# Risk assessment methodology on effects of climate change on source water

Deliverable 5.4



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| **ABSTRACT** | The amount of dissolved organic matter (DOM) in source waters influences the conditions under which disinfection by-products (DBPs) form during drinking water treatment. Understanding both current variability and potential changes is therefore important for preparing water supply systems and identifying source protection measures. Here, we introduce a geospatial risk assessment methodology that combines machine learning and globally available environmental datasets to develop a site-specific risk index. The framework uses a local target variable, such as a DOM proxy or DBP formation potential, and organises environmental influences into production, mobilisation and delivery processes. The methodology was validated at three sites, and future risks were explored using an ensemble of climate models under contrasting scenarios. The outputs are linked to a source protection matrix connecting land cover, process information and risk levels with candidate management measures. Designed for application to source waters across Europe, this approach provides a tool for identifying and prioritising source protection measures relevant | | |

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| | to DBP precursor conditions, particularly where monitoring and understanding are limited. |

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## List of abbreviations

| Abbreviation | Full description |
|---|---|
| CDOM | Chromophoric dissolved organic matter |
| CI | Confidence interval |
| CLC | CORINE Land Cover |
| CMIP6 | Coupled Model Intercomparison Project, Phase 6 |
| CORINE | Coordination of Information on the Environment |
| DBP | Disinfection by-product |
| DBP-FP | Disinfection by-product formation potential |
| DOC | Dissolved organic carbon |
| DOM | Dissolved organic matter |
| ECMWF | European Centre for Medium-Range Weather Forecasts |
| EPA | Environmental Protection Agency (Ireland) |
| ERA5 | Fifth-generation ECMWF atmospheric reanalysis |
| EU | European Union |
| FDOM | Fluorescent dissolved organic matter |
| GCM | Global climate model |
| GIS | Geographic information system |
| ISIMIP | Inter-Sectoral Impact Model Intercomparison Project |
| ISIMIP3b | Inter-Sectoral Impact Model Intercomparison Project, phase 3b |
| ML | Machine learning |
| QC | Quality control |
| RF | Random forest |
| RMSE | Root mean square error |
| SHAP | SHapley Additive exPlanations |
| SPI | Standardised Precipitation Index |
| SPI-1 | Standardised Precipitation Index calculated over one month |
| SPI-3 | Standardised Precipitation Index calculated over three months |
| SSP | Shared Socioeconomic Pathway |
| SWP | Source water protection |
| TOC | Total organic carbon |
| UV | Ultraviolet |
| UVT | Ultraviolet transmittance |
| UVT254 | Ultraviolet transmittance at a wavelength of 254 nm |
| WP | Work package |

## Executive summary

Changes in dissolved organic matter (DOM) in drinking water sources influence the conditions under which disinfection by-products (DBPs) form during treatment and supply. These changes depend on water body characteristics and catchment processes controlling organic matter production, mobilisation and delivery. Understanding current variability and potential changes under future climates is therefore important for protecting drinking water sources and preparing water supply systems. However, limited monitoring and understanding can restrict the information available to support these decisions.

Within intoDBP, we designed a risk assessment methodology intended for application across Europe using a suitable local target variable, such as a DOM proxy or DBP formation potential, with interpretation adapted accordingly. The framework combines local observations, machine learning and globally available environmental datasets to construct a site-specific index, classified into low, intermediate and high relative risk. Its five steps cover preparation of observational data, environmental and source characterisation, learning and index construction, site validation, and future climate application. We applied and evaluated the methodology at three sites in Ireland (Feeagh, an intoDBP Case Study Site and Magheracloone) using DOM proxies, which were selected based on the availability of data. Two of these sites were new to intoDBP, while Feeagh had previously been investigated within the project. DOM proxies were selected to characterise source-water precursor variability because DBP formation potential data were unavailable for Feeagh and the intoDBP Case Study Site, while only limited THM data were available for Magheracloone. Direct validation of the index against DBP formation data therefore remains outstanding. Process weights and agreement with observations varied between sites. Future conditions were explored under SSP1–2.6 and SSP5–8.5 using an ensemble of climate models, although other scenarios could be incorporated.

The index describes relative precursor conditions at each source. To connect this information with management guidance, we incorporated source protection measures identified in previous work within this work package to which a feasibility index was

applied to establish those measures which had the greatest potential for use in the mitigation of DOM. A matrix links land cover, the most relevant process and risk level to candidate protection measures. This supports prioritisation while retaining the need to confirm local pressures and the suitability of individual actions. The methodology offers a relatively accessible tool for examining current and possible future conditions, particularly where monitoring and understanding are limited. It can help water managers and relevant authorities prioritise investigations, consider source protection measures and plan longer-term adaptation strategies, supporting the management of water entering drinking water treatment plants.

# 1. Introduction

## 1.1 Background

The dynamics of dissolved organic matter (DOM) in lakes and other drinking water sources are influenced by their surrounding catchments and by processes occurring within the water body (Jennings et al., 2010; Adler, 2020). The amount and characteristics of DOM vary with land cover, soil conditions, biological activity and the pathways connecting the landscape to the source (Creed et al., 2018). Temperature and water availability influence the production and accumulation of organic matter, while soil moisture and rainfall affect its mobilisation and transport (Evans et al., 2006; Wit et al., 2021). These interactions determine when and how much material reaches the water body, producing seasonal variability as well as shorter periods of elevated concentrations (Jennings et al., 2020; Blaurock et al., 2021).

DOM is relevant to drinking water supply because some of its components can react with disinfectants and contribute to disinfection by-product (DBP) formation (Siddique et al., 2022; Pedregal-Montes et al., 2024). The resulting by-products depend on more than the total amount of organic matter (Gilca et al., 2020). Its composition and reactivity, the presence of other precursors, and treatment conditions also influence the outcome (Gonsior et al., 2014). Understanding DOM variability at the source can therefore help identify conditions that may increase the challenge of managing DBP formation during treatment (Siddique et al., 2022). Measurements of DOM or suitable proxies provide

information about these precursor conditions, although they do not directly describe the DBPs that will occur after treatment (Sohn et al., 2001).

In addition, climate change may alter the environmental conditions controlling these processes (Ritson et al., 2014). Changes in temperature, rainfall and the timing of wet and dry periods can modify DOM availability and its delivery to drinking water sources (Wu and Yao, 2022). The implications may involve changes in average conditions, but also in the timing, frequency and duration of periods with elevated precursor levels (Pedregal-Montes et al., 2024). Understanding both current variability and possible future changes is therefore important for assessing whether existing source protection and water management practices will remain suitable over the coming decades.

A preventive approach to water quality management requires an understanding of the pressures affecting the source and the processes connecting those pressures to water quality (Bradford et al., 2020; Lofton et al., 2022). This can help identify where protection measures may be needed and when additional monitoring or management attention would be useful. The suitability of a measure depends on the local setting, including land cover, soil conditions and hydrological pathways (Klante et al., 2021). Linking information about these characteristics with changing precursor conditions can support more focused source protection and complement actions undertaken during drinking water treatment.

Detailed monitoring and process models can provide valuable information for this purpose, but their data and technical requirements may limit their application (Costa et al., 2021). In some settings, the available observations consist of a single organic matter measurement or optical proxy, with limited information on the processes responsible for its variability (Kirschke et al., 2020). Globally available environmental datasets provide an opportunity to complement these local records, while machine learning can help identify associations between the observed target and environmental drivers. Combining these sources of information offers a practical basis for developing assessment tools where monitoring and understanding are limited.

Within this context, this deliverable presents a geospatial risk assessment methodology that uses a local target variable and environmental information to assess relative source water conditions associated with DBP precursors. We organise these conditions around

production, mobilisation and delivery, evaluate the resulting index against observations, and explore its application under future climate scenarios. The assessment is linked to a source protection matrix developed within this work package, connecting land cover, process information and risk levels with candidate management measures.

The purpose is to support the interpretation and prioritisation of source water conditions that deserve attention. Throughout this deliverable, risk refers to relative precursor-related conditions represented by the index. Its meaning depends on the target variable and the evidence available at each site. An index based on a DOM proxy can, therefore, support source protection decisions, while additional information remains necessary to assess treated-water DBP concentrations, human exposure and the effectiveness of individual measures.

## 1.2 Objectives

The main aim of this deliverable was to develop a risk assessment tool that is relatively straightforward to apply and requires limited local data, using a suitable target variable together with globally available environmental datasets. The framework was designed to assess current source water conditions associated with DBP precursors and indicate how relative risk may change under future climates compared with a historical baseline. Through this information, we aim to support the consideration and prioritisation of source protection measures in the context of climate change.

The specific objectives were:

1. To develop and evaluate a site-specific risk index linking local target observations with environmental drivers, organised around organic matter production, mobilisation and delivery, with particular attention to elevated target values.
2. To assess potential changes in relative risk under contrasting climate change scenarios against a historical baseline, considering the magnitude, timing and uncertainty of these changes.
3. To link risk levels, process information and land cover with candidate source protection measures, providing guidance for water managers and relevant

authorities when considering mitigation and long-term adaptation strategies, particularly where monitoring and understanding are limited.

# 2. Methods

## 2.1 Study sites

The risk assessment methodology was applied at three sites in Ireland (Lough Feeagh, an intoDBP Case Study Site and Magheracloone; Figure 1), representing different catchment characteristics and monitoring settings. Lough Feeagh is an intensively monitored catchment with extensive environmental information and a long-term record of coloured dissolved organic matter (CDOM) observations. At the intoDBP Case Study Site, observations relied on the installation of a single sensor as part of the intoDBP project providing high-frequency optical measurements of source-water organic matter over a shorter period. Magheracloone provided routine but lower-frequency laboratory measurements of untreated water arriving at the drinking water treatment plant, including UV transmittance and DOC. These contrasting datasets allowed the methodology to be evaluated under different levels of data availability, temporal coverage and sampling frequency.

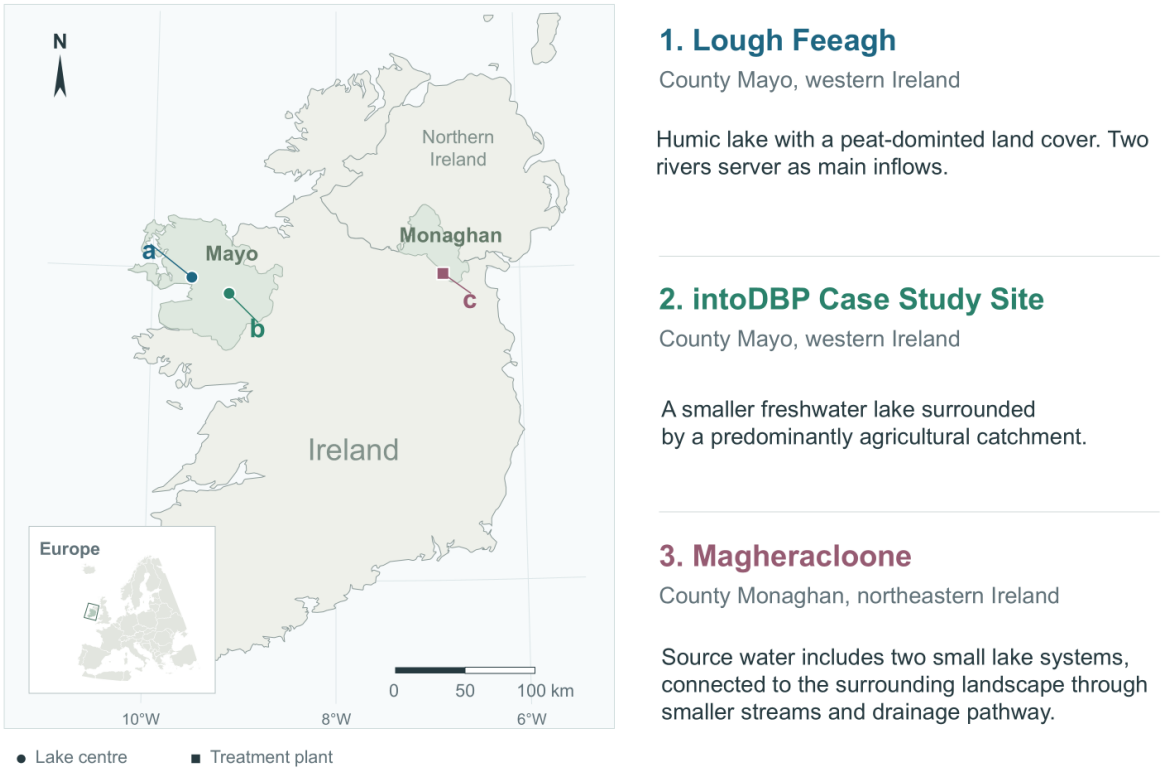



***Figure 1.*** *Location and main characteristics of the three study sites in Ireland.*

Lough Feeagh is a humic freshwater lake in County Mayo, western Ireland, within the Burrishoole catchment (Figure 2). It has a surface area of approximately 3.95 km² and a contributing catchment of approximately 84 km², with the Black and Glenamong rivers providing its main inflows (Doyle et al., 2019). The catchment is dominated by peatland across approximately 49% of the catchment, with additional areas of coniferous forest, transitional woodland and grassland (Ryder et al., 2014; Doyle et al., 2019). While Feeagh is not used as a source of potable water, it is an intensively monitored site with a large amount of available data and is representative of similar small lakes used as drinking water supplies in the region and has been investigated within the intoDBP project.

The intoDBP Case Study Site is a source of water for a Group Water Scheme in County Mayo which sources its water from a small freshwater lake. This site is one of the three Irish Case Study Sites for the intoDBP project and supplies drinking water to approximately 830 households. The Group Water Schemes in Ireland are small co-operative community managed water distribution systems that supply drinking water to mostly rural homes and farms in Ireland. The lake occupies approximately 0.63 km², within a contributing catchment of approximately 6.6 km². Its surrounding landscape is predominantly agricultural with pasture accounting for approximately 61% of the assessment area, while agricultural land interspersed with natural vegetation accounts for a further 23%. Smaller areas of peat bog and coniferous forest are also present. Compared with Feeagh, this site represents a smaller, pasture-dominated catchment, providing a different setting in which to examine the environmental conditions associated with changes in source water organic matter.

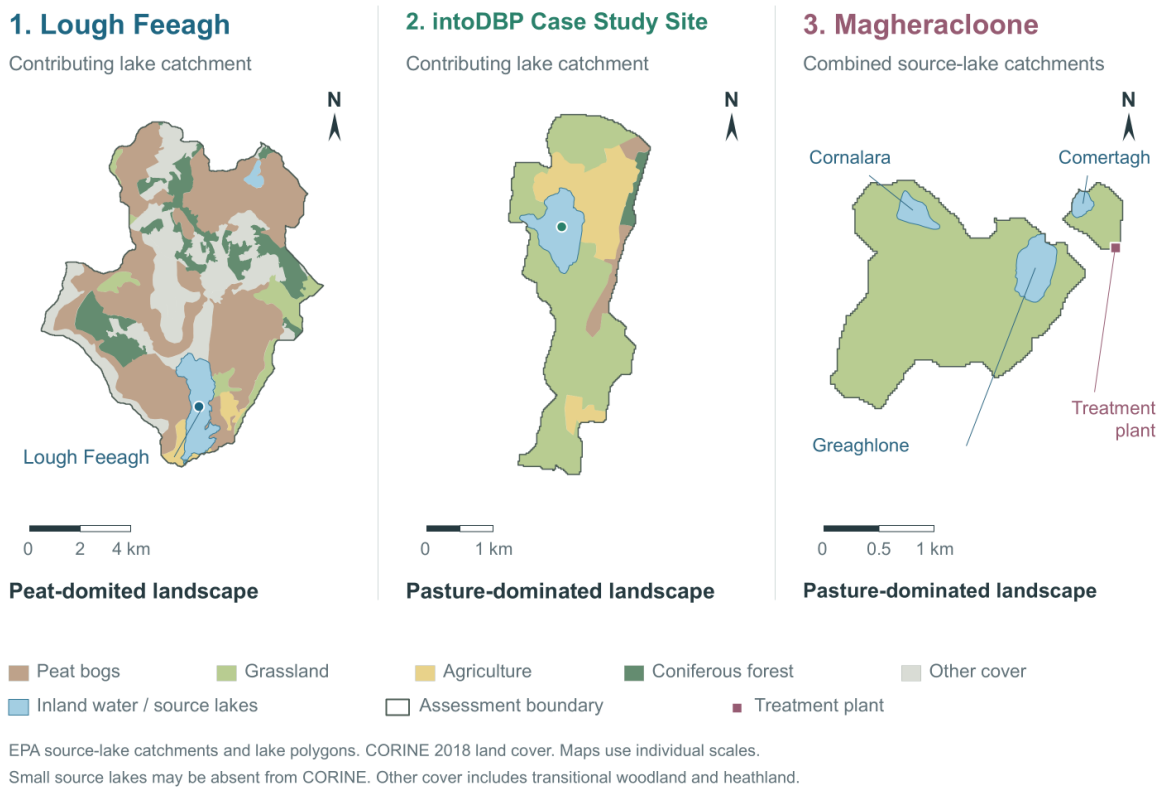



***Figure 2.*** *Source catchments and land cover at the three study sites, based on CORINE 2018 Revised and EPA lake boundaries. Maps use individual scales.*

Magheracloone represents the untreated water supplied to the Magheracloone Group Water Scheme in County Monaghan, northeastern Ireland. Its surface water sources include Cornalara and the Greaghlone–Comertagh lake system, connected to the surrounding landscape through smaller streams and drainage pathways. The area is characterised by a drumlin landscape, with pasture forming the dominant mapped land cover. For this site, the assessment considered the combined mapped surface catchments of the source lakes, rather than an area surrounding the treatment plant. This distinction is relevant because the observations represent water arriving at the plant, rather than measurements taken directly within an individual lake.

## 2.2 Observational input data

Local water quality observations were compiled separately for each site to provide the target variable used in the risk assessment methodology. All three applications used optical proxies associated with DOM, although the measurement type, temporal coverage and sampling frequency differed between sites. Each record was processed

separately and aligned with the environmental drivers on a daily time basis. Missing observations were retained as gaps rather than replaced with estimated target values.

For Lough Feeagh, the input dataset comprised daily temperature-corrected CDOM observations covering 2010–2022 (see Mercado-Bettín et al., 2026). A total of 3,583 daily values were available, with valid observations extending from March 2010 to December 2022. This series provided the longest observational record among the three sites and was used to examine associations between environmental drivers and variations in the optical properties of DOM. The measurements were temperature-corrected (see Supplementary Material in Mercado-Bettín et al., 2026) and retained as the local target variable.

For the second into DBP Case Study Site, observations were obtained from an optical sensor deployed at the lake surface, with measurements available at 350 and 440 nm. The supplied record contained 9,280 hourly observations between July 2025 and July 2026. The 350 nm signal was selected as the target variable, while the 440 nm measurements were retained as complementary information on optical variability. Daily means were calculated where at least 18 valid hourly readings were available. Following the exclusion of the sensor-error period identified in the input script, the usable record comprised 342 daily values between 10 July 2025 and 16 June 2026. These measurements describe variability at the monitoring location and depth, they do not directly represent the full water column or the total amount of DOM in the lake.

For Magheracloone, the input dataset comprised periodic laboratory measurements of untreated water sampled at the treatment plant between February 2020 and September 2025. The consolidated record contained 237 sampling dates, of which 156 provided numerical UV transmittance values accepted for calculation of the target variable. Transmittance was converted to an absorbance proxy using $-\log_{10}(\mathrm{UVT}/100)$, where UVT is expressed as a percentage. This conversion expresses lower transmittance as a higher optical absorption signal, providing a consistent direction for interpreting the target variable. Results reported only as limits, such as UVT below 70%, were not treated as exact measurements, and values flagged for review were withheld from the target series. Available DOC measurements were retained as supporting information. The resulting

series represents an optical indicator of untreated source water conditions, rather than a direct measurement of DBP formation potential.

## 2.3 Risk assessment methodology

The risk assessment methodology combines local water quality observations with globally available environmental datasets to describe relative conditions associated with DBP precursors at each source. The term “DBP risk index” reflects the framework’s intended use in identifying conditions potentially relevant to DBP formation. When DOM proxies are used as targets, higher or lower index values indicate relative precursor-related conditions. Their implications for DBP formation require site-specific evidence linking those conditions to treatment outcomes. It was designed to limit the need for additional local measurements while retaining a site-specific basis for learning and evaluation. The workflow comprises five steps: preparation of local observations, characterisation of environmental drivers and source conditions, machine learning attribution and index construction, site validation, and application to future climate conditions (Figure 3).

The framework organises environmental influences into three sub-indices representing organic matter production, mobilisation and delivery. These provide a conceptual structure for interpreting the environmental associations identified through machine learning. Their relative contributions are determined separately for each site, allowing the index to reflect differences in the relationship between the selected target variable and its environmental setting.

In this application, the target variables were DOM proxies. The resulting index therefore describes relative precursor-related conditions within each site, rather than DBP concentrations, measured formation potential or human exposure. The process grouping supports interpretation but does not constitute a mechanistic simulation of organic matter production or transport.

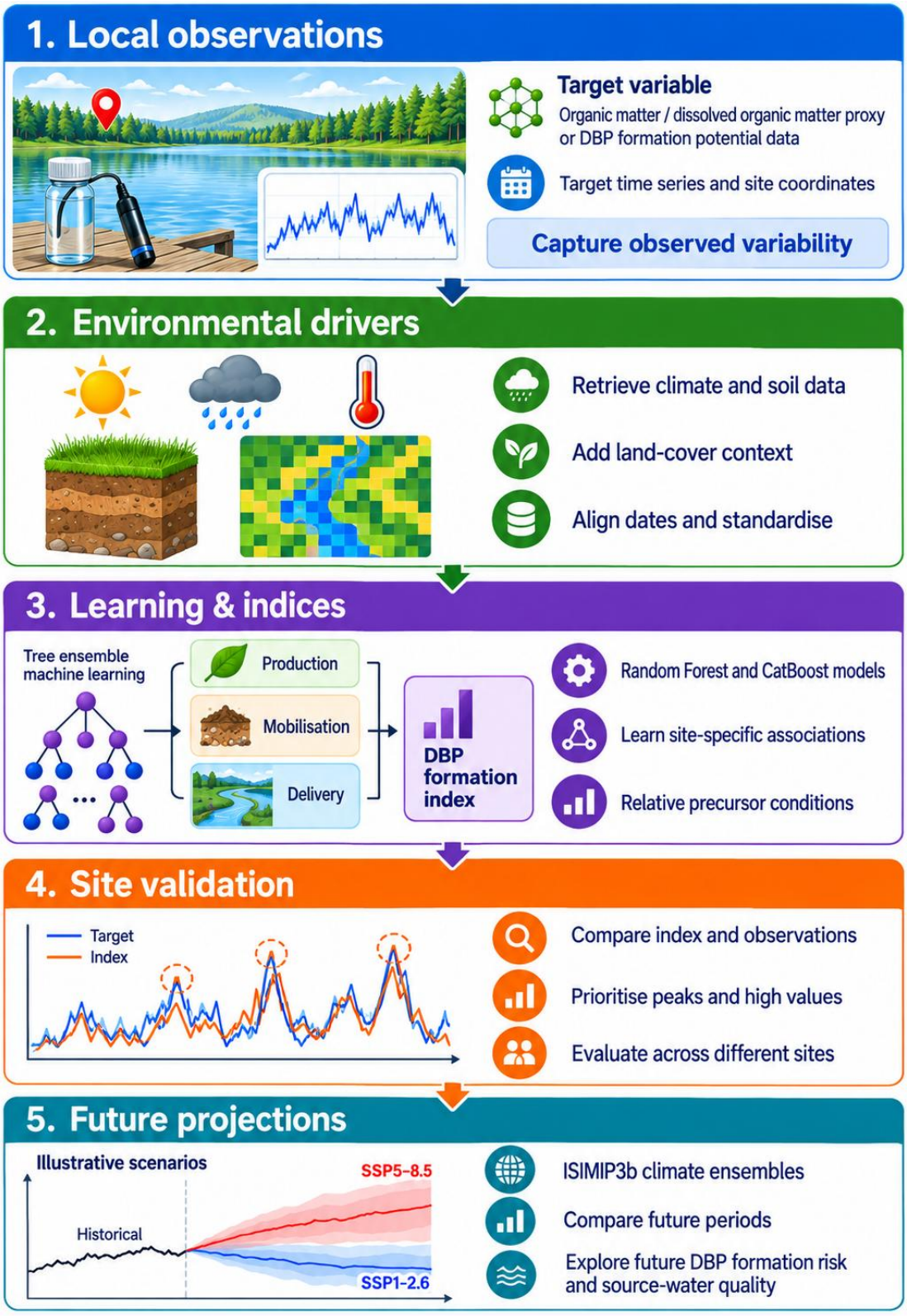



***Figure 3.*** *Overview of the five-step risk assessment methodology, from local observations and environmental drivers to index construction, site validation and future climate application.*

### 2.3.1 Step 1: Local observations

The first step involved preparing a local target time series and identifying the coordinates of the corresponding source. A suitable target should capture variability relevant to the assessment, whether through an organic matter measurement, an optical DOM proxy or DBP formation potential measurements. Its meaning determines how the resulting index should be interpreted and evaluated.

For the present study, we used temperature-corrected CDOM at Feeagh, the optical signal at 350 nm at the intoDBP Case Study Site, and a UV-transmittance-derived absorbance proxy at Magheracloone, as described in Section 2.2. The intoDBP Case Study Site measurements at 440 nm were retained as complementary observations and were not included among the environmental predictors.

Observations were organised on a daily calendar while retaining their original measurement units. Hourly observations were aggregated only where the required daily coverage was available, and existing quality flags and reporting qualifiers were respected. Missing target values were not interpolated. Model fitting and evaluation used dates with valid observations and complete environmental inputs, while the full calendar was retained for subsequent index calculation.

### 2.3.2 Step 2: Environmental drivers and source characterisation

Daily atmospheric and soil variables were obtained from ERA5 and ERA5-Land, respectively, using the coordinates of each site (Hersbach et al., 2020; Muñoz-Sabater et al., 2021). Atmospheric inputs included mean air temperature, relative humidity, precipitation, surface pressure, cloud cover, wind speed and shortwave radiation. Soil inputs comprised temperature and volumetric moisture for the 0–7, 7–28 and 28–100 cm layers, together with the integrated 0–100 cm layer. These datasets provided environmental information across the sites without requiring equivalent local monitoring networks.

The selected variables describe thermal conditions, energy availability, soil wetness and precipitation-related influences that may be associated with organic matter variability. A cosine transformation of day of year was also included to represent broad seasonality

(see Mercado-Bettín et al., 2026). Antecedent precipitation conditions were characterised using the Standardised Precipitation Index at one- and three-month scales (SPI-1 and SPI-3). SPI was calculated using calendar-month gamma distributions, including the probability of zero precipitation, fitted to the 1991–2020 ERA5 reference period. Each daily record received the SPI value for the last completed month, avoiding the use of rainfall from later in the same month.

Source conditions were characterised using the revised CORINE 2018 land-cover inventory (see Mercado-Bettín et al., 2026) and EPA nested lake-catchment boundaries. The contributing lake catchments were used for Feeagh and intoDBP Case Study Site, while the mapped surface catchments of the Magheracloone source lakes were combined, removing overlapping areas. Land-cover polygons were intersected with these boundaries, and their areas were calculated using a European equal-area projection.

Classes were grouped into organic-rich soil land cover, agriculture, grassland, urban, coniferous forest, mixed forest and inland water. This procedure was in line with the work undertaken by Mercado-Bettín et al. (2026). Peat bogs represented the organic-rich soil category. This was a land-cover proxy rather than a complete map of soil organic carbon. Percentages used the full assessment area as the denominator, with unmatched classes retained separately. Land cover provided static catchment context and was not included as a changing predictor in the models fitted separately to each site.

Environmental variables were aligned with the observations and retained in both original and standardised form. Standardisation used training-period means and standard deviations, with the same parameters applied to subsequent dates.

### *2.3.3 Step 3: Machine learning attribution and index construction*

Machine learning was applied building on the experience developed in previous published work within this work package. Random Forest and CatBoost regression models were fitted separately for each site to identify environmental associations with the local target variable (Figure 4). Both methods accommodate nonlinear relationships and interactions, allowing the importance of individual drivers to differ between sites (see more details in Mercado-Bettín et al., 2026).

The earliest 80% of eligible observations were used for model fitting and the latest 20% for variable attribution. Model settings were selected through a limited randomised search using three chronological cross-validation splits within the training data and root mean square error as the selection criterion. The tree-based models used variables in their original units, as standardisation was not required for their fitting.

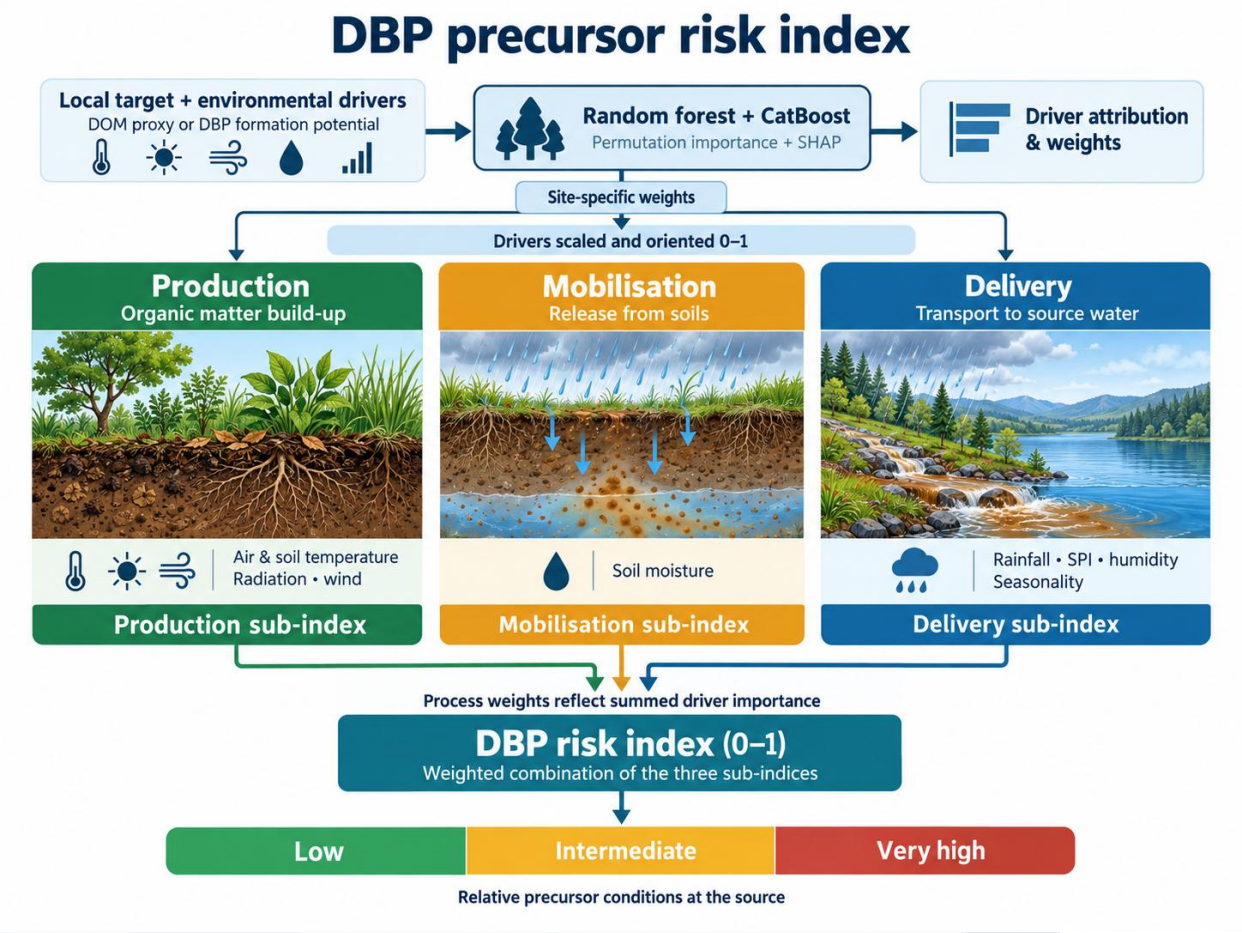



***Figure 4.*** *Conceptual framework combining machine-learning attribution and the production, mobilisation and delivery sub-indices into a relative DBP precursor risk index.*

Random Forest importance was calculated from the increase in error when individual predictors were randomly permuted in the later observation period. CatBoost importance was calculated from mean absolute SHAP values, which describe the magnitude of each predictor's contribution to model predictions. Each model's importance scores were normalised to represent proportions of its total importance, with negative Random Forest permutation scores assigned zero contribution. The two sets of scores were then combined, assigning 80% weight to Random Forest and 20% to CatBoost. This fixed

combination gave greater influence to Random Forest while retaining information from CatBoost. The resulting scores describe model reliance on the available predictors and should not be interpreted as causal effects.

Environmental variables were subsequently organised into three conceptual process groups. Production represented conditions associated with the generation, transformation and availability of organic matter. This group included air temperature, soil temperature, shortwave radiation and wind speed, with wind retained as an ancillary environmental driver within the adopted classification. Mobilisation represented soil wetness conditions associated with the release and movement of available organic matter and was described by the soil-moisture variables. Delivery represented precipitation-related and seasonal conditions associated with transport towards the source, using precipitation, SPI-1, SPI-3, relative humidity and the seasonal cosine term. These groups support interpretation but do not physically separate processes, as individual variables may influence more than one of them.

Cloud cover and surface pressure were retained during machine learning attribution but excluded from the process index under the adopted classification. Each remaining driver was scaled between zero and one using its training-period minimum and maximum. Values outside this range were assigned the corresponding endpoint. The direction of each score was determined from its training-period Spearman correlation with the target. Positively associated drivers retained their scaled values, while negatively associated drivers were inverted, so that higher scores consistently represented conditions associated with higher target values. Constant variables and variables with zero or undefined correlation were excluded.

The combined importance scores of the retained variables were then normalised again so that their weights summed to one. These weights determined both the contribution of individual drivers and the relative importance of the three processes. Within each process, the scaled driver scores were combined as a weighted average, giving greater influence to variables with higher importance. The weight assigned to that process in the overall index was the sum of its constituent variables' weights. The overall index was then calculated as the weighted average of the three sub-indices (Figure 5).

Consequently, production, mobilisation and delivery were not assigned equal contributions; their influence depended on the site-specific associations identified through machine learning.

The resulting index ranges from zero to one, with higher values representing conditions associated with higher target values within the site's observational setting. Observations were used to derive the weights and score directions but were not included as daily index components. The index could therefore be calculated on dates without target observations where all positively weighted drivers were available. Missing required drivers were not compensated for by increasing the weights of those remaining.

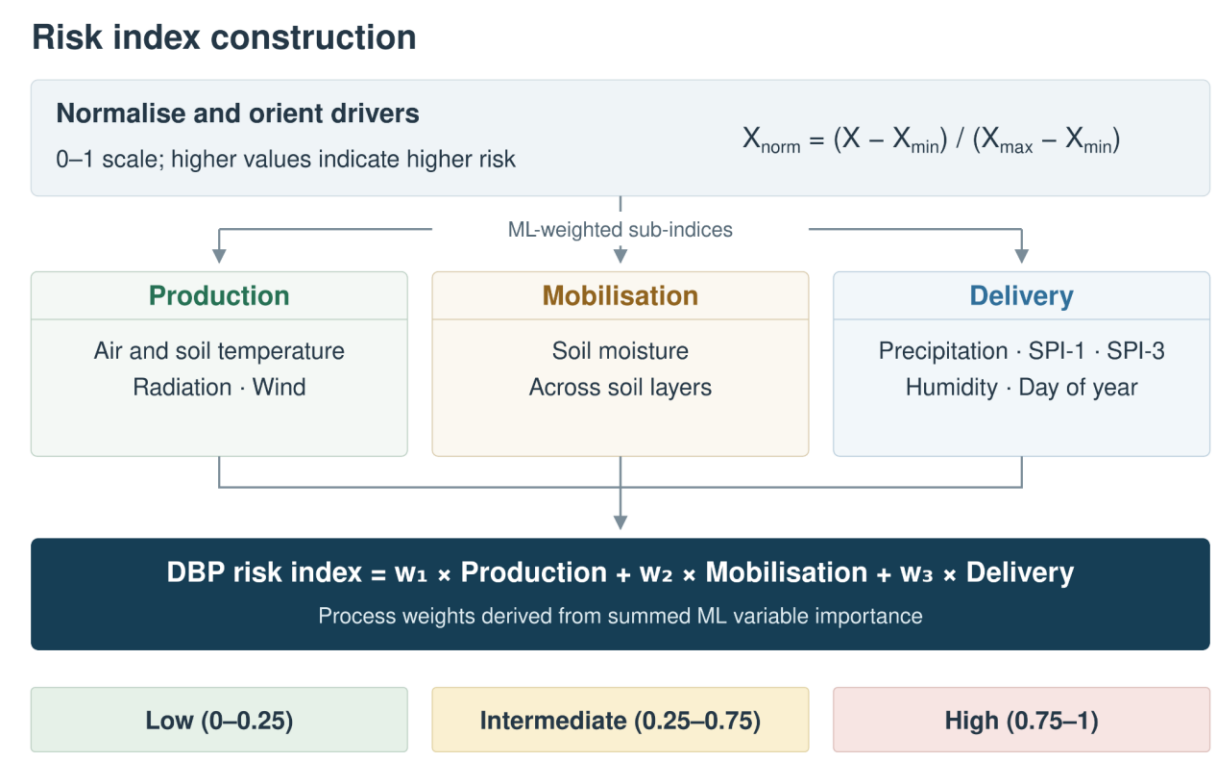



***Figure 5.*** *Construction of the DBP risk index from normalised environmental drivers, machine-learning-weighted production, mobilisation and delivery sub-indices, and classification into low, intermediate and high relative risk.*

This aggregation provides an interpretable summary of the environmental associations identified by the models. However, it simplifies those relationships into weighted contributions and does not reproduce all the nonlinear or conditional effects captured during machine learning.

### 2.3.4 Step 4: Site validation

The index-building procedure was evaluated separately at each site using three successive chronological evaluation blocks. Models, importance weights, scaling parameters and score directions were reconstructed using earlier observations, with separate fitting and calibration subsets and seven-day gaps between stages. This avoided treating the observations used to derive importance weights as independent validation data.

Validation combined quantitative performance metrics with visual inspection of the time series and observed peak episodes. High and extreme observations were defined using the 80th and 90th percentiles of the fitting-period target distribution, respectively. Index alert thresholds were selected using the calibration subset to maximise the $F_2$ score, which gives greater emphasis to recall than precision, subject to a maximum calibration alert fraction of 35%. When fewer than five high or non-high calibration observations were available, an 80th-percentile score threshold was used, adjusted where necessary to satisfy this constraint. These calibrated alert thresholds were distinct from the fixed Low, Intermediate and High screening bands used in the figures (Figure 6).

Quantitative metrics included Spearman rank correlation, precision, recall, $F_2$ and average precision. Precision measured the proportion of alerts corresponding to high observations, while recall measured the proportion of high observations detected. Average precision assessed the ranking of high observations across score thresholds. Additional diagnostics included false-alarm measures, detection of extreme observations and recall weighted by the observed excess above the high-value threshold. Consecutive high observations were grouped into sampled episodes using a maximum separation of 1.5 times the typical sampling interval, with detection assessed both within each episode and at its observed peak.

Results were calculated separately for each chronological evaluation block and pooled across blocks using reference-standardised scores. A seasonal model based on annual sine and cosine terms provided a comparator. Conditional 95% confidence intervals for selected pooled metrics were estimated using 500 moving-block bootstrap resamples, with intervals withheld where event support was insufficient. The evaluation assessed

the index-building procedure reconstructed from earlier data and its ability to identify concurrent precursor conditions, it did not establish forecasting performance or directly validate DBP formation.

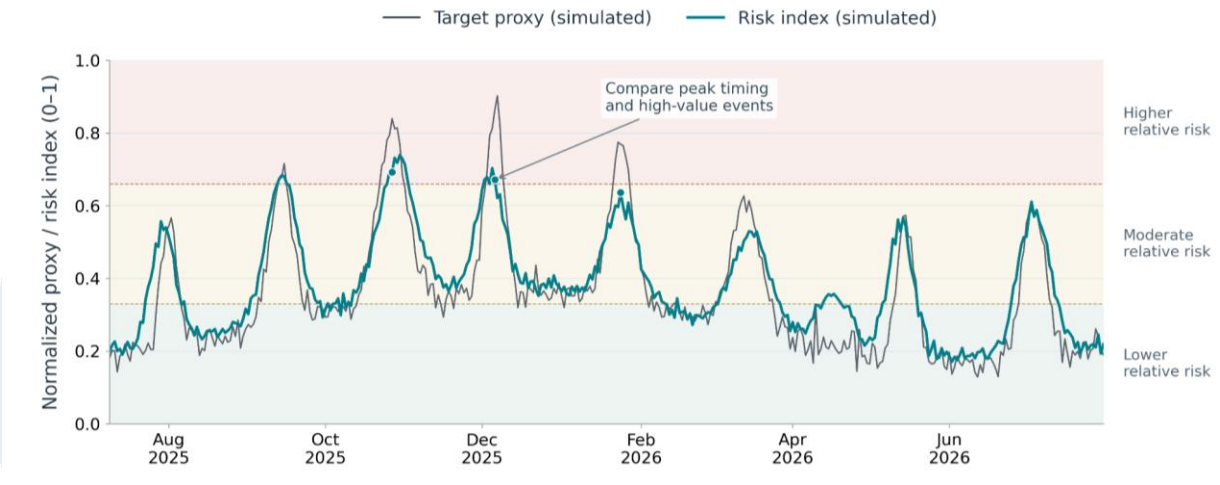



***Figure 6.*** *Illustration of site validation using simulated target and risk-index series, highlighting peak timing, elevated values and relative risk levels.*

### 2.3.5 Step 5: Future climate application

Future environmental inputs were obtained from phase 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) (Lange and Büchner, 2021). The selected atmospheric dataset provides CMIP6 climate-model outputs bias-adjusted against W5E5 on a regular 0.5° × 0.5° grid at daily resolution. Data were extracted from the grid cell nearest each site's coordinates, providing a consistent spatial basis for historical and future calculations.

An ensemble of five global climate models was used: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL. Two contrasting scenarios were considered: SSP1–2.6 and SSP5–8.5, representing comparatively low and very high emissions pathways. Other scenarios can be incorporated where compatible inputs are available.

Eleven atmospheric variables were retrieved, including mean, minimum and maximum air temperature; precipitation and snowfall; relative and specific humidity; wind speed; surface pressure; and incoming shortwave and longwave radiation. Variables required by the index were converted to the same units as the historical inputs, while additional

fields were retained separately. SPI followed the same calculation and fixed 1991–2020 ERA5 reference used in the historical framework.

The period 1985–2014 was selected as the climate-model historical baseline. Daily future inputs covered 2015–2100, with comparisons focused on 2041–2050, 2061–2070 and 2091–2100 (see Figure 7). Each climate model was processed separately, and future changes were calculated relative to that model's own historical baseline. This baseline served a different purpose from the 1991–2020 reference used to calculate SPI.

The site-specific index weights, scaling limits and score directions were retained without fitting new relationships to future data. Annual and period summaries included mean index values and the 95th percentile of daily values. Keeping individual climate models separate allowed differences between their projections to be examined alongside differences between scenarios.

The selected atmospheric dataset did not provide directly equivalent inputs for the depth-specific soil-temperature and soil-moisture variables used in the historical index. Where a positively weighted driver was unavailable, the calculation therefore retained a missing point estimate and reported lower and upper bounds obtained by allowing its unknown scaled contribution to range from zero to one. These bounds describe incomplete information about required drivers and are distinct from the spread between climate models. Complete projections of the original index require compatible soil inputs or a revised index that is independently evaluated. These omissions can affect the production sub-index through missing soil-temperature inputs and the mobilisation sub-index through missing soil-moisture inputs. However, their influence on the overall assessment is site-specific: greater weights assigned to unavailable drivers result in wider bounds and less precise estimates of future relative risk. Where these bounds span more than one risk category, the future risk level cannot be assigned unambiguously. The available atmospheric inputs therefore support a partial assessment, while conclusions about changes in average and high-risk conditions remain conditional on the contributions of the missing soil variables at the site being assessed.

An additional sensitivity calculation was used to illustrate future index distributions by fixing unavailable normalised driver scores at 0.5, the midpoint of their permitted 0–1

range. This provided an illustrative reference assumption, rather than an estimate of future soil conditions, and complemented the lower and upper bounds described above.

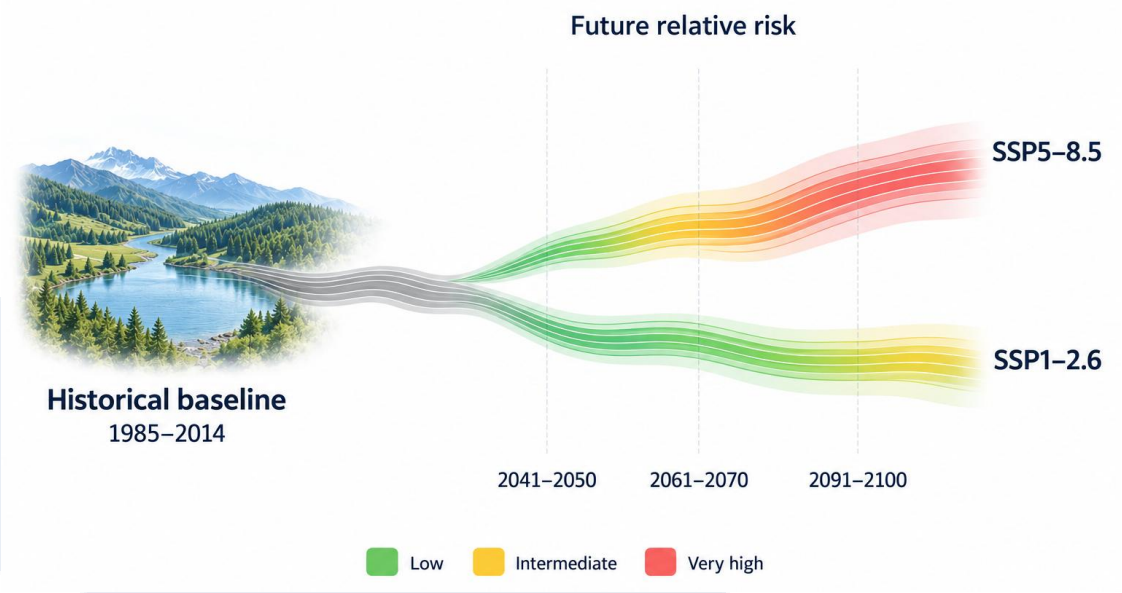



***Figure 7.*** *Conceptual illustration of future relative risk assessment under two contrasting climate scenarios, compared with the historical baseline and accounting for climate-model spread.*

The future calculations also retain uncertainty associated with transferring relationships learned from ERA5-based inputs to the ISIMIP3b climate dataset. Matching units and applying fixed scaling parameters do not establish agreement between their distributions. Furthermore, clipping at the historical training limits means that the index cannot distinguish increasingly extreme driver values beyond those limits. Future outputs were therefore treated as provisional indications of changes in relative precursor-related conditions, conditional on the available inputs and the transferability of the historical relationships.

## 2.4 Source water protection

Source water protection (SWP) refers to actions implemented within a catchment and along its connected flow pathways to maintain or improve water quality and quantity before abstraction and drinking water treatment (Islam et al., 2011). In this work, the main interest is organic matter originating in the surrounding landscape and entering the water body, together with pressures that may influence its production within the source. Protection measures can address the activities generating these inputs, the conditions

allowing their mobilisation, or the pathways through which they reach the water. The objective is to limit avoidable inputs and unfavourable changes while recognising the natural ecological role of organic matter.

Although source protection is widely used to address sediment (DTC, 2020, Strauch et al., 2013, Zhang and Zhang, 2011, Barling and Moore, 1994), nutrients (Liu et al., 2025, Zhang et al., 2021) and microbial contamination (Linnane et al., 2011), its application specifically to DOM and DBP precursors remains less developed in research, with mitigations for DBP reduction largely focused on the design and operational practice within the drinking water treatment plant. Previous work within this WP5 of the intoDBP project (D5.3) identified potential SWP measures which had the potential to mitigate against DOM input to water treatment plants and examined their practical implementation. It also highlighted that evidence of their effects on DOM is often limited, variable or dependent on local conditions. The present methodology builds on that work by connecting the assessment of precursor-related conditions with candidate actions at the source, complementing the measures undertaken during treatment.

The candidate protection measures were selected following the outcomes of D5.3 and followed by a feasibility assessment on sixteen of the twenty four identified SWP measures based on the Multi-criteria decision analyses (MCDA) framework (Ngubane et al., 2024). The selection of evaluation criteria was based primarily on the criteria from Ngubane (2024) namely Project funding, Capital costs, Community buy-in, Potential Economic Benefit. However, to comprehensively reflect multiple demands by the whole range of stakeholders who have an interest in reducing DBPs in drinking water some amendments and additions were made based on the previous literature review. The added criteria of co-benefits incorporates Ngubane's criteria of aesthetics as one of the co-benefits, but the additional co-benefits of carbon sequestration, biodiversity, flood mitigation, greenhouse gas emission reduction and other pollutants of interest were also included as subcategories under this criteria. The sustainability and feasibility criteria that were used in Ngubane (2024) were re-categorised as effectiveness in this study. The criteria of 'EU policy framework' was added to project funding as an extra criteria and the total number of papers used as evidence was also added as a criteria.

The criteria were ranked in order of importance high to low by researchers and weighted using the Rank Sum (RS) method using Eq(1), where Wi is the weight of the ith criteria of n and ri was its ranking as determined by professional expertise (Eq 1). The sum of all weights must be equal to 1.00.

$$w_i = \frac{2(n+1-r_i)}{n(n+1)} \quad \text{Eq 1.}$$

The criteria weights for the Multi-Criteria Analysis were determined using a subjective method, deeply rooted in the authors' collective professional experience in freshwater systems. This approach, which draws upon the nuances of expert judgment and preference is consistent with established methodologies for weight determination, particularly the Multiplicative Analytical Hierarchy Process (AHP) and the Simple Multi-Attribute Rating Technique (SMART) (Chen et al., 2022). A defined scope for each score (0,1,2,3) was assigned in order to assess each of the 16 measures on each criteria (Appendix A1). The scoring was informed by the literature but required judgements by the research team to assess the evidence presented from the literature. In cases where literature was insufficient, the indicator was scored as having no evidence (0). The feasibility scoring results are presented in Appendix A2. Additionally, by taking into account the particular characteristics that influence DOM movement and attenuation, the sixteen SWP measures assessed for feasibility were evaluated for their potential to mitigate against each of the processes (production, mobilisation and delivery) under each land use type as proposed in the risk assessment framework (Appendix A3).

The candidate protection measures and their links to the risk assessment are presented in Tables 1 and 2. This connection is organised through a matrix combining three elements: land cover within the contributing area, the most relevant process identified by the assessment, and the relative risk level. Land cover describes the setting in which measures could be applied, while the process weights and sub-indices help identify whether attention should focus on conditions associated with production, mobilisation or delivery. Together, these elements guide the selection of candidate measures for further assessment. They do not establish the location or magnitude of individual organic matter sources or demonstrate the effectiveness of an intervention. Where several land covers or processes are relevant, more than one matrix combination should be considered. This

can be used by water managers in combination with the feasibility criteria to select the most suitable SWP protection measures based on their own specific needs. For example, a measure which requires more community buy-in or one that provides a higher potential economic benefit may be selected under three risk category indices, Low, Intermediate and High, depending on individual conditions and local requirements.

The matrix uses Low, Intermediate and High as relative management categories. Low risk supports maintaining existing protection and checking for emerging pressures. Intermediate risk supports more targeted investigation and consideration of measures addressing identified pathways. High risk gives greater priority to confirming pressures, selecting suitable actions and evaluating their implementation. The numerical boundaries between these categories are defined in the index configuration, rather than by the protection matrix, and remain consistent when comparing historical and future conditions. Their use supports prioritisation, while the suitability of the measures presented in Tables 1 and 2 requires confirmation against local pressures, source characteristics and practical implementation conditions.

***Table 1. Source water protection measures included in the assessment. Codes correspond to the combinations in Table 2. Definitions describe the measures and their intended functions.***

| Measure group | Codes and measures | Definition and intended function |
|---|---|---|
| **Peatland rehabilitation** | A: Drain blocking; B: Revegetation; C: Gully-side reprofiling | Restore wetness in drained peat, establish vegetation on exposed surfaces and stabilise eroding gullies. |
| **Manure management** | D: Slurry-spreading exclusion areas; E: Slurry export; F: Slurry separation and/or pelleting; I: Anaerobic digestion | Manage where manure is applied, redistribute surplus material, separate slurry fractions or biologically process organic material without oxygen. Residual material and digestate still require appropriate management. |

| | | |
|---|---|---|
| **Soil inputs and application timing** | G: Organic amendments, slash mulch or biochar; H: Avoid fertiliser application before heavy rainfall | Select and manage soil inputs and ground cover, accounting for potential leaching. The matrix uses a 48-hour rainfall-forecast window to screen application timing. |
| **Vegetated buffers** | J: Riparian buffer zones; K: Vegetated filter strips; N: Riparian tree planting | Establish or retain vegetation beside water bodies or across runoff pathways to protect banks and intercept material moving from surrounding land. |
| **Forest establishment and management** | L: Reforestation; M: Mixed-species forest establishment; P: Phased felling | Restore appropriate former woodland, diversify tree cover or stagger harvesting to manage the extent and timing of disturbance. |
| **Trees and hedgerows** | O: Tree pits; Q: Mixed-species hedgerows | Provide vegetated spaces for intercepting urban runoff or establish woody boundaries across the agricultural landscape. |
| **Bank and channel restoration** | R: Bank stabilisation; DD: Restoration of natural flow pathways | Stabilise eroding banks or restore suitable channel and floodplain connections, subject to local hydrological and ecological assessment. |
| **Vegetated runoff management** | S: Constructed wetlands or reed beds; T: Bioretention areas or rain gardens; U: Bioswales or grass waterways | Intercept and manage runoff through vegetated basins, soil media or channels before it reaches the receiving water. |
| **Flow and sediment controls** | V: Sediment ponds; W: Silt traps; X: Sand filters following silt traps; EE: Check dams | Slow runoff and retain suspended material within suitable drainage pathways. |
| **Cropping and soil management** | Y: Mixed cropping; Z: Crop rotation; AA: Conservation tillage; BB: Tramline management | Maintain crop or residue cover, manage soil disturbance and reduce concentrated runoff associated with cultivation and machinery tracks. |

| | | |
|---|---|---|
| **Livestock exclusion** | CC: Fencing | Restrict direct livestock access to water and vulnerable margins, allowing vegetation to recover and reducing local disturbance and waste inputs. |
| **Management of cultivated slopes** | FF: Contour farming; GG: Contour bunding or terraces | Arrange cultivation or construct suitable features across slopes to interrupt runoff pathways and reduce erosion. |

***Table 2. Candidate source water protection measures categorised by land cover, process and relative risk level.***

| Main land cover | Process | Low | Intermediate | High |
|---|---|---|---|---|
| Organic-rich soil land cover | Production | B | W | V |
| Organic-rich soil land cover | Mobilisation | A, EE | W | V |
| Organic-rich soil land cover | Delivery | B | W | C, V |
| Agriculture | Production | D, E, J, K | G, AA, Y, BB, Z | N, F, FF, GG |
| Agriculture | Mobilisation | K, J, H | Y, Z, BB | N, Q, GG, FF |
| Agriculture | Delivery | K, J, G, H, Z, Y | N, Q, CC, AA, BB, FF | W, V, S, I, GG |
| Grassland | Production | N | N | L |
| Grassland | Mobilisation | Q | W, N | V, L |
| Grassland | Delivery | K, Q | N | V, L |
| Urban | Production | O | U, T | S |
| Urban | Mobilisation | O, Q | U, T | S |

| | | | | |
|---|---|---|---|---|
| Urban | Delivery | K, O, Q | U, T | W, X, V, S |
| Coniferous forest | Production | EE | G | P |
| Coniferous forest | Mobilisation | EE | H | — |
| Coniferous forest | Delivery | J, W, EE | G, H | P |
| Mixed forest | Production | EE | G | M |
| Mixed forest | Mobilisation | EE | H | M |
| Mixed forest | Delivery | J, W, EE | G, H | M |
| Inland water | Production | U | T | S, DD |
| Inland water | Mobilisation | U | T | S, DD |
| Inland water | Delivery | J, U, T | R | S, DD |

Figure 8 summarises how the assessment informs the selection of candidate source protection measures. Assignment to a process does not imply an exclusive or demonstrated effect, and measures that retain sediment or nutrients should not automatically be assumed to reduce dissolved organic precursors. Selection should consider local pressures and their connection to the source, existing management, maintenance requirements and the involvement of landowners and water managers. For future assessments, differences between climate models and uncertainty arising from missing drivers should remain visible when setting management priorities. The framework does not quantify the risk reduction resulting from an intervention. Its recommendations therefore require local evaluation, supported by monitoring before and after implementation and, where feasible, comparison with an untreated area.

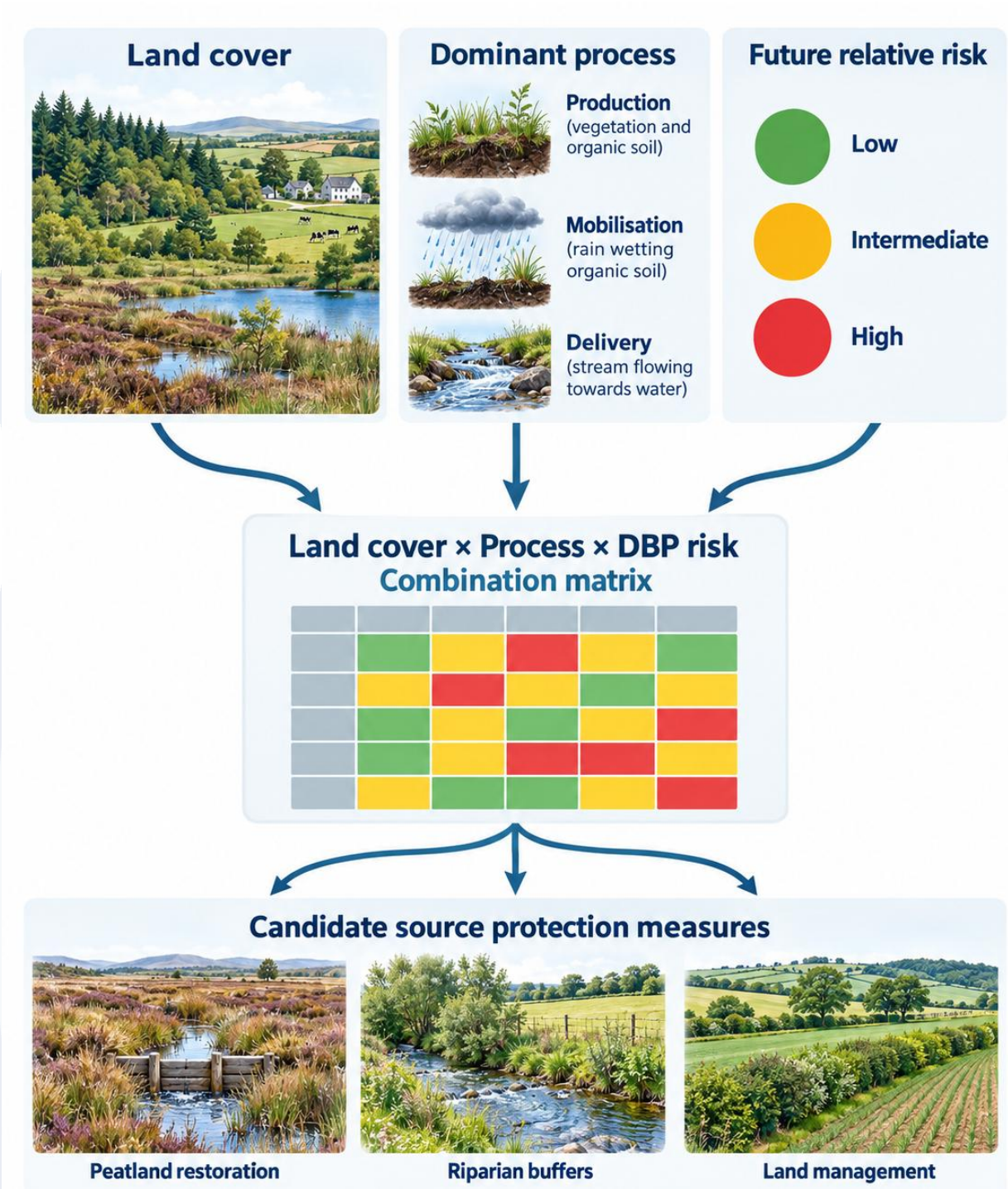



***Figure 8.*** *Linking land cover, dominant processes and future relative DBP risk to candidate source water protection measures through the combination matrix*

# 3. Results

The application of the methodology produced different temporal patterns and process weights at the three study sites. Comparisons with local observations showed periods of agreement between elevated DOM proxies and higher index values, alongside differences in their timing and magnitude. Future assessments also varied among sites, scenarios and periods, without a consistent increase in the annual mean index. These outputs were subsequently linked to the source protection matrix to identify candidate measures and the risk conditions associated with them.

## 3.1 Site validation

Quantitative forward validation showed that agreement between the index and observed precursor conditions varied between sites and evaluation periods. The metrics summarise three successive chronological evaluation blocks, with the index reconstructed from earlier observations for each block. Time-series comparisons provided a complementary visual assessment of variability and peak timing (Figures 9–11). The fixed Low, Intermediate and High screening bands shown in these figures were distinct from the calibrated alert thresholds used to calculate detection metrics.

At Lough Feeagh, the temperature-corrected CDOM observations showed substantial seasonal and interannual variability, which the index captured only partially (Figure 9). Some periods of elevated observations coincided with higher index values, but individual peaks and longer-term changes were not consistently represented. Across 1,791 paired validation observations, the pooled Spearman rank correlation was 0.447. The index detected 362 of 711 high observations, giving a recall of 50.9%, precision of 67.3% and $F_2$ score of 0.535. It detected at least one high observation in 22 of 41 sampled episodes and identified the observed peak in 20 episodes. Performance varied between evaluation blocks, with recall ranging from 21.8% to 71.8%. Average precision was similar to that of the seasonal comparator (0.695 versus 0.703), indicating limited overall improvement in distinguishing elevated conditions beyond the annual cycle.

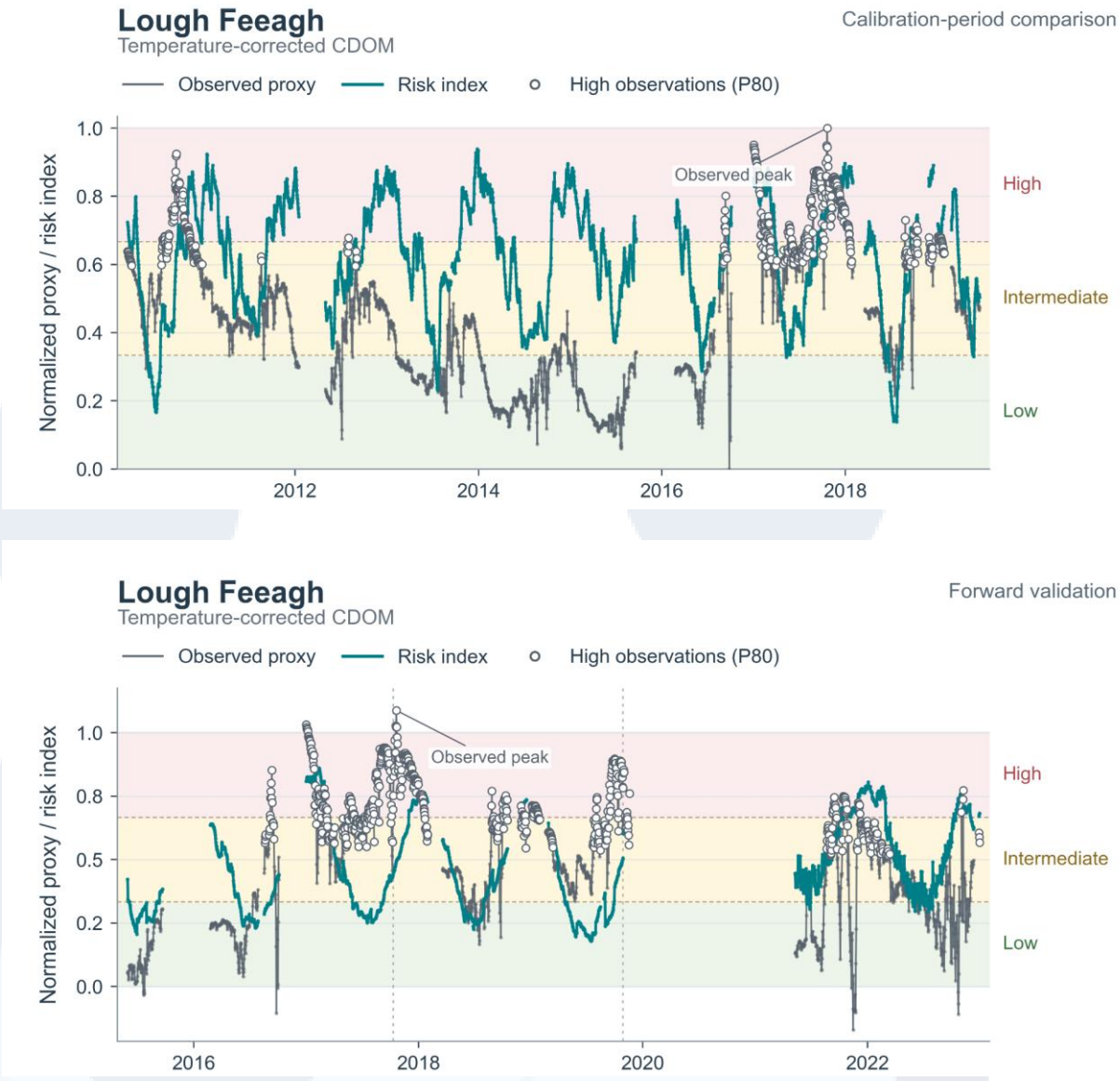



***Figure 9.*** *Calibration and validation of the relative DBP risk index at Lough Feeagh against the normalised DOM proxy. Shaded bands indicate Low, Intermediate and High risk.*

At the intoDBP Case Study Site, the 350 nm optical proxy showed short, pronounced peaks, whereas the index frequently represented elevated conditions as more sustained periods (Figure 10). Across 171 paired validation observations, the pooled Spearman rank correlation was 0.277. The index detected 17 of 20 high observations, nine of ten extreme observations and six of seven sampled high episodes. Recall was therefore high (85.0%), but precision was 24.6%, with 52 of 69 alerts occurring on sampling dates without a high observation; the $F_2$ score was 0.570. The largest validation observation in late May 2026 triggered an alert under the calibrated threshold, although it did not

coincide with a similarly pronounced index maximum. Average precision was lower than that of the seasonal comparator (0.601 versus 0.815). These findings remain preliminary because only seven high episodes were available and 19 of the 20 high observations occurred in the final evaluation block.

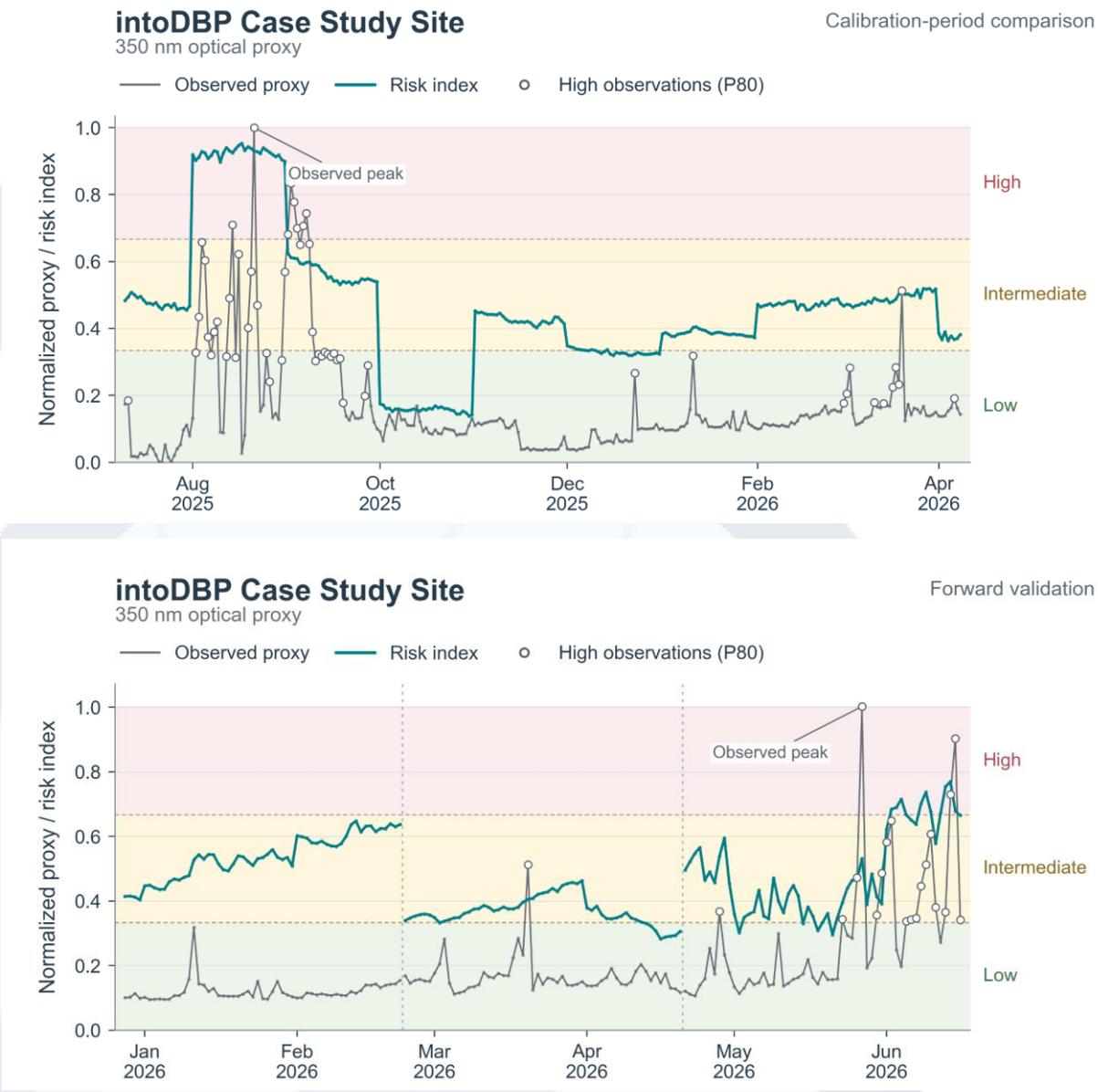



***Figure 10.*** *Calibration and validation of the relative DBP risk index at the intoDBP Case Study Site against the normalised DOM proxy. Shaded bands indicate Low, Intermediate and High risk.*

At Magheracloone, the UVT-derived absorbance proxy showed intermittent peaks and substantial variation between successive observations (Figure 11). The visual comparison indicated periods of correspondence, but the index also remained elevated when observations were comparatively low. Across 66 paired validation observations, the pooled Spearman rank correlation was 0.084. The index detected one of six high observations and one of four sampled high episodes, while none of the three extreme observations was detected, including the largest observed value in August 2025. Recall was 16.7%, precision was 5.3% and the $F_2$ score was 0.116. Average precision was 0.108, compared with 0.158 for the seasonal comparator. These results indicated weak screening performance over the evaluated period, although the small number of high observations and episodes limited the strength of inference. Bootstrap confidence intervals were withheld because the minimum event-support criteria were not met.

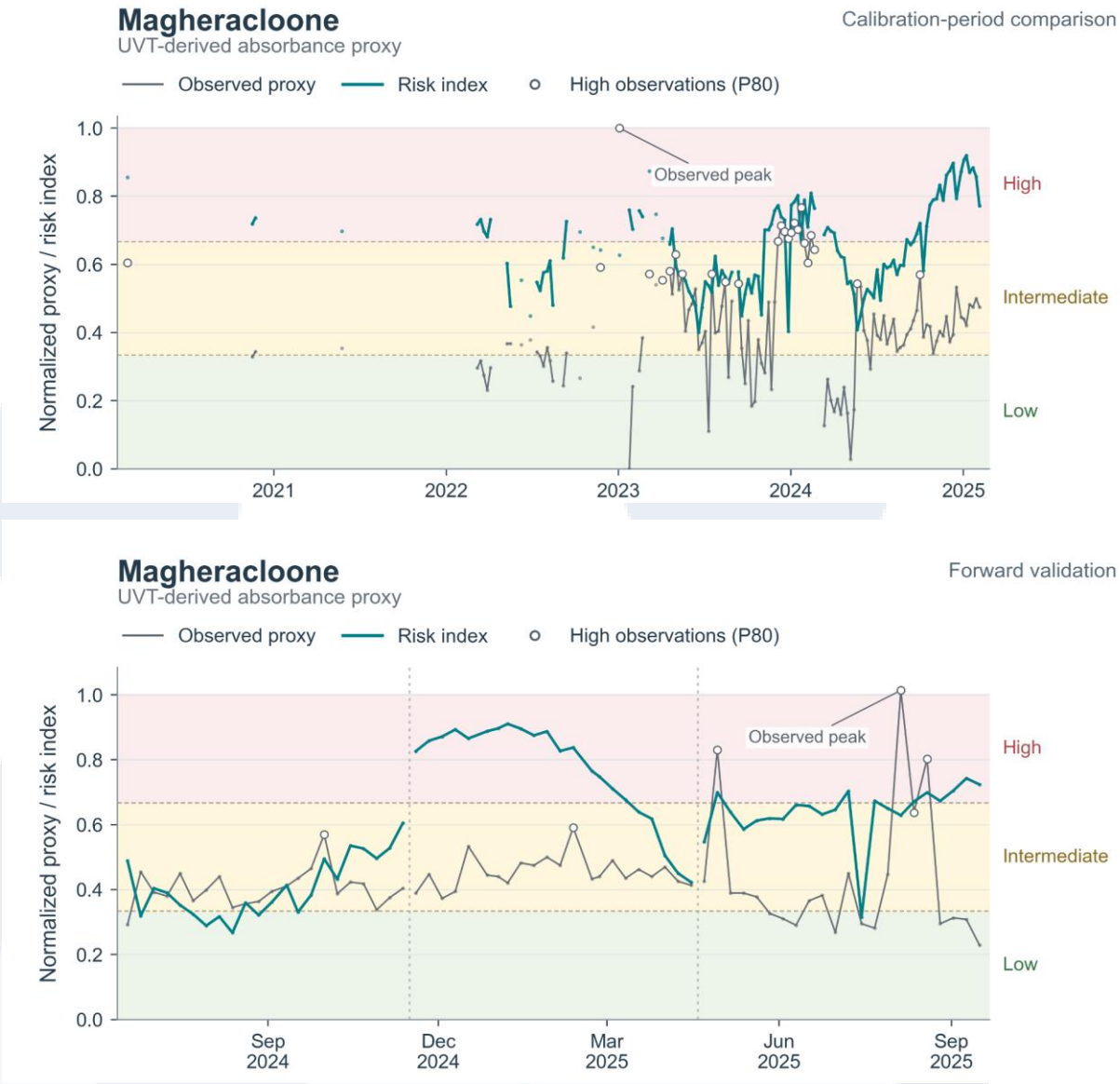



***Figure 11.*** *Calibration and validation of the relative DBP risk index at Magheracloone against the normalised DOM proxy. Shaded bands indicate Low, Intermediate and High risk.*

Overall, the evaluation showed variable screening performance and no consistent improvement over the seasonal comparator. For Lough Feeagh and the intoDBP Case Study Site, the conditional bootstrap intervals for the difference in average precision included zero, providing no clear evidence of improved discrimination. Detection of elevated observations therefore needs to be interpreted alongside false alerts, variability between evaluation periods and the number of sampled episodes available.

The historical index weights also differed among sites (Figure 12). At Lough Feeagh, mobilisation accounted for 61.4% of the total weight, followed by delivery (32.3%) and production (6.4%). Delivery dominated at the intoDBP Case Study Site (69.4%), with smaller contributions from production (19.7%) and mobilisation (10.9%). Magheracloone showed a similar ordering, with delivery contributing 73.7%, production 21.6% and mobilisation 4.7%. These percentages describe the historical index configuration; weights were re-estimated within each chronological validation block. The contrasting contributions illustrate how the index was adapted to the observational relationships identified at each site.

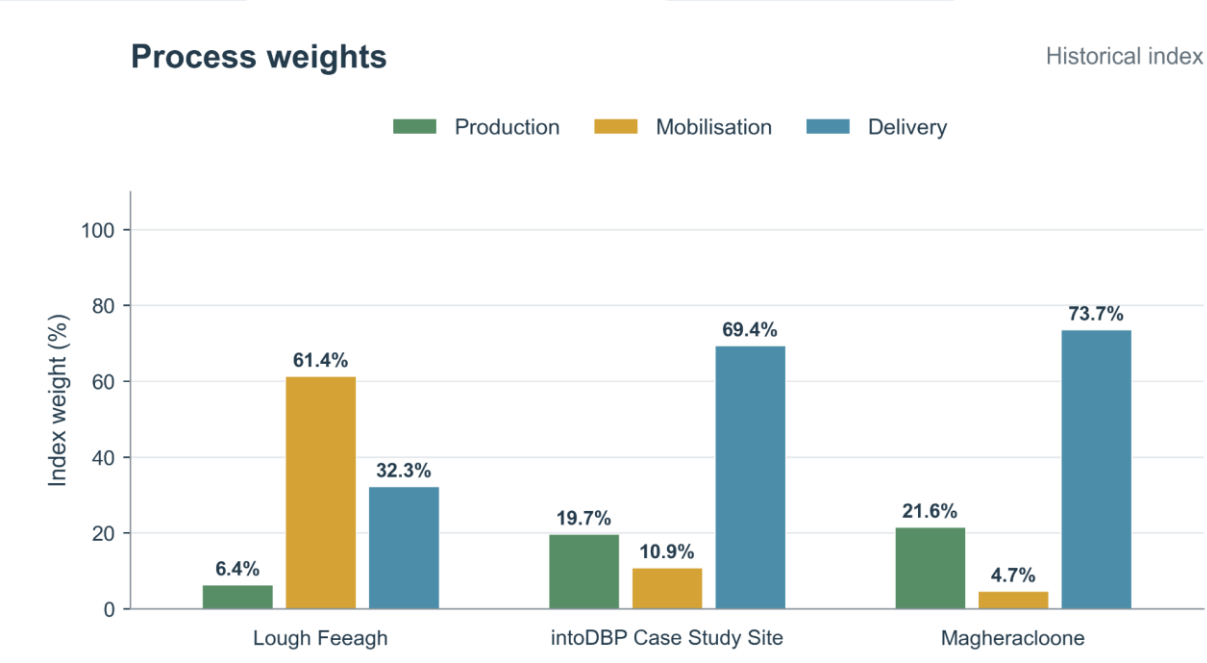



***Figure 12.*** *Relative weights of production, mobilisation and delivery in the site-specific risk indices, derived from machine-learning attribution.*

## 3.2 Potential future levels of risk

The annual distributions compared the historical baseline (1985–2014) with three future decades under SSP1–2.6 and SSP5–8.5 (Figures 13–15). The boxplots represent the sensitivity calculation in which unavailable driver scores were fixed at 0.5. Their spread therefore includes differences between climate models and years, but excludes uncertainty associated with those missing contributions. Several future distributions had

wider interquartile ranges than the baseline, although neither variability nor mean risk increased consistently across all sites and scenarios.

At Feeagh, annual mean index values remained close to the historical mean of approximately 0.465 (Figure 13). Changes relative to the baseline were small, ranging from approximately −0.001 to +0.002 index units across the future periods and scenarios. Both scenarios showed slight increases in 2041–2050, while the direction of change varied in the subsequent decades. The future distributions overlapped strongly with the baseline and with each other. Their central ranges were generally somewhat wider, but annual means remained within the Intermediate category in this sensitivity calculation.

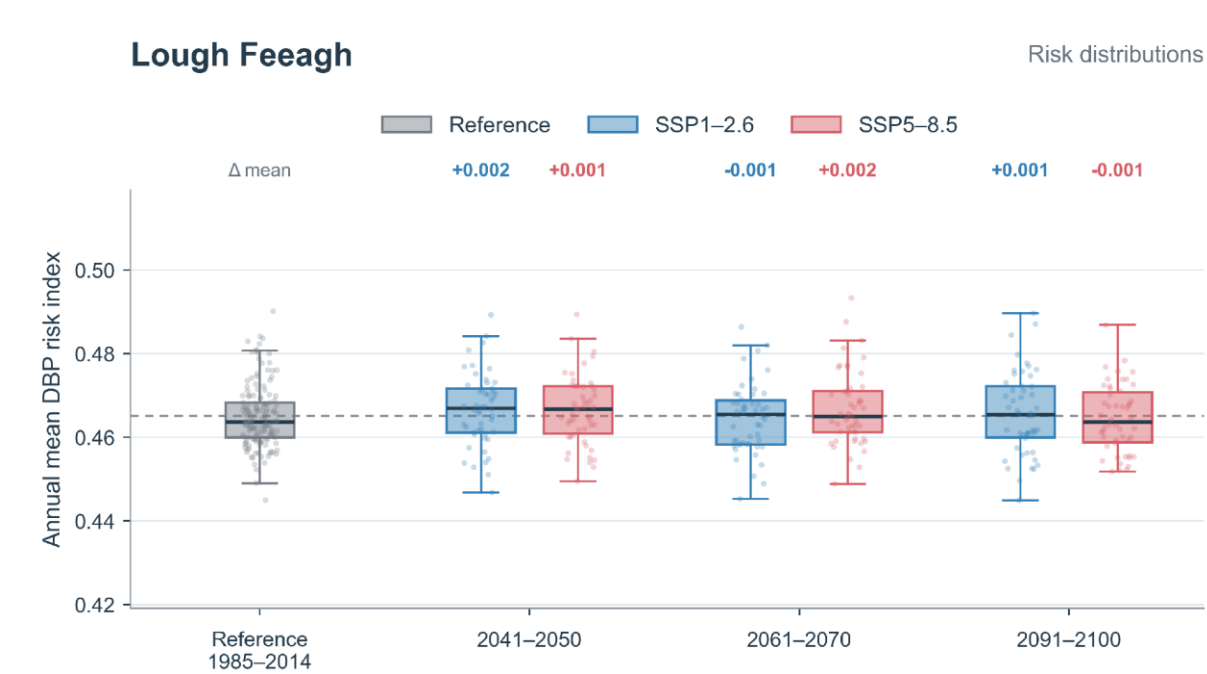



***Figure 13.*** *Annual mean DBP risk index at Lough Feeagh for the historical baseline and three future decades under SSP1–2.6 and SSP5–8.5. Boxes show the median and interquartile range; points represent individual climate-model years.*

The intoDBP Case Study Site showed a broader distribution of annual means and more variation in the direction of change (Figure 14). Relative to the baseline mean of approximately 0.452, the mean increased to approximately 0.465 under SSP1–2.6 and 0.470 under SSP5–8.5 in 2041–2050. Both scenarios remained slightly above the baseline in 2061–2070. By 2091–2100, SSP1–2.6 remained slightly higher, whereas

SSP5–8.5 decreased to approximately 0.442. The distributions overlapped substantially, with particularly broad variability under SSP1–2.6 towards the end of the century. Annual means were predominantly Intermediate, although some model-year values fell within the Low category.

At Magheracloone, the historical mean was approximately 0.668, close to the boundary between Intermediate and High (Figure 15). Under SSP1–2.6, the mean remained almost unchanged in 2041–2050 and decreased slightly in the later periods. Under SSP5–8.5, the reductions became progressively larger, reaching approximately −0.029 index units in 2091–2100, when the mean was around 0.639. Annual distributions continued to include values on both sides of the Intermediate–High boundary, despite the downward shift in their central values. The results therefore showed lower annual mean conditions under the later SSP5–8.5 periods, while retaining years with comparatively elevated index values.

Across the three sites, the annual distributions showed substantial overlap between scenarios. The changes in their central values were generally smaller than the spread among individual model-year results. These annual summaries also differed from the daily risk classification used for the source protection assessment, which retained shorter periods of elevated risk within otherwise lower annual averages.

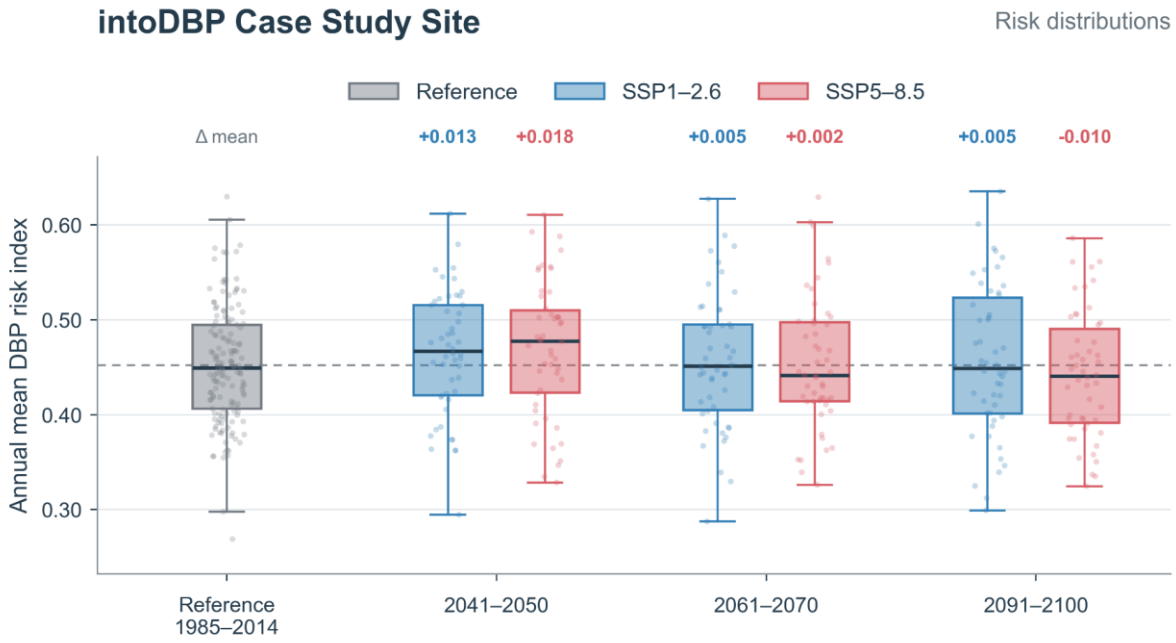



***Figure 14.*** *Annual mean DBP risk index at the intoDBP Case Study Site for the historical baseline and three future decades under SSP1–2.6 and SSP5–8.5. Boxes show the median and interquartile range; points represent individual climate-model years.*

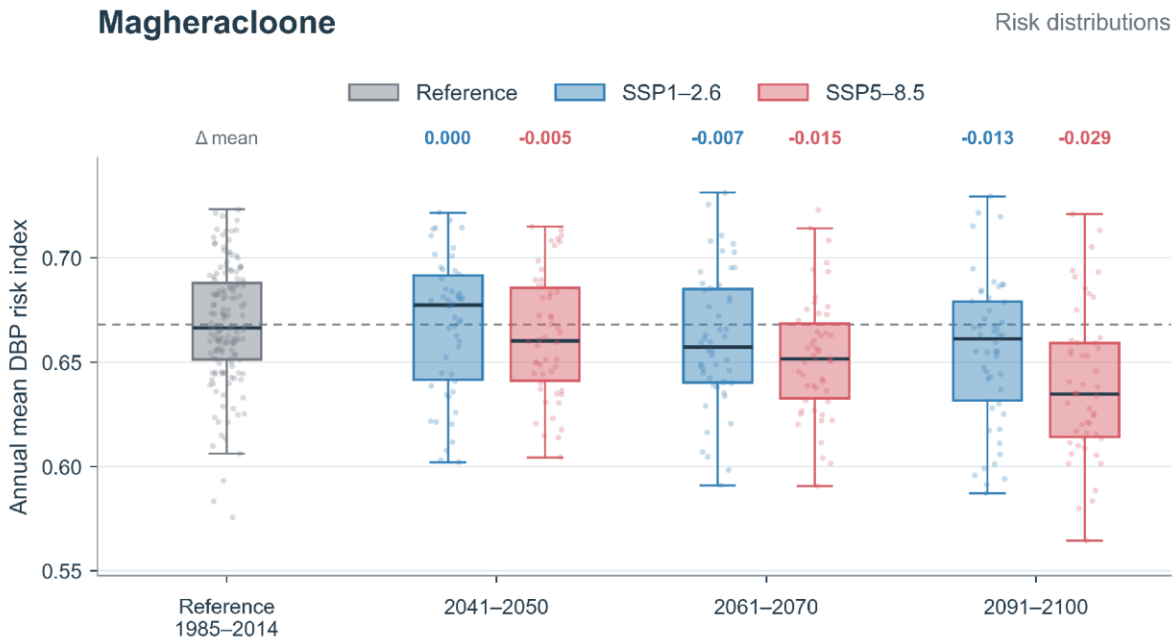



***Figure 15.*** *Annual mean DBP risk index at Magheracloone for the historical baseline and three future decades under SSP1–2.6 and SSP5–8.5. Boxes show the median and interquartile range; points represent individual climate-model years.*

## 3.3 Linking risk assessment with source water protection

The source protection assessment combined the most dominant mapped land cover, the highest-weighted historical process and the daily risk classification. This produced 21 site–scenario–period assessments and 63 corresponding land-cover–process–risk combinations. The complete recommendations table is provided through an Excel workbook included in Supplementary Material A. It contains the candidate measures, action codes, risk frequencies and associated classification bounds for each assessment.

At Lough Feeagh, the assessment paired organic-rich soils, representing approximately 48.9% of the mapped assessment area, with mobilisation, the highest-weighted historical process. For this combination, the source water protection matrix identified drain blocking and check dams as candidate measures under Low relative risk, silt traps under Intermediate risk, and sediment ponds or basins under High risk. This linkage provides a structured basis for considering protection measures in relation to catchment characteristics and precursor conditions. The suitability of each intervention would require local assessment of drainage pathways, hydrological connectivity and its potential to reduce organic matter delivery to the lake.

At the intoDBP Case Study Site and Magheracloone, grassland was the dominant mapped land use category and delivery was the highest-weighted process. Consequently, both sites were associated with the same candidate action sets: vegetated buffer strips and mixed-species hedgerows for Low conditions, riparian tree planting for Intermediate conditions, and sediment ponds or basins and reforestation for High conditions. Their risk frequencies nevertheless differed.

At the intoDBP Case Study Site, all three categories included recurrent occurrences that could be assigned despite the missing-driver uncertainty. High conditions accounted for a minimum of 14.0% of simulated days during the baseline, with future minimum frequencies ranging from 15.2% to 20.3%. These are lower bounds on frequency rather than complete estimates. At Magheracloone, Intermediate and High conditions were recurrent throughout the assessment, while Low conditions were occasional or only

potentially present. The minimum frequency of High conditions was approximately 9.8% in the baseline and ranged from 7.8% to 11.5% across the future assessments.

Because land cover and the historical process weights were held constant, the candidate action sets remained the same across periods within each site. What changed was the frequency and certainty of the risk conditions associated with those actions. The table included in Supplementary Material A preserves this distinction, including occasional elevated conditions that would not be apparent from annual means alone. The listed measures represent the outcome of the matrix lookup; their effectiveness in reducing DOM or DBP formation was not estimated by this assessment.

## 4. Discussion

The results showed differences in both the temporal patterns of relative risk and the importance assigned to each process across the three sites. Mobilisation had the greatest weight at Feeagh, whereas delivery dominated at the intoDBP Case Study Site and Magheracloone. The index identified some periods of elevated proxy values, although agreement with individual observations and peaks varied during calibration and forward validation. Future sensitivity calculations showed little change in annual mean risk at Feeagh, mixed responses at the intoDBP Case Study Site and generally decreasing means at Magheracloone, with substantial overlap between scenarios. These findings remain conditional on the treatment of missing drivers and the transferability of the historical relationships, but illustrate the different responses obtained when a common framework is adapted to local observations.

The main contribution of this geospatial risk assessment methodology is to combine local water quality observations related to DOM with accessible environmental information in a form that can support investigation and management. The applications at Feeagh, the intoDBP Case Study Site and Magheracloone demonstrate how different observational records can be incorporated while retaining a common assessment structure. This flexibility is particularly relevant where monitoring is limited and more detailed modelling approaches would require information that is not readily available. The results demonstrate the necessity of local evaluation. A common methodology does not produce the same environmental associations or the same degree of agreement with observations at every source.

The organisation of the index into production, mobilisation and delivery draws on an established body of research on catchment hydrology, organic matter cycling and source water quality. Production represents conditions associated with the generation and accumulation of organic matter (Franklin et al., 2021). Mobilisation concerns its release and availability for transport, including changes associated with soil moisture and wetting and drying (Jennings et al., 2010; Ryder et al., 2014; Wu and Yao, 2022). Delivery represents the conditions through which available material reaches the water body (Arsenault et al., 2024). These processes interact where material accumulated during

one period may be mobilised and transported during subsequent rainfall (Anderson et al., 2023). Their separation within the framework provides a practical way of organising these dynamics, although the sub-indices do not measure individual carbon fluxes or fully resolve the processes occurring within the catchment and water body.

This simplification supports the intended purpose of the tool. By identifying environmental associations and retaining their process interpretation, the framework helps identify periods that warrant closer attention and aspects of the source system that require further investigation. The process weights provide a basis for interpreting the index, without establishing the causes of individual events or future changes. Such information is useful because the relationships between catchment conditions, source water precursors and subsequent DBP formation remain incompletely characterised at many drinking water sources, in Europe and elsewhere (Moore et al., 2008; Klante et al., 2021; Anderson et al., 2023). The index therefore contributes to understanding the water entering treatment, while recognising that organic matter composition, other precursors and treatment conditions also influence the DBPs ultimately formed.

## 4.1 From the index to source water protection

The different levels of relative risk identified in the site assessments provide a basis for organising management attention. Low risk supports continued observation and maintenance of existing protection measures. Intermediate risk indicates a need for more focused investigation, potentially including additional sampling and inspection of relevant pressures or transport pathways. High risk gives greater priority to confirming the source of the signal, coordinating protection actions and preparing for periods of increased pressure on source water quality. These categories describe conditions within the local assessment; they do not establish drinking water compliance or the probability of human exposure.

The timing, duration and recurrence of elevated conditions are also important (Herzsprung et al., 2012). A short peak may justify event sampling or inspection following rainfall, whereas repeated or persistent high values may support a broader investigation. Similarly, an increase in annual mean risk has different implications from a change concentrated in a few months (Jennings et al., 2020). Retaining this temporal information

helps translate the assessment into decisions about when to monitor, where to investigate and how urgently to respond. Where confidence in the classification is limited, the immediate priority may be to improve the observations needed to interpret it.

The source protection matrix developed from previous work within the work package provides a structured connection between these risk levels, land cover and process information. For example, associations with production may direct attention towards organic matter sources and the conditions favouring their accumulation (Anderson et al., 2023). Mobilisation may draw attention to disturbed soils, drainage and antecedent moisture conditions, while delivery may highlight connected runoff routes, inflows and the placement of protective measures. The process with the greatest weight provides an indication for investigation, rather than proof that a particular mechanism or location is responsible. Land-cover extent should likewise be considered alongside hydrological connectivity, since a relatively small area connected directly to the source may exert a disproportionate influence (Ferretto et al., 2021; Klante et al., 2021).

The measures identified through the matrix remain candidates for local assessment. Peatland restoration, changes in agricultural practices, riparian protection and drainage management address different pressures and require different implementation conditions (Klante et al., 2021; Paíz et al., 2025). Their effects on dissolved organic matter cannot be inferred solely from their ability to retain sediment or reduce runoff. Selection should therefore consider the specific pressure, the receiving water and the intended water quality response. Monitoring before and after implementation, with suitable comparisons where possible, would help determine whether an action achieves that response (Kirschke et al., 2020; Weatherill et al., 2025). The framework supports this process of prioritisation, but does not calculate the effectiveness of individual measures. The most feasible measures were assessed based on review of available data in the literature using feasibility criteria, but the outcome following their implementation at individual sites has not been evaluated in this study.

## 4.2 Using present and future assessments together

Present and future assessments serve complementary purposes. The current assessment can be evaluated against observations and used to identify periods or

conditions requiring closer attention. Future applications explore whether these conditions could become more frequent, persistent or seasonally different under alternative climates. Evaluating both against a consistent historical reference allows potential changes to be interpreted within the same local framework. This consistency is particularly important when assigning risk categories, since redefining the reference for each future period could conceal changes that are relevant to management.

If confirmed by the calculated outputs, a pattern of little or no increase under SSP1–2.6 and higher relative risk under SSP5–8.5 across the three sites would indicate that the assessed precursor conditions respond differently to the two climatic pathways. Relatively stable conditions under SSP1–2.6 would suggest a smaller departure from the historical reference, while increases under SSP5–8.5 would support consideration of greater future source water pressure. Even where the direction of change is shared, its magnitude and seasonality may differ between sites because their observed targets, environmental associations and process weights differ.

Warming provides one possible explanation for increased risk where temperature-related variables contribute strongly to the production sub-index (Ritson et al., 2014; Paíz et al., 2025). However, the overall response also depends on moisture availability, precipitation and the conditions controlling mobilisation and delivery (Blaurock et al., 2021). Warmer conditions do not necessarily produce a corresponding increase in the amount of organic matter reaching the source. The process contributions can help interpret projected changes, but they do not establish warming as their sole cause. Examining which drivers change, how their contributions vary and whether the response is consistent across climate models would provide a stronger basis for attribution. This interpretability is an additional value of the framework.

For management, agreement across climate models would strengthen the case for considering measures that remain useful under several futures. Greater disagreement would favour staged actions that can be reviewed as observations and understanding improve. Changes concentrated in particular seasons could also inform the timing of monitoring and source inspections. The scenarios support this longer-term planning role, they do not predict individual future events. Additional scenarios can be incorporated

using compatible inputs, while changes in land use, management and treatment require explicit consideration if their effects are to be assessed.

### 4.3 Limitations and further applications

The usefulness of the index depends first on the observations used to construct and evaluate it. A DOM proxy represents particular aspects of organic matter and does not necessarily capture changes in composition or DBP formation potential. Differences in sampling frequency, record length and measurement methods also affect the variability available for learning and validation. A short record may capture a seasonal cycle while providing limited information about unusual events or interannual differences. Application at additional sites therefore requires a suitable target record and local evaluation.

Machine learning identifies statistical associations within those records. Correlated environmental variables can share importance, and their contributions may change with the period used for training. Organising them into process groups improves interpretation but does not establish causality or remove the limitations of the simplified index. Future application also assumes that the learned relationships remain informative under conditions that may extend beyond the observed range. Changes in organic matter sources, hydrological pathways or lake processes could weaken that assumption. Validation should consequently examine missed peaks and false alerts as well as overall agreement, and the framework should be revisited as new observations become available.

Future assessments introduce additional uncertainty through differences between climate models and scenarios, the spatial representation of the source, and the availability of compatible drivers. In the current future workflow, not all soil variables used in the historical index are available. The resulting bounds represent uncertainty associated with these unresolved contributions and should be distinguished from climate-model spread. A narrow climate ensemble range cannot establish a precise risk category if missing contributions could alter that classification. Completing these inputs, or independently validating a formulation supported by the available future drivers, is necessary before assigning firm future risk categories.

These limitations define how the tool should be used and developed. An initial application can guide targeted monitoring and investigation, while stronger validation and complementary measurements of organic matter characteristics and formation potential can support more specific interpretation. Making the workflow available for further testing provides an opportunity to examine its transferability across additional sources. Its practical value lies in making available information more useful for source protection, with the strength of the recommendations matched to the evidence supporting them.

## 5. Conclusions

This deliverable presents a geospatial risk assessment tool that combines machine learning, local observations and globally available environmental datasets to assess current and potential future relative source water conditions associated with an important DBP precursor: DOM. The approach was applied and evaluated at Feeagh, previously investigated within intoDBP, an intoDBP Case Study Site and a site new to the project, Magheracloone. Interpretability plays a central role, with environmental associations organised into production, mobilisation and delivery processes. Their relative importance and the agreement between the index and observations varied across sites, highlighting the value of local observations and site-specific evaluation.

The tool is available through the accompanying repository for further application and testing. It requires a suitable local target variable (such as a DOM proxy or DBP formation potential), with the configuration, validation and interpretation adapted accordingly. The methodology provides a relatively accessible approach for examining source water conditions, particularly where monitoring and understanding of DOM dynamics are limited. Future applications provide provisional indications of change, conditional on the availability of required drivers and the transferability of historical relationships.

By linking relative risk, land cover and process information with candidate source protection measures, the framework can help water managers prioritise investigations and consider long-term adaptation options. These recommendations provide a starting point for local assessment, without establishing the effectiveness of individual interventions. It is expected that this tool (and the examples provided here) support its application at additional sites, in Europe and elsewhere, contributing to better protection of source water quality and supporting measures aimed at mitigating against conditions favourable to DBP formation.

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# Appendix A

Appendix A1. The scope applied to define each score for each of the Source Water Protection feasibility criteria.

| EVALUATION CRITERIA | SCORE | | | |
|---|---|---|---|---|
| | 0 | 1 | 2 | 3 |
| Potential economic benefit | No evidence from systematic review | Minimal increase in benefit to farm or landowner | Moderate increase in benefit | Significant increase in benefit |
| Capital costs | No evidence from systematic review | High cost | Medium cost | Low cost |
| Effectiveness | No evidence from systematic review | No noticeable reduction in DOM but a reduction in sediments/turbidity | Moderate reduction in DOM | Substantial and long lasting reduction in DOM |
| Co-benefits (carbon sequestration, biodiversity, flood mitigation, GH gas emission reduction, other pollutants of interest, recreational/aesthetics | No evidence from systematic review | No noticeable co-benefits | Moderate no. of co-benefits | Substantial number of co-benefits |
| Community buy-in | No evidence from systematic review | Low community support | Limited community support | Widespread community support |
| EU Policy Framework & funding | No policy or funding | Weak EU policies and low funding | Strong EU policies and medium funding | Legally enforced EU policies and high funding |
| Total number of papers | 0 | 1-10 | 11-20 | 21 + |

Appendix A2. Feasibility scoring results. Weight x score for each 7 parameters added together. The highest total number is the most feasible measure highlighted in green and lowest number is the least feasible measure. *Organic fertiliser management(Organic fertiliser, exporting slurry, slurry pelleting/decanting slurry)

| SWP MEASURES | Potential economic benefit | Effectiveness | Co-benefit(sub divide) | Community buy-in | Policy framework & funding | Capital costs | No. of papers | Total |
|---|---|---|---|---|---|---|---|---|
| Riparian buffer zone | 0.418 | 0.375 | 0.233 | 0.118 | 0.642 | 0.417 | 0.108 | 2.311 |
| Bank revetment | 0 | 0.5 | 0.035 | 0 | 0.428 | 0.492 | 0.036 | 1.492 |
| Tree planting | 0.34 | 0.575 | 0.312 | 0.122 | 0.642 | 0.238 | 0.108 | 2.337 |
| Organic fertiliser mgt.* | 0.358 | 0.5 | 0.118 | 0.135 | 0.642 | 0.322 | 0.072 | 2.146 |
| Revegetation | 0.429 | 0 | 0.143 | 0.107 | 0.642 | 0 | 0.036 | 1.356 |
| Gully blocking | 0.429 | 0.388 | 0.142 | 0 | 0.642 | 0.507 | 0.072 | 2.179 |
| Mixed species hedgerows | 0.262 | 0 | 0.319 | 0.107 | 0.642 | 0.179 | 0.072 | 1.58 |
| Buffer strips | 0.215 | 0.25 | 0.157 | 0.071 | 0.642 | 0.358 | 0.072 | 1.765 |
| Fencing along waterways | 0 | 0.375 | 0.05 | 0.107 | 0.642 | 0.358 | 0.036 | 1.568 |
| Conservation tillage | 0.405 | 0.531 | 0.235 | 0.16 | 0.642 | 0.537 | 0.108 | 2.618 |
| Tramline management | 0 | 0 | 0.14 | 0 | 0.642 | 0.322 | 0.036 | 1.14 |
| Anaerobic digesters | 0.429 | 0 | 0.148 | 0.111 | 0.642 | 0.197 | 0.072 | 1.599 |
| Bioretention areas | 0 | 0.45 | 0.161 | 0 | 0.642 | 0.448 | 0.036 | 1.736 |
| Mixed cropping | 0.429 | 0.5 | 0 | 0.089 | 0.642 | 0 | 0.036 | 1.696 |
| Crop rotation | 0.422 | 0.75 | 0.045 | 0.192 | 0.428 | 0 | 0.072 | 1.909 |
| Constructed wetland | 0.333 | 0.5 | 0.203 | 0.189 | 0.642 | 0.258 | 0.108 | 2.233 |

Appendix A3. Source Water Protection (SWP) measures considered most likely to be effective to mitigate against each of the processes (production, mobilisation and delivery) in the Risk Assessment Framework including evidence for their selection under each process. To date SWP measures have primarily focused on the mitigation of contaminants such as microbial pathogens, nitrate or phosphate entering the source water with little to no attention given to dissolved organic matter (DOM) as a specific issue. While taking into account the particular characteristics that influence DOM movement and attenuation, the twenty-four SWP measures outlined below are considered in light of their potential capacity to mitigate against each of the processes (production, mobilisation and delivery).

| SWP MEASURE | LAND TYPE | LAND TYPE ACTIVITIES that measures can mitigate against | PROCESS and REASON(PRO=Production, MOB=Mobilisation, DEL=Delivery) |
|---|---|---|---|
| Blocking drainage channels - Drain blocking / grip blocking /Gully blocking | Organic-rich soil LC | Drainage activities | 1MOB: Gully blocks back up the water, creating a chain of shallow pools. This forces water sideways back into the surrounding landscape, re-hydrating the dry bog profile like a re-soaked sponge (Lees et al., 2025). |
| Revegetation | Organic-rich soil LC | Surface run-off | 1PRO: Vegetation creates a physical canopy that intercepts sunlight and prevents the bare peat from baking (Worrall et al., 2019).<br>2DEL: Sphagnum is a dense, living carpet physically cleanses water and reduces the leaching of DOC right at the point of origin (Bryan et al., 2024). |
| Reprofiling | Organic-rich soil LC | Slope | 1DEL: Prevents the gravity-driven collapse of large peat blocks into the stream channel (Crowe et al., 2008). |
| Land slurry spreading exclusion | Agricultural land | Slurry Application | 1DEL: Untreated grass or vegetation acts as a biological sponge, absorbing and processing surface sheet nutrients before they hit the river (Majumdar & Avishek, 2025). |
| Exporting the slurry | Agricultural land | Slurry Application | 1DEL: Removing the slurry ensures that complex agricultural pollutants will not enter nearby downstream water sources (Silva et al., 2025) |
| Slurry pelleting and/or decanting systems | Agricultural land | Slurry Application | 1DEL: The remaining organic carbon in the dry pellet is bound tightly into a compressed, structural fibre matrix that does not instantly dissolve upon contact with rainwater (Sung-inthara et al., 2024). |

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| Using an organic fertiliser/slash mulch / biochar | Agricultural land<br><br>Forestry | Ploughing or aggressive tillage<br><br>Clear-felling | 1PRO: Organic fertilisers add stable soil organic carbon (SOC). Higher SOC facilitates the binding of earth particles into strong aggregates, expanding the soil's macro-porosity and allowing it to hold onto cooling moisture (Yu et al., 2025).<br>2DEL: physically filtering and locking carbon into the soil matrix (Sun et al., 2025)<br><br>1PRO: The physical mulch blanket absorbs solar radiation before it hits the bare soil. This shields the exposed ground from day-time baking (Jonas et al., 2019).<br>2DEL: Biochar introduces a dense network of micro- and macro-pores into the earth. This alters the soil's structure, allowing it to act like a physical sponge. Instead of heavy rain puddling and sheeting across the surface, the water immediately sinks cleanly down into the ground (Esmaeilnezhad et al., 2025). |
| Not applying fertiliser if heavy rain forecast within 48 hrs | Agricultural land/Forestry | Surface run-off | 1MOB: The fertiliser has at least 48 hours to chemically bind (adsorb) onto clay particles, sand particles, and stable soil organic carbon complexes, locking it securely in place (Vadas et al., 2011).<br>2DEL: Prevents fertilizers from sitting on waterlogged soils where lack of crop growth and high rainfall ensure immediate runoff into watercourses (O' Flynn et al., 2013) |
| ANAEROBIC DIGESTERS | Agricultural land | Slurry Application | 1DEL: AD destroys the volatile organic compounds inside an enclosed industrial tank before the material touches the field, therefore there is less mobile organic matter left for rainfall to wash away (Christina van Midden et al., 2023) |

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| RIPARIAN BUFFER ZONE | Forestry | Clear-cutting or clear-felling | 1DEL: It physically slows down the surface water, acting as a filter that forces organic matter and sediment to drop out of the flow path before reaching the stream (Shah et al., 2022). |
| | Agricultural land | Nitrogen fertiliser application | 1DEL: Roots physically block and absorb dissolved subsurface nitrates(Stutter et al., 2019).<br>2MOB : Drives the soil into an anoxic state to trigger denitrification(Stutter et al., 2019).<br>3PRO: Prevents hot-weather microbial spikes(Stutter et al., 2019). |
| | Agricultural land | Surface run-off | 1DEL: Dense stems of buffer grasses, shrubs, and trees create friction. This roughness slows down the velocity of overland surface runoff as it exits the agricultural field(Stutter et al., 2019). |
| | Watercourse | Surface run-off | 1DEL: Open root channels dramatically increase the soil's infiltration capacity, absorbing horizontal surface runoff and redirecting it vertically down into the ground (Stutter et al., 2019). |
| | Watercourse | Harmful algae blooms (HABs) | 1DEL: Cuts off food supply by physically trapping phosphorus and absorbing nitrates before they enter the water (Tsai et al., 2022).<br>2MOB: Destroys nitrogen by creating a wet, anoxic environment that permanently vents agricultural nitrates as gas(Stutter et al., 2019). |

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| BUFFER STRIPS, grass buffer strips or, willow buffer strips or Vegetated filter strip | Agricultural land | Nitrogen fertiliser application | 1DEL: Roots physically block and absorb dissolved subsurface nitrates (B.-M. Vought et al., 1995)<br>2MOB : Drives the soil into an anoxic state to trigger denitrification (B.-M. Vought et al., 1995)<br>3PRO: Prevents hot-weather microbial spikes (B.-M. Vought et al., 1995). |
| | Agricultural land | Surface run-off | 1DEL: Dense stems of buffer grasses, shrubs, and trees create friction. This roughness slows down the velocity of overland surface runoff as it exits the agricultural field (B.-M. Vought et al., 1995). |
| | Grassland | Surface run-off | 1DEL: As horizontal surface runoff hits the buffer boundary, it is rapidly pulled downward into the soil profile. This transition from surface flow to subterranean flow is the single most effective way to stop DOM transport (Stutter et al., 2019). |
| | Urban | Surface run-off | 1DEL: Runoff moving rapidly off asphalt hits the dense, rigid vegetation of the urban buffer strip. This structural friction immediately slows down the water's velocity (Grigg, 2024). |
| REFORESTATION | Grassland | Surface run-off | 1DEL: Breaks up soil compaction and forces surface sheet runoff deep underground (Mongil-Manso et al., 2022).<br>2MOB: Develops a damp leaf-litter layer that keeps the forest floor highly absorbent (Mongil-Manso et al., 2022).<br>3PRO: Shields the ground from intense solar heat (Mongil-Manso et al., 2022). |

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| MIXED SPECIES FORESTS | Deciduous forestry | Vegetation type or Tree species | 1DEL: Deep roots and a thick, shed-leaf mat physically slow down and trap overland runoff(Jačka et al., 2021).<br>2MOB: Creates an absorbent leaf-mould layer that drives wet, nutrient-cleansing anoxic soil zones(Jačka et al., 2021).<br>3PRO: Full summer leaf-out provides maximum shading during peak heat windows (Schnabel et al., 2025). |
| TREE PLANTING within riparian buffer zones | Grassland/Agricul land | Bank erosion | 1DEL: Roots break soil compaction and force surface sheet runoff deep underground while absorbing nitrates(Rathburn et al., 2023)<br>2MOB: Drives the wet riparian zone into an anoxic state to fuel natural denitrification(B.-M. Vought et al., 1995).<br>3PRO: Shields the soil and stream banks from intense summer solar heat (Schnabel et al., 2025). |
| Tree pits | Urban | Stormwater runoff from impervious surfaces | 1DEL: Canopy blocks rainfall; engineered tree pits physically trap street runoff and filter out organic debris (Yang et al., 2019)<br>2MOB: Sustains a porous, absorbent soil zone amidst a desert of impervious concrete (Bell et al., 2025).<br>3PRO: Shades tarmac and cools the local microclimate through evapotranspiration (Yin et al., 2024). |
| PHASED FELLING | Coniferous forest | Clear cutting | 1DEL: Forces runoff from harvested patches to filter through the intact root systems of adjacent mature tree blocks (Shah et al., 2022).<br>2PRO: Intact forest borders block solar heat and provide windbreak cooling (Shah et al., 2022). |

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| MIXED SPECIES HEDGEROWS | Agricultural land | Nitrogen fertiliser application<br>High-Density Livestock Grazing | 1DEL: The deep multi-tiered underground root uptake, and root-zone microbiology intercept pollutants from nitrogen fertilisers. (Laura et al., 2017).<br>2MOB: A mixed hedge begins drying the soil early in the spring and continues late into the autumn, protecting watercourses during the wet shoulder seasons when fertilizer application and livestock grazing are at their peak (Deng et al., 2026) |
| | Grassland | Surface run-off | 1DEL: It slows down surface water runoff, causing suspended sediment and particulate phosphorus to drop out of suspension on the field side before it can ever wash into a watercourse. (Biffi et al., 2026)<br>2MOB: The diverse root systems of a mixed hedge create deep networks of macro-pores, which increases the soil's capacity to absorb water. Instead of rainwater flooding across the surface as a muddy sheet, it infiltrates cleanly into the deep water table (Wallace et al., 2021) |
| | Urban | Impervious surfaces | 1DEL: Dense woody stems strain surface trash, while root networks trap heavy metal silt (Abhijith & Kumar, 2019).<br>2MOB : maintains a permanently loose, highly porous structure and absorbs massive volumes of water during localized cloudbursts (Abhijith & Kumar, 2019). |
| BANK REVETMENT / bank stabilisation | Watercourses | Fast flowing rivers | 1DEL: Mechanically blocks soil and rotting wood from sliding into the water. It forces the organic debris to pile up safely on the land side, keeping the watercourse clear of mud, debris, and associated organic carbon pulses. (Chanson, 2014) |

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| CONSTRUCTED WETLAND or reed bed | Agricultural land | Surface run-off | 1DEL: Halts water velocity, mechanically straining out sediment and trapping dissolved field nutrients (Deasy *et al.*, 2010). |
| | Watercourses | Harmful algae blooms (HABs) | 1DEL: Starves the algae by trapping particulate phosphorus and absorbing dissolved field nutrients (West et al., 2017)<br>2MOB: Destroys nitrogen by maintaining a saturated, anoxic ecosystem that vents nitrates as gas (West et al., 2017)<br>3PRO: Cools the watershed by shading the basin, lowering discharge temperatures below the bloom threshold (West et al., 2017) |
| | Urban | High-velocity stormwater surge | 1DEL: Halts stormwater velocity, mechanically straining out street trash, tire soot, and trapping oils (Wang et al., 2021).<br>2MOB: Maintains a 100% saturated basin to fuel continuous microbial digestion of urban hydrocarbons (Wang et al., 2021)<br>3PRO: Thick reed canopy blocks summer solar radiation, cooling the runoff before discharge (Wang et al., 2021) |
| BIORETENTION areas or bioretention cells or rain gardens | Urban/ Watercourses | Surface run-off | 1DEL: Diverts runoff vertically through an engineered soil filter, trapping street carbon, oil, and soot (Sabbagh et al., 2025)<br>2MOB: Acts as a porous underground sponge that maintains moisture to fuel microbial breakdown of toxins (Sabbagh et al., 2025)<br>3PRO: Uses plant canopy shading and evapotranspiration to cool hot tarmac runoff and limit DOC dissolution (Sabbagh et al., 2025) |
| IOSWALE or grass swale or waterway, | Urban/ Watercourses | Surface run-off | 1DEL: Moves water velocity horizontally through dense plants and filters it vertically through engineered soil (Bhat et al., 2024)<br>2MOB: Maintains an uncompacted, moist soil profile to fuel the microbial digestion of trapped oils and carbon (Bhat et al., 2024)<br>3PRO: Uses plant shading and evapotranspiration to cool hot tarmac runoff and limit DOC dissolution (Bhat et al., 2024). |

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| SEDIMENT POND or sediment basin | Organic-rich soil LC | Windfarm Construction | 1MOB: The pond raises the localised water table, forcing water sideways back into the peatland. By increasing soil moisture and keeping the peat permanently waterlogged, it chokes out oxygen. This prevents aerobic microbes from breaking down the stable ground carbon, halting the generation of DOC at the source (Grieve & Gilvear, 2008)<br>2DEL: The pond intercepts the waters horizontal flow path. Because the pond is wide and deep, it reduces the water's velocity. This gives the peat particles residence time to sink to the bottom, and settle on the pond floor before the water escapes into a downstream watercourse (Grieve & Gilvear, 2008).<br>3PRO: By raising the soil moisture, the pond ensures the surrounding bog resists summer heat spikes (Grieve & Gilvear, 2008) |
| | Grassland | Wildfires | 1MOB: Water from the pond naturally seeps sideways into the surrounding soil profile, artificially raising the local water table (Schenk et al., 2025).<br>3DEL: The water dumps its load of highly alkaline ash and charcoal fragments into the basin, trapping the organic debris on land before it can pollute drinking water reservoirs down in the valley (Schenk et al., 2025). |
| | Agricultural land | Surface run-off | 1DEL: Used as a primary treatment to slow flow velocity and retain sediment, total suspended solids and particulate nutrient (Opoku et al., 2025)<br><br>1DEL: Reroutes concrete runoff into a deep basin to crash velocity, force sediment settling, and skim oils |

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| | Urban | Brownfield redevelopments / Large infrastructure projects | |

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| TRAPS or silts mats or ıent trap | Agricultural land | Agricultural drains | 1DEL: If silt enters farm drainage ditches, it clogs them, slows down water flow, and causes fields to waterlog. Silt traps keep the drainage network clear and reduce ditch-dredging costs (Needelman et al., 2007). |
| | Organic-rich soil LC | Drainage activities | 1DEL: Captures floating peat flakes before they tumble downstream and dissolve into liquid DOM(Needelman et al., 2007).<br>2MOB: Rewets the surrounding bog, creating an anaerobic environment that halts carbon decomposition(Needelman et al., 2007).<br>3PRO: Prevents summer soil temperature spikes, locking down microbial DOC generation(Needelman et al., 2007). |
| | Grassland | Wildfires | 1MOB: traps back up water during rainstorms, forcing it sideways to soak deep into the parched, baked ground(Girona-García et al., 2021). |
| | Forestry | Timber harvesting | 1DEL: Slows the water's velocity, forcing the heavy logging mud, peat flakes, and organic wood debris to drop out of suspension and settle to the bottom of the drain before the water escapes the site (Irish River Project, 2025) |
| | Urban | High-velocity stormwater surge | 1DEL: Reroutes pipeline runoff into a drop-chamber to slow velocity and mechanically strain out city grime and tyre soot (SCHOLZ, 2004). |
| ) FILTER To be used after the ap. | Urban | Impervious surfaces | 1DEL: Because cities have almost no free space for large natural wetlands or dirt sediment ponds, engineers use highly compact stormwater sand filters to clean the first flush of highly contaminated water (Ellis et al., 2025). |

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| MIXED CROPPING / polyculture / inter-cropping / co-cultivation | Agricultural land | Nitrogen fertiliser application | 1DEL: Dense leaf canopies intercept rainfall energy, while multi-tiered roots trap mobile carbon in the field (Lizarazo et al., 2020)<br>2MOB: By preventing the soil from completely drying out and cracking, it limits the intense aerobic decomposition that breaks stable ground carbon down into highly mobile(Gabbrielli et al., 2025)<br>3PRO: Having varieties of different heights and leaf shapes maximizes canopy coverage over the soil keeping summer soil temperatures significantly cooler(Lizarazo et al., 2020). |
| CROP ROTATION | Agricultural land | Continuous cropping or monocropping | 1DEL: Alternating root styles break up compaction to channel water vertically; cover crop windows eliminate open surface runoff paths (Hao et al., 2020).<br>2MOB: Elevates organic matter to turn fields into a sponge, preventing dry-spell carbon decay (Xiao et al., 2025).<br>3PRO: Eliminates bare ground to shade the soil and suppress heat-driven microbial decomposition (Gabbrielli et al., 2025) |
| CONSERVATION TILLAGE (no-till, ridge-till, strip-till, mulch-till, and reduced-till | Agricultural land | Surface run-off | 1DEL: Surface residues slow runoff velocity, while intact earthworm/root channels divert water vertically into the soil filter (Shipitalo et al., 2000).<br>2MOB: Surface mulch reduces evaporation and builds a structural sponge, keeping carbon bound in a solid state(Shipitalo et al., 2000b).<br>3PRO: Reflective residue cover shields the ground from solar heatwaves to suppress microbial carbon breakdown (Jones et al., 1990). |
| TRAMLINE MANAGEMENT | Agricultural land | Surface run-off | 1DEL: Mechanically minimises or contours smooth wheel ruts, stopping them from acting as high-speed gutters for muddy runoff (Withers et al., 2006)<br>2MOB: De-compacts the soil beneath tire tracks, allowing rainwater to infiltrate deeply rather than ponding (Withers et al., 2006)<br>3PRO: Encourages residue or plant cover in ruts to shield soil from solar baking and suppress microbial spikes (Reicosky, 1999) |

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| FENCING | Agricultural land | Agricultural drains | 1DEL: Excludes animals to allow a dense vegetative buffer to grow, physically trapping overland mud and manure runoff (Muirhead, 2019). |
| RE-ESTABLISH THE PATHWAY TO NATURAL FLOW PATH of the river. | Watercourses | Artificial land drainage | 1DEL: Diverts high velocities into winding meanders and floodplains, physically filtering out and dropping organic sediments on land (Costaz-Puyou et al., 2025).<br>2MOB: Elevates the catchment water table to maintain an anoxic soil zone, halting the microbial generation of liquid DOC (Serra-Llobet et al., 2022)<br>3PRO: Increases water mass and vegetative shading across the floodplain to suppress summer thermal carbon decay(Serra-Llobet et al., 2022). |
| CHECK DAM | Forestry | Clear felling | 1DEL: reduces drainage velocity to force clearfell silt and decaying brash to settle out before they can dissolve downstream (Mongil-Manso et al., 2019).<br>2MOB: Backs up water to hydrate the adjacent ditch banks, creating a wet, anoxic environment that anchors carbon (Yao, Song and Wei, 2021).<br>3PRO: Pools water to provide a thermal shield, keeping soils cool to suppress heat-driven microbial carbon decay (Yao, Song and Wei, 2021). |
| | Organic-rich soil LC | Drainage activities | 1MOB: backs up water to raise the water table increasing soil moisture, returning the bog to a wet, oxygen-depleted state that stops the biological generation of DOC at the source(Lees et al., 2025). |

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| CONTOUR FARMING | Agricultural land | Slope-accelerated surface runoff / Soil erosion caused by conventional straight-row cultivation | 1DEL: Horizontal crop ridges slows surface water velocity and force runoff to infiltrate vertically into the soil filter (Gathagu et al., 2018).<br>2MOB: Prolongs water contact on the slope to maximize infiltration, keeping the soil sponge hydrated to lock down carbon(PlantwisePlus, 2026).<br>3PRO: Promotes stable crop cover to shade the ground, suppressing heat-driven microbial decomposition (Mati *et al.*, 2025).. |
| CONTOUR BUNDING, TERRACES | Agricultural land | Slope-driven soil erosion / Flash surface runoff caused by the cultivation of steep hillsides | 1DEL: Transforms steep downhills into flat benches that eliminate horizontal runoff and filter water vertically (Demissie et al., 2022).<br>2MOB: Forces rainwater to pool and infiltrate deep into the soil, keeping the landscape sponge hydrated to lock down carbon (PlantwisePlus, 2026).<br>3PRO: Prevents soil erosion to maintain thick plant cover, shading the benches to suppress microbial carbon decay (Mati *et al.*, 2025). |

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## Supplementary Material A

Supplementary Material A is available in the following repository: https://doi.org/10.5281/zenodo.23030139. It includes the Python scripts, a README file and an input configuration template for applying and testing the risk assessment methodology at additional source-water sites in Europe and elsewhere. Users must provide a suitable local target variable, site coordinates and the required source and land-cover information. The workflow covers data preparation, machine-learning attribution, index construction, site evaluation, future climate assessment and links to candidate source-water protection measures. The scripts were prepared and adapted with artificial intelligence (AI) used as a coding support tool. An accompanying Excel workbook contains the compiled risk assessment and source-protection recommendations for the three study sites, including the matrix used and calculation notes (see Section 3.3).



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