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Weighted risk assessment of critical source areas for soil phosphorus losses through surface runoff mechanisms

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ABSTRACT

In intensive livestock areas, soils commonly contain elevated nutrients above the agronomic optimum which increases the risk of nutrient losses and contributing to poor ecological status waterbodies. Large within-field variability in soil nutrient content exists, and at-risk phosphorus (P) hotspots are rarely quantified due to sub-optimal soil sampling regimes. This study aims to address this issue by developing and evaluating an improved classification of P transfer risk at a sub-field scale through a weighted risk assessment model that combines gridded soil sampling data with modelled in-field surface runoff pathways. Within-field soil P variability was quantified at six field-scale sites in Northern Ireland using two different sampling techniques; traditional bulked field soil sampling (i.e. bulk analysis of W pattern sampling) and gridded sampling (at 35 m resolution) alongside interpolation. Results show that traditional bulked sampling failed to account for the sub-field scale spatial variability in soil P content. This may contribute to the poor chemical and ecological status of surface waters by frequently under-predicting soil nutrient content, and failing to identify potential contributing sources of soil P losses. In contrast, higher intensity gridded sampling and interpolation revealed wide in-field spatial variability in soil P content, facilitating the identification of contributing sources of P losses to poor water quality and aiding in the characterisation of risk for nutrient losses to waterways. Hydrological modelling of in-field runoff pathways indicated several P sources potentially contributing to runoff-based P losses. Our weighted risk assessment model was successful in identifying P hotspots and transfer potential to water courses, illustrating that a similar approach could be applied anywhere in the world where excess P poses a problem for water quality. Model validation took place using instream water quality sampling data, which showed that higher risk weighting model results correlated to poorer water quality conditions. This methodology could be a useful management tool to help countries meet their national water quality targets.

1. Introduction

Agricultural practices have been identified as major contributors to poor water quality due to the effects of sedimentation and nutrient enrichment, released by processes and activities such as fertilisation, soil erosion, and livestock grazing (Zia et al., 2013). Characterising associated diffuse agricultural pollution of water bodies is a challenge, which is complicated by the delivery process of management policies and monitoring schemes focused on the catchment scale (Voulvoulis et al., 2017; De Vito et al., 2020). For agricultural grasslands, there are specific knowledge deficiencies around the quantification of point and diffuse nutrient sources. Phosphorus (P) is particularly important as it plays a key role in eutrophication occurrence (Le Moal et al., 2019). In intensive livestock systems such as those in northwest Europe, soil P tends to exist in excessive quantities due to long-term over-application rates of P-enriched slurry and fertilisers, above what is required for agronomic production (McDonald et al., 2019). Nevertheless, there is large within-field spatial variability in soil P (Wilson et al., 2016; Fu et al., 2016; Rowe et al., 2016), which is typically uncharacterised and unaccounted for in management appraisals using bulked W soil sampling methodologies. Areas of nutrient surplus need to be identified at a higher spatial resolution and the risk of these areas contributing to nutrient losses needs to be defined to improve nutrient use efficiency on farms and reduce P losses to waterways.

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Phosphorus losses from agricultural land can be either short- or long-term. Short-term losses occur after events such as fertiliser application (chemical or slurry-based) particularly if these coincide with sub-optimal application conditions e.g. saturated soil conditions, poor timing in line with rainfall events or poor application techniques such as spreading too close to waterways (Ockenden et al., 2017). Inappropriate management of grazing animals such as allowing access to waterways or hydrologically-connected field drains or ditches through a lack of suitable fencing can promote short-term elevations in P losses through animal excretion. A 2017 case study found that livestock manure accounted for 81 % of P inputs to soils (either during the grazing process or spreading of manures) in a substance flow analysis for P within Northern Ireland (NI), indicting the considerable role that this P source plays in contributing to soil P (Rothwell et al., 2020). Chronic long-term P losses over several years can originate from legacy nutrient accumulations within soils despite no applications of P occurring. These losses typically occur through actions such as subsurface drainage, surface runoff or soil erosion occurrence which vary in the magnitude and frequency at which these remobilise soil P sources dependent on specific conditions (Sharpley et al., 2015). Furthermore, the effects of livestock grazing such as soil compaction through trampling or compaction through farm machinery can promote chronic P losses through the increased likelihood of surface runoff or soil erosion (Ockenden et al., 2017).

On most grassland farms, a field is considered a single management unit, with blanket nutrient applications applied per field. This uniform management fails to account for within-field spatial variability in soil nutrients, which can be extensive as it does not consider areas of deficient or excessive soil nutrient content which may require lower or higher fertilisation amounts (McCormick et al., 2009). Despite the known variability in soil P content at the sub-field scale and the existence of soil P hotspots across various farming regions (Tóth et al., 2014), soil sampling schemes have failed to move beyond average field sampling techniques of bulked W sampling. Gridded soil sampling is commonly used in arable systems to manage productivity (Higgins et al., 2019), but for grasslands this form of nutrient management is underutilised. The reliance on average field nutrient values in grassland systems introduces inaccuracies for fertiliser applications, with a perpetuation of soil nutrient accumulation (Tóth et al., 2014). Improving water quality requires a good understanding of the spatial variability in P content and subsequent use of variable rate fertiliser applications (e.g. balanced P applications against soil requirements). This potentially could help minimise P losses from the soil to the environment. To identify point and diffuse P sources at farm and field-scale, site-specific gridded soil sampling and nutrient management could therefore address environmental issues whilst ensuring agricultural productivity (van der Salm et al., 2017).

Of further importance is understanding how soil P hotspots may be connected to waterways via surface and subsurface flow pathways. To understand the risk of these transfer mechanisms, it is necessary to analyse characteristics that enhance the transfer risk, e.g. topographically steep and hydrologically-connected slopes promoting runoff (Boardman et al., 2019). Analysis of high-resolution elevation (e.g. LiDAR) data can provide insights into in-field hydrological flow pathways based on field microtopography. For example, Cassidy et al. (2019) used bulked field sampling for soil Olsen P and analysed at-risk areas based on a runoff model using LiDAR digital elevation models and soil hydraulic conductivity data to analyse the field to catchment scale risk of P transport. Djodjic and Markensten (2019) and Andino et al. (2020) further highlighted the need for effective risk mapping, suggesting that analyses must contain data at a high enough resolution to appreciate sub-field scale variability in P source areas. However, as demonstrated by Andino et al. (2020), little is known regarding the spatial relationship between sub-field scale P sources and the associated P losses at this resolution. As such, research is needed to understand the likelihood of nutrient losses at the sub-field scale, due to current sub-optimal soil sampling regimes failing to capture sub-field scale point and diffuse soil P sources.

Inherent difficulties are present when linking in-field runoff measurements of nutrient losses to measured instream water quality conditions with the complexities present in flow regimes (McDowell et al., 2003). Research often focuses on either P loss mechanisms from soils and agriculture (e.g. Johnston and Poulton, 2019) or the impacts and trends of P once within waterways (e.g. Smith et al., 2013), with few studies having considered the relationships between the two systems. Difficulties arise when linking the two systems as there is the potential for instream nutrient loads to consist of upstream inputs, have nutrient sources released through instream processes such as riverbed or bank erosion, or have nutrient fractions undergo chemical transformations instream. To link potential field losses with the impacts on water quality, regular sampling of waterways up- and downstream of the contributing fields of interest may overcome some of these issues.

This study aimed to address the above knowledge gaps by developing and testing a new approach that combines hydrologically modelled runoff pathways (based on the soil topographic index (STI)) with gridded sampling interpolation techniques in a risk-weighted GIS-based model. The development of risk assessments for soil P losses has been extensively outlined in Buczko and Kuchenbuch (2007). In summary, there is no one standard approach, although most methods now assess the source and transfer factors separately before combination e.g. additive or multiplicative processes (Heckrath et al., 2008). However, little to no approaches use sub-field scale soil P data, instead relying on average field sampling methods or edge-of-field soil samples which are unrepresentative of the true variability in soil P content and typically underpredict risk (Hughes et al., 2005; Heckrath et al., 2008; Cassidy et al., 2019). As per Thomas et al. (2016a), STI accounts for soil water storage capacity and considers the hydrological disconnection which exists in runoff generation and transfer of flow. Higher STI values are indicative of an increased risk of runoff generation and associated P losses. We applied and tested the approach to six field-scale sites in Northern Ireland in areas that are typical of many agricultural fields in humid temperate regions, which are characterised by high nutrient applications and frequent surface runoff. In these environments, water quality is typically below environmental targets and there is a need for effective decision-support tools for water quality management. The specific research objectives were to:

Map and quantify sub-field scale spatial variability in soil P content using gridded soil sampling and geostatistical interpolation and compare this to traditional bulked field-scale sampling methods.

Determine the risk of gridded sampling identified diffuse and point P sources to contribute to poor water quality in combination with modelled in-field runoff pathways in a weighted risk assessment model.

Evaluate the relative performance of the approach across sites using independently collected phosphorus water quality data in adjacent streams

2. Methods

2.1. Study area description

The chosen study catchment was the cross-border Blackwater catchment in NI and the Republic of Ireland (ROI), with 90 % land use classed as agricultural with a focus on sheep, beef, and dairy farms (Bastola et al., 2011). The catchment drains an area of 1480 km^2 with a geology of Carboniferous sandstone, limestone, shale, and mudstone overlain by pro-glacial boulder till to form drumlins and moraines (Bastola et al., 2011; Campbell et al., 2015). Soils are poorly draining with a seasonally perched water table promoting saturation-excess runoff. With high winter rainfall and associated runoff rates, low effective soil water storage capacity, and poor permeability, these factors all elevate the diffuse pollution risk (Bastola et al., 2011).

The spatial variability in soil nutrient status was investigated for six field-scale permanent grassland sites within the Blackwater catchment. These field sites represent a range of agricultural activities (details in Table 1, locations in Fig. 1). These sites are typical for the region with variable topography and field sizes. All of the soils underwent regular applications of fertiliser and slurry of primarily dairy or poultry origin.

This study compared soil P content for the six field-scale sites obtained via traditional bulked field soil sampling methods with P content from GPS-guided gridded sampling. This allowed for determining the appropriate sampling strategy required to quantify P point or diffuse sources at the sub-field scale.

2.2. Sample collection

ESRI software ArcMap 10.5 was used to digitise each subfield's boundaries from Ordnance Survey Northern Ireland 2017 Orthoimagery as discrete polygons. A regular sampling grid of 35 m was generated for each sub-field with samples collected in January 2020 for Sites 1 – 4 and in December 2020 for Sites 5 – 6. These dates were selected to coincide with the closed spreading period in NI (15th October to 1st February), which allowed us to establish P status before fertilisation and avoid the effects of fresh deposits of animal manure (Shi et al., 2002). The sampling grid design was chosen based on a previous grassland study in NI by Shi et al. (2002) who found that the best compromise between the accuracy of interpolation and sampling efficiency was to sample at an interval of 35.4 m on a triangular grid. A Leica Viva GPS was used to locate each sampling point to an accuracy of ± 0.5 m. At each point, 20–30 soil cores were collected within a 1 m radius of the sampling point using a 7.5 cm depth cheese-corer auger, and the 20–30 cores were bulked together to produce one bulked sample per point for analysis of soil Olsen P content. Vegetation and large stones were removed before sample bulking (Theocharopoulos et al., 2001). For details on the number of gridded sample points per sub-field see supplementary information in Table A.1.

Traditional field sampling in the UK and Ireland typically involves taking a bulked sample from walking a W pattern across each sub-field (Teagasc, 2017; AHDB, 2022). To compare the outcomes of the gridded sampling with those of the W pattern bulked sample approach, we also collected samples following the traditional way. For this, 20–30 soil cores were collected using a 7.5 cm depth auger for analysis of soil Olsen P content along the W pattern at random points. All soil cores from this W pattern were then combined to produce one bulked soil sample (comprising 20–30 soil cores) per sampled field.

2.3. Laboratory analysis to determine plant available phosphorus

Collected soil samples were air-dried at 30 °C and sieved through a 2 mm aperture sieve before analysis for plant-available P, which was determined using the Olsen P methodology (MAFF, 1986; Olsen and Sommers, 1982). Olsen P is the standard agronomic soil P test used in the UK, with the results expressed as an Index for management purposes, indicating deficient, optimum, or excessive soil P contents as shown in Table 2 (AHDB, 2019; Cassidy et al., 2019).

Table 1
Field size and predominant land use for the six study sites.

Site	Site Size (Ha)	Number of sub-fields	Predominant land use across all sub-fields	Predominant soil type across all sub-fields
1	6.52	3	Silage and Animal Grazing of Beef and Sheep	Fluviosols
2	4.71	3	Silage and Poultry Farming	Stagnosols
3	6.71	3	Silage and Animal Grazing of Dairy Cattle	Stagnosols
4	5.01	2	Animal Grazing of Beef Livestock	Stagnosols
5	3.43	NA	Silage	Stagnosols
6	5.04	NA	Silage	Stagnosols

2.4. Geostatistical data analysis

Each sub-field site had a continuous surface mapping specific P content generated using Ordinary Kriging in ArcMap 10.5. These were constrained to the boundaries of the sub-fields by setting the workspace extent in the kriging processing to the digitised sub-field site polygons used in the generation of the 35 m sampling grids. Ordinary kriging interpolation is the most robust method for one variable as it estimates the value of the variable at unsampled locations on given support, which is the region represented by the sampling regime, by maintaining the data structure (Clay and Shanahan, 2011). Interpolation allows a continuous surface to be created by predicting the values of unsampled locations based on the measured sample points (Burrough et al., 2015).

The interpolated maps allowed for the identification of P hotspots at a sub-field scale, concerning specific characteristics that may be contributing to the presence of these zones or increasing the potential for P export.

2.5. Weighted risk assessment model

The model developed here considered risk assessment values for both bulked soil P content and 35 m interpolated soil P content. It combined soil P data with LiDAR-derived STI data as the model's input datasets (as rasters). Prior research by Thomas et al. (2016b) for Irish grasslands found that STI values less than 8.5 represented hydrologically insensitive areas of little to no runoff occurrence. Research in the Blackwater catchment on runoff generation found that runoff occurred with STI values of 2.50 and above. Values less than 2.50 were set to NoData to exclude these from risk analysis using the raster calculator function.

These input rasters of STI and soil P content were rescaled to a common evaluation scale (1 to 10) to represent the magnitude of risk (given in Table 3) and converted to integer types (Thomas et al., 2016b). An additive approach was then used on the source (soil P content) and transfer (LiDAR-derived STI) model risk-assessed input datasets to give an overall risk value which was normalised to values from between 0 to 10 (Table 3). The source and transfer dataset's risk values were each multiplied individually by specific weighting factors which sum to 100 % influence within the model. Prior research on Irish grasslands by Cassidy et al. (2017) showed that elevated soil P content did not correlate to elevated runoff-based P losses and that soil moisture and rainfall conditions influenced runoff losses. With the higher influence of runoff generation on inducing runoff-based losses, risk weighting factors in this model weighted soil P content (P-Weighting factor) at 40 % influence and STI (Runoff-Weighting factor) at 60 % influence. This model design builds on previous P risk assessment work performed in Ireland by the Magette P Ranking Scheme (PRS) (Hughes et al., 2005), by Thomas et al. (2016a, b) to identify runoff delivery points, and by Cassidy et al. (2019) who developed a HSA index scheme based on a risk percentile model using LiDAR data to derive STI values. These risk assessment approaches focused on bulked soil P sampling data. As bulked sampling underestimates soil P content in some places and overestimates it in others, it indicates that risk assessment values made on this basis will be inaccurate on a spatial basis.

To risk assess sub-field scale soil P content, the field PRS (developed for Irish grasslands from the Magette PRS risk assessment based on Morgan P in Hughes at al. (2005)) was adapted to Olsen P. The original risk assessment values ranged from 1 − 4 on a field scale with non-linear increases in risk values between Morgan P classes (Hughes et al., 2005). There are issues with comparing Morgan P directly to Olsen P as Morgan P only classifies soil P into four index classes while Olsen P covers a wider index range (Vero et al., 2021). With the greater range of index

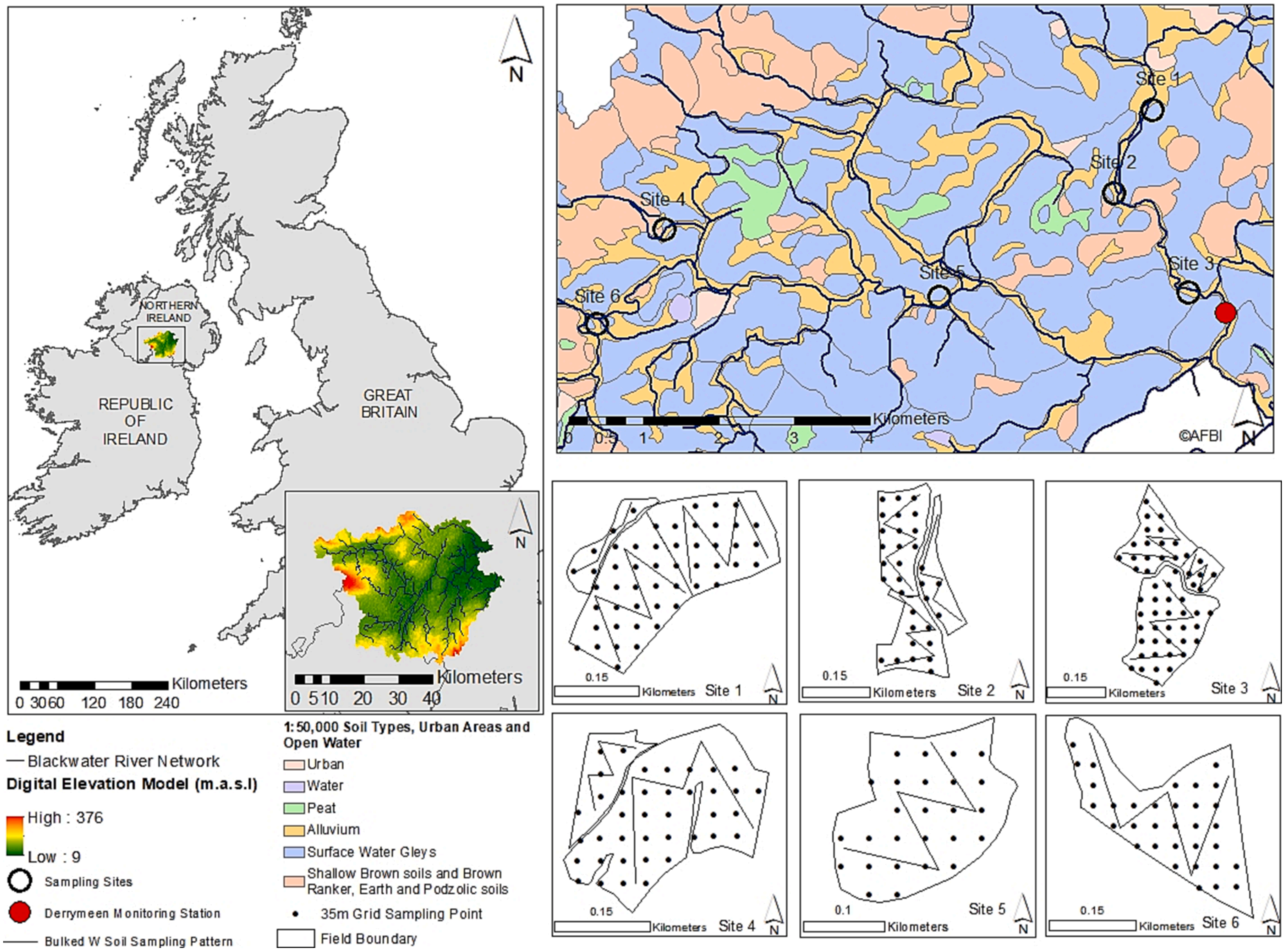

Fig. 1. Location of the Blackwater catchment study sites in Northern Ireland and the Republic of Ireland, soil types, location of Derrymeen monitoring station, and sampling strategies.

Table 2
Nutrient index values used and the corresponding nutrient content in mg L^{-1} for Phosphorus based on divisions given in Table 3.1 pg. 9 on the classification of soil nutrient indices in the RB209 Nutrient Management Guide, Section 3 Grass and Forage Crops (AHDB, 2019).

Index	Soil P Content (mg L^{-1})	Soil Nutrient Status
0	0–9	Deficient
1	10–15	Low
2-	16–20	Agronomic Optimum
2+	21–25	Agronomic Optimum
3	26–45	High
4	46–70	Very High
5	71–100	Excessive
6	101–140	Excessive
7	141–200	Excessive

Table 3
Risk values assigned to soil P Index and Flow Accumulation Values on a common evaluation scale for use within the weighted overlay risk assessment model.[1]

Soil P Index Value	Risk Value	Soil Topographic Index (STI) Value	Risk Value
0	1	2.5–4.0	1
1	2	4.0–7.0	2
2 (2- and 2 +)	2	7.0–9.0	4
3	4	9.0–11.0	6
4	6	11.0–13.0	8
5	8	13.0–15.0	10
6	10		

[1] P risk values for Olsen P adapted from the Magette PRS risk assessment for Morgan P (Hughes et al., 2005). Higher risk values indicate higher soil P content and increased risk of P losses. STI risk values based on research on runoff generation within the Blackwater catchment and previous research by Thomas et al. (2016 a, b).

values considered by Olsen P, risk factor values of Olsen P were expanded further than those given in the Magette PRS (which classed the highest risk as 15 mg L^{-1} and above, for Olsen P, this is Index 1 boundary values). Olsen P risk values are given in Table 3.

Following Thomas et al. (2016a), TWI (Topographic Wetness Index) rasters were created for each sub-field using hydrological modelling and spatial analyst tools in ArcMap on 1 m LiDAR Digital Terrain Model data to indicate runoff flow pathways. Modelling in-field runoff pathways has improved through using LiDAR given its accuracy and ability to include microtopographical features such as hedgerows or road drains, which can act as barriers to predominant hillslope flow (Thomas et al., 2017). At a sub-field scale, it is important to understand the hydrological connectivity of these features to transfer runoff into waterways e.g. connection points of a field drain or ditch. Thomas et al. (2017) showed that 1–2 m LiDAR Digital Elevation Model (DEM) resolutions were optimal for modelling HSAs as runoff breakthrough points could be predicted with an appropriate balance between microtopography and modelling the effects of natural hillslope flow movement. Typically a sink and fill methodology is followed to remove any sinks that would constrain/restrict flow. However, per Thomas et al. (2017), at a sub-field scale, sinks are important microtopographical features for partitioning runoff. TWI rasters were converted to STI rasters for each sub-field following Equation (1) as used in Thomas et al. (2016a).

$$\mathrm{STI} = \mathrm{Ln}(\text{Flow accumulation/tan slope degrees}) - \mathrm{Ln}(K_{sat}D) \tag{1}$$

For which flow accumulation is the cumulative upslope drainage area per unit contour length, slope is surface slope gradient in degrees, K_{sat} is the mean saturated hydraulic conductivity being horizon depth weighted, m day^{-1} and D as the total soil depth in m. Data on the mean saturated hydraulic conductivity were derived from bulk density and soil texture analysis (cf Jabro, 1992) extracted from each soil series from the 1:50,000 General Soil Map of Northern Ireland (AFBI, 2009) as used by Thomas et al. (2016a) and Cassidy et al. (2019).

Developing a risk model using weighted overlay approaches allowed risk to be quantified at a sub-field scale. Including all soil P indices also means that deficient soil P sources which are hydrologically at-risk are not ignored as these can contribute significant P loads to waterways through runoff. This approach allowed for direct comparison of relative risk variations within-field as well as comparisons between fields. Higher values indicated an increased likelihood of either soil P losses (due to elevated soil P content) or increased potential for runoff flow to be generated based on higher STI values. Presented risk assessment results ranged from 0 to 10 and are presented with a standardised legend across all sites.

Risk value of P losses via surface runoff = (Soil P Source Risk * P-Weighting factor) + (Surface Runoff transfer risk via STI * Runoff-Weighting factor)(2)

Fig. 2. Upstream and downstream water sampling locations for Sites 1 – 4 displayed over 2020 orthoimagery.

2.6. Water quality

Water samples were collected instream using 2-litre sampling bottles from up and downstream sampling locations of Sites 1 – 4 (shown in Fig. 2) monthly from August 2020 to August 2021 to validate determined model risk weightings against instream water quality. Sampling excluded Sites 5 – 6 as these did not undergo soil sampling until December 2020. Sampling occurred over a year-long period to cover variations in the agricultural calendar and seasonal variations in hydrology and meteorology. Soluble reactive phosphorus (SRP) and total phosphorus (TP) were determined using EPA standard methods with an uncertainty of 14 μg P at the 200 μg P 1–1 level (McKenna, 2016).

Sampling took place across a wide range of hydrometeorological conditions (Fig. 3). Despite having coarse temporal resolution grab sampling data, sampling represented the full variability represented in observed flow conditions for all sites, as these were sampled on the same dates.

3. Results

3.1. Comparisons between nutrient status determined by bulked W soil sampling versus 35 m interval gridded soil sampling for the identification of point and diffuse P sources

Fig. 4 shows the P content determined by bulked field sampling, representing mean soil P content per field, without any measure of spatial variation, side-by-side with interpolated soil P nutrient status determined by 35 m interval gridded soil sampling for Sites 1–6.

Several sites had soil P content above the agronomic optimum, predominantly for sites used for silage production as stated in Table 1. An exception to this was Site 3, which – while being used for silage – had soil P content determined as Index 2 and Index 1. Bulked sampling revealed that 54 % of the fields sampled had a P index above the agronomic optimum.

Fig. 4 shows the P content determined by 35 m interval gridded soil sampling. While the overall patterns between fields are similar to the bulked sampling results, the kriged outputs obtained by 35 m sampling revealed large within-field variability in soil P, demonstrating the limitations of bulked sampling for quantifying nutrient variability. For all sites apart from Site 5, bulked sampling under-predicted the maximum in-field soil nutrient content, often by several index categories. As bulked sampling cannot demonstrate the spatial variability in soil nutrient content, it can both under and over-predict the maximum and minimum soil P content. For example, Site 1 in Fig. 4 sub-fields A and B are predicted by bulked sampling at Index 4, whilst gridded sampling revealed soil P content ranged from Index 3 to Index 6. Visualisation of P content showed a wide spatial variability between and within each of the sites with interpolation aiding in the identification of diffuse and point P sources. Fig. 4 for Sites 1 – 2 and 4 showed a wide range of both soil P deficiencies and excessive hotspot zones, ranging from indices 0 to 6. For Site 1, a P point source was identified in sub-field A using site-specific knowledge combined with interpolation. A deposited area of animal bedding contributed to elevated P levels within the north-eastern section of sub-field A. Extensive diffuse sources of P were available for losses as shown in Sites 1 – 2 and 5 – 6. The elevated P content present at these sites suggested long-term over-application of P. Bulked sampling generally identified diffuse P sub-fields but under-predicted the maximum nutrient content. An exception to this is Site 5 due to the extensive P sources present. Bulked sampling categorised this site as Index 6, however, it failed to show the area of Index 5. Bulked sampling cannot however identify point sources of P present such as those within Site 1 sub-field A, Site 4 sub-field B, and Site 6.

Site 1 sub-field C had a P content of Index 1, which represented the majority of P content produced by gridded sampling here. This may be due to this sub-field's smaller area (0.62 ha) and thus lower potential for P variability (in terms of fertilisation regimes/accumulation zones).

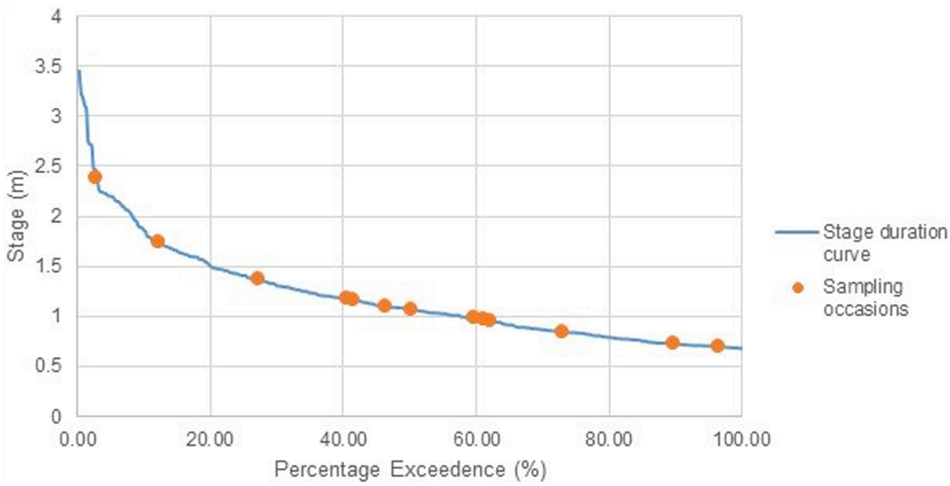

Fig. 3. Stage (m) duration curve with percentage exceedance values for the Department of Infrastructure Rivers Agency hydrometric monitoring network for the Derrymeen gauging station (located downstream of Site 3 shown in Fig. 1) and sampling occasions from Site 3 plotted, water level (m) data from 18.08.20 to 23.08.22.

Similarly, Site 4 sub-field B showed the majority of this sub-field (0.89 ha) as deficient in gridded sampling at Index 1. W sampling reflected this at Index 1.

3.2. *Likelihood of Runoff-based soil P transport*

The outputs generated by these models are shown in Figs. 5 and 6. Table 4 details the average and maximum risk scores modelled for each site for both bulked soil P content and interpolated 35 m soil P content.

Bulked sampling of soil P content for risk modelling generates outputs with less variability present in risk classification values as bulked sampling fails to identify variability in soil P content and classifies fields as singular risk values in Fig. 5. This was particularly evident in comparisons for Sites 1 – 2, and 4 between Figs. 5 and 6. For sub-field A at Site 4 in particular, significant coverage of risk values 3 – 5 is missed.

Table 4 shows that generally for bulked sampling lower average and maximum risk values are obtained in these models compared to gridded sampling risk models, further demonstrating the underprediction of soil P content and associated risk by bulked sampling. Sites 3, 5 and 6 had the same maximum risk values for both approaches. This may relate to Sites 3 and 6 soil P content being close to optimum and Site 5 being a widespread diffuse soil P source. Interestingly, Site 5 obtained a slightly higher average risk weighting value on a bulked approach, likely relating to bulked sampling failing to represent the full variability of soil P content at this site in terms of both index 5 and 6 soil P being present.

The visualisation of the outputs generated by the risk model in Fig. 6 showed greater variability in risk weighting values than in Fig. 5 due to the greater resolution afforded by 35 m gridded soil sampling. Higher risks are identified with the concurrence of modelled flow pathways and elevated soil P content.

For Site 1 in Fig. 6, sub-fields A and B are classified as medium to high risk due to extensive diffuse soil P sources. An increased risk was identified in sub-field A in the vicinity of the identified P point source, however, the lack of risk highlighted flow pathways within this feature suggests a lower risk of transfer despite being risk weighted at 5. There was a particularly high risk (risk weighted at 7 – 9) of elevated P losses within the southwestern corner. The targeted intervention in this area would be advisable to reduce losses (at the highlighted flow pathways delivery points), given the hydrological connectivity of this area with the presence of a field drainage ditch connected to the main waterway at this site.

Sub-field C of Site 1 and Site 4 sub-field B (Fig. 6) show largely a low risk of transfer (risk value 1 – 3), due to deficient and optimum soil P status and the prevailing intra-field drainage. These results were similarly reflected for Sites 2 and 3 (Fig. 6). For Site 2, even though extensive diffuse P sources were present, the overall risk was weighted at low to medium. Some higher-risk flow pathways coinciding with elevated soil P were identified (weighted at 7 – 8 in sub-field B). The occurrence of predominantly intra-field drainage reduced the likelihood of P transfer due to the site's flat topography. For Site 3, given the largely optimum soil P status, this site was weighted at low to medium risk. Interestingly, a higher risk of 6 was weighted in sub-field C, with runoff flow pathways flowing towards the waterway at this site, elevating the risk for waterway transfer of soil P by runoff. Site 6 showed that Index 4 soil P was weighted at a risk value of 6, indicating a high transfer risk at this site, despite this particular area not being hydrologically connected.

For sites of steep topography, such as Site 1 sub-fields A and B, Site 4 sub-field A and Site 5 (Fig. 6), the increased flow accumulation and associated hydrological connectivity are evident. Site 4 sub-field A demonstrated the importance of sub-field scale soil P data to inform risk-weighting. Sections of the field deficient or optimum in soil P were weighted at low risk. Elevated zones of diffuse soil P showed an increased transfer risk and with the occurrence of flow pathways in these areas, the risk was weighted higher at up to 6. Again, identified flow pathways' delivery points to the waterway at this site should be targeted for intervention techniques. Site 5 was identified to have widespread diffuse soil P present, which was evident in risk weighting, with risk weighting values assigned up to 9. Numerous flow pathways were identified that flowed towards the waterway (due to topography and predominant slope). These pathways were classified at risk 5 – 9. Similar to Sites 1 and 4 sub-fields A, the targeting of runoff delivery points at Site 5 is required. However, given the high-risk weighting assigned to this site and high hydrological connectivity, targeting the entire field base would be advisable and reducing elevated soil P content is required.

3.3. *Weighted overlay risk model validation using water quality data*

To validate quantified model risk weightings, discharge weighted average concentrations (μg L^{-1}) were used to compare the water quality parameters of SRP and TP and the highest in-field risk-determined value per site. Normalised differences between the up and downstream sampling points' parameters are included in Table 5. Discharge weighted average concentrations were chosen as a proxy for SRP and TP loads for the observation period. Table A.2 shows the average concentrations for up and downstream sampling locations per site and the average discharge for each sampling location.

Table 5 shows that generally higher discharge weighted average SRP concentrations are present at sites with higher risk weightings. Site 1,

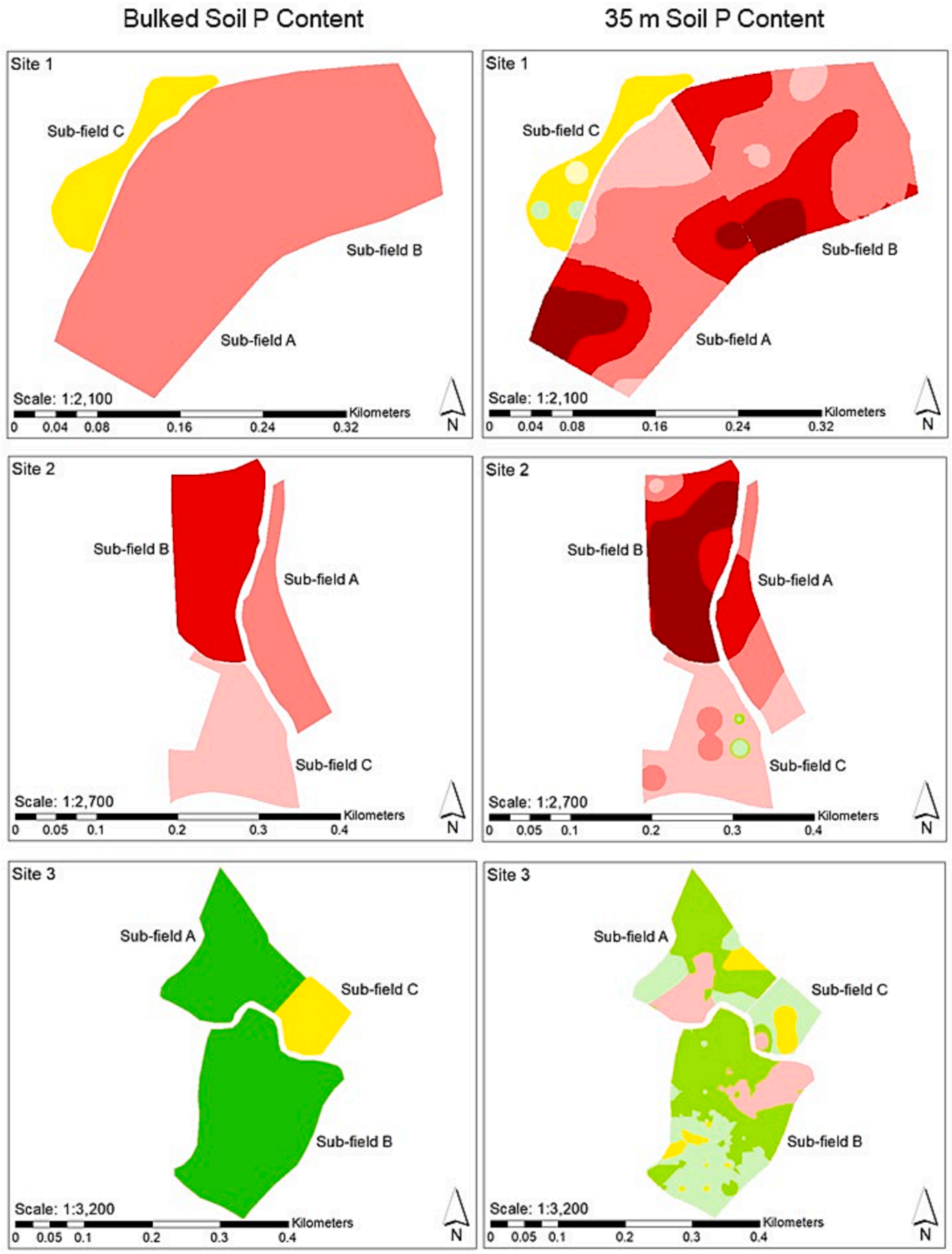

Fig. 4. Soil P nutrient status determined by bulked W soil sampling side-by-side with interpolated soil P nutrient status determined by 35 m interval gridded soil sampling for Sites 1 – 6.

which had the highest in-field risk value at 10, had the highest discharge weighted average SRP concentrations for both up and downstream sampling points. Site 2 also showed this, being the second-highest in-field risk value at 8. Increases in SRP concentration occurred at both of these sites from the up to downstream sampling locations, suggesting the transfer of identified soil P sources. Site 3, despite being classed as the lowest in-field risk of the four water sampled sites, had a higher discharge weighted average SRP concentration than Site 4 (with the lowest up and downstream discharge weighted average SRP concentrations). Both Sites 3 and 4 showed decreases in the normalised difference between the up and downstream sampling points. This suggests that low-risk weighted sites (for the transfer of soil P via surface runoff) may show decreases in SRP concentrations, suggesting improvements in water quality, with Sites 3 and 4 having the lowest risk values at 6.

For TP in Table 5, Site 1 has the highest upstream discharge weighted average concentration. Interestingly (and shown at Site 3) a decline was seen in TP from up to downstream sampling locations, although this decline was minimal. Conversely, Site 2 (also highly risk-weighted at 8) showed a large increase in discharge weighted average TP concentration, suggesting extensive transfer at this site. An even larger increase was recorded for Site 4 (risk-weighted of medium–high risk at 6) suggesting extensive TP transfer here, despite lower risk-weighted values.

Comparisons between risk-weighted values and discharge-weighted average concentrations of the analysed water quality parameters suggest that a stronger relationship exists between SRP fractions and risk-weighting approaches compared to TP. Furthermore, these relationships are stronger whenever using the 35 m gridded soil sampling approach. Higher SRP water quality concentrations instream may indicate that surrounding agricultural input fields have elevated soil P sources and increased transfer potential. Water quality data analysis

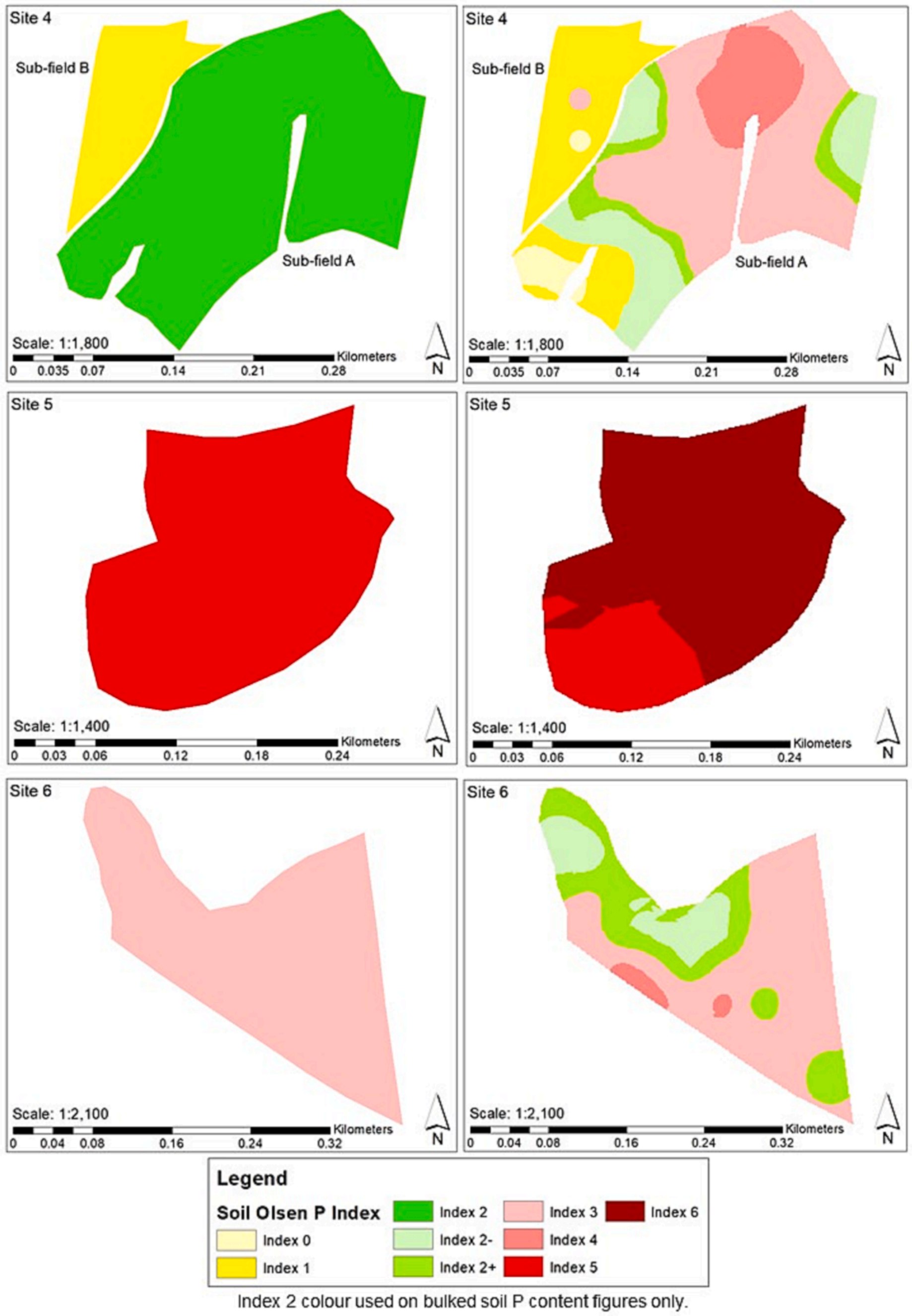

Fig. 4. (*continued*).

largely confirms risk weightings inferred with poorer status for higher risk-weighted sites. Variations in TP may originate from additional loading sources from upstream contributing source areas or through the release of P by processes occurring in-stream.

4. Discussion

4.1. Implications of gridded soil sampling compared to bulked W sampling for managing agricultural sources of phosphorus

From the comparisons in Section 3.1 between bulked and gridded sampling, it is evident that bulked sampling will not represent the full range of soil P content present due to this sampling method only considering an average singular field value, and will both under and over predict soil nutrient content. Results indicated that wide sub-field scale variability exists for P both between and within field and sub-field sites, Site 4 sub-field A in Fig. 4 exhibited the greatest within-field variability in soil P content of the sampled sites. Gridded sampling and associated geostatistical interpolation techniques allow within-field variation in nutrient content to be visualised and to quantify P losses (Fu et al., 2010; Fu et al., 2013; Lawrence et al., 2020). This will help to improve water quality from an agricultural perspective for nutrient management and aid in attaining the objectives of the WFD. Closing the gap between the scale of nutrient management and catchment water quality is vital, both to improve nutrient stewardship of agricultural areas and to improve waterway management. Of particular difficulty for managing agriculture is the identification of point and diffuse nutrient sources and their likelihood of transfer. These are highly variable and can relate to site-specific features such as farm roadways and field drains. This was demonstrated for Site 1 sub-field A around one

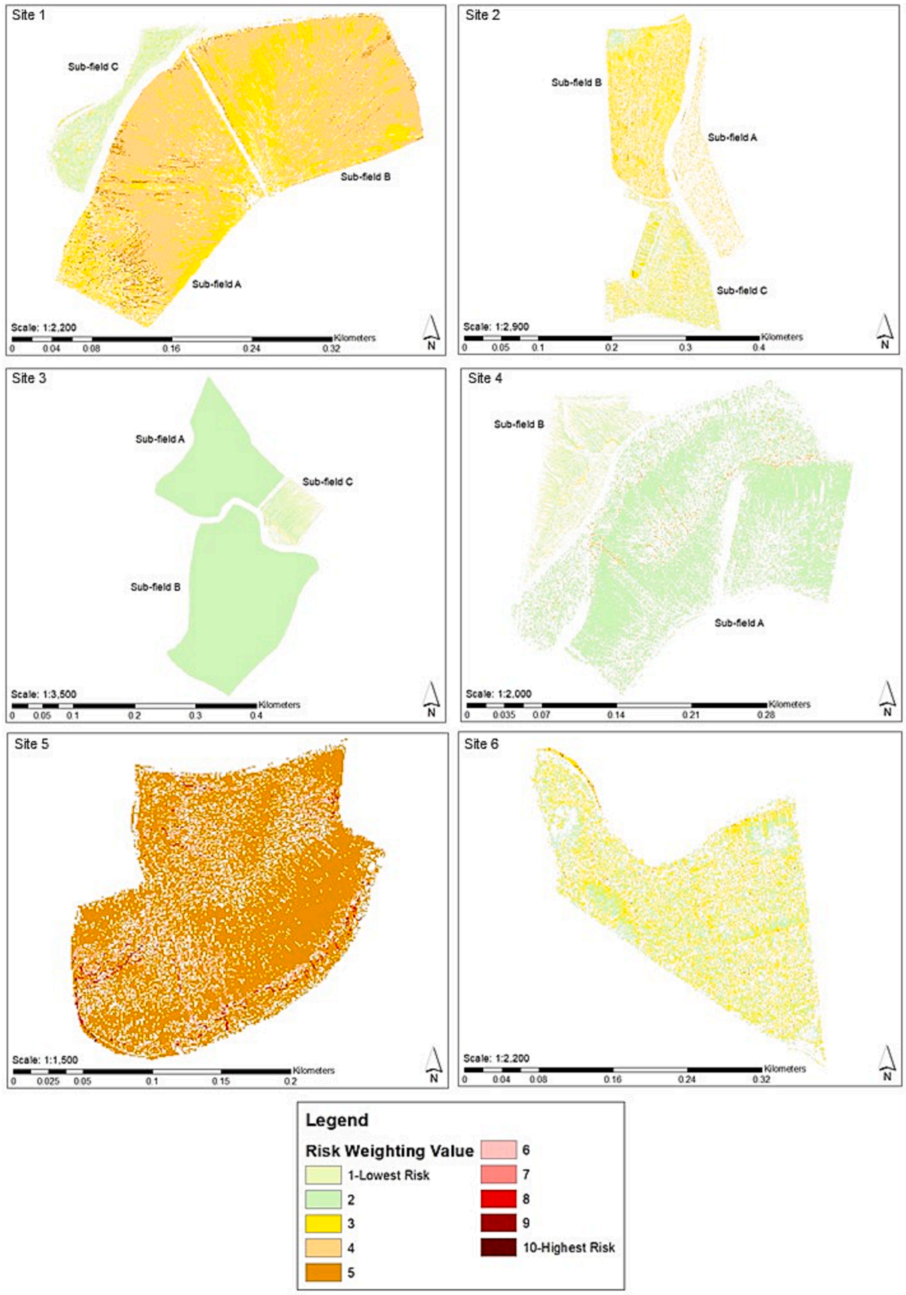

Fig. 5. Weighted risk assessment outputs generated by the combination of theSTI to bulked soil P content for Sites 1 – 6.

particular hotspot, which, when analysed relating to field data, was the location of deposited animal bedding. In terms of site management, reducing fertilisation rates and a cessation of spreading animal bedding and manure are vital (Szogi et al., 2015).

Godwin and Miller (2003) indicated that one bulked sample per hectare is commonly used in precision agriculture, however, bulked sampling beyond this size was not recommended as the potential for nutrient variability increases with increased area. This aligns well with the results, whereby bulked sampling for the small sub-field sites of ~ 1 ha (Site 1 and Site 4 sub-fields C and B respectively) adequately represented soil P content. The use of bulked sampling is of concern for Sites 3 – 4 which are predicted below or at the optimum, yet as shown in Section 3.1, both deficient and hotspot zones exist. If P application rates were based on bulked sampling for these sites in Fig. 4, inappropriate P levels would be applied, both in terms of failing to raise deficient areas to optimum and increasing P accumulation rates. Each sub-field must be treated individually for nutrient management and it cannot be assumed that sub-fields within the same site will behave the same due to differences in fertilisation rates and farming practices, soil and geological properties, and variations in topography (Kozar et al., 2002).

4.2. Managing soil P sources for improved water quality

Understanding if identified P sources are at-risk for transfer to waterways is important. This was demonstrated in Section 3.2 whereby it was shown that not all identified soil P sources were at-risk of transfer via modelled surface runoff flow pathways. When the risk assessment was performed for bulked soil P content compared to 35 m interpolated soil P content, for the majority of the sites, the risk of potential P losses was underestimated, due to the categorisation of whole fields in this approach as singular soil P content.

By risk assessing the variability in soil P content and the likelihood of

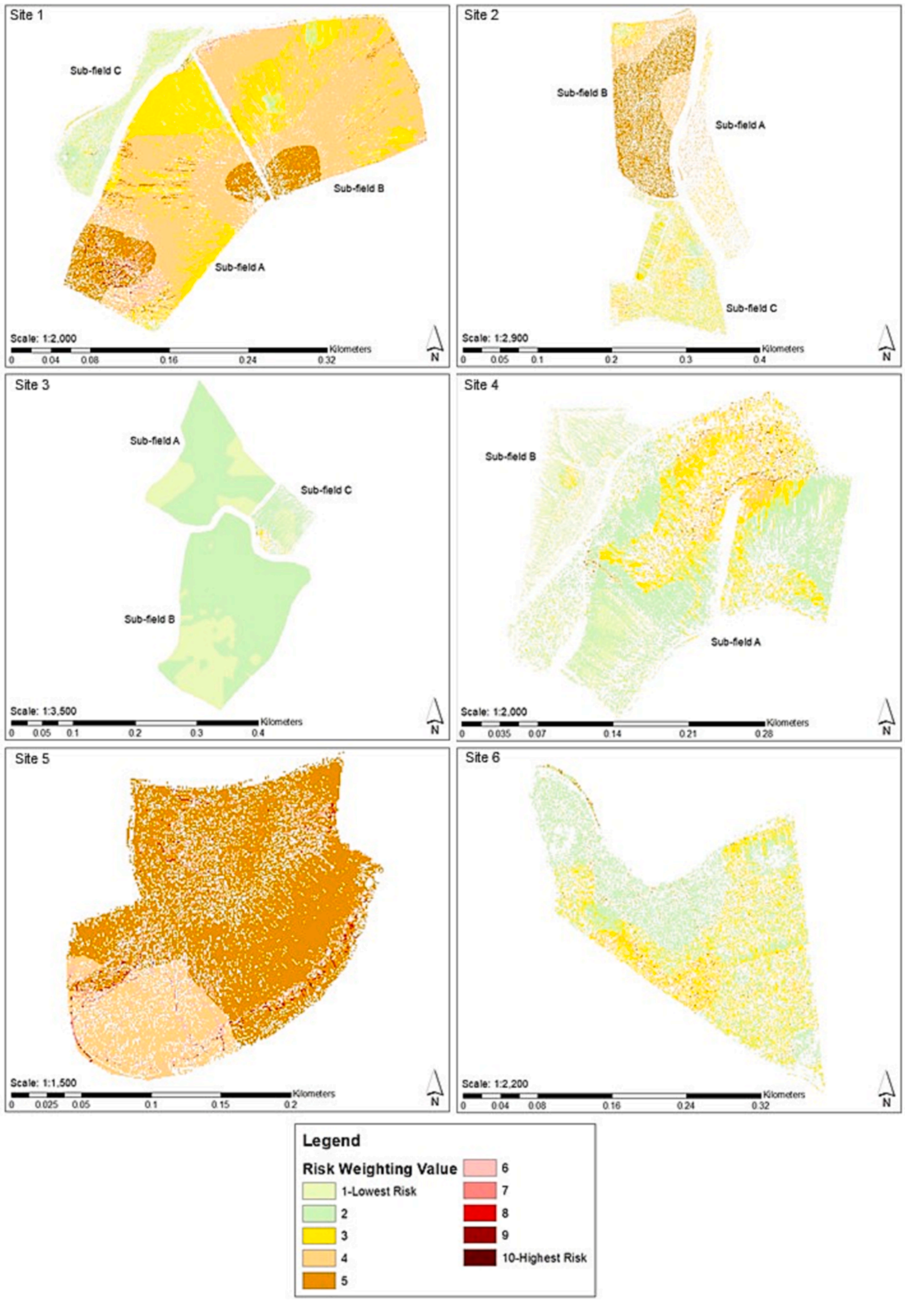

Fig. 6. Weighted risk assessment outputs generated by the combination of the STI to 35 m interpolated soil P status for Sites 1 – 6.

Table 4
Field average and maximum risks calculated for weighted risk modelling approaches for bulked W and 35 m gridded soil sampling approaches.

Bulked W Risk Model			35 m Risk Model		
Site	Average field risk	Maximum field risk	Site	Average field risk	Maximum field risk
1	4.10	8.00	1	4.50	10.00
2	3.80	6.00	2	4.20	8.00
3	2.40	6.00	3	2.20	6.00
4	3.50	7.00	4	3.40	6.00
5	7.00	9.00	5	6.50	9.00
6	4.00	6.00	6	4.00	6.00

runoff occurrence, the risk for runoff-based P losses can be inferred. Previous research such as Thomas et al., (2016b) and Cassidy et al. (2019) did not consider whole-field risk by using bulked soil sampling and STI analysis focused on specific ranges of STI values. The visualisation of the highest risk transfer zones (and an assessment of their hydrological connectivity to the wider waterway landscape) can infer the optimal zones for the introduction of strategies to intercept and reduce surface runoff losses. Targeting intervention techniques to the specific field zones representing the highest risk for P losses means that less land is removed from agricultural production to facilitate installation and less financial wastage in terms of introducing schemes on a widespread basis. Local site-specific management-based approaches are key to appropriately managing agriculture and improving water quality (Robins et al., 2017). This will overhaul the current direction of water management and focus on needing detailed high-resolution data, however, new remote sensing opportunities are emerging, e.g. LiDAR to

Table 5
Discharged weighted average SRP and TP concentrations for up and downstream sampling points at Sites 1 – 4 from August 2020 to August 2021 (and normalised differences from up to downstream sampling points compared to site average) with the highest quantified risk weighting values for both bulked and 35 m soil sampling approaches. N = 13.

Site	Highest in-field Risk Value (bulked approach)	Highest in-field Risk Value (35 m approach)	Discharge Weighted Average SRP (μg L^{-1})	Normalised Difference SRP	Discharge Weighted Average TP (μg L^{-1})	Normalised Difference TP
Site 1	8.00	10.00				
Upstream	–	–	103.37	0.04	217.36	−0.06
Downstream	–	–	108.10		205.17	
Site 2	6.00	8.00				
Upstream	–	–	86.21	0.00	129.55	0.28
Downstream	–	–	85.94		169.85	
Site 3	6.00	6.00				
Upstream	–	–	85.50	−0.05	203.64	0.00
Downstream	–	–	81.69		204.17	
Site 4	7.00	6.00				
Upstream	–	–	69.97	−0.09	186.38	0.19
Downstream	–	–	63.90		227.02	

categorise the sub-field scale likelihood of P transfer.

4.3. Limitations of research

Whilst the risk model aims to predict the risk of runoff-based soil P losses, other variables such as soil moisture content, soil hydraulic conductivity, slope, and average rainfall intensity are important when controlling runoff occurrence, which can be highly dependent on antecedent conditions and thus cause runoff to be highly variable (Doody et al., 2010: Cassidy et al., 2017: Wu et al., 2021; Gray et al., 2021). Further research considering the effects of these temporal components within risk modelling on gridded soil sampling P data is needed to understand the risk for runoff-based P losses. Research by Deasy et al. (2009) on UK-based catchments suggested that subsurface field drains (present at Sites 1 and 4) which are often present in generally poorly draining soils (characteristic of the six study sites) may provide a dominant mechanism for nutrient and sediment transport to waterbodies. Given the variable spatial nature of both subsurface drain presence and runoff generation, and, that the results within Section 3.2 show that not all P hotspots were at a high risk of surface runoff transfer, increased research and modelling approaches to understand P transfer via subsurface drainage is required, particularly research which will consider the implication of sub-field scale soil P variability.

Validation of the risk modelling approach using water quality data indicated that higher SRP water quality concentrations suggests that surrounding agricultural fields are contributing to P losses due to soil P accumulations. This validation approach provides a 'sense-check' to this modelling approach but the water sampling data does not represent continuous sampling data (i.e. that obtained using autosampler programmes) or represent water quality across all discharge levels and does not consider potential in-stream effects on P concentrations.

5. Conclusion

Soil sampling regimes must quantify nutrient content at the correct spatial scale, i.e. the sub-field scale and explore the risk of nutrient losses. This study developed a weighted risk assessment model to quantify soil P nutrient status variability in grassland sites and investigated the risk of P losses via hydrological connectivity. There was a wide degree of variability at the sub-field scale, for both P content and potential risk of runoff-based P losses, even for agricultural areas under similar landscape and management conditions. Furthermore, knowledge of the potential transfer risk that these P hotspots pose for poor water quality at a sub-field scale is necessary for effective and targeted intervention strategies to reduce the incidence and prevalence of poor water quality. A similar weighted risk assessment model could be applied to any locations where excess P poses a threat to water quality, helping countries to meet their national water quality targets.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Emma Hayes reports financial support was provided by NERC QUADRAT DTP.

Data availability

The authors do not have permission to share data.

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Data availability

No data is publicly available due to anonymity granted to landowners participating in this research.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2023.107027.

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