Journal of Environmental Management 250 (2019) 109366

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

Identifying critical source areas using multiple methods for effective diffuse pollution mitigation

S.M. Reaney[a,*,1], E.B. Mackay[b,1], P.M. Haygarth[c], M. Fisher[d], A. Molineux[d], M. Potts[d], C. McW.H. Benskin[c]

[a] Department of Geography, Durham University, Durham, DH1 3LE, UK
[b] Lake Ecosystems Group, Centre for Hydrology & Ecology, Bailrigg, Lancaster, LA1 4AP, UK
[c] Lancaster Environment Centre, Lancaster University, Lancaster, LA1 4YQ, UK
[d] Tripod Software Ltd, Salford Innovation Forum, 51 Frederick Road, Salford, M6 6FP, UK

ARTICLE INFO

Keywords:
Critical source area
Diffuse pollution
Drones
Phone app
Walkover survey
Mapping

ABSTRACT

Diffuse pollution from agriculture constitutes a key pressure on the water quality of freshwaters and is frequently the cause of ecological degradation. The problem of diffuse pollution can be conceptualised with a source-mobilisation-pathway (or delivery)-impact model, whereby the combination of high source risk and strong connected pathways leads to ‘critical source areas’ (CSAs). These areas are where most diffuse pollution will originate, and hence are the optimal places to implement mitigation measures. However, identifying the locations of these areas is a key problem across different spatial scales within catchments. A number of approaches are frequently used for this assessment, although comparisons of these assessments are rarely carried out. We evaluate the CSAs identified via traditional walkover surveys supported by three different approaches, highlighting their benefits and disadvantages. These include a custom designed smartphone app; a desktop geographic information system (GIS) and terrain analysis-based SCIMAP (Sensitive Catchment Integrated Modelling and Analysis Platform) approach; and the use of a high spatial resolution drone dataset as an improved input data for SCIMAP modelling. Each of these methods captures the locations of the CSAs, revealing similarities and differences in the prioritisation of CSA features. The differences are due to the temporal and spatial resolution of the three methods such as the use of static land cover information, the ability to capture small scale features, such as gateways and the incomplete catchment coverage of the walkover survey. The relative costs and output resolutions of the three methods indicate that they are suitable for application at different catchment scales in conjunction with other methods. Based on the results in this paper, it is recommended that a multi-evidence-based approach to diffuse pollution management is taken across catchment spatial scales, incorporating local knowledge from the walkover with the different data resolutions of the SCIMAP approach.

1. Introduction

Nutrient enrichment of water courses through ‘cultural’ eutrophication is a global environmental problem leading to a decline in water quality (Foley et al., 2005; Novotny, 2003). Frequently, for management purposes, the sources of nutrients and sediments responsible are divided into point sources (those that originate from single defined sites discharging directly into water courses), and diffuse or non-point sources (those that originate from across the land in a river or lake catchment) (Novotny, 2003). There have been significant improvements in water quality across Europe since the early 1990s, largely achieved by tackling point sources through policy mechanisms such as the European Union's Urban Wastewater Treatment Directive (Directive 91/271/EEC (Council of the European Communities, 1991)). However, to enable the additional restoration and remediation of water bodies required to achieve ‘good status’ under the more recent Water Framework Directive (WFD, Directive 2000/60/EC (Council of the European Communities, 2000)), the contribution from diffuse sources needs to be tackled. These sources of pollution are arguably more challenging to manage as there are difficulties in identifying and regulating their origin, despite the fact that they can represent a large proportion of the total pollution received by an individual water course (European Environment Agency, 2005).

Diffuse pollution from agriculture is a particular problem because it

* Corresponding author.
E-mail address: sim.reaney@durham.ac.uk (S.M. Reaney).
[1] Joint first author.

https://doi.org/10.1016/j.jenvman.2019.109366
Received 12 October 2018; Received in revised form 2 August 2019; Accepted 4 August 2019

is temporally and spatially heterogeneous. The origin of nutrients or sediments often separated from the impacted water course by large distances or long periods of time (McDowell et al., 2004; Meals et al., 2010; Haygarth et al., 2012; Jarvie et al., 2013), making source identification especially challenging. Haygarth et al. (2005) proposed a simple conceptual breakdown of the movement of diffuse pollution within a catchment to address this, collectively referred to as the transfer continuum. It is made up of four sequential components: 1. Source, being the input of the pollutant (e.g. fertilizer) to the farm system; 2. Mobilisation, involving the initial dispersal of the polluting substance from the soil itself, either by chemical or biological solubilisation, physical detachment or incidental losses recently applied to the surface; 3. Delivery, sometimes referred to as 'transport' or 'pathway', relates to the hydrological transport of the substance through various surface or below-ground pathways, and finally; 4. Impact, where the economic or ecologic impact is manifest downstream in a river, lake or estuary, perhaps many years and kilometres from the 'source'. As well as being a conceptual model that aids understanding, this has also been adopted as a way of implementing and focusing the adoption of management measures (e.g. Haygarth et al., 2009; Cuttle et al., 2016). To implement such measures, it is crucial to correctly identify and map 'high risk' areas and characteristics in the landscape, to build a comprehensive picture of the potential terrestrial source areas and link them to the delivery pathways that lead to pollutant deposition in the water courses where impact occurs. This involves identification of sources as well as key landscape and land management factors which drive nutrient mobilisation and delivery (Collins and McGonigle, 2008). Equally important is the knowledge of where sinks and barriers along the diffuse pollution transfer continuum currently exist, as these features contribute to the disconnection of sediment and nutrient flow to watercourses.

Currently, the main approaches used for identifying diffuse pollution risk areas are catchment walkover surveys and the spatial modelling of diffuse pollution risks using geomorphological and hydrological information derived from digital elevation models (DEMS; e.g. Reaney et al., 2011; Zhang et al., 2013). Walkover surveys have the potential to provide useful, highly detailed, site specific information on a range of potential sources, sinks and pathways of diffuse pollution, which can be used in mitigation planning (Newson, 2010). To achieve an adequate resolution of information at an appropriate scale for this purpose is, however, challenging, due to the broad range of areas to be surveyed, and the necessity to collect data across seasons and in all weather conditions. In particular, the spatial coverage that can be achieved by these surveys is likely to be limited relative to the 100's or 1000's of km^2 of catchment that may need to be assessed. Such data collection has traditionally been done noting observations using pen and paper, which has a number of associated problems. Data recorded on paper whilst in the field requires subsequent manual transcription into an electronic database to render data useful for analyses and mitigation planning purposes (Olson et al., 2014), presenting the opportunity for transcription and/or typographical errors. In addition, spatial location via a GPS (global position system) and photographic records are increasingly required for later analysis and data validation. This technique requires considerable time investment in the field and during data collation, resulting in additional costs.

While walkover surveys can be seen as a 'bottom up' approach to identifying diffuse pollution risks, computer based modelling usually involves a more 'top down' approach, generalising landscape risks through analysis of broader scale landscape features (Lane et al., 2006). A number of models have been developed to assess and quantify diffuse pollution at different scales using farm-based information (e.g. FARMSCOPER, Zhang et al., 2012), process-based modelling such as PSYCHIC (Davison et al., 2008) and delivery coefficients (e.g. Phosphorus Export and Delivery in Agricultural Landscapes (PEDAL) (Zhang et al., 2013)). An established method in the UK that integrates a range of spatial scales to generate predictions of risk is the Sensitive Catchment Integrated Modelling And Prediction (SCIMAP) risk mapping framework (http://www.scimap.org.uk/). It works by calculating the spatial patterns of relative potential erosion and hydrological connectivity at a particular location, defined by the resolution of the input data, and combines these data to identify possible critical source areas for diffuse pollution risk (Reaney et al., 2011). This risk is routed through the landscape and diluted according to the amount of water that would flow through the location based on the spatial pattern of observed rainfall depths. A map is then generated, showing where in the landscape the diffuse pollution risk would accumulate faster than the dilution potential, which may lead to observable in-stream water quality problems. Although the SCIMAP approach gives relatively detailed predictions of the spatial pattern of risk at the sub-field scale, these predictions are necessarily limited by the quality and type of input data, being based mainly on natural surface landscape features including slope and land use. Subtle and small scale features, such as those that might represent the enhancement or deceleration of diffuse pollution risk for mitigation planning, may not be represented in the spatial data. SCIMAP is normally applied using nationally available datasets, and within the UK the normal dataset is the NextMap 5 m DEM, Centre for Ecology & Hydrology (CEH) Land Cover map 2007 at 30 m (Morton et al., 2011) and the CEH GEAR 1 km Rainfall map (Tanguy et al., 2016). The spatial resolution of these data sets means that SCIMAP is applicable at the landscape extent with sub-field detail. However, subtle topographic features in the landscape, such as tracks, gateways and poached soil likely will not be represented in the dataset, and hence are missed from the analysis. Furthermore, SCIMAP predicts the spatial pattern of *relative* risk, i.e. areas labelled as high risk within a catchment are the highest *within that catchment* and may not be causing a problem, making it important to apply the approach to catchments with a known diffuse pollution issue. Predictions from such models are useful as tools for identifying potential areas of diffuse pollution, but they need testing to establish the importance of individual sites as potential areas of risk. Collecting and collating these data in a systematic way is currently a challenge for the validation of predictions from spatially based models.

The limitations of current walkover field surveys, alongside the need for higher resolution input data and readily useable validation data for spatial model predictions, pose challenges for mitigation planning and the management of diffuse pollution. However, the growing potential of mobile digital technologies and aerial drones with high resolution cameras in providing easy to use multi-purpose tools through the provision of geo-referencing applications (apps) and higher resolution input data could offer improved data quality for the assessment of diffuse pollution risk at the sub-field scale where management decisions are made. Mobile phone apps for the collection of scientific data have proliferated (e.g. Aanensen et al., 2009; Graham et al., 2011; Sunyoung et al., 2011; Olson et al., 2014), and can provide data for monitoring programmes (Olson et al., 2014) and engage citizen scientists (Graham et al., 2011) at relatively low costs. As data are recorded digitally, including location and image files, they are easily integrated into analysis systems such as Geographical Information Systems (GIS) for later assessment of quality control/assurance and visual assessment of small-scale catchment features. At the same time, the falling costs and increasing durability of UAVs or drones are providing new opportunities for detailed data collection using remote sensing (Schiffman, 2014). However, as yet, relatively few comparisons of these emerging techniques for data capture have been carried out, and their applicability for assessment of diffuse pollution risk remains untested.

Here we provide an evaluation of different techniques for data collection and analysis for diffuse pollution risk assessment along the transfer continuum. We focus on mobilisation and delivery, and provide a framework for integrating the use of these techniques in catchment management. Firstly, predictions of diffuse pollution risk were generated using three distinct methods: (1) running conventional input data sources through the SCIMAP model, giving a 5 m resolution output; (2) identifying locations using data collected with a bespoke mobile phone

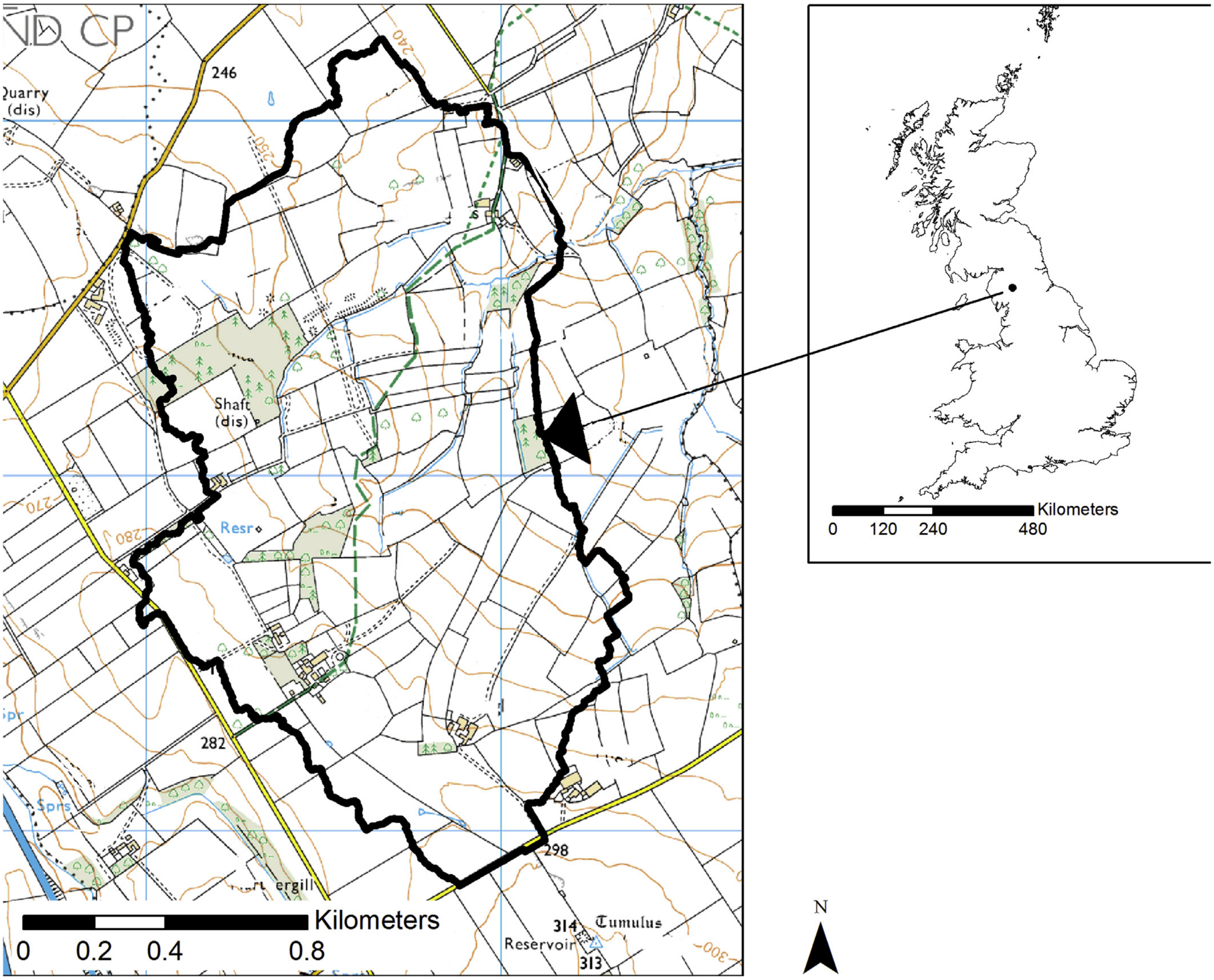

Fig. 1. Map showing the location of the study catchment, Newby Beck, which was a tributary of the River Eden, Cumbria, UK. Ordnance Survey (GB), © Crown Copyright/database right 2019. An Ordnance Survey/EDINA supplied service.

app from a walkover survey; and (3) identifying sites using drone data to build a high spatial resolution DEM and land cover map. Secondly, we assessed the performance of each approach from the perspective of potential improvements to the identification of diffuse pollution risk, the associated costs and their utility in mitigation planning and management. Finally, we show how, through the use of an integrated approach to diffuse pollution assessment, we can optimise these different techniques used across spatial scales to provide a framework for improved catchment management of diffuse pollution.

2. Materials and methods

2.1. Site description

The study site, a 2.2 km^2 headwater agricultural catchment in the River Eden valley, Cumbria, UK (Fig. 1), was within the Eden Demonstration Test Catchment (DTC) project area, and has diffuse pollution issues associated with livestock production combined with high risk rainfall-runoff patterns (Owen et al., 2012; Perks et al., 2015). The catchment predominantly consisted of improved grassland for dairy and sheep, acid grassland and some arable. The elevation range was 95 m and the mean slope gradient was 6.5°. Soils were mainly clay loam and sandy clay loam; locally deep and well-drained in the headwaters, seasonally wet in the central elevations, moving through to slowly permeable and seasonally waterlogged in lower parts of the catchment. Post-glacial till dominated the superficial geology, forming a relatively continuous cover on the limestone bedrock, which intersected with the surface at a number of points. The mean annual rainfall was 1200–1272 mm based on the 1980–2010 average from the CEH GEAR dataset (Tanguy et al., 2016), with an annual average potential evapotranspiration of 636 mm, based on the Thornthwaite equation, showing the temperate nature of the catchment and the resultant importance of lateral hydrological flow pathways.

2.2. Mobile phone app and walkover survey

The diffuse pollution mobile phone app enabled multiple data records to be captured and stored offline, enabling its use in rural areas with little or no mobile network coverage. Each record is assigned a unique ID with time and date stamp. The latitude, longitude and altitude of each survey point is returned from the GPS unit of the phone and logged as part of the record. A series of pages with explanatory text at each step enables data entry relative to the feature being recorded, logging whether the feature is enhancing (a source/pathway) or

Table 1
List of features included in the diffuse pollution app and the corresponding category in Brazier et al. (2006).

App Feature	Enhancing or Decelerating	Brazier et al. (2006) Category	Diffuse pollution transfer continuum category
Pugging and Poaching	Enhancing	Soil management within the connected area and practices likely to promote runoff and erosion e.g. soil compaction by machinery, livestock poaching	Mobilisation
Compaction	Enhancing	As above	Connectivity
Uncovered yard	Enhancing	Presence of concrete yards	Mobilisation
Septic tank outflow	Enhancing		Connectivity
Outfall pipe or field drain	Enhancing	Presence of field drains, their age and density	Connectivity
Spreading of slurry/manure	Enhancing		Mobilisation
Animals in watercourse	Enhancing		Mobilisation
Bare stream bank	Enhancing		Mobilisation
Erosion or gullying	Enhancing	Evidence of erosion features associated with concentrated flow	Mobilisation
Overland flow	Enhancing		Connectivity
Road or track	Enhancing	Presence of roads and tracks	Connectivity
Ditch	Enhancing	Presence of ditches	Connectivity
Farm machinery wheelings	Enhancing	Presence of compacted soils tracks from tractor wheels	Connectivity
Other	Enhancing		Various
Field boundary	Decelerating	Nature and position of field boundaries	Connectivity
Gateway parallel to slope	Decelerating	Position of gateways	Connectivity
Buffer strip	Decelerating	Presence and location of buffer strips	Connectivity
Marshland or pond	Decelerating	Presence and location of marshland and/or ponds	Connectivity
Area of deposition of eroded material	Decelerating	Evidence of deposition in relation to topography and related evidence of discontinuous pathways	Connectivity
Woodland	Decelerating	Presence and location of woodland	Mobilisation
Other	Decelerating		Various

decelerating/disconnecting (a sink/barrier); the type of accelerating/decelerating feature; what the weather and soil conditions are at the time of capture; distance the observer is from the feature; and the option of adding any further information relevant to the feature in a comment box. The features included in the app are based on those developed as part of the visual assessment procedure described in Brazier et al. (2006; see Table 1). ‘Wheelings’ are the result of farm machinery operated on fields and are narrow unvegetated areas of the field that are often compacted (Silgram et al., 2015). This compaction can result in increased runoff generation and transmission and associated erosion. The final data capture step gave the option of adding photographs of the feature. Once all steps have been completed, the information was summarised so the user can check that input is as comprehensive and accurate as possible, before the data are saved.

When the mobile phone was next connected to the internet, stored data can be uploaded to a central web-hosted database, which allowed users to map, visualise and analyse submitted information. This feature enables data to be quality assured, before being exported as a.csv (comma separated values) file. The.csv format facilitated the dataset use in a variety of analysis packages, including GIS software, for visual analysis to enable, for example, mitigation planning.

A walkover survey of the study site was conducted to assess sources, barriers and connectivity, i.e. factors which may accelerate or decelerate pollutant delivery to the watercourses. The diffuse pollution phone app was used to record features regarded as either enhancing or decelerating pollutant mobility, and resulting data were mapped using ESRI ArcGIS software. To determine the visual coverage of the catchment, visibility analysis was undertaken with the Viewshed tool within ArcGIS and the 0.4 m digital surface model (DSM) from the drone mapping. This DSM included landscape features that may block views, such as walls, woodlands and buildings. The analysis shows how much of the catchment could have been observed from the walkover survey observation points.

2.3. Diffuse pollution risk mapping methods

The diffuse pollution risk mapping tool SCIMAP uses a ‘minimum information requirement’ approach to identifying where in the catchment diffuse pollution is most likely to be originating (Reaney et al., 2011). SCIMAP has been successfully applied to determining the spatial pattern of diffuse pollution risk on salmon and trout (Reaney et al., 2011), nitrogen and phosphorus (Milledge et al., 2012), FIOs (Porter et al., 2017) and sediment (Perks et al., 2017). SCIMAP is based on the critical source area concept, and hence calculates maps of source and mobilisation risk and the hydrological connectivity to capture the pathways across the catchment. This information was then used to route and dilute the diffuse pollution risk across the landscape to find areas where there is a greater diffuse pollution risk than water to dilute it.

The location of the high source and mobilisation risk areas (*sourceRisk*) were defined by the balance between the erosive energy of overland flow, determined by stream power and the erodibility of the soil surface, in this application regulated by land cover:

$$sourceRisk = K \cdot uca \cdot B \tag{1}$$

where K is the erodibility of the surface on a value range 0–1, with 1 being the highest source and mobilisation risk; uca is the upslope contributing area; and B is the local slope gradient.

The ease with which material can be transmitted along a pathway was calculated with the Network Index algorithm (Lane et al., 2009). This algorithm works by tracing the flow pathway from each point in the DEM to the river channel to identify drier, disconnecting locations and thereby determines how wet the catchment needs to be for each location to be runoff generating and to have a connected pathway to the river channel.

The source and connectivity maps are scaled between 0 and 1 and were then multiplied together to give the location of the CSAs in the landscape. The diffuse pollution risk values were then accumulated through the catchment based on a weighted flow accumulation algorithm to give a risk loading the channels. The loads were converted to a concentration based on the rainfall weighted upslope contributing area. The areas where there was more diffuse pollution risk than water to dilute it were highlighted as probable key source areas. SCIMAP produced maps of the source and mobilisation risk, showing the hydrological connectivity representing the ease with which material can move along a pathway and the integrated relative in-channel concentrations of risk, which enables the selection of high-risk sub-catchments for mitigation works.

Table 2
SCIMAP standard risk weights values for the land cover classes based on Perks et al. (2017).

Land Cover	SCIMAP's Risk Weighting Value
Arable and horticulture	1.00
Broad leaved, mixed and yew woodland	0.05
Built up areas and gardens	0.01
Coniferous woodland	0.05
Dwarf shrub heath	0.1
Improved grassland	0.30
Unimproved grassland	0.15

2.3.1. Desktop SCIMAP application

For the desktop application of SCIMAP to the Newby Beck mitigation catchment, the NextMap 5 m DEM was used in combination with the CEH Land Cover map 2007 dataset. The land cover classes were grouped into eight main functional covers and the source and mobilisation risk values were assigned using the SCIMAP standard risk weights (Table 2). Due to the small size of the catchment (2.2 km^2), rainfall was assumed not to have a spatial pattern. These datasets are the standard inputs to SCIMAP since they have national coverage within the UK.

2.3.2. Drone data collection methods

The aim of the drone data collection was to build a high spatial resolution DEM and land cover map captured within the same season as the app-based walkover survey. The dataset was built using a ‘Structure from Motion’ photogrammetry approach by using a drone was used to capture multiple overlapping images of the catchment which were then processed to build a 0.4 m DEM and visible colour orthophoto. The drone was a DJI Phantom 4, with a 12-megapixel camera, which was flown at an altitude of 80 m above the land surface. This altitude was maintained over the topography to ensure that there was consistent detail and resolution in the source images. The images were captured with 90% forward overlap and 70% sideways overlap. A set of ground control points were placed across the catchment and their location recorded with Leica dGPS with an accuracy of 0.01 m. The image capture was performed over two days of consistent weather conditions and resulted in 5500 images. These images were processed within Agisoft Photoscan Pro to produce the 3D point cloud representing the catchment. This point cloud dataset was classified into ground and vegetation points and the ground points were used to build the DEM and the visible colour orthophoto.

The SCIMAP approach needs information of the spatial pattern of source areas and this map can be based on vegetation cover providing protection to the soil surface. Since near-infrared data were not available, the Visible Atmospherically Resistant Index (VARI), which enables the mapping of vegetation patterns (Gitelson et al., 2002), was used:

$$VARI = \frac{Green - Red}{Green + Red - Blue} \tag{2}$$

The drone-based datasets were then processed within SCIMAP using the same options and parameters as for the desktop-based application.

2.4. Selection of the top critical source areas

All the accelerating features identified as part of the walkover survey were selected and assigned to one of two categories indicating their dominant role as a CSA: mobilisation or connectivity. For each of the SCIMAP based maps, the top ten critical source areas were selected to represent the key locations within the catchment where mitigation measures would have the maximum effect. The mobilisation and connectivity grids were multiplied together and areas with a combined score of > 0.9 were selected. These areas were converted into single units based on four-way neighbourhood connections, and then the largest ten areas were selected.

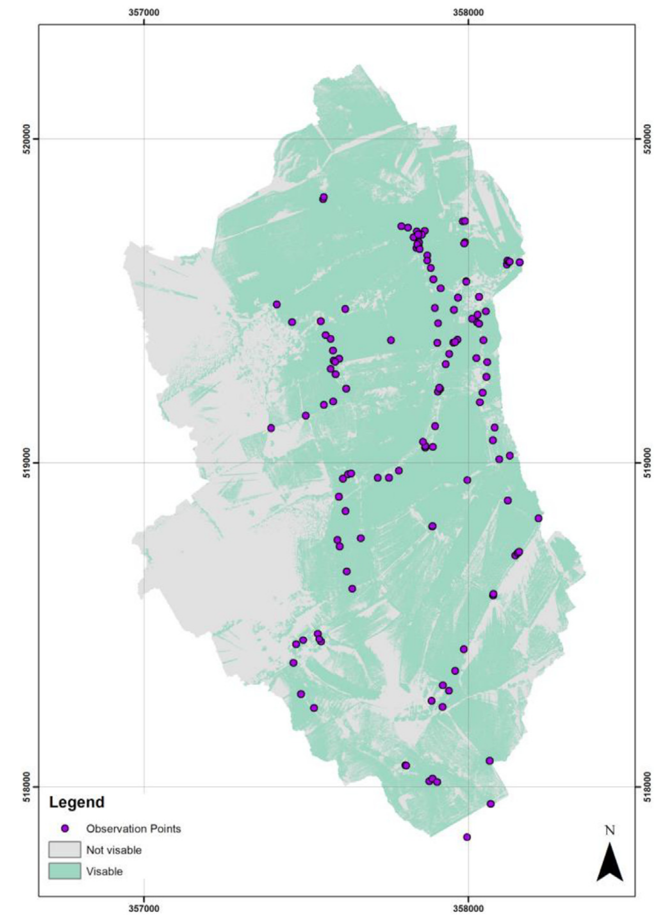

Fig. 2. Catchment map showing observed locations (purple dots) and the Viewshed visibility analysis results; areas observed in light green. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3. Results

3.1. Walkover survey

The area covered by the walkover survey accounted for just over 60% of the catchment based on the visibility analysis (Fig. 2). In total, 75 enhancing features were identified in 12 of the 14 categories available in the mobile phone app, with only septic tank outflow and animals in the watercourse not being observed. Of these 75 enhancing features, six were identified as ‘enhancing feature other’, four of which were related to animal feeding or silage, while the remaining two were an overflowing yard drain and an arable field with no buffer strip. These points were further classified into 39 mobilisation features and 36 connectivity features (Fig. 2; Table 1). The app also collected information on 52 decelerating features, including the presence of woodland, fenced buffer strips and settling ponds. A number of these measures had been installed in response to a previous desk-based SCIMAP assessment which identified areas of high diffuse pollution risk. These included online and offline sediment settling ponds, in-ditch hard-core sediment traps and fenced off riparian buffer zones with newly planted trees. This information can also be used to validate and cross reference with the modelling approaches.

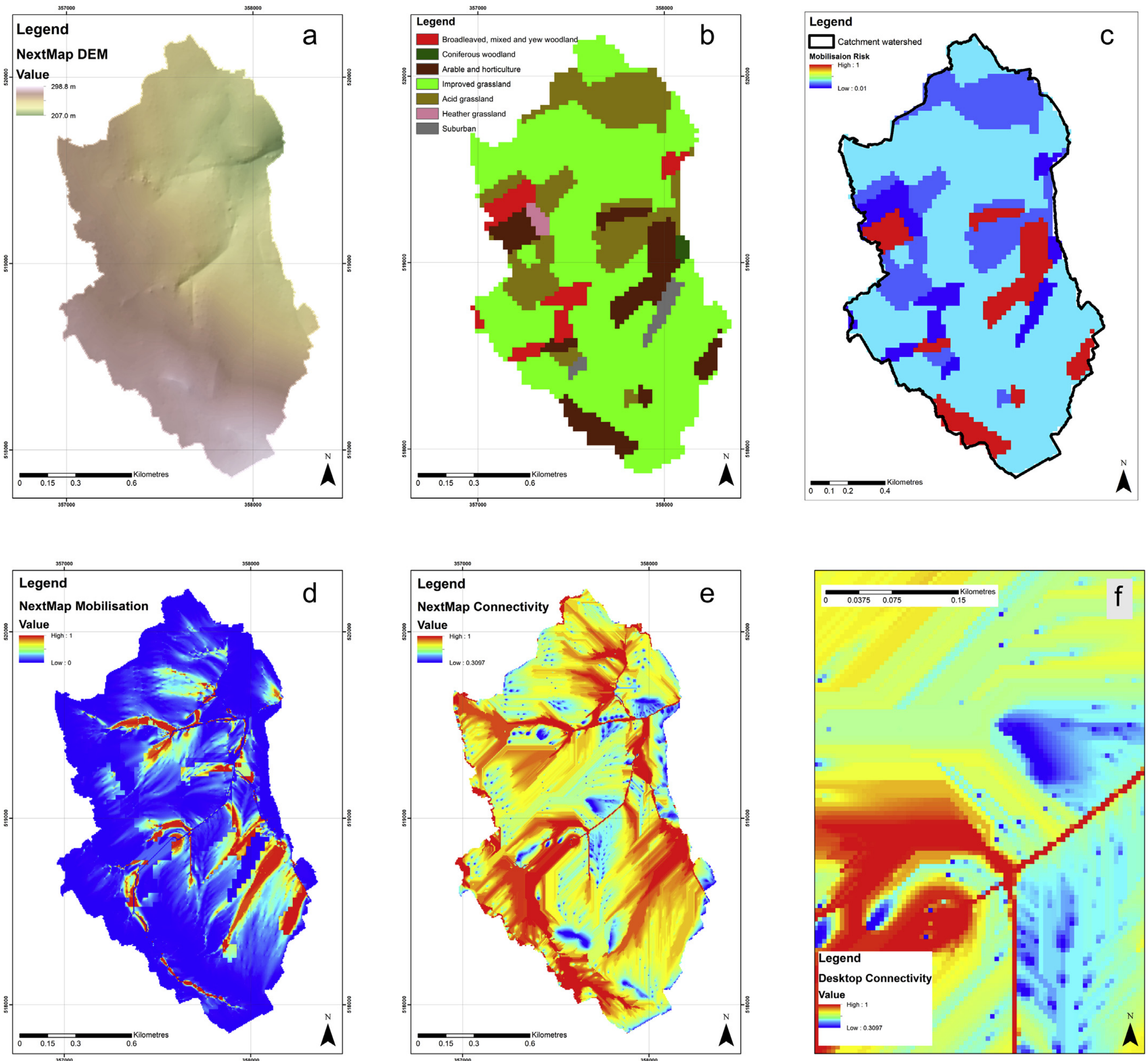

Fig. 3. a) NextMap 5 m DEM, b) land cover map, c) reclassified land cover map, d) source and mobilisation risk, e) connectivity and f) detail of the hydrological connectivity calculations.

3.2. Desktop modelling with SCIMAP

The 5 m DEM identified the main topographic highs at the southern edge of the catchment, and the lows, including the main stream channels and steeper slopes along the sides of the stream at the headwaters (Fig. 3). The Land Cover map 2007 indicated that the dominant land use within the catchment is improved (63%) or acid grassland (19%) followed by arable/horticulture (11%) and woodland (5%; Fig. 3). Some misclassification of suburban area is apparent for one area of this map. The steeper slopes linked to the stream channels drives the areas with high values on the mobilisation and connectivity maps (Fig. 3 c-d), particularly when associated with arable/horticultural land uses.

3.3. Drone data inputs and SCIMAP modelling outputs

The results from the 'Structure from Motion' processing are shown in Fig. 4. Comparison of the model to the ground control points showed a calculated error of 75 mm in the x - y plane, and 53 mm in the z plane, giving an overall error statistic of 92 mm. These errors show that the model is suitable for application in the SCIMAP processing. The maximum resolution of the DEM ground pixel size and orthophoto are 140 mm and 34 mm, respectively. However, the final version of the dataset was produced with a 400 mm ground resolution to enable compatibility with the standard terrain analysis algorithms, whilst still capturing subtle details in the catchment.

The improved resolution of the drone DEM enables the delineation of woodland areas, farm buildings and field boundaries (Fig. 4a). The bare ground identified (Fig. 4c) also revealed the dynamic pattern of land cover occurring in the catchment when compared to location of the arable/horticultural land use from the desktop study. The much greater resolution of results is clear in the mobilisation and connectivity maps (Fig. 4d and e), where the between and within field connectivity

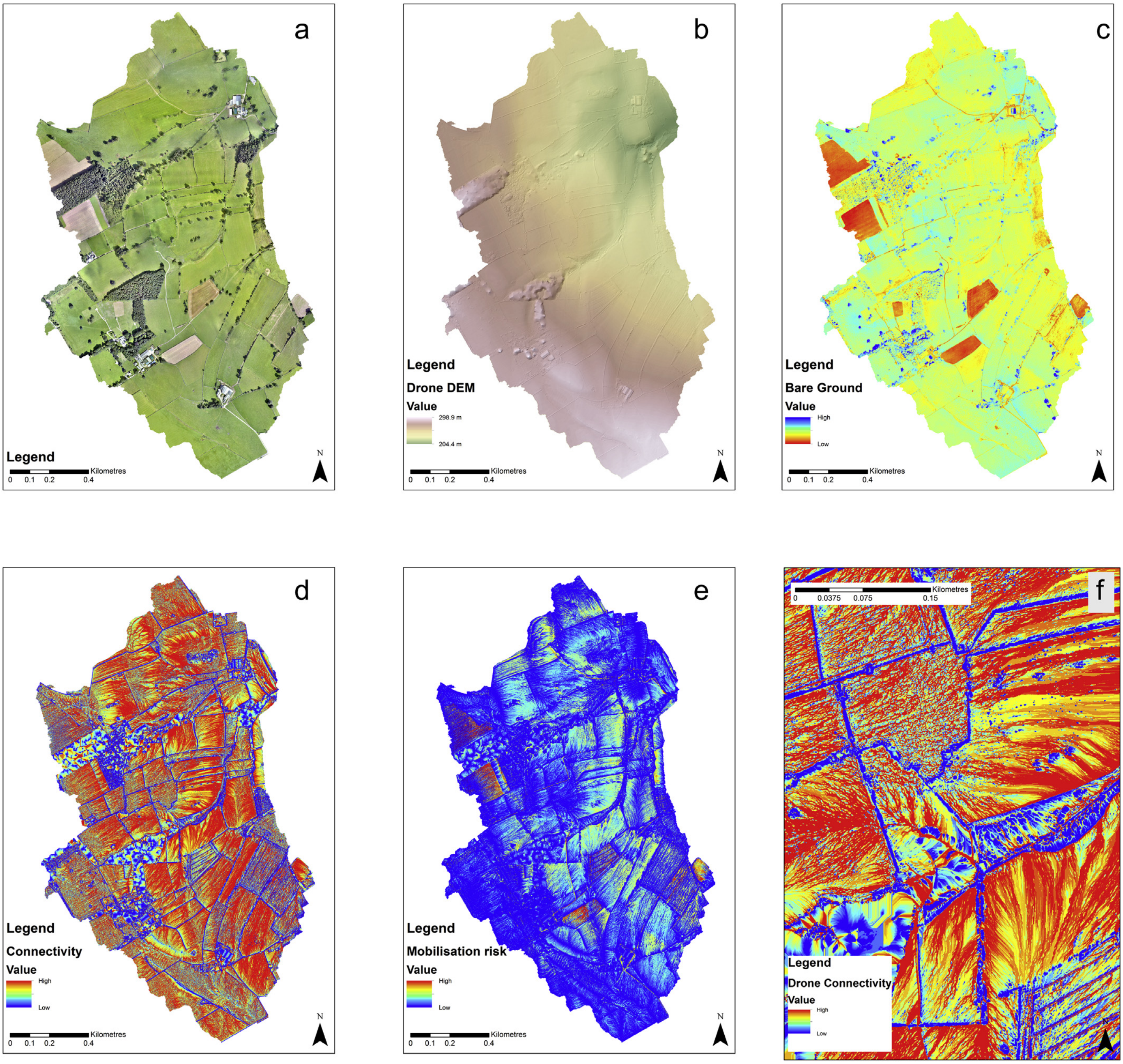

Fig. 4. a) DEM, b) orthophoto, c) bare ground, d) mobilisation risk, e) connectivity and f) detail of connectivity predictions.

and mobilisation can be clearly identified. However, the SCIMAP model has difficulty with correctly classifying the connectivity risk in areas of woodland with these data.

3.4. Comparison of the three methods

The effort required for each of the three methods used to classify diffuse pollution risk in the catchment is provided in Table 3. The desktop study was the least resource intensive and includes full catchment coverage, but has the lowest resolution and, therefore, a greater level of uncertainty in the results. In contrast, the walkover survey provides very detailed information on local scale source and connectivity effects, with visual validation of the data. However, it required a larger surveying commitment and does not attain the same coverage as either of the remote sensing methods. The drone mapping combined a higher spatial resolution than the desktop mapping and 100% catchment coverage, although validation of the data was still required through aerial image analysis or ground based checks, and it represented the most expensive option of the three.

3.5. Identified critical source areas

The identified enhancing features and top ranked critical source areas for each method are shown in Fig. 5 a-c and in Fig. 6. The walkover survey (a) showed a clear linear distribution of features, partially reflecting the route of the surveyor and the stream network. Sites also clustered around the farm buildings located within the catchment. The top 10 CSAs identified by the desktop (b) and drone-based (c) SCIMAP clearly differ, reflecting differences in the land cover and bare ground used in the analysis, as well as the resolution of the input data. The desktop mapping also identifies grassland areas with steeper slopes adjacent to the stream network as being potentially high

Table 3
Comparison of the data collection methods.

	Walkover Survey	Desktop SCIMAP	Drone SCIMAP
Time taken on site	3-person days	Zero	1.5-person days
Time taken in office	0.5-person days for visualization and interpretation	0.5-person days for visualization and interpretation, including 5 min to produce maps	1-person day for SfM processing plus 5 days CPU time in background; 0.5-person days for visualization and interpretation
Resolution	Linear pathways through the catchment	5 m	0.4 m
Confirmation	Visible on the ground	From aerial images	From aerial and drone-based images
Effort/cost scaling with area	Linear	Nonlinear - larger areas do not add proportional additional costs	Linear
Source and pathways?	Source and local connectivity effects	Source and global connectivity effects	Source and global connectivity effects
Catchment coverage	62.9%	100%	100%
Relative total costs	1	0.33x	2.94x

risk.

4. Discussion

The three approaches to identifying critical source areas for diffuse pollution provide different levels of temporal and spatial coverage and resolution. The desktop and drone-based SCIMAP model results both provide full coverage of the catchment. The more rapid and lower cost desktop-based analysis was, however, limited by the static nature of the land use data from 2007 and the 5 m DEM. This implies that the identification of diffuse pollution risk features will only be at a generic level, limited by the resolution of the input data and the assumption of a fixed land use pattern within the catchment. Comparing the 2007 land cover map data with the drone orthophoto clearly shows that in the landscape context of this catchment the changing pattern of bare fields is missed, which could act as a key CSA at particular times (Heathwaite et al., 2005). To some extent, the identification of land use or risk areas by the other two methods also face this limitation, but they also offer the opportunity for rapid reassessment and ground-truthing that is not possible with a national scale map. The high level of spatial and temporal heterogeneity associated with diffuse pollution risks illustrates one of the reasons it is considered a 'wicked' environmental problem (Patterson et al., 2013; Thornton et al., 2013).

In contrast to the comprehensive coverage of the modelling, the walkover survey provided very detailed information at individual points within the catchment. This included information on the agricultural activity at the time of the survey and details of CSAs around farm buildings, which are features that cannot be picked up by SCIMAP modelling. As is clear from the routes taken by the observers, the identification of features occurs along linear pathways, which may result in CSAs not in the immediate vicinity of a particular route being missed. However, obtaining the same level of coverage as the spatial modelling would likely require a large amount of additional effort, which is unlikely to be a cost-effective option due to time requirements, or be particularly feasible where accessibility of land may be challenging due to crop cover, topography or presence of livestock.

Each method helped identify priority CSAs (Fig. 6). This is a direct result of the different resolutions of input data or scale of observation and the ephemeral nature of CSAs in the landscape. The dominant drivers of the CSAs identified in the Newby catchment are the mobilisation risks caused by the presence of bare ground (drone-based SCIMAP), land use and slopes adjacent to the stream network (desk-based SCIMAP) and features associated with pugging/poaching (mobilisation) and roads/tracks (connectivity; walkover survey). Pugging is

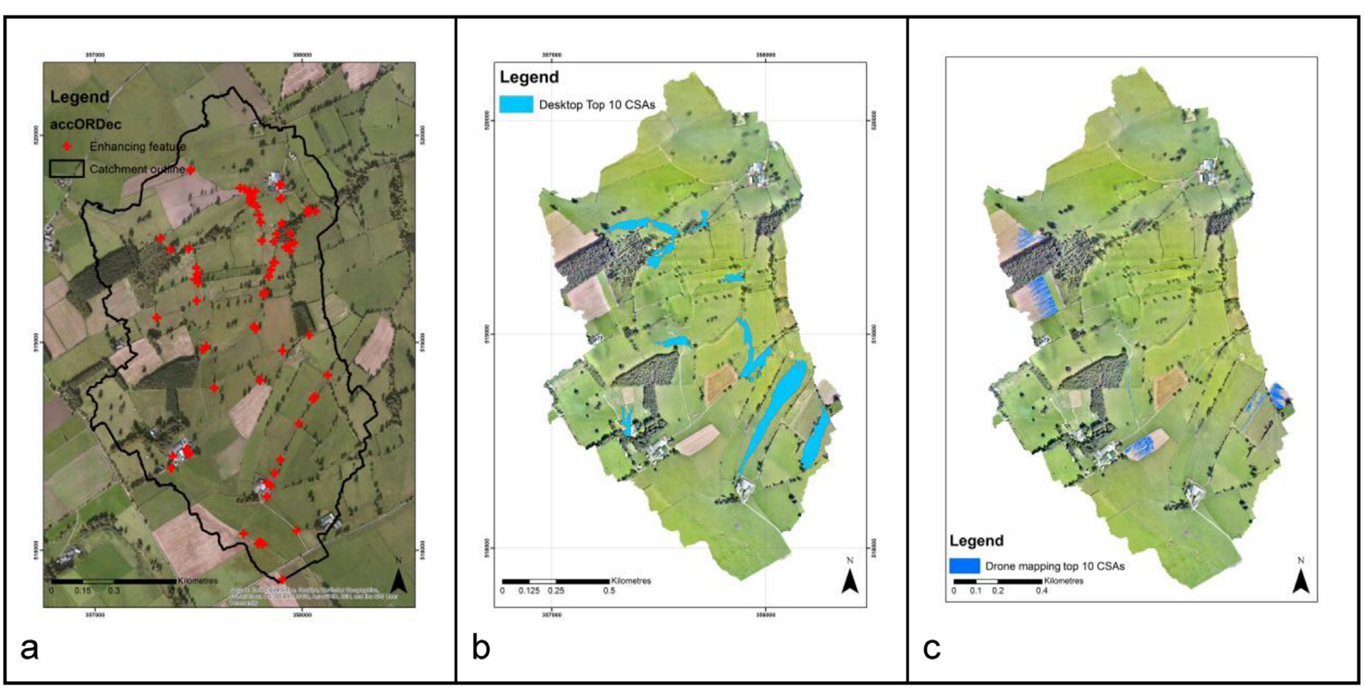

Fig. 5. Identified critical source areas with a) field mappings, b) desktop SCIMAP, and c) high resolution drone based SCIMAP.

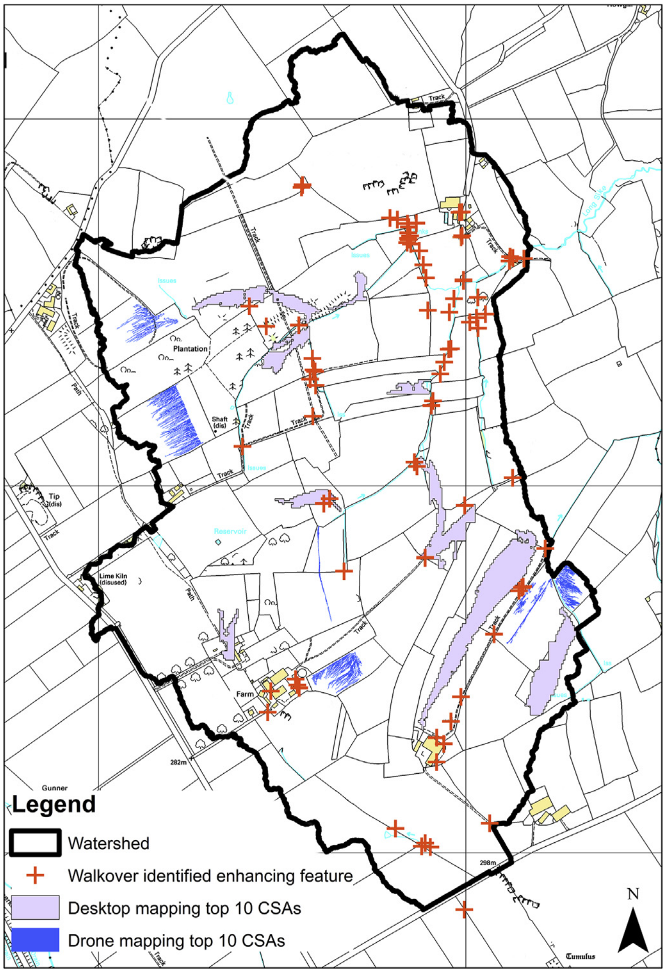

Fig. 6. Critical source areas identified by each of the methods. © Crown Copyright/database right 2019. An Ordnance Survey/EDINA supplied service.

the creation of hoof imprints in the soil and poaching is the slurry like soil conditions created when saturated soil is trampled by livestock (Bilotta et al., 2007). These conditions represent very typical CSA features within largely grassland agriculture dominated catchments (Heathwaite et al., 2005; White et al., 2009). Understanding the context of these individual CSAs will be essential when identifying the priority locations for mitigation efforts that will maximise impact downstream (Doody et al., 2012).

The desktop assessment SCIMAP based on the 5 m DEM dataset provided the most rapid assessment of diffuse pollution risk in the Newby catchment. However, the resolution of the DEM meant that it did not capture the subtle landscape features that can affect the sources, mobilisation pattern and pathways taken by diffuse pollution and hence may miss certain CSAs. This is particularly clear within the scale of the sub-catchment (~2 km^2) when comparing the map outputs in Fig. 3 with those in Fig. 4. The limitation of only using this approach to characterise CSAs is that relatively large areas are likely to be assigned similar risk categories, which may make the prioritisation of sites for mitigation measures more difficult at the field scale.

The drone-based SCIMAP assessment captured small scale features across the whole catchment relatively well, however, results in Fig. 4 identify problems with the representation of land under woodland. The photogrammetry-based Structure from Motion approach does not capture the ground surface and hence calculates the surface as being the top of the canopy. For individual trees, the approach is able to calculate the ground surface due to being able to see the land under the tree from multiple angles. An alternative approach to Structure from Motion would be the use of data capture using LiDAR, which has the advantage that it is able to detect gaps in the canopy and record the ground surface. The trade-off in this case is that a LiDAR approach would represent a significantly higher data collection cost.

Land use changes over time potentially represent an important contributory factor to the changing location of CSAs within a catchment. The land cover data used in the desktop SCIMAP assessment dates from 2007, and is almost a decade older than the drone and walkover survey carried out in 2016. This discrepancy in age resulted in very different land use categories being assigned by the two SCIMAP methods, with the importance of bare ground as a CSA from the drone-based assessment, revealing that what may be considered relatively subtle changes in land cover at a catchment scale may be strong drivers of diffuse pollution risk at the catchment and field scale. At shorter timescales, the ephemeral nature of CSAs can be revealed by repeated walkover visits using the app (Fig. 7), which illustrates the importance of considering the weather conditions and the time of year when surveys are conducted.

The three methods used to identify CSAs in the landscape represent a trade-off between a contrasting level of detail versus coverage and effort. The desk-based modelling represents the coarsest detail with high coverage and lowest effort, followed by the drone-based modelling with high detail and coverage with highest effort. The highest detail but lowest coverage was delivered by the walkover survey with intermediate effort. The cost of the drone survey renders the method suitable for sub-catchments that have been identified as high risk by the other methods. This indicates that each method has a potential application for different scales and purposes for identifying and mitigating CSAs. To improve confidence in the results and address uncertainties in the modelling outputs and observations, we recommend using a multiple evidence assessment for CSAs to maximise catchment coverage whilst allowing for ground assessment and verification in targeted locations.

Ultimately the purpose of identifying CSAs for diffuse pollution is to assist in the prioritisation of sites for targeting diffuse pollution mitigation management. The outputs of the key CSAs from the three tools (Fig. 6) can be combined by identifying the spatial clustering of features identified by one or more methods to investigate options for mitigation at that location. Features identified by the app can be ranked according to priority or likely severity of impact and assessed alongside the relative risk scores of the SCIMAP outputs. Review of the images captured during the walkover survey offers the potential to increase confidence in deciding where mitigation measures should be located. They can also be utilised in post mitigation assessments of effectiveness in a before/after comparison. Previous management measures in the catchment were targeted at locations along the stream channel and these align closely with the features identified by the app.

The challenge of mitigating diffuse pollution problems in catchments as part of the River Basin Planning approach in the Water Framework Directive, requires that areas of greatest diffuse pollution risk be identified and prioritised for mitigation from the catchment scale down to individual landscape features affecting river reaches. Considering these results, which demonstrate the wide range of features in a relatively small landscape area that contribute to diffuse pollution risk, it is recommended that a multi-evidence-based approach to identifying CSAs is taken, which incorporates local knowledge from the walkover app with the survey based SCIMAP approach to adequately capture these source areas across scales. This method can be conceptualised as a tiered approach to diffuse pollution mitigation management, which starts with an assessment of the entire river basin using national scale data and progressively scaling downwards to high-risk sub-catchment assessment using a drone survey, and ultimately to field scale verification and the identification of sites for mitigation using the app walkover survey can be performed (Fig. 8). Each of these methods provides a different view of the CSA identification problem and hence provide complimentary between the approaches. This tiered approach to assessment would enable river basin managers to effectively map

Fig. 7. Illustration of the ephemeral nature of pressures such as sediment deposition and overland flow. Pictures taken during dry conditions (A 1–3) may not accurately reflect the issues that become obvious during rainfall events (B 1–3).

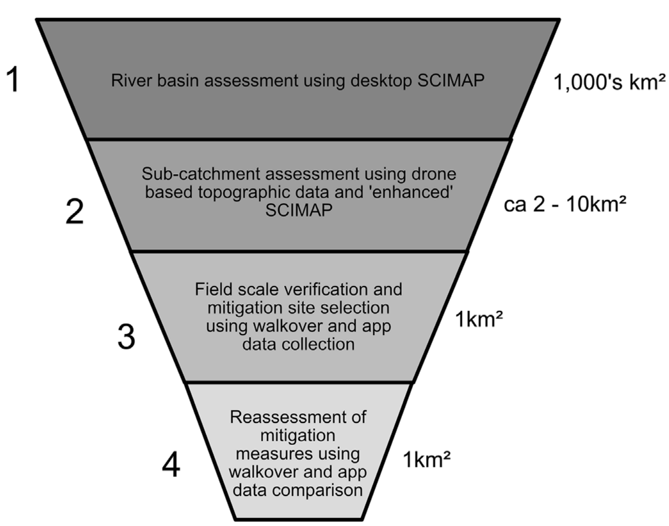

Fig. 8. Multi-evidence based approach to critical source area identification and mitigation at different catchment scales within a spatial targeting funnel of increasing spatial resolution.

diffuse pollution risks in their catchments and prioritise areas for management interventions in a more objective and cost-effective way.

5. Conclusion

The management of diffuse pollution, through the mitigation of sources, and features that drive mobilisation and delivery, is challenging due to the temporal and spatial heterogeneity of the problem. However, the increasing importance of managing this type of pollution to address persistent poor water quality requires effective approaches to identifying and prioritising the location of management interventions. This study assesses three techniques for the identification of critical source areas for diffuse pollution risk at a catchment scale to highlight how the different spatial scales of observation and coverage can alter which areas or features are identified as high risk. In addition, temporal variation in the age of input data, changing land use and the ephemeral nature of some diffuse pollution critical source areas all increase the challenge of identifying and prioritising mitigation of the most risky areas. In order to optimise the use of different datasets, techniques and to minimise the cost of these assessments, we advocate the use of a multi-tiered, multi-evidence approach to critical source area and mitigation measure identification from the river catchment to the sub-field scale.

Acknowledgements

The authors would like to acknowledge the funding for this work from the Defra Demonstration Test Catchment (DTC) project LM0304 and the NERC Environmental Virtual Observatory pilot (EVOp) project NE/I002200/1. In addition, we thank our colleagues on the Eden DTC and EVOp projects for assistance with data collection, logistics and helpful comments on the study approach. We are also very grateful to the farmers of the Newby Beck catchment for allowing us access to their land to enable us to conduct the data collection work.

References

Aanensen, D.M., Huntley, D.M., Feil, E.J., Al-Own, F., Spratt, B.G., 2009. EpiCollect: linking smartphones to web applications for epidemiology, ecology and community data collection. PLoS One 4. https://doi.org/10.1371/journal.pone.0006968.

Bilotta, G.S., Brazier, R.E., Haygarth, P.M., 2007. The impacts of grazing animals on the quality of soils, vegetation, and surface waters in intensively managed grasslands. Adv. Agron. 94, 237–279.

Brazier, R., Schärer, M., Heathwaite, L., Beven, K., Scholefield, P., Haygarth, P., Hodgkinson, R., Walling, D.E.S., Withers, P., 2006. A Framework for Predicting Delivery of Phosphorus from Agricultural Land Using a Decision-Tree Approach. pp. 514–523.

Collins, A.L., McGonigle, D.F., 2008. Monitoring and modelling diffuse pollution from agriculture for policy support: UK and European experience. Environ. Sci. Policy 11, 97–101. https://doi.org/10.1016/j.envsci.2008.01.001.

Council of the European Communities, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy. Off. J. Eur. Commun. 327, 48–54.

Council of the European Communities, 1991. Council Directive of 21 May 1991 concerning urban waste water treatment 91/271/EEC. Off. J. Eur. Commun. 94, 40–52.

Cuttle, S., Newell-Price, J., Harris, D., Chadwick, D., Shepherd, M., Anthony, S., Macleod, C., Haygarth, P.M., Chambers, B., 2016. A method-centric 'User Manual'for the mitigation of diffuse water pollution from agriculture. Soil Use Manag. 32, 162–171.

Davison, P.S., Withers, P.J.A., Lord, E.I., Betson, M.J., Strömqvist, J., 2008. PSYCHIC - a process-based model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1: model description and parameterisation. J. Hydrol. 350, 290–302. https://doi.org/10.1016/j.jhydrol.2007.10.036.

Doody, D.G., Archbold, M., Foy, R.H., Flynn, R., 2012. Approaches to the implementation of the Water Framework Directive: targeting mitigation measures at critical source areas of diffuse phosphorus in Irish catchments. J. Environ. Manag. 93, 225–234. https://doi.org/10.1016/J.JENVMAN.2011.09.002.

European Environment Agency, 2005. Source Apportionment of Nitrogen and Phosphorus Inputs into the Aquatic Environment. European Environment Agency, Copenhagen.

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science (80-.) 309, 570–574.

Gitelson, A., Stark, R., Grits, U., Rundquist, D., Kaufman, Y., Derry, D., 2002. Vegetation and soil lines in visible spectral space: a concept and technique for remote estimation of vegetation fraction. Int. J. Remote Sens. 23, 2537–2562.

Graham, E.A., Henderson, S., Schloss, A., 2011. Using mobile phones to engage citizen scientists in research. Eos 92, 313–315. https://doi.org/10.1029/2011EO380002.

Haygarth, P.M., Apsimon, H., Betson, M., Harris, D., Hodgkinson, R., W.P.J., A., 2009. Mitigating diffuse phosphorus transfer from agriculture according to cost and efficiency. J. Environ. Qual. 38, 2012–2022.

Haygarth, P.M., Condron, L.M., Heathwaite, A.L., Turner, B.L., Harris, G.P., 2005. The phosphorus transfer continuum: linking source to impact with an interdisciplinary and multi-scaled approach. Sci. Total Environ. 344, 5–14.

Haygarth, P.M., Page, T., Beven, K.J., Freer, J., Joynes, A., Butler, P., Wood, G.A., Owens, P.N., 2012. Scaling up the phosphorus signal from soil hillslopes to headwater catchments. Freshw. Biol. 57, 7–25.

Heathwaite, A.L., Quinn, P.F., Hewett, C.J.M., 2005. Modelling and managing critical source areas of diffuse pollution from agricultural land using flow connectivity simulation. J. Hydrol. 304, 446–461. https://doi.org/10.1016/J.JHYDROL.2004.07.043.

Jarvie, H.P., Sharpley, A.N., Spears, B., Buda, A.R., May, L., Kleinman, P.J.A., 2013. Water quality remediation faces unprecedented challenges from "legacy phosphorus. Environ. Sci. Technol. 47, 8997–8998. https://doi.org/10.1021/es403160a.

Lane, S.N., Brookes, C.J., Louise Heathwaite, A., Reaney, S., 2006. Surveillant science: challenges for the management of rural environments emerging from the new generation diffuse pollution models. J. Agric. Econ. 57, 239–257. https://doi.org/10.1111/j.1477-9552.2006.00050.x.

Lane, S.N., Reaney, S.M., Heathwaite, A.L., 2009. Representation of landscape hydrological connectivity using a topographically driven surface flow index. Water Resour. Res. 45. https://doi.org/10.1029/2008WR007336.

McDowell, R.W., Biggs, B.J.F., Sharpley, A.N., Nguyen, L., 2004. Connecting phosphorus loss from agricultural landscapes to surface water quality. Chem. Ecol. 20, 1–40.

Meals, D.W., Dressing, S.A., Davenport, T.E., 2010. Lag time in water quality response to best management practices: a review. J. Environ. Qual. 39, 85–96.

Milledge, D.G., Lane, S.N., Heathwaite, A.L., Reaney, S.M., 2012. A Monte Carlo approach to the inverse problem of diffuse pollution risk in agricultural catchments. Sci. Total Environ. 433, 434–449. https://doi.org/10.1016/J.SCITOTENV.2012.06.047.

Morton, D., Rowland, C., Wood, C., Meek, L., Marston, C., Smith, G., Wadsworth, R., Simpson, I.C., 2011. Final Report for LCM2007 - the New UK Land Cover Map. Countryside Survey Technical Report No. 11/07. .

Newson, M., 2010. Understanding "hot-spot" problems in catchments: the need for scale-sensitive measures and mechanisms to secure effective solutions for river management and conservation. Aquat. Conserv. Mar. Freshw. Ecosyst. 20, 62–72. https://doi.org/10.1002/aqc.1091.

Novotny, V., 2003. Water Quality: Diffuse Pollution and Watershed Management. John Wiley & Sons Ltd, New York.

Olson, D.D., Bissonette, J.A., Cramer, P.C., Green, A.D., Davis, S.T., Jackson, P.J., Coster, D.C., 2014. Monitoring wildlife-vehicle collisions in the Information Age: how smartphones can improve data collection. J. Wildl. Rehabil. 34, 7–16. https://doi.org/10.1371/journal.pone.0098613.

Owen, G.J., Perks, M.T., Benskin, C.M.H., Wilkinson, M.E., Jonczyk, J., Quinn, P.F., 2012. Monitoring agricultural diffuse pollution through a dense monitoring network in the river eden demonstration test catchment, Cumbria, UK. Area 44, 443–453.

Patterson, J.J., Smith, C., Bellamy, J., 2013. Understanding enabling capacities for managing the 'wicked problem' of nonpoint source water pollution in catchments: a conceptual framework. J. Environ. Manag. 128, 441–452. https://doi.org/10.1016/J.JENVMAN.2013.05.033.

Perks, M.T., Owen, G.J., Benskin, C.M.H., Jonczyk, J., Deasy, C., Burke, S., Reaney, S.M., Haygarth, P.M., 2015. Dominant mechanisms for the delivery of fine sediment and phosphorus to fluvial networks draining grassland dominated headwater catchments. Sci. Total Environ. 523, 178–190. https://doi.org/10.1016/j.scitotenv.2015.03.008.

Perks, M.T., Warburton, J., Bracken, L.J., Reaney, S.M., Emery, S.B., Hirst, S., 2017. Use of spatially distributed time-integrated sediment sampling networks and distributed fine sediment modelling to inform catchment management. J. Environ. Manag. 202, 469–478. https://doi.org/10.1016/J.JENVMAN.2017.01.045.

Reaney, S.M., Lane, S.N., Heathwaite, A.L., Dugdale, L.J., 2011. Risk-based modelling of diffuse land use impacts from rural landscapes upon salmonid fry abundance. Ecol. Model. 222, 1016–1029. https://doi.org/10.1016/j.ecolmodel.2010.08.022.

Schiffman, R., 2014. Drones flying high as new tool for field biologists. Science (80-.). 344, 459.

Silgram, M., Jackson, B., McKenzie, B., Quinton, J., Williams, D., Harris, D., Lee, D., Wright, P., Shanahan, P., Zhang, Y., 2015. Reducing the risks associated with autumn wheeling of combinable crops to mitigate runoff and diffuse pollution: a field and catchment scale evaluation. Agric. Hortic. Dev. Board (AHDB). Project Report No. 559.

Sunyoung, K., Robson, C., Zimmerman, T., Pierce, J., Haber, E.M., 2011. Creek watch: pairing usefulness and usability for successful citizen science. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2125–2134.

Tanguy, M., Dixon, H., Prosdocimi, I., Morris, D.G., Keller, V.D.J., 2016. Gridded Estimates of Daily and Monthly Areal Rainfall for the United Kingdom (1890-2015. ([CEH-GEAR]).

Thornton, J.A., Harding, W.R., Dent, M., Hart, R.C., Lin, H., Rast, C.L., Rast, W., Ryding, S.O., Slawski, T.M., 2013. Eutrophication as a 'wicked' problem. Lakes Reserv. Sci. Policy Manag. Sustain. Use 18, 298–316. https://doi.org/10.1111/lre.12044.

White, M.J., Storm, D.E., Busteed, P.R., Stoodley, S.H., Phillips, S.J., 2009. Evaluating nonpoint source critical source area contributions at the watershed scale. J. Environ. Qual. 38, 1654–1663. https://doi.org/10.2134/jeq2008.0375.

Zhang, T., Page, T., Heathwaite, L., Beven, K., Oliver, D.M., Haygarth, P.M., 2013. Estimating phosphorus delivery with its mitigation measures from soil to stream using fuzzy rules. Soil Use Manag. 29, 187–198. https://doi.org/10.1111/j.1475-2743.2012.00433.x.

Zhang, Y., Collins, A.L., Gooday, R.D., 2012. Application of the FARMSCOPER tool for assessing agricultural diffuse pollution mitigation methods across the Hampshire Avon Demonstration Test Catchment, UK. Environ. Sci. Policy 24, 120–131. https://doi.org/10.1016/j.envsci.2012.08.003.