Predicting diffuse microbial pollution risk across catchments: The performance of SCIMAP and recommendations for future development

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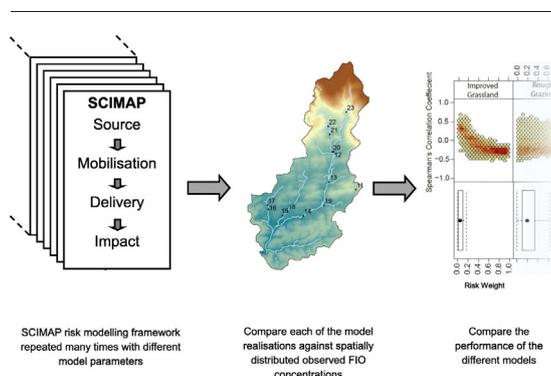[b] Department of Geography, Durham University, Durham DH1 3LE, UK
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HIGHLIGHTS

- A catchment risk modelling framework is applied to FIO pollution for the 1st time.
- Performance was variable with assignment of risk to land cover types uncertain.
- Information on livestock densities and management regimes may improve performance.
- Modelled results reinforce the importance of seasonal variation in FIO pollution.
- Varying land-use mosaic is important for the success of the SCIMAP fitted approach.

GRAPHICAL ABSTRACT

SCIMAP risk modelling framework repeated many times with different model parameters

Compare each of the model realisations against spatially distributed observed FIO concentrations

Compare the performance of the different models

ARTICLE INFO

ABSTRACT

Microbial pollution of surface waters in agricultural catchments can be a consequence of poor farm management practices, such as excessive stocking of livestock on vulnerable land or inappropriate handling of manures and slurries. Catchment interventions such as fencing of watercourses, streamside buffer strips and constructed wetlands have the potential to reduce faecal pollution of watercourses. However these interventions are expensive and occupy valuable productive land. There is, therefore, a requirement for tools to assist in the spatial targeting of such interventions to areas where they will have the biggest impact on water quality improvements whist occupying the minimal amount of productive land. SCIMAP is a risk-based model that has been developed for this purpose but with a focus on diffuse sediment and nutrient pollution. In this study we investigated the performance of SCIMAP in predicting microbial pollution of watercourses and assessed modelled outputs of *E. coli*, a common faecal indicator organism (FIO), against observed water quality information. SCIMAP was applied to two river catchments in the UK. SCIMAP uses land cover risk weightings, which are routed through the landscape based on hydrological connectivity to generate catchment scale maps of relative in-stream pollution risk. Assessment of the model's performance and derivation of optimum land cover risk weightings was achieved using a Monte-Carlo sampling approach. Performance of the SCIMAP framework for informing on FIO risk was variable with better performance in the Yealm catchment ($r_s = 0.88$; $p < 0.01$) than the Wyre ($r_s = -0.36$; $p > 0.05$). Across both catchments much uncertainty was associated with the application of optimum risk weightings

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attributed to different land use classes. Overall, SCIMAP showed potential as a useful tool in the spatial targeting of FIO diffuse pollution management strategies; however, improvements are required to transition the existing SCIMAP framework to a robust FIO risk-mapping tool.

1. Introduction

Faecal pollution has the potential to negatively impact upon ecosystem services associated with clean and safe recreational bathing and shellfish harvesting water (Clements et al., 2015; Wu and Jackson, 2016). Microbial contamination of such aquatic environments can expose humans to harmful pathogens that may cause gastro intestinal illness (Wade et al., 2006). Direct measurement of pathogens in environmental water samples is uncommon due to challenges associated with their enumeration in the laboratory, e.g. cost, detection limits etc., and so faecal indicator organisms (FIOs) such as *Escherichia coli* and intestinal enterococci provide an internationally accepted framework for the assessment of faecal pollution of water bodies. In the European Union, the health risks of faecal pollution of aquatic environments are recognised via the Bathing Water (EU, 2006a) and Shellfish Water (EU, 2006b) Directives. Regulators must compare measured FIOs against stringent standards of microbial water quality in order to comply with these directives. Risk assessment tools that can identify 'hotspots' of FIO pollution in catchment systems are therefore welcomed by regulatory agencies as a mechanism to help understand origins of pollution and to spatially target catchment management and interventions for improvements in microbiological water quality (Dymond et al., 2016).

Diffuse sources of FIO pollution, such as organic fertilisers applied to land and excretion of faeces by grazing livestock to pasture, provide challenges to water quality managers. This is because the loading of diffuse sources, and their propensity to connect to watercourses, varies spatially and temporally (Heathwaite et al., 2005). The impact of diffuse sources of microbial pollution on watercourses can be reduced through the use of mitigation measures such as streamside fencing (Kay et al., 2007a), vegetated buffer strips (Tate et al., 2006), wetlands (Morató et al., 2014) and retention ponds (Jenkins et al., 2015). These measures can be expensive and occupy valuable productive land. Therefore, methods to spatially identify and target locations in catchments where interventions will provide the best improvement in water quality are warranted. Past research has used regression approaches to attribute sources of FIOs to different land cover types and/or discrete point sources (Kay et al., 2010; Tetzlaff et al., 2012; McGrane et al., 2014). However, these approaches do not account for the spatial heterogeneity of landscape to watercourse connectivity (Tetzlaff et al., 2012).

Alternative approaches include the development of fully process-based models that attempt to account for the mechanisms that govern FIO fate and transfer in more detail. For example, the modified Soil and Water Assessment Tool (Cho et al., 2016a) and INCA-pathogens (Rankinen et al., 2016). There are, however, limitations in our understanding of FIO fate and transfer that can amplify uncertainties in fully quantitative, process-based risk assessment approaches. For example, there are knowledge gaps regarding the complex behaviour of FIO persistence in different matrices such as faecal deposits (Soupir et al., 2008; Martinez et al., 2013; Oliver and Page, 2016), soil (Muirhead and Littlejohn, 2009; Park et al., 2016) and stream bed sediment (Pachepsky and Shelton, 2011; Shelton et al., 2014; Pandey and Soupir, 2013; Pandey et al., 2016). Such limits in understanding make it difficult for all processes to be considered in complex process-based models (Beven, 2006, Cho et al., 2016b). These complex models also require a significant amount of data for model parameterisation and validation. This is especially problematic in the field of catchment microbial dynamics due to the relative scarcity of data on FIO concentrations and loads compared to nutrient and sediment flux (Muirhead, 2015; Oliver

et al., 2016). Semi-quantitative risk assessment frameworks, which provide a basis for decision support, are therefore useful tools to inform on relative risk of FIO transfers in space and time. This is because, despite gaps or limitations in the current evidence-base concerning FIO behaviour in complex catchment systems, they are able to provide a '1st approximation' of risk (Goss and Richards, 2008; Oliver et al., 2010).

The Sensitive Catchment Integrated Mapping Analysis Platform (SCIMAP) has demonstrated significant potential as a framework to inform on catchment-scale risks for diffuse nutrient and sediment pollution (Reaney et al., 2011). The approach provides an estimate of in-stream risk relative to the catchment being considered, and provides information at multiple spatial scales but within a time integrated framework. SCIMAP is underpinned by the source-mobilisation-delivery-impact (SMDI) continuum (Haygarth et al., 2005) and critical source area (CSA) concepts, which describe how a source of pollution can only convert to a pollution risk if there are no interruptions to the SMDI continuum (Heathwaite et al., 2005). At present, the SCIMAP approach is optimised for diffuse fine sediment (Reaney et al., 2011) and nutrient pollution (Milledge et al., 2012) but offers scope for addressing a number of additional diffuse pollutants, including FIOs. Given the growing interest and uptake in the use of SCIMAP among different stakeholder communities in the UK, its continued development to account for a wider array of pollutants is justified. Furthermore there are, at present, few risk-based modelling approaches for informing on FIO impairment of surface waters at the catchment scale.

The aim of this study was to assess the effectiveness of the current SCIMAP framework for informing on risk of FIO pollution in contrasting catchment systems by comparing FIO pollution risk predicted by SCIMAP with observed FIO risk, e.g. FIO concentrations. To deliver on this aim the objectives were to: (i) quantify variation in model performance as a result of risk weightings being assigned to a particular land cover type; and (ii) determine whether there was an association between SCIMAP predicted FIO risk and observed FIO risk in our study catchments. The intention was to develop initial risk weightings for land cover types and benchmark model performance on the assumption that FIOs behave similarly to sediment, albeit in a 'living' form.

2. Methods

Most modelling frameworks predict in-stream pollution by defining a function, e.g. a relationship derived from regression analysis, and these can be described as forward models. Our study adopted an inverse approach (Reaney et al., 2011; Milledge et al., 2012), because it defined a function (in the case of SCIMAP, land cover risk weightings) based on observed FIO concentrations, i.e. the approach queries how a model needs to be parameterised in order to simulate observed pollution, and is therefore 'fitted' to observed data. This 'fitted' approach is described in detail in Milledge et al. (2012). Briefly, the fitted approach involves pseudo randomly generating simulations from forward models whose output is compared to observed data. In this case the forward model used is SCIMAP and the user definable parameters are risk weightings for different land cover types. Model outputs were compared against a spatial FIO water quality dataset provided by the Environment Agency. This dataset spans 6 years (2007–2012) and was collected as part of the Catchment Sensitive Farming (CSF) initiative (Environment Agency, 2016). The FIO dataset reported here concerns *E. coli* concentrations, measured using the standard method of membrane filtration, reported across two catchments in England: The River Wyre, Lancashire and The River Yealm, Devon (Fig. 1).
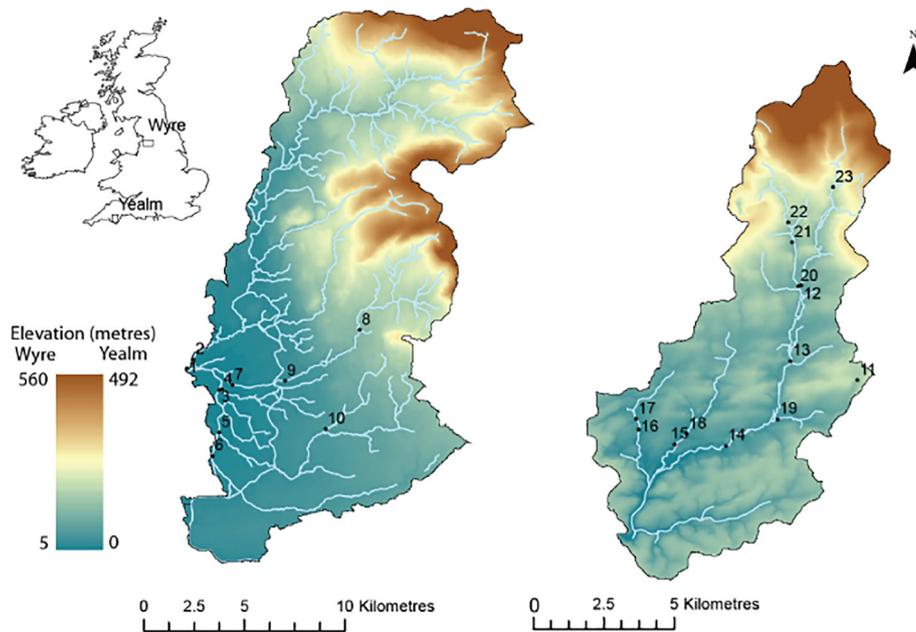
Fig. 1. Maps illustrating the two study catchments: The Wyre in Lancashire, North West England (left); and The Yealm in Devon, South West England (right). Numbered points indicate sample locations and associate with the sample locations indicated in Fig. 2 and Table 2. River data is from an Ordnance Survey MasterMap Topography layer (OS MasterMap Topography layer [GML geospatial data], 2015).

To evaluate the SCIMAP approach when applied to a FIO dataset we used the same SCIMAP framework that was developed for prediction of diffuse fine sediment risk. This approach was implemented within the SAGA geographical information system (Conrad et al., 2015). The SCIMAP risk mapping approach is described in detail in Lane et al. (2009) and Reaney et al. (2011). Briefly, the approach involves determining the risk of a sediment (or other pollutant) source being generated and the risk of the sediment (or other pollutant) source becoming connected to a watercourse, capturing the CSA concept described earlier. For sediment pollution, the risk of a source being generated is defined as a function of topography, land cover and rainfall. These datasets are used to calculate local erodibility based on the land cover, and the erosive potential of overland flow, which is driven by the local slope gradient and the upslope contributing area. Therefore, due to the combination of these factors, each land cover is associated with its own risk weighting. The risk of the source connecting to the stream network is determined using the network index of hydrological connectivity (Lane et al., 2009), which can be derived from the topographic wetness index. The topographic wetness index calculates the propensity for part of the landscape to generate saturation excess overland flow from topographic information (Beven and Kirkby, 1979). The propensity for a point in the landscape to connect to a watercourse is then defined as the lowest value of topographic wetness index along the flow path to the watercourse. If overland flow is not generated at any point along a flow path, it is not possible for that cell to transmit water further downslope and hence the source of risk is disconnected from the stream network (Lane et al., 2009). Once a pollution source has been delivered to a watercourse, pollution risk is concentrated as it is routed downstream and diluted based on the rainfall weighted upslope contributing area, with higher risk inputs concentrating risk and lower risk inputs diluting risk.

SCIMAP adopts a minimum information requirement approach, and the standard version requires three inputs: the generation of a source of risk requires a land cover map and spatially distributed rainfall information; the derivation of a topographic wetness index requires a detailed digital elevation model (DEM); and the concentration and dilution of risk utilises the same rainfall information described previously. In this study; the land cover map utilised was the Centre for Ecology and Hydrology (CEH) Land Cover Map 2007 (Morton et al., 2011); rainfall

information was Met Office UKCP09: 5 km gridded data - annual averages (Met Office, 2014); and the NextMap digital elevation model (DEM) at a grid resolution of 5 m × 5 m, developed by Intermap, was used. It is important to balance the information content of the observed dataset with the complexity of the modelling approach. Therefore, for the purposes of this experiment the 23 land cover classes described in the CEH land cover map were condensed into eight classes: improved grassland, rough grazing, moorland, bog, arable, urban, woodland and other. Table 1 shows which of the CEH land cover classes were included in each of these new classes. The rationale for the reduction and merging of classes was that a number of separate classes within the larger CEH Land Cover map were listed where we would not expect a significant difference in the risk weights associated with the cover. For example, the deciduous and coniferous woodland classes were merged since they will have similarly low levels of livestock and represent similar availabilities of FIOs. Here, the fitted approach was used to establish how these land covers needed to be weighted in order to best represent in-stream measured E. coli risk. The SCIMAP fitted approach uses a Monte Carlo sampling framework based on the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992). Here 25,000 model realisations with varying land cover risk weightings were generated.

Modelled risk values for 10 locations in the River Wyre catchment and 13 locations in the River Yealm catchment were compared with associated observed measurements of E. coli concentration. An overview of catchment characteristics for each location, including land use composition, is shown in Fig. 2 and Table 2. Briefly, the dominant land use in both catchments is agriculture, with expected FIO contributions from manure management practices and grazing livestock. Previous studies have found that >90% of FIO loading to water occurs during high flow conditions following rainfall (Kay et al., 2007b; McKergow and Davies-Colley, 2010; Kay et al., 2010) and Kay et al. (2007b) noted that many studies employ a regular sampling regime which biases toward low flow and while this was observed in the EA dataset, sufficient data representative of high flow conditions were deemed to be present. In order to avoid a bias toward the many base flow samples present within the EA dataset for both catchments, the data that was associated with flow that was > = 60% of the highest flow were subset. This operationally defined exceedance threshold retained high flow

Table 1
A description of SCIMAP land cover classes and how they are derived from CEH LCM land cover classes.

CEH LCM broad habitat class	SCIMAP class	Description
Broadleaved mixed and Yew woodland Coniferous woodland	Woodland	Deciduous, mixed, conifer, larch, evergreen and felled forest.
Arable and horticulture	Arable	Freshly ploughed land and annual and perennial crops.
Improved grassland	Improved grassland	Intensively managed grassland for hay, silage. and/or grazing of livestock
Rough grassland Neutral grassland Calcareous grassland Acid grassland	Rough grazing	Semi-natural grassland and managed low productivity grassland.
Fen marsh and swamp Bog	Bog	Herbaceous and mossy swards with a peat depth of >0.5 m. Fen, fen meadows, rush pasture, swamp, flushes and springs.
Dwarf shrub heath Montane habitats Inland rock	Moorland	Heather grassland and exposed rock as well as habitats occurring at higher altitudes.
Salt water Fresh water Supra-littoral rock Supra-littoral sediment Littoral rock Littoral sediment	Other	Coastal water, rivers, canals and standing water. Coastal rock and sediment.
Built -up areas and Gardens	Urban	Built up areas including towns, cities, dock sides, industrial estates and car parks. Suburban areas with a mix of built up areas and vegetation.

events while excluding data associated with base flow conditions. Flow data was not available for all of the locations used in this experiment so flow information from a local gauging station was used; location 9 for the Wyre and location 14 for the Yealm (Fig. 1). This approach assumed that if it was high flow at one point in the catchment it was also high flow at the other points in the catchment. While this approach represented an approximation we argue that it remains valid given that it is being used within a risk-based framework, i.e. it is the relative magnitude of E. coli concentrations that is important rather than the absolute concentration. The number of records remaining at each site after this sub-setting procedure was used is shown in Table 2. A high number of samples were associated with locations 1 and 9 in the Yealm catchment and location 14 in the Wyre catchment. These locations were equipped with autosamplers programmed to sample after a flow threshold considered to be high flow was met. Samples from other sites were acquired using manual grab sampling.

2.1. Statistical analysis

All statistical analysis was carried out using the R statistics package (R Core Team, 2015) and third party packages (Auguie, 2015; Carr, 2014; Sarkar and Andrews, 2013; Neuwirth, 2014; Wickham, 2007, 2014, 2015; Wickham and Francois, 2015; Deepayan, 2008). All E. coli counts underwent $\log_{10}$ transformation prior to statistical analysis. The observed E. coli measurements used in our study were derived from a median of the subset data for each location and were converted into risk values by determining their rank order to allow comparison with the relative risk nature of the SCIMAP output. The Spearman's rank correlation coefficient (r_s) comparing observed risk with the simulation output was used as the objective function. This statistical comparison measures the extent to which the relative order of the locations in the observed and simulated datasets match, and avoids assuming the observed dataset includes the most and least risky locations in the catchment. For each catchment this assessment provided 25,000 Spearman's correlation coefficients; one associated with the
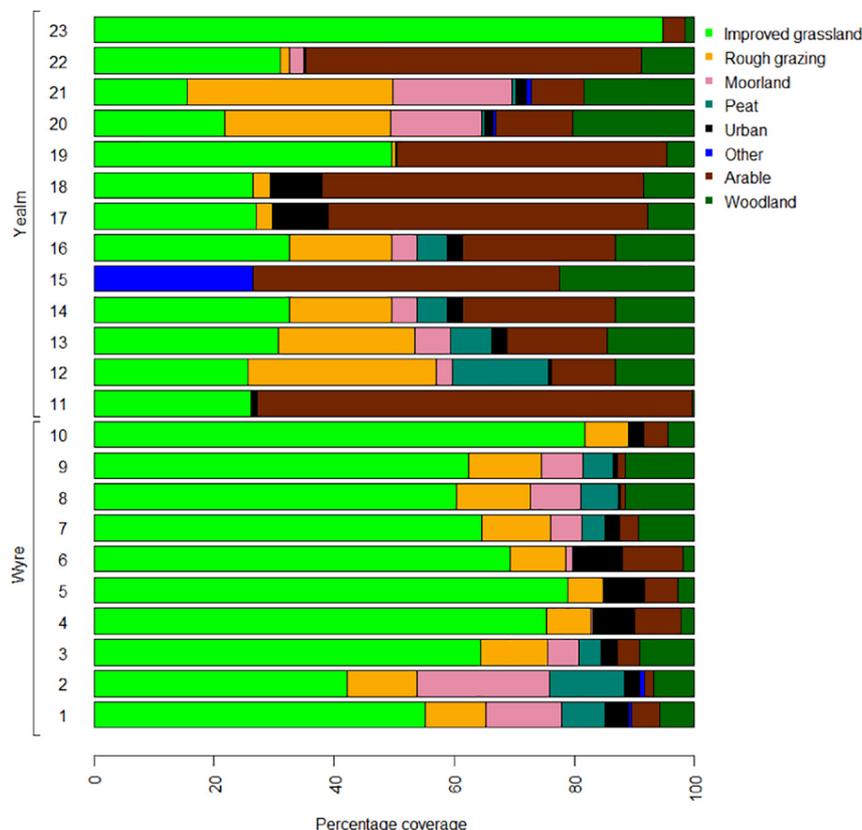

Fig. 2. A bar plot illustrating the proportions of the contributing area associated with each sample point occupied by different land cover types. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2

Catchment characteristics of each of the sub-catchments investigated. Connectivity is defined as the lowest value of topographical wetness index along a flow path as per Lane et al. (2009). Number of samples indicates the number of records remaining after sub setting all the available data by the days where flow is >60% of the highest flow recorded.

	Location	Mean connectivity/standard deviation	Mean slope(°)/standard deviation	Mean elevation (metres)/standard deviation	Number of samples
Wyre	1	0.71/0.04	0.24/0.66	8.6/0.4	706
	2	0.63/0.13	5.41/5.63	141.33/129.28	20
	3	0.71/0.14	0.89/1.00	13.72/3.71	21
	4	0.75/0.13	0.62/0.79	12.06/3.06	21
	5	0.69/0.12	1.78/1.93	56.32/33.92	20
	6	0.68/0.13	1.75/2.28	45.35/25.38	20
	7	0.67/0.12	1.97/1.65	42.62/20.2	19
	8	0.62/0.12	7.49/7.26	223.17/95.61	21
	9	0.62/0.12	6.88/7.05	199/99.89	888
	10	0.64/0.11	3.39/3.36	104.54/42.18	23
Yealm	11	0.88/0.10	3.42/1.71	128.91/8.76	40
	12	0.83/0.12	7.34/4.66	274.93/123.84	40
	13	0.59/0.05	7.16/1.79	44.08/2.39	42
	14	0.81/0.14	6.51/4.74	125.58/85.16	193
	15	0.77/0.04	6.05/3.32	33.49/13.81	47
	16	0.45/0.07	14.1/5.06	20.98/4.57	41
	17	0.78/0.13	5.96/4.61	59.72/19.29	30
	18	0.78/0.14	5.64/4.13	55.08/18.18	50
	19	0.83/0.12	5.82/3.62	85.25/32.87	41
	20	0.79/0.11	2.45/0.82	57.8/0.56	42
	21	0.63/0.13	7.23/2.84	87.19/3.32	27
	22	0.49/0.05	20.4/7.14	122.77/10.83	28
	23	0.88/0.07	5.00/2.47	262.31/44.18	42

comparison of each of the randomly generated combinations of land cover risk values and the observed in-stream *E. coli* risk. One sample *t*-tests were used to assess whether the land cover risk values associated with the best modelled outputs (i.e. top 1% of r_s) were significantly different from 0.5. Because *E. coli* concentrations in the Wyre catchment were not normally distributed, a Kruskal Wallis test was used to
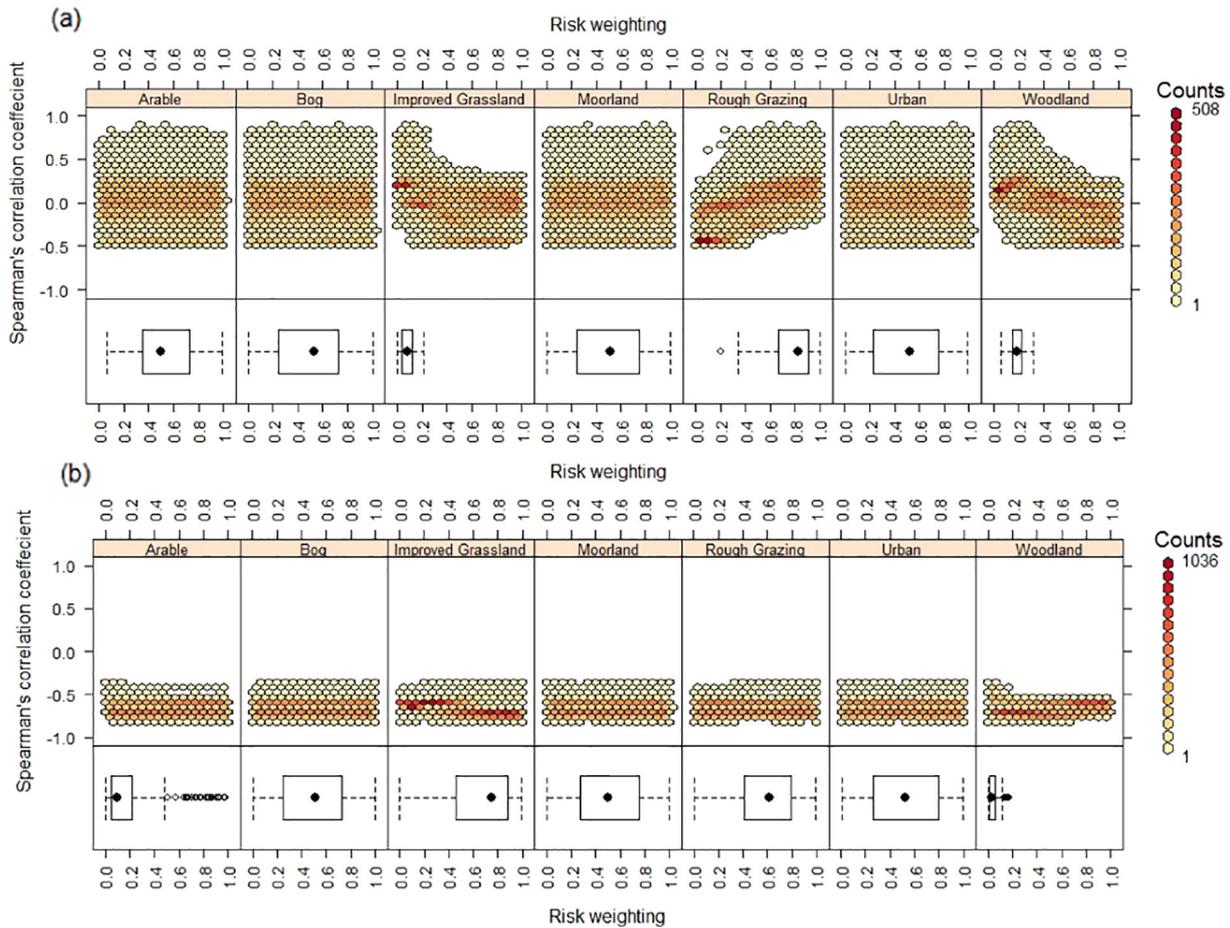

Fig. 3. SCIMAP fitted results for (a) the Yealm and (b) the Wyre. The top panels show hexagonally binned scatterplots depicting how model performance changes with changing the risk weighting for each land cover. The colour of the hexagonal bin depicts how many simulations fall into that part of the plot. The bottom panels show boxplots which depict the variation in the risk weighting of the 1% best performing simulations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

investigate differences in *E. coli* concentration among the observed data across all sites of the Wyre, with a Dunns test used to determine which sites were different from one another. Differences at the $p < 0.05$ level (95% confidence interval) were considered statistically significant.

3. Results

The SCIMAP fitted approach provided three outputs that elicit information on the influence of different land covers on the risk of FIO pollution in streams and rivers. Two-dimensional density (2-Dd) plots and boxplots (Fig. 3) depict the relationship between land cover risk weighting and model performance. The 2-Dd plot is a scatter plot of risk value against the Spearman's correlation coefficient, derived from comparing the SCIMAP output associated with that risk value and observed FIO risk. The scatterplot is divided into hexagonal sections whose saturation determines the number of models that fall into that part of the plot. Results from *t*-tests (Table 3) determine the confidence with which we can reject the null hypothesis that the mean risk weighting of the 1% best performing models is significantly different from 0.5 and therefore either contributes to diffuse pollution (risk weightings >0.5) or dilutes pollution (risk weightings <0.5). Together these results provide insight into the performance of SCIMAP's prediction of diffuse FIO pollution risk by providing the maximum correlation achieved and the potential uncertainty associated with model outputs, which is driven by the 'identifiability' of optimum risk weightings for land cover types. Identifiability, or the ease at which an optimum risk weighting can be derived, is represented by the standard deviation of risk value in the 1% best performing models. Larger standard deviations suggest that it is harder to identify an optimum risk weighting for land cover types.

3.1. The river Yealm catchment

The results for the Yealm catchment suggest that improved grassland and woodland should be assigned low risk values with respect to their contribution to FIO pollution of water. The 2-Dd plots (Fig. 3) show improvement in model performance as the risk weighting for these land covers decreases. In addition, the boxplots (Fig. 3) show low mean risk weightings associated with best 1% performing models. By contrast, the results suggest that rough grazing should be assigned high risk weightings with the 2-Dd plots showing improving performance of SCIMAP as the risk weighting increases. The boxplot shows a high mean risk weighting for the best 1% performing models affirming this result. The 2-Dd plot infers that arable land cover should be associated with a medium amount of risk, with model performance peaking at risk values approaching 0.54. This was supported further by both the box plots (Fig. 3) and mean risk weighting of the best 1% performing models (Table 3). Risk weightings associated with the remaining land cover types (moorland, bog and urban) were not influential on the performance of the model predicting in-stream FIO risk. The mean risk weighting for these land covers was approaching 0.5 with a large standard deviation (Table 3); therefore the mean risk weighting was not significantly different from 0.5 (Table 3). This was also apparent in the 2-Dd plots, as represented by a 'flat top' in the output (Fig. 3).

Of the land covers shown to have an impact on FIO diffuse pollution risk, only the risk weightings associated with improved grassland and woodland were highly identifiable. The optimum risk weighting for rough grazing was harder to identify (Table 3). Overall the performance of SCIMAP in the prediction of FIO risk in the Yealm catchment was good with a maximum r_s of 0.88 ($p < 0.01$).

3.2. The river Wyre catchment

The performance of SCIMAP in predicting FIO risk in the Wyre catchment was poor with no correlation between predicted risk and observed risk ($r_s = -0.357$, $p > 0.05$). The 2-Dd plots in Fig. 3 provide little insight into the influence of all land cover risk weightings on model performance.

However when the risk weightings from the best 1% models are depicted as boxplots (Fig. 3) relationships can be seen. Arable and woodland show better model performance with lower risk weightings while model performance appears to improve when improved grassland and rough grazing is assigned a medium risk weighting. Land covers associated with moorland, bog and urban areas do not appear

Table 3
Table summarising the influence of land cover risk weighting on SCIMAP performance. Mean risk weightings and associated standard deviation for the 1% best performing models. *p* value indicates the results from a *t*-test and the confidence with which we can reject the null hypothesis that there is no variation in model performance as a result of the risk weighting assigned to a land cover type.

Land cover type	Yealm		
	Optimum mean/standard deviation	*p* value	Summary of influence on FIO risk
Improved Grassland	0.08/0.05	<0.001	Low risk
Rough Grazing	0.78/0.16	<0.001	High risk
Moorland	0.5/0.29	>0.05	Not influential
Bog	0.5/0.29	>0.05	Not influential
Urban	0.5/0.29	>0.05	Not influential
Arable	0.54/0.23	<0.01	Medium risk
Woodland	0.19/0.05	<0.001	Low risk

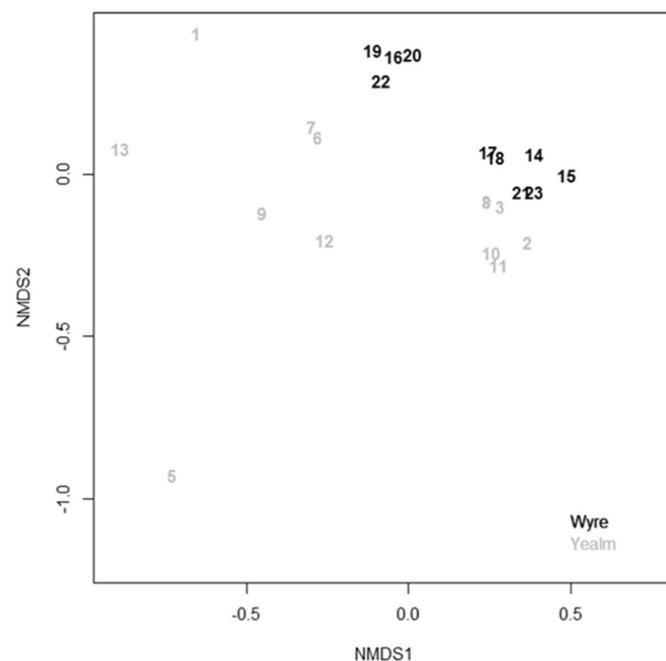| Land cover type	Wyre		
	Optimum mean/standard deviation	*p* value	Summary of influence on FIO risk
Improved Grassland	0.63/0.32	<0.001	Medium risk
Rough Grazing	0.58/0.26	<0.001	Medium risk
Moorland	0.52/0.29	>0.05	Not influential
Bog	0.49/0.30	>0.05	Not influential
Urban	0.52/0.30	>0.05	Not influential
Arable	0.18/0.22	<0.001	Low risk
Woodland	0.04/0.04	<0.001	Low risk

Fig. 4. An ordination plot showing the dissimilarity in land cover mosaic across the contributing catchments associated with sample points from the Yealm (grey) and Wyre (black). Increasing distance between points illustrates increasing dissimilarity in land cover make up between catchments.
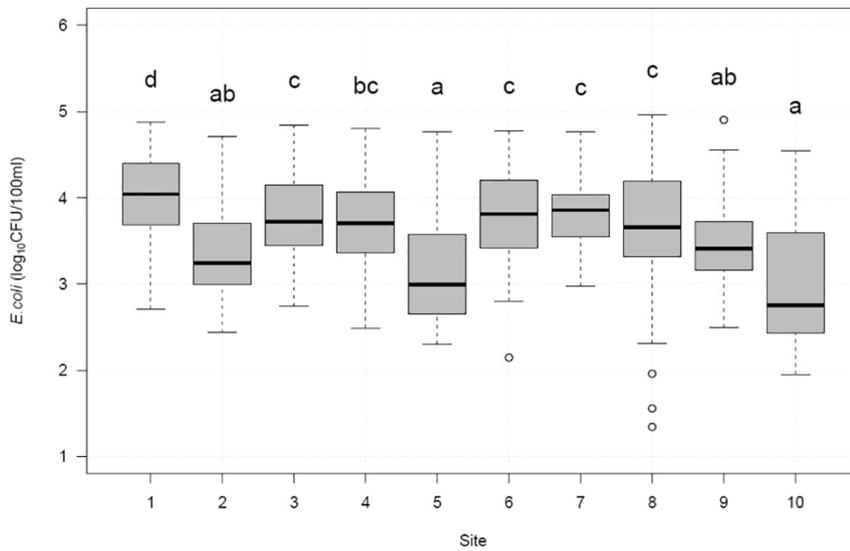
Fig. 5. Boxplot illustrating the variability in the concentration of *E. coli* across samples from the Wyre catchment. Letters above the boxes indicate significant differences in FIO concentrations between sites as determined by a Dunns test.

to influence model performance. These results are supported by the results of a *t*-test (Table 3). The risk weighting associated with woodland is more identifiable while risk weightings associated with the remaining land covers of influence are less identifiable (Table 3).

Ordination plots can be used to illustrate the variability in land cover between the contributing catchments associated with the sample points in the Wyre. Here non-metric multidimensional scaling (NMDS) (Kruskal, 1964) was used, utilising a Bray Curtis dissimilarity index (Bray and Curtis, 1957) (Fig. 4). Each point on the plot represents one sub catchment. Increasing dissimilarity in land cover make up is associated with increasing distance between points, and in this particular case the NMDS procedure was associated with a stress value of 0.09. It was clear from this plot that the sub catchments associated with the Yealm river basin were more dissimilar than those associated with the Wyre river basin. There was less variability in the composition of land cover in the Wyre and sub catchments appear to gather into two clusters. This similarity between sub catchments was also apparent in the FIO concentrations observed in the Wyre. Fig. 5 shows a boxplot illustrating the variability in FIO concentration at each of the sampling points in the Wyre catchment and a significant difference in the distributions of FIO concentrations at each of the sites was observed ($p < 0.01$). The Dunns test did reveal that there was a degree of clustering of sites. For example five of the ten sites were associated with group a and/or b and five were associated with group c (Fig. 5).

The potential for seasonal differences in SCIMAP's performance can be investigated by comparing model output with observed data split into winter or summer months. This revealed that there was some variance in model performance depending on the season of interest (Fig. 6). For the Yealm, SCIMAP performance appeared to reduce during winter months while an opposite more pronounced effect was observed for the Wyre. Fig. 7 shows that as the percent coverage of a land cover class increased the identifiability of an optimum risk weighting appeared to decrease. The pattern was more pronounced in the Yealm catchment.

4. Discussion

This study provides a novel application of the SCIMAP model fitted against historical *E. coli* data collected across two UK catchments. The performance of SCIMAP in the prediction of diffuse FIO risk in the catchments studied was variable, with a higher degree of agreement between predicted and observed FIO risk in the Yealm than in the Wyre catchment. Even where SCIMAP performed well there was variability in the certainty with which risk weightings could be applied to land cover types. Nonetheless, the outcomes from this study are positive. While in its current form SCIMAP is not yet optimised for mapping FIO risks, it would be surprising for a model developed to describe an inert pollutant such as fine sediment to perfectly describe the fate and transfer of a living organism and these results should not be viewed as a failure of a
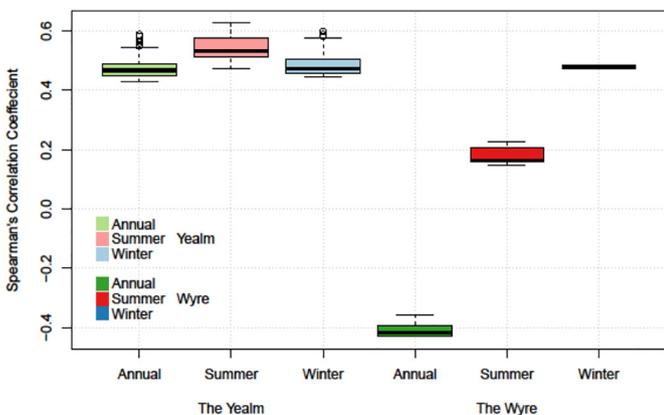

Fig. 6. Boxplot illustrating the variance in performance associated with the 1% best performing simulations when observed data is subset according to season.
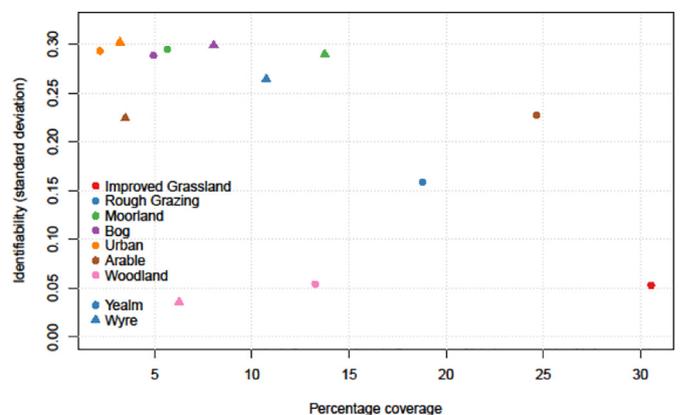

Fig. 7. A scatterplot of optimum risk weighting identifiability and percent coverage of the associated land cover.

modelling framework, but rather as a learning process in which the development of new hypotheses can be framed, and further developments of SCIMAP for predicting FIO risks can occur (Beven, 2007).There are several reasons why model performance might be poor or why assignment of land cover risk weightings was uncertain. First, high risk weightings may offset low risk weightings resulting in a wide range of optimum risk values; this problem is associated with covariance between one or more land covers where the land cover mosaic is similar between catchments. Second, it is possible that a land use either does not exist in a catchment or represents only a small proportion of the catchment meaning that the signal from this land use is weak. Third, a land cover class may be too broad combining too many different availabilities of FIOs (Reaney et al., 2011). Finally processes that influence FIO fate (e.g. die-off, persistence, affinity to particles, etc.) may be important to consider alongside processes that govern transfer and SCIMAP, in its current form, does not adequately account for the former.

In the Wyre catchment, areas associated with improved grassland and rough grazing were assigned a medium risk which was unexpected as these areas are associated with agricultural practices such as increased spreading of farmyard manure and slurry and livestock grazing providing a high availability of FIOs (Kay et al., 2010). When the relative coverages of land covers are similar between catchments the fitted approach cannot determine which land cover is responsible for a change in in-stream risk, resulting in high risk weightings being offset by low risk weightings or vice versa. It is possible that there was too much similarity in land cover between the sub-catchments investigated in the Wyre catchment. The overall composition of land covers in the sub catchments shows how sub catchments of the Wyre largely fall into two groups of similar land cover mosaic. Statistical analysis revealed that there was a difference in the *E. coli* concentration between sites of the Wyre, however it was not apparent whether this difference was large enough for the SCIMAP fitted approach to delineate risk values for the different land covers. In a previous study, Milledge et al. (2012) investigated 11 catchments across England and that dataset was used to determine how identifiability of land cover risk values associated with increasing diversity of land cover types in catchments. However, Milledge et al. (2012) used a diffuse nutrient pollution dataset, whereas for FIOs we were limited to two catchments, largely because in the UK there are a limited number of spatial datasets of FIOs across catchment systems (Oliver et al., 2016).

Previously, a positive relationship between percentage coverage of land cover in a catchment and the identifiability of its optimum weighting has been observed when considering nutrient pollution (Milledge et al., 2012). This also appeared to be the case for FIO pollution, with decreasing standard deviation in optimum risk weightings as percent coverage of a land cover class increased. All of the catchments studied in the Wyre were dominated by improved grassland leaving little space for other land covers. This may, in part, explain the large standard deviations observed for this catchment for all of the land covers. In contrast, the increased variation in land covers in the Yealm may have resulted in smaller standard deviations recorded for improved grassland, rough grazing and woodland land covers. It has been shown that the use of the SCIMAP fitted approach can be improved when close consideration is given to the location of sampling points (Reaney et al., 2011). Thus, ensuring that contributing catchments of monitoring points vary in their land cover make up as much as possible is a clear priority in order to maximise the identifiability of land cover risk weightings and this reinforces the need for good quality monitoring distributed across stream networks, not just end-point receptors.

Optimum risk weightings may be hard to identify if a land cover class is too broad encompassing many different availabilities of FIOs. It is possible that the availability of FIOs in the landscape depends, in part, on livestock density and that livestock density will vary between farms. Incorporating this information into land cover classes associated with agriculture is possible through use of Agricultural Census data which provides information on livestock density in $2km^2$ grid squares.

However there are potential issues with using this information (Winter et al., 2011). Nevertheless such data may provide an adequate compromise in terms of understanding the variation of FIO pollution risk across catchments resulting from variable stocking densities.

In addition, the improved grassland land cover class is likely to encompass many different management regimes that are likely to represent different availabilities of FIOs, which may have influenced modelled outputs from SCIMAP. For example improved grassland can be managed for livestock grazing and the source of FIOs will come in the form of faecal deposits from livestock. Improved grasslands can also be managed for silage production where spreading of slurry is likely to present a risk of FIO pollution. Further, some dairy farms are now opting to house dairy cows on a permanent basis, particularly in wetter regions of the UK, whereas others continue to adopt a more traditional split between summer pasture grazing and winter housing for cows, and the environmental risks that these contrasting management systems pose will differ (Harmel et al., 2010). The concentration of FIOs and dynamics of their mobilisation will vary between faecal, slurry and manure matrices driving variability in their respective risk to watercourse microbial quality (Hodgson et al., 2009; Guber et al., 2013; Blaustein et al., 2015). Thus, augmenting the improved grassland land cover with management regime and livestock density may improve SCIMAP's characterisation of the spatial variability of FIO risk.

At present SCIMAP's prediction of diffuse pollution risk is time integrated and an annual average risk is predicted. An approach which considers seasons separately may be more appropriate when considering diffuse FIO pollution because the extent to which watercourses receive FIO pollution is likely to vary between seasons (Kay et al., 2008a). For example the persistence of FIOs in the landscape is dependent on abiotic conditions such as temperature (Martinez et al., 2013) and moisture (Moriarty and Gilpin, 2014), which will vary between seasons (Oliver and Page, 2016). Additionally, mobilisation of FIOs from landscape reservoirs will vary depending on patterns of rainfall (Blaustein et al., 2015) and, from a UK perspective, the regulatory end-point receptors, i.e. bathing waters, are monitored seasonally over the summer. The seasonal differences in SCIMAP's performance were more pronounced in the Wyre catchment. Therefore it may be possible that an improvement in model performance can be achieved through accounting for characteristics of FIO fate and transfer that vary seasonally.

An interesting and surprising observation in this study was that for the Yealm catchment improved grassland was assigned a low risk value. This was unexpected because this land cover type can be associated with activities that might produce a high availability of FIOs (McGrane et al., 2014). Improved grassland is used to graze livestock, which deposit fresh faeces into the landscape or it can be amended using slurry and manure for silage production creating a source of FIOs in the environment. This has been further supported by regression (Kay et al., 2010; Tetzlaff et al., 2012) and export coefficient (Kay et al., 2008b) approaches that have suggested an association between FIO pollution and land covers linked with the management of livestock and their manure. Our study assigned risk to land cover types relative to all other land cover types in the catchment. It is possible that, for this particular catchment, another land cover type was more risky than improved grassland. In the Yealm catchment, areas of rough grazing were assigned a high risk value and an optimum mean value of 0.78. Perhaps rough grazing in this catchment provides more FIO pollution to the river network than improved grassland and therefore inputs from extensive grazing, most likely via sheep, are more important than inputs from areas of improved pasture for this particular catchment. Similarly, in the Wyre catchment, a medium risk value (0.58) was assigned to areas associated with rough grazing but our confidence in the interpretation of this finding is low given the covariance of land cover types in the catchment. Of course, the fact that land cover information is derived from remote sensing techniques may also influence results. There is some overlap in the spectral properties of improved grassland and rough grazing, neutral, acid and calcareous grasslands meaning in

some cases it can be difficult to delineate between these land covers (Morton et al., 2011), which are likely to vary in their susceptibility to FIO contamination.

5. Conclusion

This research has provided a 'bench-marking' modelling experiment to determine how well the current SCIMAP framework for diffuse fine sediment pollution can be applied to map diffuse FIO pollution risk in catchment systems. Overall performance was variable with reasonable performance of the model for the Yealm catchment but poor outputs when tested in the Wyre catchment. In addition, assignment of risk weightings to land cover types exhibited uncertainty for all land covers, excluding woodland in both catchments and improved grassland in the Yealm catchment. However, a number of opportunities for the development of SCIMAP to account for diffuse FIO pollution risks have been identified. SCIMAP has proven useful for the targeting of interventions for conservative nutrient and fine sediment pollution and the framework shows promise in its consideration of FIOs. However the unconservative nature of FIOs undoubtedly provides a different set of challenges for this model. Opportunities for addressing these challenges exist and this study has provided the necessary evidence to highlight that the adaptation of SCIMAP to account for FIO fate and transfer will likely mark a significant departure from previous iterations of this risk-based framework. In doing so, it should provide a useful tool for those attempting to reduce the impact of faecal contamination of watercourses at the catchment scale.

Acknowledgements

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