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Research article

Reducing uncertainty of estimated nitrogen load reductions to aquatic systems through spatially targeting agricultural mitigation measures using groundwater nitrogen reduction

Fatemeh Hashemi [a,*], Jørgen E. Olesen [a], Mohamed Jabloun [a,b], Anne L. Hansen [c]

[a] Department of Agroecology, Aarhus University, Blichers Allé 20, 8830, Tjele, Denmark
[b] School of Biosciences, University of Nottingham, Loughborough, LE12 5RD, UK
[c] Department of Hydrology, Geological Survey of Denmark and Greenland (GEUS), Øster Voldgade 10, 1350, København K, Denmark

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ABSTRACT

The need to further abate agricultural nitrate (N)-loadings to coastal waters in Denmark represents the main driver for development of a new spatially targeted regulation that focus on locating N-mitigation measures in agricultural areas with high N-load. This targeting makes use of the spatial variation across the landscape in natural N-reduction (denitrification) of leached nitrate in the groundwater and surface water systems. A critical basis for including spatial targeting in regulation of N-load in Denmark is the uncertainty associated with the effect of spatially targeting measures, since the effect will be critically affected by uncertainty in the quantification of the spatial variation in N-reduction. In this study, we used 30 equally plausible N-reduction maps, at 100 m grid and sub-catchment resolutions, for the 85-km^2 groundwater dominated Norsminde catchment in Denmark, applying set-aside as the measure on high N-load areas to reach a N-load reduction target of 20%. The uncertainty on these N-reduction maps resulted in uncertainty on the estimated N-load and on the required set-aside area. We tested several methods for spatially targeting set-aside that took into account the uncertainty on set-aside area and developed methods to reduce uncertainty on the estimated N-load reductions. These methods includes application of set-aside based on each individual N-reduction map compared to a mean N-reduction map, using spatial frequency of high N-load and using spatial frequency of low N-reduction. The results revealed that increasing the ensemble size for averaging the N-reduction maps would decrease the uncertainty on the estimated set-aside area with a stable effect when using an ensemble of 15 or more maps. The spatial resolution of the groundwater N-reduction map is essential for the effectiveness of set-aside, but uncertainty of the finer spatial resolution of N-reduction is greater compared to sub-catchment scale, and application of a spatially targeted strategy with uncertain N-reduction maps will result in incorrect set-aside area and uncertain estimations of N-load reductions. To reduce the uncertainty on estimated N-load reductions, this study finds the method of set-aside application based on spatial frequency of high N-load to be more effective than other methods tested.

1. Introduction

Leaching of nitrogen (N) in the form of nitrate (NO_3^-) from agricultural land is a significant environmental issue in many parts of the world, since this severely affects the quality of groundwater and surface waters (Hashemi et al., 2016). In Denmark, the N-load from agriculture to surface waters caused the eutrophication of marine environments that is one of the major problems (Højberg et al., 2017; Hansen et al., 2018) in water resource management. By imposing national regulations on agricultural land and nutrient management, the N-load has been halved over the last two decades (Dalgaard et al., 2014; Jacobsen et al., 2017). However, the obtained abatements are not sufficient (Danish Nature Agency, 2016) and further reduction is required to reach N-abatement targets of the Baltic Sea Action Plan (BSAP) for "good ecological status" in the Baltic Sea by 2021 (Backer et al., 2010) and environmental acceptable levels for coastal waters set by the EU Water Framework Directive (WFD).

* Corresponding author.
E-mail address: fatemeh.hashemi@agro.au.dk (F. Hashemi).

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The most straightforward measures under uniform regulation (e.g. N fertilizer application based on crops, soil type and irrigation use, time restrictions for slurry and manure application and mandatory cover crops) and partially targeted measures (e.g. constructed wetlands, buffer strips and 2 m riparian zones along streams and lakes) have already been implemented on agricultural fields in Denmark. The Danish Parliament adopted in 2015 a new policy (the Food and Agriculture Package), which allows Danish farmers to increase fertilization levels to economic optimum, while also introducing spatially targeted measures for reducing N-loads to ground and surface waters in areas where the measures have greatest effect. These measures are meant to be targeted to meet required N-load reductions for the individual water bodies. Nevertheless, the policy of targeted measures are by 2018 still not implemented, since deciding how and where to implement the targeted measures is no simple task.

The focus for enacting a new regulation in Denmark on reducing N-load to the aquatic environments aims to make better use of the considerable spatial variation in the natural N-reduction in groundwater and surface water systems (i.e. removal by biogeochemical processes (denitrification) or sedimentation) (Dalgaard et al., 2014; Mikkelsen et al., 2010; Refsgaard et al., 2014). The construction of a spatially targeted regulation for reducing N-load from agriculture can be performed in different ways. This involves selecting an approach to target areas for applying land use/management measures for mitigating N-load. The target areas can be selected either as the areas with low N-reduction (i.e. where there is no or little N-reduction in groundwater and surface waters) (Hansen et al., 2017) or as the areas with a high N-load (i.e. areas with low N-reduction and high N-leaching) (Hashemi et al., 2018). Another approach for developing a spatially targeted regulation is to maximize the total N-reduction (i.e. groundwater and surface water N-reduction) by considering changes in agricultural management and relocating current land management options according to the N-reduction, so that management with high N-leaching rates are placed on the areas with high N-reduction (Hansen et al., 2017; Hashemi et al., 2018). The approach of spatial targeting has been explored for Denmark; however, it is also relevant for other regions with large N-reduction potential in the groundwater, such as catchments of Germany and Poland draining into the Baltic Sea (Højberg et al., 2017).

Recently, Hansen et al. (2017) analyzed the potential benefits of spatially targeted N-mitigation based on detailed N-reduction maps in the Norsminde catchment in Denmark. Hansen et al. (2017) focused on decreasing root zone N-leaching on target areas with low total N-reduction (groundwater and surface water N-reduction). The findings showed that there are potential benefits of implementing a spatially targeted N-mitigation approach based on detailed N-reduction maps. In another study based on detailed N-reduction maps, Hashemi et al. (2018) investigated how spatially differentiated strategies on agricultural land would achieve a target N-load reduction with least effect on agricultural production (set-aside on agriculture land area) for the two catchments of Norsminde and Odense in Denmark. The focus of the study by Hashemi et al. (2018) was on decreasing the root zone N-leaching on target areas where mitigation measure (set-aside) should be prioritized to areas with high N-loading. The findings showed that the correct placement of spatially differentiated measures plays an important role to achieve maximum N-load reduction while minimizing cost of losing agricultural production. The analysis demonstrated a clear advantage of availability of spatially detailed input data (e.g. N-reduction maps) in terms of correct placement of measures.

Detailed mapping of groundwater N-reduction in Denmark have been reported by Refsgaard et al. (2007) for Ringkøbing, Hansen et al. (2009) for Odense and Hansen et al. (2014) for Norsminde catchments in Denmark. These studies applied the MIKE SHE model and then based on groundwater flow paths and depth to the redox interface constructed gridded groundwater N-reduction maps. Hansen et al. (2014) explored the uncertainty of the groundwater N-reduction maps due to uncertainty on the geology and on the location of the redox interface. They constructed an ensemble of geological models (10) and redox interfaces (3) and thereby developed 30 equally plausible N-reduction maps for the Norsminde catchment. Hansen et al. (2014) found the detailed N-reduction maps to be associated with considerable uncertainty, which will propagate to the results of using the maps for spatially targeting mitigation measures. However, the uncertainty on the N-reduction maps was found to decrease when aggregating the maps to a lower spatial resolution (Hansen et al., 2014).

There is no clear-cut answer how to assess uncertainties of spatial modelling outputs from uncertain input data. Over the last decade, various approaches have been used to evaluate input data uncertainty and resulting modelling uncertainty (Georgakakos et al., 2004; Breuer et al., 2009; Kronvang et al., 2009; Viney et al., 2009; Grenouillet et al., 2011; O'Hagan, 2012; Cha and Stow, 2014; Lehikoinen et al., 2014, 2014; Trolle et al., 2014; Maiorano et al., 2017).

Given that the models quantifying the processes are constructed on a fine spatial and temporal scale, and the management strategies often focuses on larger scales (lakes, catchments, protected areas, etc.) and longer-time (seasonal, yearly) averages (Uusitalo et al., 2015), there is need to study how these spatial and temporal scales are best aligned. Some of the studies have used observation averages for input as a proxies for the unknown mean (Cha and Stow, 2014), and this approach has been applied to model predicted spatial variability as an estimate of the possible variance, and therefore as a proxy for the uncertainty (Lehikoinen et al., 2014). The method of using the probable range of values of the model output (frequency distribution of the modelling results) can also be examined by analyzing how the output value would behave if some other, fixed variable values was changed within a reasonable range or assigned a probability distribution (O'Hagan, 2012).

In some studies, with the aim to reduce the uncertainty of model predictions, different methods have been developed for combining models results (Georgakakos et al., 2004; Breuer et al., 2009; Kronvang et al., 2009; Viney et al., 2009; Grenouillet et al., 2011; Gal et al., 2014; Trolle et al., 2014; Maiorano et al., 2017). In this regard ensemble modelling is used both for a single model ensemble (i.e. running a single model multiple times with different sets of initial input data) and for multiple-models within an ensemble. Ensemble modelling has principally been applied to make a “best” predictive model (Kronvang et al., 2009; Viney et al., 2009; Grenouillet et al., 2011; Trolle et al., 2014), and/or to evaluate the uncertainty (Georgakakos et al., 2004; Breuer et al., 2009; Gal et al., 2014; Maiorano et al., 2017).

The use of geographic information systems (GIS) has enabled spatially distributed modelling, combining spatially heterogeneous catchment information such as groundwater N-reduction, surface water N-reduction, land use, soil type and root zone N-leaching. However, the main concern is the spatial scale at which any simulation model is assumed accurate, and the spatial scale at which model inputs are available. Because GIS-based water quality modelling is sensitive to the spatial resolution of the input data (Wolock and McCabe, 1995), numerous studies have assessed the effect of spatial resolution of input data on model output uncertainty (Chaubey et al., 2005; Murphy et al., 2008; Li et al., 2013; Ruiz et al., 2013; Chen, 2013; Xu et al., 2016). Selecting an appropriate approach depends on the definitions of the spatial model and the amount and quality of information available for scenario analysis.

Hansen et al. (2017) analyzed the effect of uncertainty of