

Faecal pollution from rural septic tank systems: Modelling environmental risk and understanding human perceptions

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Declaration Statement

I, Chisha Chongo Mzyece, submit this thesis in accordance with the University of Stirling research degree regulations. Ethical approval was granted for all research reported in this thesis under reference numbers EC2022 7547 6444, GUEP 2022 9178 7276 and GUEP 2024 20351 15240.

I declare that the thesis embodies the results of my own research and was composed by me. Where appropriate, I have acknowledged the nature and extent of work carried out in collaboration with others. All research materials, sources, and contributions from collaborators have been duly acknowledged and cited. I consent to the use of plagiarism detection software for the purpose of assessing the originality of this thesis.

This thesis includes sections where artificial intelligence (AI) tools were used to assist with improving language clarity, sentence structure, and overall readability. At all times, I reviewed, edited, and determined the final content of the thesis. All academic interpretation, analysis, argumentation, and conclusions are entirely my own. I confirm that this thesis represents my original work, except where due acknowledgment has been made.

Abstract

Septic tank systems (STS) are widely used in rural areas without centralised sewerage, but they are increasingly recognised as potential sources of faecal pollution, especially under changing climate conditions. Such pollution, commonly measured by reporting levels of faecal indicator organisms (FIOs), typically *Escherichia coli* (*E. coli*), arises when effluent containing high loads of FIOs bypasses adequate attenuation processes and reaches surface and groundwater. Quantifying STS-related pollution is difficult in large catchments with multiple sources, as traditional FIO monitoring lacks source specificity. This challenge is compounded by fragmented STS-specific data (e.g., condition, treatment performance), limited understanding of user perceptions of STS-related pollution risks and maintenance practices, both critical for pollution management. This thesis applied a mixed-methods approach using a Bayesian Network (BN) and user surveys to provide a holistic understanding of STS-related faecal pollution. The specific objectives were to 1) adapt an existing phosphorus risk BN model and extend it to account for FIO pollution from STS; 2) elicit expert judgements to inform BN structure and aid our understanding of FIO losses from STS to the wider environment; 3) validate a BN model against observed data to characterise FIO losses from STS in rural catchments, and 4) understand user perceptions and attitudes towards STS-related faecal pollution risks. Findings show that BNs can be effectively adapted for pollutants such as phosphorus and FIOs, applied from catchment to national scales, and be informed by expert judgement to assess STS pollution risks. Validation confirmed that the BN presented in this thesis is fit for purpose and provides credible risk assessments of STS contributions to watercourses. Self-reported STS user data proved valuable for refining model outputs and capturing awareness and perceptions of pollution risks. This research advances the application of BNs in modelling faecal pollution from STS and highlights the importance of integrating user-reported data. Future work should explore the extent to which such data can enhance model

performance, supporting both scientific understanding and effective management of STS-related pollution risks.

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1 General Introduction and critical literature review of Septic tank systems as wastewater treatment systems in rural areas

1.1 Septic tanks and microbial water quality in rural catchments

Septic tank systems (STS) are widely used onsite wastewater treatment facilities, particularly in rural areas where centralised sewerage networks are impractical or economically unfeasible. While these systems play a vital role in providing sanitation to dispersed populations, they are also increasingly recognized as potential sources of faecal pollution to groundwater and surface water especially under changing climate conditions (Mester et al., 2023; Murphy et al., 2020; Richards et al., 2016). Globally, rural communities remain disproportionately affected by inadequate sanitation and unsafe water supplies. According to the World Health Organisation (2023), 41% of the rural population is at risk of exposure to faecal contamination and diarrhoeal diseases through drinking water, compared to only 12% in urban settings. This disparity reflects both infrastructural limitations and the uneven distribution of safely managed sanitation across regions. For example, exposure rates remain particularly high in the global south, with up to 53% of the population in Africa and 35% in South-East Asia at risk, largely due to the absence of improved sanitation facilities and the persistence of open defecation practices.

Within this wider context, STS are a critical but understudied component of rural sanitation. Poorly designed, aging, or inadequately maintained systems can contribute significantly to

faecal pollution of nearby watercourses, with contaminants including pathogenic microorganisms, nutrients, and emerging pollutants such as pharmaceuticals, personal care products and antibiotic-resistant genes in microorganisms (Birch et al., 2015; Szopińska et al., 2022; Wilschnack et al., 2024). Pollution from STS is not, however, confined to low- and middle-income countries. Studies from high-income contexts have also demonstrated the role of STS in impairing microbial water quality, highlighting their contribution to faecal pollution, waterborne disease risks and ecosystem degradation even where sanitation coverage is considered high (Hunter et al., 2011; Iverson et al., 2020). As rural populations grow and dependence on decentralised sanitation continues, understanding and addressing the contribution of STS to faecal pollution of water is an urgent public health and environmental management priority.

1.2 Septic tank systems design and installation

STS consist of an underground tank that receives waterborne waste, allowing solids to separate from liquid effluent via gravity (Beal et al., 2005). Traditional systems were usually rectangular tanks constructed from brick and concrete (Dudley and May 2007), but more modern systems are often spherical and made of fiberglass or high-density polyethylene—which offer enhanced durability relative to corrosion-prone concrete (Rafie et al., 2024). In some designs, the resultant effluent from the tank may be discharged direct into the ground or nearby watercourse with adequate capacity to dilute the effluent (O’keeffe et al., 2015; SEPA, 2024). Other designs incorporate a secondary unit which further treats the effluent before discharge to the environment. Examples of secondary treatment units include a soak away which is a pit filled with granular material to facilitate infiltration of treated STS effluent to the ground (British Standards Institution, 2007) (Figure 1), or a drainage field — a network of

perforated pipes arranged in trenches to distribute effluent evenly across an area for infiltration into the ground or a constructed wetland — a combination of a sand medium, which filters STS effluent, and plants that take up nutrients from the effluent (Vymazal, 2022). Tertiary treatment units (commonly filtration or ultraviolet disinfection units) may also be used to treat STS effluent for discharge to environmentally sensitive areas with poor soil conditions or high groundwater tables where conventional systems are not practical. However, uptake of these treatment systems is low due to increased installation and maintenance costs as well as high energy requirements (Abbassi et al., 2018; Gallagher & Gill, 2021). Further, conventional STS combining primary and secondary level treatment are considered adequate to treat STS effluent, so tertiary treatment systems will normally be installed only in situations where conventional treatment systems are not practical (Franceschini et al., 2021).

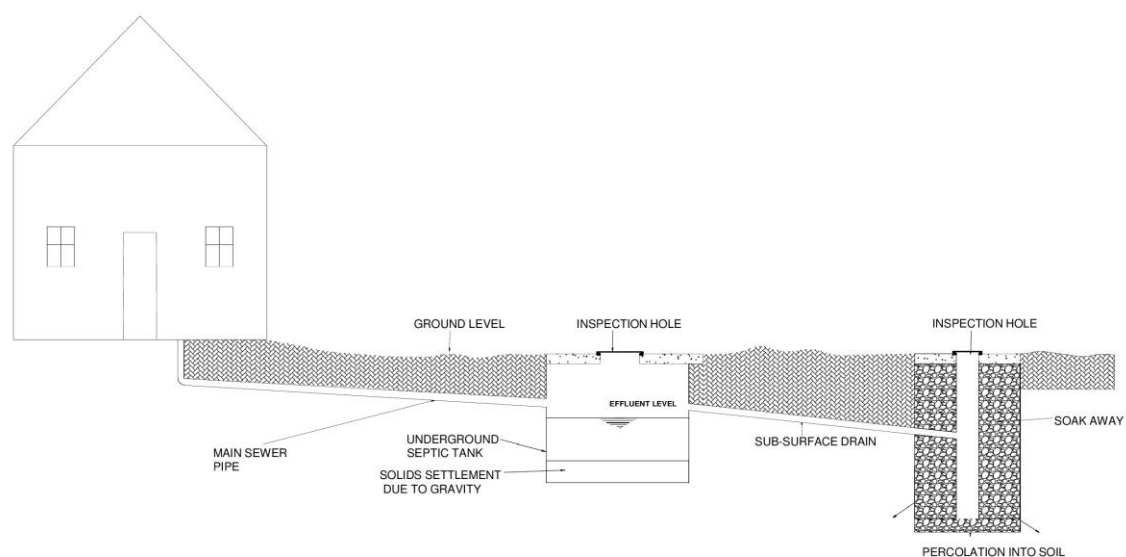


Figure 1: Underground septic tank with soakaway system.

Proper installation is just as critical as sound design and appropriate management to ensure STS effectiveness and environmental safety. Key considerations during installation include slope, soil conditions, and, importantly, separation distances from watercourses (Canter & Knox, 2017). Thresholds are established around these factors to help prevent pollution to the

environment and are determined based on factors such as water source type, flood risk, effluent treatment level, and local authority regulations. In Scotland, for instance, drainage fields must be located at least 10 m from any watercourse, but a higher setback distance of at least 50 m from any water abstraction point, such as a borehole, which may be for drinking, and a minimum of 15 m to any building are required (Scottish Environmental Protection Agency, 2025). Similarly, in the United States, setback distances typically range from 50 to 100 feet (15.2 – 30.5 m), depending on jurisdictional regulations (USEPA, 2025), while in Australia, a minimum of 30 m from watercourses is commonly applied (Queensland Government, 2019). In areas prone to flooding or where STS with minimal treatment are installed, larger separation distances to watercourses are necessary.

Regarding slope requirements, STS should be sited on gentle slopes to promote adequate effluent retention within the soil, particularly in systems incorporating filtration. For example, UK construction standards like the National Housing Building Council recommend slopes no steeper than 2% for inflow connections to STS, to reduce influent velocity and disturbance in the tank, and no steeper than 0.5% for effluent pipes in drain fields, to allow for extended retention and effective treatment. Generally, slopes under 5% are considered appropriate for siting STS, whereas slopes above 30% are unsuitable, as they do not support sufficient retention of effluent in the surrounding soil (USEPA, 2024; Glendell et al., 2021).

Soil permeability is a critical determinant of STS performance. Highly permeable soils can increase the risk of groundwater contamination, particularly where the water table is shallow, while soils with low permeability may cause effluent to back up into dwellings or pond on the surface, leading to STS failure. To assess suitability of soil conditions, a percolation test, also known as a 'perc test' is typically conducted. The perc test determines how fast soil absorbs liquid by timing water drainage from a pre-soaked hole mimicking the drainage capacity of an STS. To conduct this test, several holes are dug into the soil, then filled with water and left to

soak for several hours or overnight to mimic saturated conditions. Water is then added to a specified depth and the time it takes for the water to drop a set amount is measured. The measurement is often expressed in minutes per inch (MPI) indicating the soil's absorption rate. The test methods encompassing parameters such as dimensions and shape of test holes, required water depth and duration of pre-test soaking period, initial and final water heights for testing, the percolation and time calculation method, and the range of acceptable threshold values vary considerably between jurisdictions (Reynolds, 2016). This lack of standardisation makes comparing the results and threshold values from different countries extremely challenging. Threshold values available in the literature for jurisdictions in the USA, Canada and for the UK and Ireland are presented in MacMahon et al. (2023). Table 1 shows thresholds applied in three selected jurisdictions, illustrating differences in how soil suitability is defined in different regions of the world and the implications for STS design and operation. In the United States, percolation rates are expressed in minutes per inch, while in the UK and Ireland values are given in minutes per 25 mm.

Table 1: Soil percolation thresholds for septic tank systems in selected jurisdictions.

Detailed table showing thresholds for more jurisdictions is available in MacMahon, Knappe and Gill, 2023. PV=Percolation Value

Jurisdiction	High Permeability Threshold	Low Permeability Threshold	Implications	Reference
USA (Nebraska)	< 5 min per inch (too fast)	> 60 min per inch (too slow)	Too fast → groundwater contamination risk; too slow → effluent backup or surface ponding	(Hygnstrom et al., 2011)
UK	< 6.25 min per 25 mm	> 41.7 min per 25 mm	Below lower limit → too permeable; above upper limit → too impermeable for effective drainage	(MacMahon et al., 2023)
Ireland	PV < 3 min per 25 mm (too fast)	PV > 120 min per 25 mm (too slow)	3–50 → suitable for STS; 50–75 → enhanced treatment required (e.g. secondary treatment with polishing filters); >120 → unsuitable, alternative discharge required	(MacMahon et al., 2023)

1.3 Treatment processes and reduction of faecal indicator organisms in STS effluent

The quality of STS effluent is commonly described by reporting levels of faecal indicator organisms (FIOs). *Escherichia coli* (*E. coli*) is the most common FIO used; however, reports of faecal coliform and intestinal enterococci concentrations also serve as measures of faecal pollution. For *E. coli*, reported values range anywhere between 10^4 to 10^{10} colony forming units (CFU) per 100mL in raw sewage depending on the number of people utilising an STS and daily water consumption (Kootatep et al., 2020; Tan et al., 2021; Thaíssa et al., 2021). These values can also vary depending on environmental factors, and there is often uncertainty associated with reported values. For example, Gooday et al. (2017) estimated that the faecal coliform flux from a typical STS in Scotland is approximately $23,000 \times 10^6$ CFU day⁻¹ assuming an average water consumption of 152 litres per head and 2.1 persons per household. In-tank primary treatment through gravitational settling of solids can reduce FIO load in the resultant supernatant effluent by 57% (Kay et al., 2008) with up to 97.9% removal possible in optimised designs with higher hydraulic retention time (Nasr & Mikhaeil, 2015). Beyond the tank, additional treatment processes may occur in secondary or tertiary units and surrounding soil. These involve a range of naturally occurring biochemical and physical processes—including filtration, adsorption, biotransformation, predation, and oxidation—that further reduce FIO concentrations (Beal, Gardner and Menzies, 2005; O'keeffe et al., 2015; Tan et al., 2021). Table 2 shows literature FIO concentration values associated with untreated STS effluent and values at different STS treatment levels. In most cases, tertiary treatment systems can reduce FIO levels to those considered compliant with regulatory thresholds, but conventional primary and secondary treatment units can equally achieve this if STS are properly installed (observing distance and slope requirements) and maintained frequently. The European Union Bathing

Table 2: FIO concentrations values associated with wastes typical of both STS and municipal wastewater treatment.

Effluent type/STS treatment level	FIO mean concentration, CFU/100mL			Source
	Faecal coliforms	<i>E. coli</i>	Enterococci	
Untreated sewage		1.98 x 10 ⁷		Gikas & Tsihrintzis, 2012
	1.2 x 10 ⁷			O'keeffe et al., 2015
	a ¹ 1.7 x 10 ⁷		a ¹ 1.9 x 10 ⁶	Kay et al., 2008
	b ¹ 2.8 x 10 ⁶		b ¹ 4.9 x 10 ⁵	
Primary	c 7.2 x 10 ⁶		c 9.3 x 10 ⁵	Kay et al., 2008
	d 4.8 x 10 ⁶		d 4.3 x 10 ⁵	
	2.9 x 10 ⁵			Pundsack et al., 2001
		5.0 x 10 ⁵		Gill et al., 2007
		2.1 x 10 ⁶		Gill & Mockler, 2016
Secondary		5.0 x 10 ²		Gill et al., 2007
		7.3 x 10 ⁴		Gill & Mockler, 2016
Constructed wetlands	g 4.0 x 10 ²			Pundsack et al., 2001
	g 5.0 x 10 ²			
	h 5.9 x 10 ³			
	h 7.1 x 10 ³			
Tertiary				
Reedbed/grass plot	e 1.3 x 10 ⁴		e 1.9 x 10 ³	Kay et al., 2008
	f 1.5 x 10 ⁴		f 2.3 x 10 ³	
Ultraviolet disinfection	e2.8 x 10 ²		e8.3 x 10 ¹	
	f3.6 x 10 ²		f9.7 x 10 ¹	
Sand filters	g 3.5 x 10 ¹			Pundsack et al., 2001
	g 6.0 x 10 ¹			
	h 1.1 x 10 ²			
	h 0.2 x 10 ³			
Peat filters	g 6			
	g 6			
	h 4			
	h5			

^{a1} Geometric mean concentration in untreated sewage effluent under base flow conditions

^b Geometric mean concentration in untreated sewage effluent under high flow conditions

^c Geometric mean in settled septic tank effluent under base flow conditions

^d Geometric mean in settled septic tank effluent under high flow conditions

^e Geometric mean under base flow conditions

^f Geometric mean under high flow conditions

^g Concentration during summer (average effluent temperature was between 2.4 and 8 °C)

^h Concentration during winter (average effluent temperature was between 14.0 and 16.1 °C)

Water Directive specifies that *E. coli* concentrations of ≤ 1000 CFU/100 mL in bathing water are required to achieve “good” bathing water quality in inland waters, which are typically lakes and some rivers (Environment Agency, 2025). As seen in Table 2, effluent after primary and/or secondary treatment alone still has high FIO concentration, which would require further treatment through soil filtration before the effluent reaches a watercourse. If discharged into a water body, adequate dilution capacity is indeed key to reduce concentration levels to meet regulatory requirements. As proof of this, Kay et al. (2008) found geometric mean (GM) FIO concentration in untreated effluent under base flow conditions to be significantly higher ($p < 0.05$) than the GM concentrations under high flow conditions, highlighting the role of dilution under high flow conditions (Table 2). FIO loads from STS to the environment and receiving waters are indeed influenced by a complex interplay of system condition, soil characteristics, and hydrological factors, underscoring the need for robust monitoring approaches and targeted strategies to mitigate pollution risks from STS.

1.4 State of the science on faecal pollution from STS within catchments

Faecal pollution from STS arises when effluent containing high loads of FIOs and other contaminants such as phosphorus and nitrate bypasses adequate attenuation processes and enters hydrological pathways that connect STS to surface and groundwater. Pathways of contamination include seepage into shallow groundwater aquifers, overflows during high hydraulic loading resulting from rainwater ingress (Naughton & Hynds, 2014) or flooding, and lateral migration through preferential flow pathways in fractured bedrock or coarse soils (Gill & Mockler, 2016). Catchment studies show that groundwater beneath high STS density areas

frequently exceeds WHO microbial safety thresholds for drinking water, while nearby streams and recreational waters often present elevated levels of *E. coli* (Sowah et al., 2014).

Recent advances in microbial source tracking (MST), including host-associated genetic markers and molecular methods such as qPCR and metagenomics, have significantly improved attribution of faecal pollution to animal versus human sources, yet these methods cannot quantify levels of FIOs from sources and adequately assess the risk of each pollutant source (Boehm et al., 2013; Holcomb & Stewart, 2020). MST techniques not only detect specific faecal microorganisms, including pathogens, but also allow for identification of antimicrobial resistance genes, linking sanitation failures to broader public health risks. In addition, nutrient-rich effluents discharged from high density STS areas can potentially contribute to eutrophication in water bodies, within catchments with fast draining soils, where STS are near water bodies, compounding ecological pressures alongside faecal pollution. Collectively, the scientific literature highlights STS as both localised and diffuse sources of pollution (Glendell et al., 2022; Richards et al., 2016), whose cumulative impacts on catchments are often underestimated due to fragmented monitoring and the complexity of hydrological systems.

Understanding the spatial and temporal variability of faecal pollution from STS within catchments requires integrating multiple layers of environmental and system-specific factors. Soil permeability, groundwater depth, and hydrogeological conditions are central determinants of faecal pollutant fate and transport (Lusk et al., 2017), while STS design, age, maintenance practices, and density of systems within catchments further modulate pollution risk. Catchments characterised by shallow water tables, karst geology, or sandy soils are especially vulnerable to rapid FIO transport, due to minimal attenuation, and densely clustered systems may result in high pollution risk (Buckerfield, Quilliam, et al., 2019; Sowah et al., 2014). Despite widespread recognition of these risks, significant knowledge gaps persist. Scaling up local

observations to the catchment scale to reflect wider pollution risks remains a challenge due to limited long-term datasets and the inherent variability in microbial fluxes (Biddulph et al., 2017; Geary & Lucas, 2019). Moreover, models predicting faecal pollution transport have advanced from simple mass-balance approaches, for example, Steets & Holden (2003), to more sophisticated, process-based catchment models (Abbas et al., 2021), yet the latter often lack sufficient monitoring data to parameterise the model and ascertain that it is fit for purpose. These gaps constrain the ability of regulators and water managers to use these models to help prioritise interventions or assess cumulative impacts of pollutant sources such as STS, especially in mixed land-use catchments where multiple pollutant sources exist. Encouragingly, recent research is moving toward integrated approaches, combining MST, hydrological modelling, and geospatial tools to map hotspots and forecast risks of faecal pollution under different land-use or climate scenarios (Derx et al., 2021; Wang et al., 2024; Wu et al., 2021). There is also growing interest in upgrading STS performance through engineered leach fields, constructed wetlands, and other nature-based solutions that enhance FIO removal before effluent reaches water bodies (Choi et al., 2024; Koottatep et al., 2020). Taken together, the current state of the science underscores that STS are not insignificant, but important contributors to catchment-scale FIO pollution, requiring improved monitoring and modelling, regulation, and technological innovation. Continued interdisciplinary research linking sanitation, hydrology, and microbial ecology is essential to close knowledge gaps and to safeguard both public health and aquatic ecosystem integrity in catchments dependent on decentralised wastewater management.

1.5 The role of water quality models in assessing faecal pollution risk in catchments

Modelling approaches have long been used to support understanding of water pollution processes and to guide land management and policy interventions at different spatial scales. Water quality models are particularly important for evaluating pollution from STS, as limited data availability constrains direct empirical assessment of pollution risk from these systems. Nevertheless, reliance on models remains essential, since avoiding the use of such tools because of data limitations, would leave critical aspects of STS pollution unexamined due to their inherent complexity. Over the past century, water quality models have diversified from relatively simple representations of dissolved oxygen dynamics to sophisticated process-based frameworks capable of simulating multiple pollutants, sources, and hydrological conditions. However, there remains a significant disparity between the modelling of chemical pollutants such as biochemical oxygen demand (BOD), phosphorus, and nitrate, and the modelling of FIOs. While models of chemical pollutant fate and transfer have undergone sustained development since the Streeter–Phelps model of 1925 (Chapra, 2008), FIO water quality models have only been consistently developed since the 1990s, reflecting the comparatively weak evidence base surrounding the fate and transport of FIOs in the environment (Oliver et al., 2015).

The consequences of the lag in the development of FIO water quality models are substantial. Despite faecal contamination being a leading cause of surface water quality impairment worldwide, FIO water quality models remain relatively immature. Current modelling approaches are often either too complex and data-intensive to be applied in real-world rural catchments, or too simplistic to adequately represent FIO dynamics at landscape scales. This limitation is particularly critical when considering STS, which have been less studied compared to other pollutant sources such as agriculture and sewage discharges. STS represent diffuse,

spatially dispersed sources of FIO pollution that are challenging to monitor directly, leading to large uncertainties in their contribution to downstream water quality (Richards et al., 2016). The importance of STS as a potential contributor to downstream FIO pollution is therefore an area of growing interest for scientists, catchment managers, regulators and policymakers. Given the challenges associated with monitoring STS, there is a strong rationale for improving the modelling capability of these systems to help understand their relative contribution to watercourse FIO pollution in rural catchments. This makes the selection of appropriate modelling tools central to understanding and managing the impacts of STS on watercourses.

1.5.1 Historical development of water quality models

Water quality modelling began with the Streeter–Phelps model (1925), which described dissolved oxygen (DO) dynamics in the Ohio River using simple linear kinetics (Chapra, 2008). Early models were one-dimensional and steady state, lacking temporal resolution. Major advances occurred in the 1970s–1980s, driven by increasing computational power (Wang et al., 2013) and increased interest in environmental protection following the enactment of the Safe Drinking Water Act in the United States in 1974. Models progressed from simple steady-state equations to simulations of phenomena like eutrophication in rivers. Subsequent developments integrated atmospheric deposition, diffuse agricultural runoff, and point-source discharges, enabling assessment of multiple pollutant sources (Wang et al., 2013; Thomas et al., 2019). Key models developed included: Water Quality Analysis Simulation Program (WASP), foundational for modelling nutrient transport and eutrophication; the quality (QUAL) series, with QUAL2E extending steady state DO models to include more advanced nutrient dynamics in river systems and Hydrologic Simulation Program-Fortran (HSPF), a comprehensive watershed model for hydrology, nutrient transport, and pesticide fate (Barnwell et al., 1987; Bicknell et al., 1996; Wool et al., 1987). By the 1990s–2000s, modelling expanded from individual waterbodies to entire watersheds. The Soil and Water Assessment Tool

(SWAT) emerged to predict long-term land management impacts on water, sediment, and nutrients (Gassman et al., 2007), while the Better Assessment Science Integrating Point and Non-point Sources (BASINS) integrated GIS, databases, and modelling frameworks for watershed-scale analysis (US Environmental Protection Agency, 2019).

From 2010 onwards, nutrient water quality models have developed significantly, supported by extensive datasets, long-term monitoring and well-developed conceptual frameworks. Central to their success is the concept of critical source areas (CSAs), defined as small areas of a field, farm, or catchment that contribute disproportionately to nutrient losses due to the co-occurrence of high contaminant availability and transport potential (McDowell et al., 2025). The CSA approach has proven particularly effective for targeting interventions, and it exemplifies the strong link between nutrient modelling and practical land management. By contrast, FIO water quality modelling has received less attention and remains less advanced, largely due to the reasons discussed above. FIOs are more difficult to model due to their complex ecology, including processes of die-off, regrowth, attachment to sediments, and strong dependence on environmental conditions. These challenges are compounded by the scarcity of long-term microbial monitoring data compared with nutrient datasets (Molina-Navarro et al., 2020), and predictive models often rely on simple statistical relationships that lack rigorous validation (Beven & Lane, 2022).

Given these limitations, FIO water quality modelling has frequently adapted concepts from nutrient studies, particularly the CSA framework (which is appropriate, because essentially FIO pollution is greatest when a large FIO source combines with significant opportunity for hydrological transfer/delivery). This adaptation has enabled the identification of pollution “hotspots,” such as manured fields, livestock access points, and to a lesser extent failing septic systems, that are disproportionately important for faecal contamination (Oliver et al., 2010; Pachepsky & Shelton, 2011). While this approach has provided a useful starting point, FIO

pollution differs from nutrient transport in both source diversity and environmental behaviour. While both nutrients (for example phosphorus) and FIOs may persist in sediments and resuspend during storm events, FIOs are inactivated rapidly under solar exposure or die-off under unfavourable environmental conditions; these are processes not captured by nutrient-focused paradigms. Moreover, process-based models that align well with this concept are data hungry because they are built on complex, high-dimensional, and physically detailed representations of systems that require extensive, high-quality data to function accurately. Consequently, future advances require FIO-specific datasets, data-parsimonious models that integrate ecological and hydrological dynamics, and novel approaches in faecal pollution risk assessment. This need is particularly relevant for STS, which remain comparatively understudied relative to agricultural and sewage sources. As diffuse, spatially dispersed contributors of FIOs, STS are challenging to monitor directly, leading to substantial uncertainty about their relative impact on downstream water quality (Glendell et al., 2021; Richards et al., 2016). Addressing this gap calls for data-flexible models—capable of functioning with limited input datasets—so that risks from STS can be better represented in catchment-scale assessments. Developing such modelling approaches is central not only to improving scientific understanding but also to supporting decision-making by catchment managers, regulators, and policymakers tasked with mitigating microbial risks in rural watercourses.

1.5.2 Data requirements of current microbial water quality models

The water quality models discussed in this section can all be classed as predictive models because they are often used to anticipate pollution events to optimise mitigation strategies. Predictive models utilise various data inputs, including environmental variables, land use patterns, and historical contamination data, to simulate potential contamination scenarios and assess the effectiveness of intervention strategies (Saeidi et al., 2018). Various types of predictive modelling approaches previously used for mapping microbial contaminants in water

are listed in Izah & Ogwu (2025), and Table 3 presents an adapted version comparing the modelling approaches in terms of data requirements and flexibility in handling data gaps. The section below discusses a selection of those models.

Process-Based Models

Process-based models such as SWAT and HSPF explicitly simulate hydrological, physical, and biological processes affecting microbial transport as seen in Iqbal et al. (2022), and they offer the advantage of mechanistic representation and transferability to different catchments (Srinivasan et al., 2021). Importantly, they can be expanded to simulate FIO pollution processes but their application to STS is constrained by their high data demands. Accurate calibration requires detailed information on septic tank numbers, maintenance condition, locations, effluent loads, soil characteristics, and hydrological pathways—data that are often incomplete or unavailable in rural areas. For example, Hernandez-Suarez et al. (2020) coupled the SWAT with a Bacterial Source Load Calculator (BSLC) to develop alternative scenarios of agricultural best management practice (BMP) implementation and septic system repair to achieve total maximum daily load (TMDL) targets for *E. coli* in a small agricultural watershed. While their approach worked reasonably well, they acknowledged weaknesses in it due to uncertainties in the data that made it difficult to know for example, how many STS were failing and consequently the actual *E. coli* loads from these systems. To improve accuracy in prediction of *E. coli* loads from the various sources, the authors recommended MST data to give more precise information about which source (i.e. human versus animal) contributes how much. In addition to huge data requirements, the complexity of process-based models can hinder stakeholder engagement and real-world adoption because these models are not particularly user-friendly. The development of a graphical user interface (GUI) to accompany a model helps to promote end-user engagement with modelling tools and improve accessibility for catchment managers and policy makers (Oliver et al., 2017).

Table 3: Comparison of modelling techniques for microbial contamination in the environment, in terms of data requirements and flexibility, adapted from Izah & Ogwu (2025).

Modelling Technique	Data Requirements	Flexibility in Handling Data Gaps	Suitability
Bayesian Networks	Requires detailed knowledge and probabilistic data	Explicitly incorporates uncertainty; can integrate incomplete and expert-derived data	High
Sensitive Catchment Integrated Mapping Analysis Platform (SCIMAP)	Requires land cover, rainfall, DEM/topography, and hydrological connectivity indices	High flexibility: operates with widely available geospatial datasets; produces relative risk maps	Medium–High
Regression Analysis	Assumes linearity; relatively modest data needs	Can operate with small or incomplete datasets, but may oversimplify	Medium–High
GIS-Based Approaches	Requires integration with other data sources for accuracy	Useful for hotspot screening using proxy datasets (e.g., land use, septic density)	Medium
Stochastic Models	Requires accurate parameter estimation	Can represent uncertainty but needs robust parameterisation	Medium
Visualising Pathogen & Environmental Risk (ViPER)	Requires livestock numbers, manure application rates, grazing extent, and <i>E. coli</i> shedding rates	Moderate flexibility: empirical and transferable, but accuracy depends on livestock/pathogen datasets	Medium
Hydrological Modelling	Requires hydrological datasets and computational resources	Limited flexibility; performance declines under missing data	Low–Medium
Time Series Analysis	Needs continuous historical data	Performs poorly with gaps and cannot capture unprecedented events	Low–Medium
Machine Learning (general)	Requires large, high-quality datasets	Performs poorly with missing or noisy data	Low
Artificial Neural Networks (ANNs)	Requires very large datasets and computational power	Highly data-dependent; not robust under sparse data	Low
Agent-Based Modelling	Requires detailed behavioural and system-level data	Difficult to parameterise under uncertainty	Low
Quantitative Microbial Risk Assessment (QMRA)	Requires pathogen, exposure, and dose–response data	Data-intensive; not feasible with sparse monitoring	Low

Risk-based models

Risk-based models for microbial water quality can be broadly grouped into two categories: (1) catchment-scale models that predict the risk of microbial pollution to watercourses, exemplified by the Sensitive Catchment Integrated Mapping Analysis Platform (SCIMAP) (Porter et al., 2017), and (2) Quantitative Microbial Risk Assessment (QMRA), which estimates health risks by identifying hazards, characterising dose–response relationships, and evaluating exposure to determine the probability and severity of adverse health impacts (US Environmental Protection Agency, 2025). Risk-based models also qualify as predictive models and are therefore revisited later in the section on predictive approaches.

SCIMAP is a risk-based model that predicts pollution of watercourses by assigning land cover risk weightings and routing them through the landscape according to hydrological connectivity to generate catchment-scale maps of relative pollution risk within the drainage network (Porter et al., 2017). The concept behind this model is about spatial targeting of pollution risk within the drainage network to prioritise where to investigate pollution first in terms of relative risk. The performance of the original SCIMAP model (designed to evaluate risk of fine sediment pollution in catchments) in predicting FIO pollution risk has been tested in catchments with contrasting land uses, with variable results ranging from reasonable ($r_s = 0.88$; $p < 0.01$) to poor ($r_s = -0.36$; $p > 0.05$) (Porter et al., 2017). Given that *E. coli* behaves differently to fine sediment, effort was invested in converting the SCIMAP framework to consider *E. coli*; this involved integrating the Visualising Pathogen and Environmental Risk (ViPER) model developed to predict *E. coli* burden on pastures from grazing animals (Oliver et al., 2018) with the original SCIMAP framework, which resulted in SCIMAP-FIO designed to model diffuse microbial pollution risk within agricultural catchments (<http://fio.scimap.org.uk/>). SCIMAP-FIO evaluates both the likelihood of pollutant sources being generated and their probability of becoming connected to a watercourse, thereby operationalising the CSA concept. Importantly,

SCIMAP adopts a minimum information requirement approach: the standard version requires only three key inputs—(i) a land cover map and spatially distributed rainfall data to estimate source generation (replaced with an *E. coli* burden layer in the FIO version); (ii) a digital elevation model (DEM) to calculate the topographic wetness index and connectivity; and (iii) rainfall data to account for concentration and dilution processes (Reaney et al., 2011).

By contrast, models that adopt a QMRA approach are considerably more data intensive. QMRA requires data on FIO or pathogen occurrence and concentration in the source, data on behaviour of pathogens between their source and point of human exposure, exposure assessment data detailing how humans come in contact with the contaminated water, laboratory or epidemiological data linking the ingested dose of a pathogen to illness and population level data such as outbreak reports or epidemiological studies for model validation or calibration (Nag et al., 2021). Compared to catchment scale models such as SCIMAP, QMRA techniques go a step further by linking pollution to human infection and illness risk. However, the need for extensive data by QMRA approaches is limiting in their potential application in modelling the risk of FIO pollution from STS. First, STS are diffuse and spatially dispersed, with failure rates that are poorly quantified and highly variable across regions. This would make it difficult to characterise source strength reliably. Second, pathogen-specific data from STS effluent are even more scarce than FIO data, and assessments often rely on FIOs such as *E. coli*, which may not correlate consistently with actual pathogen risks to human health. Third, the fate and transport of microbes from STS are highly uncertain: effluent can infiltrate soils, enter groundwater, or discharge to surface waters, with survival and attenuation depending on site-specific factors such as soil type, hydrology, and climate (Calderon et al., 2022; Gill & Mockler, 2016; Petersen & Hubbart, 2020). For modelling catchment-scale FIO pollution risk from STS, SCIMAP represents a more feasible approach due to its modest data requirements and emphasis on relative risk mapping. Its suitability for STS applications is further examined in the section on predictive models.

Export Coefficient Models

Export coefficient models (ECMs) estimate pollutant loads by assigning average coefficients to different land uses or sources. More advanced versions incorporate modifying factors such as rainfall, topography, and soil properties to improve accuracy, for example the dynamic ECM developed by Wang et al. (2020) or integrated ECM proposed by Wang et al. (2025). Classical ECMs are attractive because they are straightforward, require minimal data, and have been applied at catchment scale to apportion microbial loads from broad sources such as agriculture. However, they assume homogeneity within source categories and fail to capture variability in pollutant behaviour or management. This is particularly problematic for STS, which differ in age, design, maintenance, and density, resulting in highly heterogeneous contributions to faecal pollution.

While ECMs may offer a first approximation of pollutant load, they oversimplify the diffuse and uncertain nature of STS contributions. Improved ECMs may enhance accuracy of modelling FIOs from STS but they still rely on export coefficients derived from empirical studies or 'borrowed' from other catchments. Because STS failure rates and pollutant loads vary widely, using average coefficients can misrepresent local conditions necessitating fine tuning to suit local conditions (Wang et al., 2022). Furthermore, export coefficient approaches assume clearly quantifiable sources, such as hectares of cropland or livestock numbers, whereas STS are often unmapped, with uncertain numbers, locations, and failure rates. This makes coefficient assignment highly uncertain. Although dynamic ECMs can incorporate drivers such as rainfall variability, they do not capture fine-scale microbial fluctuations arising from septic systems, including episodic pollution flushes linked to rainfall infiltration or seasonal occupancy, for example in holiday homes.

Statistical and probabilistic models

Statistical models utilise observed data to infer the underlying probability distribution or model that best explains the data (Chambers & Trevor, 2017). Data including water quality, environmental factors like land use, and discharge data are analysed to understand relationships between these variables and forecast future conditions. Schreiber et al. (2022) found that correlation and linear regression are by far the most utilised statistical tools. Although closely related to statistical models, probabilistic models are slightly different in that these describe the probabilities of events, using a known probability distribution to predict outcomes (Katz, 2019). Probabilistic models can therefore be the opposite of statistical models in that the former use a known probability distribution to predict an outcome (data) while the latter use observed data to infer an underlying probability distribution. Consequently, statistical models have higher data requirements compared to probabilistic models. A common type of probabilistic model, which is also growing in environmental risk assessment and particularly water resource management is the Bayesian networks (BNs) (Phan et al., 2016). Among the predictive models discussed in this section, BNs emerge as the most suitable modelling approach under data-scarce conditions because they explicitly incorporate uncertainty in both data and knowledge and integrate diverse data types including empirical evidence and expert knowledge (Moe, Carriger and Glendell, 2021; Glendell et al., 2022). SCIMAP also offers a highly data-flexible option by leveraging widely available geospatial datasets to produce relative risk maps, though it does not quantify microbial concentrations directly (Porter et al., 2017). Regression and GIS-based models provide pragmatic alternatives where only proxy data (e.g., land use, STS density) are available, though they risk oversimplifying microbial dynamics. By contrast, data-intensive approaches such as QMRA, hydrological modelling, and machine learning remain constrained by their reliance on detailed

monitoring, highlighting the importance of prioritising data-flexible tools in microbial risk assessment.

1.6 Overview of Bayesian networks in Environmental Risk Assessment

BNs are probability-based graphical models that represent a set of random variables and their conditional interdependencies via Directed Acyclic Graphs (DAG) (Pollino & Henderson, 2010). The structure of a BN illustrates causal relationships among components of a system. These models are composed of three fundamental elements: (1) nodes, which denote random variables within the system; (2) arcs, which indicate causal relationships between these variables; and (3) Conditional Probability Tables (CPTs), which quantify the strength of the relationships and are used to compute the probability distributions of the nodes. BNs utilise Bayes' theorem within a DAG framework—free from feedback loops—to model uncertainties and support decision-making processes, thus functioning as a form of Decision Support System (DSS) grounded in probability theory (Jensen, 1996; Pearl, 2014).

Due to their ability to represent relationships in a system through conditional probability distributions (CPDs) within a graphical structure, BNs naturally support the integration of different data types while explicitly accounting for uncertainty (Chen and Pollino, 2012; Govender, Sahlin and O'Brien, 2022). This notion is further supported by Phan et al. (2016) who found no significant difference in the use of quantitative or qualitative data across BN-based decision support tools, suggesting that BNs are equally capable of incorporating both types of information without compromising analytical robustness. The graphical nature of BNs also makes them more accessible and engaging for end-users. The dash-board interface, or graphical user interface (GUI), is often viewed as more user-friendly, helping to serve as a modelling framework that can be coupled with participatory approaches and thus capitalising

on stakeholder engagement to inform the model-building process from conception to implementation (Bertone, Purandare and Durand, 2019; Glendell et al., 2022). Based on these attributes, BNs are increasingly used to model environmental systems to integrate multiple issues and system components utilising information from different sources including empirical measurements, literature data and expert opinion (Chen & Pollino, 2012; Govender et al., 2022). A systematic review of BN application in environmental risk assessment (ERA) revealed 72 studies published between 2004 and 2019 demonstrating application across varied science disciplines and domains in environmental risk assessment with 27 of these addressing all stages of the ERA process (risk identification, analysis and evaluation) (Kaikkonen et al., 2021).

BNs have been used to predict diffuse pollution risk and resultant water quality and ecological impacts to guide decision-making at various landscape scales. Applications at varying landscape scales include diffuse pollution management in small riparian buffer strips (McVittie et al., 2015), in relatively simple catchments that are predominantly agriculture and forestry (Moe et al., 2019), and in complex river catchments with mixed agriculture and urban-related activities (Molina-Navarro et al., 2020). BNs have also been used at a national scale to guide high-level decision-making based on holistic assessment of diffuse pollution risk (van Looy et al., 2015). Some of the pollutants modelled include pesticide leaching risk to ground and surface water (Trolborg et al., 2021), and phosphorus pollution risk in Scottish rivers (Glendell et al., 2022). Their application in microbial water pollution has been limited, although interest in the approach is increasing and has been applied to assessments of FIOs in bathing waters (Bertone, Purandare and Durand, 2019; Panidhapu et al., 2020).

1.6.1 Factors that drive an effective BN for water quality risk assessment

Constructing an effective BN requires adherence to established procedures and guidelines, beginning with a clear articulation of the model's intended purpose (Marcot et al., 2006). The most effective way to achieve this is through co-design, using participatory approaches that actively involving end-users. Such approaches are valuable because they allow model developers to better understand user requirements (Hewitt & Macleod, 2017), and ensure stakeholder involvement at key stages of development, increasing the likelihood of acceptance by managers and decision-makers (Bertone et al., 2019). Castelletti & Soncini-Sessa (2007) further argue that participatory modelling should ideally enable stakeholders to follow the same reasoning process as the modeller. Moving beyond simple consultation towards meaningful participation fosters trust in model outcomes, enhances uptake, and promotes ownership among end-users (Oliver et al., 2017). In the long run, this is beneficial for both model developers and end-users as it allows for continuous improvement of the model through feedback.

An effective BN for water pollution risk modelling should integrate empirical data from the monitored system wherever possible. Relevant datasets may include weather records, and physical, chemical, or biological monitoring data suited to the application of the BN. These inputs are critical for testing and validating model performance, thereby enhancing credibility and robustness. Without such empirical grounding, BNs risk being based solely on expert judgement, reflecting unverified beliefs or theoretical assumptions rather than tested system behaviour (Marcot et al., 2006). While these factors provide a foundation for developing effective BNs in water quality risk assessment, their consistent implementation remains challenging. In practice, limitations in data availability, stakeholder engagement, and methodological standardisation often constrain the extent to which BNs can achieve their full

potential. These challenges highlight important knowledge gaps that need to be addressed to strengthen both the credibility and utility of BN applications in water pollution risk assessment.

1.7 Key knowledge gaps

The application of BNs in environmental risk assessment has grown substantially in recent years. However, their use in water quality management has largely focused on diffuse chemical pollution, particularly phosphorus (Glendell et al., 2019; Negri et al., 2025; Negri, Mellander, et al., 2024). By contrast, BN applications to microbial pollution remain limited, reflecting uncertainties about their effectiveness as decision-support tools for faecal contamination, particularly from understudied sources such as STS. This underrepresentation is notable given the increasing policy emphasis on managing faecal pollution in watercourses within the EU Water Framework Directive and similar global and national strategies (Essex et al., 2020; Oliver, 2025). Four key knowledge gaps (KGs) are identified:

KG1: Transferability of BNs across pollutants, systems, and scales

The extent to which BN models can be transferred between pollutant types (e.g. nutrients versus microbial contaminants) and adapted across systems of varying characteristics and scales remains poorly understood (Landis, 2020). For example, it is unclear how findings from catchment-scale studies can be extrapolated to inform regional or national management. Addressing this gap will clarify the robustness and adaptability of BNs, reducing reliance on resource-intensive model development from inception and instead allowing research teams to capitalise on existing frameworks of relevance.

KG 2: Contribution of STS to faecal pollution under varying landscape conditions

Empirical studies often examine individual factors, such as pollutant-source, distance or soil type, in isolation. However, there is limited knowledge of how multiple landscape variables interact—for example, STS proximity to watercourses, slope, and soil properties—in shaping FIO pollution pathways. Improved understanding of these interactions would allow more realistic modelling of pollutant behaviour under catchment conditions, strengthening evidence for targeted interventions.

KG 3: Lack of validation against observed data

Many BN applications lack validation against empirical datasets, primarily due to the limited availability of observed microbial pollution data. This absence reduces confidence in model performance and restricts uptake as decision-support tools. Addressing this gap would clarify data requirements for model validation and increase trust in BN-based risk assessments.

KG4: Limited information on STS maintenance and user perceptions

Critical STS attributes—such as age, maintenance practices, and treatment efficiency—are rarely documented, particularly in rural settings (Richards et al., 2016). Furthermore, little is known about user perceptions of STS-related pollution risks, despite the recognised importance of promoting stakeholder engagement (including public participation) to help foster positive behavioural change for environmental benefits. Addressing this gap would provide essential data for modelling faecal pollution while also supporting participatory approaches to catchment management.

1.8 PhD thesis Aim and objectives

The overarching aim of this thesis is to assess faecal pollution risks from STS through a mixed-methods approach that integrates Bayesian modelling with wider understanding of both expert and STS-user perceptions. This dual focus strengthens the contribution of the research by combining technical modelling of pollution risks with insights into human behaviours, expert understanding and management practices, thereby providing a more holistic understanding of STS-related water quality impacts.

The specific objectives relate to the key knowledge gaps outlined above:

Objective 1: To adapt an existing phosphorus (P) risk BN model and extend it to account for FIO pollution from STS;

Objective 2: To elicit expert judgements to inform BN structure and aid our understanding of FIO losses from STS to the wider environment;

Objective 3: To validate a BN model against observed data to characterise FIO losses from STS in rural catchments;

Objective 4: To understand user perceptions and attitudes towards STS-related faecal pollution risks.

1.9 Thesis structure

This thesis is composed of six chapters (Cs) including this combined introduction and critical literature review. **C 2** is a method development-style chapter that underpins the empirical

chapters that follow. It presents a concept and justification for adapting an existing P BN model to account for FIO losses from STS. Key model structural modifications are identified and implemented, data requirements determined and future needs for testing the FIO BN model assessed. **C 3 - C 5** are data chapters. **C 3** is an expert elicitation of the proportion of FIOs likely to be delivered to surface watercourses from STS based on a pre-defined set of 36 scenarios of STS soil effluent movement risk, distance to watercourse and slope. Individual expert judgements were determined followed by a deliberative approach to derive consensus judgement across a range of experts for the 36 scenarios under investigation. **C 4** is a validation of the FIO BN model against empirical data to characterise FIO loss from STS in rural catchments. The FIO BN model is evaluated relative to observed human-derived FIO loads in two Scottish rural catchments and upscaled to predict FIO pollution risk at the national scale. **C 5** is a national scale survey of STS users in rural catchments aimed at understanding their perceptions and attitudes regarding STS as potential sources of FIO pollution to watercourses. The focus here was on identifying system types, maintenance practices, and user awareness to inform strategies for reducing FIO pollution. Finally, **C 6** provides a synthesis of the research findings and recommendations for future research and opportunities to improve policy.

1.10 Author/ publication statement

Two of the chapters (C3 and C4) of this thesis have been published in peer-reviewed academic journals. Table 4 provides the details of each publication and the corresponding chapter. The doctoral candidate (Chisha Chongo Mzyece) was the lead author on all the publications and author contributions for each publication are detailed at the beginning of each chapter via a CRediT statement.

Chisha Chongo Mzyece (30.09.2025)

Table 4: Manuscript details of published chapters.

Chapter	Publication details
3	Mzyece, C. C., Glendell, M., Gagkas, Z., Quilliam, R. S., Jones, I., Pagaling, E., Akoumianaki, I., Newman, C. & Oliver, D. M. (2024). Eliciting expert judgements to underpin our understanding of faecal indicator organism loss from septic tank systems. <i>Science of the Total Environment</i>, 921, 171074 https://doi.org/10.1016/j.scitotenv.2024.171074
4	Mzyece, C. C., Glendell, M., Gagkas, Z., Troldborg, M., Negri, C., Pagaling, E., Jones, I. & Oliver, D. M. (unpublished). Validating a Bayesian network model to characterise faecal indicator organism loss from septic tank systems in rural catchments https://doi.org/10.1016/j.watres.2025.124715

2 Concept and need for a Bayesian network model to aid our understanding of FIO pollution from Septic tank systems

2.1 Abstract

Quantifying the risk of faecal pollution in river catchments is challenging due to diverse sources, including sewage treatment works (STWs), agriculture, failing septic tank systems (STS), and wildlife. Climate change further complicates assessments of pollution risk, as intense rainfall and storm events enhance overland flow and in turn the delivery of faecal indicator organisms (FIOs) to receiving waters from diffuse catchment sources. While water quality models are valuable for characterising pollution risk, they are often constrained by limited data. Bayesian networks (BNs) provide a flexible alternative to data-intensive models, due to their capability to integrate diverse datasets to account for missing or limited data that may otherwise inhibit model parameterisation. However, most existing agricultural pollution BN models have been developed for chemical contaminants, with no BN framework currently available for assessing FIO pollution from STS. In response, the aim of this study was to outline the development needs of converting an existing BN model designed to assess phosphorus (P) pollution from STS so that it could instead account for FIO losses from STS. The objectives were to: (1) identify and implement structural modifications to the P BN model for developing an FIO BN model; (2) determine data requirements for parameterising the proposed FIO BN; and (3) assess future needs for testing the proposed FIO BN model. To convert the existing BN structure, P-specific nodes (e.g., effluent concentration, leaching risk, and leachfield removal probabilities) were replaced with nodes representing FIO concentration at different treatment levels and estimated FIO delivery proportions influenced by topography, distance to watercourses, and soil–hydrological conditions. A mix of data types including spatial data, literature-derived data concerning STS treatment efficiencies and expert derived data were identified as key requirements in developing the FIO BN. To operationalise the conceptual FIO BN model developed in this study, further development and testing would be required in catchments that combine suitable landscape characteristics with adequate data availability. Key requirements within the test catchments include dominance of STS as sewage treatment

facilities, and ideally the absence of municipal sewage treatment works (STWs), and availability of good quality FIO monitoring data at a resolution that reflects concentrations across different discharge conditions in the catchment. Incorporating Microbial Source Tracking data to distinguish human- from animal-derived FIOs will be critical for robust validation and refinement of model predictions, helping to understand the contributions of observed FIO concentrations sourced from STS relative to BN predictions.

2.2 Introduction

Water pollution in landscapes arises from multiple sources. Pollutants from point sources, such as ‘end-of-pipe’ sewage discharges, can be directly measured (Alkhadher et al., 2020; Campos et al., 2020), but quantifying pollutants from diffuse sources —such as agriculture and onsite sewage treatment systems (e.g., septic tanks) —remains challenging. This is particularly problematic in large, complex catchments where numerous environmental factors influence pollutant behaviour, making it difficult to interpret pollution signals and their points of origin (Heal et al., 2025; Vinten, 2021).

Widely studied chemical pollutants such as phosphorus (P) illustrate the complexity of quantifying pollutants from diffuse sources. Phosphorus has diverse sources (e.g., manure, mineral fertilisers, effluent discharges) and transfers through the environment via different hydrological pathways (e.g., overland flow, subsurface drains, groundwater flow), all of which vary temporally and spatially (Bowes et al., 2015; Mellander et al., 2016; Thomas et al., 2016). Similarly, microbial pollutant risk, indexed via faecal indicator organisms (FIOs), can be difficult to characterise due to multiple diffuse sources of FIOs — including agricultural practices, failing STS, and wildlife (Afolabi et al., 2023; Porter et al., 2017; Richards et al., 2016). The contribution of FIOs to watercourses depends on land use and hydrometeorological conditions (e.g., rainfall, temperature, flow), often making it difficult to isolate the influence of individual sources especially under changing climate conditions (Murphy et al., 2015).

While advances in Microbial Source Tracking (MST) techniques have improved source identification through increased genetic markers and routine validation in new geographic regions (Boehm et al., 2013; Holcomb et al., 2020), challenges persist in source apportionment, risk characterisation, and impact evaluation (Holcomb & Stewart, 2020). Water quality models partially address these issues by simulating pollutant transport and fate to

quantify pollutants from different sources (Oliver et al., 2016); enabling exposure assessments to estimate concentrations in recreational and drinking water and thus predict risk to human health (Das, 2025); and via scenario analysis modelling to evaluate the impact of different management practices (Glendell et al., 2022).

Bayesian networks (BNs) have been increasingly applied to assess pollution risk in complex environmental systems such as large catchments with multiple pollutant sources. BNs offer a probabilistic framework for representing dependencies among variables and explicitly handling uncertainty (Jensen, 1996; Pearl, 2014; Pollino & Henderson, 2010). Structured as directed acyclic graphs (DAGs), BNs consist of nodes (variables), arcs (causal relationships), and conditional probability tables (CPTs) that quantify dependencies. Uncertainty analysis is inherent in BNs through CPTs, which encode variable dependencies, probability distributions representing continuous parameters, and causal structures describing environmental processes influencing pollutant dynamics. These features, supported by the stochastic nature of BNs, allow for representation of both epistemic and aleatory uncertainties (Glendell et al., 2022; Sahlin et al., 2020), making them valuable decision-support tools.

Notable applications of BNs in water pollutant risk assessment include: use of a copula-based BN to comprehensively model complexities and dependencies between multiple environmental indicators driving water pollution risk from chemical pollution (Yu & Zhang, 2021), simulation of pesticide leaching to ground and surface water (Trolborg et al., 2022) and P risk modelling in Scottish rivers to help target effective intervention measures (Glendell et al., 2022). Previous studies have demonstrated the flexibility of BNs in integrating other functions such as copula (cumulative distribution function that allows for construction of a multivariate distribution from a one-dimensional marginal distribution) to address the limitation of traditional BN approaches challenged with constructing CPTs to describe dependencies when faced with a multitude of parent nodes and states (Laitila & Virtanen, 2022). This flexibility

extends to the ability of BNs to integrate different data types enabling field scale assessments where empirical data may be sparse (Trolldborg et al., 2022). The graphical nature of BNs enhances usability by different stakeholder groups and brings together expert insight to co-construct the model and facilitate systems-level thinking regarding water pollution risk (Glendell et al., 2022). Through a validation process, Glendell et al. (2022) concluded that their BN approach was a ‘fit for purpose’ decision support tool simulating the probabilities of different management options to attain good ecological water status of Scottish rivers. The same authors also identified STS as important but poorly characterised contributors to faecal pollution in watercourses.

STS are acknowledged as potential sources of faecal pollution, particularly in rural areas where their use is widespread, but modelling pollution from these systems is challenging as there is typically limited information on their operational capacity, condition/age and maintenance, and critical factors determining operational efficiency (Richards et al., 2016). Existing process-based models (e.g., Pang et al., 2006; Morales et al., 2014; Morales, Amador and Boving, 2015) are often data-intensive and can fail to progress where data are sparse as is mostly the case with STS. In contrast, BNs provide a flexible framework for integrating incomplete data because they can incorporate different data types while capturing uncertainty (Kaikkonen et al., 2021). To date, however, most BN applications have focused on chemical pollutants, with limited deployment for assessing FIO pollution. Where BN development for assessing FIO pollution risk has occurred, it has focused on sources such as recycled water, sewer overflows and river sediments and stormwater (Donald et al., 2009; Goulding et al., 2012; Staley et al., 2012). Crucially, no development of BNs for evaluating STS as a source of FIO pollution has been reported.

This study addresses this gap by developing a conceptual BN model to aid understanding of FIO pollution from STS. Building on an existing P BN model (Glendell et al., 2022), we adapt

and extend its structure to account for STS-related faecal pollution risk and present a detailed justification for this approach. The specific objectives were to: 1. Identify and implement structural modifications required to develop an FIO BN model, 2. Determine data requirements for parameterising the proposed FIO BN model; and 3. Assess future needs for testing the FIO BN model.

2.3 Methodology

2.3.1 Identifying and implementing key structural modifications to build the FIO BN model

To develop the conceptual FIO BN, we implemented steps 1 and 2 of the 6 steps for BN model development outlined by Pollino and Henderson (2010) (Figure 2). The model objectives were developed in consultation with experts from the University of Stirling, Scottish Environmental Protection Agency (SEPA), and the James Hutton Institute (JHI). An initial virtual meeting with SEPA focused on discussing the relative importance of STS as potential sources of pollution to watercourses in Scotland compared to other pollution sources. Subsequent meetings with JHI and University of Stirling experts refined the model objectives to clearly define the model purpose. Structural modifications to the existing BN model were implemented in GeNIe modeller (<https://www.bayesfusion.com/genie/>) by replacing P-specific nodes with FIO-specific nodes. For example, nodes representing P concentration in STS effluent, leaching risks under different soil and hydrological conditions, and leachfield removal probabilities were substituted with nodes representing FIO concentration in STS effluent at different treatment levels and STS maintenance condition, and FIO delivery coefficients as influenced by topography, STS distance to watercourses, and soil–hydrological condition. Nodes representing STS characteristics (e.g., treatment, condition, STS distance to watercourse, slope on which the STS is located and direct effluent discharge), as well as those describing soil hydrology and

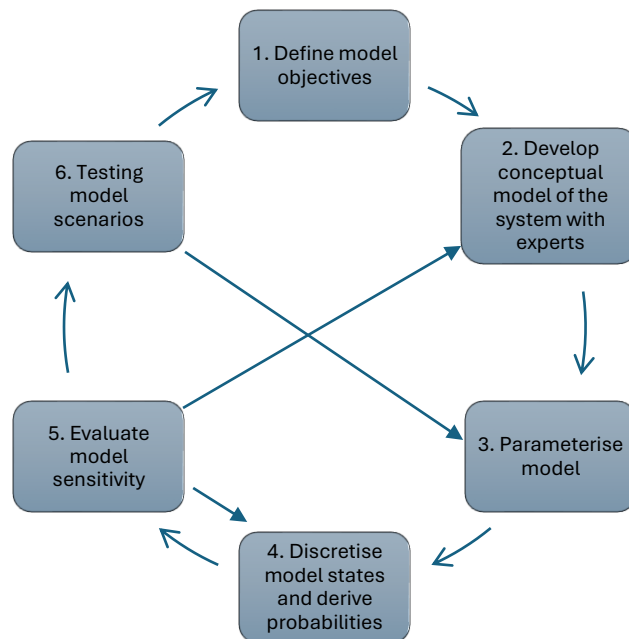


Figure 2: Steps in BN model development with clockwise arrows showing the order of implementation of the steps 1-7 in succession. Anti-clockwise arrows show feedback to improve steps already carried out. Adapted from Pollino & Henderson (2010).

topography were retained from the P model since they remained applicable to the FIO BN and would require the same parameterisation data.

The proposed model structure was presented to an expert panel for final approval. The panel included a catchment scientist, a catchment modeller, an environmental microbiologist, an environment and health scientist and a water resources management expert. There was consensus that the model structure was logical and represented the discussions used to build the proposed model structure.

The model was structured in three groups: A) STS site specific variables describing the STS condition or factors that determine the final concentration of FIOs in STS effluent, B) Calculated variables of STS FIO concentration and STS FIO load in STS effluent, and C) Connectivity variables describing factors that influence FIO transfer from STS to watercourses. Essentially, the model was structured to align with the source-pathway-receptor (S-P-R) framework, widely

used to describe the flow of environmental pollutants from a source through different pathways to a receptor, which in this case would be a receiving water (Holdgate, 1979-1980; Waldschläger et al., 2020)

2.3.2 Determining data requirements for the FIO BN model

Data requirements for the model were defined based on the key processes contributing to FIO pollution risk from STS to watercourses. Three main categories of data were identified: spatial data, literature-derived data, and expert-elicited data. Table 5 summarises the essential datasets in relation to the model variables, their sources, formats, and the rationale for their inclusion. A critical dataset was the Scottish Environment Protection Agency (SEPA) modelled locations of STS, which would enable estimation of spatially dependent variables such as STS distance to the nearest watercourse and slope at the STS site. It is worth noting here that there is no definitive spatial dataset of all STS in Scotland, and so inverse modelling is used to estimate STS location based on residences not connected to the mains sewerage. Literature-based values of FIO concentrations in STS effluent at different treatment levels would be required to parameterise the FIO concentration variable. In addition, elicitation of expert judgement was identified as a key requirement for representing the proportion of FIOs likely to be delivered to a watercourse under varying combinations of distance, slope, and soil–hydrological conditions, because currently this information is unavailable. Detailed justifications for the inclusion of each dataset are provided in Table 5.

Table 5: Summary of variables included in the model, data needs and rationale for including each variable in the model.

Variable (Units)	Data needed	Data format	Source	Rationale
Variables representing STS site specific conditions				
Treatment (%)	Proportions of STS with different treatment levels	Spatial	SEPA national dataset of STS locations	STS treatment level is a critical determinant of the level of FIOs in STS effluent as elaborated in Chapter 1. Tertiary treatment can reduce FIOs to negligible levels while levels in primary treated effluent are typically higher than the required thresholds in bathing waters. It is against this background that a node representing the effects of different STS treatment levels was included in the model. The treatment node is a parent to STS FIO concentration demonstrating causal influence on STS FIO concentration.
Condition (%)	Proportions of well-maintained versus failing STS	Literature and expert knowledge	SEPA data	The condition of an STS reflects its state of upkeep, such as compliance with legal requirements for regular desludging (Scottish Environmental Protection Agency, 2025). Poorly maintained systems are more likely to release elevated levels of FIOs in their effluent, while well-maintained systems tend to produce effluent with lower FIO concentrations (Mills et al., 2024). Including STS condition in the model is therefore essential to capture the influence of maintenance practices on effluent quality. Without this variable, the model would underestimate the role of inadequate upkeep as a driver of elevated FIO loads and overestimate the effectiveness of systems assumed to be functioning optimally.
STS FIO concentration (CFU/100ml)	Concentration of FIOs in STS effluent at different treatment levels	Literature	Literature	FIO concentration in STS is a key variable for assessing pollution risk. It directly influences the FIO load from the STS and reflects the condition and treatment level of the STS. Effluent from failing systems typically contains very high concentrations ($\geq 10^7$ CFU/100 ml), while secondary or primary treatment produces medium to high concentrations (10^4 – 10^6 CFU/100 ml). Tertiary treatment generally results in low concentrations ($< 10^4$ CFU/100 ml) (See Table 2 in Chapter 1). Including FIO concentration in the model is therefore essential, as it captures the effect of system performance on pollution risk.

Variable (Units)	Data needed	Data format	Source	Rationale
Direct discharge (%)	Proportion of STS directly discharging effluent to watercourses	Spatial	SEPA data	The direct discharge variable was included in the model to capture the contribution of STS that discharge effluent directly to watercourses. Such systems are particularly important to consider because their effluent typically undergoes only primary settling within the tank and therefore receives no further treatment before entering the receiving environment. As a result, these systems have a higher potential to elevate FIO loads in watercourses compared with systems that benefit from secondary treatment or discharge to land. Including this variable is especially relevant in the Scottish context, where direct discharge systems are known to be present (estimated to range between 11% and 45% across seven catchments in Scotland, (Glendell et al., 2022)). Therefore, including this variable ensures that the model reflects the range of discharge practices present in Scotland and adequately represents their differing impacts on water quality.
Soil connectivity-related variables				
STS distance to watercourse (m)	Proportion of STS located in the distance categories specified as low risk (>50 m), medium risk (10-50 m) and high risk (< 10 m)	Spatial	SEPA data	Distance from each STS to the nearest watercourse was included in the model as it represents a key risk pathway for FIO transport. Effluent travel distance influences opportunities for filtration, adsorption, microbial die-off, and dilution before reaching watercourses. Previous studies have highlighted the importance of this factor: Glendell et al. (2022) identified distance as critical for P delivery, while Gill and Mockler (2016) showed that in low-permeability soils, STS within 50 m of a watercourse may deliver almost all effluent FIOs, whereas those beyond 200 m deliver negligible loads. Regulatory guidance (SEPA; USEPA; Queensland Government) typically recommends 10–50 m setbacks, assuming these provide sufficient attenuation. To reflect both empirical evidence and policy, we classified distance into three categories: <10 m (high risk), 10–50 m (moderate risk, aligned with regulatory setbacks), and >50 m (lower risk, reflecting greater attenuation potential). This variable enables the model to capture the non-linear decline in FIO pollution risk with increasing distance while also supporting the identification of STS located closest to watercourses as priority targets for regulatory oversight and remediation.

Variable (Units)	Data needed	Data format	Source	Rationale
Slope (%)	Proportion of STS located in the slope categories specified as low risk (0-5%), medium risk (5-25%) and high risk (>50%)	Spatial	SEPA data	Slope was included in the model as it is a key factor influencing both STS performance and the risk of effluent transfer to surface waters. Steeper gradients reduce wastewater retention in the soil profile and compromise drainage field function (USEPA, 2001), while also increasing runoff velocity and the likelihood of faecal indicator organism (FIO) contamination (Appeals et al., 2016). Conversely, gentle slopes may reduce runoff but can enhance subsurface transport depending on soil structure. Regulatory and construction guidelines generally recommend siting STS on gentle slopes, with gradients >30% considered unsuitable, and Glendell et al. (2021) classified slopes ≤5% as low risk and >25% as high risk for pollutant transfer. To reflect both empirical evidence and regulatory thresholds, we defined three categories: 0–5% (low risk), 5–25% (moderate risk), and >25% (high risk).
Effluent movement risk (Inferred from HOST-based risk factors)	Proportion of STS associated with each HOST risk classification	Literature	HOST-derived risk classifications	STS effluent risk, derived from Hydrology of Soil Types (HOST) classifications, was included in the model to represent the potential for effluent movement under different soil–hydrological conditions (Gagkas & Lilly, 2019; Glendell et al., 2018). HOST is a UK-wide system that links soil morphology (e.g., gleying, slowly permeable layers, peaty topsoils) and hydrology (infiltration and percolation characteristics) to conceptual flow pathways (Boorman et al., 1995; Gagkas & Lilly, 2021). Risk was categorised as Low, Medium, High, or Very High depending on the likelihood of surface runoff and/or leaching to groundwater. Low risk occurs where soils are free draining, ungleyed, and groundwater lies deeper than 2 m, whereas Very High risk is associated with poorly drained soils and shallow groundwater (<2 m). Incorporating this factor ensures the model accounts for how soil and hydrological conditions mediate STS effluent transfer pathways and associated contamination risks.

Variable (Units)	Data needed	Data format	Source	Rationale
FIO delivery (proportion)	Proportions of FIOs likely to be delivered to a watercourse under different landscape conditions	Probability Density Functions	Expert knowledge	This node represents the proportion of FIOs likely to be delivered to a watercourse, based on the risk of effluent movement derived from HOST class groupings, the distance of the STS to a watercourse, and the slope on which the STS is located. Including this variable in the model is important to capture the influence of landscape conditions on FIO delivery. Under high-risk conditions (e.g., high HOST-derived risk classification indicating strong effluent movement potential, short STS–watercourse distance, and steep slopes), a greater proportion of FIOs is expected to reach the watercourse. Conversely, under low-risk conditions (e.g., low HOST-derived risk classification, long STS–watercourse distance, and gentle slopes), only a small proportion of FIOs is likely to be delivered.
Calculated variables				
STS FIO load (CFU/yr)	Water use Average property occupancy rate	Literature	Literature	This variable represents the annual FIO load per STS, calculated at the point of effluent discharge from the STS. It reflects the load prior to any influence of landscape conditions or siting factors, such as STS–watercourse separation distance or slope. The variable is conditional on the STS FIO concentration and is estimated using the equation: $ST\ load = STS\ FIO\ concentration\ (CFU/100ml) / 10 * 180(L) * 365 * 2.1$ In this equation, 180 L represents the average daily water consumption per person, as estimated by Scottish Water. This value is then multiplied by the number of days in a year (365) and the average household occupancy in Scotland (2.1 persons).
STS FIO load (CFU/yr)				This is the target variable in the model, representing the annual FIO load per STS that reaches a watercourse. It is conditional on direct discharge, the STS FIO load, and the proportion of FIOs delivered. As such, it reflects the combined influence of all the variables described above and incorporated into the model.

2.4 Results

Figure 3 presents the conceptual P BN model showing P-specific variables (in tan) that were adapted for use in the FIO BN model and STS-specific and environmental-related variables (in blue) that were retained. The figure illustrates both the differences in the variables influencing P transfer from STS to watercourses compared with those driving FIO transfer, as well as the areas where the two models require different parameterisation data. All these variables are in located the 'Pathway' component of the S-P-R framework. The variable 'STS density' (shown in green) was excluded from the FIO model. In the P BN model, this variable was important because it estimated P risk within land parcels based on the density of STS in an area. By contrast, the purpose of the FIO BN model was to estimate loads per individual STS, making this density-based approach irrelevant to its objectives. The variable 'Leachfield connectedness', which in the P model defined STS connectedness to a watercourse based on landscape conditions (e.g. slope), proximity of STS to watercourse, and the presence of direct discharges, was restructured in the FIO BN model and defined by slope and distance variables to still represent STS connectedness to a watercourse. 'STS connectedness', which in the P model was conditional on both P removal and leachfield connectedness, was not included in the FIO model. This is because the processes governing P removal as effluent moves from STS to watercourses differ from those controlling FIO attenuation and therefore require different datasets.

The resultant conceptual FIO BN model is also structured in accordance with the S-P-R framework, with variables distinguished according to the level of certainty in data availability (Figure 4). Variables in the 'Source' component capture factors influencing the level of FIOs generated from STS, such as STS treatment level, maintenance condition and whether the STS discharges directly to STS. The variables in the 'Pathway' component show factors that influence transfer of FIOs to watercourses, which is the 'Receptor' in our study. Table 5 has

already outlined how these variables influence FIO generation at either the source, during transfer through landscapes, or with respect to delivery to the receptor.

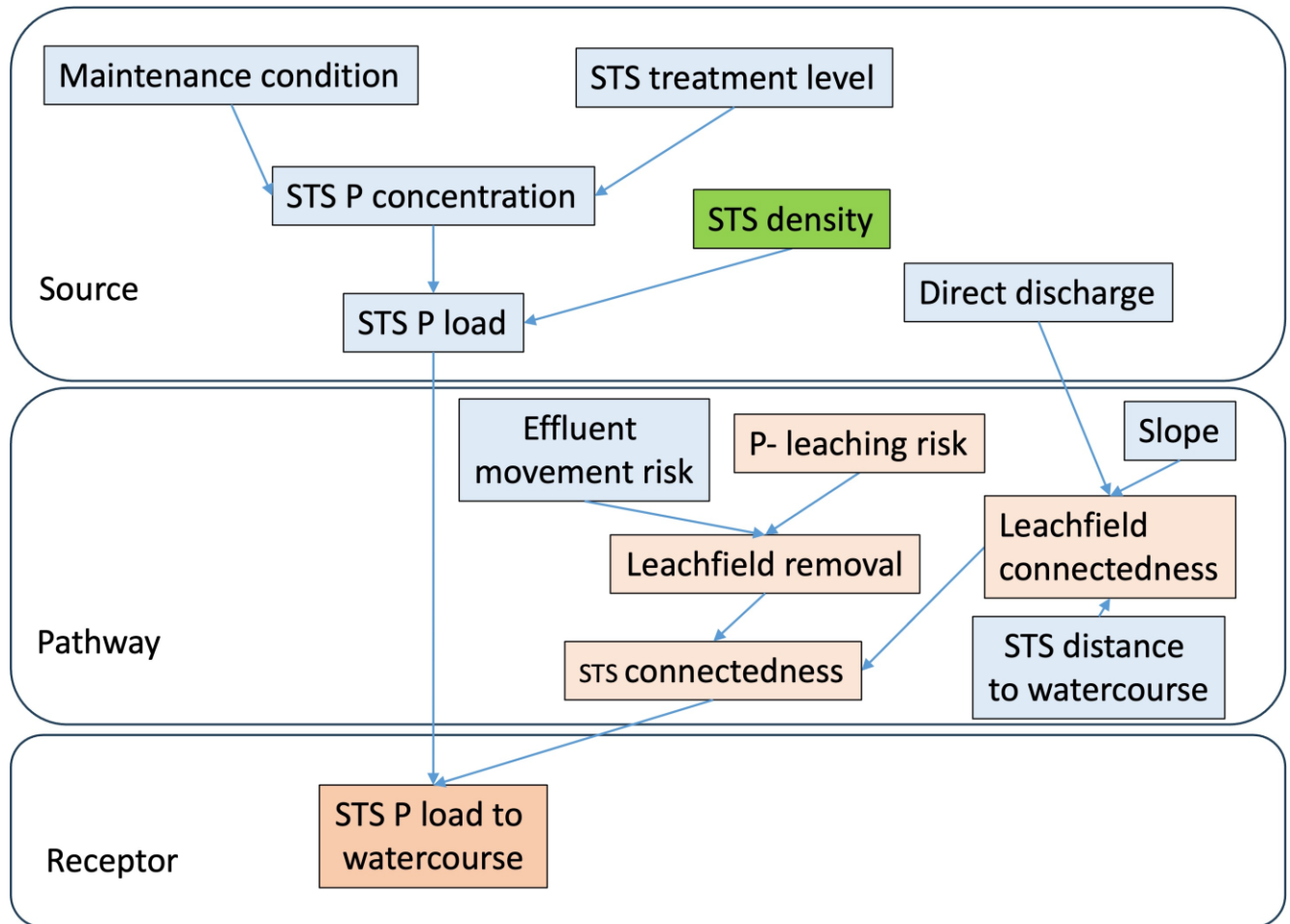


Figure 3: Conceptual P risk model showing variables in tan that were changed in the adapted FIO BN model. Variables in blue were maintained.

Overall, uncertainties exist in the data requirements of variables across all components of the S-P-R framework, though they are most pronounced within the ‘Source’ component. Within the ‘Pathway’ component, data availability is generally stronger, helping to reduce uncertainty, as variables such as slope and STS–watercourse distance can be readily derived from spatial data as done by Glendell et al. (2022), while effluent movement risk can be assessed by overlaying STS locations with soil and hydrological maps to identify STS associated with high-

risk conditions. Within the ‘Receptor’ component, uncertainty is particularly high regarding the proportion of FIOs ultimately reaching watercourses, as this depends strongly on a combination of complex landscape and environmental factors, and the condition of individual STS as visualised in Figure 4.

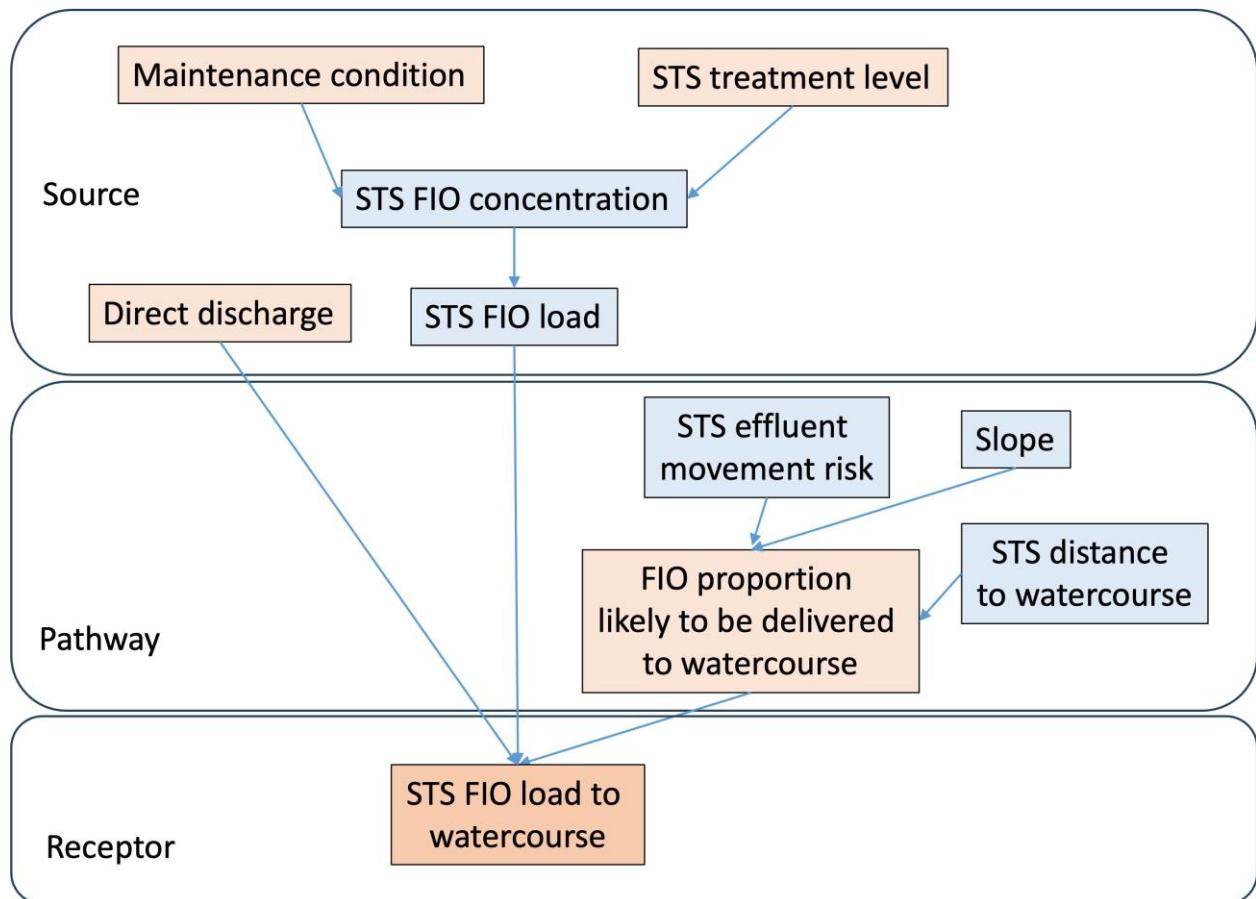


Figure 4: Conceptual FIO BN model structured along the S-P-R framework. The variables in tan are those associated with high uncertainty in terms of the data requirements while those in blue can be estimated with empirical or literature review data.

The perceptual models communicated through discussion with experts from different disciplinary backgrounds and regulatory staff at SEPA formed the basis of the conceptual model shown in Figure 4. The conceptual model was then operationalised via coding of the FIO BN procedural model (Figure 5). This operational version of the FIO BN model was developed in GeNIe modeller version 3.0.R2 (<https://www.bayesfusion.com/genie/>). The

boxes are the nodes, which represent the variables in the model, and the arcs represent causal influences between the nodes. Variables with a small yellow circle in the top left corner are discrete variables, while those with a blue circle are continuous variables. This combination of both discrete and continuous nodes in one model exemplifies a hybrid model. The nodes coloured in tan are the STS-specific variables accounting for factors that drive FIO generation at the source (STS), those in blue are the connectivity-related variables accounting for factors that determine STS-watercourse connectivity and drive FIO transfer from STS to watercourse. The variable 'STload' in orange represents the FIO load generated at the source and does not account for attenuation in soil as the effluent is transferred from an STS. The variable 'RealisedFIO load' is the target variable, which is the proportion of FIOs reaching a watercourse from an STS following further reduction in soil as effluent moves from STS to watercourses. Since this variable represents the FIO load from one STS, it can be multiplied by the number of STS in an area, for example, a catchment to obtain the total FIO load generated from STS within that area. The states that each node could take, for example Primary, Secondary or Tertiary for the variable 'Treatment' are already explained in Table 5.

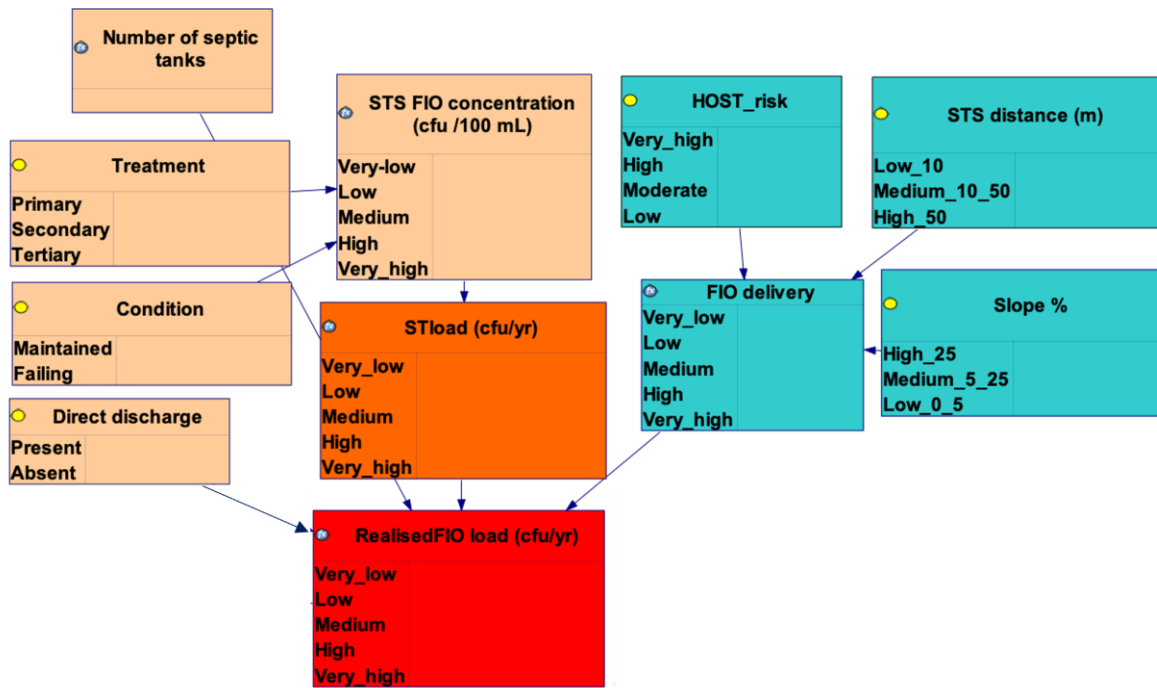


Figure 5: Operational FIO BN model developed in GeNIe modeller.

2.5 Discussion

This study has presented a concept and need for a BN model to aid our understanding of FIO pollution from STS. This section discusses the concept in three parts. First, the rationale for adapting an existing P BN to account for FIO losses from STS is presented. Second, the implications of our findings regarding data requirements for the FIO BN model are discussed, and finally, future needs for further developing and testing the FIO BN model are assessed.

The rationale for adapting an existing P BN rather than develop a completely new model was based on three core considerations. First, the P BN was designed to simulate pollution from both point and diffuse sources, including STS, meaning that many of the model factors considered under the STS sub-model—such as topography, hydrology, and STS

characteristics as identified in Glendell et al. (2021), are also relevant for understanding FIO pollution. For instance, steeper slopes promote runoff of both P and FIOs, and hydrological connectivity in the landscape enhances both P and FIO transfer (Lei et al., 2025). The key difference lies in pollutant behaviour: P may occur in different forms, such as soluble or particle-bound P, which can later be released from soils and sediments (Negri et al., 2025), whereas FIOs, though capable of adsorbing to soil particles, are more likely to die-off before reaching watercourses under unfavourable conditions (Afolabi et al., 2020; Petersen & Hubbart, 2020). Incorporating complex FIO dynamics into models is challenging, but BN approaches also allow for incorporation of expert judgements in situations where data are scarce or where competing viewpoints may arise from an uncertain evidence base (Mzyece et al., 2024).

Second, the P risk model was developed iteratively with domain experts including a biogeochemist, soil scientists, a catchment modeller and SEPA staff, ensuring that key drivers of P pollution dynamics were identified and represented in the BN structure (Chen & Pollino, 2012). This collaborative process enhanced the robustness of the P model structure and increased confidence among likely users. Building on this expert-informed framework ensures that the adapted FIO model inherits the same rigour and credibility, which is critical for its acceptance in both scientific and management contexts. The model was further refined through input from experts in catchment science, microbiology, water resource management and environment and health, which helped streamline variable relationships and retain only essential states (Mzyece et al., 2024). Third, the P BN was validated against observed data across seven Scottish catchments (Glendell et al., 2022), some of which are also relevant for FIO pollution assessment. This provides a valuable basis for expanding the approach to consider other pollutants, given that the testing of the P BN demonstrated that the approach was fit for purpose. Of course, the development of a resulting FIO BN would in turn require testing against real world data to validate its predictive capability.

Beyond these core reasons, further justification lies in efficiency and resource optimisation. Developing a BN can be resource-intensive due to the amount of time required to build and learn the network structure, and the significant effort in eliciting probabilistic information from disciplinary experts of especially complex systems. Large models with many variables require increased data to support the parameterisation process (Govender et al., 2022), and too many nodes in a BN can result in highly complex CPTs, which become increasingly difficult to parameterise (Marcot, 2017). By leveraging an existing validated framework, resources can be focused on refining and extending the model rather than recreating foundational elements. Further, building on a framework already known by researchers, regulators and catchment managers increases transparency, builds trust and enhances the likelihood of uptake compared to introducing an entirely new framework. Finally, using a common BN framework for both phosphorus and FIOs supports integrated catchment management and the potential for accounting for trade-offs, and pollution swapping in catchment systems on the introduction of interventions or management decisions concerning STS pollution, and demonstrates the flexibility of BNs to be extended to other pollutants (Crossman et al., 2021; Glendell et al., 2021). Together, these factors provide a strong justification for modifying the P BN as the foundation for an FIO BN.

Both the conceptual P BN model and the FIO BN model highlighted two important findings regarding the data requirements for the model, which have important methodological implications. Firstly, major changes between the two models were required in pollutant-specific variables describing how pollutants interact with the environment as they transfer to a source, and secondly, uncertainty regarding data requirements was highest in STS-specific variables (in the 'Source' component), describing how FIOs are generated at the source. P removal in soil can be inferred from indices like the P Sorption Index (Psi) and P Saturation Index (PSI), which are used to predict the P loss potential by measuring a soil's P retention capacity (Campos et al., 2016). By contrast, no such indices are available for FIOs, and this lies in the different characteristics of the two pollutants. While P is chemical in nature and can hold or

sorb to soil particles and be released to the environment at a later point (Negri et al., 2025), FIOs are biological in nature, and the soil environment encompasses a dynamic interplay of conditions affecting them. High soil moisture content can prolong FIO survival in the environment while dry periods resulting from high temperature and solar radiation generally increase die-off (Buckerfield, Quilliam, et al., 2019). These differences in behaviour specific to the respective pollutants highlights the need for different parametrisation data for the nodes describing FIO pollutant transport from STS and delivery to watercourses.

One type of such data as specified in Table 5 is FIOs delivery coefficients to a watercourse under different landscape conditions. Delivery coefficients (and their associated uncertainty) have been evaluated for other agricultural pollutants, perhaps most notably P, see for example Zhang et al. (2013). These are difficult to estimate empirically because of the spatially diffuse nature of STS within landscapes and multiple FIO pathways, i.e., surface, sub-surface and underground (Gill & Mockler, 2016), which are also influenced by variations in water flow conditions driven by rainfall activity (high flow can promote transfer within landscapes while low flow can concentrate FIOs in watercourses) (Oliver et al., 2015). Furthermore, field-relevant monitoring of FIO loss from STS is challenging, hampered by poor understanding of STS infrastructure locations in the landscape and suitable access points for sampling both the STS itself and then having confidence that the FIO signal measured at a receiving water is attributed to the STS of interest. Chemical or microbiological tracers could be used to help confirm source (Wyer et al., 2010), but realistically this type of monitoring would need to be undertaken across a large number of permutations that combine different slope angles, distances from STS to watercourse and effluent movement risk categorisations. Doing this at the landscape scale would be a significant investment of resource and effort, and of course true replication at landscape scales is impossible meaning uncertainty would be high in terms of assigning delivery coefficients to a series of slope/distance/effluent movement risk combinations. A more cost-effective alternative approach would be to capitalise on expert

judgements, and to use expert elicitation protocols to draw together best estimates of how different environmental factors combine to influence FIO delivery from STS. Such approaches have been used to elicit proportions of soluble reactive phosphorus (SRP) that can be delivered to a watercourse from an STS (Glendell et al., 2021) and can account for uncertainty and variability by gauging expert confidence in their judgements. Given that BN frameworks can easily accommodate expert data, this approach would appear to represent a future research opportunity to further develop the FIO BN proposed in this chapter.

Data scarcity remains one of the most significant challenges in modelling FIO pollution risk from STS (Richards et al., 2016), particularly STS-specific data within the 'Source' component of the S-P-R framework. STS treatment level and maintenance condition, which are key variables within the 'Source' component are critical yet poorly documented variables, reflecting the lack of systematic, centralised monitoring of household systems. Most STS-specific information is available only at household level and there are inconsistencies in the way the data are recorded and, in most cases, there is not even any information recorded or passed on to property owners at the point of a property sale (Naughton & Hynds, 2014). This limitation has also been emphasised in recent literature (Bian et al., 2024; Mills et al., 2024), and it reinforces the importance of developing mechanisms to improve data collection at scale. In contrast, the relative certainty associated with direct discharge illustrates how spatial datasets can, in some cases, help overcome these gaps as seen in Glendell et al. (2022). For the 'Pathway' and 'Receptor' components, the findings reinforce both the strengths and limitations of current methods. Spatial data provide robust inputs for variables such as slope, soil and hydrological risk and distance, but greater uncertainty remains around estimating STS effluent movement risk and the ultimate proportion of FIOs reaching watercourses. Taken together, the findings earlier highlighted, practical constraints of estimating STS FIO delivery coefficients empirically to understand contributions of STS to faecal pollution in watercourses, and lack of STS-specific data to understand the factors driving generation of FIO pollutants at the source

emphasise the need for other approaches to obtain these data. Future research should therefore prioritise obtaining data to parameterise the model through other approaches, for example expert elicitation utilising expert judgement to obtain data that cannot be empirically measured (Mikkola et al., 2024), and survey methods to obtain STS-specific data which are primarily available at household level (Naughton & Hynds, 2014).

Once parameterised, the FIO BN model should be tested to assess model accuracy and reliability in predicting FIO pollution from STS to watercourses. This is a crucial step to secure confidence among potential users in the model outputs (Avila et al., 2018). Initially, the model should be tested within a relatively simple catchment where STS represent the dominant form of domestic sewage treatment because this controlled setting will provide an opportunity to assess baseline model performance before testing in more complex catchments (Coffey et al., 2016). Importantly, catchments containing STWs should be avoided at this stage, as distinguishing human-derived FIOs originating from STWs versus those from dispersed STSs is challenging. Therefore, careful site selection is fundamental to ensuring meaningful validation of the model. A key requirement for model testing will be the availability of appropriate datasets. Robust time-series data are essential for evaluating model outputs, but these are often hard to find due to limited FIO monitoring of watercourses; for example, in the UK FIO monitoring is only typical at designated bathing sites (typically coastal, and currently no rivers designated in Scotland), and this is only done during the bathing season in summer with little sampling outside the bathing season (Oliver, 2025). Identification of contender 'test catchments' could be done in consultation with environmental regulators, such as SEPA, who do undertake catchment 'blitz' monitoring in priority catchments where FIO impacts on water quality have been recognised, and these targeted sampling campaigns do often include accompanying MST that distinguishes between animal- and human-derived FIOs (Wiesner-Friedman et al., 2022). These data will enable direct comparisons between observed and modelled human-derived FIO levels, providing a critical test of model accuracy and reliability.

Without such supporting datasets, model validation would be limited and potentially misleading to users.

Following successful application in a simplified catchment, the FIO BN model should then be extended to more complex systems characterised by diverse landscape features and multiple FIO sources. Such progressive testing will allow for the evaluation of model performance under increasingly realistic conditions. Based on performance in complex catchments, the model can potentially be developed as a spatial tool for national-scale application, enabling assessments of STS-related FIO pollution risk across Scotland (Negri, Schurch, et al., 2024). Finally, consideration should be given to testing different formulations of the model, including hybrid and discretised versions, to address recognised limitations of BNs such as information loss after discretisation as identified in the literature (Kaikkonen et al., 2021; Nojavan et al., 2017). Exploring these alternative structures may enhance model robustness and applicability, ensuring the tool remains relevant for both scientific and policy-driven purposes.

The development and testing of the FIO BN model have significant implications for research, catchment management and regulatory practice. Demonstrating that the FIO BN model can accurately predict FIO losses from STS would give confidence to other researchers to extend the model to other STS-related pollutants such as microplastics and emerging pollutants of concern including pharmaceuticals, detergents and antibiotic-resistant genes (Birch et al., 2015; Szopińska et al., 2022; Wilschnack et al., 2024). The model can also serve as a testbed for coupling with other models, for example climate change models to predict how climate change will influence STS-related pollution to watercourses and enable planning of mitigation measures as demonstrated by Negri et al. (2025) for a P BN model. The model might also be used in interdisciplinary research, for example by ecologists to link model predictions of FIO pollution from STS to ecosystem health indicators, such as impacts on shellfish waters or biodiversity. By providing a probabilistic framework for assessing FIO pollution risks

associated with STS, the model offers catchment managers and regulators a transparent and evidence-based decision-support tool that can enable more efficient targeting of monitoring and mitigation measures, reducing reliance on resource-intensive water quality sampling (Oliver, 2025). The model's capacity to explore "what-if" scenarios, such as changes in land use, STS management practices, or climate-driven rainfall patterns, also provides a valuable mechanism for forward planning and adaptive management (Glendell et al., 2022).

Importantly, the model can support compliance with statutory water quality standards, including those under the EU Bathing Water Directive, the Drinking Water Directive, and the Water Framework Directive (WFD). In the Scottish context, the model could directly inform the development and delivery of River Basin Management Plans and contribute to meeting obligations under the Scottish Government's regulatory framework for private sewage treatment systems (Scottish Environmental Protection Agency, 2025). At a broader scale, the potential to apply the model nationally would allow agencies such as SEPA to adopt a consistent framework for assessing FIO risks across Scotland, thereby strengthening both strategic planning and policy implementation in support of national and international water quality objectives.

Finally, while the strengths that lie in adapting an existing P BN model to account for FIO pollution from STS are outlined, one major limitation is acknowledged. There is a possibility of potentially inheriting data gaps and uncertainties from the P BN as assessing STS pollution risk depends heavily on site-specific factors such as system age, condition, and maintenance, for which reliable data are often scarce. To mitigate this, Chapter 5 of this thesis reports on a Scotland-wide survey of STS users designed to capture these critical factors. This information will not only contribute to refining the FIO BN, but it can potentially contribute to improving the P BN model and future models of additional pollutant losses from STS, such as pharmaceuticals.

2.6 Conclusion

This study has demonstrated the flexibility of BN models by adapting a P risk BN model to represent FIO pollution risk from STS to watercourses. To capture causal relationships specific to STS-related pollution, the FIO BN was adapted from a P model originally developed to account for risks from multiple sources, including STS. Key structural modifications included replacing P-specific nodes—such as STS effluent concentrations, leaching risks under varying soil and hydrological conditions, and leachfield removal probabilities—with nodes representing FIO concentrations in STS effluent at different treatment levels, alongside elicited FIO delivery proportions influenced by topography, STS proximity to watercourses, and soil–hydrological conditions. The study highlighted data scarcity regarding STS maintenance condition and treatment level together with complex environmental factors driving STS effluent movement risk within landscapes as major drivers of uncertainty in estimating the levels of FIO pollutants delivered to watercourses from STS. To further develop the model, future research should prioritise testing in catchments where STS are the dominant form of sewage treatment, where no STWs are present, and where high-resolution FIO monitoring data are available. Incorporating MST data to distinguish human- from animal-derived FIOs will be critical for robust validation and refinement of model predictions.

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

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3.1 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 <10m, 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 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.

3.2 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 & 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 & 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, Waldron, et al., 2019). 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., 2023).

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 & 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 & 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 & 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 are 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, Burgman, et al., 2018); 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.

3.3 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.

3.3.1 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 a 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 by using the Hydrology of Soil Types (HOST) (Boorman et al., 1995) conceptual models (Figure 6), 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 & Lilly, 2019). To guide this elicitation, experts used HOST classes (Table 6) grouped based on their conceptual soil and hydrological pathways and translated into STS effluent movement risk, and pathways driving risk (Glendell et al., 2021). This classification was informed by previous assessment of the role of soils in determining water quality risks (Lilly & 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 & Mockler, 2016). Slope

Table 6: 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, HOST27	Relatively free draining soil & deep GW	Leaching to GW, some runoff
		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

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 factors, STS effluent movement risk, STS distance to watercourse, and slope, were used to generate 36 Scenarios, presented under the Results section, for which experts gave a range of values characterising the QoI.

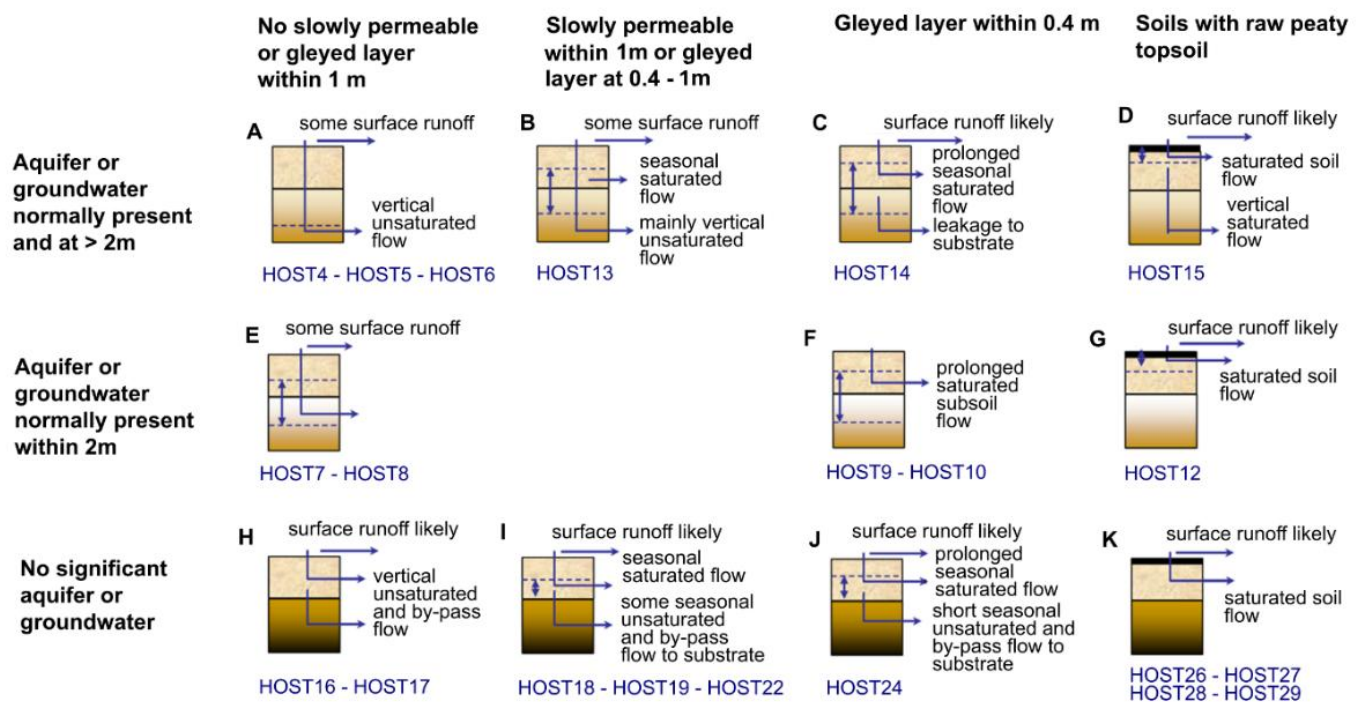


Figure 6: HOST conceptual models of water movement and respective HOST classes present in Scotland (Gagkas et al., 2021).

3.3.2 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 is primarily expertise in a field of relevance to the defined quantity of interest. Potential experts were identified and 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 (Appendix 1), 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 hrs), starting with an information sharing session to discuss any issues from the evidence dossier and the e-learning course.

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 $pFIO$ was likely to lie for all scenarios. For each scenario, experts individually elicited a median value at which they judged it equally

likely for $pFIO$ 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.

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).

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.

3.4 Results

Five experts participated in the elicitation workshop. The individual expert judgements elicited for each of the 36 scenarios are available in Appendix 2. 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 7). 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 Figure 7 and Figure 8, respectively. High uncertainty in the expert judgements for intermediate risk scenarios is represented by less overlap in the individual probability distribution curves (e.g., Figure 9). In instances where experts could not reach a consensus, they relied on a linear pool (e.g., Figure 10). Figure 11 shows the distribution curves for all the 36 scenarios.

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 (Figure 7) 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

(Figure 8). 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.

Table 7: Elicitation Scenarios, consensus values and summary statistics² of the consensus plots and linear aggregation plots³ 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	Very High	<10	>25	90	93	95	17.7	1.65	0.915	0.004	79.4	98.8
2			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		10 to 50	>25	65	70	75	10.8	4.77	0.694	0.013	49.3	86.5
5			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		>50	>25	65	67	72	19	9.07	0.677	0.008	52.7	81.2
8			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	High	<10	>25	65	78	81	3.54	1.37	0.721	0.034	37.1	96.4
11			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		10 to 50	>25	60*	65*	70*	10.9	5.98	0.646	0.013	45	82.2
14			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		>50	>25	40	50	58	2.95	3	0.496	0.036	18.5	80.8
17			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	Moderate	<10	>25	55	60	64	13.1	8.88	0.596	0.010	42.1	75.9
20			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		10 to 50	>25	36*	43*	52*	3.23	4.07	0.442	0.030	16.8	73.6
23			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		>50	>25	25	30	40	2.32	4.66	0.332	0.028	8.86	63.3
26			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	Low	<10	>25	27	33	40	3.4	6.49	0.344	0.021	12.6	59.9
29			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		10 to 50	>25	13*	19*	28*	1.23	4.1	0.231	0.028	2.37	55.8
32			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		>50	>25	4.5	8	13.5	0.77	5.61	0.121	0.014	0.33	36.9
35			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

² x and y are shape parameters specifying the beta distribution and used to calculate the mean and variance.

³ 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.

Uncertainty in individual expert judgements was high in scenarios 7 - 24 representing intermediate conditions (Figure 11). 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 $pFIO$ from the median. Scenario 9 had the largest CI of 13.3 - 88% and therefore the highest uncertainty (Figure 9). The experts could not reach a consensus for this scenario and therefore agreed to use a linear pool (Figure 10) that averaged their individual judgements. 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 was 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.

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 $pFIO$ 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 $pFIO$ if the STS was located less than 10m from a watercourse, compared to being >50 m away. A steep slope of 25% compared to gentle slope of 5% increased $pFIO$ 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 $pFIO$ by approximately 20% if the STS distance to a watercourse was <10 m. Similarly, the influence of distance on $pFIO$ 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 50m) resulted in reduction of $pFIO$ delivered by an average of 19%.

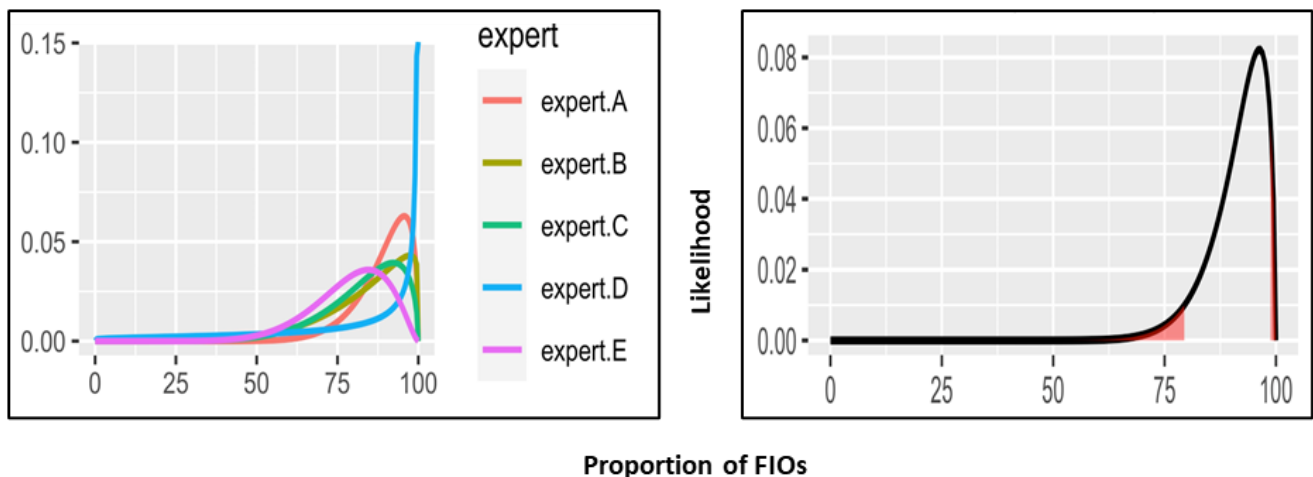


Figure 7: Probability density curves of 5 individual expert judgements (**left**) and consensus beta distribution (**right**) of the proportion of FIOs (median 93) likely to be delivered to a watercourse under the highest risk Scenario 1 combining very high STS effluent movement risk, septic tank distance to watercourse of <10m and steep slope >25%. The red regions in figure 2b represent the 5th (79.4) and 95th percentiles (98.8).

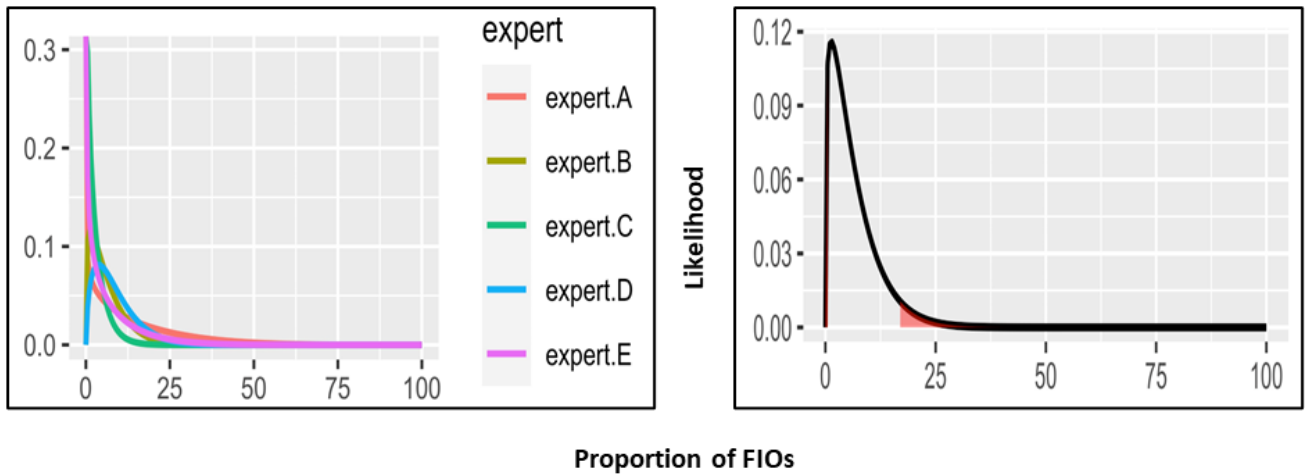


Figure 8: Individual expert probability density curves (**left**) and consensus beta distribution curve (**right**) of the proportion of FIOs (median 5%) likely to be delivered to a watercourse under Scenario 36 combining low STS effluent movement risk, septic tank distance to watercourse of >50m and gentle slope 0-5%. The red regions on figure 3b represent the 5th (0.55) and 95th percentiles (17.0).

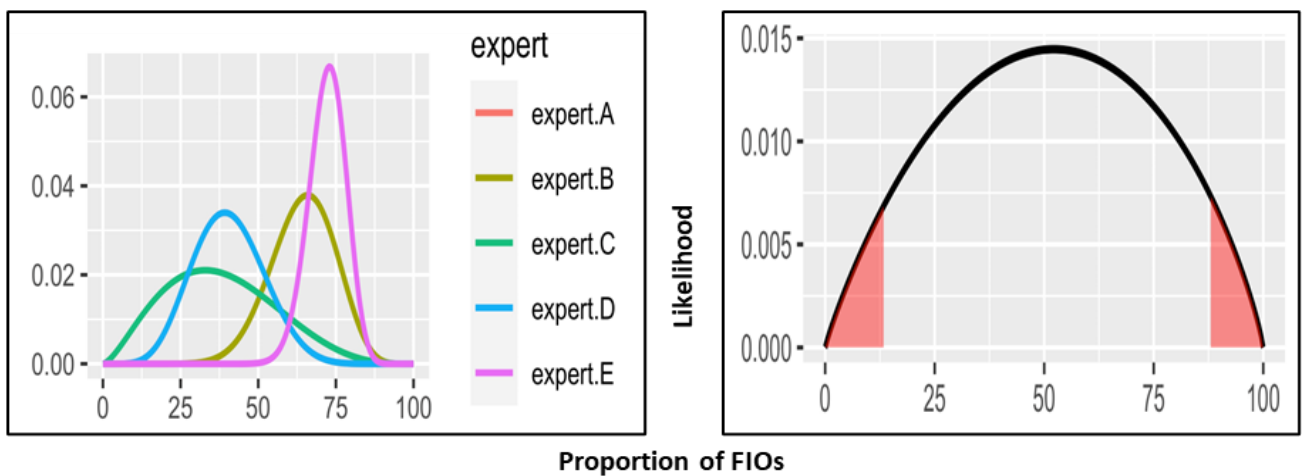


Figure 9: Individual probability density curves with less overlap (**left**) and wide range consensus beta distribution curve (**right**) showing high uncertainty in judgements given for Scenario 9 combining very high STS effluent movement risk, septic tank distance to watercourse of >50m and gentle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

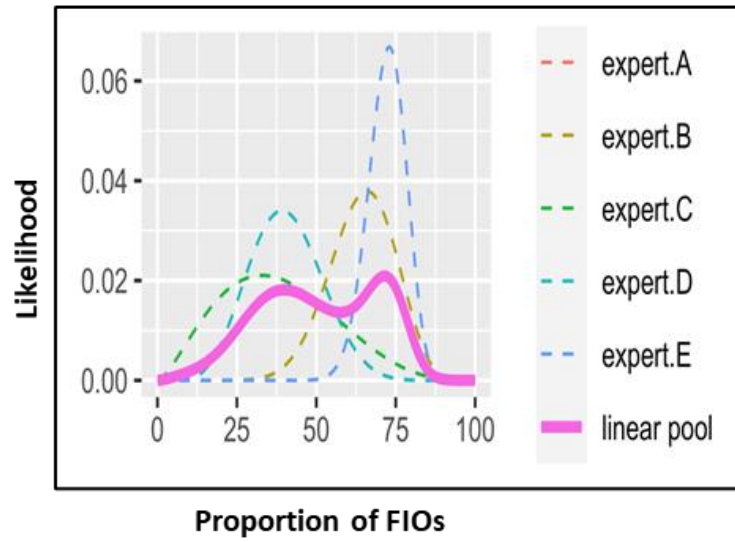


Figure 10: Linear pool (LP) of individual expert judgements which experts used for Scenario 9 where they could not reach a consensus. The LP tertile and median values were used to plot the consensus probability density curve for Scenario 9 in Figure 4(b).

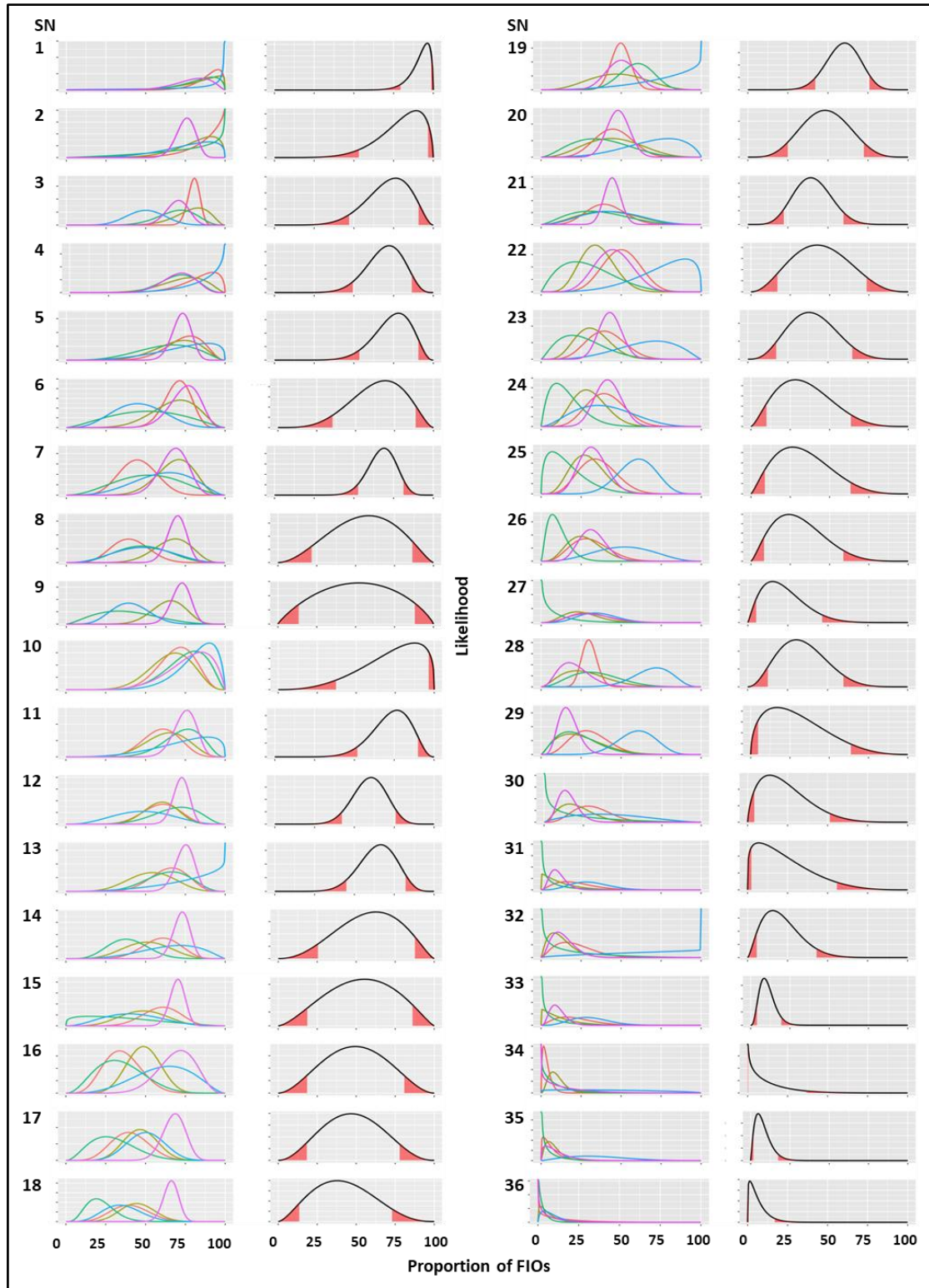


Figure 11: Individual expert distribution curves (left) vs probability density functions (right) for the 36 elicitation Scenarios. SN denotes Scenario Numbers. The x-axis shows the elicited proportions of FIOs on a scale of 0-100. The y-axis shows the likelihood of observing these proportions on a probability 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 Appendix 3 for the original plots with actual scales of axes.

3.5 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. 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 7). 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 & 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., 2019; Gagkas & 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 & 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 & 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 more than 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 the process 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 visualisation 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 2010) 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, McBride, et al., 2018); 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., 2021), 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.

3.6 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.

4 Validating a Bayesian network model to characterise faecal indicator organism loss from septic tank systems in rural catchments

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4.1 Abstract

Validating model predictions with observed data is crucial for fostering confidence in model results, yet it is often overlooked in Bayesian Network (BN) studies. This research validates a BN model designed to predict faecal indicator organism (FIO) loss from septic tank systems (STS) in rural catchments. Both a hybrid model (combining continuous and discrete variables) and a fully discretised model were assessed. The approach to model validation employed four methods: (1) comparing probability distributions of simulated and observed FIO loads in the hybrid model, (2) sensitivity analysis in the discrete model to identify key variables influencing results, (3) estimating percentage bias to evaluate the average difference between predicted and observed FIO loads in the hybrid model, and (4) applying Shannon entropy to measure uncertainty in the discrete model's spatial application. Predicted FIO loads per STS were consistent across models, with the hybrid network estimating 4.63×10^{10} colony forming units per year (CFU/yr) in the Cessnock catchment and 4.36×10^{10} CFU/yr in the Mein catchment, while the discrete network predicted 3.85×10^{10} CFU/yr and 3.65×10^{10} CFU/yr, respectively, closely aligning with observed values of 6.17×10^{10} CFU/yr and 5.10×10^{10} CFU/yr. Sensitivity analysis identified STS condition and treatment level as critical factors influencing FIO loss. Shannon entropy values (1.60 – 1.85) revealed significant uncertainty in model predictions in the catchment where STS were associated with a variability of Hydrology of Soil Types (HOST)-derived risk factors. When applied at national scale, greater confidence in model results was associated with Central, East and West Scotland where most STS were associated with a moderate to high HOST-derived risk classification. Our research is the first to show how BN models can predict FIO pollution from STS to watercourses, and the findings suggest that refining model predictions requires more accurate data on STS treatment levels and maintenance as well as access to good quality high-resolution stream water quality monitoring data.

4.2 Introduction

Septic tank systems (STS) are used worldwide for treating domestic wastewater in areas where conventional sewer networks are inaccessible, impractical, or costly, such as rural regions. For example, in the USA, approximately 18% of households (equivalent to 21.7 million homes) utilise STS or cesspools (USEPA, 2021). Across Africa, there has been a notable increase in STS usage classed as improved sanitation, which accounts for close to 40% of sanitation development, particularly in peri-urban areas, to accommodate the expanding urban regions (African Development Bank, 2020). In Australia, 7% of the population rely on onsite sewage treatment with ~93% of the population being consistently linked to a public sewer network since 2010 (OECD, 2023). The prevalence of STS across Europe varies depending on factors such as urban population density and stringent local regulations regarding installation and maintenance. Conservative estimates suggest that ~4% of the population in the UK rely on STS and small private sewage treatment systems for sewage disposal (Defra, 2002; O'keeffe et al., 2015; Richards et al. 2016)

Treating wastewater in STS primarily involves the settling of solids through primary sedimentation, which may be followed by additional treatment in soakaway fields. The effectiveness of this treatment relies on good STS maintenance, its age, and the filtration capacity of the surrounding soil (Beal et al., 2005). Poor maintenance, outdated infrastructure, and inadequate filtration of effluent can result in contaminated wastewater high in nutrient and faecal indicator organism (FIO) concentrations, which poses a contamination risk to both ground and surface water (Richards et al., 2016). While STS are recognised as potential sources of FIOs in rural catchments, there remain substantial knowledge gaps with respect to their overall contribution to water pollution (Mzyece et al., 2024). Although FIO removal rates of 50 - 95% in conventional septic tanks have been documented (Kay et al., 2008), under certain environmental conditions, there is a possibility of bacterial proliferation, leading to higher FIO export from STS compared to the influent

wastewater load (Appling et al., 2013). Microbial retention within soil pore architecture reduces FIOs available for transfer from land to water; however, further investigation is needed to fully understand the transfer dynamics of FIOs between soil compartments and groundwater (Bradford & Harvey, 2017), along with considering other environmental factors such as topography and proximity of STS to water bodies.

Mitigating FIO contamination is essential for preserving water quality and protecting public health, particularly in catchments that drain to recreational waters designated for bathing or to shellfish harvesting waters, both of which provide human exposure pathways to faecal pollution (Oliver et al., 2024). Water quality models play a vital role in helping to manage FIO pollution of water catchments; they can be used to predict pollution throughout the microbial source-mobilisation-delivery-impact continuum within landscapes (Glendell et al., 2022). For example, models can be applied at the catchment scale to predict *E. coli* burden on agricultural land from livestock sources, considering FIO accumulation and depletion over time (Oliver et al., 2018). Various hydrological models have been used to underpin predictions of nutrient and FIO pollutant transport, e.g., by estimating overland flow and utilising pollutant export coefficient methods (Yuan et al. 2020). Additionally, multiple linear regression-based models use environmental factors to predict FIO loads at downstream receptors such as bathing beaches (Madani & Seth, 2020; Rossi et al., 2020).

Bayesian Networks represent another modelling approach for understanding FIO risks in the environment. Bayesian Networks (BNs) are probabilistic graphical models that represent a collection of random variables and their conditional dependencies through a Directed Acyclic Graph (DAG) (Pollino & Henderson, 2010). These models consist of three fundamental elements (nodes, arcs and conditional probability tables, see Section 1.6 for details).

The application of BNs in environmental risk assessment of complex systems such as water catchments has been increasing (Phan et al., 2016). This is attributed to several of their characteristics, including good predictive power even when variables have missing data, which would result in imputation or omission in other models such as Markov chain, classification trees, and random forests (Moe et al., 2021). In this study, BNs were chosen for their flexibility in incorporating multiple data types, including expert judgements and for their ability to explicitly account for uncertainty. These attributes render them particularly suitable for modelling FIO pollution risk from STS, where monitoring data are sparse and the fate and transport of microbial contaminants are influenced by complex, interacting environmental processes. BNs inherently accommodate uncertainty analysis. This is achieved using CPTs to encode dependencies between variables, probability distributions to represent uncertainty in continuous parameters, and causal structures to describe environmental processes governing pollutant dynamics. Collectively, these features, underpinned by the stochastic nature of BNs, enable the quantification of both epistemic and aleatory uncertainties (Glendell et al., 2022; Sahlin et al., 2020) and facilitate the systematic identification of uncertainty sources within the model (Sperotto et al., 2019).

Despite their advantages, BN modelling applications face challenges, such as loss of accuracy from the discretisation of continuous variables (Kaikkonen et al., 2021; Rohmer, 2020, Fenton 2019); difficulties in validating BNs developed solely from expert-elicited knowledge due to lack of observed data and limited quantification of model confidence demonstrated by credible intervals around posterior probability distributions (Marcot & Penman, 2019).

To overcome the challenges associated with BN modelling, our study employed a hybrid network that incorporates both discrete and continuous variables, following the methodologies of Glendell et al. (2022) and Aguilera et al. (2010) and a discrete network to assess the extent of information loss after discretisation. Additionally, we utilized monitoring data alongside expert-elicited data

(Mzyece et al., 2024) to validate model outcomes against observed data. Model performance was assessed by comparing predictions with relatively high temporal resolution data from two rural catchments with similar grassland-dominated land use, no sewage treatment works (STWs) inputs and with available microbial source tracking (MST) data. This experimental design allowed us to semi-quantitatively evaluate the FIO model and distinguish between FIO load from STS, STWs and livestock/wildlife. Model uncertainty was quantified by estimating the Shannon entropy index, which sums the product of the probability of each model's outcome and the natural logarithm of that probability across all possible outcomes (Ellerman, 2021). This measure is appropriate for estimating uncertainty in random variables with discrete values (Feutrill & Roughan, 2021), making it suitable for the discrete version of our BN.

The overarching aim of our study was to develop and test a probabilistic BN model to better understand the contribution of STS to faecal pollution in rural catchments. Specifically, our study objectives were to: I) predict FIO load from STS in two rural test catchments in Scotland; II) evaluate BN model performance relative to observed FIO load, using microbial source tracking to apportion human and ruminant contributions; and III) Upscale the model to predict FIO pollution risk from STS at the national scale.

4.3 Methodology

4.3.1 Study catchments

Two study catchments in Scotland were used to predict annual FIO load. The Cessnock catchment (Latitude 55.54568, Longitude -4.39248; area 22 km²) and Mein catchment (Latitude 55.06482, Longitude -3.22122, area 12 km²) (Figure 12), which are typical rural catchments that primarily rely on STS for domestic wastewater treatment, with no STWs or sewer overflows

present (Scottish Water, 2025). For our study, this helps to constrain uncertainty concerning the source of any human-derived FIOs within our observed data used to evaluate the model predictions, suggesting that all human-derived FIOs originate from STS. Importantly, historical FIO water quality monitoring data covering September 2018 to September 2019 is available for both catchments, which includes MST information that provides an indication of the relative contribution of livestock versus human FIO contributions necessary for validating our predictive model. Detailed descriptions of the catchment characteristics can be found in Glendell et al. (2022), while additional visual representations of primary land use, STS locations relative to the drainage network, and Scottish Environmental Protection Agency (SEPA) water monitoring sites are provided in Figure 12.

The Cessnock and Mein catchments are situated in southwest Scotland, predominantly characterised by improved grassland (64% and 65% of land cover, respectively). The primary soil types are stagnosols (61%) in Cessnock and cambisols (59%) in Mein, both of which are classified as slowly permeable with a moderate to high risk of septic tank effluent movement (Gagkas et al., 2021; Hudson et al., 2012). In total, there are 65 and 36 STS in the Cessnock and Mein catchments, respectively, inferred from modelled STS locations provided by the SEPA. Most STS (87% in Mein and 90% in Cessnock) are situated more than 50 m away from watercourses, with 13% and 10% respectively falling within the range of 10 - 50 m, and none closer than 10 m. Approximately 78% of STS in Cessnock and 44% in Mein are located on gentle slope gradients (0 - 5%), while the remainder are situated on moderate slopes (>5 - 25%). SEPA has established water quality monitoring points in Cessnock Water and Mein Water positioned at the outlet of each catchment. Parameters monitored at these outlets include water chemistry, discharge, FIOs (*E. coli* and intestinal enterococci), and MST targets.

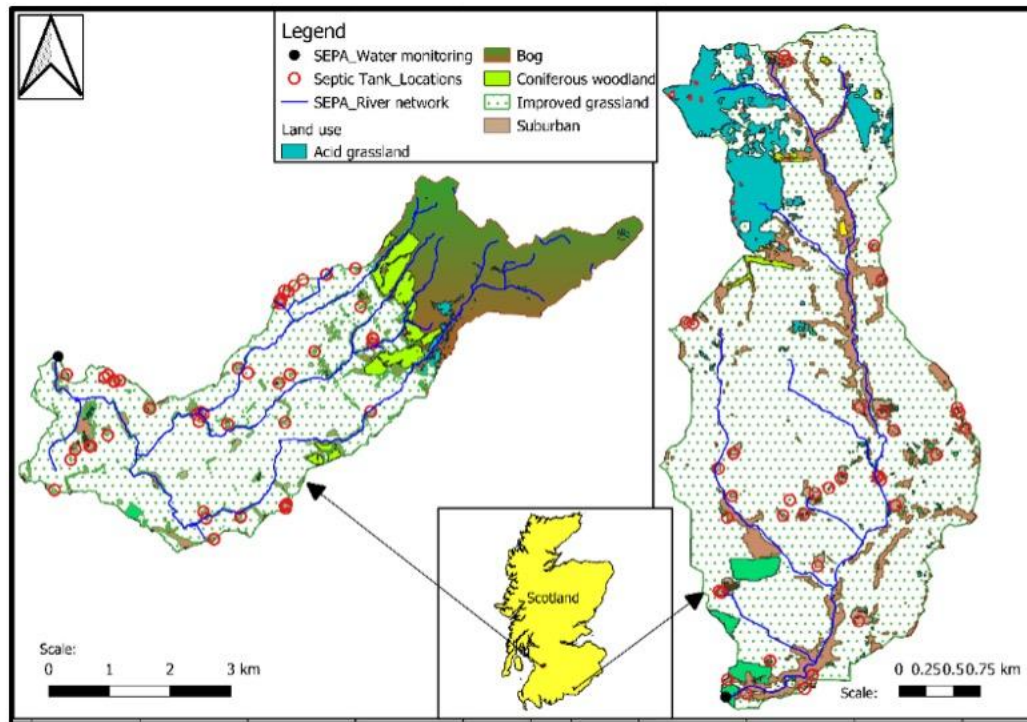


Figure 12: Land use in the Cessnock and Mein catchments (Morton et al., 2024).

4.3.2 Model development and parametrisation

The model structure was modified from a phosphorus pollution risk model developed in Glendell et al. (2022). The detailed description of the conceptual model development process is presented in Chapter 2. Key datasets utilised for model parameterisation were STS locations from SEPA, FIO concentrations for different STS treatment levels obtained from literature (Gill et al., 2007; Kay et al., 2008), STS to watercourse FIO delivery proportions elicited from experts as detailed in Mzyece et al. (2024) and probabilities of effluent movement risk inferred from HOST-derived risk classifications (Gagkas et al., 2021). The model was developed in the proprietary Bayesian network software GeNIe vs. 4.1 (BayesFusion, 2024).

4.3.3 Model discretisation

To enable sensitivity analysis and spatial implementation, the model was discretised by converting continuous equation nodes into discrete chance nodes, as outlined in the GeNIe manual, Version 4.1 (BayesFusion, 2024). Two methods were employed to set discretisation boundaries: (i) equal intervals dividing the continuous data into a predefined number of intervals with equal widths as seen in e.g., Aguilera et al. (2011) and Chen & Pollino (2012), and (ii) interpolation (a form of supervised discretisation (Beuzen et al., 2018) where boundaries were manually adjusted to obtain plausible probabilities). Initially, FIO load values in the target node (Realised FIO load) were logged to address skewness of the sample probability distribution (Nojavan et al., 2017). However, values in other equation nodes remained unlogged to allow FIO concentration calculations using original values. For equal intervals discretisation, the sample probability distribution specified by the lower and upper bound was divided into equal intervals representing the states in each of the equation nodes. Conditional Probability Tables (CPTs) were reviewed, and discretisation boundaries were adjusted through interpolation to obtain plausible probabilities for matching states (Low/Low, Medium/Medium, High/High). This resulted in different marginal probabilities for the states in the Realised FIO load node between the two discretisation methods. To assess which method generated predicted FIO loads closer to the observed loads in the discrete network, we estimated the sum of squared errors (SSE). Based on the SSE and additional factors such as calculation of plausible probabilities in the CPTs and final marginal distributions in the target node, an appropriate discretisation method was selected.

4.3.4 Model evaluation

Model evaluation followed the approach of Glendell et al. (2022) and Troldborg et al. (2021), being implemented through four approaches: (1) sensitivity analysis to identify highly sensitive parameters that significantly affected reasoning in the model results; (2) comparing the

distributions of predicted FIO load against observed FIO load in the two catchments; (3) calculating PBIAS to determine the difference between predicted and observed FIO load in the hybrid model; and (4) using Shannon entropy to assess uncertainty in the discrete version of the model applied spatially.

Sensitivity analysis

Sensitivity analysis was undertaken on the discretised version of the model to identify highly sensitive parameters that significantly affected reasoning in the model results. This was done within GeNIe 4.1, implementing the algorithm proposed by Kjaerulff & van der Gaag (2000). This algorithm calculated a set of derivatives of the posterior probability distributions over the target node (realised FIO load) utilising each of the numerical parameters in the BN. Sensitive parameters were identified by observing the colour intensity of nodes in our BN and inspecting maximum node sensitivity values in the node properties table. Sensitivity analysis enabled targeted inspection of significant nodes to ensure correct parametrisation and therefore model outcomes.

Comparison of predicted against observed data

Two types of comparisons were made, namely the predicted versus observed catchment FIO load and the predicted versus observed FIO load per STS. Sections 2.4.2.1 and 2.4.2.2 describe the dataset including calculations made to enable comparison of observed values with model predictions.

Daily E. coli concentration

This dataset included 56 time-series data points for daily composite samples of *E. coli* concentration (CFU/100ml) and daily mean discharge data (m³/s) at the Cessnock outlet and 78

data points at the Mein outlet, between September 2018 and September 2019. Samples were collected twice weekly (Tuesdays and Thursdays) using 24-hour composite sampling with a refrigerated autosampler (Avalanche Teledyne ISCO). Each composite sample represents an integrated signal from 24 hourly subsamples, reducing the influence of short-term flow variability (Cassidy et al., 2018). Refrigeration has been shown to minimise FIO die-off during storage (Oliver et al., 2015).

Sampling was consistent (~8 samples/month) between September – November 2018 and March–August 2019. However, coverage varied across sites and years: Cessnock had only 11 data points in 2019 compared to 51 at Mein, and both catchments had limited data (1–3 records) in December – January. No Cessnock samples were collected in June – July 2019. Discharge–*E. coli* concentration plots are presented in Appendix 4 and Appendix 5. These plots demonstrate that FIOs were sampled across a broad range of discharge quantiles and indicate the minimum and maximum quantiles recorded in each catchment.

Escherichia coli was selected as the most specific indicator of human-sourced faecal pollution (Price & Wildeboer, 2017) and therefore used in the validation. As our model aimed to estimate annual FIO load, we standardised the monitoring data to match the units in our model. First, the daily FIO load was calculated (*Equation 1*).

$$\text{Daily FIO load} = EC_{1L} \times Q \quad \text{Equation 1}$$

where:

EC_{1L} is the *E. coli* in 1L, and

*Q is the Daily mean discharge (Q in L/second * 86400 seconds/day)*

Next, gaps in the data were filled by interpolation using two methods to ensure robustness. Last observation carried forward' (LOCF) was undertaken in Excel by replacing missing data points with the last observed FIO load (Lachin, 2016). Additionally, linear interpolation was done in Python version 3.8 (Van Rossum & Drake, 2009) estimating missing values for FIO loads using linear regression. Daily mean FIO loads were then calculated separately for both methods, exported to GeNIe 4.1, and multiplied by 365 to obtain annual FIO loads. For each method, a distribution of 10,000 Monte Carlo simulations was generated and compared with the BN-predicted FIO load distribution. Potential uncertainties associated with interpolation are discussed in Section 4.

Using MST data

Microbial source tracking (MST) data were provided by JHI. The quantification method involved using a multiplex qPCR assay targeting human- and ruminant-specific *Bacteroides*. Human-specific primers (HF183F/HF183R) and probes (BacHum193p) were applied as described by Seurinck et al. (2005) and Kildare et al. (2007), while ruminant-specific primers (BacR-F/BacR-R) and probe (BacR-P) followed Reischer et al. (2006). An internal amplification control (IAC) was included to detect inhibition. DNA was extracted from water samples using the DNeasy PowerWater Kit (Qiagen). qPCR reactions were prepared with BioRad iQ Multiplex Powermix, primers and probes for each target and the IAC, and up to 10 ng of template DNA, and run on a Bio-Rad CFX96. Standard curves were generated from plasmids containing target gene inserts, and only assays with efficiencies between 90 – 110% were accepted. Absolute abundances of human- and ruminant-specific *Bacteroides* were used for further analysis. MST sampling was conducted twice weekly for two years.

Since the observed annual total FIO load ($FIOload_{(OAT)}$) calculated from the *E. coli* concentration in section 2.4.2.1 was indicative of *E. coli* from both human and animal sources, we used MST data available in both catchments to estimate the proportion of human-derived *E. coli* from daily human and ruminant *Bacteroides* in 1L pHDE (Equation 2). Overall, average human *Bacteroides* concentrations were higher than ruminant *Bacteroides* over one-year sampling period in both catchments: 8.21×10^7 HuBac/L versus 6.89×10^5 RuBac/L in Cessnock, and 1.35×10^7 HuBac/L versus 7.18×10^5 RuBac/L in Mein. (See plots in Appendix 6 and Appendix 7). The annual average proportion was then applied as a fixed factor to the $FIOload_{(OAT)}$ to derive the observed FIO load from human sources ($FIOload_{(HS)}$) (Equation 3). Next, the distribution of the $FIOload_{(HS)}$ per catchment was compared to that of the predicted FIO load per catchment in GeNle and visualised using the ggdist R package (Kay, 2024).

$$pHDE = \frac{Hubac}{Hubac + Rubac} \quad \text{Equation 2}$$

where:

$pHDE$ is the proportion of human-derived *E. coli*

$Hubac$ represents human *bacteroides* in 1L, and

$Rubac$ is ruminant *bacteroides* in 1L

$$FIOload_{(HS)} = FIOload_{(OAT)} * pHDE \quad \text{Equation 3}$$

where:

$FIOload_{(HS)}$ represents the FIO load from human sources per catchment.

$FIOload_{(OAT)}$ is the observed annual total *E. coli* from both human and animal sources.

$pHDE$ is the proportion of human-derived *E. coli* calculated in Equation 3.

Estimation of model bias

Finally, we adopted the approach of Glendell et al. (2022) in using PBIAS to assess the model performance by comparing the model-predicted FIO load to the observed FIO load:

$$PBIAS = \left(\frac{\sum (X_{sim} - X_{obs})}{\sum X_{obs}} \right) \times 100 \quad \text{Equation 4}$$

where:

X_{sim} are FIO loads from 10,000 Monte Carlo model simulations at the catchment outlet and

X_{obs} are 10, 000 samples resampled from a truncated normal distribution fitted to observed *E. coli* data at the catchment outlet.

The distribution of the calculated bias was then observed, with closeness to zero indicating that the model's predictions closely matched the observed data. Additionally, the biased distribution was discretised to establish an optimal interval ranging from -50% to +50%. Instances where

probabilities fell below 50% indicated that the model underestimated, whereas those exceeding 50% indicated that the model overestimated.

Shannon entropy

The Shannon entropy index was used to evaluate uncertainty in the model outcomes in the spatial application of the discrete BN. Entropy was calculated over the target node in R by first defining the Shannon entropy function, then applying this function to each row representing a STS in our dataframe. Before performing the calculation, we verified that each row was numeric and removed any rows with a value of 0 to avoid log (0) errors. Shannon entropy was then calculated as follows:

$$H(X) = - \sum_{i=1}^n p_i \ln(p_i) \quad \text{Equation 5}$$

where:

- p_i is the probability associated with the state i of the target node
- $\ln(p_i)$ is the natural logarithm of the probability p_i
- negative sign in front indicates that the sum is negated, ensuring that the entropy is a positive value.

Entropy quantifies the information content within a node; it equals zero if p_i is known with certainty and is maximised when p_i is unknown (Trolborg et al., 2021).

4.3.5 Spatial implementation of the discrete model

To predict annual FIO load per STS, we applied the discrete version of our BN spatially, firstly to the STS locations in our study catchments, and secondly to a national scale STS dataset in Scotland. The spatial application was done in R using the gRain (Hojsgaard, 2012) and bnlearn (Scutari, 2010) packages and basically involved using the BN model to simulate FIO load from each STS one at a time.

Spatial data, including X and Y coordinates of STS locations, distance to the nearest watercourse, slope inclination, and associated HOST-derived risk factors, was loaded into R and discretised to match the BN states. The BN was then run with the spatial data for each STS, setting distance, HOST-derived risk, and slope as evidence, and the RealisedSTload as the target node.

The resulting simulated probabilities were combined with spatial coordinates in a data frame and used to calculate the FIO load per STS.

Calculation and visualisation of FIO load per STS

The annual FIO load per STS was calculated as a sum of the mid values of the target node states weighted by their probabilities (p):

$$FIO\ load = p_1 * mid_1 + p_2 * mid_2 + \dots + p_n * mid_n \quad \text{Equation 6}$$

where mid_n is the mid value of the n th state of the target node.

Maps were created in QGIS software version 3.82.2 (QGIS Development Team, 2021), to visualise FIO load for each STS in the study catchments and then upscaled to model FIO pollution risk from STS for the whole of Scotland. Further, STS points were weighted based on FIO load levels to differentiate risk categories: 1) STS with FIO load less than Quartile 1 assigned weight 1 and all other STS assigned 0; 2) STS with FIO load less than the median assigned weight 1, others 0; 3) STS with FIO load > Median assigned weight 1, others 0 and 4) STS with FIO load > Quartile 3 assigned weight 1, others 0. Maps were made for each category to help visualise pollution risk. A 5 mm heatmap radius was chosen to clearly show variations in pollution density

4.4 Results

4.4.1 Model parameterisation

Figure 13 presents the parameterized hybrid BN model, illustrating the posterior probability distributions for each variable and the detailed model description is presented in Table 8. For continuous equation nodes and discrete nodes, distributions are visualized as histogram plots of samples and marginal likelihood proportions for different states, respectively. The nodes in the top left corner of the model visualisation pertain to variables related to STS site conditions within the catchments (in this case for Cessnock). The nodes in the top right corner of the model represent variables ('Distance', 'Slope' and 'Hydrology of Soil Types') associated with the connectivity between STS and watercourses, which influence the risk of STS effluent movement. The nodes in the middle section of the model calculate variables representing the FIO concentration (CFU/100mL) based on STS conditions, followed by the resulting annual FIO load per STS. The target node, 'Realised FIO load', highlighted in red is our variable of interest calculating the FIO load per STS reaching a watercourse. In Figure 13, this has been multiplied by the number of STS in Cessnock to give the annual total catchment FIO load from STS. The 'Predicted load' node is a dummy node, equivalent to the 'Realised FIO load' node, added for convenient calculation of bias relative to the observed load. Bias is visualized as a continuous

distribution of values around zero in an equation node and as a discrete node showing the overall model performance compared to observed data where +/- 50% bias is considered acceptable.

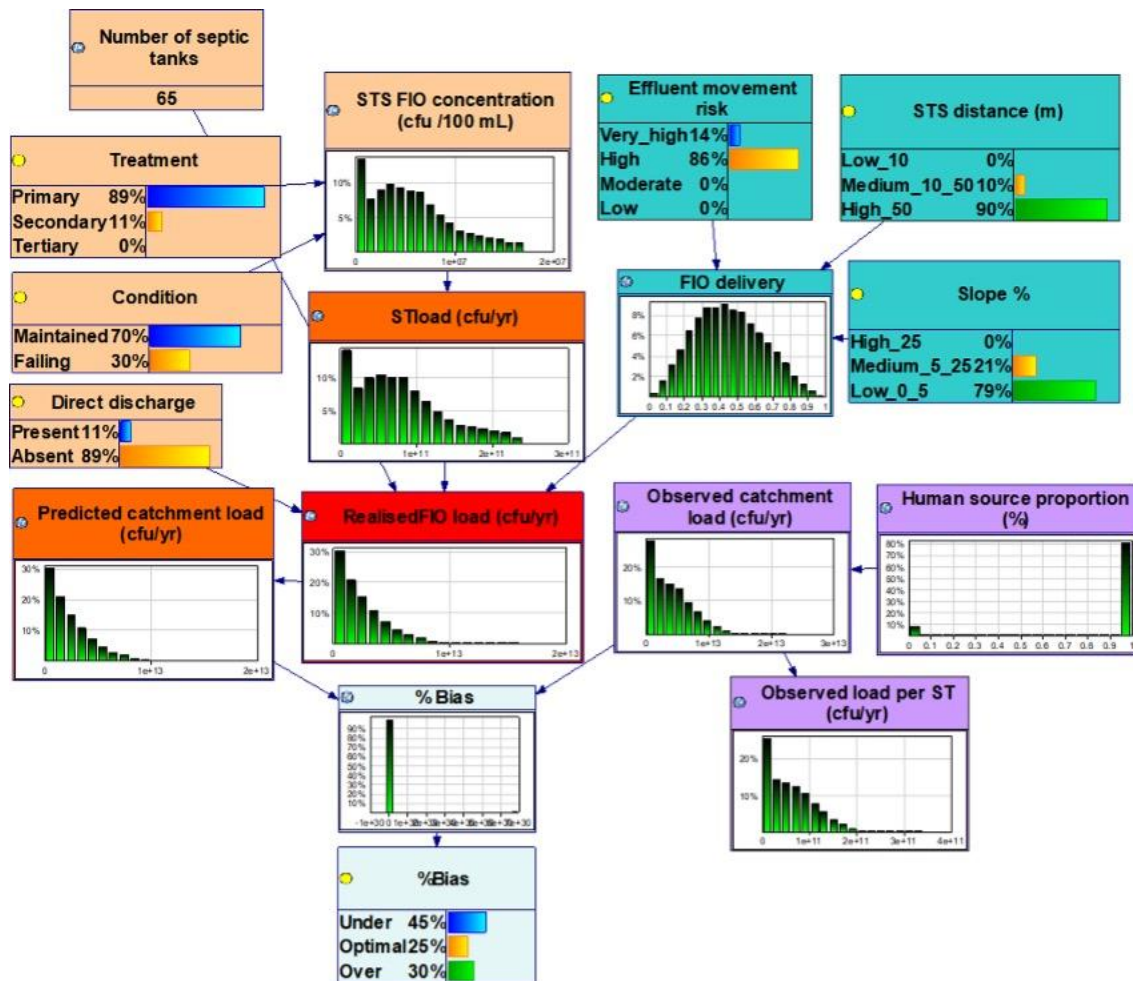


Figure 13: Parameterised hybrid model showing 25% optimal predictions, 45% under optimum and 30% over for the Cessnock catchment. Discrete nodes visualise probability distributions in form of bars of percentage likelihood of the states of the variable and equation nodes show this in the form of a continuous histogram plot.

4.4.2 Model discretisation

Equal intervals were chosen as a more accurate discretisation method for the BN model's sensitivity analysis and spatial application. This choice was based on the following factors: no

Table 8: Detailed model description showing model variables, states and parameterisation methods.

Variable [Units]	States	Prior probabilities/ Discretisation boundaries	Description												
STS site specific variables															
Treatment (%)	Primary	80	Probabilities for each treatment level were adopted from Glendell et al 2022. <table><tr><th>Treatment level</th><th>Mein</th><th>Cessnock</th></tr><tr><td>Primary</td><td>0.89</td><td>0.71</td></tr><tr><td>Secondary</td><td>0.11</td><td>0.29</td></tr><tr><td>Tertiary</td><td>1 x10⁻¹²</td><td>1 x10⁻¹²</td></tr></table>	Treatment level	Mein	Cessnock	Primary	0.89	0.71	Secondary	0.11	0.29	Tertiary	1 x10 ⁻¹²	1 x10 ⁻¹²
	Treatment level	Mein		Cessnock											
	Primary	0.89		0.71											
	Secondary	0.11		0.29											
	Tertiary	1 x10 ⁻¹²		1 x10 ⁻¹²											
Secondary	20														
Tertiary	0														
Condition (%)	Maintained	70	Prior probabilities of STS condition were based on literature review and expert opinion of the SEPA steering group as detailed in Glendell et al. (2021).												
	Failing	30													
STS FIO concentration (cfu/100ml)	Very low	0- 1.6 x 10 ⁴	STS FIO concentration depends on the treatment level and the STS condition. Concentrations for different treatment levels were obtained from literature (Gill et al., 2007; Kay et al., 2008) and defined using a truncated normal distribution, specifying a mean (m) and standard deviation (s) for each treatment level with a minimum concentration of 0. These concentrations were assumed for maintained STS. For failing STS, typical raw wastewater concentration was assumed regardless of the treatment level. In the discrete model, the lower bound was set at 0 and the likely maximum concentration (1.7 x 10 ⁷ cfu/100ml) as the upper bound. Discretisation boundaries were initially assigned by dividing the range between the lower and upper bound into 5 equal intervals. Probabilities were then checked and discretisation boundaries adjusted to obtain plausible concentration ranges appropriate for the specified risk categories (using interpolation as in Glendell et al. (2022)). <table><tr><th>Treatment level</th><th>Maintained (cfu/100ml)</th><th>Failing (cfu/100ml)</th></tr><tr><td>Primary</td><td>μ= 4.1x10⁶; s= 3.5 x10⁶</td><td>μ=1.06 x10⁷; s= 7.2 x10⁶</td></tr><tr><td>Secondary</td><td>μ= 3.68 x10⁴; s= 5.1 x 10⁴</td><td>μ=1.06 x10⁷; s= 7.2 x10⁶</td></tr><tr><td>Tertiary</td><td>μ= 3.0 x10³; s= 5.21 x10³</td><td>μ=1.06 x10⁷; s= 7.2 x10⁶</td></tr></table>	Treatment level	Maintained (cfu/100ml)	Failing (cfu/100ml)	Primary	μ= 4.1x10 ⁶ ; s= 3.5 x10 ⁶	μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶	Secondary	μ= 3.68 x10 ⁴ ; s= 5.1 x 10 ⁴	μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶	Tertiary	μ= 3.0 x10 ³ ; s= 5.21 x10 ³	μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶
	Treatment level	Maintained (cfu/100ml)		Failing (cfu/100ml)											
	Primary	μ= 4.1x10 ⁶ ; s= 3.5 x10 ⁶		μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶											
	Secondary	μ= 3.68 x10 ⁴ ; s= 5.1 x 10 ⁴		μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶											
	Tertiary	μ= 3.0 x10 ³ ; s= 5.21 x10 ³		μ=1.06 x10 ⁷ ; s= 7.2 x10 ⁶											
Low	1.6 x10 ⁴ - 7.3x 10 ⁴														
Medium	7.3 x10 ⁴ - 4.8 x10 ⁶														
High	4.8 x10 ⁶ - 7.2 x10 ⁶														

	Very high	7.2 x10 ⁶ - 1.7 x10 ⁷													
Direct discharge	Present	11	Probabilities calculated from a national database shared by SEPA that specified whether discharge was direct i.e., to 'inland water' or absent, i.e., to a 'soakaway' (absent) were adopted from Glendell et al. (2022).												
	Absent	89													
Soil connectivity-related variables															
STS distance to watercourse (m)	Low	<10	The straight-line distance between each STS and the nearest watercourse was calculated in QGIS for each catchment. The number of STS occurring within each distance category was counted and expressed as proportions in the node representing distance. Discretisation boundaries were informed by literature review (Gill & Mockler, 2016) and finalised based on expert input. For example, location of a septic tank less than 10m to a watercourse was considered low and greater than 50m high. Proportions of septic tanks in each distance category in the two catchments is as follows: <table><tr><th>Distance (m)</th><th>Mein (%)</th><th>Cessnock (%)</th></tr><tr><td><10</td><td>0</td><td>0</td></tr><tr><td>10-50</td><td>13</td><td>10</td></tr><tr><td>>50</td><td>87</td><td>90</td></tr></table>	Distance (m)	Mein (%)	Cessnock (%)	<10	0	0	10-50	13	10	>50	87	90
	Distance (m)	Mein (%)		Cessnock (%)											
	<10	0		0											
	10-50	13		10											
>50	87	90													
Medium	10-50														
High	>50														
Slope (%)	High	>25	Percentage slope associated with each STS was calculated using a 5m digital terrain model (DTM) in QGIS for each catchment. The number of STS in specified slope categories (discretisation boundaries) was counted and expressed as proportions in the node representing slope. Discretisation boundaries were informed by literature review in Glendell 2022 and finalised based on expert input. <table><tr><th>Slope (%)</th><th>Mein (%)</th><th>Cessnock (%)</th></tr><tr><td>>25</td><td>0</td><td>0</td></tr><tr><td>5-25</td><td>55</td><td>22</td></tr><tr><td>0-5</td><td>45</td><td>78</td></tr></table>	Slope (%)	Mein (%)	Cessnock (%)	>25	0	0	5-25	55	22	0-5	45	78
	Slope (%)	Mein (%)		Cessnock (%)											
	>25	0		0											
	5-25	55		22											
0-5	45	78													
Medium	5-25														
Low	0-5														
Effluent movement risk	Very high		Probabilities derived from spatial GIS data were adopted from Glendell et al. (2022). High risk represents soils with high probability of overland flow generation or high infiltration rate.												
	High														

(Inferred from HOST-based risk factors)	Moderate			HOST-derived risk factor	Cessnock	Mein						
	Low			Very high	0.33	0.14						
				High	0.66	0.74						
				Moderate	0.10	0.10						
				Low	0	0.02						
FIO delivery (proportion)	Very low	0-0.2	FIO delivery is conditional on septic tank effluent movement risk based on HOST, ST distance to watercourse and slope. Delivery proportions on a scale of 1-100 were elicited from experts as detailed in (Mzyece et al., 2024). Elicited lower and upper limits, mean and tertile values were to calculate alpha and beta parameters in the SHELF R package which were then exported into GeNIe and fitted to a beta distribution. <table><tr><td></td><td>Mein</td><td>Cessnock</td></tr><tr><td>Mean FIO proportion</td><td>0.42</td><td>0.45</td></tr><tr><td>Standard deviation</td><td>0.23</td><td>0.21</td></tr></table>		Mein	Cessnock	Mean FIO proportion	0.42	0.45	Standard deviation	0.23	0.21
		Mein		Cessnock								
	Mean FIO proportion	0.42		0.45								
	Standard deviation	0.23		0.21								
	Low	0.2-0.4										
	Medium	0.4-0.6										
High	0.6-0.8											
Very high	0.8-1											
Calculated variables												
ST load (cfu/yr)	Very low	1- 1 x10 ¹⁰	The ST load is the FIO load per STS per year. It is conditional on the STS FIO concentration and calculated using the equation: ST load=STS FIO concentration (cfu/100ml)/10*180(L)*365*2.1. Here, 180 L represents the daily average water consumption per person, multiplied by the number of days in a year and the average property occupancy of 2.1 persons in Scotland. In the discrete model, the lower bound was set at 0 and the upper bound at 9.8×10 ¹¹ cfu/yr. Initially, discretisations were created by dividing this range into five equal intervals, then refined by interpolation to achieve plausible combinations of most probable intervals (Fenton & Neil, 2019).									
	Low	1 x10 ¹⁰ - 3 x10 ¹⁰										
	Medium	3 x10 ¹⁰ - 9.0 x10 ¹⁰										
	High	9.0 x10 ¹⁰ - 1.0 x 10 ¹¹										
	Very high	1.0 x10 ¹¹ - 9.8 x10 ¹¹										
Realised FIO load (log ₁₀ cfu/yr)	Very low	4- 8.9	This is the FIO load per STS per year reaching a watercourse and is conditional on direct discharge, STS load, FIO delivery. In the hybrid network, this represents the total catchment load (since it has been multiplied by the number of STS in the catchment). In the discrete model, this represents the FIO load per STS which has been summed after applying the model spatially to obtain the total catchment load. For ease of discretisation, the load values in this node were firstly log transformed. Discretisation boundaries were then assigned in a similar manner to STS load, and further details are given in section 2.3.									
	Low	8.9-9.5										
	Medium	9.5-10.8										
	High	10.8-11.5										

	Very high	11.5-15	
Observed catchment load (cfu/yr)			The observed load is the human-derived <i>E. coli</i> load calculated from daily <i>E. coli</i> and discharge data from September 2018 to 2019 at SEPA water quality monitoring points at the catchment outlet, as detailed in Section 2.4.2. The observed load is defined using a truncated normal distribution with mean, standard deviation and minimum load of 0.
Observed load per ST (cfu/yr)			This is the observed FIO load per STS which was calculated by dividing the observed catchment load by the number of STS in a particular catchment.
Human source proportion			This node represents daily proportions of human-derived FIOs relative to total FIOs (human and animal). The proportions were calculated in excel from microbial source-tracking data (<i>Equation 3</i>). The mean (μ) and standard deviation (σ) of the proportions were used to calculate alpha, $\alpha = ((1 - \mu) / \sigma - 1 / \mu) * \mu^2$ and beta, $\beta = \alpha * (1 / \alpha - 1)$, parameters required to model the proportions using a Beta distribution in GeNIe. To verify the accuracy of this calculation, the derived α and β parameters were used to produce a random dataset consisting of 10,000 data points. Subsequently, the distribution of this generated dataset was compared visually to that of the original dataset to confirm coherence.
PBIAS			PBIAS is the total bias as a percentage of the observed FIO load, defined as $(S \text{ (Simulated)} - S \text{ (Observed)}) / S \text{ (Observed)} * 100$. This was used to assess the model performance through comparison of the simulated to the observed FIO load. In the hybrid model, negative values indicated that the model was underpredicting while positive values indicated that the model over-predicted. In the discrete model, the distribution was discretised into 3 intervals, i.e. <50% defined as under predicting, at 50% defined as optimum and over 50% defined as over predicting.

instances of over/under estimating probabilities in conditional probability tables (CPTs), lower sum of squared errors (SSE) and standard deviation (SD) (see Table 9), and lower Shannon entropy values compared to interpolation.

Unlike interpolation, which occasionally overestimated probabilities in the CPTs, for scenarios where lower probabilities were expected and vice versa, (e.g., 91% for Realised FIO load without direct discharge vs. 62% with direct discharge), there were no instances of such calculation errors observed after equal intervals discretisation. Although there were some differences in state boundaries (as shown in Table 9) and marginal probabilities, both methods produced similar results. Calculated marginal probabilities from equal intervals for the five states in the target node (Realised FIO load) are shown in Figure 14. Recalculated marginal probabilities after interpolation were 5% Very low, 6% Low, 51% Medium, 36% High and 2% Very_high.

Table 9: Comparison of predicted $\log_{10}$ annual FIO load per STS from Equal intervals discretisation and interpolation.

	State/Statistic	Unit	Method		
			<u>Equal intervals</u>	<u>Interpolation</u>	<u>Observed</u>
States boundaries	Very low		4 - 6.2	4 - 8.9	
	Low		6.2 - 8.4	8.9 - 9.5	
	Medium		8.4 - 10.6	9.5 - 10.8	
	High		10.6 - 12.8	10.8 - 12.8	
	Very high		12.8 - 15	12.8 - 15	
Cessnock	Mean	($\log_{10}$ CFU/yr)	10.54	10.55	10.79
	SD		1.44	1.48	-
	SSE		59,936	60,401	-
Mein	Mean	($\log_{10}$ CFU/yr)	10.49	10.51	10.71
	SD		1.43	1.74	-
	SSE		57,988	67,519	-

4.4.3 Model evaluation

Sensitivity analysis

Sensitivity analysis revealed that the primary factors affecting FIO pollution risk from STS were the treatment level and condition of the tank. These influenced the FIO concentration and subsequently the FIO load from the STS. Effluent directly discharged from STS to watercourses greatly affected the realised FIO load to a watercourse. The proportion of FIO delivery was primarily influenced by the HOST-derived risk, and to a lesser extent, by distance and slope. Figure 14 illustrates the importance of these factors, with red shading indicating their significance and summary information relating to the sensitivity of each node is provided in Table 10.

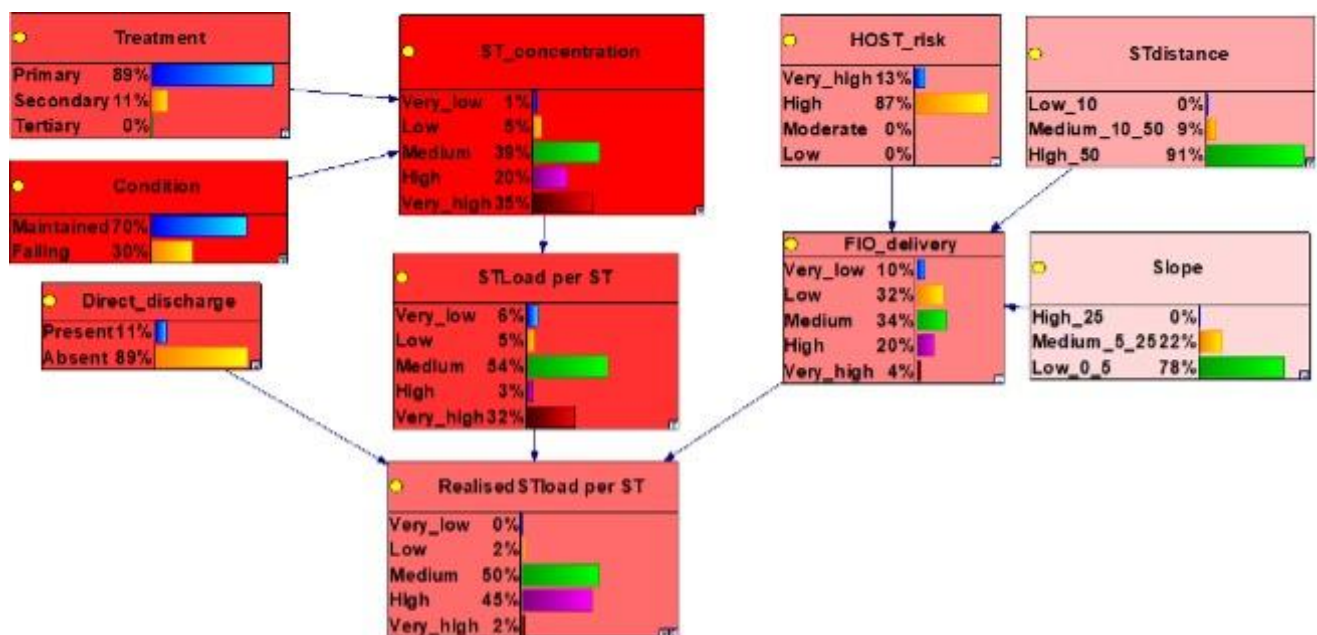


Figure 14: Results of model discretisation showing marginal probability distributions for states in all the model variables and sensitivity analysis showing most influential factors in deep red shading in the Cessnock catchment.

Table 10: Summary information relating to the sensitivity of each node.

Node	Sensitivity		
	Minimum	Maximum	Average
Treatment	0	0.478	0.200
Condition	0	0.450	0.194
Direct discharge	0	0.181	0.084
ST_concentration	0	0.521	0.049
STload	0	0.328	0.028
HOST_risk	0	0.091	0.029
ST_distance	0	0.037	0.014
Slope	0	0.014	0.005
FIO delivery	0	0.032	0.001
Realised STload	0	0.133	0.003

Validation against observed data

Overall, the model's predicted loads were comparable to the observed FIO loads, as illustrated in Figure 15 and statistical summary given in Table 11. Both predicted and observed loads were of the same order of magnitude, although the predicted loads were lower than the observed loads. This underprediction is confirmed by negative PBIAS values in the hybrid model and observed in the discrete model. In Cessnock, the discrete model under-predicted 52% of FIO load values, which fell below the acceptable bias threshold of 50%, while 22% were within the acceptable range of +/-50%, and 26% were overpredicted, when compared to observed values from LOCF interpolation. When compared against linearly interpolated observations, simulation bias showed slight improvement, with 45% underprediction, 25% within the acceptable range, and 30% overprediction. In the Mein catchment, the model showed significant underprediction at 83%, with only 5% falling within the acceptable range and 33% being overpredicted when compared to observed values from linear interpolation. However, against observations from LOCF

interpolation, model performance improved, with underprediction at 42%, 25% within the acceptable range, and 33% overprediction.

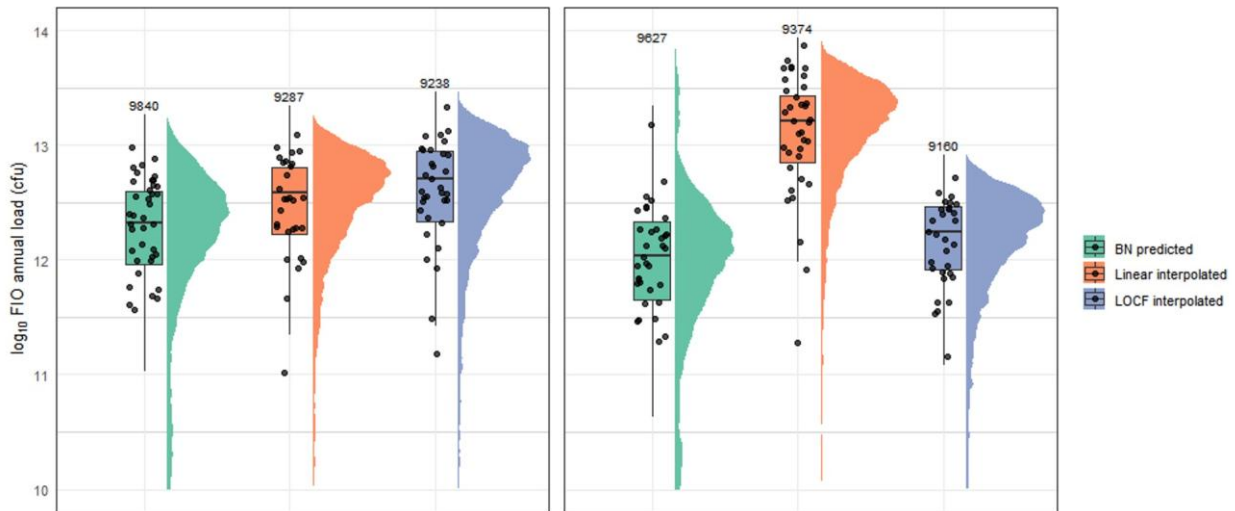


Figure 15: Overall distribution of BN model predicted $\log_{10}$ FIO annual load (CFU) versus observed loads interpolated using the Last Observation Carried Forward and Linear interpolation methods in Cessnock (left) and Mein (right). BN predicted FIO loads are comparable to observed loads across both interpolation methods in Cessnock but under predict compared to Linear interpolated observed data in Mein. Outliers were excluded from the plots and the values above the boxplots show the number of samples plotted in each distribution. The distributions were plotted using the *ggdist* R package version 3.3.2.9000 (Kay 2024) with modified R code from Negri (2024).

Table 11: Predicted and observed FIO load per STS and load per catchment from the hybrid and discrete models.

			Predicted					Observed			
			Total FIO load per catchment from hybrid BN	Total FIO load per catchment from equal intervals discretised BN	Total FIO load per catchment from interpolated discretised BN	FIO load per STS from hybrid BN	FIO load per STS from equal intervals discretised BN	FIO load per STS from interpolated discretised BN	Total FIO load per catchment from Linear interpolation method	Total FIO load per catchment from LOCF interpolation method	FIO load per STS
Cessnock	Mean	CFU/yr	2.76x10 ¹²	-	-	4.63x10 ¹⁰	3.59x10 ¹⁰	3.85x10 ¹⁰	4.05x10 ¹²	5.55x10 ¹²	6.17x10 ¹⁰
	Median		2.04x10 ¹²	-	-	3.22x10 ¹⁰	3.25x10 ¹⁰	3.6x10 ¹⁰	3.47x10 ¹²	4.58x10 ¹²	5.25x10 ¹⁰
	Sum		-	2.34x10 ¹²	2.50x10 ¹²	-	-	-	-	-	-
	Minimum		2.09x10 ⁹	-	-	-	-	-	6.18x10 ⁻¹⁵	8.32x10 ⁻¹⁹	-
	5th quantile		8.61x10 ¹¹	-	-	-	-	-	1.25x10 ¹²	1.51x10 ¹²	-
	75th quantile		3.88x10 ¹²	-	-	-	-	-	6.15x10 ¹²	8.52x10 ¹²	-
	Maximum		1.84x10 ¹³	-	-	-	-	-	2.22x10 ¹³	2.90x10 ¹³	-
	SD		2.48x10 ¹²	-	-	4.85x10 ¹⁰	5.42x10 ⁹	3.87 x 10 ⁹	3.37x10 ¹²	4.8x10 ¹²	5.14x10 ¹⁰
	PBIAS	%	-	-	-	-	-	-	-41.21	-55.46	-
	Under		-	-	-	-	-	-	45	52	-
	Optimal		-	-	-	-	-	-	25	22	-
	Over		-	-	-	-	-	-	30	26	-
	Shannon entropy		-	-	-	-	1.26	1.62	-	-	-
Mein	Mean	CFU/yr	2.31x10 ¹²	-	-	4.36x10 ¹⁰	3.32x10 ¹⁰	3.65x10 ¹⁰	1.74x10 ¹³	1.85x10 ¹²	5.10x10 ¹⁰
	Median		1.04x10 ¹²	-	-	2.86x10 ¹⁰	3.57x10 ¹⁰	3.10x10 ¹⁰	1.49x10 ¹³	1.58x10 ¹²	4.34x10 ¹⁰
	Sum		-	1.31x10 ¹²	1.16x10 ¹²	-	-	-	-	-	-
	Minimum		2.23x10 ⁸	-	-	-	-	-	1.76x10 ⁻¹⁰	1.64x10 ⁻²³	-
	5th quantile		3.85x10 ¹¹	-	-	-	-	-	5.26x10 ¹²	5.64x10 ¹¹	-
	75th quantile		2.09x10 ¹²	-	-	-	-	-	2.63x10 ¹³	2.81x10 ¹²	-
	Maximum		7.25x10 ¹³	-	-	-	-	-	8.72x10 ¹³	8.24x10 ¹²	-
	SD		1.38x10 ¹²	-	-	4.82x10 ¹⁰	4.48x10 ⁹	5.12 x 10 ⁹	1.44x10 ¹³	1.55x10 ¹²	4.28x10 ¹⁰
	PBIAS	%	-	-	-	-	-	-	-93.02	-34.18	-
	Under		-	-	-	-	-	-	83	42	-
	Optimal		-	-	-	-	-	-	5	25	-
	Over		-	-	-	-	-	-	12	33	-
	Shannon entropy		-	-	-	-	1.26	1.62	-	-	-

4.4.4 Spatial implementation of the model

The predicted FIO load per STS was generally higher and showed less variation in the Cessnock catchment (ranging from 3.51×10^{10} to 4.81×10^{10} CFU/year) compared to Mein (1.22×10^{10} to 4.51×10^{10} CFU/year) (Figure 16).

In Cessnock, STS with the lowest FIO loads (3.51×10^{10} CFU/year) were linked to a high HOST-derived risk factor, positioned at least 50 meters from a watercourse on a gentle slope (0 - 5%). When the slope increased to 5 - 25%, FIO load increased to 4.04×10^{10} CFU/year, indicating a 13% increase due to slope variation. In contrast, STS located closer (10 - 50 meters from a watercourse) produced an FIO load of 4.57×10^{10} CFU/year, reflecting a 23% increase due to reduced distance. The highest FIO load in Cessnock (4.81×10^{10} CFU/year) was observed in STS with a very high HOST-derived risk factor, situated at least 50 meters from a watercourse on a moderate slope (5 - 25%).

In Mein, only 8% of STS (three units) showed the lowest FIO load (1.22×10^{10} CFU/year). These were characterized by a low HOST-derived risk factor, a distance of at least 50 meters from a watercourse, and a slope of 5-25%. The highest FIO load in Mein (4.51×10^{10} CFU/year) was linked to STS with a high HOST-risk classification, at least 50 meters from a watercourse, and a moderate slope (5 - 25%). However, when the slope was gentler (0-5%) under the same HOST and distance conditions, the FIO load dropped to 3.57×10^{10} CFU/year, showing a 15% reduction due to slope effects.

Model uncertainty estimated through Shannon entropy was moderate to high (1.60 - 1.85) (Glendell et al., 2022), and was particularly high for STS where the predicted FIO load was low in Mein. These entropy values are between 71% and 80% of the maximum possible

entropy (2.32^4) for our target node which has 5 states (Vajapeyam, 2014). Although the BN predicted distribution of the realised FIO load is spread out as observed in Figure 15, it is not completely uniform showing that the model still prefers certain states (medium to high FIO loads) in the target node. Further, the BN predicted distributions are comparable to the probability distributions of observed data.

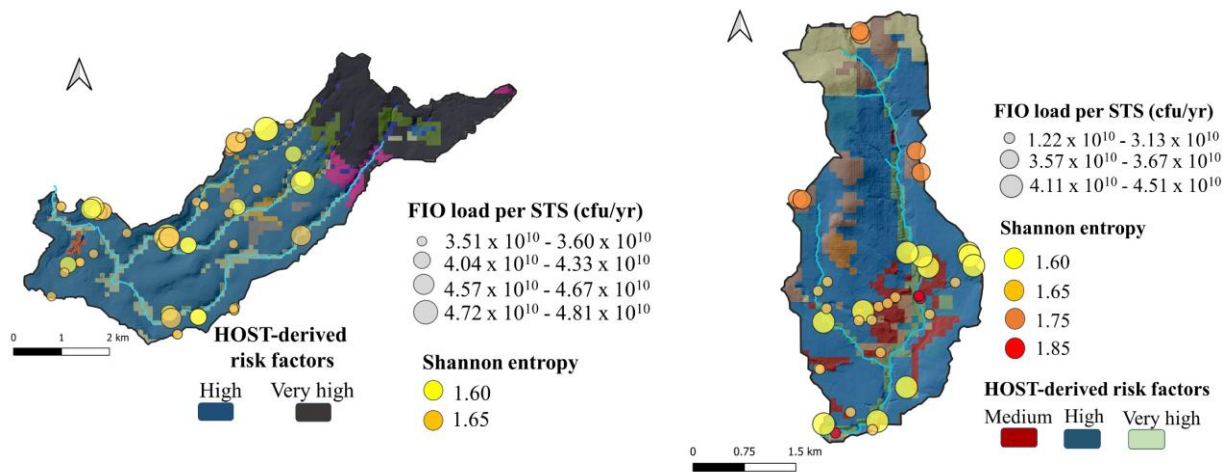


Figure 16: Predicted FIO load per septic tank in Cessnock (left) and Mein (right). Circle size indicates the magnitude of the load, with smaller circles denoting lower FIO loads and larger circles indicating higher loads. Circle colour reflects entropy levels. The background map shows the HOST-derived risk factors. Note that the scale used to depict the predicted FIO load differs between the two catchments.

Figure 17 illustrates heat maps displaying STS density and corresponding FIO load levels across Scotland. The eastern and central parts of Scotland have a high concentration of STS accounting for 32.9% and 22.7% respectively, of the 174, 567 STS captured on the SEPA database (Figure 17- a). West Scotland has the lowest concentration accounting for 12.4% while the South has 14.9% and the North 17.2%. Most STS with low (1,529) and moderate

⁴ Maximum entropy calculated as $H_{max} = \log_2(5)$ where 5 is the number of states in the target node.

(22, 515) HOST-derived risk factor are in East Scotland. Most STS with high HOST-derived risk factor are located in Central (29, 893) and East Scotland (26, 955). Most STS with very high HOST-derived risk factor are located in the East (6, 365) and West regions (5, 643). A table of STS counts and HOST-derived risk factors by regions is available in Appendix 8. While Aberdeenshire has a high STS density, a significant proportion generate an FIO load below the median as observed from the clustering of weighted points visualised by deep blue shading in Figure 17- b & c. In total, six local authority areas (LAs) in East and South Scotland out of 32 have been identified as high-risk zones for FIO pollution from STS (Figure 17- d). These areas combine a high STS density with FIO loads exceeding the median. Ayrshire and East Renfrewshire show the highest risk, as highlighted in Figure 17- e, where deep red shading represents STS with FIO loads above the third quartile.

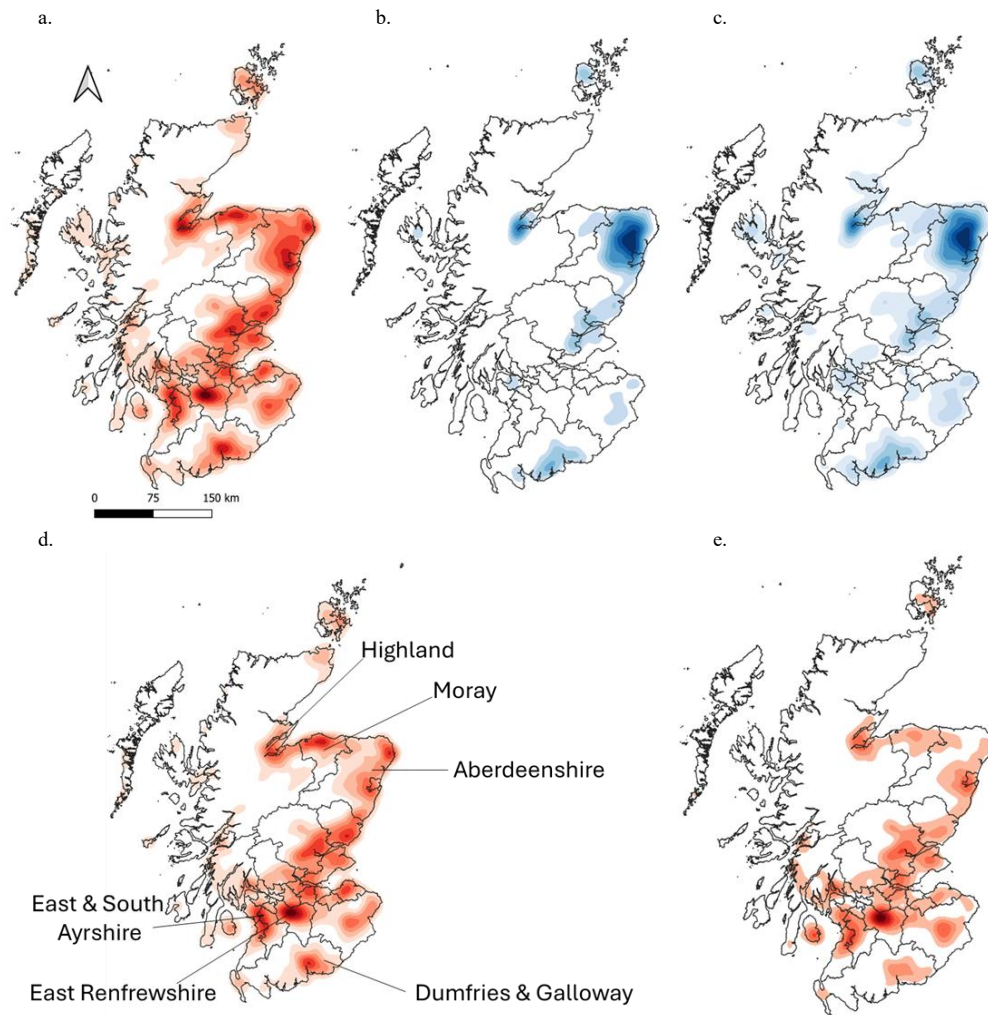


Figure 17: Heatmaps visualising: a. STS density calculated using kernel density estimation with high density represented by deep red colour shading and lower density represented by light shading. The points representing STS are weighted as follows: b. STS with FIO load less than Q1 (5.60×10^{10} CFU/yr); c. STS with FIO load less than the Median (7.88×10^{10} CFU/yr); d. STS with FIO load greater than the Median (7.88×10^{10} CFU/yr) and e. STS with FIO load greater than the Q3 (9.13×10^{10} CFU/yr). The black lines in the maps represent boundaries of local authority areas in Scotland.

4.5 Discussion

Validating model predictions with observed data is essential to demonstrate a model's appropriateness for its intended use and to foster trust in outcomes. Our study successfully

validated, for the first time, a BN model designed to characterise FIO losses from STS in rural catchments. Here, we discuss our findings in four key areas: (1) novel contributions of the research; (2) landscape features impacting FIO pollution from STS; (3) uncertainty and variability in model predictions, alongside implications from sensitivity analysis; (4) model transferability to other regions and from catchment to national scale, and potential policy interventions.

Our research is the first to show how BN models can predict FIO pollution from STS to watercourses. Other research utilising BNs to investigate FIO pollution of water has focused on sources such as recycled water (Donald et al., 2009), sewer outflows (Goulding et al., 2012) and other matrices such as submerged aquatic vegetation (SAV), sediments, and stormwater (Staley et al., 2012). We have thus contributed unique insight into understanding FIO pollution from STS by using a BN model to integrate diverse data types, such as expert opinion (Mzyece et al., 2024), modelled locations of STS (SEPA 2020), and STS FIO concentration data (Kay et al., 2008). This approach not only enabled effective model predictions when challenged with gaps in data but also facilitated model validation—an area where BNs based entirely on expert knowledge face challenges (Constantinou et al., 2016; Kleemann et al., 2017). By deploying a hybrid and discrete BN to quantify information loss due to discretization we have addressed concerns raised in prior research (Aguilera et al., 2010; Glendell et al., 2022). In addition, our use of two interpolation methods ensured a robust methodology (Lepot et al., 2017), with better validation outcomes observed when using LOCF over linear interpolation, avoiding significant underprediction. Furthermore, our study explored FIO pollution in relation to a combination of landscape factors at a catchment scale, contributing new knowledge beyond previous studies that focused on individual factors considered in isolation, such as soil properties at laboratory scale (Billian et al., 2018) or STS proximity to watercourses at a watershed scale (Sowah et al., 2014). Limited research, whether empirical or modelled, exists on the combined effect of landscape factors on FIO transfer from STS to watercourses.

Our BN model combined three critical landscape factors: HOST-derived effluent movement risk, slope, and proximity to watercourses. The effluent movement risk provides an integrated assessment for surface runoff, groundwater leaching and the presence/absence of groundwater within 2 m depth as key FIO transfer pathways (Glendell et al., 2021). According to our BN model, the risk of FIO transfer is exacerbated by steep slopes and shorter distances to watercourses, which complements understanding of FIO transfer dynamics informed by both reductionist approaches using replicated soil boxes (Hodgson et al., 2016) and empirical field observations (Oliver et al., 2015; Srinivasan et al., 2021).

The riskiest combination of landscape features resulting in the highest STS FIO load (4.8×10^{10} CFU/yr) to a watercourse was very high HOST-derived risk classification, medium slope (5-25%) and STS distance to a watercourse of ≤ 50 m. Here, both surface runoff (where soils are peaty or a shallow gleyed layer is present that inhibits drainage) and leaching to groundwater (where soils are free draining and an aquifer is also normally present within 2 m), are possible pollution pathways (Gagkas & Lilly, 2019). In contrast, the lowest FIO load of 1.22×10^{10} CFU/yr was generated from STS in soils with a low HOST-based risk classification, moderate slope and STS distance to a watercourse of > 50 m. These areas featured relatively free-draining soils, no gleyed layer within 1 m, and no significant aquifer or groundwater. Here, the absence of an aquifer or groundwater contributed to low risk by preventing FIOs from reaching groundwater and later surface water via subsurface pathways (Buckerfield, Quilliam, et al., 2019). Although some surface runoff is likely in soils with this HOST-derived classification, gentle slopes can reduce surface runoff resulting in water ponding and subsequently there might be increased FIO losses through leachate (Appels et al., 2016). For STS in soils with medium HOST-based risk —characterised by slow permeability within 1 m or gleying at 0.4 to 1 m and groundwater normally present at > 2 m depth, the FIO load reaching a watercourse was slightly higher (3.7×10^{10} CFU/yr) compared to the previous scenario.

This increase is likely due to greater FIO losses through surface runoff over the gleyed layer, as well as the influence of moderate slopes (5 - 25%), which enhance FIO transport via surface runoff. While a moderate slope can increase the FIO load to a watercourse by promoting surface runoff, the proximity of an STS to a watercourse plays a more significant role. This is evident in the higher FIO load increase (23%) observed when the distance between the STS and the watercourse is reduced from 50 m to 10 – 50 m, compared to a 13% increase associated with a slope change from 0–5% to 5 – 25%. These results are reinforced by the findings of Mzyece et al. (2024) where experts judged that the proportion of FIOs from a STS reaching a watercourse would increase by 20% if the STS was located 10 - 50 m to a watercourse compared to 9% if it was located >50 m from the watercourse. The greater FIO load due to reduced distance is attributed to fewer environmental barriers intercepting the STS effluent before it reaches the watercourse. For example, Stall et al. (2014), found that for STS effluent moving in an unsaturated zone of sandy soil via matrix flow, 30 - 45 cm to the groundwater table was less effective in straining bacterial colloids from the effluent and preventing groundwater pollution while 60 cm proved to be more effective. A similar principle applies to STS effluent transport to surface water and highlights the importance of maintaining a minimum 10 m buffer between an STS discharge and the nearest watercourse if not used as a drinking water source (Scottish Environmental Protection Agency, 2025). Longer distances, ranging from 50 m to 1.5 km, may be required depending on: the number of properties connected to the STS; whether it includes a soakaway; and the presence of a drinking water source in the area.

Although guidelines on appropriate slopes for STS placement are limited, UK construction standards like National Housing Building Council recommend slopes no steeper than 2% for inflow connections to STS, to reduce influent velocity and disturbance in the tank, and no steeper than 0.5% for effluent pipes in drain fields, to allow for extended retention and effective treatment. Our study further advises that STS planned for locations approximately 10 m from a watercourse should be constructed on slopes not exceeding 5%. This approach can

minimize runoff and reduce FIO loads by up to 13%, compared to systems built on steeper slopes of 5 – 25%.

Our study did not investigate the wider impact of land cover, e.g., improved grasslands, on water quality because this was beyond our scope. However, this topic has been addressed using the SCIMAP model, which demonstrated that variations in land management practices and coverage can affect FIO transfer within catchments (Porter et al., 2017). Typically, rural catchments with extensive grassland cover are more likely to experience animal-derived FIO pollution from agricultural applications of manure and slurries, livestock faeces and human FIO pollution from STS (Hodgson et al., 2016; Oliver et al., 2018; Richards et al., 2016). Therefore, of crucial importance to our model evaluation was a need to differentiate between human sources of FIOs and those contributed via agricultural practices. We capitalised on the availability of accompanying MST data collected within our test catchments, which allowed us to distinguish between human and livestock FIO pollution signals in surface water and in turn deliver credible predictions of FIO loads contributed from STS in rural catchments. The integration of MST data with modelling results is increasing and can provide an effective approach to help differentiate sources of other pollutants in catchments too, for example nitrogen (Zimmer-Faust et al., 2025)

The BN model's ability to predict mean and median values in the same order of magnitude as the observed data demonstrates that our model is fit for purpose (Neill et al., 2020b). It assigned risk of FIO pollution from STS based on STS condition, location and the additional effects of landscape features in either reducing or increasing FIO transfer to waterbodies. However, the model underpredicted FIO loads, potentially due to overestimated treatment levels or the proportion of well-maintained STS (Glendell et al., 2021). Observed data limitations, such as seasonal sampling biases, may have also contributed to discrepancies (Sorensen et al., 2021; Torres et al., 2022) since in-stream FIO data are scarce, in part

because the UK does not routinely monitor all rivers for microbial pollution (Oliver et al., 2016b). Accessing good quality long-term data for model testing can therefore be challenging.

We were able to access FIO data collected over an annual period by SEPA; however, one year of data cannot capture the full range of hydrological variability likely to influence uncertainty of observations. The dataset comprised twice-weekly 24-h composite samples—an unusually high sampling frequency. For comparison, McDowell et al. (2024) suggest that twice-monthly sampling can be sufficient to detect long-term water quality trends and inform policy. Nonetheless, gaps within the twice-weekly design may not fully capture seasonal and flow variability affecting FIO mobilisation. For example, human FIO loads observed in summer to early autumn (September to November) are likely to be high due to nearby terrestrial sources benefitting from warmer temperatures (Cho et al., 2010) and therefore not representative of year-round conditions. Our accompanying MST data also represent a point in time for each sample and therefore may not accurately represent the dynamic changes in human/livestock proportions, as influenced by seasonality and temporal factors (Ahmed et al., 2013; Duncan et al., 2013). While such factors can be critical when estimating absolute diffuse-source FIO loads, this study's aim was to evaluate a model of septic tank inputs. Observed load estimates were used primarily as a “sense check” to confirm that model predictions did not exceed plausible catchment-scale loads.

Interpolation can introduce uncertainty, particularly when data gaps are large. LOCF often underestimates variability and can overemphasise a sample collected immediately before a pause in sampling, potentially skewing the inferred daily load if conditions at that time were atypical (Mavridis et al., 2019). To address this, we also applied linear interpolation, which assumes a constant rate of change between observations and reduces—but does not remove—bias under changing conditions (Juhan et al., 2025). The use of both approaches provides a range of plausible load estimates, serving as a safeguard against unrealistic predictions rather than as a definitive quantification of total load. Future work could test the

model in even more data-rich catchments if supported by targeted sampling campaigns — ideally with little or no wastewater treatment influence—paired with high-resolution FIO sampling to better capture the full range of water quality dynamics.

Our BN model generally exhibited high uncertainty, particularly when predicting low FIO loads. This indicated lower confidence in assessing low-risk scenarios compared to high-risk ones. This discrepancy may have been due to a data imbalance (Fanconi et al., 2023), as fewer STS exhibited low FIO loads (8% in Mein) compared to the majority (92%) showing medium to high loads. As a result, the BN model was better trained to recognize high FIO load patterns (Lambert et al., 2022). Furthermore, the limited data on the condition and maintenance of STS with low FIO loads increased prediction uncertainty. To reduce this uncertainty, high-quality data on STS condition and maintenance—identified as critical parameters through sensitivity analysis (Kaikkonen et al., 2021)—are needed. Therefore, future research should prioritize gathering more reliable data on STS condition and maintenance, including targeted surveys of septic tank owners to gain insight into their system management practices and perceptions of STS-related risks.

Uncertainty analysis also provided valuable insights into the model's transferability with respect to soil and hydrological characteristics. BN application to areas with relatively homogeneous soil hydrological characteristics resulted in greater confidence in modelled outputs. However, BN predictions were susceptible to increased uncertainty when applied in a catchment with diverse soil-hydrological characteristics. As catchments become larger and more complex, whether due to underlying soil, hydrological and geological characteristics or because of greater diversity and nuance in land use or management approaches, we can expect model predictions to be accompanied with higher uncertainty, and this is not uncommon (Boodoo et al., 2025; Woodward et al., 2017; Yao et al., 2025). Therefore, when the BN was applied to the national scale STS data for Scotland, greater confidence in model results was associated with Central, East and West Scotland where most STS, i.e., 29,873,

26, 955 and 17, 051 respectively, were associated with a moderate to high HOST-derived risk classification. In contrast, predictions were more uncertain for South Scotland, which featured STS associated with a variability of HOST-derived risk factors. Here, the model predictions can be utilised as a first approximation of FIO water pollution risk from STS, helping to prioritise spatial investigation on-the-ground, recognising that further data input on the condition/maintenance of STS would help to improve model outcomes.

The model offers further critical insight into areas in Scotland at high risk of FIO pollution from STS, particularly rural and agricultural regions where livestock-driven FIO pollution has been widely studied (Neill et al., 2018; Oliver et al., 2016; Scottish Government RESAS, 2017). In rural agricultural catchments, STS are rarely considered in terms of their overall contribution to the FIO load of receiving waters, in part because they are challenging to monitor and due to difficulties in differentiating the human/livestock FIO signal (Diaz-Elsayed et al., 2017; Harwood et al., 2013). To date, greater emphasis has been given to understanding the relative importance of different agricultural sources of FIOs, (e.g. Hodgson et al., 2016; Murphy et al., 2015; Neill et al., 2020; Oliver et al., 2018; Zimmer-Faust et al., 2025), and more recently wildlife contributions (Afolabi et al., 2020). Therefore, the development of tools and modelling approaches, built on credible evidence as demonstrated in our study, helps to identify the contribution of STS is essential to ensure these sources are not overlooked.

Using Scotland as a case study, our findings highlight that a high density of STS does not necessarily translate to high FIO loading of receiving waters, as observed for northeast Scotland, where risks appear to be well constrained. In contrast, southwest Scotland contributed higher FIO loads from STS and exceeded the 3rd quartile, which is significantly higher than the EU bathing water standards for inland waters and therefore a cause for concern. Indeed, bathing water quality in some areas across SW Scotland has been of lower quality relative to other bathing waters in Scotland (Scottish Environment Protection Agency, 2016). This is often attributed to intensive dairy farming and wetter weather (Edwards et al.,

2008; Vinten et al., 2008); however, our findings raise the prospect that STS contributions to FIO loading of receiving waters may also play an important role in influencing microbial pollution in this region of Scotland.

4.6 Conclusion

Our BN model effectively predicts FIO losses from STS to watercourses in rural catchments, demonstrating how STS condition and maintenance influence FIO loads. Additionally, our approach highlights how soil hydrology, slope, and the distance between the STS and watercourses either hinder or facilitate FIO transfer from STS to receiving waters. The multi-scale application of the BN model from catchment to national scale further demonstrates its use and value to policy-makers and land managers with a responsibility for water quality assessment. Enhancing model performance, especially in catchments with varied soil-hydrological characteristics, will require future research to refine data on STS condition and maintenance while validating model predictions with high-resolution and longer-term data. Improved data will not only enhance model accuracy but also aid regulators and researchers in understanding septic tank users' perceptions of faecal pollution risks to watercourses. Ultimately, this BN model demonstrates a crucial step in developing a tool that regulators can use to mitigate pollution from often-overlooked sources such as STS, thus contributing to further safeguarding of bathing water quality and public health. Expanding the BN model framework to account for a wider range of FIO sources typical of more complex mixed land use catchments represents an important next step. This would help to improve holistic assessment of FIO contributions from diffuse agricultural sources, municipal wastewater effluent discharges and wildlife, in addition to STS.

5 Perceptions of, and attitudes towards, faecal pollution risk to watercourses among septic tank users in rural catchments

5.1 Abstract

Septic tank systems (STS) are widely used in rural areas lacking access to centralised sewage infrastructure. However, there is limited understanding of how users perceive the environmental risks posed by STS, particularly regarding faecal indicator organism (FIO) pollution of nearby watercourses. Our study aimed to assess perceptions and attitudes towards faecal pollution risk to water from STS among users in rural Scotland. A cross-sectional online survey was used to gather responses from 302 participants and enabled investigation of patterns, associations and trends in STS characteristics, management approaches, and perceived risks to the water environment across different demographic groups. Results revealed a significant and strong association between water quality concerns and participant age. Younger respondents (18 – 24 years) expressed higher concern about STS-related water impacts (70.8% strongly agreed), while concern decreased among older users, particularly those over 55. Concern was also significantly and strongly associated with STS age; 31.1% of users with systems under five years old were highly concerned, compared to 13.5% of those with systems over 20 years old. STS type also influenced concerns about water quality impacts, with 50% of users of modern systems expressing strong concern, compared to 19.0% of traditional 'Tank only' system users. These findings highlight generational and system-related differences in risk perception, suggesting that older users, who utilise aging systems, may underestimate potential environmental impacts. The study recommends targeted communication strategies focusing on older demographics to enhance awareness and promote responsible STS management. Future research should investigate

how shifts in STS performance or targeted communication strategies influence user engagement in the upkeep of these systems over time.

5.2 Introduction

Faecal pollution in rural catchments poses a risk to water quality and can originate from a range of sources, including diffuse agricultural runoff, inputs from wildlife, and point discharges from wastewater treatment plants and sewer overflows (Afolabi et al., 2023; Igere et al., 2020; Oliver et al., 2018). Agricultural sources and wastewater treatment plants have received significant research attention, and strategies have been developed to monitor and mitigate their impacts. In contrast, decentralised household wastewater treatment systems, such as septic tank systems (STS), remain relatively understudied despite their widespread use in rural catchments. In many parts of Scotland and the wider UK, rural households are not connected to mains sewerage infrastructure and instead rely on private STS for wastewater disposal (Richards et al., 2016). These systems, when poorly designed, maintained, or sited in unsuitable conditions, may become important contributors of faecal pollution to local watercourses. However, their diffuse and decentralised nature means that they are harder to monitor and regulate than centralised treatment plants (Canter & Knox, 2017).

Understanding the contribution of STS to microbial pollution remains challenging for several reasons. First, household-level data on system type, age, condition, and maintenance are rarely available in centralised repositories (Naughton & Hynds, 2014). Second, there is substantial heterogeneity in STS design and performance, with removal efficiencies varying depending on hydraulic retention time, soil type, and the presence of secondary treatment features such as soakaways, drainage fields, or reed beds (Kay et al., 2008; Nasr & Mikhaeil, 2015). Third, where STS are numerous within a catchment, their collective impact can be difficult to isolate from other pollution sources. As a result, microbial risk models often rely on

assumptions regarding STS functioning and user behaviour, which introduces uncertainty into predictions of pollution risk (Mzyece et al., 2024).

Against this backdrop, the role of STS users becomes particularly important. Because these systems are decentralised, their proper functioning relies largely on household responsibility for maintenance and management. User behaviour—including frequency of desludging, use of chemical additives, or timely repair of malfunctioning systems—directly affects the likelihood of pollution occurring (Capps et al., 2020). At the same time, the extent to which homeowners perceive their STS as a potential source of environmental or public health risk influences their willingness to invest in maintenance or to adopt best practice. For instance, if users perceive their septic tank as benign, or if pollution is seen as the responsibility of others (such as farmers or industry), they may not prioritise regular servicing. Conversely, heightened awareness of pollution risks, coupled with regulatory enforcement or targeted education campaigns, may encourage more proactive maintenance behaviours (Devitt et al., 2016; Fizer et al., 2018).

However, existing research into user perceptions of STS is limited. Most studies of faecal pollution in rural catchments have focused on agricultural diffuse pollution or urban point sources, leaving household systems comparatively underexplored. The few studies that have examined user attitudes suggest wide variability in awareness: some homeowners understand the link between septic tanks and drinking water contamination, while others view these systems primarily as a private convenience, disconnected from broader environmental concerns (Naughton & Hynds, 2014). In addition, householders' decisions are shaped by a range of factors including financial constraints, knowledge of regulatory requirements, trust in water authorities, and cultural norms around wastewater management (Kryston et al., 2024; Lawson et al., 2024). These factors can create barriers to effective maintenance, even where the technical capacity to manage systems exists.

Understanding these perceptions is critical for two main reasons. First, from a practical perspective, user behaviour has a direct influence on the risk of microbial pollution from STS, making it a crucial determinant of catchment water quality. Second, from a policy perspective, designing effective interventions—whether through regulation, financial incentives, or education campaigns—requires insight into the attitudes, motivations, and barriers experienced by STS users (Arévalo-Durazno et al., 2024; Rudman et al., 2023). Without this, management strategies may fail to achieve compliance or risk reduction at the household level.

This study therefore seeks to address these gaps by investigating the perceptions and attitudes of STS users in rural Scottish catchments regarding faecal pollution risk. By combining information on system types, treatment features, and maintenance practices with an assessment of user awareness, the study aims to generate new insights that can inform more accurate microbial risk modelling and more effective management strategies. Specifically, the objectives are to: 1) establish the types of STS, associated treatment and maintenance practices across Scotland to reduce uncertainties in STS FIO pollution risk models; and 2) assess the awareness of STS users regarding STS as potential sources of FIO pollution in receiving waters to support the development of targeted recommendations for improving maintenance and reducing pollution risks.

5.3 Materials and methods

5.3.1 Study area and context

Scotland, with a population of approximately 6 million, was selected as the study area. The country spans 78,782 km², of which 98% is classified as rural. In the Scottish context, rural areas are defined as settlements with fewer than 3,000 inhabitants. A settlement—typically separated by low-density postcodes—is considered a grouping of high-density postcodes with

a combined population of 500 or more (Rural and Environmental Science and Analytical Services, RESAS, 2021). Rural areas are further categorised based on drive times to larger settlements: accessible rural areas are those within a 30-minute drive of a settlement with a population of 10,000 or more while remote rural areas are located more than 30 minutes from such settlements. Approximately 17% of Scotland's population resides in rural areas with 11% in accessible rural areas and 6% in remote rural areas (RESAS, 2021). Most of the rural population are older people with a median age of 52 (National Records of Scotland, 2024). An estimated 4% of the rural population in Scotland relies on STS for domestic wastewater treatment (Richards et al., 2016).

5.3.2 STS distribution and pollution risk

Figure 18 shows the regions of Scotland from which study participants were drawn, along with the estimated number of STS per region. These estimates are based on a composite dataset compiled from licensed records maintained by the Scottish Environment protection Agency (SEPA), Scottish Water, local Assessors, and selected Local Authorities. This dataset is available under the UK Open Government Licence (Spatial Hub, 2025).

As shown in Figure 18, there is a high concentration of STS in Strathclyde in the southwest while the Borders region have the fewest STS. Historically the SW has struggled with bathing water quality; often this has been attributed to intensive dairy farming practices (Edwards et al., 2008; Vinten et al., 2008); however, contributions from STS may have played a role as seen in Chapter 4.

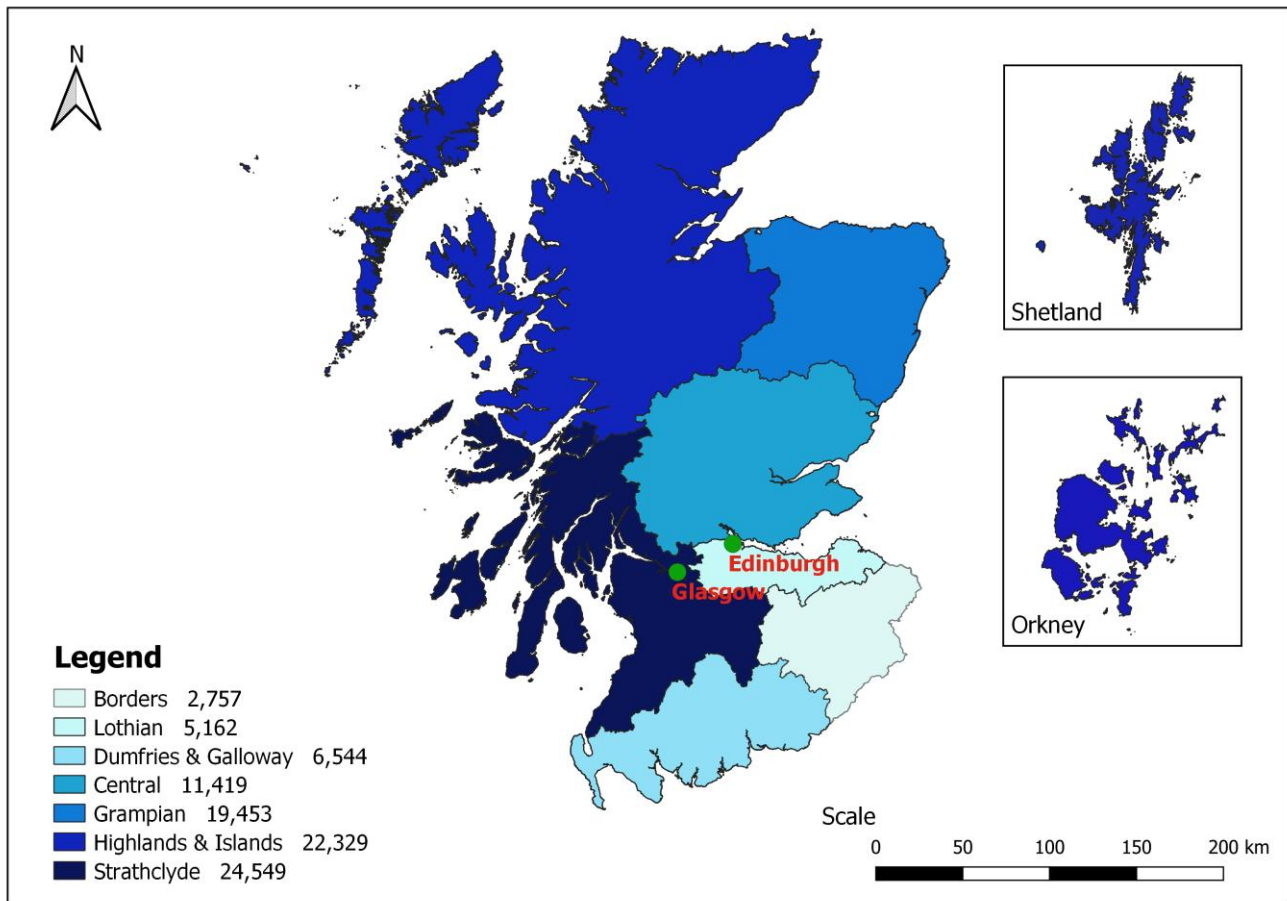


Figure 18: Regions of Scotland and estimated number of STS in each region.

5.3.3 Data collection

A nationwide online survey was developed to obtain responses from STS users in Scotland. This survey was designed and administered through the Qualtrics platform (<https://www.qualtrics.com/>). The sample frame consisted of Scottish residents 18 years or older who use an STS for domestic wastewater treatment. All participants were recruited through the Qualtrics platform. All data were anonymous, with no identifying information available to the authors. Ethical approval was granted by the University of Stirling General University Ethics Panel (2024 20351 15240).

A pilot version of the survey was tested on 30 participants through a soft launch to evaluate survey length and language prior to the full launch, with only minimal edits subsequently made to improve clarity. The survey was conducted between 20 and 27 February 2025, during which 310 participants were recruited. However, eight respondents were excluded because they completed the survey in an unrealistically short time (speeders). As a result, the final analysis was based on the responses of 302 participants who fully engaged with and completed the survey.

The cross-sectional survey comprised 19 core questions; participants were asked a series of questions to identify the types of STS they use and their corresponding treatment levels. Additional questions explored the management practices they engage in, including factors that support or hinder the effective maintenance of their STS. Participants were also asked about their awareness and perceptions of STS as potential sources of faecal pollution to water environments. Socio-demographic information was collected, including age, gender, and region of residence within Scotland.

The survey used two types of question formats: multiple-choice questions and a four-point Likert scale presented in a matrix table. The Likert scale was chosen for its simplicity and effectiveness in measuring attitudes, as well as its compatibility with non-parametric statistical analyses such as Chi-Square (cross-tabulation) (Chyung et al., 2017). A copy of the survey instrument is provided in Appendix 9.

5.3.4 Data analysis

Chi-Square test of association was used to analyse the associations between categorical variables. For each test, the null hypothesis stated that there was no association between the variables, while the alternative hypothesis stated that a statistically significant association existed between the variables. These tests were used to evaluate research hypotheses

derived from the study objectives concerning relationships between STS characteristics, user management practices, and perceptions of faecal pollution risk. The following research hypotheses were tested:

- H 1: Users with less frequent maintenance practices are more likely to own older or less advanced STS.
- H 2: Perceptions of STS as a potential source of FIO pollution is associated with user maintenance behaviour.
- H 3: Awareness of pollution risk differs according to user characteristics or STS characteristics such as STS age, location and treatment level.

Chi-square significance thresholds were set at $P < 0.05$ and Cramer's analysis (Φ_C) was subsequently performed for any statistically significant associations to determine association strength. Thresholds of Φ_C for association strength were classified as: Very Strong > 0.25 , Strong > 0.15 , Moderate > 0.10 , Weak > 0.05 , Very weak > 0 (Akoglu, 2018). All statistical analysis was done using R software Version 2024.12.1+563. Binomial confidence intervals were estimated in R for the counts data and reported around percentages.

5.4 Results

A total of 302 responses were received. Gender distribution among participants was balanced, with 53.3% ($n = 161$) identifying as female and 46.4% ($n = 140$) as male. Age distribution varied amongst the different age groups, with the largest proportion of participants (19.2%, $n = 58$) falling within the 45–54 age range, equally split by gender. The 18 - 24 yr age group was the least represented (11.9%, $n = 36$), with a higher proportion of female participants (61.1%, $n = 22$) compared to 38.9% ($n = 14$) male participants. The age distribution of female respondents was positively skewed (0.728), indicating a greater representation in younger age

groups (under 44 yrs), while the male age distribution showed a slight negative skew (- 0.187), reflecting higher representation in older age groups (over 44 yrs).

Regionally, most participants (33.4%, $n = 101$) came from central Scotland where most of the country's population resides, while the Borders region accounted for the lowest proportion (3.0%, $n = 9$) (Table 12). A significant and strong association was found between the participants' region of residence and the type of STS used ($P = 0.002$, $\Phi_C = 0.19$).

Table 12: Demographics of survey participants.

Total number of respondents	Number and percentage of respondents	
	Number	Percentage
Total number	302	100%
Gender		
Male	140	46.4
Female	161	53.3
Transgender	1	0.3
Age		
18-24	36	11.9
25-34	58	19.2
35-44	54	17.9
45-54	58	19.2
55-65	48	15.9
Over 65	47	15.6
Prefer not to say	1	0.3
Region of Scotland in which respondent resides		
Highlands & Islands	29	9.6
Grampian	35	11.6
Central	101	33.4
Strathclyde	69	22.8
Lothian	49	16.2
Borders	9	3.0
Dumfries & Galloway	10	3.3

5.4.1 Types of septic tanks, associated treatment and maintenance practices across Scotland

Participants were asked a range of questions relating to their STS type, the discharge point, age, proximity to the nearest surface watercourse and the maintenance practices they engage in.

Types of STS

While nearly half of the participants (43.7%, $n = 132$, 95% CI: 38.1 - 49.4%) were unaware of the type of STS they use for domestic wastewater treatment, our findings indicated that the most utilised STS type was the 'tank only system', used by 26.2% ($n = 79$, 95% CI: 21.5% - 31.4%) of the respondents. This system was particularly common in Central Scotland (8.6%, $n = 26$, 95% CI: 5.9% - 12.3%), Strathclyde (8.0%, $n = 24$, 95% CI: 5.4% - 11.5%)) and Lothian (6.0%, $n = 18$, 95% CI: 3.8% - 9.2%), but recorded low usage in the Borders (0.3%, $n = 1$, 95% CI: 0.06% - 1.9%), Dumfries and Galloway (0.7%, $n = 2$, 95% CI: 0.2% - 2.4%), Grampian (1.0%, $n = 3$, 95% CI: 0.3% - 2.9%) and the Highlands and Islands (1.7%, $n = 5$, 95% CI: 0.7% - 3.8%) (Figure 19). The 'tank+soakaway field' was the second most utilised, reported by 20.6% ($n = 63$, 95% CI: 16.7% - 25.8%) of the total participants while the Shallow dig STS ranked third with reported use by 6.0% ($n = 18$, 95% CI: 3.8% - 9.2%) of participants. The Onion shape STS was the least utilised (2.7%, $n = 8$, 95% CI: 1.3% - 5.1%) with no reported use of this STS type in the Borders region, Dumfries and Galloway and the Highlands and Islands. Similarly, no participants in the Borders reported using a 'tank+soakaway field' STS system. Additionally, 0.7% ($n = 2$, 95% CI: 0.2% - 2.4%) of participants (one from Grampian and one from the Highlands and Islands) reported using other types of STS not listed in the survey, though they did not specify which.

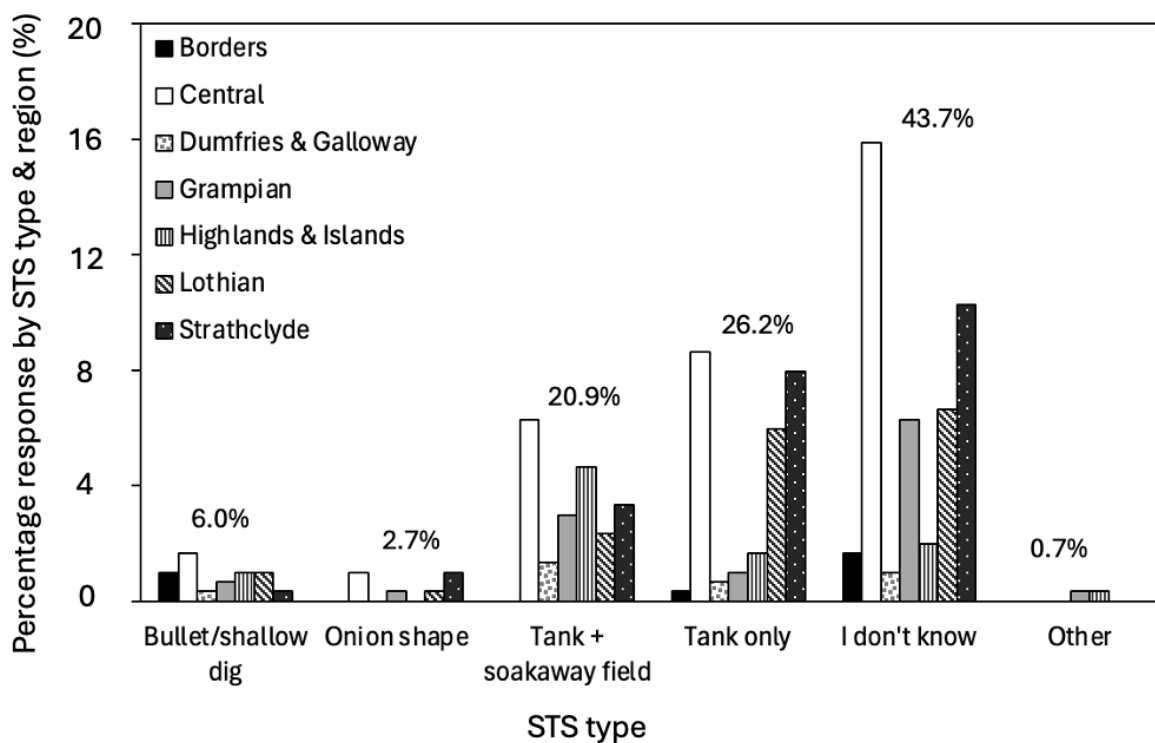


Figure 19: STS types utilised across Scotland. The percentages at the top of the bars indicate the proportion of participants utilising that STS type.

STS treatment levels, age and proximity to waterbodies

Discharge end-point receptors were significantly and strongly associated with the type of STS utilised ($P < 0.001$, $\Phi_c = 0.47$). Overall, discharge into a soakaway field was the most common across all STS types—reported by 30.5% of participants ($n = 92$, 95% CI: 25.5% - 35.9%)—except for the shallow dig systems (Figure 20). Among users of shallow dig STS, discharging into a nearby waterbody was more prevalent, reported by 44.4% ($n = 8$, 95% CI: 24.6% - 66.3%) of respondents. This was also the second most reported discharge point across all STS types, accounting for 18.9% ($n = 57$, 95% CI: 14.9% - 23.7%) of total participants. The least reported discharge point was the reedbed system, used by only 6.6% ($n = 20$, 95% CI: 4.3% - 10.0%) of participants.

In terms of treatment levels, the 18.9% of systems discharging to a nearby waterbody represent primary treatment usage. When combined, the systems discharging into a soakaway field or reedbed system account for 37.1% ($n = 122$, 95% CI: 31.8% - 42.7%) of respondents, indicating secondary treatment features.

Notably, 40.5% ($n = 32$, 95% CI: 30.5% - 51.5%) of users with a 'tank only' system reported discharging into a soakaway field. This is unexpected and probably reflects a general lack of understanding among owners of STS, as the typical discharge point for this system is directly into a waterbody—reported by 31.7% ($n = 25$, 95% CI: 22.4% - 42.5%) of 'tank only' users. Similarly, 15.9% ($n = 10$, 95% CI: 8.8% - 26.8%) of 'tank + soakaway' users reported direct discharge to a nearby waterbody, which is also atypical for this system type. Finally, a significant portion of respondents—44.0% ($n = 133$, 95% CI: 38.5% - 49.7%)—were unaware of where their STS discharges to.

Discharge end-point receptors were also significantly and strongly associated with STS proximity to a watercourse ($P = 0.007$, $\Phi_C = 0.17$). STS located less than 50 m from a watercourse (47.5%, $n = 143$, 95% CI: 41.7% - 52.9%) tended to discharge directly into a nearby watercourse compared to only 11.9% ($n = 36$, 95% CI: 8.7% - 16.1%) of those located more than 50 m from a watercourse. Discharging STS effluent into a reedbed system was generally low (5.0 - 7.9%) for all STS types across all distance categories (<10, 10-50 and >50 m) but this discharge point was the least common for STS located less than 10 m to a watercourse.

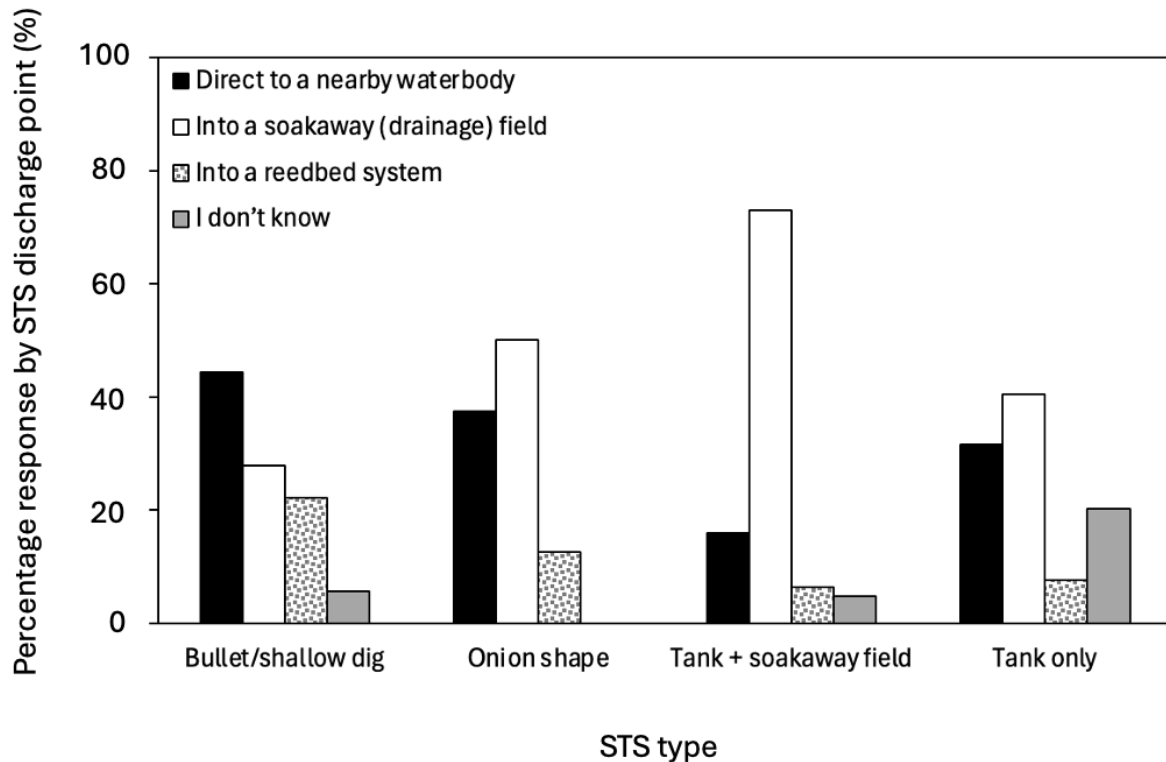


Figure 20: Association between discharge end point receptors and STS type. Participants who did not know their STS type have been excluded ($n = 132$).

Age of STS system was significantly and strongly associated with the STS type ($P < 0.0001$, $\Phi_C = 0.35$). Multiple respondents—36.1% ($n = 52$, 95% CI: 28.7% - 44.2%) across all STS types indicated that their STS were between 5 -10 years old, with those utilising the onion shape STS accounting for a large proportion (62.5%, $n = 5$ out of 8, 95% CI: 30.6% - 86.3%) followed by users of the shallow dig STS (56.3%, $n = 9$ out of 16, 95% CI: 33.2% - 76.9%) (Figure 21). None of these two STS types was reported to be more than 20 years old, when compared to the ‘tank+soakaway’ and ‘tank only’ systems where 18.2% ($n = 10$, 95% CI: 8.9% - 26.8%) and 21.5% ($n = 14$, 95% CI: 10.8% - 27.6%) of users, respectively, reported systems older than 20 years.

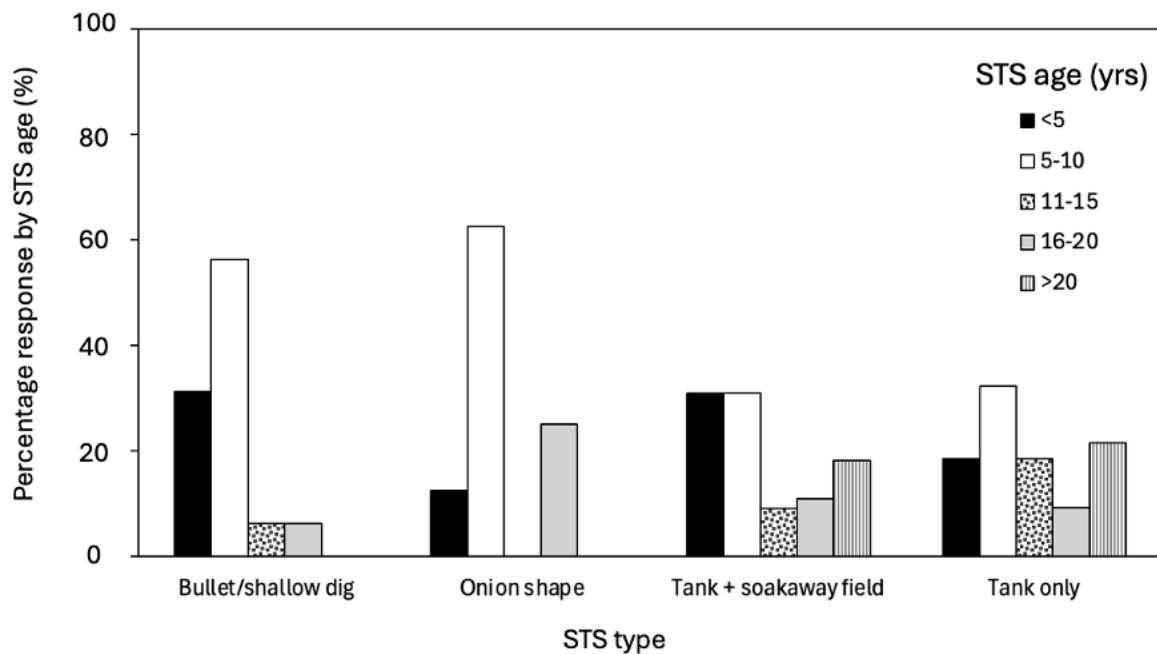


Figure 21: Association between STS age (in years) given by percentage response on the Y-axis and STS type on the X-axis.

Similarly, the proximity of STS to surface water was significantly and strongly associated to the STS type ($P = 0.0007$, $\Phi_C = 0.23$). Multiple respondents (48.2%, $n = 81$, 95% CI: 42.7% - 54.0%) across all STS types reported that their STS were located between 10 - 50 m away from the nearest waterbody. Most Onion shape STS users (75%, $n = 6$ out of 8, 95% CI: 40.9% - 93.0%) fell in this category. (Figure 22). Notably, no respondent utilising the onion shape STS reported systems less than 10 m from a waterbody compared with 26.6% ($n = 21$, 95% CI: 18.1% - 37.2%) of those using a 'tank only' system who had STS within 10 m of the nearest waterbody. Of the STS type reported to be located more than 50 m from a waterbody, shallow dig were the most prominent (38.9%, $n = 7$ out of 18, 95% CI: 20.3% - 61.3%) followed by 'tank+soakaway' systems (34.9%, $n = 22$ out of 63, 95% CI: 24.3% - 47.2%) while 'tank only' systems were the least prominent (25.0%, $n = 20$ out of 79, 95% CI: 17.0% - 35.8%).

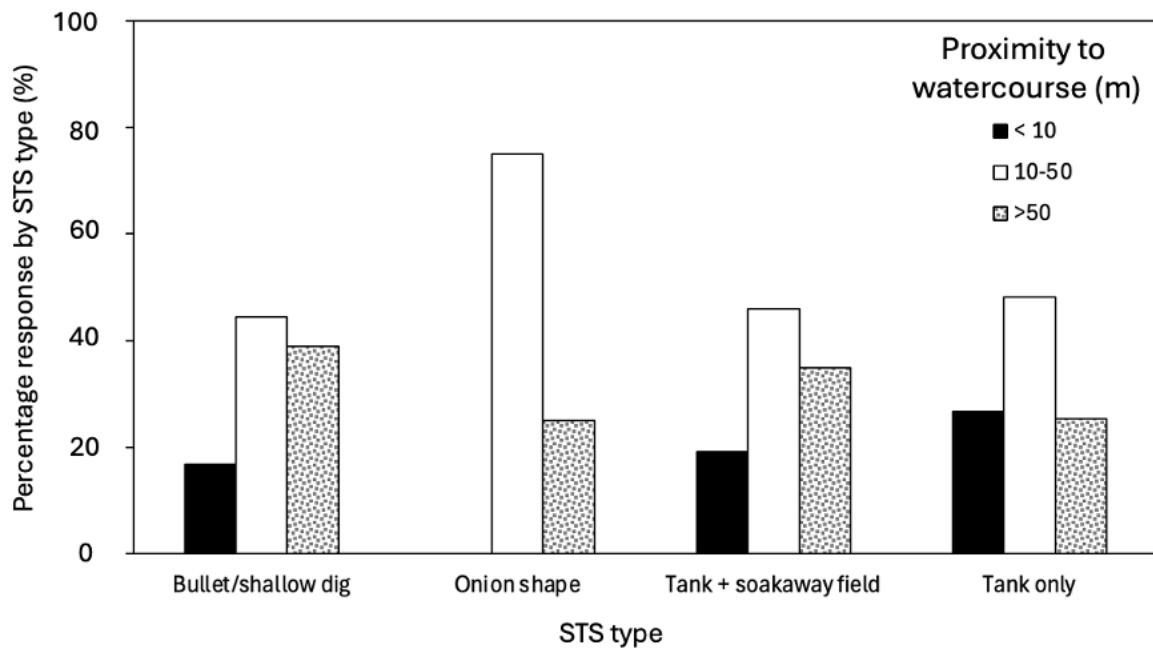


Figure 22: Association between STS proximity to a nearby waterbody (in metres) and STS type.

STS maintenance practices

Participants were asked questions to explore potential factors influencing STS maintenance practices. Potential factors influencing STS emptying included: the location and accessibility of the STS, the number of properties connected to it, duration of residence at the property, ownership status, access to maintenance information from the previous property owner, ease of finding a specialist for routine and emergency services, cost of maintenance, and issues such as blockages, flooding, or damage to the system. Further, participants were asked about maintenance practices they actively engage in. These included: inspecting the STS, not putting harsh chemicals down the drain, conserving water use in the house, preventing the STS area from flooding, keeping trees and construction away from the STS area and keeping detailed records of the STS.

Overall, 39.7% ($n = 120$, 95% CI: 34.4% - 45.3%) did not know how often their STS was emptied while 28.8% ($n = 87$, 95% CI: 24.0% - 34.2%), 16.2% ($n = 49$, 95% CI: 12.5% - 20.8%), 7.9% ($n = 24$, 95% CI: 5.4% - 11.6%), 2.0% ($n = 6$, 95% CI: 0.9 - 4.3%) and 3.0% ($n = 9$, 95% CI: 1.6% - 5.6%) reported emptying their STS every one, two, three, four and five years, respectively. A significant association between the frequency of STS emptying and several of these factors was identified, with accompanying strength of association of those factors influencing STS emptying frequency shown in Figure 23. Notably, knowledge of the STS location showed the strongest association with emptying frequency ($P < 0.001$, $\Phi_C = 0.46$) among all the influencing factors, with those who knew the location of their STS reporting higher emptying frequencies compared to those who did not. In fact, 72.1% of respondents who were unaware of their STS location were uncertain about its emptying frequency, compared to just 11.1% who knew the location of their STS but were uncertain of its emptying frequency.

The number of properties connected to an STS was also significantly associated with emptying frequency ($P < 0.001$, $\Phi_C = 0.40$). Multiple respondents (34.1%, $n = 103$, 95% CI: 30.0% - 40.0%) reported their STS served a single property, while 15.6% ($n = 46$, 95% CI: 11.6% - 19.7%) said it served two properties, 18.2% ($n = 55$, 95% CI: 14.3% - 23.0%) reported it served three or more, and 32.1% ($n = 97$, 95% CI: 27.1% - 37.6%) were unsure. The data indicated that STS serving a single property tended to be emptied more frequently than those serving two or more properties. Furthermore, uncertainty about the frequency of STS emptying was more prevalent among respondents whose systems served three or more properties (32.7%) than among those with systems serving just one property (15.5%).

Although ease of physically accessing their STS for inspection and maintenance was significantly associated to its emptying frequency ($P = 0.049$), the association was moderate

($\Phi_C = 0.18$). The presence of an STS within a respondent's property was also significantly associated with higher emptying frequent ($P < 0.001$, $\Phi_C = 0.32$).

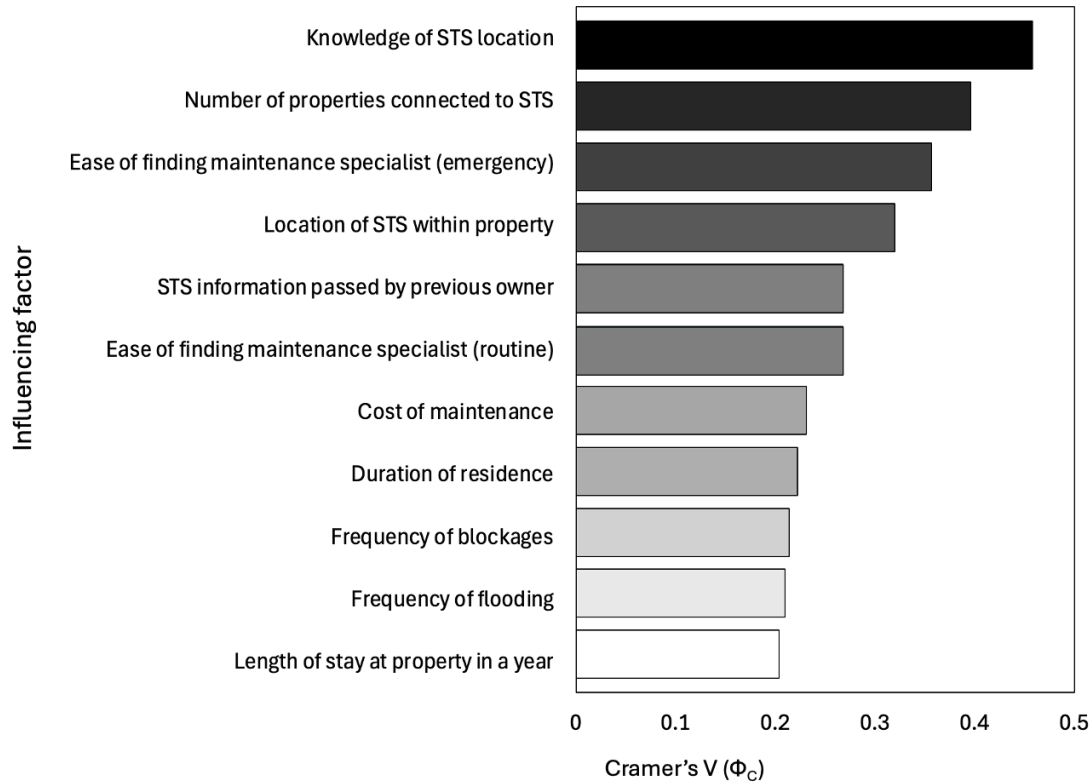


Figure 23: Strength of association between STS emptying frequency and key influencing factors.

The frequency of STS emptying was found to be significantly and strongly associated with both the duration of residence within a year and the total length of occupation at a property ($P = 0.004$, $\Phi_C = 0.20$ and $P = 0.0005$, $\Phi_C = 0.22$, respectively). Among respondents residing at their property for 7 months or more ($n = 290$), 29.7% ($n = 86$, 95% CI: 24.7% - 35.1%) reported emptying their STS annually. In contrast, among those staying less than 7 months ($n = 12$), 16.7 % ($n = 2$, 95% CI: 4.7% - 44.8%) emptied their STS every 3 years, and 25.5% ($n = 3$, 95% CI: 8.9 - 53.2%) every 5 years. Among those who indicated that they empty their STS every 5 years ($n = 9$), 77.8% ($n = 7$, 95% CI: 45.3% - 94.0%) reported that they had occupied

their property for more than 10 years compared to 18.4% (n = 16 out of 87, 95% CI: 11.6% - 27.8%) who emptied their system every year. In contrast, respondents who tended to empty their STS at more regular intervals of one year, two years or every three years, had a shorter residence duration of 1 – 5 years (Figure 24).

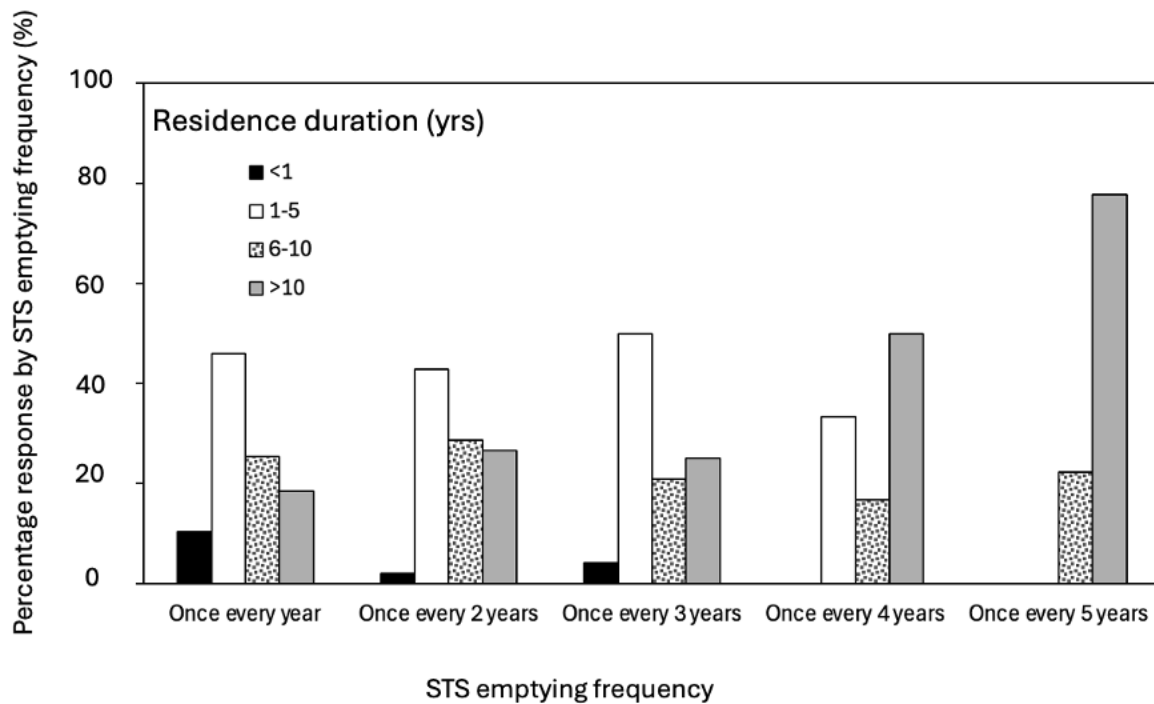


Figure 24: Association of STS emptying frequency with residence duration.

While property ownership status (owner vs. renter) showed no significant association with STS emptying frequency, the transfer of information from a previous property owner to the current one did ($P < 0.001$, $\Phi_C = 0.268$). Nearly half (49%, n = 24 out of 49, 95% CI: 35.6% - 62.5%) of respondents who received such information emptied their STS annually, compared to only 25.3% (n = 59 out of 233, 95% CI: 20.2% - 31.3%) of those who did not.

Access to STS specialists for both routine maintenance and emergencies also showed a significant and strong association with emptying frequency ($P < 0.001$, $\Phi_C > 0.35$ for both).

Among participants who emptied their STS annually ($n = 87$), 65.5% ($n = 57$, 95% CI: 55.1 - 74.7%) reported easy access to specialists for routine maintenance, whereas only 25.3% ($n = 22$, 95% CI: 17.3 - 35.3%) reported difficulty. This trend was consistent across all emptying intervals, with ease of access to maintenance specialist consistently linked to more frequent emptying.

Finally, the frequency of STS blockages and flooding was significantly associated with emptying frequency ($P = 0.001$, $\Phi_C = 0.21$; flooding: $P = 0.002$, $\Phi_C = 0.21$). Among those who emptied their STS annually ($n = 87$), 63.2% ($n = 55$, 95% CI: 52.7% - 72.6%) disagreed that blockages were frequent, compared to 36.8% ($n = 32$, 95% CI: 27.4% - 47.3%) who agreed. The most common 'good practice' among participants and their family members was not putting harsh chemicals into the tank or down the drain, practised by 49% ($n = 148$, 95% CI: 43.4% - 54.6%) of the survey participants. Keeping all construction at least 4 m away from the STS was the most poorly adopted best management practice, with only 22% ($n = 17.6\% - 26.8\%$) of participants reporting doing so (Figure 25).

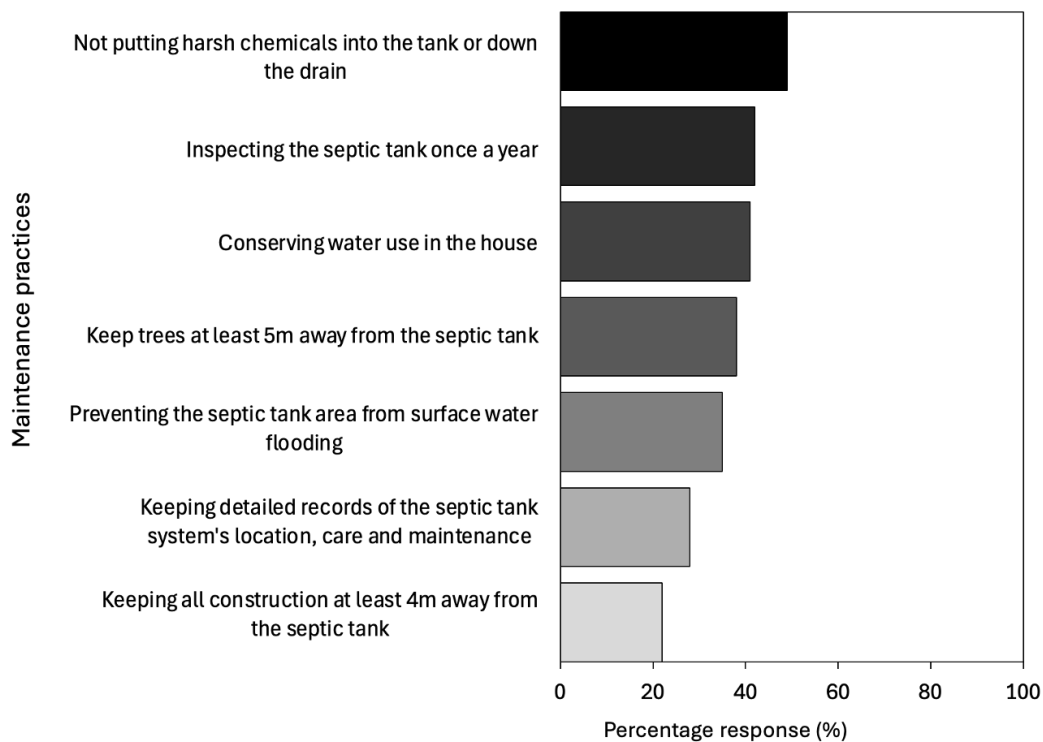


Figure 25: Ranking of common STS maintenance practices based on percentage response of participants.

5.4.2 Awareness of STS users regarding STS as potential sources of FIO pollution

Participants responded to a series of awareness and perception-based statements on a four-point Likert scale, indicating their level of agreement or disagreement. The statements addressed concerns about water quality impacts from STS, environmental risks of leaking effluent, the effectiveness of additional treatment in reducing microbial pollution, health risks from poorly maintained STS, adequacy of STS regulations, and knowledge of potential system damage from deep-rooted vegetation and improper rainwater connections.

Concerns about water pollution impacts to the environment vs STS type, STS age and STS proximity to waterbody

The distribution of responses regarding participants' concerns about water quality impacts from their STS approximated a normal distribution, as evidenced by the symmetrical spread

of responses across the Likert scale: 18.5% ($n = 56$, 95% CI: 14.6% - 23.3%) strongly agreed, 32.5% ($n = 98$, 95% CI: 27.4% - 37.9%) somewhat agreed, 33.4% ($n = 101$, 95% CI: 28.4% - 38.9%) somewhat disagreed, and 15.6% ($n = 47$, 95% CI: 11.9% - 20.1%) strongly disagreed. A significant and strong association was observed between participants' concern about water quality impacts arising from their STS and the type of STS used ($P = 0.048$; $\Phi_C = 0.17$). Among participants who did not know their STS type ($n = 132$), a lower proportion (4.5%, $n = 6$, 95% CI: 2.1% - 9.6%) strongly agreed that they were concerned about water quality impacts from their STS compared to 41.6% ($n = 55$, 95% CI: 33.6% - 50.2%) who strongly disagreed. Of the participants who knew their STS type, the highest proportion who strongly agreed that they were concerned about water quality impacts from their STS were those using an onion shape STS (50%, $n = 4$ out of 8, 95% CI: 21.5% - 78.4%), followed by shallow dig STS users (22.2%, $n = 4$ out of 18, 95% CI: 9.0% - 45.2%). In contrast, the lowest proportion of respondents who strongly agreed that they were concerned about water quality impacts from their STS was recorded among users of the 'tank only' system (19.0%, $n = 15$ out of 79, 95% CI: 11.9% - 29.0%) just slightly below 25.4% ($n = 16$ out of 63, 95% CI: 16.3% - 29.0%) who utilise a 'tank+soakaway' system (Figure 26). These findings confirmed our hypothesis that users with less frequent maintenance practices were likely to own older systems.

Similarly, a significant and strong association was found between the type of STS used and frequency of blockages in the system ($P = 0.002$; $\Phi_C = 0.20$). More than half (61.1%, $n = 11$, 95% CI: 38.6% - 79.7%) of shallow dig STS users agreed that blockages were a frequent occurrence in their system. Conversely, users of onion shape STS (75.0%, $n = 6$, 95% CI: 40.9% - 92.9%), 'tank+soakaway' (61.9%, $n = 39$, 95% CI: 49.6% - 72.9%) and 'tank only' (65.8%, $n = 52$, 95% CI: 54.8% - 75.3%) systems tended to disagree about blockages being a frequent occurrence in their systems.

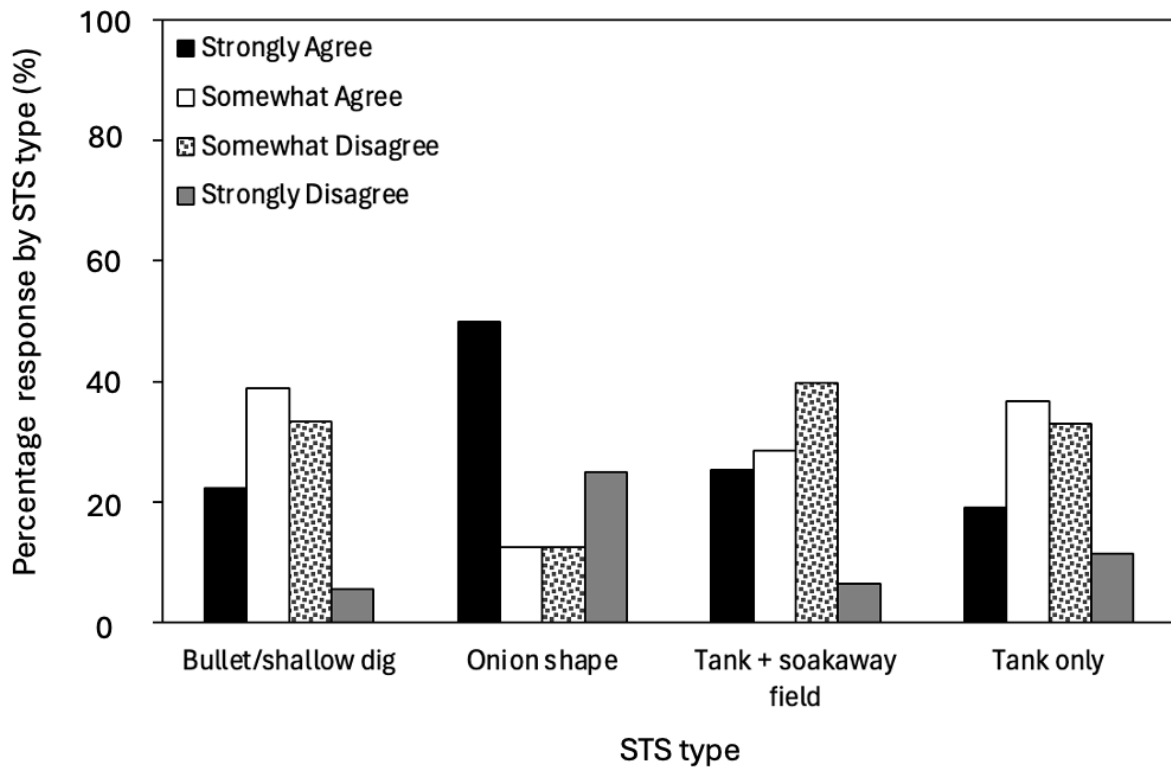


Figure 26: Concern about water quality impacts from participants' STS by STS type. Respondents who said they did not know their STS type or used other type of STS but did not specify the type, have been excluded (n=134).

Concern about water quality impacts was significantly and strongly associated with STS age ($P = 0.0049$, $\Phi_C = 0.20$). Notably, a fair proportion of participants who were unaware of the age of their STS *strongly disagreed* that they were concerned about its water quality impacts (24.8%, $n = 30$ out of 121, 95% CI: 18.0% - 33.2%). Overall, concern about water quality impacts tended to decrease with increasing STS age (Figure 27). For instance, 31.1% ($n = 14$ out of 45, 95% CI: 19.5% - 45.7%) of participants with systems less than 5 years old strongly agreed they were concerned, compared to only 13.5% ($n = 5$ out 37, 95% CI: 5.9% - 28.0%) of those with systems older than 20 years. Conversely, 16.5% ($n = 6$, 95% CI: 7.7% - 31.1%) of participants with systems older than 20 years strongly disagreed with being concerned about water quality impacts, compared to 4.4% ($n = 2$, 95% CI: 1.2% - 14.8%) of those whose systems were less than 5 years old.

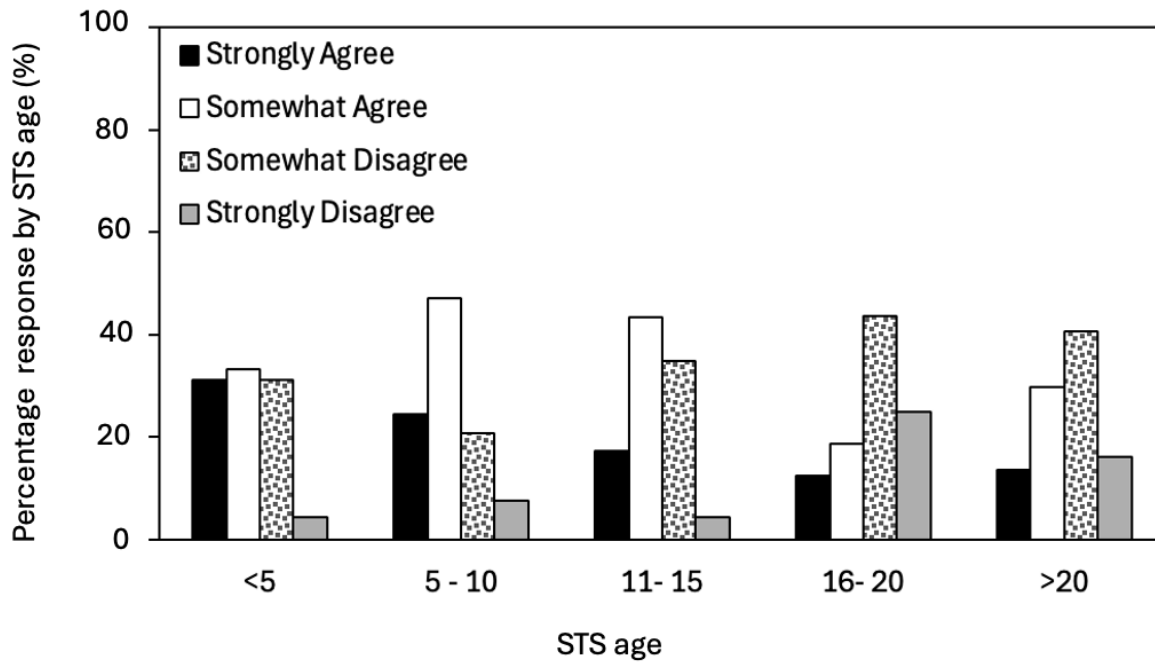


Figure 27: Concern about water quality impacts by STS age (years). Respondents who said they did not know their STS age or opted not to share this information have been excluded (n=128).

A significant and moderately strong association was observed between concern about water quality impacts from STS and the distance of the STS to the nearest waterbody ($P = 0.037$, $\Phi_C = 0.15$). In general, the proportion of participants who strongly agreed with being concerned about water quality impacts decreased as the distance between the STS and the nearest watercourse increased (Figure 28). For example, 23.3% ($n = 14$ out of 60, 95% CI: 14.4% - 35.4%) of participants with STS located less than 10 metres from a waterbody agreed with the concern, compared to 19.8% ($n = 23$ out of 160, 95% CI: 9.8% - 20.6%) of those with STS located 10–50 meters away, and 15.1% ($n = 19$ out of 126, 95% CI: 9.9% - 22.3%) of those whose STS were situated more than 50 meters from a waterbody.

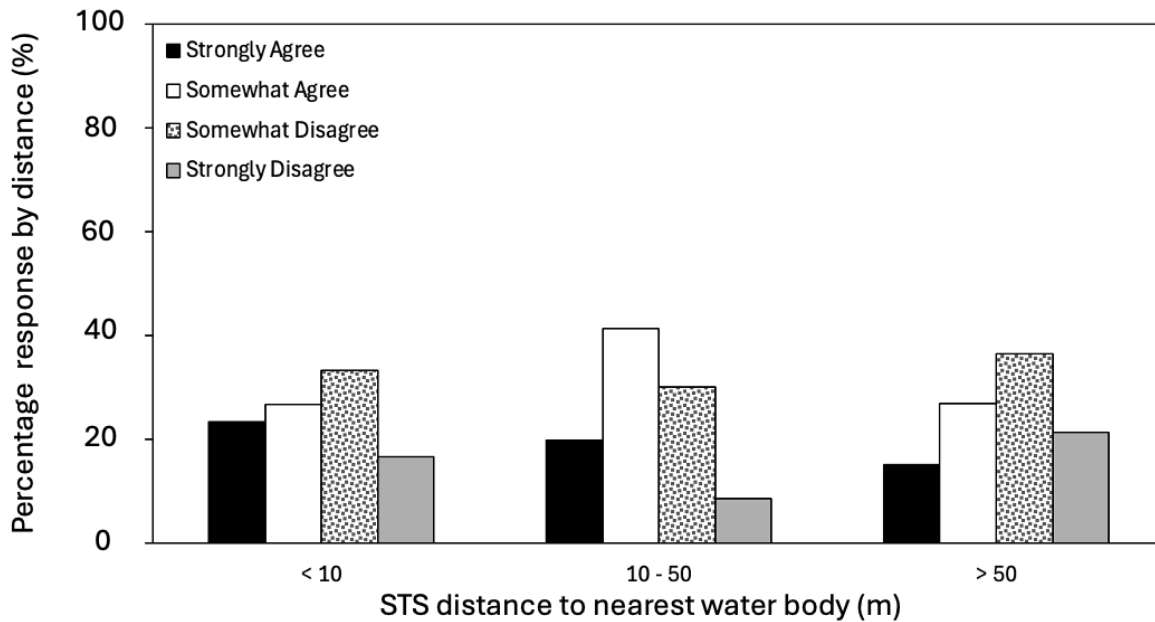


Figure 28: Concern about water quality impacts from STS by STS proximity to nearest watercourse.

No significant association was found between the participants' perception of leaking effluent from STS being an environmental concern and STS type ($P = 0.7$). Similarly, there was no association between participants' perception that additional treatment of STS effluent is effective in reducing microbial pollution risks to the environment and STS type ($P = 0.08$).

Concerns about STS water pollution impacts to the environment vs participants' demographics, property ownership status and access to information

There were significant and strong to very strong associations between the participants' age and responses to the following 3 statements: *"I am concerned about water quality impacts arising from my STS"* ($P = 0.001$, $\Phi_C = 0.23$); *"The risk of microbial pollution to the environment from my STS is negligible"* ($P = 0.03$, $\Phi_C = 0.18$); and *"Regulation of STS is adequate to ensure proper management and reduced microbial pollution of the environment"* ($P = 0.04$, $\Phi_C = 0.17$). Overall, the highest proportion of participants who indicated that they were concerned about water quality impacts from their STS were those below the age of 44, with the highest

proportion (75.0%, $n = 26$ out of 37, 95% CI: 58.9% - 86.2%) being recorded in the 18-24 age group. Conversely, 70.8% ($n = 34$ out of 48, 95% CI: 56.8% - 81.8%) of participants aged 55-64 and 63.8% ($n = 30$ out of 47, 95% CI: 49.5% - 76.0%) of those over 65 disagreed with this concern (Figure 29). This perception was mirrored in the responses given when participants were asked about their perception of the risk of microbial pollution from their STS to the environment being negligible, 38.3% ($n = 18$, 95% CI: 25.8% - 52.3%) of participants aged over 65, strongly agreed that water quality impacts from their STS were negligible compared to only 8.5% ($n = 4$, 95% CI: 3.4% - 19.9%) of those who strongly disagreed (Figure 30). Notably, none of the participants in the 18-24 age group strongly disagreed with the perception that microbial pollution risk from their STS was negligible, while only 16.7% ($n = 7$, 95% CI: 7.9% - 31.9%) strongly agreed with this perception. These findings agree with our third hypothesis (H3) that awareness of pollution risks from STS differs according to user characteristics, such as participant age or STS characteristics such as STS age, location and treatment level.

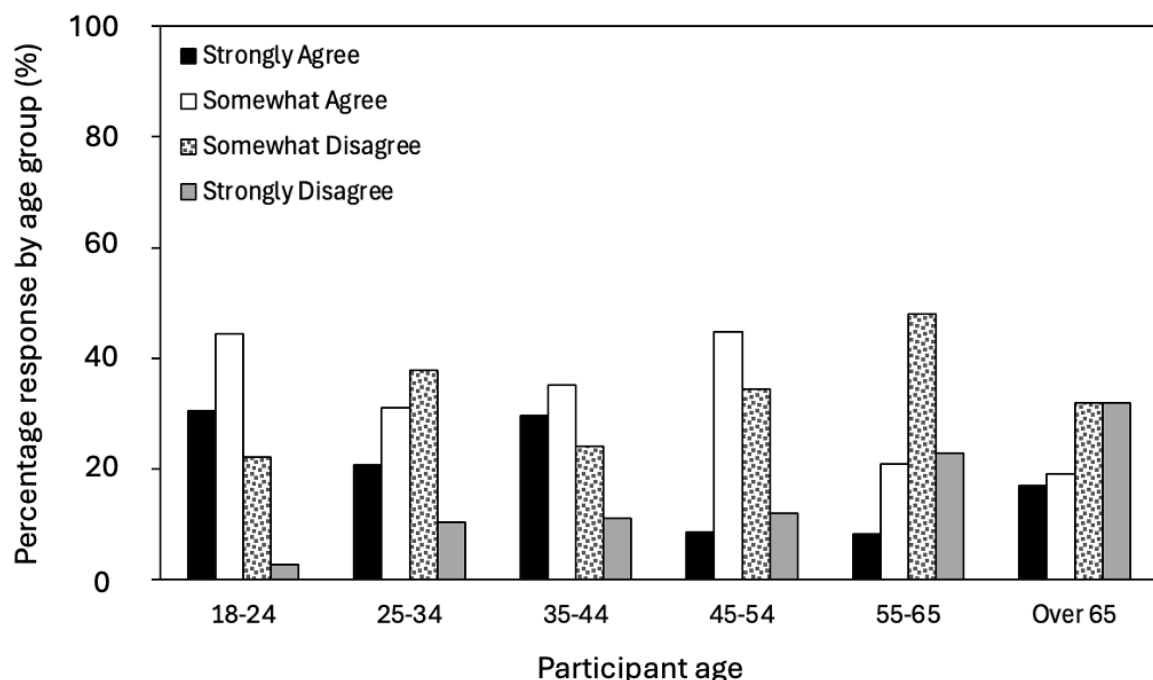


Figure 29: Concern about water quality impacts arising from STS by participant age. Agree means that participants are concerned about water quality impacts from their STS while disagree means they are not concerned.

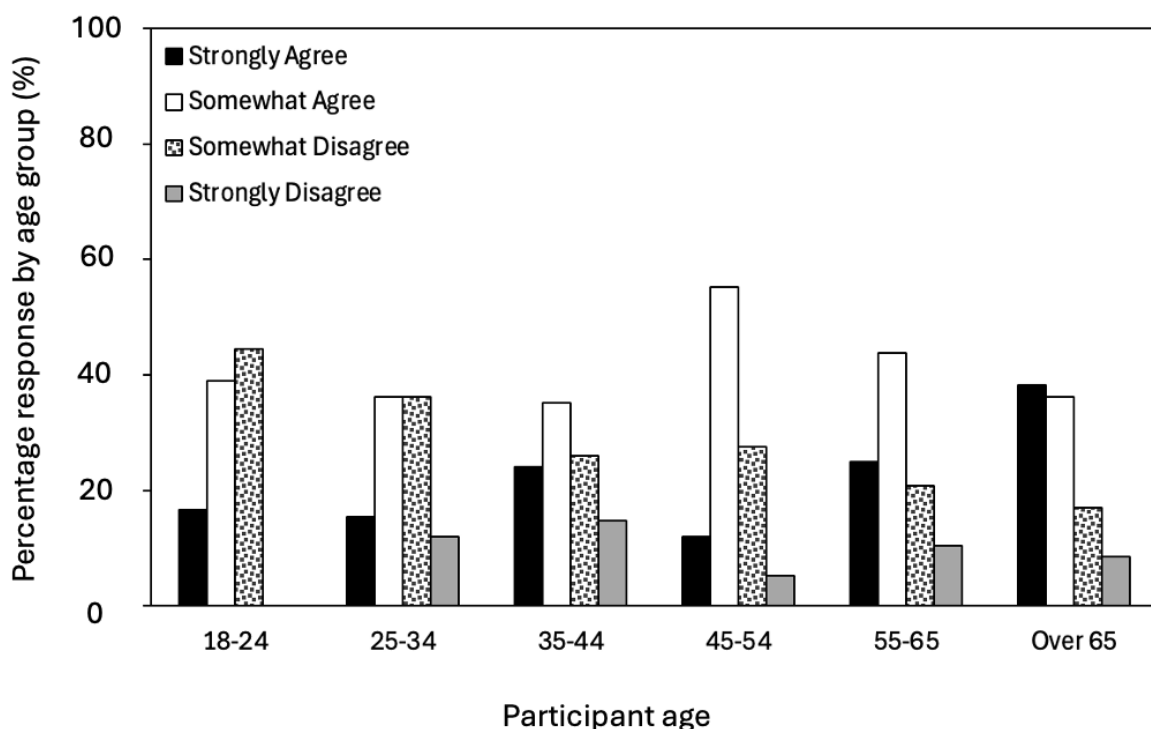


Figure 30: Perception that water quality impacts from users' STS is negligible by participant age. Agree means that participants perceive water quality impacts from their STS to be negligible while disagree means participants perceive impacts to be high.

On the contrary, participant age was not significantly associated with responses to several awareness- and perception-based statements presented in Table 13. Despite this lack of statistical association, over 80% of participants consistently demonstrated awareness of key issues. These included the potential for pollution from poorly maintained STS, the effectiveness of additional treatment of STS effluent in reducing pollution, the risk of damage to STS caused by plants, and the legal responsibility to maintain STS in good working order. This was evident from the high percentage of responses falling under the categories “Strongly agree” and “Somewhat agree,” in contrast to the relatively low number of responses under “Somewhat disagree” and “Strongly disagree”.

Table 13: Awareness about STS as potential sources of pollution.

Awareness statements	Strongly Agree (%)	Somewhat Agree (%)	Somewhat Disagree (%)	Strongly Disagree (%)
I maintain my septic tank in optimal working condition	27.15	48.01	15.56	9.27
There are potential risks to human health if septic tanks are poorly maintained	50.00	36.42	8.61	4.97
Rainwater drainage pipes should not be connected into my septic tank	34.11	48.34	12.58	4.97
The presence of deep-rooted trees and shrubs near to a septic tank can damage the system	36.09	48.34	12.91	2.65
Additional treatment of septic tank effluent (e.g., filtration) is effective in reducing microbial pollution risks to the environment	33.77	49.34	13.25	3.64
I have a legal responsibility to maintain my septic tank in good working order	37.75	43.38	15.56	3.31

While participant age was not significantly associated with responses to the statement “*I have a legal responsibility to maintain my septic tank in good working order*”, property ownership status showed a significant and moderate association ($P = 0.021$, $\Phi_C = 0.15$). A slightly higher proportion of property owners (84.2%, $n = 171$ out of 203, 95% CI: 78.6% - 88.6%) agreed with this statement compared to renters (74.7%, $n = 65$ out of 87, 95% CI: 64.7% - 82.7%), indicating a generally high level of agreement across both groups (Figure 31). Among those who disagreed, 25.3% ($n = 22$, 95% CI: 17.3% - 35.3%) were renters, while 15.8% ($n = 32$, 95% CI: 11.4% - 21.4%) were property owners. Notably, participants who selected “Other” for property ownership—such as those living with parents—also largely agreed that they have a legal responsibility to maintain their STS in good working order, with agreement exceeding disagreement within this group.

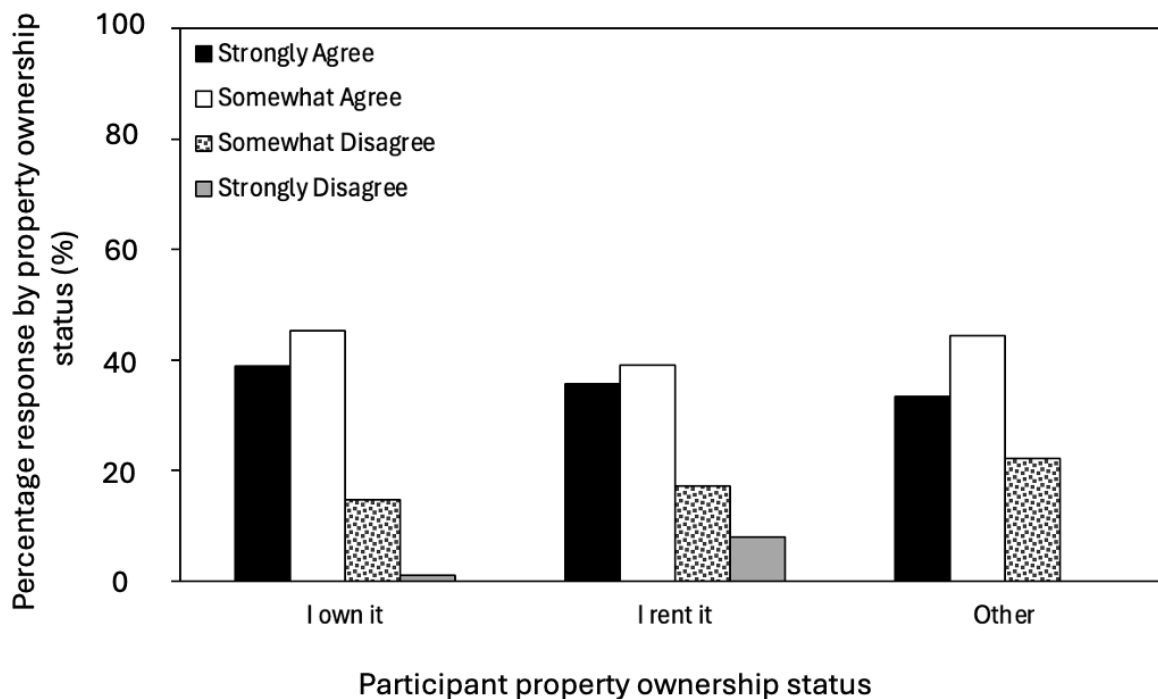


Figure 31: Awareness of legal responsibility to maintain STS in good working order by property ownership status (renter or owner).

5.5 Discussion

Understanding how people perceive environmental pollution risk is crucial for informing effective pollution management strategies. Perceptions of environmental pollution risk encompass not only awareness of pollutants but also the implications individuals associate with pollution—particularly its impact on personal health, well-being, and the environment. Sjöberg (2020) defines perceived risk as how an individual understands and experiences a phenomenon. Therefore, perceptions are shaped by lived experience, media exposure, social norms, and personal values (Devitt et al., 2016).

Environmental attitudes, defined as the beliefs, emotions, and behavioural intentions individuals hold towards environmental issues, are known predictors of pro-environmental behaviour and play a key role in shaping how pollution risks are perceived (Ones et al., 2015). Recognising this, our research aimed to uncover how such perceptions and attitudes influence behaviour around STS use and maintenance, a potentially important factor in mitigating surface water pollution in some rural catchments. In addition to offering insights into user understanding of STS pollution risks, the study highlights the value of survey methods in gathering critical user-level data on STS characteristics (e.g., system age, type, and maintenance practices). This information is vital for enhancing models of FIO risk associated with STS, given the challenges in accessing quality national-scale data on STS.

5.5.1 Reducing uncertainties in STS-related FIO modelling

Models assessing the risk of FIO pollution from STS to receiving watercourses often depend on spatial datasets that describe physical and topographic factors such as proximity to watercourses, slope, and soil type as demonstrated in Chapter 4 and wider literature e.g. Norat-Ramírez et al. (2019). However, critical STS-specific (infrastructural) information—such as system age, maintenance status, and treatment efficiency—is rarely available, requiring modellers to make assumptions to advance model development (Glendell et al., 2022). While necessary, these assumptions can introduce considerable uncertainty, particularly when actual conditions deviate from assumed scenarios, thereby reducing user confidence and limiting model transferability (Negri, Schurch, et al., 2024; Simoen et al., 2015).

The present study helps to address this data gap by providing empirical evidence on the regional variation of STS types across Scotland, thereby supporting efforts to improve the robustness of water pollution risk models, for example the BN models developed to assess FIO pollution risk to watercourse in Chapter 4 or the P BN model (Glendell et al., 2022; Mzyece et al., unpublished). Although the widespread use of Tank-only systems aligns with historical

usage patterns in Scotland (Dudley & May, 2007), the significant association between STS type and geographic region demonstrates that the deployment of this STS type is not spatially uniform. While Tank-only systems were the most common overall, their use was notably limited in the Borders region, where shallow-dig systems were more prevalent. However, there is a caveat in these findings in that approximately 40% of the participants had no idea of their STS type so the results here might not be a true reflection of the prevalence of different STS types and variable use across regions. Nonetheless, low deployment of Tank-only systems in the Borders region likely reflects site constraints such as shallow soils or high-water tables, which deter the installation of systems requiring deep trenching—such as tank only and tank+soakaway systems (British Standards, 2016). These findings, therefore, underscore the importance of incorporating regional variation in STS types and discharge configurations into faecal pollution risk models to enhance model accuracy and region-specific mitigation strategies. In a model developed to assess P pollution risk in Scottish rivers from agricultural sources and STS across seven study catchments, Glendell et al. (2022) estimated the probability of STS discharging directly into watercourses to range from 11% to 45%, varying by catchment. The highest probability of direct discharge was observed in Strathclyde, while the lowest was in the Grampian region. This regional variation in discharge end-point receptors is supported by findings from the current study.

All three discharge end-point receptor types considered in our study—direct discharge to water bodies, soakaways, and reedbed systems—were commonly reported in Central Scotland. However, direct discharges were less prevalent in the Borders, Dumfries and Galloway, and Grampian regions, where STS effluent was more often routed through secondary treatment systems. This pattern likely reflects regulatory restrictions on direct discharges in areas where low flow in water bodies limit dilution capacity (Ramsay et al., 2022). Furthermore, enforcement of the 2015 general binding rules on small sewage discharges to surface waters—particularly Rule 6, which requires owners to connect to public sewers, upgrade to

compliant systems, or install infiltration systems—has further reduced the prevalence of direct discharges (Environmental Agency, 2023).

Consistent with these policy changes, in Chapter 4, the estimated national direct discharge probability of 11% in the FIO risk model, is slightly lower than the 18.9% ($n = 59$) reported by participants in the current study. Therefore, updating the direct discharge probabilities in the FIO risk model would help to constrain uncertainties in assumptions and improve reliability of modelled outputs.

Discharge permissions are primarily determined by the dilution capacity of the receiving waterbody (SEPA, 2022), and direct discharge into low-flow or seasonally dry streams is not permitted (Ramsay et al., 2022). Our analysis indicated that proximity is a key determinant of discharge type. This suggests that incorporating STS distance into FIO models as a predictive factor for direct discharge would enhance model accuracy. Moreover, this relationship offers practical value for regulatory and inspection efforts. Spatial targeting of STS installations located closer to watercourses—where direct discharges are more likely—can improve the efficiency of monitoring and mitigation strategies by prioritising high-risk STS, similar to the strategy of targeting critical source areas in diffuse pollution management.

Tank-only systems are likely to represent high-risk STS, not only due to their close proximity to watercourses but also because a notable proportion (21.5%, $n = 14$) were reported to be over 20 years old. This aligns with the average STS age assumed by Glendell et al. (2021) in their P risk model and is reasonable given the dominance of Tank-only systems. However, in models that consider all STS types, it is important to note that a considerable proportion of systems are likely to be under 20 years old. Specifically, 83.3% of participants reported systems younger than 20 years, with 24.3% indicating an age of approximately 10 years—considered the optimal age for STS functionality (Hoghooghi et al., 2017). In addition to system characteristics, user-reported behaviours—such as maintenance frequency and management

practices—can offer valuable insights and should be incorporated to further enhance model accuracy.

There is considerable uncertainty surrounding the maintenance frequency, especially of privately owned STS in Scotland. Despite legal requirements for annual desludging (DEFRA, 2014), only 28.8% of respondents reported adhering to this. This is similar to the 32.6% frequent desludging rate reported among Irish participants who reported desludging their STS every two years in a study by Naughton & Hynds (2014). In contrast, community STS—typically managed by the national water company—showed higher and more consistent emptying frequencies, influenced by system size, population served, and compliance requirements (Wilschnack et al., 2024). Our results confirmed a strong association between emptying frequency and number of properties served ($P < 0.0001$, $\Phi_C = 0.40$) and several other factors as shown in Figure 7. Contrary to higher emptying frequencies for community STS in previous studies, lower emptying frequencies were indicated for private STS serving more than three properties. User-reported information highlighted in Figure 7, particularly knowledge of where the STS is located and whether the STS is located within the user's property, appear to strongly influence desludging practices, and is particularly relevant for systems serving multiple properties. Therefore, pollution load estimates from models should consider both the number of properties served and whether STS are privately or publicly managed. While estimating that 70% of STS in Scotland are well maintained, as proposed by Glendell et al. (2021) and in Chapter 4 may hold true for community STS, this figure is likely lower for privately owned STS serving one property and much lower for systems serving multiple properties.

5.5.2 Recommendations for improving maintenance and pollution reduction efforts

Based on the factors influencing STS maintenance and awareness of users regarding STS as potential sources of FIO pollution, we devised targeted recommendations for improving maintenance and pollution reduction efforts.

Our study recommends stricter enforcement of the requirement for property owners to share information about STS when selling a property (Environmental Agency, 2023). Findings suggest weak compliance with Rule 13 of the General Binding Rules for small sewage discharges to the ground, which requires sellers to provide details such as a system description, the location of key components including the discharge point, and maintenance records. Although these rules were introduced in 2015, 25.2% ($n = 76$) participants reported receiving no STS information—despite living in their property for up to ten years after the rules took effect. Naughton & Hynds (2014) reported a significantly higher non-compliance rate of 70.5% in Ireland, suggesting this issue may be widespread across the UK. In the USA and Australia, compliance with similar requirements varies by state and local authority, but poor homeowner knowledge of system operation and maintenance is widely recognised as a major contributor to system failure (Gunady et al., 2015).

These findings highlight the need for increased transparency between buyers and sellers, and better notification practices at the point of sale. In the USA, stricter “Time of Transfer” laws—requiring septic tank inspections before property sales—are thought to improve compliance. Meanwhile, the Finnish Environment Institute advocates for a service-oriented approach that supports property owners throughout the lifecycle of their STS, including system planning, installation, and maintenance (Laukka et al., 2022). A service-oriented model could further enable the systematic recording of maintenance activities with local authorities or certified service providers (Hashimoto, 2021). Such a system would help ensure the availability of up-

to-date STS information and maintenance records, thereby increasing sellers' willingness and ability to share accurate information about the STS during property transactions. Additionally, continuous support from an STS service provider would eliminate the challenge of having to find a maintenance specialist only when the STS is due for emptying. Conversely, in the absence of current documentation, sellers may be reluctant to disclose system details, undermining both transparency and regulatory compliance.

Regarding low compliance of STS serving more than two properties with required emptying frequencies, one of the contributing factors may be the difficulty proactive owners face in trying to secure agreement from the others to carry out maintenance. This challenge arises due to the shared ownership of such systems among multiple households connected to them (Scottish Government, 2012). To address this issue, the Water Resources (Scotland) Act 2013 includes provisions that empower pro-active owners to arrange for the tank to be emptied and recover an appropriate share of the costs from the other owners. Additionally, proposals have been made for owners of community tanks to request Scottish Water (the national water company) to adopt the community tank into its asset base (Scottish Government, 2012). This would effectively integrate the community into the public sewerage network, making them subject to standard sewerage charges. Such a framework could be extended to shared STS, serving fewer properties and Scottish Water could collaborate with smaller private service providers to provide efficient STS maintenance services.

Our study also recommends targeted communication, particularly aimed at older users who form a disproportionately greater part of the rural population, to address decreased concern about water quality impacts from their STS (Borg et al., 2021; Hine et al., 2014). A potential contributing factor to lower levels of concern about water impacts from STS is that some participants—especially those using traditional STS—did not frequently observe visible signs of failure such as blockages or flooding. This aligns with findings from Fizer et al. (2018), who reported that participants often relied on sensory perceptions (e.g., sight or smell) to assess

pollution risk and determine the need for STS maintenance. Some users believed that STS pose a contamination risk only when they appear full or emit an unpleasant odour. Targeted communication strategies can help address these misconceptions by providing clear, evidence-based explanations of how STS can cause pollution even in the absence of visible symptoms. For instance, older STS—particularly when poorly maintained—are at increased risk of developing cracks, allowing effluent to seep into the ground and potentially contaminate groundwater sources (Canter & Knox, 2017). These risks can be effectively illustrated through visual aids that show how system components degrade over time and contribute to environmental harm without causing immediate or obvious failures (Czerniewska et al., 2023). To improve effectiveness and build trust, messages should be delivered via trusted local channels, such as community newsletters, and could include testimonials or case studies from residents who have experienced pollution from malfunctioning or deteriorated systems (Klonek et al., 2015; Ngigi & Busolo, 2018; Williams et al., 2019). Additionally, communication should emphasise ancillary benefits of proactive STS maintenance, including reduced pollution risk to bathing waters and improved environmental protection (Oliver et al., 2023).

While self-reported data are valuable for identifying behavioural patterns and informing targeted interventions, they are subject to limitations that may affect their accuracy and reliability. These include potential biases such as social desirability, where individuals may misreport behaviours to appear more favourable, as well as recall bias or limited understanding of the subject matter (Fisher & Katz, 2000; Fryer & Dinsmore, 2020; Shields et al., 2016). A particular case in our study potentially reflecting limited understanding of how STS operate relates to some users of tank+soakaway systems reporting that the STS discharged directly into a watercourse when such systems essentially discharge into a soakaway. It is therefore important to acknowledge these limitations, while also recognising the potential of these findings to be integrated with broader datasets—such as property age, land use, or rural infrastructure—to support predictive modelling and reduce uncertainty in future analyses.

5.6 Conclusion

Our study contributes to the growing body of evidence highlighting the limited understanding of STS as potential sources of pollution to watercourses among users. Perceptions of, and attitudes toward, STS as contributors to faecal pollution vary considerably depending on demographic factors such as age, as well as system characteristics including STS type, age, and the frequency of operational issues such as blockages and flooding. These perceptions significantly influence the extent to which users engage in maintenance practices that can mitigate pollution risks. User-reported data, therefore, not only offer valuable insights into behavioural patterns but also serve as a critical input for refining faecal pollution risk models and targeting interventions more effectively. However, there is still a lack of comprehensive understanding of why STS are not widely perceived as significant pollution sources, even in contexts where empirical evidence suggests otherwise. Future research should explore the cognitive, cultural, and informational factors that underpin these perceptions. Additionally, longitudinal studies could examine how shifts in STS performance or targeted communication strategies affect user engagement in the upkeep of these systems over time.

6 Synthesis and Conclusion

The overarching aim of this thesis was to assess FIO pollution risk from STS in rural areas through a mixed-methods approach that utilised probability-based modelling and a national-scale survey of user perceptions. This dual focus enhances the contribution of the research through quantitative modelling of FIO pollution risks associated with STS followed by qualitative insights into STS user behaviours and maintenance practices, thereby providing a more holistic understanding of STS-related water quality impacts. Interdisciplinary approaches are increasingly being applied to improve water quality management, and the equal importance of modelling, user-reported data, and government agency involvement and support is widely recognised (Buckerfield, Waldron, et al., 2019; Mishra et al., 2024).

In this synthesis chapter, the main findings are presented and critically evaluated in relation to the wider academic literature. The chapter not only highlights how these findings support, challenge, or diverge from previous work, but also draws attention to the ways in which the technical and social dimensions of sustainable STS management intersect (Maliga et al., 2025). For example, user perceptions can directly influence the management of STS, while improvements in monitoring of watercourses can foster stronger community engagement by providing real-time transparent data enabling communities to build trust, identify local sources of pollution and act. By situating findings alongside existing studies, the synthesis builds a more robust, evidence-based case for actionable solutions and policy relevance in addressing FIO pollution from STS (Ndiokubwayo, 2023). In the thesis, each chapter contributes novel insights to help support more cost-effective management strategies, but collectively, these findings help address key knowledge gaps in our understanding of the role of STS as sources of FIO pollution in rural areas identified in Chapter 1 and signal important directions for future research. The practical implications of the research are synthesised into three interrelated themes: 1. Expanding monitoring data to improve FIO model validation, 2. Strengthening the

management of STS, and 3. Increasing awareness of STS as potential pollution sources to enhance collective management efforts. Table 14 summarises how findings from each chapter map against the research priorities addressing the knowledge gaps identified in Chapter 1, suggests future directions for research, outlines scientific implications and provides suggestions for policy and practical recommendations. Table 14 provides a useful starting point and the remainder of this chapter expands on this summary table to provide further detail and consideration of how the integrated thesis is bigger than the sum of the individual chapters.

The chapter is structured in four parts. First, the scientific implications of each key finding are discussed, including uncertainties, limitations and directions for future research, alongside a summary of their combined value to the state of knowledge. Second, practical measures are outlined for implementation across landscape, policy, and community contexts, considering their efficacy, suitability, and cost. Third, the results are situated within a global context to consider wider relevance. Finally, the chapter concludes by synthesising the overall contributions of the thesis to both science and practice.

Table 14: Summary of key research findings addressing knowledge gaps, suggested future directions for research, scientific implications and practical recommendations.

Research priority	Findings	Future direction	Scientific implications	Practical/Policy recommendations
Transferability of BNs across pollutants, systems, and scales.	Chapter 2: A phosphorus (P) BN model can be adapted to map STS FIO pollution risk to watercourses. P-specific variables such as concentration in STS effluent and leaching risk need to be replaced with FIO-specific variables to distinguish pollutant-specific behaviour in the environment. STS-specific variables including maintenance condition, age, distance to watercourse and environmental factors such as slope and soil hydrology can be retained across both model types because they require the same parametrisation data. Chapter 4: A catchment scale FIO BN can be upscaled to characterise FIO pollution risk from	Validate the FIO BN model in catchments with high resolution FIO monitoring and MST data to apportion FIO load from STS Develop and validate BNs across additional water pollutants (e.g. microplastics, pharmaceuticals) to further test model generalisability	Findings demonstrate that BNs can serve as multi-pollutant modelling tools, reducing reliance on resource intensive model development from inception and allowing research teams to capitalise on existing frameworks. Environmental drivers can act as stable modelling variables across pollutants, while pollutant specific variables must be tailored within the model.	Regulators can adopt BN-based risk assessment frameworks for managing P and FIO pollutants from STS in rural catchments as a cost-effective integrated approach Government can support catchment management policies that leverage scalable BN models, enabling consistent pollution risk assessments from household to regional scales.

Research priority	Findings	Future direction	Scientific implications	Practical/Policy recommendations
	STS. Model uncertainty increases with increased scale			
Contribution of STS to FIO pollution of watercourses under varying landscape conditions.	Chapter 3: Under high-risk landscape conditions where surface runoff or leaching to groundwater drive STS effluent movement risk, STS are located <10 m to a watercourse on a steep slope >25%, experts judge that 93% of FIOs can be delivered to a watercourse from STS. Under low-risk conditions, the STS FIO proportion likely to be delivered to a watercourse reduces to 5%. Chapter 4: Soil morphology and hydrology primarily influence pathways that drive STS effluent movement and FIO pollution risk within landscapes. STS proximity	Additional empirical research of FIO contributions to watercourses from STS under diverse soil and hydrological regimes, especially in intermediate-risk settings.	Findings confirm that landscape conditions are primary controls driving FIO contributions from STS to watercourses, with STS proximity to watercourse and slope increasing or decreasing contributions. Findings suggest that STS contributions to FIO pollution of watercourses are highly context-dependent, reinforcing the need for spatially explicit risk assessments and data collection.	Reassess setback distance regulations for new STS installations, prioritising longer distances to reduce FIO contribution to watercourses. For old STS located less than 50 m to a watercourse, additional treatment of effluent should be encouraged before discharge to the environment.

Research priority	Findings	Future direction	Scientific implications	Practical/Policy recommendations
	to watercourse and distance are secondary. STS proximity to a watercourse plays a more significant role in either increasing or reducing FIO transfer to watercourses compared to the effect of slope.			
Validation of BN model outcomes against observed data to assess model accuracy.	Chapter 4: Model predicted FIO loads align with observed FIO loads. STS condition and treatment level are critical factors in influencing predicted FIO load. Model uncertainty is high in the catchment where STS are associated with more variable hydrology of soil types.	Enhancing model performance in catchments with varied soil and hydrological conditions, high resolution FIO monitoring data and improved information on STS condition and maintenance.	The importance of STS condition and treatment in influencing FIO loads from STS highlights the need for improved datasets on STS condition, usage and maintenance schedules to strengthen predictive modelling. Catchment-scale variability in soils and hydrology controls on FIO transfer from STS to watercourses imply that future modelling efforts must integrate finer-scale data on FIO losses from STS in catchments with higher hydrological and	Implement landscape risk-based inspections and monitoring of FIO losses, focussing efforts on STS in high-risk soils or hydrological settings for targeted mitigation to reduce FIO losses from STS. Increase frequency of FIO monitoring in riverine systems although this hard to achieve under a tight budget, therefore collaborative cost-sharing approaches can be considered.

Research priority	Findings	Future direction	Scientific implications	Practical/Policy recommendations
			topographical variability to enhance prediction reliability across diverse rural landscapes.	
STS maintenance practices and user perceptions of STS as potential FIO pollutant sources.	Chapter 5: Low awareness of STS emptying frequency among users. Older users are less concerned about STS-related water quality impacts compared to younger users who are more concerned. Concern about water quality impacts is higher among users of modern STS types <5 years old compared to those with traditional systems >20 years old.	Exploration of the cognitive, cultural and informational factors that underpin perceptions of STS as potential pollutant sources to effectively design pollution intervention efforts. Longitudinal studies examining how shifts in STS performance or targeted communication strategies affect user engagement in the upkeep of STS over time.	Findings highlight generational and STS-related differences in risk perception, suggesting that older users, who utilise aging systems, may underestimate potential environmental impacts.	Targeted communication strategies focusing on older demographics to enhance awareness and promote responsible STS management. Mandate transfer of information about STS location and maintenance between household owners at point of sale.

6.1 Scientific implications and future research needs

6.1.1 Transferability of BNs across pollutants, systems, and scales

Findings from Chapters 2 and 4 confirm that a P risk BN model can be adapted to map FIO pollution risk from STS to watercourses. This is possible because STS-specific variables such as maintenance condition, age, distance to watercourse and environmental factors including slope and soil hydrology are relevant to both pollutant types and require the same parametrisation data. This highlights that environmental drivers can act as stable model predictors across different pollutant typologies, and this is reflected in concepts such as critical source area (CSA), which emphasise that pollution risks emerge from the coincidence of pollutant sources and effective pollutant transport pathways irrespective of the pollutant type (McDowell et al., 2025). While there is a high likelihood that pollution to watercourses will occur when both a pollutant source and pathway exist, uncertainties remain at three key points: (1) source strength, which for the topic of this thesis is governed by the condition of the STS; (2) FIO behaviour, such as die-off and regrowth, shaped by environmental conditions; and (3) variability in soil and hydrological factors impacting FIO loss from STS across the landscape scale. These uncertainties limit the transferability of models between catchments with differing soil and hydrological characteristics, necessitating model tailoring to specific catchments to improve predictive accuracy (Negri et al., 2024). This is confirmed in findings from Chapter 4, which show that the FIO BN model has higher uncertainty in predicted FIO loads for STS located in landscapes with variable soil and hydrological characteristics. Therefore, while the findings demonstrate that BNs can serve as multi-pollutant modelling tools, reducing reliance on resource intensive model development from inception and allowing research teams to capitalise on existing frameworks, future research on how spatial and temporal variability influences pollutant-specific BN adaptations is warranted.

6.1.2 Contribution of STS to FIO pollution of watercourses under varying landscape conditions

Findings from the expert elicitation process in Chapter 2 highlight the central role of landscape conditions in mediating STS-derived FIO loads to watercourses. Under high-risk conditions—where effluent movement is promoted by surface runoff or leaching to groundwater, a shallow water table, short STS-watercourse separation distance, and a steep slope—as much as 93% of FIOs are likely to reach the receiving water. By contrast, increasing the separation distance and siting the STS on a gentle slope reduces the proportion of FIO likely to be delivered to a watercourse to only 5%. The reduction in FIO delivery under greater distance and gentle slope is possible because longer flow paths enhance effluent straining and filtration, while gentle gradients reduce runoff velocity (Sowah et al., 2014; Tamang et al., 2022).

Chapters 3 and 4 combine to further demonstrate that soil and hydrological conditions are primary controls on STS-derived FIO loads to watercourses, with proximity and slope being key modifiers that either amplify or mitigate contributions. Importantly, this implies that STS contributions to watercourses vary spatially according to local soil and hydrological characteristics within landscapes and cannot be generalised using simple distance or slope thresholds alone. Both expert-derived estimates of STS FIO contributions to watercourses and model-predicted contributions under intermediate risk conditions and variable soil–hydrological settings respectively, were associated with high uncertainty. Future research should therefore prioritise empirical assessments that quantify FIO contributions from STS under diverse soil and hydrological regimes, especially in intermediate-risk settings. Such work is critical to reduce uncertainty and to strengthen the evidence base on how landscape factors govern STS-derived FIO loads, thereby advancing our understanding of their contribution to watercourse pollution.

6.1.3 Validation of BN model outcomes against observed data to assess model accuracy

In Chapter 4, model validation, often missing in BN projects, was undertaken to compare predicted FIO loads with observed monitoring data. Key findings show that the model predicted FIO loads aligned well with the observed FIO loads. The alignment between modelled and observed FIO loads in two rural catchments gives confidence that the FIO BN model is fit for purpose, and it can provide credible risk assessments of STS FIO contributions to watercourses, but further testing in more complex catchments is an important next step (Neill et al., 2020). The BN assigns risk of FIO pollution from STS based on STS condition, location and the additional effects of landscape features in either reducing or increasing FIO transfer to waterbodies. However, in certain conditions, the model underpredicts resulting in high uncertainty especially for STS with low FIO loads in the catchment where STS are associated with a variability of soil and hydrological conditions. This indicates that the model has lower confidence in assessing low-risk scenarios compared to high-risk ones. This discrepancy may be due to a data imbalance (Fanconi et al., 2023), as fewer STS exhibit low FIO loads (8% in Mein) compared to the majority (92%) showing medium to high loads. Consequently, the BN model is better trained to recognise high FIO load patterns (Lambert et al., 2022). Future modelling efforts must therefore integrate finer-scale data of STS FIO losses to enhance prediction reliability in catchments with varied soil and hydrological variability. Furthermore, high-quality data on STS condition and maintenance—identified as critical parameters through sensitivity analysis, and high resolution FIO monitoring data are expected to improve model predictive accuracy.

6.1.4 STS maintenance practices and user perceptions of STS as potential FIO pollutant sources

Findings from a Scotland-wide survey of STS users reveal low awareness of STS as potential sources of FIO pollution to watercourses. Nearly half of the respondents (43.7%, $n = 132$ out of 302) were unaware of the type of STS they use for domestic wastewater treatment or even its location (46.4%, $n = 140$). Similarly, almost 40% of respondents are unsure how often their system is emptied, with only 28.8% reporting annual desludging. Comparisons with Ireland highlight both differences in knowledge of STS type and location, and a shared challenge of poor maintenance practices. Although more than 90% of Irish survey participants exhibited some knowledge of the type of decentralised wastewater treatment system they used and its location, only 32.6% stated it had been desludged within the past two years. This suggests that awareness of STS location alone does not necessarily translate into appropriate maintenance practices. Other factors may act as barriers, including lack of knowledge of when desludging is required, the high cost of desludging, or limited access to qualified maintenance specialists (Akoumianaki & Ibiyemi, 2022; Lawson et al., 2024). These findings highlight the importance of communication strategies that not only raise awareness of STS as potential pollutant sources but also emphasise the practical benefits of regular desludging, while addressing structural barriers such as cost and maintenance service availability.

Moreover, Chapter 5 highlights generational and system-related differences in STS FIO pollution risk perception: younger users and owners of newer systems expressed greater concern than older users with traditional systems. This suggests that younger users with newer systems are likely more conscious of potential risks while older users with aging systems may underestimate environmental impacts of STS. These insights have important implications. They indicate a need for targeted communication strategies, particularly directed at older demographics, to improve awareness and to promote responsible STS maintenance.

Strengthening communication may also help reposition STS within the broader public discourse on pollution risks, which currently emphasises discharges from conventional STWs. Future research, potentially linking with environmental psychology, should explore how targeted risk communication influences user perceptions and long-term engagement with maintenance practices.

6.1.5 Scientific synthesis and outlook

This research advances understanding of how STS contribute to FIO pollution of watercourses and how BN models can be adapted and validated to predict these risks. The findings provide new insights into the transferability of models across pollutants and systems, the role of landscape factors in shaping STS contributions, the importance of model validation, and the social dimensions of STS management. Taken together, these findings highlight the need for a holistic approach to managing STS-related pollution risks. High-quality monitoring data underpin robust BN validation and model transferability. Models, in turn, can inform policy by identifying high-risk landscapes and prioritising interventions. However, technical advances alone are insufficient without addressing the human dimension: user awareness, maintenance behaviour, and effective communication of environmental pollution risk. A coordinated strategy that links data, models, landscape understanding, and social behaviour will be essential for advancing both scientific knowledge and practical management of FIO risks.

Key future research directions include: (1) Empirical studies of STS contributions under diverse soil and hydrological regimes, particularly intermediate-risk settings. This will enable deeper understanding of STS FIO contributions under diverse soil and hydrological regimes, and intermediate risk settings where uncertainty was high both in the model predicted values and the expert-derived estimates; (2) Integration of high-resolution monitoring and maintenance data into BN models to generate high quality data for model validation and

parameterisation thereby enhancing model accuracy; (3) Development of pollutant-specific BN adaptations that account for spatial and temporal variability in other water pollutants such as microplastics and pharmaceuticals; and (4) Social research on targeted communication strategies and structural barriers to STS maintenance. Addressing these priorities will close critical knowledge gaps and strengthen the evidence base needed to safeguard water quality and public health.

6.2 Policy/practical recommendations

Achieving the UN Sustainable Development Goal 6—to *ensure the availability and sustainable management of water and sanitation for all*—requires holistic strategies that integrate modelling approaches, landscape understanding, and social behaviour to reduce watercourse pollution and safeguard both public health and ecosystems (Mustafa et al., 2022; Naylor, 2023). The findings of this study provide an evidence base to support decisions on effective management strategies and policies to support FIO pollution control in watercourses. Globally, rural communities are disproportionately affected by inadequate sanitation and unsafe water supplies. According to the World Health Organisation (2023), 41% of rural populations are at risk of exposure to FIO pollution and diarrhoeal diseases through drinking water, compared to only 12% in urban areas. This results in an estimated 1–1.4 million annual deaths from diarrhoeal diseases linked to unsafe water, sanitation, and hygiene—a burden heaviest in low-income countries but not confined to these country contexts. This is also evident in high-income country settings, where FIO pollution of watercourses threatens both ecosystem integrity and public health (Hunter et al., 2011; Iverson et al., 2020).

Despite progress in expanding safe, managed water and sanitation in developed countries, failures in infrastructure and extreme weather events such as storms can cause both chronic and acute FIO pollution to watercourses, posing dual public health and ecological risks

(Büttner et al., 2022; Olds et al., 2018). Proactive management of key, yet understudied sources of FIO pollution such as STS is therefore essential. Improved STS management not only reduces human health risks associated with FIO pollution of watercourses but also delivers wider environmental co-benefits, including reduced nutrient loading resulting in fewer algal blooms, and decreased release of emerging pollutants such as pharmaceuticals to watercourses (Glendell et al., 2022; Wilschnack et al., 2024). The World Health Organization highlights the link between ecosystem health and human well-being in their definition of health. The One Health concept acknowledges the interconnectedness of human, environmental and animal health. Therefore, working towards the reduction of FIO pollution to watercourses should be viewed as a critical component of a broader agenda to improve environmental health with humans as one of the many beneficiaries.

This section presents proposed actions tailored to the geographic and socio-economic setting, with a focus on enhancing STS management and reducing FIO pollution risks from STS to watercourses. To structure these recommendations, the source–pathway–receptor (S-P-R) framework is adopted, which provides a systematic approach for evaluating mitigation strategies, considering their effectiveness, co-benefits, and trade-offs. Together with the multiple-barrier approach, widely applied in the water industry, this framework ensures interventions are positioned strategically across the S-P-R sequence to prioritise where to focus resources by highlighting the most significant risks and the most effective points for intervention. Three recommendations are made: 1. Increasing awareness of STS as potential pollution sources to enhance collective STS management efforts to reduce generation of FIO pollutants at the ‘Source’ (STS), 2. Reducing FIO transfer through ‘Pathways’ from STS to watercourses through proper STS siting and 3. Expanding monitoring efforts to improve data quality at the ‘Receptor’ for FIO model validation.

6.2.1 Increasing awareness of STS as potential pollution sources to enhance collective STS management efforts

STS are often overlooked as significant sources of FIO pollution, yet their contributions can pose serious risks to both public health and aquatic ecosystems (Withers et al., 2014). A major barrier to effective management is the limited awareness among users of how inadequately maintained systems degrade water quality. Although annual desludging is a legal requirement to ensure optimal STS performance, compliance remains low. Even when users know the location of their STS, many delay emptying until visible or olfactory problems such as foul odours, pipe blockages, or surface ponding occur (Devitt et al., 2016). Contributing factors include poor risk perception, difficulty recognising early signs of system failure, and concerns about the financial burden of maintenance (Akoumianaki & Ibiyemi, 2022). Evidence from Chapter 5 supports this: households reporting blockages or flooding are more likely to empty their tanks, and those with systems located on their properties or prior knowledge from property sellers are also more compliant. Yet over three-quarters of property buyers report not receiving STS maintenance information during purchase, beyond minimal reference in home reports.

To address these gaps, targeted education and outreach campaigns—directed at households, communities, and local authorities—are therefore essential to increase understanding of pollution risks and promote shared responsibility (O'keeffe et al., 2015). Clear messaging should correct the misconception that STS only require desludging when visibly failing, emphasising that pollution risks persist even without obvious symptoms. Communication should also highlight the added risks of older systems, which—when poorly maintained—are more prone to cracks and leakage, potentially contaminating groundwater (Canter & Knox, 2017). From a policy perspective, incorporating STS risk communication into water quality and public health strategies would promote shared responsibility. Additionally, strengthening

implementation of the requirement to disclose of STS condition during property transactions (both in terms of ensuring detailed information about the STS is provided in home reports and raising awareness about the information buyers should request when purchasing a property) could all enhance compliance and accountability (SEPA, 2025). At the practical level, collective management schemes such as community-based maintenance funds and coordinated inspection programs could reduce individual costs while improving compliance. Integrating STS monitoring into existing catchment management frameworks would further align household-level actions with broader water quality protection goals (Naughton & Hynds, 2014). Finally, while these recommendations can enhance STS management and reduce pollution risks, it is important to acknowledge limitations in the supporting evidence. Much of the data are self-reported, and nearly half of the participants in this study admitted limited knowledge of their STS, which may affect data reliability.

Table 15: Key policy/practical recommendations for enhancing STS management.

1. **Raise awareness:** Launch targeted education and outreach campaigns for households, communities, and local authorities to improve understanding of pollution risks and promote shared STS management responsibility.
2. **Correct misconceptions:** Communicate that STS can cause pollution even without visible failure, and that older systems pose higher risks of leakage and groundwater contamination.
3. **Strengthen policy integration:** Embed STS risk communication within national and local water quality and public health strategies.
4. **Improve transparency:** Enforce disclosure of STS condition during property transactions and ensure buyers know what information to request.
5. **Support collective action:** Promote community-based maintenance funds and coordinated inspection programs to reduce individual costs and improve compliance.
6. **Align with catchment goals:** Integrate STS monitoring into existing catchment management frameworks to link household practices with broader water quality protection.

6.2.2 Reducing FIO transfer from STS to watercourses

Faecal pollution from STS occurs when effluent containing high loads of FIOs and other contaminants bypasses natural attenuation processes and enters hydrological pathways connecting STS to surface and groundwater. Key contamination pathways include seepage into shallow aquifers, overflows during periods of high hydraulic loading or flooding, and lateral migration through fractured bedrock or coarse soils (Gill and Mockler, 2016). Findings from Chapters 3 and 4 combine to demonstrate that careful siting can substantially reduce FIO transfer to watercourses. For instance, systems located more than 50 m from a watercourse and on gentle slopes (<5%) are associated with only 5% FIO transfer, compared to up to 93% when located just 10 m away on steep slopes. Even at 10 m, siting STS on a gentle slope reduces FIO transfer to watercourses by up to 13% compared with steep slope locations. Based on these findings, four policy and practical recommendations emerge: 1) Minimum slope requirements (<5%) should be incorporated into the UK General Binding Rules governing STS placement. At present, slope criteria are only specified for STS influent and effluent pipe construction in the British Standards, BS EN12566 for influent pipes to the tank and BS 6297 for the drainage field. Broader adoption is warranted, as gentle slopes (<5%) are generally suitable for STS siting, while steep slopes (>30%) increase the risk of rapid effluent transfer via surface runoff (Glendell et al., 2021; USEPA, 2001). 2) Before SEPA grants permits for new STS, site-specific assessments should confirm that local soil and slope conditions support adequate effluent attenuation. These assessments should also account for the projected impacts of climate change, particularly increased flood risks in the UK (Bates et al., 2023). Findings from Chapter 2 showed that 24.5% of STS experience STS flooding as a problem, highlighting the scale of this risk; 3) Regular monitoring should be prioritised for STS in vulnerable locations, such as those near watercourses or within intermediate risk conditions where complex catchment dynamics create high uncertainty regarding FIO transfer from STS to watercourses; 4) In areas where individual siting standards cannot be met, shared treatment

systems or small-scale constructed wetlands offer practical, low-cost alternatives to reduce pollution risks (Plaimart et al., 2024).

Table 16: Key policy & practical recommendations to reduce FIO transfer from STS.

1. **Incorporate slope requirement into standards:** Update UK General Binding Rules to include minimum slope requirements (<5%) for STS siting which are currently not included.
2. **Strengthen permitting assessments:** Require SEPA to confirm soil and slope suitability, accounting for climate change and flood risk before granting new STS permits.
3. **Prioritise monitoring in vulnerable areas:** Implement regular monitoring for STS near watercourses or in catchments with high uncertainty about FIO transfer.
4. **Promote shared solutions:** Where siting standards cannot be met, support shared treatment systems or small-scale constructed wetlands as practical, low-cost alternatives.

6.2.3 Expanding monitoring efforts to improve data quality for FIO model validation

Validating model predictions with robust observed data is essential for demonstrating a model's suitability for its intended purpose and for building trust in its outcomes. However, high-quality monitoring data are often lacking. In the UK, river sampling for FIOs is typically ad hoc, infrequent (usually during summer low-flow periods), and spatially sparse (Oliver, 2025). For example, the dataset used for validation in Chapter 4 comprised only 56 monitoring points in one catchment and 78 in another over a single year. Although these were 24-hour composite samples, which provided valuable high-resolution data by capturing short-term flow variability (Cassidy et al., 2018), the absence of sampling in other seasons limits the ability to characterise FIO dynamics under longer-term hydrological variability, which can result in high uncertainty in predictions from water quality models relying on these data. Findings from Chapter 4 showed that the FIO BN model generated FIO load predictions closely aligned with

observed data, confirming that it is fit for purpose. However, the model tended to underpredict loads and exhibited high uncertainty, particularly for low FIO loads from STS in catchments with highly variable soil and hydrological conditions. These limitations are largely attributable to gaps in STS-specific information (e.g., system maintenance condition) and the lack of comprehensive monitoring data.

Based on these findings, increased and more systematic sampling of watercourses is recommended—covering not only the summer bathing season but also storm events, high-flow periods, and other hydrological conditions throughout the year. Policy recommendations include: 1). Establishing a coordinated national framework for FIO river monitoring, ensuring consistency in sampling methods, frequency, and reporting across catchments. This is a proactive approach in building a robust database to support research in addition to the current compliance-driven approach in monitoring river systems designated as bathing waters (of which there are only 15 in the UK), 2) Continuing sampling twice a week throughout the year at key sites to capture pollutant response to storm and high-flow conditions, in addition to current summer low-flow sampling. This helps to capture intermittent peaks in FIO levels associated with storm events, but many bathing waters lack sufficient event-based samples to enable modellers to understand or predict these spikes (Krupska et al., 2024), and 3) Mandating water companies, regulators, and research institutions to share FIO datasets in open-access repositories to support wider model validation and cross-catchment learning. This will help to pave the way for the current ad-hoc FIO datasets generated via research projects, non-governmental organisations and citizen science projects to become more integrated into the national datasets. Practical recommendations in support include: 1) Expanding current monitoring by implementing event-based sampling in key locations and building on surveillance tools that allow near-real-time multiple time-point measurements (Good et al., 2025) 2) Building stronger partnerships between SEPA, local authorities, universities, and citizen science groups and learning from international best practice to

increase monitoring capacity and reduce costs. Together, these measures would enable models to capture the full spectrum of FIO dynamics in catchments and improve their reliability for supporting water quality management decisions.

Table 17: Key policy and practical recommendations to expand water quality monitoring.

1. **Establish a national monitoring framework:** Develop a coordinated UK-wide system for FIO river monitoring with consistent methods, frequency, and reporting across catchments.
2. **Extend monitoring beyond bathing season at key sites:** Continue year-round sampling (including storm events and high-flow periods) at key sites and adopt near-real-time surveillance tools for multiple time-point measurements. This will help to capture intermittent peaks in FIO levels associated with high flow conditions.
3. **Mandate data sharing:** Require water companies, regulators, and research institutions to share FIO datasets in open-access repositories to strengthen model validation and cross-catchment learning.
4. **Strengthen partnerships:** Build collaborations between SEPA, local authorities, universities, and citizen science groups, learning from international best practice to increase capacity and reduce costs.

6.2.4 Practical recommendations synthesis

This section outlines practical recommendations for reducing FIO loads from STS to watercourses to safeguard both environmental and public health. Drawing on findings from this study and wider literature, the recommendations focus on raising user awareness, strengthening siting standards, and expanding monitoring. Their effectiveness depends on coordinated, multi-level governance and collaboration between regulators, industry, researchers, and communities. A shift is needed from the current compliance-driven approach in water quality monitoring to a proactive, evidence-led framework that generates robust datasets for model validation and supports long-term water quality management (Krupska et al., 2024). National regulators such as SEPA could lead in establishing a coordinated monitoring framework with minimum standards for sampling frequency, storm-event coverage, and reporting. Local authorities could oversee inspections and community engagement, while

water companies expand event-based water sampling or high-resolution sensor monitoring, where appropriate. Research institutions would drive methodological innovation, with NGOs and citizen science groups broadening monitoring at low cost. Property owners also play a key role through compliance with maintenance requirements. Public health agencies could integrate STS risks into health frameworks, while planning authorities enforce siting rules, and innovation agencies like Innovate UK support real-time monitoring technologies (Good et al., 2025).

Although systematic monitoring entails upfront investment in sensors, autosamplers, training, and data infrastructure, long-term benefits include reduced remediation costs, improved public health, and greater resilience to climate extremes (Oliver, 2025). Costs can be shared among stakeholders to ensure financial sustainability. International examples such as Finland's historical harmonised monitoring network which utilises both traditional methods and sensors to monitor water quality in inland waters including streams, rivers, lakes and coastal and transboundary waters by network of organisations demonstrates feasibility and value (European Environmental Agency, 1996). New Zealand also recognises the value of a robust water quality monitoring system and implements a state of the art environmental monitoring programme whereby regional councils collect data on FIOs as part of broader water quality monitoring programmes to assess the general condition of river and other water bodies in addition to bathing water surveillance (Davies-Colley & Scott, 2024). The need for multi-stakeholder participation is emphasised for the success of such water quality monitoring programmes (Westerhoff et al., 2022). Risks of failure include fragmented datasets, inadequate funding, and weak household engagement. These can be mitigated by mandating open-access repositories to increase data sharing and reduce costs of generating new data each time its need, blended funding to enhance cost sharing among all stakeholders, and targeted outreach to households to improve compliance (Akoumianaki and Ibiyemi, 2022). While UK-based, the principles of coordinated monitoring and shared responsibility are

globally relevant. In developing contexts, low-cost tools like portable microbial kits could bridge monitoring gaps, linking this research to global efforts under SDG 6 on clean water and sanitation.

Table 18: Key stakeholders & their roles in reducing FIO risks from STS to watercourses.

1. **National regulators (e.g., SEPA):** Lead on establishing a coordinated monitoring framework with minimum standards for sampling frequency, storm-event coverage, and reporting.
2. **Local authorities:** Oversee inspections, ensure compliance, and engage communities on pollution risks and responsibilities.
3. **Water companies:** Expand event-based sampling and adopt high-resolution sensor monitoring where appropriate.
4. **Research institutions:** Drive methodological innovation and improve tools for monitoring, modelling, and validation.
5. **NGOs & citizen science groups:** Support broad, low-cost monitoring and raise public awareness of water quality risks.
6. **Property owners:** Pass on information about location and maintenance of STS at the point of sale.
7. **Public health agencies:** Integrate STS-related pollution risks into health protection and awareness frameworks.
8. **Planning authorities:** Enforce siting rules to reduce pollution transfer risks from poorly located systems.
9. **Innovation agencies (e.g., Innovate UK):** Fund and promote real-time monitoring technologies to strengthen national capacity.

6.3 Global relevance

The findings of this research, though grounded in the UK context, have broader significance for global efforts to safeguard water quality and public health. The study demonstrates that STS, often overlooked as diffuse pollution sources, can be major contributors of FIOs to watercourses when poorly managed or inadequately sited. STS can contribute FIO concentrations as high as 10^{10} CFU/100ml to watercourses which are far above different thresholds for recreational waters determined by national regulatory agencies but guided by the WHO (WHO, 2021). This insight is highly relevant to many regions worldwide where

decentralised sanitation remains widespread, and regulation or monitoring is limited. While developed country contexts have low to medium onsite sanitation usage rates (for example, 7% of overall population in Australia and 18% of households in the USA) (USEPA, 2021; OECD, 2023), prevalence is particularly high (40%) in Africa (African Development Bank, 2020). Therefore, the findings of this research are cross-cutting in terms of relevance to different contexts. The evidence that siting conditions such as slope and proximity to watercourses significantly influence pollution risks, and that user awareness and maintenance behaviour strongly affect system performance, highlights universal challenges of managing onsite sanitation. Similarly, the need for systematic, event-based monitoring to capture FIO dynamics is not unique to the UK but applies across contexts where climatic variability and storm-driven pollution are increasing under climate change (Herrig et al., 2019). These findings align with global priorities under Sustainable Development Goal 6, particularly the call for safely managed sanitation and improved water quality. In resource-limited settings, the principles identified here—integrating risk communication, coordinated monitoring, and community participation—can inform the development of low-cost, context-appropriate solutions, reinforcing the global relevance of this research in advancing sustainable water management. Importantly, BNs are capable of modelling pollution risk in data sparse situations—which are often the norm across the world.

6.4 Conclusion

The programme of research reported in this thesis has assessed FIO pollution risk from STS using a mixed-methods approach that combined Bayesian modelling, expert elicitations and a survey of STS user perceptions. Bayesian networks (BNs) are flexible, probability-based modelling tools that can be adapted to different pollutants, such as phosphorus and FIOs, and applied across spatial scales from catchment to national levels, and in data sparse situations. Sensitivity analysis of the BN model identified STS condition and treatment level as key

determinants of FIO loads released from STS. Additionally, landscape features such as soil hydrology were found to be primary controls influencing FIO contributions from STS to watercourses, with factors like STS proximity to watercourses and slope either amplifying or reducing contributions. Model validation demonstrated that the BN presented in this thesis is fit for purpose and can provide credible risk assessments of STS FIO contributions to watercourses. However, underprediction in model outputs introduced uncertainty, highlighting the need for both additional STS-specific data and high-resolution monitoring to improve model accuracy. Self-reported data from STS users proved valuable not only for refining model outputs but also for understanding user awareness and perceptions regarding STS as potential FIO sources. Future research should therefore focus on integrating user-reported data into BN models to evaluate the extent to which such data can enhance model accuracy. Overall, the research contributes new knowledge by advancing the application of BNs for modelling FIO pollution from STS. The recommendations arising from this study are valuable not only for improving modelling efforts but also for informing the development of low-cost, context-appropriate solutions. These findings reinforce the global relevance of this research in advancing sustainable water management.

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8 Appendices

Appendix 1: Evidence dossier- Microbial contamination of surface waters from septic tank systems

Context

Septic Tank Systems (STS) are domestic wastewater treatment systems commonly used in residential areas not serviced by conventional wastewater treatment plants. Sewage in STS is treated by *primary* gravity sedimentation resulting in the separation of solids from the effluent which may undergo additional *secondary* or *tertiary* treatment to further reduce microbes and other contaminants. Microbial quality in STS effluent is determined through laboratory investigations of the presence and level of faecal indicator organisms (FIOs), commonly, *E. coli* and intestinal enterococci. Additionally, water quality models are used to predict and map cumulative catchment scale FIO pollution from various sources, including STS, to inform targeted land management interventions. However, empirical data concerning FIO fate and transfer associated with STS are sparse, and evidence of what proportion of FIOs may be delivered to surface water from STS is in short supply. A lack of quantitative understanding of FIO fate and transfer associated with STS in catchments can therefore limit the parameterisation of water quality models that attempt to account for these catchment sources. However, eliciting expert knowledge can help to characterise relatively unknown parameters using informed judgements. In this study, a Bayesian Network (BN) model is being developed to account for FIO pollution from STS by modifying an existing Phosphorus risk model. The BN will be parameterised using SEPA's spatial GIS dataset of STS locations, evidence and data collated from peer-reviewed publications and grey literature, and expert opinion from this workshop.

The Quantity of Interest (QoI)

The QoI is the proportion of FIOs that could be delivered to a surface water body from STS depending on the risk of effluent movement, STS distance to watercourse and slope. Figure shows three conceptual pathways of FIOs in STS effluent. For the purposes of this elicitation, we are assuming that all STS are associated with a soakaway. In reality, some inappropriate and ad-hoc systems may exist, including STS that directly discharge to watercourses; however, to constrain uncertainties such STS are not under consideration in the workshop. Therefore, our focus is on FIOs that would be delivered via, pathways 1, 2 and 3 which represent FIO transfer in surface, sub-surface and groundwater. FIOs are quantified as colony forming units (CFU/100ml), which represent the number of viable microbial cells in a 100 ml water sample. In this elicitation exercise, proportion of FIOs ($pFIO$) is defined as the portion of FIOs relative to the total FIO concentration in effluent discharged from STS that could be delivered to a watercourse. The value of $pFIO$ will be judged to lie between 0 and 1 where proportions closer to 0 mean that you judge the value of $pFIO$ to be less likely and proportions closer to 1 mean that you judge the value of $pFIO$ to be more likely. You will give judgements for 36 scenarios described in the Expert elicitation guide. You will be asked to give a plausible range within which you judge $pFIO$ to lie, by eliciting an upper (U) and lower (L) limit. You will then be asked to give a median (M) and lastly tertiles (T1 and T2). M is not necessarily the mid-point between U and L but the value at which you judge it to be equally likely that $pFIO$ is above or below M. T1 and T2 divide your plausible range into three equiprobable regions meaning that you judge it equally likely that $pFIO$ lies in any of the three regions. $pFIO$ is dependent on STS effluent movement risk, STS distance to watercourse and slope. Scientific evidence of the relationship between $pFIO$ and these variables is presented under section 0 of this dossier.

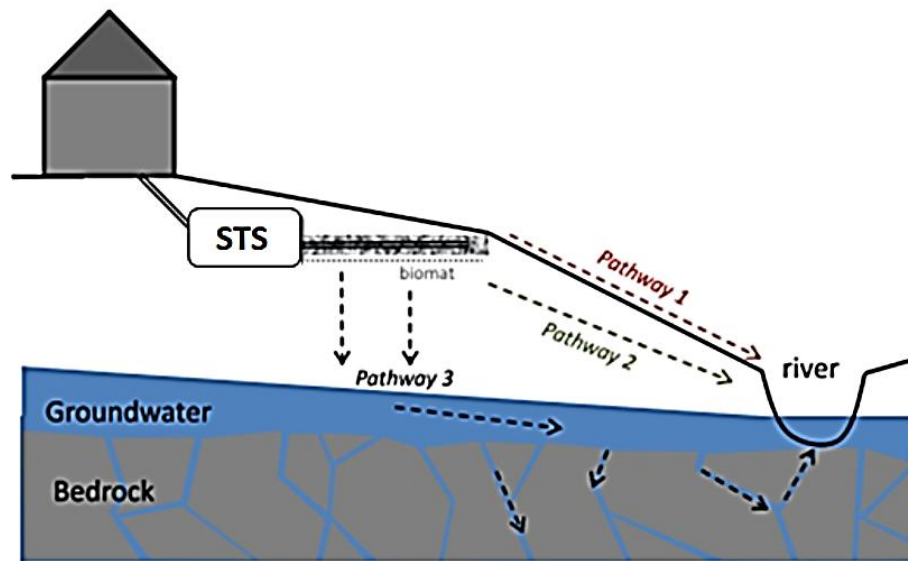


Figure 1: Schematic cross section showing the three conceptual pathways of FIOs in STS effluent based on Gill and Mockler 2016

Scientific Evidence

There is uncertainty over *p*FIO due to:

- Limited documented evidence of microbial pollution from STS. In most cases, pollution is attributed to the widespread use of STS rather than documented evidence (Beal et al., 2005).
- Uncertainty over the condition of STS, particularly those that are privately-owned (Dudley & May, 2007).
- Challenges of sampling from complex and intricate diffuse STS effluent pathways in space and time (Tamang et al., 2022).
- Complex FIO fate and transfer dynamics in response to a suite of varying and interacting environmental variables (Afolabi et al., 2020).

Factors that influence FIO transfer from STS and delivery to watercourses

For this elicitation exercise, the factors that influence FIO transfer from STS and delivery to watercourses have been grouped into:

- Primary factors (FIO STS concentration and STS density) which form important background information.
- Secondary factors (STS effluent movement risk, distance from STS to watercourse and slope) which influence further reduction of FIOs in the environment and will guide the elicitation.

A concise summary of useful information and evidence linked to these factors is detailed below:

- STS FIO concentration:** This factor represents the concentration of FIOs in STS effluent and is dependent on the population utilising the STS. Whereas it may be easy to estimate the number of persons utilising the STS, assumptions are usually made about things such as average property occupancy rate and rate of effluent production (Bergion et al., 2017; Reder et al., 2015). Assuming an average water consumption of 152 litres per head and 2.1 persons per household, the faecal coliform flux from each septic tank in Scotland has been estimated to be $23,000 \times 10^6$ CFU day⁻¹ (Goody et al., 2017). Typical FIO concentrations at various STS treatment levels are shown in **Error! Reference source not found.** These concentrations relate to values of FIOs associated with wastes typical of both STS and municipal wastewater treatment, and we can assume that similar levels of treatment efficiency would be achievable in properly functioning STS dependent on condition, maintenance and age of the septic tank. Here in the UK, desludging STS at intervals not exceeding 12 months is recommended (Butler & Paynet, 1995). Although there is uncertainty over the maintenance of privately-owned sewage systems, the Scottish Environmental Protection Agency (SEPA) estimates that in Scotland 70% of STS are well-maintained and 30% of STS are failing.
- STS density:** This factor relates to the number of STS that are spatially distributed in the landscape. Glendell et al. (2018) defined a high STS density as >20 STS per km² for Phosphorus pollution risk from STS in Scotland. Humphrey et al. (2018), in contrast, defined high STS density as >77 STS

Table 1

Effluent type/STS treatment level	FIO mean concentration, CFU/100mL			Source
	Faecal coliforms	<i>E. coli</i>	Enterococci	
Raw wastewater		1.98×10^7		Gikas & Tsihrintzis, 2012

	1.2 x 10 ⁷			O'keeffe et al., 2015
	^{a5} 1.7 x 10 ⁷ ^b 2.8 x 10 ⁶		^{a1} 1.9 x 10 ⁶ ^b 4.9 x 10 ⁵	(D. Kay et al., 2008b)
Primary	^a 7.2 x 10 ⁶ ^b 4.8 x 10 ⁶		^a 9.3 x 10 ⁵ ^b 4.3 x 10 ⁵	
	2.9 x 10 ⁵			Pundsack et al., 2001
		5.0 x 10 ⁵		Gill et al., 2007
		2.1 x 10 ⁶		Gill & Mockler, 2016
Secondary		5 x 10 ⁻²		Gill et al., 2007
		7.3 x 10 ⁴		Gill & Mockler, 2016
Tertiary				
1. Reedbed/grass plot	^a 1.3 x 10 ⁴ ^b 1.5 x 10 ⁴		^a 1.9 x 10 ³ ^b 2.3 x 10 ³	(D. Kay et al., 2008b)
2. Constructed wetlands	^c 4.0 x 10 ² ^c 5.0 x 10 ² ^d 5.9 x 10 ³ ^d 7.1 x 10 ³			Pundsack et al., 2001
3. Sand filters	^c 3.5 x 10 ¹ ^c 6.0 x 10 ¹ ^d 1.1 x 10 ² ^d 0.2 x 10 ³			
4. Peat filters	^c 6 ^c 6 ^d 4 ^d 5			

per km² and low density as <77 STS per km² for FIO pollution risk for STS located in the United States of America. The differences in STS density thresholds highlight some discrepancies as to how

^{a1} Concentration under dry weather conditions

^b Concentration under wet weather conditions

^c Concentration during summer (average effluent temperature was between 2.4 and 8 °C)

^d Concentration during winter (average effluent temperature was between 14.0 and 16.1 °C)

we rank risks from STS. Humphrey et al. (2018) found that streams draining catchments with high STS density had high median concentration of *E. coli* (2014 MPN 100ml⁻¹) and enterococci (168 MPN 100 ml⁻¹) compared to streams draining watersheds with low density which had *E. coli* (204 MPN 100 ml⁻¹) and enterococci (88 MPN 100 ml⁻¹).

- c. Risk of STS effluent movement: This factor denotes risk of STS effluent movement categorised as Low, Medium, High or Very high depending on surface runoff potential and/or leaching to groundwater based on Hydrology of Soil Types (HOST) (Gagkas & Lilly, 2019a; Glendell et al., 2021). HOST is a UK soil classification scheme that links soil morphology (presence of a gleyed layer, a slowly permeable layer or peaty top soil) and hydrology (soil infiltration and percolation) to conceptual models of surface/sub-surface flow pathways through the soil profile (**Figure**) (Boorman et al., 1995; Gagkas and Lilly, 2019a). To guide this elicitation, simplified HOST models translated into STS effluent movement risk and pathways driving risk are presented in Table 6: STS effluent movement risk factors based on HOST classes and pathways driving risk. Low risk of STS effluent movement is associated with low surface runoff potential and low groundwater leaching risk, for instance, in cases where soils are relatively free draining, there is no gleying and no groundwater within 2m. Very high risk of STS movement is driven by high likelihood of surface run off and/or leaching to groundwater, for example, when soils are poorly drained and the groundwater depth is less than 2m.

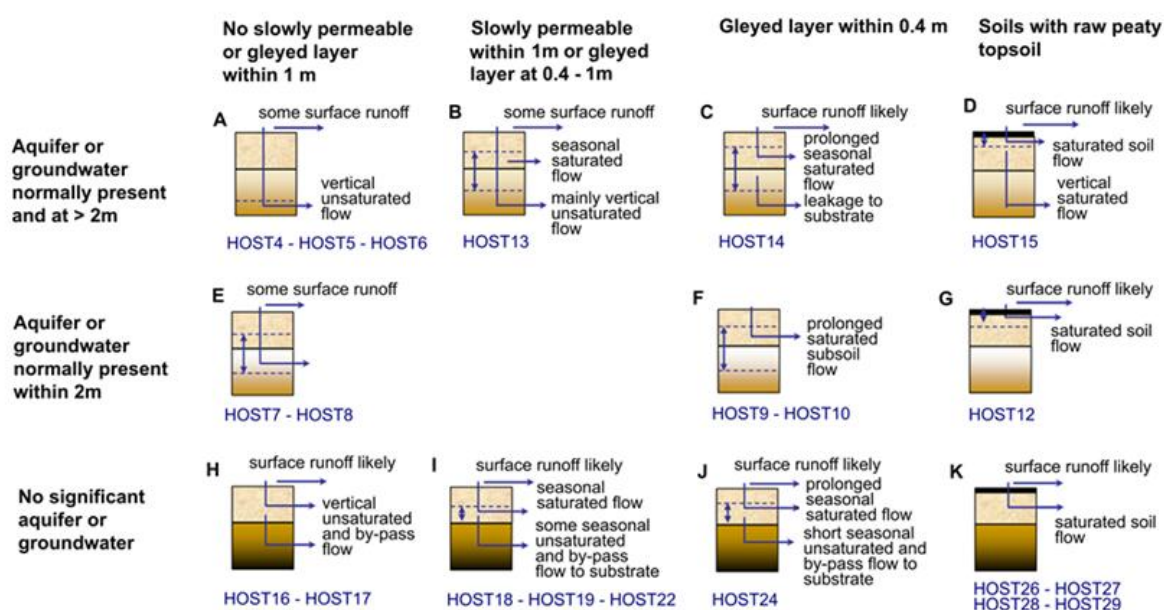


Figure 2: HOST class models

Table 2: STS effluent movement risk factors based on HOST class 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 HOST27	Relatively free draining soil & deep GW	Leaching to GW, some runoff
		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

- d. STS distance to receiving water: This factor provides a measure of the Euclidean distance between the STS discharge point and nearest receiving water. Gill & Mockler (2016) assumed 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%). Specific evidence of the influence of STS distance to watercourse on FIO delivery is scarce, hence this expert workshop.
- e. Slope: This factor represents the angle of sloping land associated with the STS distance to a receiving water. Steeper slopes are associated with higher surface water FIO contamination risk because they promote more rapid water flow compared to gentle slopes. Glendell et al. (2018) rated a slope of 5% to be of low risk and greater than 25% to be of high risk, with respect to Phosphorus loss from STS to receiving waters. In their study of Phosphorus loss from 2338 STS in seven catchments located in the eastern and southern parts of Scotland, they found 73% (n=1,708) STS to have equal or less than 5% slope and 2.5% (n=59) to have a slope greater than 15%. To provide some illustration, a rise of 1m over 20m gives a gentle slope of 5% while a rise of 5m over the same distance gives a steep slope of 25% (Figure)

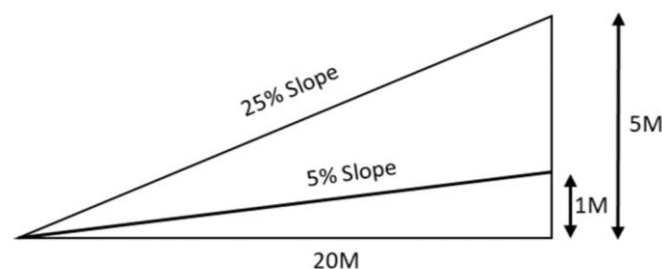


Figure 3: Illustration of 5% gentle slope and 25% steep slope

Appendix 2: Completed expert elicitation guides

EXPERT KNOWLEDGE ELICITATION GUIDE- EXPERT A								
Question:	What proportion of Faecal Indicator Organisms (FIOs) would get delivered to a surface water body from a septic tank system under the scenarios given below over a year?							
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
Number	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
1	Very high	<10	0-5	70	79	80	82	100
2			5-25	80	87	90	95	100
3			>25	85	88	90	94	100
4		10-50	0-5	60	67	70	74	90
5			5-25	65	70	75	80	90
6			>25	70	80	85	90	100
7		>50	0-5	30	35	40	45	50
8			5-25	30	35	40	45	50
9			>25	30	40	45	50	55
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
10	High	<10	0-5	50	55	60	65	80
11			5-25	50	55	60	65	80
12			>25	60	65	70	75	80
13		10-50	0-5	40	55	60	65	70
14			5-25	50	55	60	65	75
15			>25	50	60	65	70	80
16		>50	0-5	30	35	40	45	50
17			5-25	30	35	40	45	50
18			>25	25	30	35	40	50
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
19	Moderate	<10	0-5	30	35	40	45	50
20			5-25	35	40	45	50	55
21			>25	35	47	50	52	60
22		10-50	0-5	30	35	40	45	50
23			5-25	30	35	40	45	50
24			>25	40	45	50	55	60
25		>50	0-5	20	25	30	35	40
26			5-25	20	25	30	35	40
27			>25	25	30	35	40	50
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
28	Low	<10	0-5	20	25	30	35	40
29			5-25	20	25	30	35	40
30			>25	25	28	30	32	45
31		10-50	0-5	10	15	20	25	30
32			5-25	10	15	20	25	30
33			>25	10	15	20	25	30
34		>50	0-5	0	5	10	15	20
35			5-25	0	3	5	7	10
36			>25	0	2	3	4	6

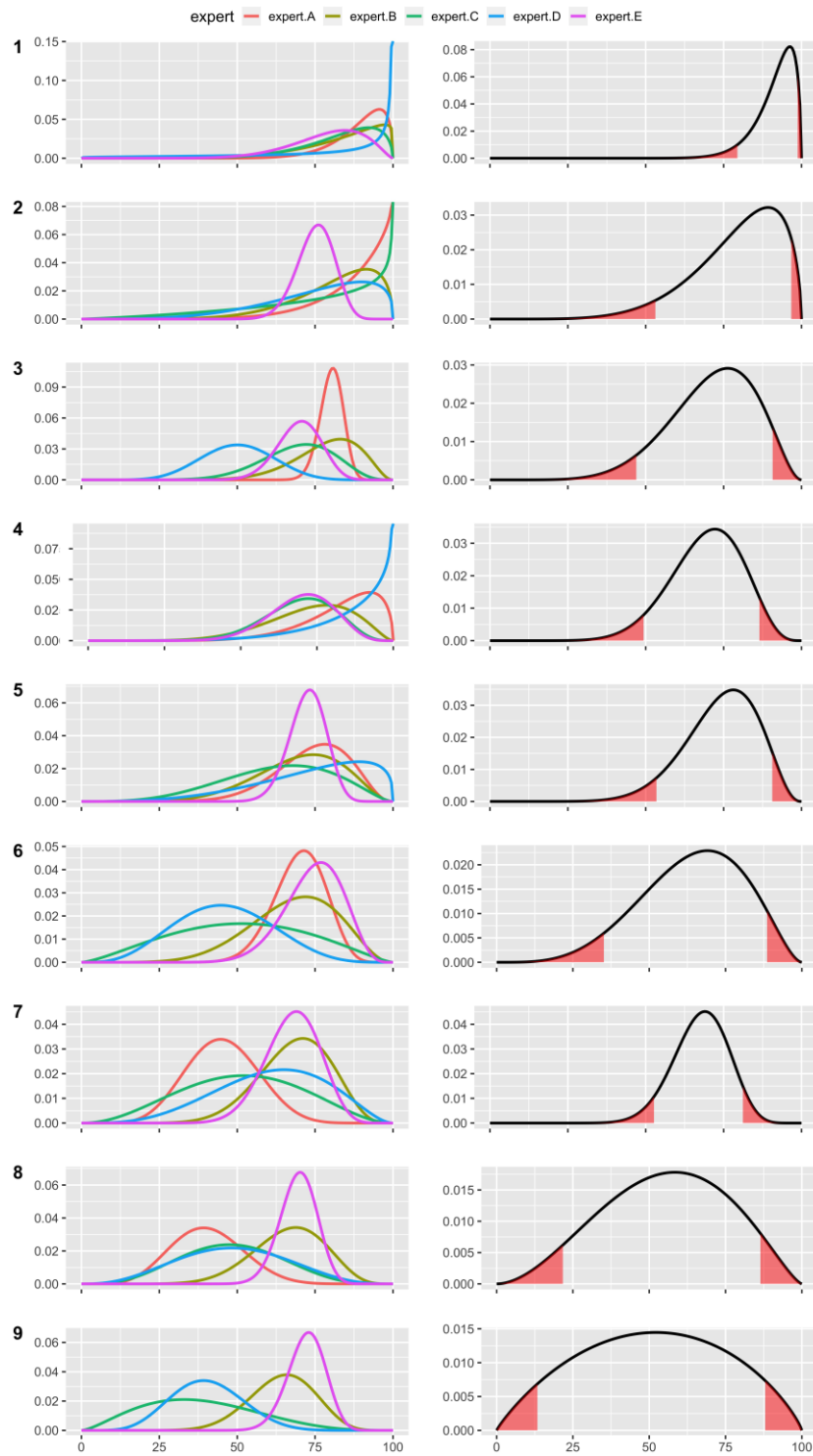
EXPERT KNOWLEDGE ELICITATION GUIDE- EXPERT B								
Question: What proportion of Faecal Indicator Organisms (FIOs) would get delivered to a surface water body from a septic tank system under the scenarios given below over a year?								
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
Number	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
1	Very high	<10	0-5	75	80	84		
2			5-25	77	85	88		
3			>25	80	88	91		
4		10-50	0-5	62	70	74		
5			5-25	64	72	76		
6			>25	67	75	79		
7		>50	0-5	60	65	69		
8			5-25	62	67	72		
9			>25	64	69	74		
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
10	High	<10	0-5	55	60	64		
11			5-25	57	65	68		
12			>25	60	68	71		
13		10-50	0-5	42	50	54		
14			5-25	44	52	56		
15			>25	47	55	59		
16		51-200	0-5	40	45	49		
17			5-25	42	47	51		
18			>25	44	49	53		
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
19	Moderate	<10	0-5	35	40	50		
20			5-25	37	45	52		
21			>25	40	48	55		
22		10-50	0-5	25	30	34		
23			5-25	27	32	36		
24			>25	30	35	39		
25		51-200	0-5	20	25	29		
26			5-25	22	27	31		
27			>25	24	29	33		
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
28	Low	<10	0-5	15	20	24		
29			5-25	17	25	28		
30			>25	20	28	31		
31		10-50	0-5	5	10	12		
32			5-25	8	12	14		
33			>25	11	15	17		
34		51-200	0-5	3	5	7		
35			5-25	5	7	9		
36			>25	7	9	11		

EXPERT KNOWLEDGE ELICITATION GUIDE - EXPERT C								
Question:	What proportion of Faecal Indicator Organisms (FIOs) would get delivered to a surface water body from a septic tank system under the scenarios given below over a year?							
	Scenario							
Number	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
1	Very high	<10	0-5		67	70	73	
2			5-25		73	75	78	
3			>25		75	80	85	
4		10-50	0-5		71	75	79	
5			5-25		70	73	75	
6			>25		66	70	75	
7		>50	0-5		70	72	75	
8			5-25		67	70	72	
9			>25		65	67	72	
	Scenario							
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
10	High	<10	0-5		70	73	75	
11			5-25		72	75	78	
12			>25		72	80	84	
13		10-50	0-5		68	70	72	
14			5-25		71	72	75	
15			>25		72	75	77	
16		>50	0-5		64	66	68	
17			5-25		65	68	71	
18			>25		65	70	75	
	Scenario							
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
19	Moderate	<10	0-5		42	45	46	
20			5-25		45	48	51	
21			>25		46	50	54	
22		10-50	0-5		38	42	45	
23			5-25		40	43	46	
24			>25		40	45	50	
25		>50	0-5		25	31	36	
26			5-25		28	32	35	
27			>25		28	33	35	
	Scenario							
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
28	Low	<10	0-5		12	15	17	
29			5-25		14	17	19	
30			>25		16	20	24	
31		10-50	0-5		8	10	12	
32			5-25		10	13	16	
33			>25		10	15	20	
34		>50	0-5		2	5	7	
35			5-25		5	8	11	
36			>25		5	10	15	

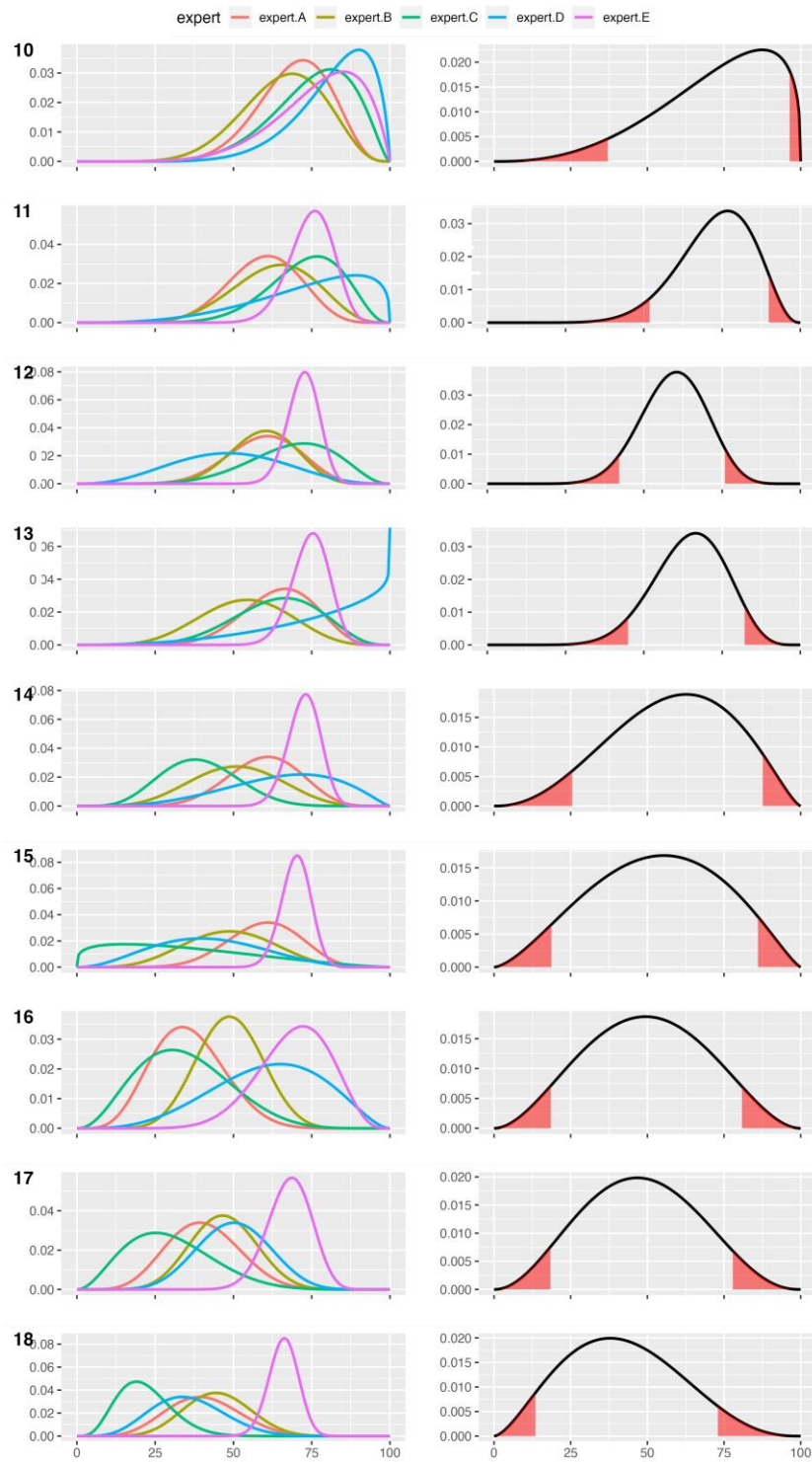
EXPERT KNOWLEDGE ELICITATION GUIDE- EXPERT D								
Question: What proportion of Faecal Indicator Organisms (FIOs) would get delivered to a surface water body from a septic tank system under the scenarios given below over a year?								
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely to be delivered to the stream (U)
Number	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
1	Very high	<10	0-5	0	45	50	55	100
2			5-25	0	70	80	85	100
3			>25	0	90	93	95	100
4		10-50	0-5	0	38	48	50	100
5			5-25	0	70	75	85	100
6			>25	0	85	88	90	100
7		>50	0-5	0	35	40	45	100
8			5-25	0	40	50	55	100
9			>25	0	55	60	70	100
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
10	High	<10	0-5	0	40	50	55	100
11			5-25	0	70	75	80	
12			>25	0	78	85	88	*
13		10-50	0-5	0	35	40	50	
14			5-25	0	60	65	75	
15			>25	0	75	80	85	*
16		>50	0-5	0	30	35	40	
17			5-25	0	45	50	55	
18			>25	0	55	60	70	*
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
19	Moderate	<10	0-5	0	35	45	50	
20			5-25	0	65	70	80	
21			>25	0	75	80	85	*
22		10-50	0-5	0	30	40	45	
23			5-25	0	60	65	75	
24			>25	0	70	80	85	
25		>50	0-5	0	15	21	36	*
26			5-25	0	45	50	60	
27			>25	0	55	60	65	
Scenario				Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely to be delivered to the stream (U)
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)					
28	Low	<10	0-5	0	30	40	50	100
29			5-25	0	55	60	65	100
30			>25	0	65	70	75	100
31		10-50	0-5	0	25	30	35	100
32			5-25	0	50	55	75	100
33			>25	0	55	60	70	100
34		>50	0-5	0	5	7	10	100
35			5-25	0	25	35	40	100
36			>25	0	30	35	55	100

EXPERT KNOWLEDGE ELICITATION GUIDE- EXPERT E								
Question:	What proportion of Faecal Indicator Organisms (FIOs) would get delivered to a surface water body from a septic tank system under the scenarios given below over a year?							
Scenario								
Number	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
1	Very high	<10	0-5		65	70	75	
2			5-25		70	80	90	
3			>25		80	85	90	
4		10-50	0-5		40	55	57	
5			5-25		55	66	70	
6			>25		65	70	75	
7		>50	0-5		28	39	43	
8			5-25		40	50	53	
9			>25		42	55	57	
Scenario								
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
10	High	<10	0-5		63	70	85	
11			5-25		68	75	88	
12			>25		70	80	90	
13		10-50	0-5		20	35	38	
14			5-25		33	40	43	
15			>25		58	65	70	
16		>50	0-5		18	20	25	
17			5-25		23	28	35	
18			>25		27	33	40	
Scenario								
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
19	Moderate	<10	0-5		28	33	43	
20			5-25		30	35	45	
21			>25		55	60	64	
22		10-50	0-5		10	15	18	
23			5-25		18	25	30	
24			>25		20	30	33	
25		>50	0-5		3	5	10	
26			5-25		7	10	12	
27			>25		9	15	18	
Scenario								
	STS effluent movement risk	STS distance to watercourse (m)	Slope (%)	Lowest estimated fraction to be delivered to the stream (L)	Tertile 1 (T1)	Median (M)	Tertile 2 (T2)	Uppermost fraction likely fraction to be delivered to the stream (U)
28	Low	<10	0-5		5	15	17	
29			5-25		18	20	28	
30			>25		27	33	40	
31		10-50	0-5		1	3	6	
32			5-25		6	8	20	
33			>25		8	10	20	
34		>50	0-5		1	2	3	
35			5-25		1	2	5	
36			>25		4	5	10	

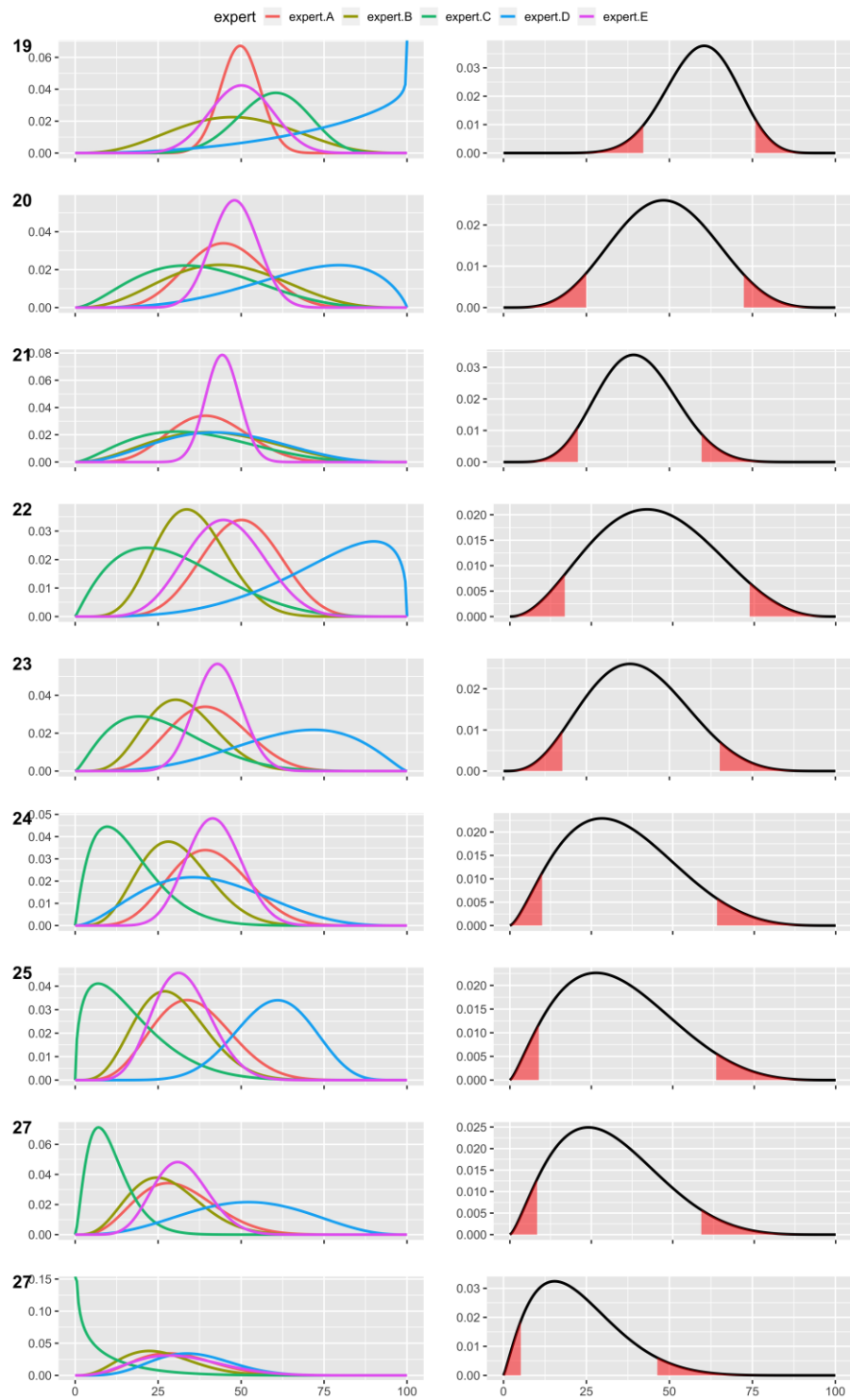
Appendix 3 (i)-(iv): Original expert elicitation plots with actual scales of axes, (i)



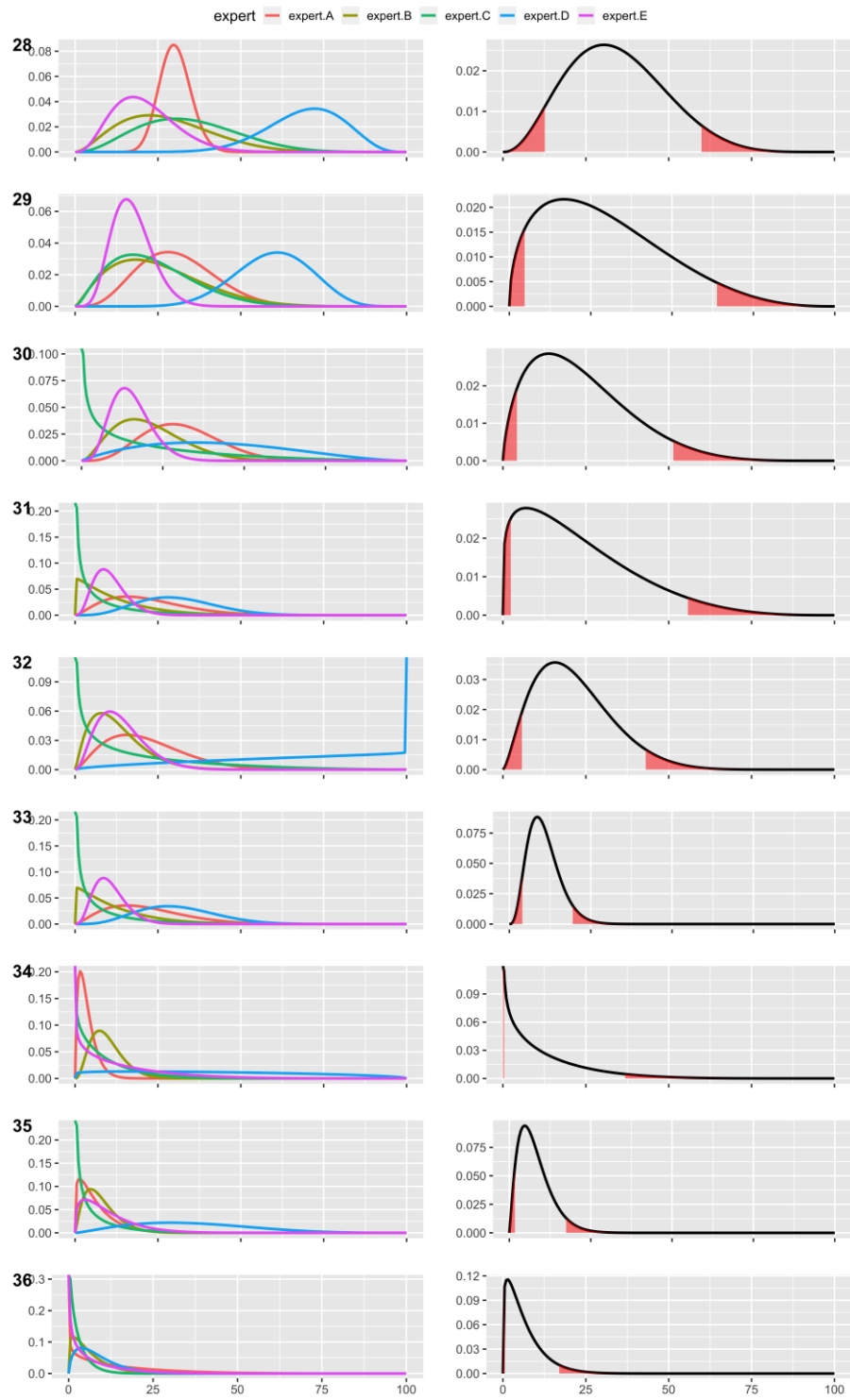
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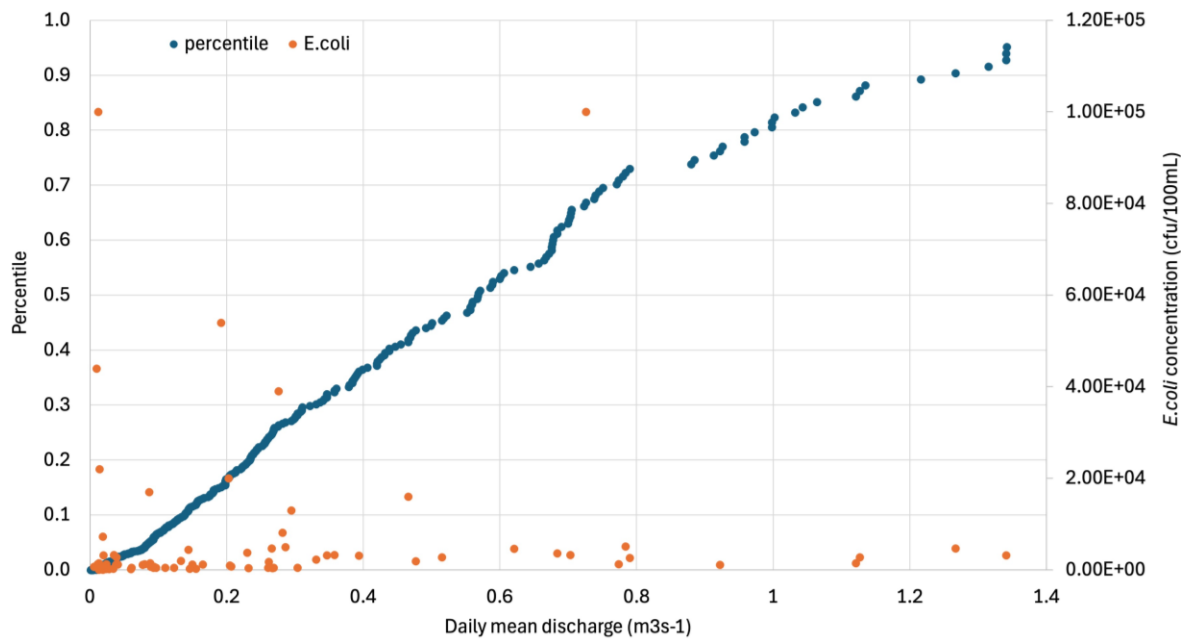


(iii)

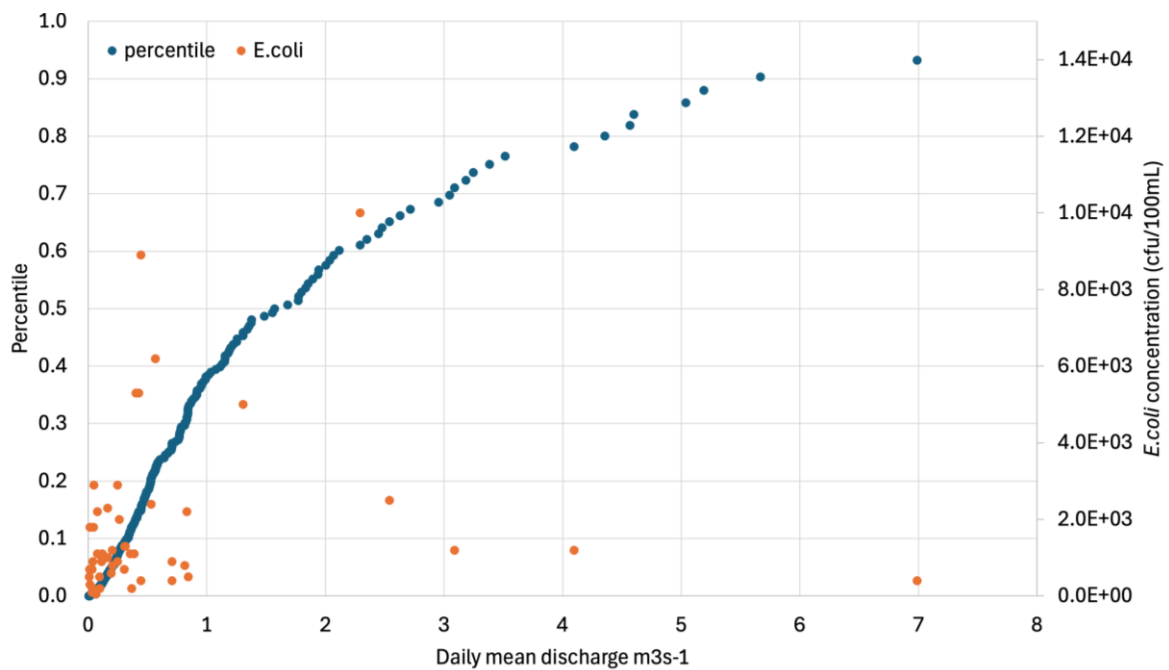


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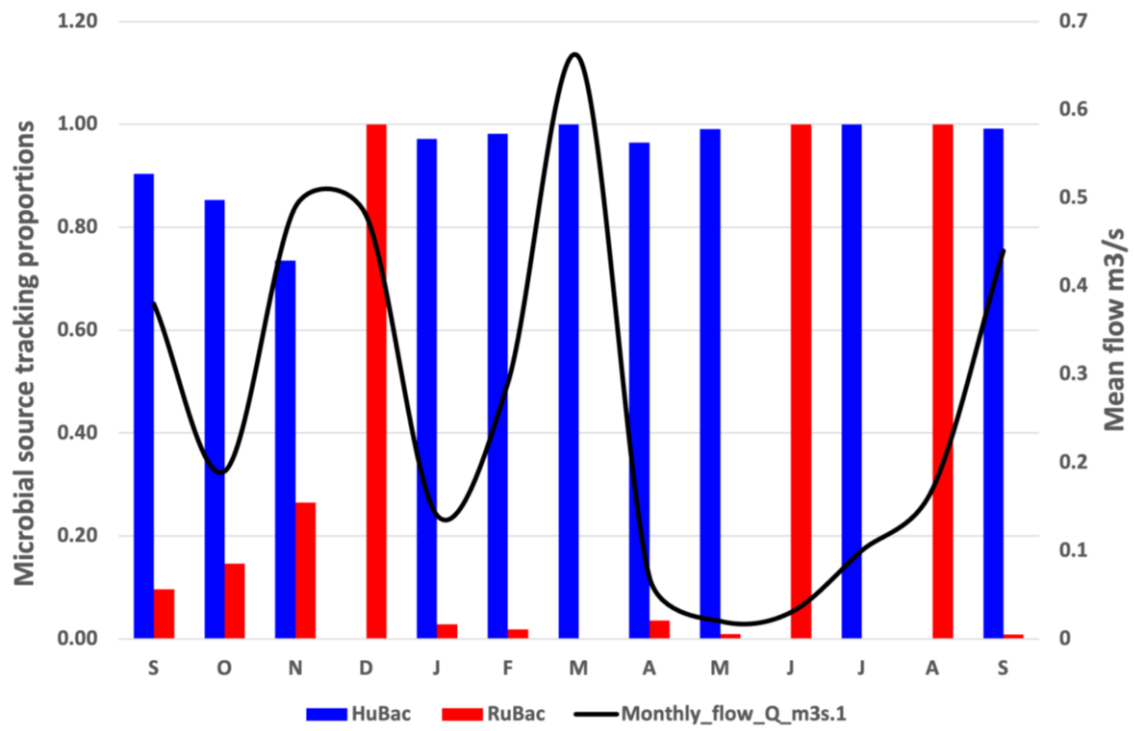




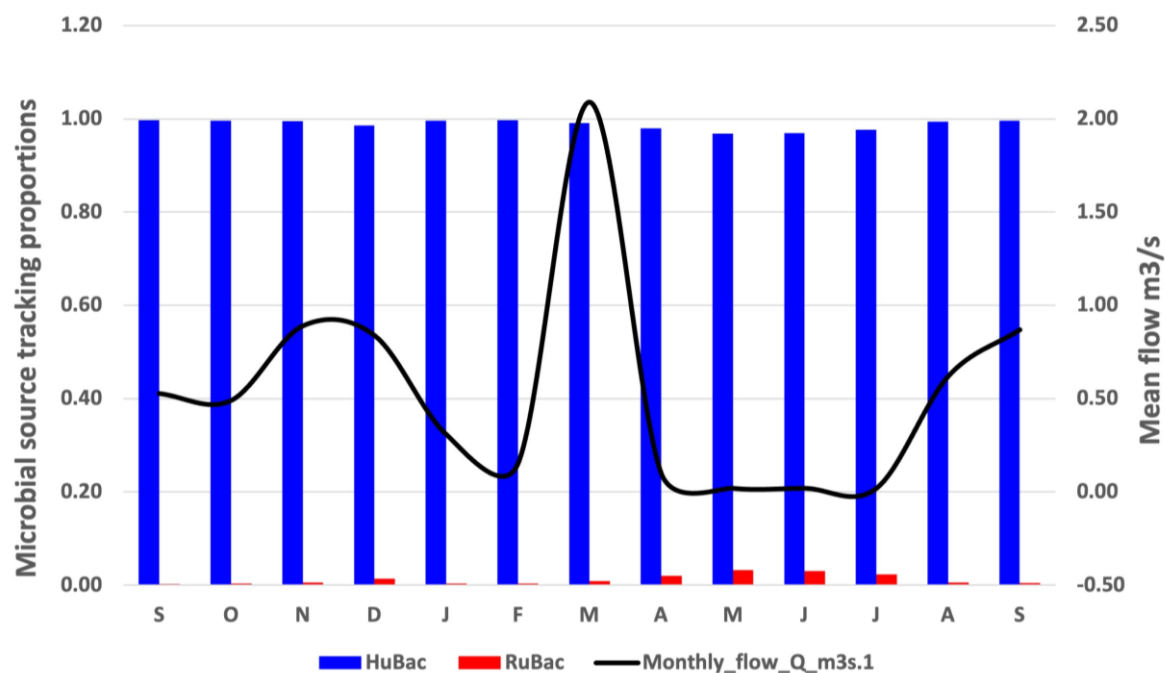
Appendix 4: Cumulative frequency for discharge vs *E. coli* concentration in Mein



Appendix 5: Cumulative frequency for discharge vs *E. coli* concentration in Cessnock



Appendix 6: Human bacterioide proportions (in blue) versus Ruminant bacterioide proportions (in red) and mean flow from September 2018 to September 2019 in Mein



Appendix 7: Human bacteroides proportions (in blue) versus Ruminant bacteroides proportions (in red) and mean flow from September 2018 to September 2019 in Cessnock

Appendix 8: STS and associated HOST-derived risk class by region of Scotland

ST_HOST_Region_Props											
Risk Factor	Central	East	North	South	West	Counts	Central%	East%	North%	South%	West%
Low	761	1529	292	1043	0	3625	21	42	8	29	0
Moderate	5767	22515	9014	9373	5728	52397	11	43	17	18	11
High	29873	26955	17051	12218	10199	96296	31	28	18	13	11
Very high	3196	6365	3662	3383	5643	22249	14	29	16	15	25

Appendix 9: Septic tanks survey questionnaire

Septic tanks survey

Working title: Perceptions and attitudes of faecal pollution risk to watercourses among septic tank users in rural catchments

Aim: To understand the perceptions and attitudes of septic tank users in rural catchments regarding septic tanks as potential sources of faecal indicator organism (FIO) pollution to watercourses.

Objectives:

1. To establish the types of septic tanks and their associated treatment levels currently utilised across Scotland
2. To identify factors that influence the maintenance of septic tank systems, including those that either promote or impede proper upkeep
3. To determine the level of awareness among property owners about septic tanks systems as potential sources of FIO pollution
4. To determine the proportion of property owners who actively engage in maintenance of septic tanks

Eligibility criteria (yes for all to proceed)

Do you have a septic tank associated with your property?

Do you currently live in Scotland?

Are you 18 years old or above?

1. Types of septic tanks and their associated treatment levels

1.1	Which of the following best describes your septic tank:
	☐ Tank unit only
	☐ Tank + soakaway field
	☐ Onion Shape Septic Tank
	☐ Bullet/shallow dig septic tank
	☐ Other (Specify if known.....)

	☐ I don't know			
1.2	Where does your septic tank wastewater discharge?			
	☐ Into a soakaway (drainage) field	☐ Direct to a nearby waterbody	☐ Into a reedbed system	☐ I don't know
1.3	Do you know approximately how old your septic tank is?			
	☐ Less than 5 years			
	☐ Between 5 and 10 years			
	☐ Between 11 and 15 years			
	☐ Between 16 and 20 years			
	☐ More than 20 years			
	☐ I don't know			
	☐ Prefer not to say			
1.4	Approximately how far is your septic tank located from the nearest surface water (stream, river, loch, coastline)			
	Less than 10 m away	Between 10 to 50 m	More than 50 m away	

2. Upkeep of septic tank systems

2.1	Do you know where your septic tank is located?			
	Yes ☐	No ☐	Prefer not to say ☐	
2.2	Is the septic tank located within your property?			
	Yes ☐	No ☐	Prefer not to say ☐	
2.3	How many properties does the septic tank serve?			
	☐ 1	☐ 2	☐ 3 or more	☐ I don't know
2.4	How long have you lived at your current address?			

	☐ Less than 1 year	☐ 1-5 years	☐ 6-10 years	☐ More than 10 years	
2.5	Do you rent or own your property?				
	☐ I rent it	☐ I own it	☐ Other	☐ Prefer not to say	
2.7	If you own your property, other than reference to the septic tank in the home report, was any further information left for you by the previous owner?				
	☐ Yes	☐ No	☐ Prefer not to say		
2.8	Do you live at this property for the entire year? If not, how many months do you stay there?				
	☐ Less than 5	☐ Between 5-7	☐ Between 7 and 11	☐ Other	
2.9	How many people reside in your property?				
	☐ 1	☐ 2	☐ 3	☐ Other (please specify.....)	
2.10	How easy is it to find a septic tank maintenance specialist in your area to routinely check your septic tank?				
	☐ Very easy	☐ Easy	☐ Difficult	☐ Very difficult	☐ I don't know
2.11	How easy is it to get a septic tank maintenance specialist to respond in an emergency?				
	☐ Very easy	☐ Easy	☐ Difficult	☐ Very difficult	☐ I don't know

2.12 For each of the following statements, indicate the level to which you agree or disagree.				
	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree
The cost of maintaining my septic tank influences how often I service it				
Blockages frequently occur in my septic tank system				

Flooding is a frequent problem affecting my septic tank system				
My septic tank has been damaged in the past by nearby activity such as tree root growth, or construction				
I find it difficult to access information on how to maintain my septic tank				
Physically accessing my septic tank for inspection and maintenance is challenging				

3. Awareness about septic tanks systems as potential sources of pollution

3.1 For each of the following statements, indicate the level to which you agree or disagree.				
	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree
I maintain my septic tank in optimal working condition				
I am concerned about water quality impacts arising from my septic tank				
The risk of microbial pollution to the environment from my septic tank is negligible				
Leaking effluent from septic tanks is an environmental concern				
There are potential risks to human health if septic tanks are poorly maintained				
Additional treatment of septic tank effluent (e.g., filtration) is effective in reducing microbial pollution risks to the environment				
Regulation of septic tanks is adequate to ensure proper management and				

reduced microbial pollution of the environment				
I have a legal responsibility to maintain my septic tank in good working order				
The presence of deep-rooted trees and shrubs near to a septic tank can damage the system				
I often notice an unpleasant smell from my septic tank				
Rainwater drainage pipes should not be connected into my septic tank				

4. Active engagement in maintenance of septic tanks

4.1	How often do you have your septic tank emptied?
	☐ Once every year
	☐ Once every 2 years
	☐ Once every 3 years
	☐ Once every 4 years
	☐ More than every 5 years
	☐ Other (Please specify interval if known.....)
	☐ I don't know
4.2	Do you know approximately when it was last emptied?
	☐ Within the last 1 year
	☐ Within the last 2 years
	☐ Within the last 3 years
	☐ Within the last 4 years
	☐ More than 4 years ago

	☐ I don't know
4.3	Which of the following septic tank maintenance practices do you (or your family) follow? (Choose all that apply)
	☐ Inspecting the septic tank once a year
	☐ Not putting harsh chemicals into the tank or down the drain
	☐ Conserving water use in the house
	☐ Preventing the septic tank area from surface water flooding
	☐ Keeping trees at least 5 metres away from the septic tank
	☐ Keeping all construction at least 4 metres away from the septic tank
	☐ Keeping detailed records of the septic system's location, care, and maintenance

Finally, we would like to learn a little more about you and where you live to help us better understand our participants.

Which age group do you belong to?

- ☐ 18-24
- ☐ 25-34
- ☐ 35-44
- ☐ 45-54
- ☐ 55-65
- ☐ Over 65
- ☐ Prefer not to say

How do you identify your gender?

- ☐ Male
- ☐ Female
- ☐ Non-binary

- ☐ Transgender
- ☐ Self-describe (.....)
- ☐ Prefer not to say

In which region of Scotland do you reside? The regions of Scotland are indicated in the map to the right to guide you if needed.

- Highlands & Islands
- Grampian
- Central
- Strathclyde
- Lothian
- Borders
- Dumfries & Galloway

