**Development of a GIS method to localize critical source areas of diffuse nitrate pollution**

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**ABSTRACT**

The present study aimed at developing a universal method for the localization of critical source areas (CSAs) of diffuse nitrate (NO$_3^-$) pollution in rural catchments with low data availability. Based on existing methods, land use, soil, slope, riparian buffer strips and distance to surface waters were identified as the most relevant indicator parameters for diffuse agricultural NO$_3^-$ pollution. The five parameters were averaged in a GIS-overlay to localize areas with low, medium and high risk of NO$_3^-$ pollution. A first application of the GIS approach to the Ic catchment in France, showed that identified CSAs were in good agreement with results from river monitoring and numerical modelling. Additionally, the GIS approach showed low sensitivity to single parameters, which makes it robust to varying data availability. As a result, the tested GIS-approach provides a promising, easy-to-use CSA identification concept, applicable for a wide range of rural catchments.

**Key words** | critical source areas, diffuse NO$_3^-$ pollution, GIS

**INTRODUCTION**

Diffuse nitrate (NO$_3^-$) pollution from intense agriculture adversely impacts freshwater ecosystems, but can also pose a risk to human health, if the water is used for drinking water abstraction (Di & Cameron 2002; Gächter et al. 2004). Typical countermeasures, such as the implementation of mitigation zones or changed agricultural practice, are most efficient if they focus on critical source areas (CSAs) of diffuse NO$_3^-$ pollution within a given catchment (e.g. Trepel & Palmeri 2002).

Commonly, numerical models are used for identification of CSAs (e.g. Skop & Sørensen 1998; Kuderna et al. 2000). However, in many catchments the application of numerical models is limited, because of their high data requirements (Kuderna et al. 2000; Trepel & Palmeri 2002). Therefore, we reviewed methods with less data and time requirements as alternatives to numerical models for CSA identification (Bugey 2009). Many of these alternative approaches use Geographic Information Systems (GIS) (e.g. Soyeux et al. 1995; Jordan 1994; Trepel & Palmeri 2002; Bae & Ha 2003). However, most available GIS methods are site-specific and therefore not transferable to other catchments. The more developed ones focus on the vulnerability of groundwater rather than surface water (e.g. Aller et al. 1987; Vernoux et al. 2007).

The aim of the present work was to assemble a universal GIS-approach for CSA localization based on existing concepts, for application in rural catchments with low data availability. The idea of the method was to provide a ranking of areas within a catchment regarding their potential as NO$_3^-$ sources for surface water, but not to predict actual NO$_3^-$ concentrations or loads in surface waters. The presented approach focuses on small to medium size catchments with fairly homogeneous climate conditions.
For a first case study the approach was validated with measured loads and numerical model results for a catchment in Brittany, France. Finally, a detailed sensitivity analysis was performed.

MATERIAL AND METHODS

Approach

General approach

In order to keep the GIS-approach as simple as possible and maximize transferability, existing concepts of catchment analysis and CSA identification (Kuderna et al. 2000; Trepel & Palmeri 2002; MUNLV 2005) were broken down to the most basic and available parameters. The following five parameters were identified:

- Land use
- Soil
- Slope steepness (slope)
- Riparian buffer strips (buffer)
- Distance to surface waters (distance)

In this first approach, all parameters were classified into the three classes of low (1), medium (2) or high risk (3). For the sake of transferability, the risk classes were defined by relating them to the full range of possible values for each parameter, independent from the range of values found in a given catchment. In the following, the rationale, as well as the defined classification are outlined for each of the five parameters.

Land use

A number of studies showed that land use is one of the governing parameters for NO₃⁻ export from land surfaces (e.g. Crétaz & Barten 2007; Maillard & Pinheiro Santos 2008). The main reason for differences in NO₃⁻ export between land use types is the N-salut which is lost to subsurface or surface flow. Agricultural land use typically leads to elevated NO₃⁻ input on (cultivated) land surfaces, higher share of surface runoff and more erosion, which in turn cause an increase in NO₃⁻ loss to surface waters (Magdoff et al. 1997).

Based on the performed literature study, the parameter land use was classified into the three categories ‘unfertilized areas’, such as forests or uncultivated grassland (risk class 1), ‘other fertilized areas’ such as fertilized grassland and grazed pastures (risk class 2) and ‘cropland’ (risk class 3). The classification agrees with a review by Di & Cameron (2002), who ranked forest as least contributive followed by cut grassland, cropland and horticulture.

Soil

In most catchments, subsurface passage is the main NO₃⁻ pathway to surface water bodies (e.g. Gächter et al. 2004) and soil properties are a major controlling factor for this pathway. Therefore, in the present work, soil was considered by using the parameter root zone available soil water capacity (RZAWC), i.e. the soil water available for plants. The higher the RZAWC, the more water is retained by plants and consequently less water and NO₃⁻ leaches to the groundwater. RZAWC can be obtained from the soil texture and soil depth, data which are available for most catchments.

An existing RZAWC-ranking by the German Soil Scientific Mapping Directive (Ad-hoc-Arbeitsgruppe Boden 2005) was reclassified into three classes: loamy silt to clay loam with RZAWC ≥140 mm (risk class 1), loamy to silty sand or clay with RZAWC between 90 and <140 mm (risk class 2) and coarse to fine sand with RZAWC <90 mm (risk class 3).

Slope

Even though NO₃⁻ is predominantly lost to infiltration, transport via surface runoff also occurs (Mayer et al. 2005). Moreover, organic N can be transported to rivers via erosion, where it is mineralized to NH₄⁺ and oxidized to NO₃⁻ (e.g. Brunet et al. 2008). In order to account for surface runoff, slope was identified as the most relevant parameter.

The slope parameter is based only on slope steepness, as suggested in the modified Universal Soil Loss Equation (USLE) (Sivertun et al. 1988). For the purpose of this study the full range of the USLE slope steepness factor S by Nearing (1997) was evenly divided into the three classes: 0' to 17.4' (risk class 1), 17.5' to 29.9' (risk class 2) and 30' to 90' (risk class 3).

Riparian buffer strips

An important factor influencing how much NO₃⁻ reaches the surface waters is the land use within a close distance to the surface waters (Basnyat et al. 2000). If the land
of NO$_3^-$ export is followed by a combination of all five layers with equal weight. Technically the overlay was performed by averaging raster cells of the GIS layers in ArcGIS 9.1. The resolution of the input data is mainly dependent on their availability. In turn, the resolution of the results is dependent on the parameter with the most highly resolved input data. To avoid false precision, the raster size of each parameter should be appropriate to represent the major variability within the catchment. In the following, the term ‘overlay’ refers to the calculation of the mean risk class for each cell. The results were float values from 1 to 3. In order to make the results comparable, the values had to be assigned to low, medium and high risk classes. An equidistant distribution was chosen:

- Low risk class = 1.000–1.666
- Medium risk class = 1.667–2.333
- High risk class = 2.334–3.000

### Study site

#### General description

The Ic catchment is located in the north of the department Côtes-d’Armor in Brittany, France. It covers an area of 92 km$^2$ and the elevation ranges between 206 m a.s.l. in the south and the sea in the north-east (Julich et al. 2009). The predominant soil texture in the Ic catchment is silt loam in the floodplains and sandy silt in the remaining areas with predominantly less than 60 cm soil depth in the north, and more than 60 cm in the south. Land use in the Ic catchment is clearly dominated by agricultural use with 64% of cropland, while grassland and forests account for about 20% and 16%, respectively. Due to the intensive crop production and animal husbandry NO$_3^-$ concentration in the river exceeds 50 mg·NO$_3^-$·L$^{-1}$ almost year-round. Since the area has no major aquifers, river water was used for drinking water production until the beginning of 2009, when waterworks had to be closed down as a result of high NO$_3^-$ levels.

#### Data

The available spatial data include:

- 50 m digital terrain model of 2003 (MNT BD Altï 50) (Source: IGN),
- land use map digitized from aerial photographs of 1996/1997 (Source: Conseil Général des Côtes d’Armor),
- soil texture map, 1:100,000 of 1987 (Source: BDPA SCETAGRI),
- soil depth map, 1:100,000 of 1987 (Source: BDPA SCETAGRI),
- stream network map, digitized from aerial photographs of 2008 (Source: SMEGA).

The catchment boundaries were delineated from the digital terrain model. Monthly manual discharge measurements and NO$_3^-$ concentrations were available for monitoring stations at the outlet of the seven subcatchments (see Figure 1) between 1996 and 2007 (Source: DDE). Additionally, the results of the numerical catchment model Soil and Water Assessment Tool (SWAT) could be used for comparison with the GIS-results (Julich et al. 2009).
RESULTS AND DISCUSSION

Application to the Ic case study

The full overlay of the five individual parameters of the Ic catchment had a leveling effect (Figure 1). Most areas belong to medium risk class 2 (63.1%), high risk class 3 exists mainly in the south-east and east of the catchment (17.6%), while low risk class 1 can be found along the main rivers (19.3%). Concerning CSA identification, the full overlay map delivered spatially detailed information compared to other approaches.

Validation

Comparison with measured nitrate loads

In order to validate the applied overlay, the results were compared with average NO$_3^-$ loads obtained from ten years of monthly NO$_3^-$ and discharge measurements at seven monitoring stations in the catchment. It is important to note that the measurements do not include any data during major storm events (Julich et al. 2009). As a result, the calculation of average NO$_3^-$ loads can be subject to large but unknown errors.

A ranking of the seven subcatchments based on measured loads did not correspond to the results for mean risk classes for all subcatchments (Figure 2). For instance, the subcatchment with the lowest mean risk class (Ic Centre (I4)) showed higher measured NO$_3^-$ loads than some other catchments (Ic Littoral (I6), Lantic(L)) and almost as much as the catchment with the third highest mean risk class (Rodo (R2)). For a more systematic overview, measured loads were plotted against mean risk classes in Figure 2. Correlation was not significant ($p = 0.057$) concerning a confidence interval of 95%. Nevertheless, a general trend of higher mean risk class in a subcatchment with higher NO$_3^-$ load could be shown.

Comparison with SWAT simulation

SWAT focuses at predicting NO$_3^-$ loads, whereas the GIS-approach aims at a CSA identification. Nevertheless, the results compared relatively well. Both the SWAT model applied to the Ic catchment and the GIS-approach predicted CSAs in the north-east and in the south of the catchment (Figure 3).

Major differences between the two approaches existed in the north-west where SWAT predicted low NO$_3^-$ loads, whereas the present study expected several CSAs. An explanation could be found in the parameters buffers and distance, which were strongly influenced by the presence of drainage ditches, which occur in the two subcatchments

Figure 1 | Overlay of five parameters.

Figure 2 | Measured NO$_3^-$ loads against mean risk class of subcatchments after overlay of all parameters.
to a moderate extent, but were neglected in the SWAT analysis (compare river networks in Figure 3(a) (SWAT) and Figure 3(b) (GIS). This example indicates that not only the approach itself but also the different input data can explain the deviations in the results. For the GIS approach it can be recommended to use preferably river networks digitized from aerial views, especially in catchments characterized by agriculture with extensive channelization.

Sensitivity analysis

For the applicability of a similar GIS-based approach to catchments with varying data availability, it is important to know its sensitivity to each parameter. In order to assess this sensitivity, overlay was undertaken for each combination of four parameters, i.e. excluding each parameter in turn (Table 1).

Table 1 | Ranking of seven subcatchments based on average risk class for full overlay and with each parameter omitted in turn

<table>
<thead>
<tr>
<th>Sub-catchment</th>
<th>Ranking</th>
<th>Full overlay</th>
<th>Without land use</th>
<th>Without soil</th>
<th>Without slope</th>
<th>Without riparian buffers</th>
<th>Without distance</th>
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<tr>
<td>VS – Ville Serho</td>
<td>1</td>
<td>1</td>
<td>3&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>1&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>R2 – Rodo</td>
<td>3</td>
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<td>2&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>I2 – Ic Amont</td>
<td>5</td>
<td>5</td>
<td>4&lt;sup&gt;a&lt;/sup&gt;</td>
<td>5</td>
<td>4&lt;sup&gt;a&lt;/sup&gt;</td>
<td>4&lt;sup&gt;a&lt;/sup&gt;</td>
<td>4&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>I6 – Ic Littoral</td>
<td>6</td>
<td>6</td>
<td>7&lt;sup&gt;a&lt;/sup&gt;</td>
<td>6</td>
<td>5&lt;sup&gt;a&lt;/sup&gt;</td>
<td>5&lt;sup&gt;a&lt;/sup&gt;</td>
<td>5&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>I4 – Ic Centre</td>
<td>7</td>
<td>7</td>
<td>6&lt;sup&gt;a&lt;/sup&gt;</td>
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<sup>a</sup>Ranks that differ in comparison with the full overlay of all five parameters.
Results of this analysis indicate that the GIS overlay is not very sensitive to the single input parameters. For most parameters no more than two of the seven subcatchments changed their position in a ranking according to their average risk class, when one parameter is omitted. Solely the parameter soil had a strong effect on the full overlay, leading to a different ranking of all seven subcatchments and a significant shift of CSAs. But even for the parameter soil, the three subcatchments with the highest mean risk class stayed among the top three subcatchments and the four subcatchments with the lowest mean risk class stayed among the bottom four subcatchments.

Although sensitivity was lower than expected, it has to be kept in mind that even the change of two subcatchments in the ranking could change the decision on where mitigation measures are considered. Consequently, single parameters can still have a significant influence on the result. The extent of their influence is strongly dependent on the distribution of their risk classes over the considered spatial scale. For example, in the Ic catchment, the parameter soil showed uniform high risk in the north and uniform low risk in the south. As a result it had a strong impact on risk class distribution on a catchment level. However, if only a northern subcatchment was considered soil had a homogeneous character. In this case, the parameter had no impact on the CSA identification, because it only decreased or increased risk classes uniformly.

CONCLUSIONS

The comparably simple GIS approach adopted in this study provided reasonable CSA identification for NO₃⁻ in a test catchment. The results compared well to CSAs from measured loads and numerical model results. Identified differences to these two approaches could not be judged directly, since they were also prone to significant uncertainties. Surprisingly, the tested GIS approach showed relatively low sensitivity to single parameters, which makes it a robust method for catchments with varying data availability.

While the first results were promising, several open points need to be assessed to move towards the development of a future GIS method, universally applicable to catchments, which are affected by diffuse agricultural pollution. In particular it has to be tested on a range of catchments, where similar validation is possible as outlined above to identify shortcomings and need for adaptation. Moreover, possible weighting of the five parameters should be considered.

Regarding application, the tested approach is of interest, given its relatively simple application, its high flexibility to varying data availability and resolution, as well as its high transparency of how final results were achieved. Compared to other approaches, such as monitoring approaches (e.g. Tang et al. 2008) or numerical modelling (e.g. Kuderna et al. 2000), the presented GIS method is more time efficient, less costly and can be applied by local engineers. In contrast to other GIS-approaches (e.g. Jordan 1994; Skop & Sørensen 1998) no specific farming data (e.g. fertilizer input, cattle numbers) is needed and transferability is guaranteed by consideration of the full range of values. Furthermore, it can be applied even if a data layer is missing. However, it has to be clear that GIS-based CSA identification can only be a first step, which has to be followed by a reality check in the field. For the detailed planning of measures, local information (soil type, topography, cooperation of land-owner) needs to be collected and cannot be replaced by a GIS-based approach alone.

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REFERENCES


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