgements and has been listening to their discussions. After all scenarios in each effluent movement risk category were judged by the experts, we reviewed all 9 scenarios as a series to discuss and confirm the determined probability distributions. Therefore, any unusual distributions were discussed, and revisions made as needed.

3. Results

Five experts participated in the elicitation workshop. The individual expert judgements elicited for each of the 36 scenarios are presented in the supplementary material. Consensus values determined during the group discussion stage together with the 36 scenarios that guided the elicitation and summary statistics describing the consensus probability density functions provide a detailed overview of the discussion (Table 2). Exemplars of individual and consensus probability density functions depicting judgements for the highest and lowest proportion of FIOs likely to be delivered to a watercourse from an STS are represented in Figs. 2 and 3, respectively. High uncertainty in the expert judgements for intermediate risk scenarios is represented by less overlap in the individual probability distribution curves (e.g., Fig. 4). In instances where experts could not reach a consensus, they relied on a linear pool (e.g., Fig. 5). Fig. 6 shows the distribution curves for all the 36 scenarios.

3.1. Overview of findings

The experts judged that scenario 1 with very high STS effluent movement risk where STS were located within 10 m of a watercourse on a steep slope with gradient >25 %, posed the highest risk of FIO export, with 93 % of FIOs judged likely to be transferred from an STS to the watercourse. The high confidence in this value is evident from the overlap of the individual expert probability distribution curves, the narrow range of the consensus curve (Fig. 2) and constrained 90 % credible interval (CI) of 79.4–98.8 %. For scenario 36, which represented low risk conditions where STS effluent movement risk was low, STS were located at a distance >50 m from a watercourse on a gentle slope of 0–5 %, experts were confident that the FIO proportion likely to be transferred to the watercourse was reduced to 5 %. In common with scenario 1, there was strong consensus in the range of values provided for scenario 36 as evidenced in the high overlap of individual probability distribution curves and narrow range of the consensus curve (Fig. 3). Expert confidence in the elicited values for these two scenarios is attributed to the combination of driving factors representing extreme conditions that were likely to increase or decrease the proportion of FIOs that would be transferred to a watercourse.

Uncertainty in individual expert judgements was high in scenarios 7–24 representing intermediate conditions (Fig. 6). Individual probability distribution curves for these scenarios had less overlap and the resultant consensus curves had a wide CI implying a wide dispersion of the value of *p*FIO from the median. Scenario 9 had the largest CI of 13.3–88 % and therefore the highest uncertainty (Fig. 4). The experts could not reach a consensus for this scenario and therefore agreed to use a linear pool that averaged their individual judgements (Fig. 5). The linear pool generated tertile values (T1 = 40 %, T2 = 63 %) and a median of 50 %, giving the proportion of FIOs likely to be delivered to a watercourse for this scenario equally likely to be below or above 50 %. There were a total of 10 scenarios for which experts opted to use a linear pool as an alternative to reaching consensus. Of those 10 scenarios, 60 % were within the moderate to high STS effluent movement risk category, demonstrating increased uncertainty within these categories. High uncertainty for these scenarios is evidence that different experts attached different levels of importance to the factors included in the elicitation.

3.2. Factors that were considered more influential than others

Three experts considered STS effluent movement risk classifications under the HOST model to be the most influential factor. Their assessment was grounded in their prior experience with HOST models and the perception that soil characteristics played a significant role in determining the hydrological connectivity of a system, which, in turn, facilitated the transfer of FIOs. Two experts deemed the angle of slope to be the primary factor influencing the transportation of FIOs. They noted that steep slopes encourage overland flow, leading to the delivery of FIOs to watercourses. In contrast, gentle slopes facilitate the retention of effluent within the landscape, resulting in the natural die-off of FIOs and preventing their entry into watercourses. Distance was secondary as effluent surface runoff potential or leaching to groundwater was likely to be influenced first by soil hydro-morphological properties and slope, irrespective of whether a STS was located close to a watercourse or not. The high importance of STS effluent movement risk relative to the HOST classes is reflected in the shift in the range of values elicited for *p*FIO in relation to low (5–33 %), medium (21–43 %), high (41–78 %) or very high (50–93 %) STS effluent movement risk. Slope was considered to have a significant influence on *p*FIO if the STS was located <10 m from a

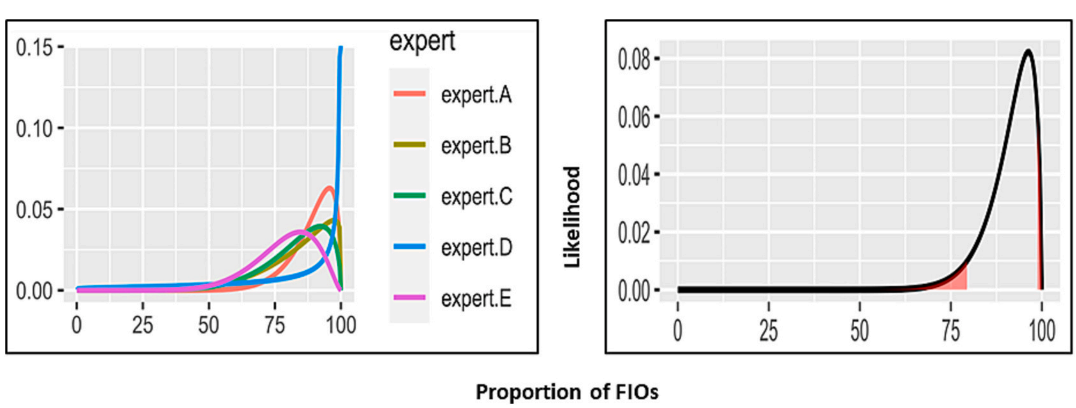


Fig. 2. Probability density curves of 5 individual expert judgements (left) and consensus beta distribution (right) of the proportion of FIOs (median 93) likely to be delivered to a watercourse under the highest risk Scenario 1 combining very high STS effluent movement risk, septic tank distance to watercourse of <10 m and steep slope > 25 %. The red regions in panel b represent the 5th (79.4) and 95th percentiles (98.8).

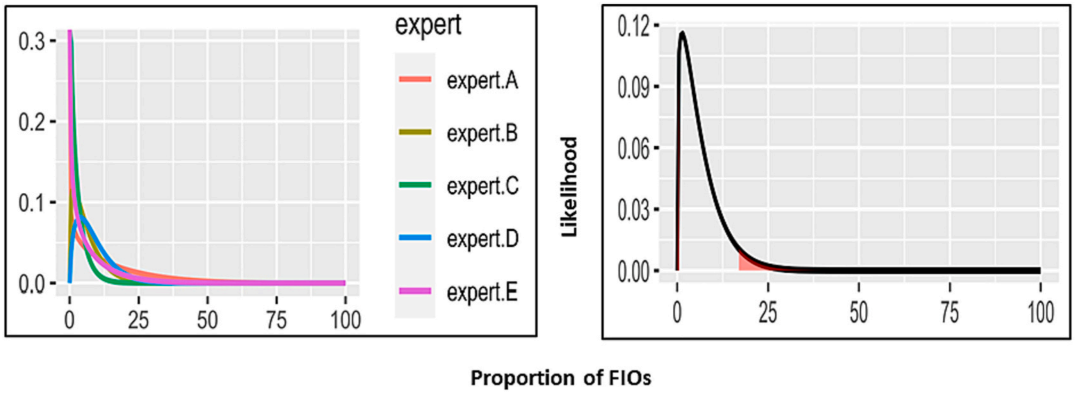


Fig. 3. Individual expert probability density curves (left) and consensus beta distribution curve (right) of the proportion of FIOs (median 5 %) likely to be delivered to a watercourse under Scenario 36 combining low STS effluent movement risk, septic tank distance to watercourse of >50 m and gentle slope 0–5 %. The red regions on panel b represent the 5th (0.55) and 95th percentiles (17.0).

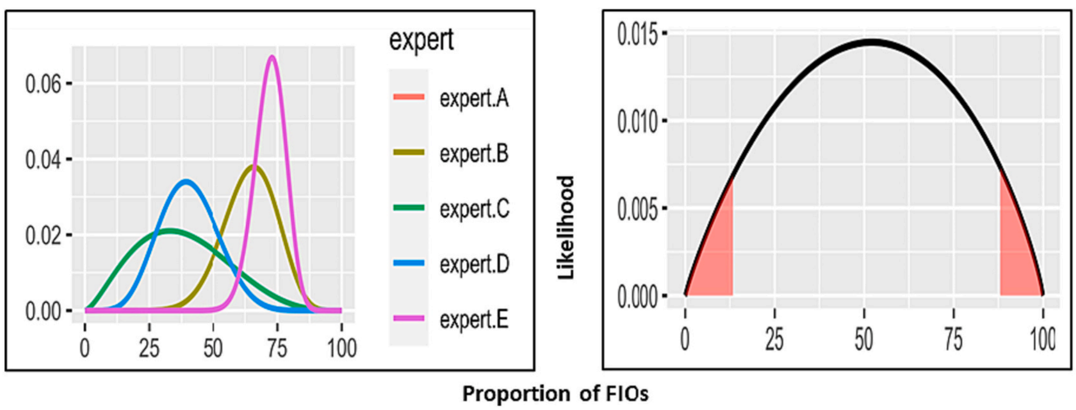


Fig. 4. Individual probability density curves with less overlap (left) and wide range consensus beta distribution curve (right) showing high uncertainty in judgements given for Scenario 9 combining very high STS effluent movement risk, septic tank distance to watercourse of >50 m and gentle slope 0–5 %. The red regions on panel b represent the 5th (13.3) and 95th percentiles (88.0).

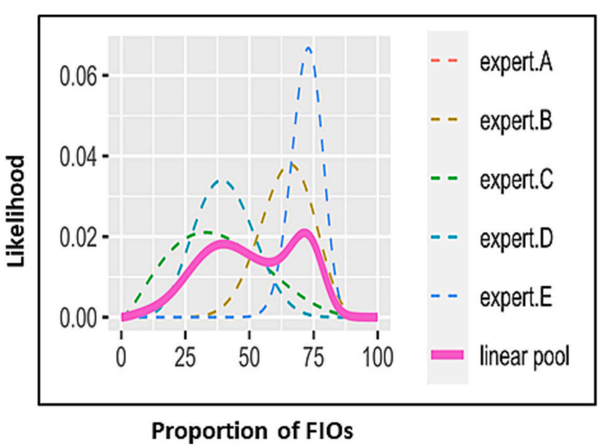


Fig. 5. Linear pool (LP) of individual expert judgements which experts used for Scenario 9 where they could not reach a consensus. The LP tertile and median values were used to plot the consensus probability density curve for Scenario 9 in Fig. 4(b).

watercourse, compared to being >50 m away. A steep slope of 25 % compared to gentle slope of 5 % increased *p*FIO by an average of 9 % if a STS was located >50 m from a watercourse across all four STS effluent movement risk classes. However, the same change in gradient (5 % to 25 %) increased *p*FIO by approximately 20 % if the STS distance to a watercourse was <10 m. Similarly, the influence of distance on *p*FIO was considered significant if a STS was located on a steep slope compared to a gentle slope. STS located on a steep slope, <10 m to a watercourse would deliver approximately 27 % more FIOs compared to those located >50 m away. If a STS was located on a gentle slope, the same change in distance (10 to 50 m) resulted in reduction of *pFIO* delivered by an average of 19 %.

4. Discussion

Here, we have successfully used the SHELF approach to elicit expert judgements on the proportion of FIOs that could be potentially transferred from STS to receiving waters. Our study, therefore, provides useful findings linking different scenarios of STS locations in catchments (as governed by effluent movement risk properties of soils, slope and proximity to water) and expert judgements of FIO transfer to receiving waters. Levels of uncertainty associated with expert judgements in the estimated risk of FIO loss from STS to water varied across different scenarios, but the information derived from the elicitation procedure provides useful data on relative importance of STS site characteristics and magnitudes of uncertainty attributed to different scenarios. To improve our predictions of FIO risk to water quality within a catchment, we need to understand the role of different FIO sources, including contributions from STS (Beal et al., 2005; Richards et al., 2016; Tuholske et al., 2021). In the absence of empirical data, the expert judgements obtained in this study provide both a first estimate for FIO transfer from STS to watercourses and a quantification of the uncertainty involved.

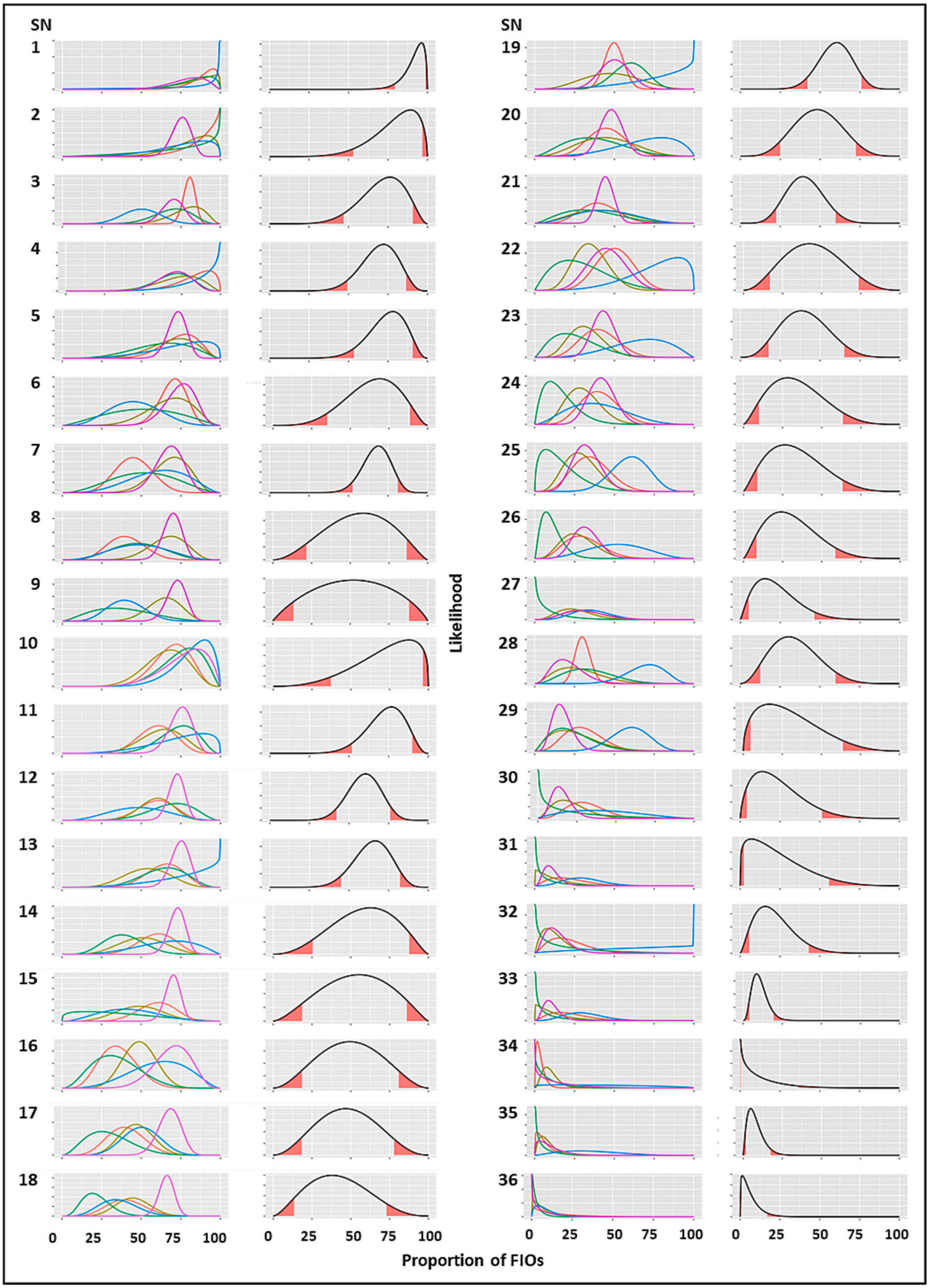


Fig. 6. Individual expert distribution curves (left) vs probability density functions (right) for the 36 elicitation Scenarios. SN denotes Scenario Numbers. The x-axis shows the elicited proportions of FIOs on a scale of 0–100. The y-axis shows the likelihood of observing these proportions on a probability distribution function. The scale of the y-axis varies from 0 to 0.2 for the individual expert distribution curves and 0 to 0.12 on the consensus probability density functions. See the Supplementary material for the original plots with actual scales of axes.

These outputs contribute to an improved understanding of how FIO loss from STS may vary in different catchment situations, which is fundamentally important for informing accurate risk assessment approaches at the landscape scale and to parameterise risk-based models (Fish et al., 2009; Oliver et al., 2009).

Our findings highlighted strong consensus in expert judgements made for scenarios representing extreme conditions, for example, the scenario representing the highest and lowest risks. Uncertainty was high for scenarios representing intermediate conditions revealing different weighting of the factors that drive FIO transfer from STS to watercourses and highlighting important areas for future investigation to ensure targeted interventions to minimise potential pollution. There was a general pattern of decline in the median FIO loss with increasing scenario number within each of the effluent movement risk categories (Table 2). However, closer inspection revealed occasional increases in FIO loss that reflects the trade-off in how experts perceived risk associated with distance to watercourse vs slope. The patterns are consistent across each effluent movement risk category, signalling a degree of robustness in how experts assigned and reflected on their judgements.

Expert values and preferences may differ based on expertise and previous research experience, but extreme scenarios can be points of agreement when several factors are under consideration as interactions between factors are probably more obvious and can be imagined with relative ease (Ban et al., 2014). Our approach used a combination of three factors (effluent movement risk, distance and slope) and the extreme scenarios represented areas with combined effect of extreme levels of these three factors for which interactions were obvious and resulted in experts reaching consensus with relative ease. This demonstrated that the experts assigned similar levels of importance to the factors that guided the elicitation since making predictive judgements is a matter of value and preference of those making the judgements (O'Hagan, 2006). Further, the judgements made for these scenarios were supported by available evidence from the literature that reports FIO delivery loads from STS relative to distance to watercourse thresholds, i.e., 100 % delivery if STS are located <50 m to a watercourse and significant reduction to negligible levels if STS are situated >200 m from a watercourse (Gill and Mockler, 2016). As the factors varied in the intermediate scenarios, uncertainty increased demonstrating that experts attached different levels of importance to the factors and interactions thereof (Donfrancesco et al., 2023). However, these scenarios were highly debatable due to limited evidence on the influence of, for example, 50 m distance or slope of 5–25 % even if the effluent movement risk was high (Jansen et al., 2020).

While there is very limited evidence for the specific context of FIO delivery from STS to receiving waters, experts will likely be aware of the evidence base that supports ideas of FIO transfer from land to water (e.g., by different soil types and field slopes), and FIO delivery being influenced by distance to streams or buffer strips (Buckerfield et al., 2019a, 2019b; Gagkas and Lilly, 2019; Glendell et al., 2018; Murphy et al., 2015; Neill et al., 2020). The challenge for this elicitation process then becomes one of translating that wider expert understanding to the STS scenarios devised for this study. To aid this process, a clear definition of the QoI supported by scientific evidence is important to avoid ambiguity and potential misinterpretation of the elicitation results by the end users (Gosling, 2018; Verzobio et al., 2021). While other studies in conservation biology have involved experts in structuring the identified QoI to determine what was most manageable (Fitzgerald et al., 2021), in this study, the experts were presented with pre-defined scenarios that they discussed and revised accordingly. This was necessary to avoid any ambiguity, which can potentially be high when the structure of the QoI is pre-defined (Höfer et al., 2020). This approach was also more straightforward as it averted potential conflicting views among the experts in structuring the QoI and reduced the duration required for the elicitation workshop. In large scale elicitation processes, such an approach can potentially increase efficiency as parts of the elicitation process can be outsourced to specialised contractors (European Food Safety Authority, 2014).

The discussions preceding the elicitation helped to clarify ambiguities in the QoI, highlighting the importance of close engagement of experts prior to and in the initial stages of elicitation (von Haefen et al., 2023). One such ambiguity clarified before the elicitation procedure was that of the FIO delivery timeframe under consideration. The experts observed that the timeframe for FIO delivery from STS to receiving waters could be on an annual, seasonal or event-driven basis, all of which would have different outcomes dependent on prevailing hydrological and environmental conditions. Therefore, the delivery of FIOs over an annual timeframe was confirmed for our investigation, establishing a measurement timeframe meaningful to the experts and ultimately the users of the results of this elicitation process (Quigley and Walls, 2021). A further source of uncertainty was in the phrasing used to define distance. For instance, >50 m could be interpreted as 51 m or any distance thereafter; slope of >25 % could be 26 % through to 100 %. Using discrete values rather than a range would likely be less ambiguous in structuring the QoI because a discrete value can form a common reference point; however, this would present a challenge for future FIO model parameterisation using the probability density functions determined through elicitation for any STS not included in the specified distance or slope.

Eliciting the QoI based on a single factor, for example just slope, rather than integrating all three factors would have been conceptually easier but would not represent how these factors interact in reality. Furthermore, evidence is available for how these factors in isolation influence FIO STS effluent movement risk based on factors such as distance (Tamang et al., 2022), soil properties (Gagkas and Lilly, 2019) and slope (Glendell et al., 2022). Thus the 36 scenarios devised in our study intended to bring this evidence together to explore expert opinion of how these conditions interact to influence FIO delivery. While this was desirable for our study, having many scenarios can potentially increase elicitation burden, resulting in declining quality of information provided by the experts due to a longer elicitation process and participant fatigue (Fraser et al., 2023). Similar studies utilising the IDEA (Investigate, Discuss, Estimate, Aggregate) protocol, recommend asking no >15–20 questions in a single day of face-to-face elicitation to avoid expert fatigue (Hemming et al., 2020; Speirs-Bridge et al., 2010), although this will depend on the complexity of the questions, available time, and motivations of the experts. In our study, experts indicated that the number of scenarios was daunting at first but became easy to work through as the workshop progressed. Structuring the elicitation scenarios into four categories helped to break the 36 scenarios into a manageable workload, and reduce expert fatigue (Falconer et al., 2021). Another strategy the experts used, which made the process less daunting, was to begin by making judgements for the two extreme scenarios 1 and 36, followed by a consensus discussion of these two scenarios. This helped the experts to familiarise themselves with the process, build confidence to work through the rest of the scenarios and provided an important calibration step to help deal with the issue of relativity across scenarios. During post elicitation workshop discussion, the experts suggested that a longer workshop, for example, focussed on individual elicitations in one day and the consensus discussions on another day would have made the process less tiring; however, approaches are often constrained by competing demands on availability, time and resources (Fitzgerald et al., 2021).

The experts adopted different methods to arrive at a consensus and this varied between scenarios. For some scenarios, experts who specified widely varying distributions shifted their judgements to reflect the beliefs of the group. For other scenarios, the experts selected a single expert distribution they found representative of their joint beliefs and adjusted their judgements accordingly. Where experts could not reach a consensus, they used a linear pool which was a weighted average of their individual distributions generated in the SHELF R package. To avoid distraction, which can potentially arise from some experts preferring to use the linear pool as a fall-back for a seemingly objective way of combining their judgements (Gosling, 2018), the linear pool was not included in the visualization of the density curves shown at the beginning of the consensus discussion. Rather, it was shown to experts after they opted to use it. Where experts felt that the linear pool did not represent their beliefs, they used an average of the values generated by the linear pool and a single expert distribution they found representative of their beliefs. This consensus building process not only reveals the level of flexibility within SHELF, but most importantly allows for iterative discussion of the QoI considering relevant evidence and has been found to be effective at capturing group opinion (Kahneman et al., 2021). The flexibility of the experts during this consensus building stage speaks to the group dynamics during elicitation. The results of an elicitation process are prone to biases such as overconfidence and groupthink, i.e., when a group reaches consensus without critical reasoning, if one expert dominates the discussion. Structured elicitation processes managed by an experienced facilitator who understands the dynamics of group discussions and decision-making based on group consensus, can help to ensure that the knowledge of all experts is recognised and therefore incorporated in the outcome of the elicitation (O'Hagan, 2006; Randle et al., 2019; Speirs-Bridge et al., 2010). Further, providing initial judgements privately and independently helps experts to retain independence in their judgements, thus mitigating against groupthink and deference to dominating personalities (Hanea et al., 2022).

Some limitations inherent in the analysis of expert judgements include: determining how representative the judgements are of all the experts and typical values likely to be obtained through laboratory analysis (O'Hagan, 2006); and reproducibility of the judgements over an ensemble of cases (Kahneman et al., 2021) and with a different group of experts. Unlike the IDEA protocol which has two rounds of individual elicitation before and after discussion (Hemming et al., 2018), the SHELF approach asks experts to create a consensus distribution after discussion and feedback, which corresponds to the group only, making it difficult to assess the impact of group discussions on individual distributions. Our study therefore relied on feedback from the experts on the level of engagement during discussions. All experts agreed that everyone was involved in the workshop and listened to others' opinions, and that no one dominated the discussion. One expert in the group was outspoken but posed reflective questions that encouraged discussion among the group. Experiments show that this group discussion phase often improves group judgements by improving both expert confidence and accuracy, denoting correspondence between the expert predictions and the observed outcomes (Hanea et al., 2018b); and improving individual judgements in terms of calibration and statistical accuracy (Hemming et al., 2020). The behavioural aggregation process embedded in SHELF significantly improves the quality of expert elicited data as the resultant consensus probability distribution represents the experts' subjective belief and collective uncertainty in a quantitative way consistent with probability theory and available evidence (O'Hagan, 2006). Our elicitation relied on this consensus building process to refine elicitation results. Additionally, experts took the SHELF e-learning course to equip them with knowledge and practice in eliciting personal probability distributions to enhance the quality of the judgements given.

It is important to highlight the transferability of the expert judgements, and combined probability density functions, that characterise the risk of FIO delivery from STS to watercourses across different scenarios derived from our study. The scenarios we used conceptualised STS-to-watercourse transfer using three key risk factors that are generally applicable across large areas of the world where STS are used as a decentralised wastewater management system. The degree of slope on which STS are situated and their proximity to a watercourse are highly transferable environmental variables and well recognised risk factors (Tyre et al., 2023; Wiesner-Friedman et al., 2022). Although the notion of effluent movement risk, represented by HOST in our study, makes the elicited proportions more representative of the UK, these can be modified to fit classifications of soils and associated hydrological pathways outside of the UK as a generalised concept (Baykus et al., 2022; Tamang et al., 2022). While the three risk factors integrated into our combined scenarios are recognised as key drivers of FIO risk (Glendell et al., 2018), the expert judgements provide only a first approximation of the likelihood of annual FIO delivery from STS to watercourses. This is because FIO transfer processes and their successful delivery to surface waters will be influenced by other environmental factors, such as potential impacts of artificial drainage networks, vegetation cover and landscape features, including microtopography (Lane et al., 2009; Reaney et al., 2019; Thomas et al., 2017). However, the level of influence on FIO transfer and delivery of such environmental variables is secondary to the main environmental factors considered in our elicitation approach; they contribute a degree of nuance to the over-riding patterns of FIO transfer as influenced by slope, distance and effluent movement risk. Their importance will also vary depending on geographic region, catchment type and landscape management approaches, and to determine the influence of different vegetation, drainage and microtopography requires more tailored, site-specific investigation, which is currently lacking. By linking together existing knowledge and structured expert judgements it is possible to develop first approximation assessments of FIO risks associated with STS as driven by generalised risk factors and in turn constrain the parameterisation of models that include FIO delivery coefficients from STS to better reflect a wider range of catchment risks.

5. Conclusion

In this study, we have demonstrated the usefulness of expert elicitation via the SHELF protocol for the acquisition of FIO proportions likely to be delivered from septic tanks to watercourses. Expert consensus was strong that the highest risk conditions would deliver over 90 % FIOs to the nearest watercourse and the proportion significantly dropped to 5 % for low-risk conditions. The high uncertainty surrounding FIO proportions likely to be delivered to watercourses from septic tanks under intermediate risk conditions highlighted important areas for further investigation through empirical research. Therefore, our application of the SHELF approach has delivered novel data to underpin risk assessment and model development in support of better land management decisions aimed at mitigating risk of pollution from septic tanks. In the absence of empirical data, the probability density functions derived from our expert elicitation provide an important dataset to help parameterise models designed to predict FIO pollution risk from multiple sources at the landscape scale.

Funding

This study was conducted as part of a PhD research funded by the Commonwealth Scholarship Commission in the UK awarded under the theme Science and Technology for Development.

CRediT authorship contribution statement

Chisha Chongo Mzyece: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. **Miriam Glendell:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing. **Zisis Gagkas:** Methodology, Validation, Writing – review & editing. **Richard S. Quilliam:** Data curation, Supervision, Validation, Writing – review & editing. **Ian Jones:** Methodology, Supervision, Writing – review & editing. **Eulyn Pagaling:** Data curation, Formal analysis, Validation, Writing – review & editing. **Ioanna Akoumianaki:** Data curation, Formal analysis, Investigation. **Claire Newman:** Data curation, Formal analysis, Investigation. **David M. Oliver:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

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

Data availability

We have shared the data in the supplementary materials. The R code used to generate the probability distribution curves can be shared on request

Acknowledgements

We acknowledge the UK Commonwealth Scholarship Commission for funding this PhD research. We thank Prof. Tony O'Hagan and Prof. Jeremy Oakley for the SHELF training and access to materials used in the elicitation. Thank you to Camilla Negri from the James Hutton Institute for recording the workshop discussion and Dr. Anastasia Frantsuzova from Biomathematics and Statistics Scotland for guidance throughout the elicitation process. Many thanks to Dr. Kutemba Kakoma from the National Institute for Scientific and Industrial Research for editing the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.171074.

References

Afolabi, E.O., Quilliam, R.S., Oliver, D.M., 2020. Impact of freeze–thaw cycles on die-off of E. Coli and intestinal enterococci in deer and dairy faeces: implications for landscape contamination of watercourses. Int. J. Environ. Res. Public Health 17 (19), 1–16. https://doi.org/10.3390/ijerph17196999.

Akoumianaki, I., Ibiyemi, A., 2022. Understanding Problems Associated with Small-Scale Private Sewage Systems (PSS) from regulators' Perspectives Appendices Ioanna Akoumianaki and Adekunle Ibiyemi.

Ban, S.S., Pressey, R.L., Graham, N.A.J., 2014. Assessing interactions of multiple stressors when data are limited: a Bayesian belief network applied to coral reefs. Glob. Environ. Chang. 27 (1), 64–72. https://doi.org/10.1016/j.gloenvcha.2014.04.018.

Baykus, N., Karpuzcu, M., Yurtsever, A., 2022. An investigation into the role of treatment performance and soil characteristics of soil-based wastewater treatment systems. Water Sci. Technol. 85 (1), 125–140. https://doi.org/10.2166/wst.2021.512.

Beal, C.D., Gardner, E.A., Menzies, N.W., 2005. Process, performance, and pollution potential: a review of septic tank–soil absorption systems. Soil Research 43 (7), 781–802. https://doi.org/10.1071/SR05018.

Best, N., Dallow, N., Montague, T., 2020. Prior elicitation. Bayesian methods in pharmaceutical research. In: Lesaffre, E., Baio, G., Boulanger, B. (Eds.), Bayesian Methods in Pharmaceutical Research, illustrated ed. CRC Press, pp. 87–109.

Boorman, D.B., Hollis, J.M., John, M., Lilly, A., Soil Survey & Land Research Centre (Great Britain), Macaulay Land Use Research Institute, Natural Environment Research Council (Great Britain), 1995. Hydrology of Soil Types: A Hydrologically-Based Classification of the Soils of the United Kingdom (Institute of Hydrology).

Brewton, R.A., Kreiger, L.B., Tyre, K.N., Baladi, D., Wilking, L.E., Herren, L.W., Lapointe, B.E., 2022. Septic system–groundwater–surface water couplings in waterfront communities contribute to harmful algal blooms in Southwest Florida. Sci. Total Environ. 837 https://doi.org/10.1016/j.scitotenv.2022.155319.

Buckerfield, S.J., Quilliam, R.S., Waldron, S., Naylor, L.A., Li, S., Oliver, D.M., 2019a. Rainfall-driven E. Coli transfer to the stream-conduit network observed through increasing spatial scales in mixed land-use paddy farming karst terrain. Water Research X 5. https://doi.org/10.1016/j.wroa.2019.100038.

Buckerfield, S.J., Waldron, S., Quilliam, R.S., Naylor, L.A., Li, S., Oliver, D.M., 2019b. How can we improve understanding of faecal indicator dynamics in karst systems under changing climatic, population, and land use stressors? – Research opportunities in SW China. In: Science of the Total Environment, vol. 646. Elsevier B. V, pp. 438–447. https://doi.org/10.1016/j.scitotenv.2018.07.292.

Courtney Jones, S.K., Geange, S.R., Hanea, A., Camac, J., Hemming, V., Doobov, B., Leigh, A., Nicotra, A.B., 2023. IDEAcology: an interface to streamline and facilitate efficient, rigorous expert elicitation in ecology. Methods Ecol. Evol. https://doi.org/10.1111/2041-210X.14017.

D'Arcy, B.J., Kay, D., Napier, F., Haygarth, P., Sun, Y.Y., Wada, K., 2022. Land use and diffuse pollution: Are perceptions part of the problem?. In: Land Use and Water Quality: The Impacts of Diffuse Pollution. IWA Publishing, pp. 1–24. https://doi.org/10.2166/9781789061123_001.

Donfrancesco, V., Allen, B.L., Appleby, R., Behrendorff, L., Conroy, G., Crowther, M.S., Dickman, C.R., Doherty, T., Fancourt, B.A., Gordon, C.E., Jackson, S.M., Johnson, C. N., Kennedy, M.S., Koungoulos, L., Letnic, M., Leung, L.K.P., Mitchell, K.J., Nesbitt, B., Newsome, T., Cairns, K.M., 2023. Understanding conflict among experts working on controversial species: a case study on the Australian dingo. Conservation Science and Practice 5 (3). https://doi.org/10.1111/csp2.12900.

European Food Safety Authority, 2014. Guidance on expert knowledge elicitation in food and feed safety risk assessment. In: EFSA Journal, vol. 12, Issue 6. Wiley-Blackwell Publishing Ltd. https://doi.org/10.2903/j.efsa.2014.3734

Falconer, J. R., Frank, E., Polaschek, D. L. L., & Joshi, C. (2021). Methods for Eliciting Informative Prior Distributions: A Critical Review. http://arxiv.org/abs/2112.07090.

Fish, R., Winter, M., Oliver, D.M., Chadwick, D., Selfa, T., Heathwaite, A.L., Hodgson, C., 2009. Unruly pathogens: eliciting values for environmental risk in the context of heterogeneous expert knowledge. Environ Sci Policy 12 (3), 281–296. https://doi.org/10.1016/j.envsci.2009.02.002.

Fitzgerald, D.B., Smith, D.R., Culver, D.C., Feller, D., Fong, D.W., Hajenga, J., Niemiller, M.L., Nolfi, D.C., Orndorff, W.D., Douglas, B., Maloney, K.O., Young, J.A., 2021. Using expert knowledge to support endangered species act decision-making for data-deficient species. Conserv. Biol. 35 (5), 1627–1638. https://doi.org/10.1111/cobi.13694.

Fraser, H., Bush, M., Wintle, B.C., Mody, F., Smith, E.T., Hanea, A.M., Gould, E., Hemming, V., Hamilton, D.G., Rumpff, L., Wilkinson, D.P., Pearson, R., Thorn, F.S., Ashton, R., Willcox, A., Gray, C.T., Head, A., Ross, M., Groenewegen, R., Fidler, F., 2023. Predicting reliability through structured expert elicitation with the repliCATS (Collaborative Assessments for Trustworthy Science) process. PLoS ONE 18 (1 January). https://doi.org/10.1371/journal.pone.0274429.

Gagkas, Z., Lilly, A., 2019. Downscaling soil hydrological mapping used to predict catchment hydrological response with random forests. Geoderma 341, 216–235. https://doi.org/10.1016/j.geoderma.2019.01.048.

Gagkas, Z., Lilly, A., Baggaley, N.J., 2021. Digital soil maps can perform as well as large-scale conventional soil maps for the prediction of catchment baseflows. Geoderma 400. https://doi.org/10.1016/j.geoderma.2021.115230.

Gill, L.W., Mockler, E.M., 2016. Modeling the pathways and attenuation of nutrients from domestic wastewater treatment systems at a catchment scale. Environmental Modelling and Software 84, 363–377. https://doi.org/10.1016/j.envsoft.2016.07.006.

Glendell, M., Gagkas, Z., Richards, S., Halliday, S., 2018. Developing a Probabilistic Risk Model to Estimate Phosphorus, Nitrogen and Microbial Pollution to Water from Septic Tanks Full Report.

Glendell, M., Gagkas, Z., Stutter, M., Richards, S., Lilly, A., Vinten, A., Coull, M., 2022. A systems approach to modelling phosphorus pollution risk in Scottish rivers using a spatial Bayesian belief network helps targeting effective mitigation measures. Front. Environ. Sci. 10 https://doi.org/10.3389/fenvs.2022.976933.

Gosling, J.P., 2018. SHELF: the Sheffield elicitation framework. In: Elicitation. The Science and Art of Structuring Judgement, pp. 61–93. https://doi.org/10.1007/978-3-319-65052-4_4.

Hanea, A.M., Burgman, M., Hemming, V., 2018a. IDEA for Uncertainty Quantification, pp. 95–117. https://doi.org/10.1007/978-3-319-65052-4_5.

Hanea, A.M., McBride, M.F., Burgman, M.A., Wintle, B.C., 2018b. The value of performance weights and discussion in aggregated expert judgments. Risk Anal. 38 (9), 1781–1794. https://doi.org/10.1111/risa.12992.

Hanea, A.M., Hemming, V., Nane, G.F., 2022. Uncertainty quantification with experts: Present status and research needs. In: Risk Analysis, Vol. 42. John Wiley and Sons Inc., pp. 254–263. https://doi.org/10.1111/risa.13718 (Issue 2).

Hemming, V., Burgman, M.A., Hanea, A.M., McBride, M.F., Wintle, B.C., 2018. A practical guide to structured expert elicitation using the IDEA protocol. Methods Ecol. Evol. 9 (1), 169–180. https://doi.org/10.1111/2041-210X.12857.

Hemming, V., Armstrong, N., Burgman, M.A., Hanea, A.M., 2020. Improving expert forecasts in reliability: application and evidence for structured elicitation protocols. Quality and Reliability Engineering International 36 (2), 623–641. https://doi.org/10.1002/qre.2596.

Höfer, S., Ziemba, A., El Serafy, G., 2020. A Bayesian approach to ecosystem service trade-off analysis utilizing expert knowledge. Environ. Syst. Decis. 40 (1), 67–83. https://doi.org/10.1007/s10669-019-09742-2.

Humphrey, C.P., Sanderford, C., Iverson, G., 2018. Concentrations and exports of fecal Indicator Bacteria in watersheds with varying densities of onsite wastewater systems. Water Air Soil Pollut. 229 (8) https://doi.org/10.1007/s11270-018-3929-4.

Igere, B.E., Okoh, A.I., Nwodo, U.U., 2020. Wastewater treatment plants and release: The vase of Odin for emerging bacterial contaminants, resistance and determinant of environmental wellness. In: Emerging Contaminants, vol. 6. KeAi Communications Co., pp. 212–224. https://doi.org/10.1016/j.emcon.2020.05.003

Iverson, G., Humphrey, C.P., O'Driscoll, M.A., Sanderford, C., Jernigan, J., Serozi, B., 2018. Nutrient exports from watersheds with varying septic system densities in the North Carolina Piedmont. J. Environ. Manage. 211, 206–217. https://doi.org/10.1016/j.jenvman.2018.01.063.

Iverson, G., Sanderford, C., Humphrey, C.P., Etheridge, J.R., Kelley, T., 2020. Fecal indicator bacteria transport from watersheds with differing wastewater technologies and septic system densities. Applied Sciences (Switzerland) 10 (18). https://doi.org/10.3390/APP10186525.

Jansen, J.O., Wang, H., Holcomb, J.B., Harvin, J.A., Richman, J., Avritscher, E., Stephens, S.W., Truong, V.T.T., Marques, M.B., DeSantis, S.M., Yamal, J.M., Pedroza, C., 2020. Elicitation of prior probability distributions for a proposed Bayesian randomized clinical trial of whole blood for trauma resuscitation. Transfusion 60 (3), 498–506. https://doi.org/10.1111/trf.15675.

Kahneman, D., Sibony, O., Sunstein, C.R., 2021. Noise: A Flaw in Human Judgment. Little, Brown.

Krueger, T., Page, T., Hubacek, K., Smith, L., Hiscock, K., 2012. The role of expert opinion in environmental modelling. Environmental Modelling and Software 36, 4–18. https://doi.org/10.1016/j.envsoft.2012.01.011.
Lane, S.N., Reaney, S.M., Heathwaite, A.L., 2009. Representation of landscape hydrological connectivity using a topographically driven surface flow index. Water Resour. Res. 45 (8) https://doi.org/10.1029/2008WR007336.
Li, B., Ju, F., Cai, L., Zhang, T., 2015. Profile and fate of bacterial pathogens in sewage treatment plants revealed by high-throughput metagenomic approach. Environ. Sci. Tech. 49 (17), 10492–10502. https://doi.org/10.1021/acs.est.5b02345.
Lilly A, & Baggaley N. (2014). Developing simple indicators to assess the role of soils in determining risks to water quality. www.crew.ac.uk/publications.
Murphy, H.M., McGinnis, S., Blunt, R., Stokdyk, J., Wu, J., Cagle, A., Denno, D.M., Spencer, S., Firnstahl, A., Borchardt, M.A., 2020. Septic systems and rainfall influence human fecal marker and Indicator organism occurrence in Private Wells in southeastern Pennsylvania. Environ. Sci. Tech. 54 (6), 3159–3168. https://doi.org/10.1021/acs.est.9b05405.
Murphy, S., Jordan, P., Mellander, P.E., O' Flaherty, V., 2015. Quantifying faecal indicator organism hydrological transfer pathways and phases in agricultural catchments. Sci. Total Environ. 520, 286–299. https://doi.org/10.1016/j.scitotenv.2015.02.017.
Naidoo, S., Olaniran, A.O., 2013. Treated wastewater effluent as a source of microbial pollution of surface water resources. In: International Journal of Environmental Research and Public Health, Vol. 11. MDPI, pp. 249–270. https://doi.org/10.3390/ijerph110100249 (Issue 1).
Neill, A.J., Tetzlaff, D., Strachan, N.J.C., Hough, R.L., Avery, L.M., Watson, H., Soulsby, C., 2018. Using spatial-stream-network models and long-term data to understand and predict dynamics of faecal contamination in a mixed land-use catchment. Sci. Total Environ. 612, 840–852. https://doi.org/10.1016/j.scitotenv.2017.08.151.
Neill, A.J., Tetzlaff, D., Strachan, N.J.C., Hough, R.L., Avery, L.M., Maneta, M.P., Soulsby, C., 2020. An agent-based model that simulates the spatio-temporal dynamics of sources and transfer mechanisms contributing faecal indicator organisms to streams. Part 2: application to a small agricultural catchment. J. Environ. Manage. 270 https://doi.org/10.1016/j.jenvman.2020.110905.
O'Hagan, Anthony, 2006. Uncertain Judgements: Eliciting experts' Probabilities. Wiley.
Oliver, D.M., Fish, R.D., Hodgson, C.J., Heathwaite, A.L., Chadwick, D.R., Winter, M., 2009. A cross-disciplinary toolkit to assess the risk of faecal indicator loss from grassland farm systems to surface waters. Agric. Ecosyst. Environ. 129 (4), 401–412. https://doi.org/10.1016/j.agee.2008.10.019.
Oliver, D.M., Page, T., Hodgson, C.J., Heathwaite, A.L., Chadwick, D.R., Fish, R.D., Winter, M., 2010. Development and testing of a risk indexing framework to determine field-scale critical source areas of faecal bacteria on grassland. Environ. Model. Softw. 25 (4), 503–512. https://doi.org/10.1016/j.envsoft.2009.10.003.
Oliver, D.M., Porter, K.D.H., Pachepsky, Y.A., Muirhead, R.W., Reaney, S.M., Coffey, R., Kay, D., Milledge, D.G., Hong, E., Anthony, S.G., Page, T., Bloodworth, J.W., Mellander, P.E., Carbonneau, P.E., McGrane, S.J., Quilliam, R.S., 2016. Predicting microbial water quality with models: Over-arching questions for managing risk in agricultural catchments. In: Science of the Total Environment, vol. 544. Elsevier B.V, pp. 39–47. https://doi.org/10.1016/j.scitotenv.2015.11.086.
Porter, K.D.H., Quilliam, R.S., Reaney, S.M., Oliver, D.M., 2019. High resolution characterisation of E. Coli proliferation profiles in livestock faeces. Waste Manag. 87, 537–545. https://doi.org/10.1016/j.wasman.2019.02.037.
Quigley, J., Walls, L., 2021. Characteristics of a Process for Subjective Probability Elicitation, pp. 287–318. https://doi.org/10.1007/978-3-030-46474-5_13.
Quigley, J., Colson, A., Aspinall, W., Cooke, R.M., 2018. Elicitation in the Classical Model, pp. 15–36. https://doi.org/10.1007/978-3-319-65052-4_2.
Randle, C.H., Bond, C.E., Lark, R.M., Monaghan, A.A., 2019. Uncertainty in geological interpretations: Effectiveness of expert elicitations. In: Geosphere, Vol. 15. Geological Society of America, pp. 108–118. https://doi.org/10.1130/GES01586.1 (Issue 1).
Reaney, S.M., Mackay, E.B., Haygarth, P.M., Fisher, M., Molineux, A., Potts, M., Benskin, C.M.W.H., 2019. Identifying critical source areas using multiple methods for effective diffuse pollution mitigation. J. Environ. Manage. 250 https://doi.org/10.1016/j.jenvman.2019.109366.
Richards, S., Paterson, E., Withers, P.J.A., Stutter, M., 2016. Septic tank discharges as multi-pollutant hotspots in catchments. Sci. Total Environ. 542, 854–863. https://doi.org/10.1016/j.scitotenv.2015.10.160.
Schwetschenau, S.E., Kovankaya, Y., Elliott, M.A., Allaire, M., White, K.D., Lall, U., 2022. Optimizing scale for decentralized wastewater treatment: a tool to address failing wastewater infrastructure in the United States. ACS ES&T Eng. 3 (1), 1–14.
Speirs-Bridge, A., Fidler, F., McBride, M., Flander, L., Cumming, G., Burgman, M., 2010. Reducing overconfidence in the interval judgments of experts. Risk Anal. 30 (3), 512–523. https://doi.org/10.1111/j.1539-6924.2009.01337.x.
Tamang, A., Roy, J.W., Boreux, M.P., Robinson, C.E., 2022. Variation in septic system effluent inputs to tributaries in multiple subwatersheds and approaches to distinguish contributing pathways and areas. Sci. Total Environ. 807 https://doi.org/10.1016/j.scitotenv.2021.151054.
Thomas, I.A., Jordan, P., Shine, O., Fenton, O., Mellander, P.E., Dunlop, P., Murphy, P.N. C., 2017. Defining optimal DEM resolutions and point densities for modelling hydrologically sensitive areas in agricultural catchments dominated by microtopography. Int. J. Appl. Earth Obs. Geoinf. 54, 38–52. https://doi.org/10.1016/j.jag.2016.08.012.
Tuholske, C., Halpern, B.S., Blasco, G., Carlos Villasenor, J., Frazier, M., Caylor, K., 2021. Mapping global inputs and impacts from of human sewage in coastal ecosystems. https://doi.org/10.1371/journal.pone.0258898.
Tyre, K.N., Brewton, R.A., Kreiger, L.B., Lapointe, B.E., 2023. Widespread human waste pollution in surface waters observed throughout the urbanized, coastal communities of Lee County, Florida, USA. Sci. Total Environ. 879 https://doi.org/10.1016/j.scitotenv.2023.162716.
Verzobio, A., El-Awady, A., Ponnambalam, K., Quigley, J., Zonta, D., 2021. An elicitation process to quantify Bayesian networks for dam failure analysis. Can. J. Civ. Eng. 48 (10), 1235–1244. https://doi.org/10.1139/cjce-2020-0089.
von der Gracht, H.A., 2012. Consensus measurement in Delphi studies. Review and implications for future quality assurance. Technol. Forecast. Soc. Chang. 79 (8), 1525–1536. https://doi.org/10.1016/j.techfore.2012.04.013.
von Haefen, R.H., Van Houtven, G., Naumenko, A., Obenour, D.R., Miller, J.W., Kenney, M.A., Gerst, M.D., Waters, H., 2023. Estimating the benefits of stream water quality improvements in urbanizing watersheds: an ecological production function approach. Proc. Natl. Acad. Sci. U. S. A. 120 (118) https://doi.org/10.1073/pnas.2120252120.
Wiesner-Friedman, C., Beattie, R.E., Stewart, J.R., Hristova, K.R., Serre, M.L., 2022. Characterizing differences in sources of and contributions to fecal contamination of sediment and surface water with the microbial FIT framework. Environ. Sci. Tech. 56 (7), 4231–4240. https://doi.org/10.1021/acs.est.2c00224.
Withers, P.J.A., May, L., Jarvie, H.P., Jordan, P., Doody, D., Foy, R.H., Bechmann, M., Cooksley, S., Dils, R., Deal, N., 2012. Nutrient emissions to water from septic tank systems in rural catchments: uncertainties and implications for policy. Environmental Science and Policy 24, 71–82. https://doi.org/10.1016/j.envsci.2012.07.023.
Withers, P.J.A., Jordan, P., May, L., Jarvie, H.P., Deal, N.E., 2014. Do septic tank systems pose a hidden threat to water quality?. In: Frontiers in Ecology and the Environment, Vol. 12. Ecological Society of America, pp. 123–130. https://doi.org/10.1890/130131 (Issue 2).