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Assessment and mapping of diffuse water pollution risks of northeast England Coast using geographical information system.

[1,2]Yahaya Sharhabil Musa; [1]Gowing John 1; and [3]Brotherthon Robert

[1]School of Natural and Environmental Science, Newcastle University, United Kingdom

[2]Department of Soil Science, Ahmadu Bello University, Nigeria

[3]Environment Agency, Tyneside House, Newcastle upon Tyne

Abstract

Intensification in agricultural activities results in the enrichment of nutrients from diffuse sources into water bodies, degrading the surface water quality throughout the world. This assesses diffuse pollution a critical task in the non-point source (NPS) pollution management. The existing methods used in the diffuse pollution assessment were often dependent on the availability of local data, long time calibration and model complexity. This study developed a spatial multi-criteria analysis to evaluate the potential of diffuse pollution risk of Northeast England coast due to the importance attached to the area. Four criteria were identified and used to develop a risk assessment map based on the source capacity of pollutant, the efficiency of runoff generation, and the proximity of pollutant to surface water bodies. The criteria include land use, soil type, Euclidean distance rivers and slope. All the analyses were implemented in GIS (ArcGIS version 10.5) environment, and maps were generated for each criterion. Each of the criteria maps was reclassified into 3, i.e. high, moderate and low pollution risk to provide equal weighting such that the maps with different units were treated equally. The ranking method was used to assign a weight to each criterion which shows the relative influence of the analysis criteria. Boolean operators were used to multiplying each criterion by its assigned weight and combined all the maps to give an output risk assessment map showing the spatial distribution of the diffuse pollution risk across the study area. The risk assessment map generated will help demarcate and examine the pattern of diffuse pollution in the catchments and facilitate NPS pollution management decisions at the catchments.

Keywords: Diffuse pollution, Multi-criteria evaluation, GIS.

Corresponding Author's E-mail Address: abulmahbub@gmail.com: Phone: +2347066688874
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1.0 Introduction

Human activities, through the changes in land use, hydrologic flows, fertilizer application, soil destabilization, urbanization, etc., have adversely modified the environment over a thousand years (Mahmood et al., 2010). The human activities coupled with inherent variation in climate, relief, hydrology, and soil type results in a significant temporal and spatial variation of nutrient concentration in surface water runoff (Cherry et al., 2008, Finlay et al., 2013). The nutrients together with sediments were diffusely transported into water bodies through runoff, leaching, and erosion (Owens et al., 2008, Maryna et al., 2016), causing a significant threat to coastal habitat and aquatic ecosystem, declines in habitat quality, changes in species composition, low oxygen availability, changes in water clarity, and ultimately affecting the biogeochemical function of freshwater ecosystems (Hoegh-Guldberg and Bruno, 2010, Williams et al., 2016). One of the important detrimental impacts is the pollution and nutrient enrichment of freshwater ecosystems leading to eutrophication, caused as a result of non-point source losses of nutrients from farmlands (Huang et al., 2017), generally termed as diffuse water pollution from agriculture (Smith and Siciliano, 2015). The diffuse water pollution is challenging to assess and control (Cho et al., 2016), hence it has become a priority task in water monitoring and restoration in many countries (Hoppe et al., 2015).

Point source pollution is usually determined by assessing and monitoring influents and effluents, based on flow and water quality indicators (Ogunfowokan et al., 2005; Vrzel et al., 2016). In contrast, diffuse source pollution is more difficult to assess, as it is distributed over a large area diffusely, making it difficult to measure directly. Most of the models use in point source pollution assessment involve the simulation of water quality and quantity using sediments, nutrients, pesticides and other agricultural inputs from agricultural areas. At the same time, the methods rely on the nutrient inputs and losses in the agricultural areas. However, these models require many data, limited by long time calibration, and may be constrained by model complexity and the need for high skilled personnel to operate them. While nutrient budget methods require many farm input records and are sensitive to climate, topography, soil properties and land use system (Zhang and Huang, 2011).

In recent years Geographical Information System (GIS) software has been increasingly used in diffuse pollution assessment. For example, Batbayar et al. (2018) used GIS and multivariate analysis using altitude, settlements, forest, cropland and distance to spring to predict river water quality of Kharaa River Basin. Ferreira et al. (2017) used nested partial least squares regression and GIS to assess anthropogenic impacts on riverine ecosystems. Yaghi and Salim (2017) integrated remote sensing and GIS to assess Al-Abrash Syrian Coastal Basin's surface water quality. Şener et al. (2017) evaluate water quality using water quality index (WQI) and GIS in Aksu River. In the present study, the ArcGIS software was used to develop some multi-criteria analysis (MCA) to assess diffuse pollution in the study area. Multi-criteria analysis (MCA) provides comprehensive analysis with relatively low efforts in terms of data requirements and time. It involves using multiple conflicting evaluation criteria to combine spatial data and value judgements to give environmental management decisions for diffuse water pollution. It involves the use of Boolean operators (Eastman, 1999) to overlay several maps with potentially unrelated data in a meaningful way to guide assessment and proper decision making (Janke, 2010). Hence it will be a beneficial tool in the assessment of diffuse pollution.

Holy Island and Budle Bay (Lindisfarne NNR) coastal water are among the UK's important designated coastal areas for overwintering birds and North East's only shellfish water. They contain Special Area of Conservation (EC Habitats Directives), Special Protection Area (EC Birds Directives), wetlands of international importance (Ramsar Convention) and Site of Special Scientific Interest (Wildlife and Countryside Act 1981, as amended) (Johnston et al., 2002). They are also part of the Northumberland coast area of outstanding natural beauty and heritage (Anderson, 1980). These coastal waters are facing diffuse water pollution from nutrient discharge of the neighbouring catchments (North Low, South Low, Fenham, Ross Low and Waren Burn catchments). There is evidence of paralytic shellfish poisoning (PSP) since two decades ago (Joint et al., 1997), changing of phytoplankton community (Bresnan et al., 2009), epigeal beetle community (Eyre and Luff, 2005), and algal blooms (Tett and Edwards, 2002). Maier (2009) associated the diffuse pollution with increased nutrients input from river runoff, sewage discharges, atmospheric inputs and possibly submarine groundwater discharges. These currently make the Lindisfarne NNR failing to meet the EU water framework directive (WFD: 2000/60/EC) standards (Chave, 2001), and was designated as a polluted water (eutrophic) since 2002 (Maier, 2009). Therefore, there is need for scale assessments of diffuse pollution in the Northeast coastal catchments to know the spatial characteristic of the pollution to identify areas that are more influential in causing diffuse pollution, hence facilitating the characterization of the pollution in different landscapes and the development of long-time pollution control strategy.

This study aims to develop a geographical information system multi-criteria analysis, to assess diffuse water pollution risk at Northeast England coast catchments showing areas of different pollution potentials for inform management decisions.

2.0. Materials and methods

2.1. Study area

The study area includes North Low, South Low, Fenham, Ross Low and Waren Burn catchments, located close to Scotland border on the northeast coast of England (OS X-easting and Y-northing 394721, 418004, and 648814, 628282 respectively) (Figure 1). The study area is widely covered by arable and horticultural land use with patches of woodland (Rowland et al., 2017), soil group consist mainly of medium to heavy and medium to light (silty) soils (Lawley, 2011), and rainfall ranges between 660 to 750mm (Rainfall, 2019). Streams of water network pass through the catchments and discharge into the large water bodies of Holy Island and Budle Bay.

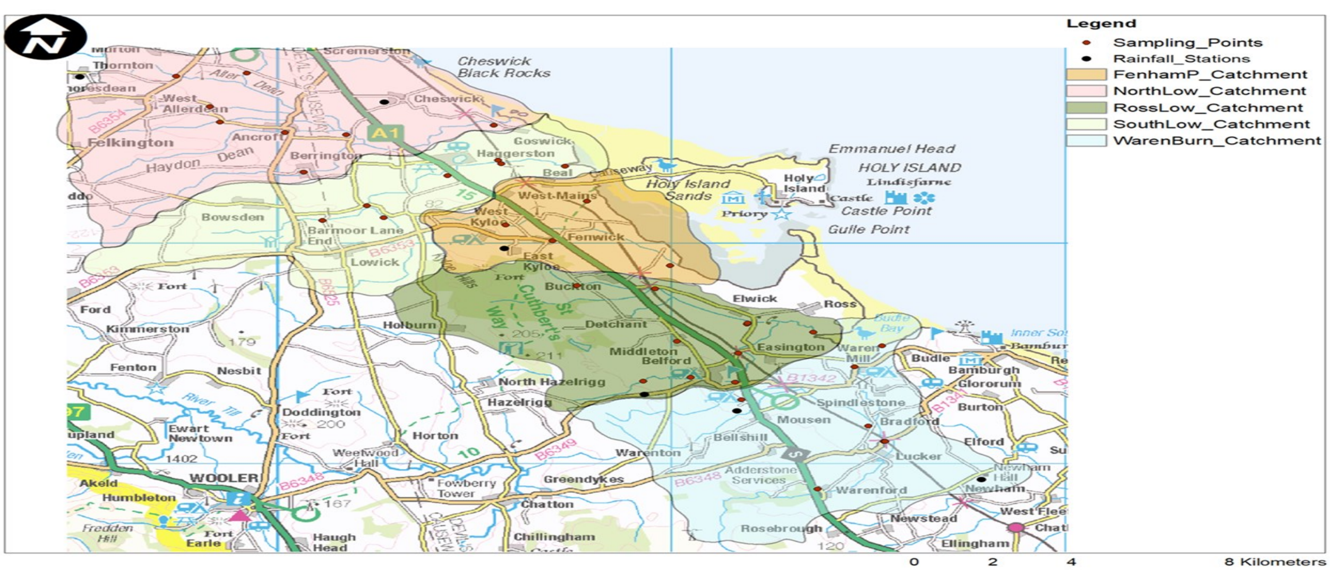

Figure 1: Map of the study area showing catchments, sampling points and rainfall stations

2.2. Development of evaluation criteria

To conduct multi-criteria analysis in GIS, criteria need to be identified. The criterion is obtained through measurable parameters that define an objective's degree of achievement (Geneletti, 2007). The criteria should encompass all the problem (Zhang and Huang, 2011), but at the same time should be limited to the most important ones to reduce the complexity of analysis process (Keeney and Raiffa, 1993). Four criteria were selected to assess the potential of diffuse water pollution in the study area. These include land use, soil type, slope and rainfall.

2.2.1. Extraction of land use information

Land cover/land use is believed to be a significant contributing factor that controls nutrient pollution in a given area (Abdulkareem et al., 2018). To obtain the information on land use, land cover map was obtained from the environmental data download of Digimap (Rowland et al., 2017). The map is for the whole Great Britain in a scale of 1:2,500 in a file geodatabase format containing polygons of separate classes of land uses. To obtain only the study area land use map, a polygon of the study area was used to clip the land cover map of Great Britain using clip tool of ArcGIS, which gives an output land use map of only the study area. The clipped map was dissolved using land use field in dissolve tool of ArcToolbox into a similar polygon to aggregate each different land use to be represented by a single feature/polygon for the analysis (Table 1).

Table 1: Proportion of land use types in the study area

Land Use Type	Land Area (m^2)	Percentage Area Cover (%)
Acid grassland	2299710.972	0.99
Arable and horticulture	132526706.9	57.02
Bog	251482.6847	0.11
Broadleaf woodland	12375945.03	5.32
Calcareous grassland	284825.6556	0.12
Coniferous woodland	9029897.728	3.89
Freshwater	156885.4762	0.07
Heather grassland	2091243.512	0.90
Improved grassland	53627272.25	23.07
Inland rock	10982.95574	0.01
Littoral rock	68136.51727	0.03
Littoral sediment	5113871.291	2.20
Saltmarsh	9443045.921	4.06
Suburban	3257825.242	1.40
Supralittoral sediment	1624477.195	0.70
Urban	264611.974	0.11

2.2.2. Extraction of soil type information

The amount of nutrient/pollutant losses through the runoff is believed to be a function of soil type and slope (Taye et al., 2013, Wang et al., 2017). To obtain information on soil type, soil parent material map was obtained from the geology data download of Digimap (Lawley, 2011). The map contains tiles of 23km by 23km with a scale of 1:50,000 in shapefile format. The study area falls within four (4) tiles, i.e. ew001, ew002, ew003 and ew004. The four tiles were merged using the merge tool of ArcToolbox into one layer for subsequent analysis. The merged map was then dissolved using soil group field in dissolve tool of ArcToolbox into similar polygons to aggregate each different soil group to be represented by a single feature/polygon for the analysis (Table 2).

Table 2: Proportion of soil group types in the study area

Soil Type	Land Area (m^2)	Percentage Area Cover (%)
All	20398781.01	8.80
Heavy to medium to light(silty)	35710186.71	15.41
Light to medium	12052435.99	5.20
Light(sandy)	5989736.08	2.59
Light(sandy) to medium(sandy)	6795565.54	2.93
Light(silty) to medium(silty)	15947330.66	6.88
Medium	20177973.84	8.71
Medium to heavy	73380002.28	31.67
Medium to light(silty)	11021068.90	4.76
Medium to light(silty) to heavy	25718950.25	11.10
Medium(silty) to light(silty) to heavy	4499633.61	1.94

2.2.3. Slope map creation

Slope plays a vital role in the movement of pollutants from source to water bodies (El Kateb et al., 2013). To obtain information on a slope, slope map was created using a digital terrain model (DTM) map. The DTM map was obtained from OS data download of Digimap (DTM, 2018). The map contains tiles of 5km by 5km with a scale of 1:10,000 in ASC/raster format. About thirty (30) tiles were contained within the study area. The thirty mosaic tiles were merged into a single new raster using mosaic to new raster tool of ArcToolbox for easy and subsequent analysis. Slope map was computed from the new raster using slope tool of ArcToolbox with output measurement in degree.

2.2.4. Euclidean distance rivers

The distance of pollutants from the source to the water bodies is an essential factor determining the number of pollutants discharged to water bodies. Water network map of the study area obtained from Digimap was used to create the Euclidean distance (i.e. distance of cell of interest to the nearest point of interest) map.

2.3. Multi-criteria analysis (MCA) for diffuse pollution risk assessment

The multi-criteria analysis involves using multiple conflicting evaluation criteria to combine spatial data and value judgements to give environmental management decisions for diffuse water pollution. Based on the preliminary analysis conducted and literature, it was discovered that land cover/land use (Abdulkareem et al., 2018), soil type (Taye et al., 2013, Wang et al., 2017), slope (Haggard et al., 2005, El Kateb et al., 2013) and proximity of pollutant to surface water (Zampella et al., 2007, Anteneh et al., 2018) were the significant factors used to assess the potential of diffuse water pollution. They characterize the amount of pollutant generated per area, the pollutant's losses to surface water, the proximity of pollutant to surface water, and the climatic driving force. Thus, we identify the land use type, soil group, slope, and Euclidean distance rivers as our evaluation criteria. They were used as the multi-criteria analysis factors for the risk assessment of diffuse pollution in the study area to identify areas of high, moderate and low diffuse pollution risk.

Before multi-criteria analysis, all the factor maps need to be converted into a raster format and reclassified into uniform classes to satisfy the condition of multi-criteria analysis (Voogd, 1983). This is to provide equal weighting such that maps with different units will be treated equally. All the maps were reclassified into 3 classes, i.e. high, moderate and low pollution risk as 3, 2 and 1.

2.3.1 Conversion and reclassification of land use map

The dissolved land use map of the study area was used as the input features in the polygon to raster the conversion tools of ArcGIS to convert the map into a raster format. The output map was then used as the input raster in the reclassify tool of spatial analyst tools of ArcGIS to reclassify the map into 3 classes; high, moderate and low risk as 3, 2 and 1 respectively based on the potential of each land use type. High-risk areas consist of arable and horticultural land areas, moderate risk consists of improved grassland, suburban and urban land areas, while the remaining land use areas were classified as low-risk areas (Koo and O'Connell, 2006). These give the land use map for MCA.

2.3.2 Conversion and reclassification of soil group map

The dissolved soil group map was used as the input features in the polygon to raster the conversion tools of ArcGIS to convert the map into a raster format. The output map was then used as the input raster in the reclassify tool of spatial analyst tools of ArcGIS to reclassify the map into 3 classes; high, moderate and low risk as 3, 2 and 1 respectively based on dominant soil group in each class. High-risk areas consist of groups with heavy soils, moderate risk consisting of groups with medium soils, and low-risk groups with light soils. These give the soil group map for MCA.

2.3.3 Reclassification of slope map

The slope map created was used as the input raster in the reclassify tool of spatial analyst tools of ArcGIS to reclassify the slope map into 3 classes; high, moderate and low risk as 3, 2 and 1 respectively. Based on Chiang's (1971) assumption that 7^0 is the baseline for runoff potential, high -risk areas with a slope above 90, moderate risk are those with a slope between 5^0 and 9^0, and low-risk areas are those with a slope below 5^0. These give the slope map for MCA.

2.3.4 Reclassification of Euclidean distance map

The Euclidean distance map was reclassified into three classes using reclassify tool of spatial analyst tools of ArcGIS into high, moderate and low risk as 3, 2 and 1 respectively. Shortest distances were assigned as 3 while highest distances were assigned as 1. These give the Euclidean distance map for MCA.

2.3.5 Multi-criteria analysis

Before implementing multi-criteria analysis, weights need to be assigned to each criterion to indicate its importance relative to other criteria under consideration (Malczewski and Rinner, 2015). It determines the relative influence of criteria in the analysis and has a crucial impact on the evaluation results (Zhang and Huang, 2011). The ranking method used in several GIS multi-criteria analysis (Proulx et al., 2007; Zucca et al., 2008; Ozturk and Batuk, 2011) was used to assign the weight to each criterion. The first step is straight ranking were all the criteria were arranged from the most important as 1, second important as 2 up to the last criterion. Secondly, the rank-sum weights for each criterion were calculated using the following equation (Proulx et al., 2007):

$$W_j = ((F - 1) * ((R_{max} - R_j)/ (R_{max} - R_{min}))) + 1$$

Where Wj is the weight of criterion; F is the weight of the most important criterion (greatest weight); Rmax is maximum rank (rank of the less important criterion); Rj is the rank of criterion "j" and Rmin is 1 (minimum rank: rank of the most important criterion).

The multi-criteria analysis was then implemented in the raster calculator tool of spatial analyst tool of ArcGIS. It was done using the Boolean operators to multiply each criterion by its assigned weight and combined all the maps to give an output risk assessment map showing the spatial distribution of diffuse pollution across the study area.

3.0 Results and discussion

3.1. Evaluation criteria

The study area consists of 16 different land cover/land use (Figure 2). Arable and horticulture occupied 57.02%, improved grassland occupied 23.07%, broadleaf woodland occupied 5.32%, coniferous woodland occupied 0.12%, suburban settlements occupied 1.40%, and urban settlement occupied 0.11% respectively. This shows that the catchments received a significant amount of agricultural inputs due the high percentage of areas occupied by arable production, hence can serve as the primary source of nutrients in the surface water (Dupas et al., 2015).

The study area consists of 11 different soil groups (Figure 3). North Low and South Low catchments were widely covered by medium to heavy soil group with strips of heavy to medium to light (silty) soil group. Waren Burn catchment is widely covered by medium to light (silty) to heavy soil group. Although Fenham and Ross Low catchments were covered with medium to heavy soil group, they contain a significant amount of light (sandy) and medium soil groups. This shows that all the catchments contain a significant amount of heavy soils. García-Díaz et al. (2017) show that different soil and soil groundcover types generate different amounts of nitrogen concentration in runoff with conventional arable, generating more runoff with higher nitrogen concentration. Therefore, soil group was considered as a factor of diffuse pollution risk evaluation.

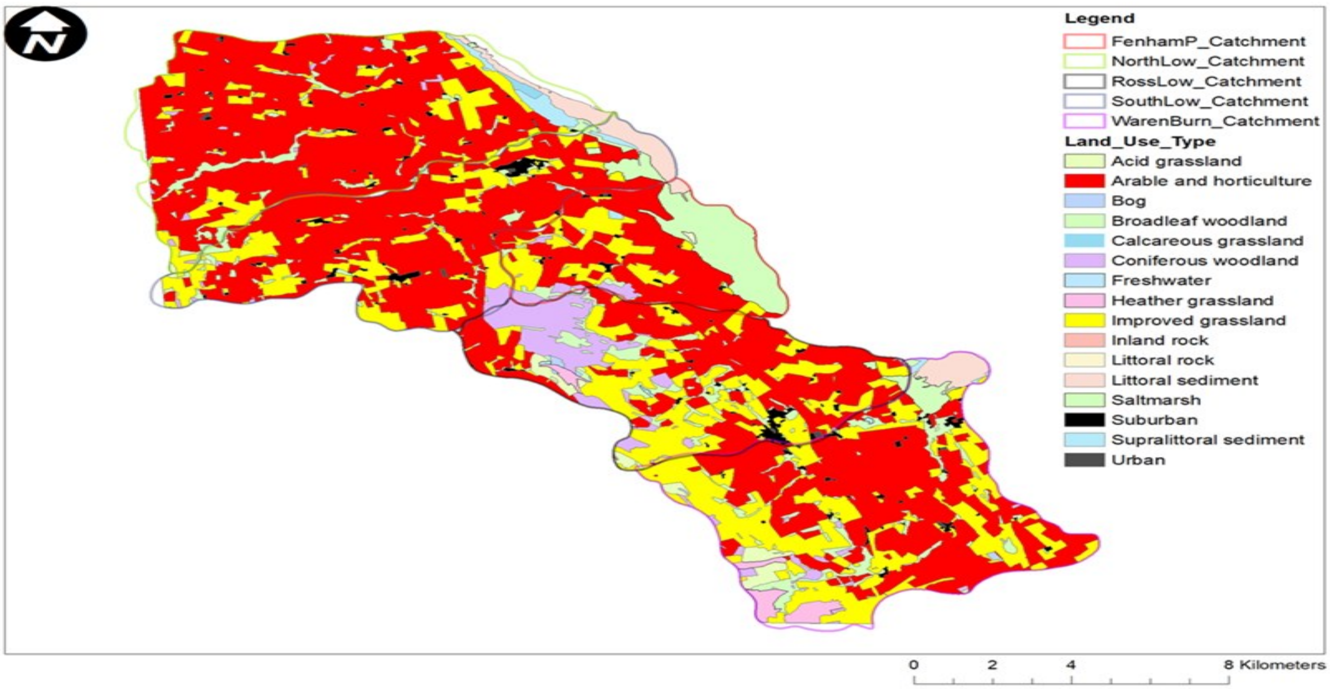

Figure 2: Land cover/Landuse map of the study area

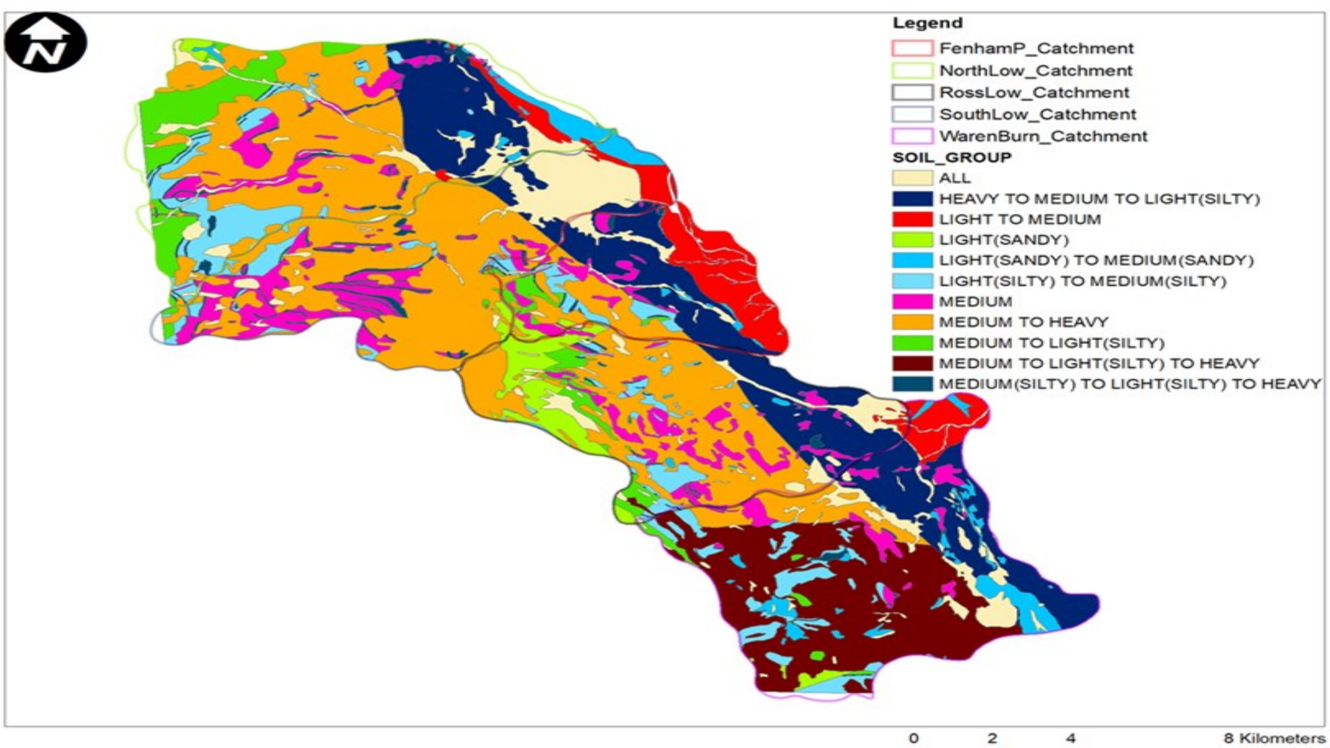

Figure 3: Soil group map of the study area

Slope map of the study area was created in ArcGIS (Figure 4). The slope map was computed in degrees with 71.43^0 as the highest slope. Most of the catchments were covered with a lower slope with higher slope along depressions. Waren Burn catchment have significantly higher slopes with Ross Low catchment having the lowest, and this shows that different places will have different potentials to runoff, hence different amount of pollutants to water bodies. This is true based on the studies of Ghanizadeh et al. (2019) and (Mu et al., 2015) that runoff intensity increases with increase in slope, therefore, most of the nutrients will be washed down leaving higher slope areas with less nutrients. The slope is among the dominant parameters used to determine runoff and nitrogen losses to surface water (Ghanizadeh et al., 2019, Dai et al., 2017, Cao et al., 2015).

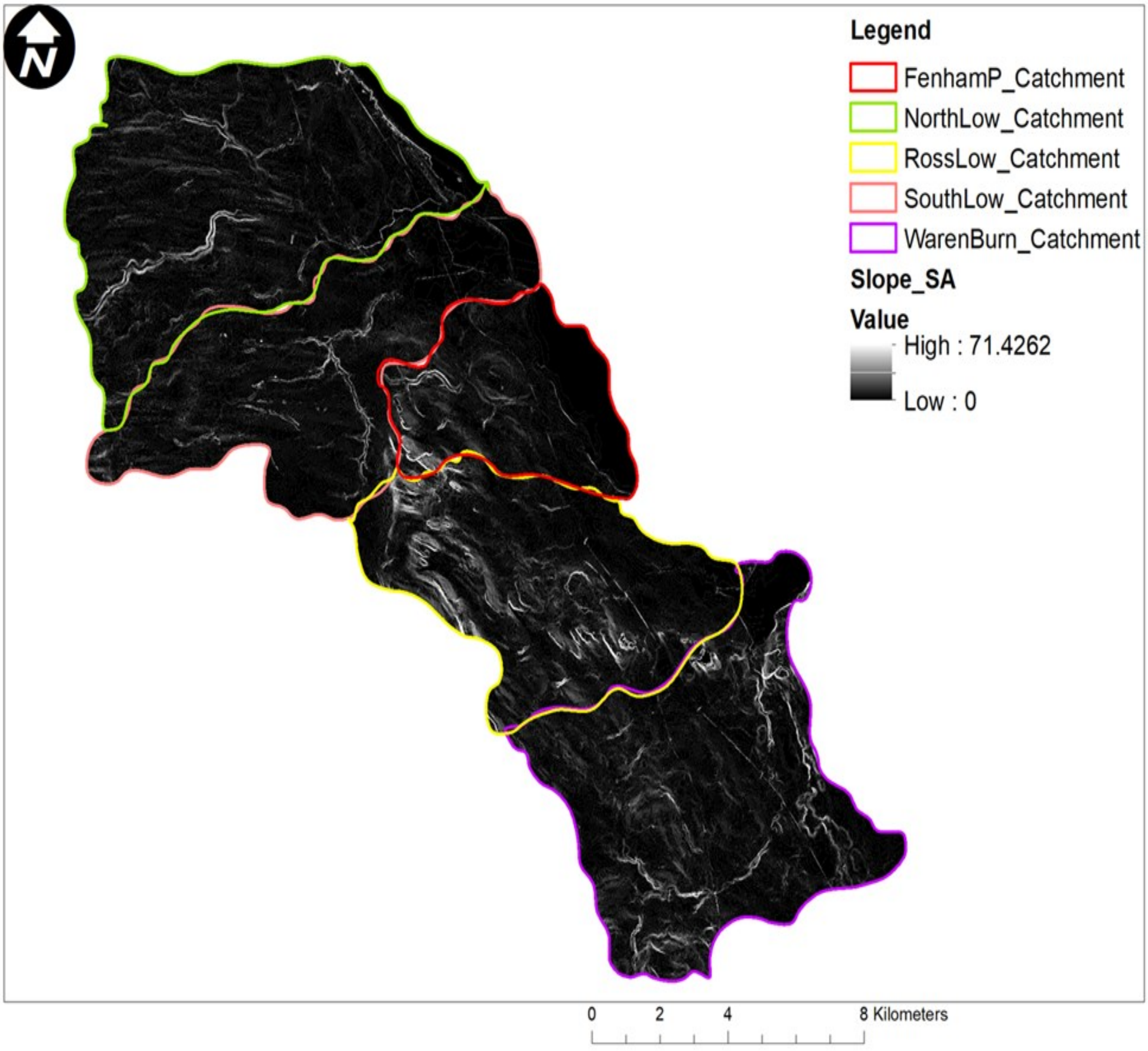

Figure 4: Slope map of the study area (measurement in degree)

3.2 Multi-criteria analysis

Based on the established literature, land cover/land use (Abdulkareem et al., 2018), soil type (Taye et al., 2013, Wang et al., 2017), slope (Haggard et al., 2005, El Kateb et al., 2013) and proximity of pollutant to surface water (Zampella et al., 2007, Anteneh et al., 2018) were the significant factors use to consider in diffuse pollution risk assessment. Therefore, land use, soil group, slope and Euclidean distance rivers were identified as the factors for multi-criteria analysis for diffuse pollution risk assessment. All the factor maps (Figure 5) for multi-criteria analysis were obtained using the ArcGIS. Each map shows areas of high, moderate and low risk of diffuse pollution based on the criterion. A Boolean operator multiply (*) and add (+) were used to combine the factor maps for multi-criteria analysis. Multiply sign times the map based on its relative importance to the other while the add sign combined all the maps to give the output MCA map.

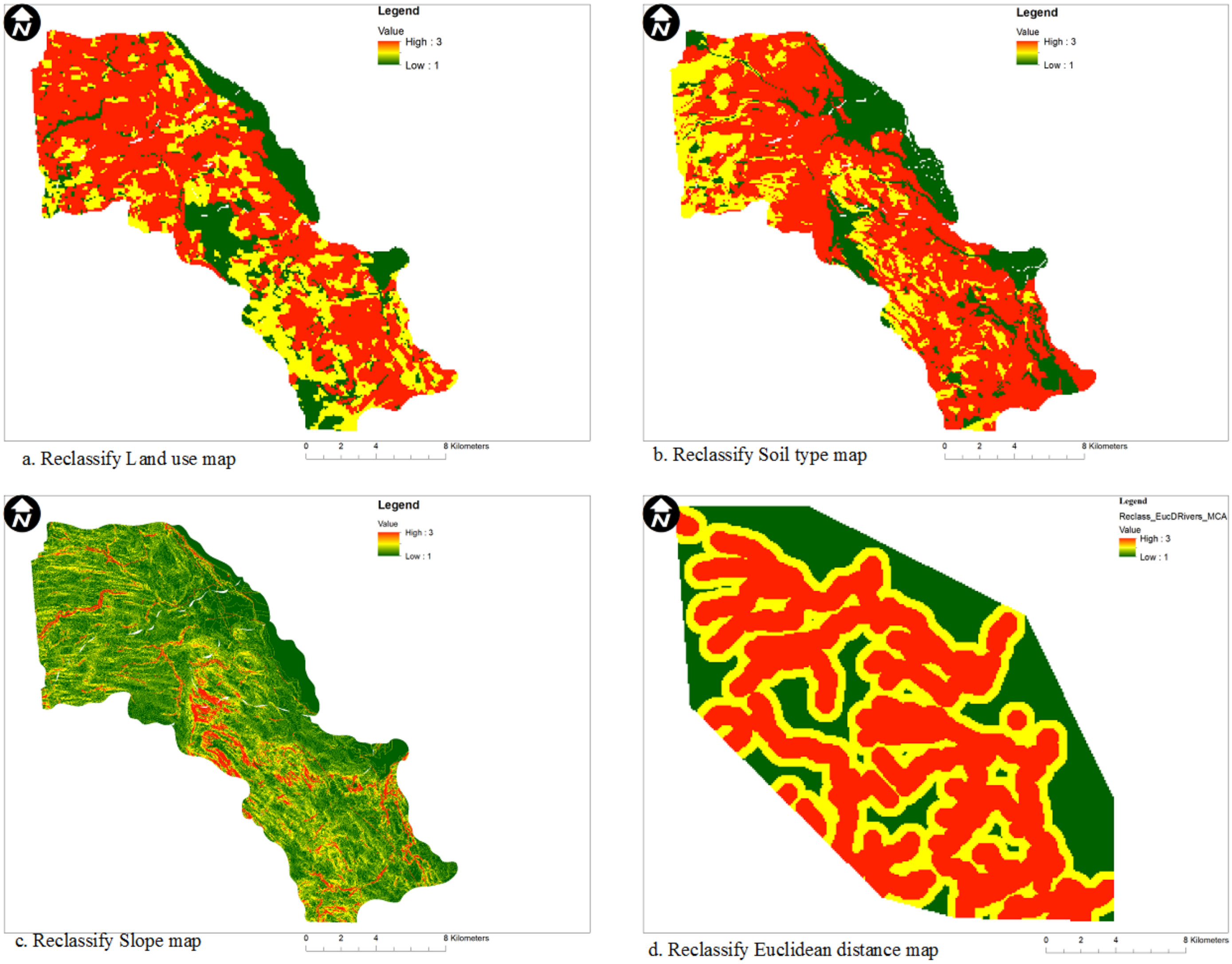

Figure 5: Multi-criteria analysis factor maps

Based on the ranking method, as explained in material and methods, weights were obtained for each criterion (Table 3). Land-use has been the most crucial criterion, scored 10, soil type scored 7, and slope scored 4, and Euclidean distance scored 1. This shows the relative importance of each criterion in relation to the other. The multi-criteria analysis was implemented in the raster calculator tool of spatial analyst tool of ArcGIS using the equation below;

Output = ("10*Land-use" + "7*Soil type" + "4*Slope" + "Euclidean distance")

This gives the output multi-criteria analysis map (Figure 6) of the study area based on the criteria of land use, soil type, slope and Euclidean distance rivers. The map shows the risk assessment of diffuse pollution distribution in the study area showing areas of high, moderate and low pollution risk.

Table 3: Ranking and weighting of criteria

Criteria	**Rank**	**Weight**
Land use	1	10
Soil type	2	7
Slope	3	4
Euclidean distance	4	1

From the map (Figure 6), North Low catchments areas recorded the highest abundance of high-risk areas. This is attributed to the high percentage of arable and horticultural activities taken place in the area. The diffuse risk assessment distribution is quite like the distribution of land use types, where areas occupied by arable and horticultural production recorded the highest risk. Kyloe Hills area recorded the lowest potential to the diffuse pollution risk. This is also attributed to the high abundance of coniferous woodland in the area, i.e. less intense agricultural activities. Another factor is the nature of soil type dominated with light (sandy) soil group and high slope. Therefore, in targeting diffuse pollution management, land use should be given adequate importance.

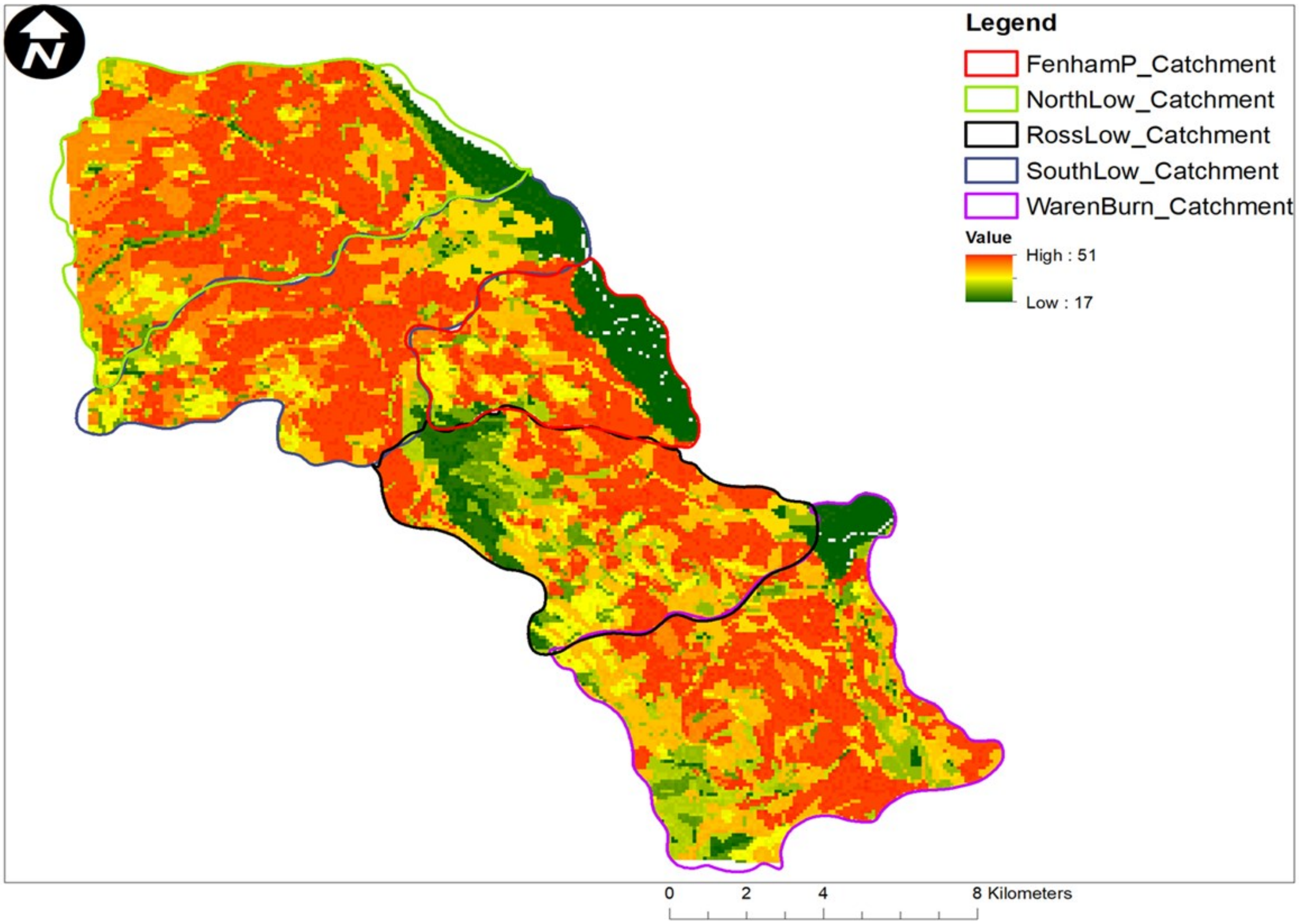

Figure 6: Multi-criteria analysis risk assessment map of the study area

4.0 Conclusion

Assessing the contribution of different land areas to the potential of non-point source pollution has become a priority task in watershed management and aquatic ecosystem protection. However, existing methods depend on the availability of local data, long time calibration and model complexity. This study developed a multi-criteria analysis GIS-supported method to evaluate the potentials of different land areas to diffuse water pollution in Holy Island and Budle Bay catchments. Five catchments were surrounding the study area, and these include North Low, Fenham, South Low, Ross Low and Waren Burn. Four criteria were identified and developed to map each land area's source capacity to water pollution, the efficiency of runoff generation, the flow path to a water body, and the climatic driving force. The criteria include land use, soil type, slope, and Euclidean distance rivers. The proposed method is a low-effort, and less time-consuming approach since most of the required data is either already available (e.g. landcover map, soil group map, river network map) or quickly produced with limited inputs.

Geographical Information System (ArcGIS version 10.5) environment provided the best ground to implement the analysis, and maps were generated that could be easily interpreted to support the decision-making process. The maps aim at facilitating the comparisons between different land areas in the catchments. They can be utilized and improved and detailed information on the chemical and biological conditions of receiving surface water bodies. The MCA map is useful for various decision-making, such as identifying high-priority areas of nitrogen export and improving the areas for pollution prevention. The results also helped evaluate the patterns of environmental conditions that facilitate nitrogen pollution and release to water bodies, which will help ecological conservation and environmental protection.

On the other hand, the assessment method is constrained by the lack of detailed information on the nitrogen and other pollutants balance. The various farming practices, different crops, fertilizer and other inputs application intensity, and irrigation condition were not classified. Also, the nitrogen pollution from livestock farms and sewage discharges was not assessed, increasing concern in the pollution assessment. Improvement can be made to the assessment method by considering other nitrogen pollution pathways, such as volatilization from the soil, removal by lateral flow and leaching into deep soil and groundwater. Furthermore, for the better validation process, information on wastewater treatment and discharge will help understand the relationship between diffuse water pollution and the affected open water quality.

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