



# Water pollution from food production: lessons for optimistic and optimal solutions

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Food production is a source of various pollutants in aquatic systems. For example, nutrients are lost from fertilized fields, and pathogens from livestock production. Water pollution may impact society and nature. Large-scale water pollution assessments, however, often focus on single pollutants and not on multiple pollutants simultaneously. This study draws lessons from air pollution control for large-scale water quality assessments, where multi-pollutant approaches are more common. To this end, we present a framework for future water pollution assessments searching for optimistic and optimal solutions. We argue that future studies could shift their focus to better account for societal and economic targets. Participatory approaches can help to ensure the feasibility of future solutions to reduce water pollution from food production.

## Addresses

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## Introduction

Food production is expected to intensify in the coming years [1,2]. This is a result of the growing population that need more food [2]. Intensified food production is, however, a source of multiple pollutants in aquatic systems [3–5]. Overuse of chemicals and poor management strategies in the crop production sector result in losses of pesticides [3], heavy metals, pathogens [5], and

nutrients [6–9] in rivers from fertilized fields. Intensified livestock production is often a source of nutrients [6–9], pathogens [5], and antibiotics in rivers [1]. In many world regions, aquatic systems experience multi-pollutant problems [10]. China is one of the examples, where aquatic systems are largely contaminated by pollutants from food production [6–9,11]. Multi-pollutant problems are also reported for many rivers of North America and Europe. This holds especially for densely populated areas. In the future, food production may add more pollutants to aquatic systems, impacting society (e.g. diarrhoea from pathogen contamination) and nature (e.g. harmful algae blooms from excess nutrients). The existing studies differ in their search for solutions to reduce water pollution from food production. Here we focus on two types of analyses: searches for *optimistic* and for *optimal* solutions.

*Optimistic solutions* show us to what extent environmental problems can be solved in scenarios reflecting maximum technical, economic, and societal potentials to solve environmental problems. In scenarios searching for optimistic solutions, the full implementation of management strategies is often assumed to reduce pollution from human activities, for example, food production [6–9].

*Optimal solutions* account for trade-offs, and show us how environmental targets can be met in the most cost-effective, equitable, or acceptable ways. Optimization analyses typically aim to achieve certain targets while looking for the optimal combination of environmental measures [13,14]. Optimization analyses can be combined with participatory approach to include stakeholders' interest. This is particularly relevant for sustainability targets, such as the Sustainable Development Goals (SDGs).

Multi-pollutant, large-scale optimization analysis are more commonly applied in air quality control [14–16] than in water pollution control. Water quality studies often analyze single pollutants and not multiple pollutants simultaneously [3,5–9,11,12]. This holds especially for large-scale water quality assessments.

In this study, we, therefore, draw lessons from air pollution control for large-scale water quality assessments, where multi-pollutant approaches are more common. We present a framework for future water quality assessments searching for optimistic and optimal solutions. Finally, we provide concluding remarks.

## Lessons from air pollution control for water quality assessments

In the following, we draw three main lessons from existing models. In our discussion, we refer to the representative models that have been successfully applied for air pollution control at a continental or global scale and take a multi-pollutant perspective. We use these models as illustrative examples for water quality assessments. We identify opportunities for further development of existing water quality models.

### Lesson 1: Integrated models for air pollution control have been more successful tools for international decision making than water pollution models

Several integrated models exist for air pollution control taking a multi-pollutant perspective. RAINS (Regional Air Pollution Information and Simulation) model and its extended version for greenhouse gasses, GAINS (Greenhouse Gas and Air Pollution Interactions and Synergies) are illustrative examples of how integrated models can successfully be used in international negotiations related to environmental problems. RAINS and GAINS can be used to quantify emissions and air pollution impacts, and to identify least-cost strategies for air pollution control (cost-optimization). RAINS supported the formulation of 'the European Commission's 1995 Acidification Strategy' (<http://www.iiasa.ac.at/>). RAINS and GAINS played an essential role in international negotiations on the Convention on Long-Range Transboundary Air Pollution (LRTAP, <http://www.unece.org/fileadmin/DAM/env/lrtap/welcome.html>). This convention was an international agreement to deal with air pollution in Europe signed in 1979. The convention was extended to eight protocols on emission reduction targets for multiple pollutants in the air. Today, more than 50 countries in the world are taking part in this convention. The role of the models is in providing scientific information to support negotiations. This information includes quantified emissions of air pollutants (e.g. sulfur dioxide, nitrogen oxides, ammonia, and volatile organic compound) and greenhouse gasses (e.g. carbon dioxide, methane, and nitrous oxide) from European countries, environmental impacts of those emissions, effects of reduction strategies and costs of emission control [14–16].

The success of the RAINS and GAINS models in international negotiations can be explained by three main reasons. First, these models integrated multiple pollutants and their multiple effects. For example, emissions of sulfur dioxide, nitrogen oxides, and ammonia cause acidification of forests and water. Nitrogen oxides and ammonia are also important contributors to eutrophication problems. Second, the models considered regional differences in socio-economic development and ecosystem sensitivities. The models contributed to an increased awareness among different stakeholders of the need to develop regional solutions, while accounting for transboundary emissions. Third, the

models are able to provide a scientific basis to support a dialogue between different stakeholders. Models support the identification of optimal solutions (e.g. cost-effective) for reducing air pollution [14,15]. Today, these models are applied to many world regions (for China and India) with a 5-year time step up to 2050.

Water pollution models for multiple pollutants have not been as widely used as air pollution models in international negotiations. An important reason is that multi-pollutant models are successful in water quality assessment for the present day, but rather limited for future assessments of water quality at the continental or global scale. Several continental and global water quality models exist for individual groups of water quality parameters (e.g. nutrients). Examples of such models are Global NEWS-2 (Nutrient Export from WaterSheds) for nutrients [23,24], IMAGE-GNM (Global Nutrient Model) for nutrients [25], GloWPa (Global Waterborne Pathogen) for pathogens [5,26], VIC-RBM (Variable Infiltration Capacity – River Basin Model) for water temperature [27], Global TCS (Triclosan) for triclosan [28], global plastic model [29], and the global pesticide model [3]. Some water quality models exist for national assessments of water quality. Examples of such models are SPARROW (SPatially Referenced Regressions On Watershed attributes) for the United States [30] and MARINA (Model to Assess River Inputs of Nutrients to seAs) for China [4], with both models designed for nutrient pollution assessment. The WorldQual model accounts for more than one group of pollutants in continental water quality assessments, but not for the future [12]. WorldQual quantifies biochemical oxygen demand, faecal coliform bacteria, total dissolved solids and total phosphorus (P) in river reaches for Africa, Latin America and Asia. A few more models account for multiple pollutants in aquatic systems at the national or continental scale [31]. Detailed review of existing, large-scale water quality models is presented in Stokral *et al.* [12].

Lesson 1 highlights the opportunity for existing global and continental water quality models to further develop toward multi-pollutant assessments. This is needed to explore scenarios in which we search for optimistic and optimal solutions that could simultaneously reduce water pollution of multiple pollutants (see Lesson 2 below).

### Lesson 2: Models can support the search for optimistic and optimal solutions for multi-pollutant problems in water, by assessing maximum technical feasibility and cost-effectiveness

Models are often used as scenario tools to analyze future water quality. Models are able to project the future water quality by Business as Usual (BAU) scenarios. In scenarios searching for solutions, BAU scenario often used as a baseline scenario, accounting for climate change and socio-economic developments. Climate change scenarios

exist, for example, the IPCC Specific Report on Emissions Scenarios (SRES) [32] or the Representative Concentration Pathways (RCPs) [33]. Scenarios exploring changes in socio-economic development in the future are, for example, the Millennium Ecosystem Assessment (MA) scenarios [34], or the Shared Socioeconomic Pathways (SSPs) [35]. Storylines of the climate and socio-economic scenarios are incorporated into water quality models (e.g. GlobalNEWS-2, GloWPA). These storylines often form the basis of the alternative scenarios that aim at searching for optimistic and optimal solutions to reduce water pollution.

We can use water quality models to assess the maximum technical feasibility and cost-effectiveness of solutions for pollution abatement [8,9]. Some of the existing water quality models (e.g. *MARINA*) are used to assess the maximum technical feasibility of solutions for reducing eutrophication problems [1]. Differences in socio-economic development and climate change among subbasins are considered. For example, focusing on the maximum technical potential to avoid coastal eutrophication in 2050, Stokal *et al.* [8] showed the possibility to avoid coastal eutrophication by implementing advanced technologies (e.g. recycling animal manure to replace synthetic fertilizer) aiming at reducing losses of nutrients to aquatic systems. Similar study has also been conducted for the pathogens [5]. Scenarios reflecting the maximum economic and societal potential to solve multi-pollutant problems are less studied for large-scale water quality assessments.

Use of models for cost-effectiveness analyses are, however, less common for multi-pollutant water quality assessments [17–20]. This is more common for models for air pollution assessments as we highlighted before. RAINS and GAINS are able to explore solutions with the maximum technical potential, and identify the least-cost strategies to reduce emissions of multi-pollutants to the atmosphere [14,15] (see Lesson 1 above). Taking the cost-optimization approaches from air pollution model as example, such as RAINS and GAINS [36], water quality models can develop further as tools for cost-effectiveness analyses from a multi-pollutant perspective. Another similar example is the Hydro-Economic Optimization model (ECHO) [13]. ECHO gives insights on cost-effective allocation of water across different sectors for Africa in a spatially explicit way. A few studies allocate wastewater discharge permits to cities in the most fair way, while considering socio-economic development [21,22,37,38]. These insights from existing optimization approaches can form a good basis to develop a cost-optimization model for water quality assessments at the large scale.

### **Lesson 3: To account for societal feasibility in water pollution assessment participatory approaches may be needed**

Accounting for the societal feasibility of implementing environmental solutions is important. This is because it

gives us a better understanding of whether society is prone to accept certain measures or not. This will improve our water quality assessments, where technical, economic, and societal aspects are accounted for. Such assessments will facilitate the formulation of effective environmental policies to reduce water pollution in the future.

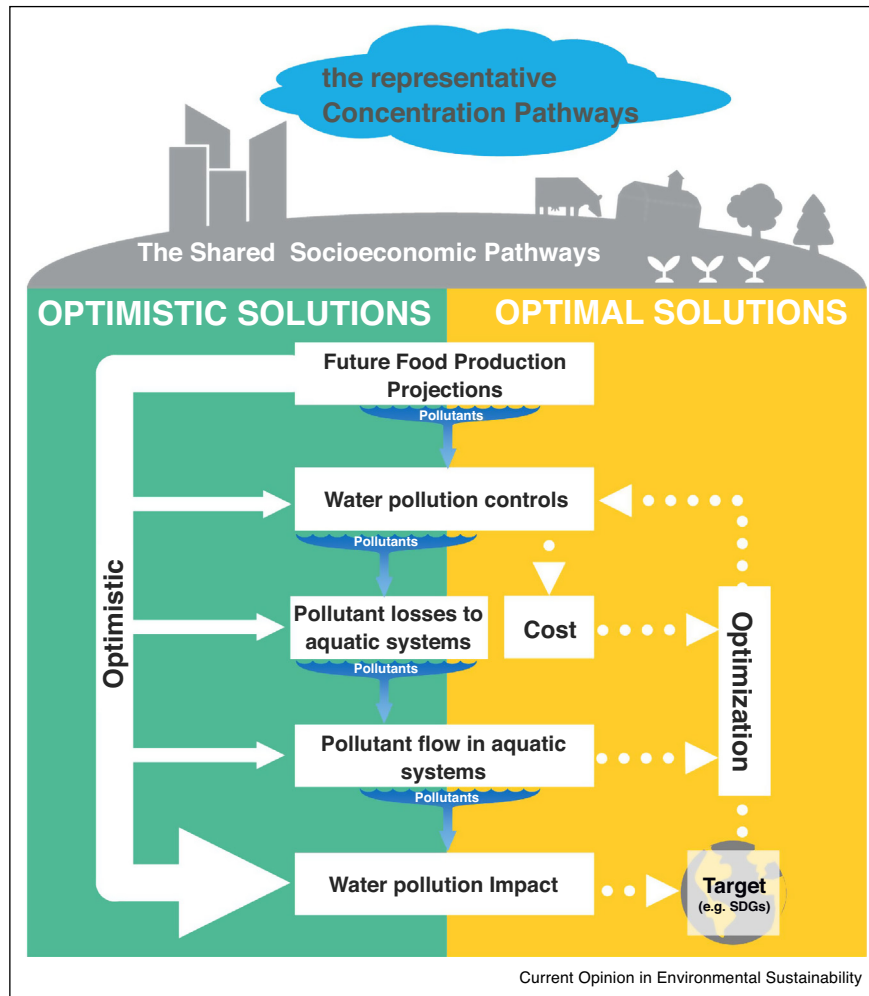
Accounting for societal aspects is challenging, but not impossible. Several ways to do this exist. One is to invite stakeholders to co-design solutions based on existing scenarios (e.g. based on SSPs). Then, effects of such solutions can be tested by models. Another way is to involve stakeholders in the whole cycle of developing scenarios. Participatory approaches can help [39–41]. An example is the ‘Story-And-Simulation’ approach (SAS). This approach has been used to develop scenarios for environmental problems [39]. Experts (e.g. modellers) together with stakeholders translate qualitative narratives into quantitative scenarios for models. This process is iterative and consists of several steps in which stakeholders are involved [see Refs. 39–41 as example]. Participatory approaches are part of the Water Future and Solutions Initiative, launched by the International Institute for Applied Systems Analysis (IIASA, <http://www.iiasa.ac.at/>). This initiative is a good example how to bridge science to society and policy at different scales using various modelling tools [42]. There is a need to link the relevant sustainable development goals (SDGs) to the participatory approaches. For example, SDG 2 Zero Hunger (food production) and SDG 6 Clean water and sanitation (water quality) can be used as a scientific basis to support co-design of solutions with stakeholders during the participatory workshops.

### **Framework for future water quality assessments**

We present a framework for future water quality assessments searching for optimistic and optimal solutions (Figures 1 and 2). We design this framework based on the lessons that we draw for large-scale water quality assessments (Section 2). Our framework provides an illustrative example of how different modelling approaches can be combined, to explore optimistic and optimal solutions for water pollution from food production or other pollution sources (e.g. human waste) taking a multi-pollutant perspective. The framework covers drivers (food production and water pollution controls), pressure (pollutant losses), state (pollutant loads and concentrations), and impact (water pollution impact on nature and society) (Figure 1). For the water pollution impact, various indicators can be integrated into the framework. For example, Indicators for Coastal Eutrophication Potential can be used to reflect the impact of nutrient enrichment in the coastal water [43].

*The framework* allows for two types of analyses: exploring optimistic and optimal solutions for water pollution (Figure 1). It focuses on water pollutants from food

Figure 1



Framework for future water quality assessments searching for optimistic and optimal solutions. Examples of targets are shown in Figure 2.

\*Optimistic scenario analysis: [6–9].

\*\*Cost optimization: [51–54].

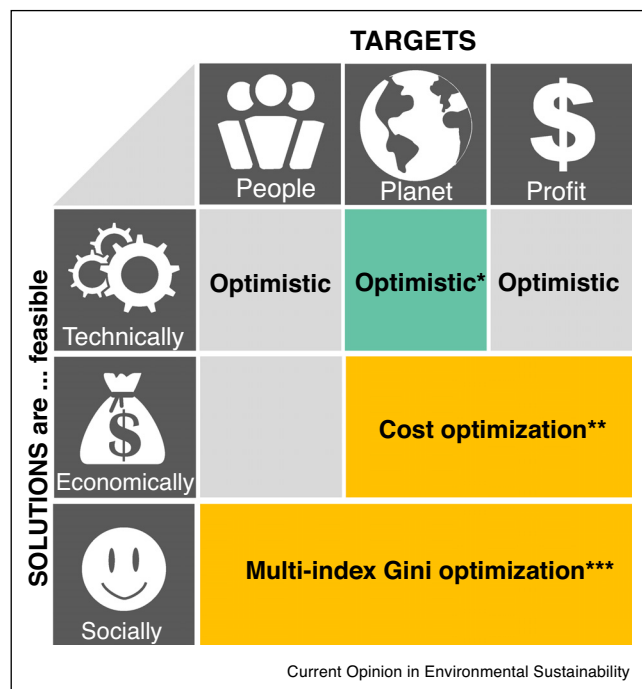
\*\*\*Multi-index Gini optimization: [21,22,37,38].

production, such as nutrients, pesticides, and pathogens [3,5,25]. Exploring optimistic futures can be done through scenario analyses: starting from storylines, and optimistic assumptions about emission control. We can analyze future trends in water pollution, the costs of emission control, and the impacts of pollution on nature and society. Exploring optimal solutions typically starts from environmental targets, and aims at analyzing optimal (e.g. cost-effective) solutions to reach these targets. Our framework thus follows Lessons 1 and 2 as formulated above.

Existing models could form the basis of the framework. To address the impact of food production on water quality, the framework should be able to quantify the pollutant losses to waters from the food production chain. It should also include control measures to reduce the

pollutant losses from the food production chain. It also needs to account for the transport of pollutants through the environment, and retention processes. Pollutants may be transported by rivers from upstream to downstream and eventually entering the seas. During the transportation, pollutants can be lost or retained in the river systems. Examples are nitrogen losses due to denitrification, P retentions in sediments and retentions of various pollutants due to river damming. Finally, the framework should account for effects of pollutants in the environment, on nature and society. Several models exist to quantify pollutant flows from food production to the aquatic systems at large scales [12,44,45]. These models can be used to identify ‘hotspots’ of water pollution, and to analyze past and future trends in water pollution [12,46]. They could form the basis of the framework.

Figure 2



Overview of how targets (for people, planet and profit) and solutions are linked. Colors in the cells follow the colors in Figure 1. So far, scenario analyses searching for optimistic solutions for water quality focused mostly on meeting *environmental* targets by *technical* solutions (the green box in the graph). Yellow boxes refers to optimization analyses that can be applied to large-scale water quality issues, of which some examples can be found in the literature. Grey cells indicate types of analyses that are not yet widely performed.

Exploring *optimistic* solutions could start from optimistic storylines about future trends in society, and about what is technically feasible in terms of pollution control (Figure 1). Models can then be used for scenario analysis, analyzing future trends in water pollution while assuming full implementation of existing and future technologies to reduce water pollution. One could compare the results with, for instance, targets for pollution control deduced from people, planet or profit boundaries (Figure 2). For China, some examples exist of modelling studies exploring optimistic scenarios for reducing nutrient pollution by technically feasible options at basin or national scale [8,9,47]. These examples indicate that it is technically possible to reduce pollution to low levels in the future. So far, scenario analyses searching for optimistic solutions focused mostly on meeting environmental targets by technical solutions (green box in Figure 2). In addition to optimism about technologies, one could also add optimistic assumptions about human behavior. For instance, storylines may assume sustainable development in society, reflected, for instance, by environment-friendly behavior. In such futures, farmers and consumers will be concerned about the environment and

thus do not overuse agrochemicals in crop productions, and move to vegetarian diets. Optimistic futures may, furthermore, assume that industry and waste water treatment may aim for green development.

Exploring *optimal* solutions for water pollution, could start from environmental targets, to be reached in an optimal way (Figure 1). Optimal can be interpreted here as economic, technical or social optimum (Figure 2, Section 1). In Figure 1, we give an example of searching for cost-effective solutions. Cost-optimization has been successfully applied in controlling the air pollution in European countries (see Section 2). To account for people, planet and profit simultaneously in optimization analyses, the Gini coefficient could be used (Figure 2). The Gini coefficient reflects equality of income or wealth within society according to the Lorenz curve [48,49]. The Gini coefficient can also be used to reflect the equality in use of environmental resources, such as allocating the waste discharge permit [21,22,37,38]. Absolute equality in a country is reached when all people have an equal share in resources, or in economy. The Gini coefficient can be used in optimization analysis to search for strategies to meet targets (for people, planet or profit) in such a way that social equality is maximized. The Gini coefficient for pollutant discharge can be quantified for various indexes, such as population density or gross domestic product. Multi-index optimization involves optimization of the equality in the discharge of water pollution for multiple indexes. One could apply this approach in water pollution assessment, for instance to allocate pollution rights [22].

*Optimistic scenarios and optimization approaches* can assist decision makers in their search for solution to water pollution (see Lessons 1 and 2). To implement the framework proposed in Figure 1, some hurdles have to be taken if we want to apply it for multi-pollutant problems. First, existing large scale water quality models run at different spatial and temporal scales. The abovementioned global and regional water quality models (Sections 1 and 2) calculate pollutant flows at scales of 0.5° grid (e.g. IMAGE-GNM, GloWPa, VIC-RBM), basin scale (e.g. Global NEWS-2, Triclosan model), or subbasin scale (e.g. MARINA, WorldQual) [3,5,12,25]. Some of them are process-based (e.g. IMAGE-GNM, VIC-RBM) while others take a lumped, parameter-based modelling approach (e.g. Global NEWS-2, MARINA). Most of them are steady-state models that quantify the annual pollutant flows [details on model reviews are in Ref. 12]. A few models quantify seasonal nutrient flows from land to seas globally [50] or nationally [30]. However, pollution control typically takes place at international, national, or local scales (administrative scale), and in shorter timeframes. It is a challenge to integrate biophysical and administrative scales in water assessments.

A second challenge is how to account for societal feasibility. Lesson 3 above calls for participatory approaches.

Stakeholders could be involved in formulating storylines, targets and in identifying optimistic and optimal solutions, while using the modelling framework presented in Figure 1. This will help to ensure that optimistic futures are realistic, and that optimal solutions account for trade-offs.

Our presented framework can 1) advance the field of water quality modelling; 2) help to integrate people, planet, and profit-related targets with technical, economic, and social solutions; 3) help to link water and food security assessments. The framework can help to achieve the Sustainable Development Goals (SDGs) for Clean Water and Sanitation (SDG 6) and Zero Hunger (SDG 2) at the same time. For example, targets for food production (related to SDG 2) and water quality (SDG 6) can be used as multiple constraints in optimization analyses. This may help to identify possible synergies and trade-offs.

### Concluding remarks

In this study, we argue that large-scale water quality assessments can learn from air pollution control to identify optimistic and optimal solutions. Both optimistic (e.g. technically feasible) and optimal (e.g. cost-effective) solutions are needed for effective reduction of future water pollution from food production. We draw three main lessons from air pollution control for water quality assessments, searching for optimistic and optimal solutions. These lessons are: 1) Integrated models for air pollution control have been more successful tools for international decision making than water pollution models; 2) Models can support the search for optimistic and optimal solutions for multiple pollutant problems in water, by assessing maximum technical feasibility and cost-effectiveness; 3) To account for societal feasibility in water pollution assessment participatory approaches may be needed. Next, we present a framework for exploring optimistic and optimal solutions for water quality problems. The framework combines optimistic scenarios and optimization approaches with water quality models to explore the optimistic and optimal solutions for water pollution. We show that current water quality studies focus on environmental targets and technical solutions. We argue that future studies could shift their focus to better account for societal and economic targets. Participatory approaches may be needed to ensure feasibility of future solutions to reduce water pollution from food production.

### Conflict of interest statement

Nothing declared.

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