A novel spatially explicit hydro-economic modelling procedure to design cost-effective agri-environment schemes for mitigating nitrogen and phosphorus from agricultural land

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A novel spatially explicit hydro-economic modelling procedure to design cost-effective agri-environment schemes for mitigating nitrogen and phosphorus from agricultural land

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Abstract

Agricultural intensification is a key driver of water pollution in many parts of the world. A frequent policy response is to implement agri-environment schemes (AES) which compensate farmers for land use measures that are beneficial to the environment but costly for them. We develop a hydro-economic modelling procedure which is able to design cost-effective AES to mitigate water pollution from nitrogen and phosphorus from cropland. Our procedure goes beyond existing research as it considers spatial heterogeneity of both mitigation impacts and costs of cropland management measures and takes into account the decision of farmers to participate in an AES. We demonstrate how the procedure works by applying it to the Baishahe watershed in Shanxi Province, China.

Keywords: payments for environmental services; integrated modelling; non-point source water pollution; SWAT; agri-economic costs; spatial heterogeneity; cropland; China

1. Introduction

Efforts to increase food security have led to agricultural intensification all over the world in the last decades (Ickowitz *et al.*, 2019). This in turn has induced many negative environmental consequences, with water pollution from nutrients, in particular nitrogen (N) and phosphorus (P), being a key challenge in many countries (Evans *et al.*, 2019). Nutrient excess is caused mainly by the overuse of synthetic fertilizer and manure on cropland (Mateo-Sagasta *et al.*, 2018). It may lead to algae bloom due to eutrophication, which in turn has severe negative impacts on aquatic ecosystems, recreational opportunities, and commercial fishing (Le Moal *et al.*, 2019). Human health is also affected due to toxic algae and tainted drinking water containing nitrate or byproducts of disinfectants for toxic algae (US EPA, 2020).

A key policy instrument aimed at mitigating environmental problems from agricultural intensification with the cooperation of farmers are agri-environment schemes (AES). They have been applied worldwide, especially in Europe and the United States where several billion euros are paid annually for AES programs (Ansell *et al.*, 2016). However, they exist also in other countries. For example, the Grain-to-Green Program in China is one of the largest programs in the world with a total payment of more than 500 billion RMB (approximately 65 billion euros) until 2019 (CRG-PRC, 2019). However, the expected improvement of water quality from AES has often not materialized in practice (Jones *et al.*, 2017), and, in particular in many developing and emerging countries, with China being a prominent example, tackling water pollution remains a huge challenge (Han *et al.*, 2016). This lack of success has led to calls in many countries for an improvement of AES (European Court of Auditors, 2011; Yang *et al.*, 2013).

Economics can contribute to improved AES by developing methods to design them in a way that they are more cost-effective. Regarding the reduction of N and P from cropland, an AES typically consists of a (set of) cropland management measure(s) and associated payment(s) that farmers receive if they implement one (or several) cropland measure(s) on their land. In the context of this paper, an AES is said to be cost-effective when measures and payments are designed in a way that they are able to achieve a weighted minimized N and P load in a waterbody with a given budget (Balana *et al.*, 2011; Elofsson, 2010; Wätzold and Schwerdtner, 2005).

Designing a cost-effective AES is challenging for several reasons. (I) Different cropland management measures to mitigate N and P typically have different mitigation impacts and also different opportunity costs of land use (for simplification henceforth referred to as costs), each of which needs to be quantified. (II) The impacts of the cropland management measures differ spatially, i.e. depending on where they are carried out. (III) Similarly, the costs of the measures also differ spatially. (IV) Bearing in mind that participation in AES and the selection of cropland management measures is typically voluntary, the different payments for the different measures have to be designed in a way that they incentivize the farmers in a region to implement the cost-effective (set of) cropland management measure(s) to the appropriate extent. In summary, designing cost-effective AES for N and P mitigation is a complex numerical optimization problem which requires the integration of knowledge and data from economics, agronomy and hydrology, and has to take into account the behavior of farmers.

Taking up this challenge, we present a hydro-economic modelling procedure that combines agri-economic cost data and data from the impact of cropland management measures on N and P mitigation from a SWAT (Soil & Water Assessment Tool) model with heuristic numerical optimization. Moreover, the procedure takes into account that participation of farmers in AES is voluntary and that they may choose between different cropland management measures. We explain how the modelling procedure works by applying it to the design of cost-effective AES for the Baishahe watershed in Shanxi Province in China. Given data limitations, this is meant for illustration purposes rather than for developing concrete policy recommendations for the Baishahe watershed. The development of the modelling procedure is motivated by Wätzold *et al.* (2016), who present a similar procedure, albeit for the design of cost-effective AES for the conservation of endangered species.

Our work is related to research on cost-effective nutrient reduction, which has attracted increasing attention over the past two decades (Gren *et al.*, 1997). In general, this research combines assessments of the environmental effects of nutrient mitigation measures and of their costs for a cost-effectiveness analysis, applying methods such as linear and nonlinear optimization models (see Balana *et al.*, 2011 for an overview), but also statistical and econometric methods (Fezzi *et al.*, 2010). Some research takes the ranking of the cost-effective ratio of measures or combinations of measures in a certain area as the basis for further analysis (Cools *et al.*, 2011; Fröschl *et al.*, 2008). However, this research often ignores the spatial differentiation of mitigation impacts and costs of measures within a landscape, which is important for cost-effectiveness considerations (Hasler *et al.*, 2019; Konrad *et al.*, 2014). Some studies go one step further and consider the heterogeneity of the measures' mitigation impacts in analyzing the cost-effective spatial allocation of measures in a watershed (Arabi *et al.*, 2006; Geng *et al.*, 2019; Maringanti *et al.*, 2011), with a few developing integrated hydro-economic models (Harou *et al.*, 2009). Regarding hydro-economic modelling, a key challenge is the integration of spatially heterogeneous information from the environmental/hydrological and economic components of the model, as the data needs to be available on the same spatial level (Brouwer and Hofkes, 2008; Hasler *et al.*, 2014). Therefore, only few studies (examples include Hasler *et al.*, 2014 and Konrad *et al.*, 2014) consider spatial heterogeneities of mitigation impacts and of costs of measures in hydro-economic models to identify the cost-effective allocation of measures. While all these studies provide important contributions to our understanding of the cost-effective spatial allocation of mitigation measures, they – often implicitly – adopt the perspective of a social planner who is able to make top-down decisions on the cost-effective allocation of measures.

However, participation in AES is typically voluntary and payments to farmers have to be designed in a way that they provide the appropriate incentives for a cost-effective allocation of mitigation measures to emerge in a landscape. Only few studies consider this aspect when designing measures to reduce N and P pollution from agricultural production. One example is Sidemo-Holm *et al.* (2018), who show for a case study that result-based AES are more cost-effective than action-based AES for mitigating phosphorus pollution from arable land. Another example is Hérivaux *et al.* (2013), who apply hydro-economic modelling to identify cost-effective AES combinations for groundwater pollution mitigation, but without considering spatial heterogeneity of either mitigation impacts or costs of measures. In summary, none of this research has developed an optimization procedure that is able to design a (set of) cost-effective mitigation measure(s) and related payment(s) in the context of an AES taking into account the spatial heterogeneity of costs and mitigation impacts of the measures and the voluntary decisions of farmers to implement measures.

2. Study region

The Baishahe watershed has a size of about 56 km^2 and is part of the Sushui River Basin, which is the first tributary of the Yellow River (Figure 1). Administratively, it belongs to Yuncheng City, which is part of Shanxi Province in China. The area has a semi-arid monsoonal climate, with the mean annual temperature being 12.5~13.5℃ and the mean annual precipitation being 500~600 mm (Huang *et al.*, 2007). The rainfall is mainly between June and October, and the annual average evapotranspiration exceeds the annual average rainfall (Li *et al.*, 2015).

The Baishahe watershed is a mountainous and agricultural area scattered with several villages with small farms and no major commercial firms (Figure 1). The population density in the watershed is a bit less than the county average (approximately 266 residents/km^2) (XCPG, 2020), with residents being almost all farmers who mainly live on crop cultivation. The major crops are winter wheat and corn, with smaller areas being planted with vegetables, medicinal plants, oil crops, and cash trees (local farmers, personal communication, July, 2018; J.J. Jin, C. Guo, Water Conservancy Bureau, Xia County, personal communication, January, 2018).

Agricultural land and forests dominate the area with cropland covering 41%, forests 46% and pasture 13% of the watershed (RESDC, 2015). Irrigated cropland close to a creek or river allows the cultivation of both winter wheat and corn within a year whereas only wheat cultivation is feasible in areas without irrigation. Crop production is the main source of water pollution, with N and P being explicitly named as the dominant pollutants in the government report of the local Environmental Protection Bureau (EPBX, 2012). Creeks and rivers in the watershed flow into the Baishahe Reservoir, which is located about 5 km further downstream (Figure 1). The reservoir supplies drinking water for parts of Xia County and Yuncheng City.

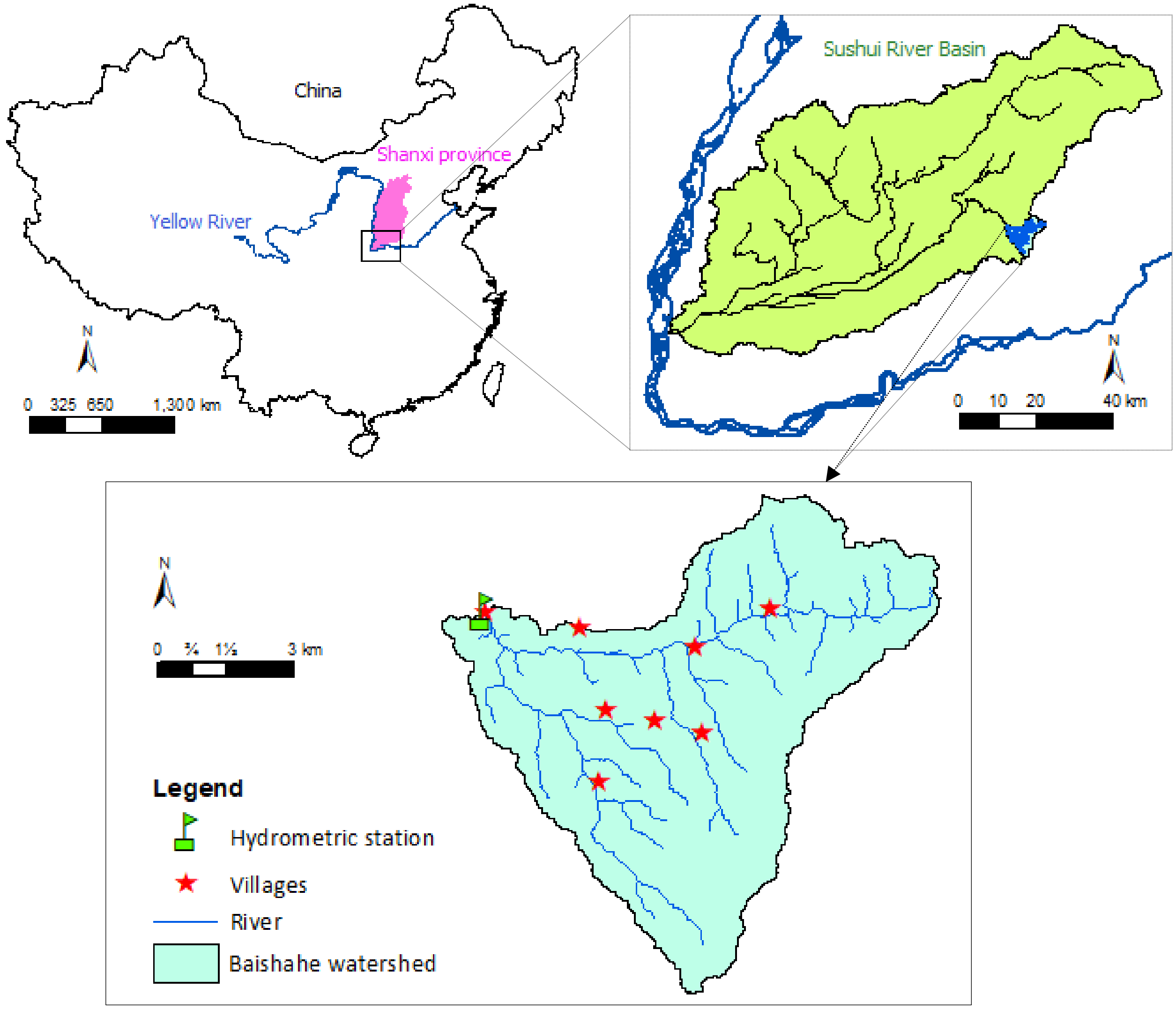


Figure 1: Maps showing location and shape of the Baishahe watershed

3. Integrated hydro-economic modelling procedure

This chapter starts with an illustration of the overall framework and technique routes of the developed methodology (section 3.1), followed by a detailed explanation of the task of each component in the framework demonstrated for the situation in the study region of the Baishahe watershed.

3.1. Overview of the procedure

The developed hydro-economic modelling procedure consists of different components, each of which fulfils specific tasks. Figure 2 shows the components and the connections between them.

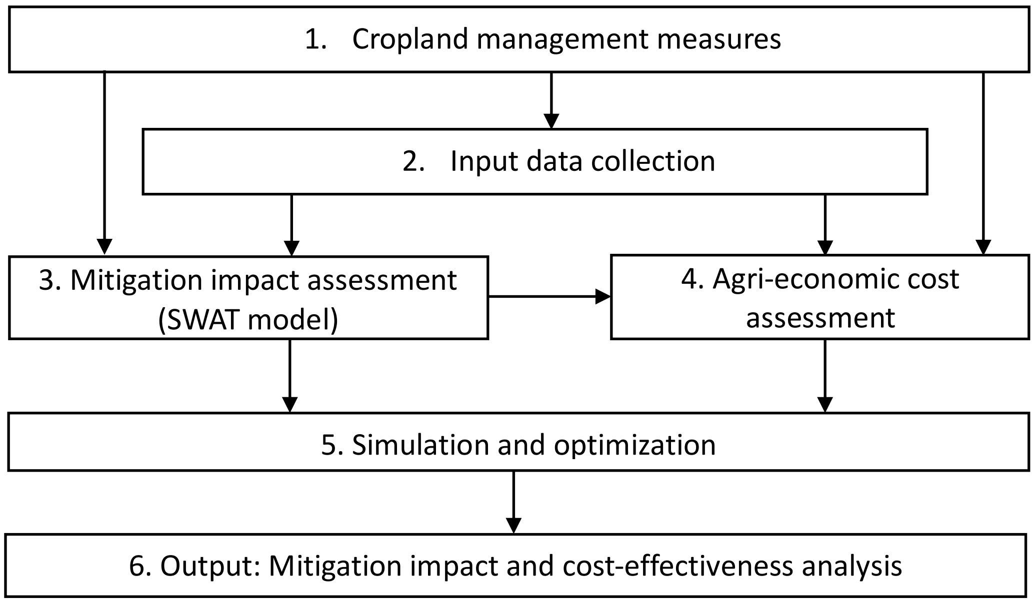


Figure 2: Overview of integrated hydro-economic modelling procedure

In a first step, potential cropland management measures need to be identified, taking into account the water quality targets and the situation in the study region (Figure 2, box 1). Depending on the choice of cropland management measures, the procedure requires spatially differentiated data on land cover, soil types, altitude, climate, land management and agri-economic costs (Figure 2, box 2). This data provides input for the assessment of the impact of the different cropland management measures on the water quality targets (Figure 2, box 3) and of the costs of the measures (Figure 2, box 4).

The impact assessment is done by applying the SWAT model (Arnold *et al.*, 2012) (Figure 2, box 3). The SWAT model divides the watershed into sub-watersheds and hydrologic response units (HRUs), each of which consists of homogeneous land use, soil properties, land management and topographical characteristics (Arabi *et al.*, 2008; Arnold *et al.*, 2012). The SWAT model provides the annual pollution loads of N and P for a business-as-usual (BAU) scenario and for each cropland management measure for each of the HRUs during the contract duration of the AES. By comparing the average of the annual values of the BAU scenario with those of a cropland management measure over the duration of an AES contract, we receive the mitigation impact of this measure. We consider contracts to have a duration of five years, which is common for AES (Drechsler *et al.*, 2017; Hérivaux *et al.*, 2013; Uthes *et al.*, 2010).

Information on cropland management (Figure 2, box 2) as well as on the crop yield changes due to measures and the size and location of the HRUs (Figure 2, box 3) goes into the agri-economic cost assessment (Figure 2, box 4), along with other cost data and information. The agri-economic cost assessment estimates the opportunity costs of each measure in comparison to the BAU scenario for each HRU. As we do not have detailed data on land ownership, and costs are likely to be similar within a HRU, we consider one HRU to be one (hypothetical) farmer.

The spatially differentiated results of the mitigation impacts and the agri-economic costs of each measure provide the basis for the simulation and optimization of AES (Figure 2, box 5). The simulation of AES mimics the farmers' measure selection behavior, based on the information on the costs and payments for each measure in each HRU. The aim of the optimization is to identify an AES consisting of a set of measures and related payments, which induces farmers to select measures in a way that the resulting cropland management pattern of an AES generates the maximum weighted total mitigation impact for a given budget level for AES. With the simulation and optimization, the mitigation impacts of hypothetical AES can be assessed and cost-effective AES for different budget levels can be designed (Figure 2, box 6).

3.2. Cropland management measures

We selected cropland management measures based on the following principles: (I) Measures should be able to reduce pollution loads of N and P. (II) It must be possible to implement them on cropland as implementing measures on other land is not feasible due to the special institution of land use rights in China (Dean and Damm-Luhr, 2010). (III) Measures must be suitable for the Baishahe watershed with its characteristics of mountainous rain-fed cropland. (IV) Measures that already exist without payments were excluded (e.g. terraces and contour farming). (V) It needs to be possible to represent measures in the SWAT, and (VI) to assess costs for their implementation. (VII) Measures recommended by the local government (ABXC, 2015) were selected as long as they did not violate principles I-VI. Based on these considerations, nine measures were identified (Table 1).

Table 1: Potential measures for this study

general approach and type of measures		identified measures	codes
structural measures	vegetative filter strip of pennisetum*	filter strip: 5 meters	M_1
		filter strip: 10 meters	M_2
		filter strip: 15 meters	M_3
nutrient management	chemical fertilizer reduction	chemical fertilizer reduction by 25%	M_4
		chemical fertilizer reduction by 40%	M_5
	manure application	chemical fertilizer reduction by 50%, plus increasing swine manure 1000kg/ha	M_6
		chemical fertilizer reduction by 50%, plus increasing sheep manure 1000kg/ha	M_7
crop planting	cover crop	cover crop: soybean	M_8
		cover crop: corn	M_9

* Pennisetum is the native grass in the Baishahe watershed (Xiao *et al.*, 2010).

3.3. Input data collection

For the Baishahe watershed, we obtained altitude data of digital elevation models (DEM) (30x30 m^2) from the Geospatial Data Cloud (GDC, 2015), soil data (1x1 km^2) from the Harmonized World Soil Database (HWSD, 2012), and land use data (30x30 m^2) from the Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences (RESDC, 2015). Climate data (daily, 1/4°x1/4°)[1] from 2008 until 2016 were taken from the China Meteorological Assimilation Driving Datasets (CARD, 2019). Information on land management (major crops planted in different parts of the watershed, timing of cropping activities from sowing to harvest, type and amount of fertilizer, situation for irrigation and mechanical usage) and most cost data was obtained from members of the local Water Conservancy Bureau through telephone calls and local farmers during a field trip by one of the authors from June to July 2018. During the field trip, altogether 40 farmers were surveyed (5 farmers in each of the 8 villages) with face-to-face

[1] 1/4°x1/4° is the spatial resolution of climate stations (see Figure A1 in the appendix for the allocation of climate stations around the study watershed).

interviews based on semi-structured questionnaires. Interviewed farmers were identified by recommendations from village leaders along with snowball sampling, judgement sampling and convenience sampling (Harrell and Bradley, 2009). Further cost data was gathered through an internet search as well as taken from the literature (details about all cost data provide Tables A4 and A5 in the Appendix) and data on yield, area, and distance between fields and villages came from the SWAT model.

3.4. Mitigation impact assessment

(1) Model selection

We applied the SWAT model for the assessment of the impact of cropland management measures on N and P. SWAT was selected because it satisfies the following requirements for this study. (I) It is designed for agricultural land, adaptable to the size of the study region, and has sub-modules for N and P simulation as one major function. (II) It provides quantified spatially differentiated results regarding the mitigation impacts of different cropland management measures. (III) It enables a simulation of more measures compared to other relevant models (e.g. AnnAGNPS, HSPF) (Xie *et al.*, 2015). (IV) It is applicable to ungauged rural basins with variable environmental conditions (Gassman *et al.*, 2007). (V) It provides information on crop yield changes for each measure in each HRU, which is required for the agri-economic cost assessment. Regarding spatial scales, SWAT divides a watershed into sub-watersheds, which may be further divided into HRUs. Regarding temporal scales, the model can generate daily, monthly and annual simulation outputs at the scales of HRUs, sub-watersheds and the whole watershed. Research (Gassman *et al.*, 2007) suggests that it performs well for long-term continuous simulations at monthly and annual scales.

(2) SWAT setup, calibration and validation

We used the SWAT version ArcSWAT (version 2012). The Baishahe watershed has only two soil types (Calcic Luvisols, Calcaric Cambisols), three dominant land covers (woodland, grassland, upland arable land), and one uniform climate situation. Due to data access limitations, we assumed that the climate data from 2013 to 2016 is able to represent the climate situation for the AES design life (from 2018 to 2022). The model divided the Baishahe watershed into 83 sub-watersheds and 83 HRUs (we defined only one HRU in each sub-watershed), of which 50 are cropland covered[2]. Among these, 16 HRUs are close to the river where manual irrigation is common and typically two crops (winter wheat and corn) are planted within one year (turquoise colored HRUs in Figure 3). In the other 34 HRUs, there is no irrigation and only winter wheat is being planted (yellow ocher colored HRUs in Figure 3).

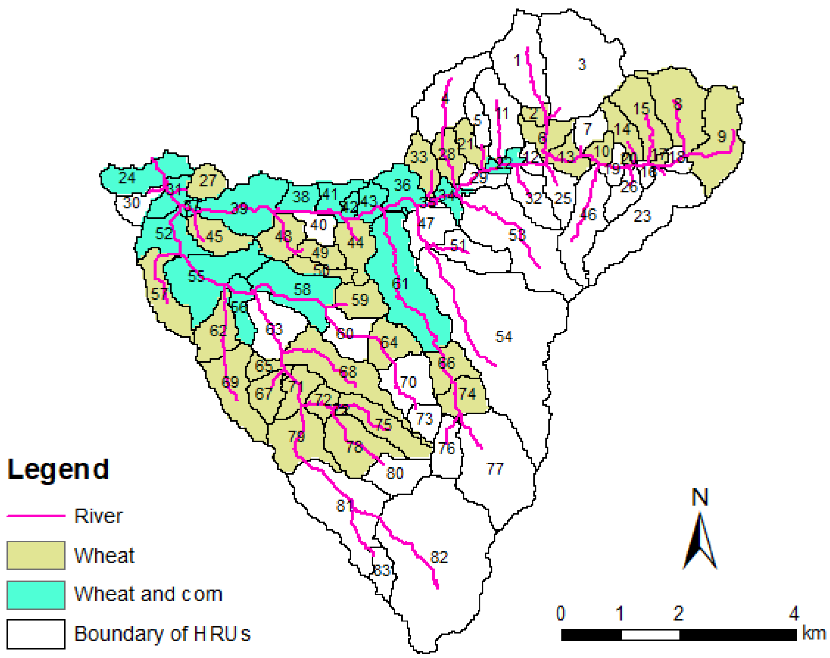


Figure 3: The Baishahe watershed delineated by SWAT model

Due to data limitations, calibration and validation of the SWAT model was carried out only for crop yield of winter wheat, streamflow and sediment load. The calibration for crop yield was done manually using statistical data on average crop yield between 2000 and 2014 from Yuncheng (Liu and Zhao, 2015) (see Table A1 in the appendix for relevant parameters). For

[2] The number of sub-watersheds is controlled by the value of the parameter "critical stream area threshold" in ArcSWAT, the minimum area of water concentration that can be treated as streams in the model, which we set as 25 hectares. The size of 25 ha is a compromise between a sufficient consideration of spatial heterogeneity of the watershed and the resulting number of HRUs, which needs to be reasonably small due to computational time restrictions, in particular for the optimization.

streamflow and sediment, SWAT-CUP (SWAT-Calibration and Uncertainty Procedures), a computer program developed for calibration of SWAT (Abbaspour *et al.*, 2015), was adopted for auto-calibration and validation using monthly data from 2009 to 2012 from the Hydrological Bureau in Xia County (HBXC, 2018) (see Table A2 and Figure A2 in the appendix for parameters and results).

(3) Measures simulation

We applied the validated SWAT model for the Baishahe watershed to simulate the mitigation impacts of the different cropland management measures (Table 1). To represent each measure in SWAT we followed the guideline by Arabi *et al.* (2008) and Waidler *et al.* (2011). In order to take into account the in-stream process of pollutant transport, we simulated the impact of each measure in each HRU for the final outlet of the watershed. With 9 measures and 50 cropland HRUs for the Baishahe watershed, we performed 450 simulations in total.

3.5. Agri-economic cost assessment

(1) Cost categories

The agri-economic cost assessment aims to estimate the costs that occur to farmers if they implement a cropland management measure. Costs to farmers in the context of AES may be generally categorized into production costs, transaction costs and uncertainty costs (Mettepenningen *et al.*, 2009). As we are only interested in demonstrating the applicability of the modelling procedure, we focus on production costs and ignore the other cost types. We divide production costs into establishment costs, maintenance costs, and foregone profits due to the implementation of cropland management measures (Ahlvik *et al.*, 2014; Arabi *et al.*, 2006). Establishment costs and maintenance costs occur only for structural measures, while foregone profits occur for all measures (Table 1).

Establishment costs $c_{em}^{h_i,M_j}$ occur only at the beginning of an AES contract for the construction of structural measures like filter strips. Maintenance costs $c_{mt}^{H_i,M_j}$ occur every year during an AES contract for maintaining the function of structural measures. For filter strips, maintenance costs include the costs of cutting the grass of filter strips and of general maintenance, for example replanting dead vegetation. Foregone profits $c_{fp}^{H_i,M_j}$ refer to the difference of yearly net profits of the BAU scenario and a specific cropland management measure. Eqs. 1-3 describe how the different cost types are calculated for a measure M_j in a HRU H_i (with subscript j indicating a specific measure j=1, …, 9 and subscript i a specific HRU i=1, …,50).

$$c_{em}^{H_i,M_j} = c_v^{H_i,M_j} \cdot a_s^{H_i,M_j} \qquad \text{Eq. 1}$$

$$c_{mt}^{H_i,M_j} = rm \cdot c_{em}^{H_i,M_j} + N \cdot c_c^{H_i,M_j} \cdot a_s^{H_i,M_j} \qquad \text{Eq. 2}$$

$$c_{fp}^{H_i,M_j} = \begin{cases} \left[\left(r_{y,ref}^{H_i} - r_y^{H_i,M_j}\right) - \left(c_{v,ref}^{H_i} - c_v^{H_i,M_j}\right)\right] \cdot a_s^{H_i,M_j}, \ M_j : structural\ measures \\ \left[\left(r_{y,ref}^{H_i} - r_y^{H_i,M_j}\right) - \left(c_{v,ref}^{H_i} - c_v^{H_i,M_j}\right)\right] \cdot A^{H_i}, \ M_j : non-structural\ measures \end{cases} \qquad \text{Eq. 3}$$

The total variable costs needed for a measure implementation are denoted by $c_v^{H_i,M_j}$. They include material input costs (for seeds, fertilizer, herbicide, etc.), mechanical operation costs (for plowing, harrowing, and seeding typically performed by specialized agencies), labor costs (for land cleaning, weeding, etc.), and transport costs (for labor and material) (see Table A3 in the appendix for further explanations for each type of variable cost). Following Arabi *et al.*(2006) and Maringanti *et al.* (2011), the general maintenance cost of structural measures, $rm \cdot c_{em}^{H_i,M_j}$, are calculated as a proportion of $c_{em}^{H_i,M_j}$ with rm being the ratio of maintenance to establishment cost. $N \cdot c_c^{H_i,M_j} \cdot a_s^{H_i,M_j}$ represents the cost for mowing the filter strip, with $c_c^{H_i,M_j}$ being the unit cost per cut and N being the number of cuts per year. Similar to Mewes et al. (2015), we calculate foregone profits $c_{fp}^{H_i,M_j}$ as the difference between yield revenue plus variable costs of the BAU-scenario and yield revenue plus variable costs of measure M_j in HRU H_i. Yield revenue and total variable costs in the BAU scenario are represented by $r_{y,ref}^{H_i}$ and $c_{v,ref}^{H_i}$, whereas $r_y^{H_i,M_j}$and $c_v^{H_i,M_j}$

refer to yield revenue and total variable costs of measure M_j (see Table A3 in the appendix for detailed calculations of them). We assume that non-structural measures are applied on the whole area of a HRU, A^{H_i}, whereas structural measures are applied only on a share of a HRU, $a_s^{H_i,M_j}$.

(2) Average annual costs

In order to calculate and compare the different costs of measures, which occur at different points in time throughout the contract period of an AES we introduce a discount factor (Boardman *et al.*, 2017), and calculate c^{H_i,M_j} which is the average annual cost of measure M_j in HRU H_i

$$c^{H_i,M_j} = c_{em}^{H_i,M_j} \cdot \frac{r \cdot (1+r)^{n-1}}{(1+r)^n - 1} + c_{mt}^{H_i,M_j} + c_{fp}^{H_i,M_j}, \quad \text{Eq. 4}$$

where $\frac{r \cdot (1+r)^{n-1}}{(1+r)^n - 1}$ results from calculating the total discounted costs of a measure over the AES contract period of *n* years (see Figure A5 in the appendix for a detailed explanation), and r is the discount rate.

3.6. Simulation and optimization of AES

(1) Simulation of AES

For the simulation, we consider an AES to consist of a set of measures M_j, and the related payments p^{M_j}, with p^{M_j} referring to the amount of compensation per unit area farmers receive for implementing a specific measure M_j. We assume that the payment for a specific measure M_j is uniform across the study region which is common in AES design (Wätzold *et al.*, 2016). The simulation also contains the option to set a maximum area to which a measure can be applied ($A_{max}^{M_j}$), and a pre-specified budget for the AES as a whole (B_0). In order to mimic farmers' decisions about whether to participate in an AES, and, if so, which measure to select, we assume that farmers are profit-maximizing. Farmers compare the (HRU-specific) net economic benefits NB^{H_i,M_j} from implementing different measures M_j, and will select the measure with the highest

NB^{H_i,M_j}, provided it is positive. Otherwise, the farmer will continue with the BAU scenario. The calculation of NB^{H_i,M_j} for a measure M_j in a HRU H_i is as follows:

$$NB^{H_i,M_j} = \begin{cases} p^{M_j} - \frac{c^{H_i,M_j}}{a_s^{H_i,M_j}}, \ M_j : structural\ measures \\ p^{M_j} - \frac{c^{H_i,M_j}}{A^{H_i}}, \ M_j : non-structural\ measures \end{cases} \quad \text{Eq. 5}$$

Similar to Wätzold *et al.* (2016), the simulation of farmers' participation in an AES is as follows: (I) For each measure M_j, we generate a list with all HRUs ranking from lowest unit area cost ($\frac{c^{H_i,M_j}}{a_s^{H_i,M_j}}$ or $\frac{c^{H_i,M_j}}{A^h}$ in Eq. 5) to highest unit area cost. As p^{M_j} is uniform across all HRUs for a specific measure M_j, the generated list mirrors the ranking of the net economic benefits of farmers (NB^{H_i,M_j}) from highest to lowest. (II) We then compare the NB^{H_i,M_j} of the first HRUs in all lists, and attach the measure to the HRU for which the NB^{H_i,M_j} is highest. This selection is based on the assumption that farmers behave in a profit-maximizing manner. (III) The selected HRU is then taken from the list, with the former second HRU becoming the first HRU in this list. (IV) Operations II-III are repeated until either all HRUs are attached to a measure, or the NB^{H_i,M_j} of the remaining HRUs in the lists are negative, or the defined maximum area $A_{max}^{M_j}$ for each measure is covered, or the AES budget B_0 is used up (see Figure A4 in the appendix for detailed operations with a hypothetical example). As the sizes of the HRUs differ, a HRU with a low unit area cost might have a high total cost due to its area size. If the selection of a large HRU exceeds the AES budget, this HRU will not be considered anymore in the simulation process.

The simulation of an AES results in a specific land use pattern, i.e. the information for each HRU on whether the BAU scenario or a specific measure is implemented. The total mitigation impact E_{AES} of this land use pattern is

$$E_{AES} = \sum_{j=1}^{9} \sum_{i=1}^{50} k^{H_i,M_j} \cdot E^{H_i,M_j} \quad \text{Eq. 6}$$

where k^{H_i,M_j} is 1 if a measure M_j is applied in the corresponding HRU H_i during the simulation process, otherwise k^{H_i,M_j} is zero, and the reduced amount of pollution load for a measure M_j in HRU H_i compared to BAU is indicated as E^{H_i,M_j}. Finally, the total amount of payments SP_{AES} that farmers receive is calculated as

$$SP_{AES} = \sum_{j=1}^{9} \sum_{i=1}^{50} k^{H_i,M_j} \cdot p^{M_j} \cdot area^{H_i,M_j},$$

$$with, area^{H_i,M_j} = \begin{cases} a_s^{H_i,M_j}, \ M_j : structural\ measures \\ A^{H_i}, \ M_j : non-structural\ measures \end{cases} \qquad \text{Eq. 7}$$

(2) Optimization of AES

The aim of the optimization is to obtain an AES (i.e. a (set of) measure(s) and related payment(s)), which maximizes the mitigation impact E_{AES} for a given budget B_0.

$$E_{AES} = \sum_{i=1}^{50} k^{H_i} \cdot E^{H_i,M_j} \quad \rightarrow \text{max, subject to} \quad SP_{AES} \leq B_0. \qquad \text{Eq. 8}$$

The reduction of N and P might be of different importance to the regulator. In order to take this into account, we introduce the weight factors w_N and w_P, which represent the relative importance of the mitigation impacts of N and P.

$$E^{H_i,M_j} = \frac{E_N^{H_i,M_j}}{L_P} \cdot w_N + \frac{E_P^{H_i,M_j}}{L_N} \cdot w_P. \qquad \text{Eq. 9}$$

The mitigation impacts of measure M_j in HRU H_i for N and P are indicated by $E_N^{H_i,M_j}$ and $E_P^{H_i,M_j}$ respectively in terms of mitigated amount of pollution load. The original pollution load in the whole watershed under BAU for N and P are indicated by L_P and L_N respectively[3].

[3] Considering the limitation of information regarding the meaning of reduced amount of pollution load in unit weight for N and P respectively in the study region, the reduction percentage of pollutant load compared with BAU is

Similar to Wätzold *et al.* (2016) and Sturm *et al.* (2018), we apply for the optimization the heuristic optimization method of simulated annealing, which is capable of getting an approximate global optimum. We refer the interested reader to Kirkpatrick *et al.* (1983) for an explanation of how simulated annealing works and to Wätzold *et al.* (2016) for details of how it is applied to identify cost-effective AES.

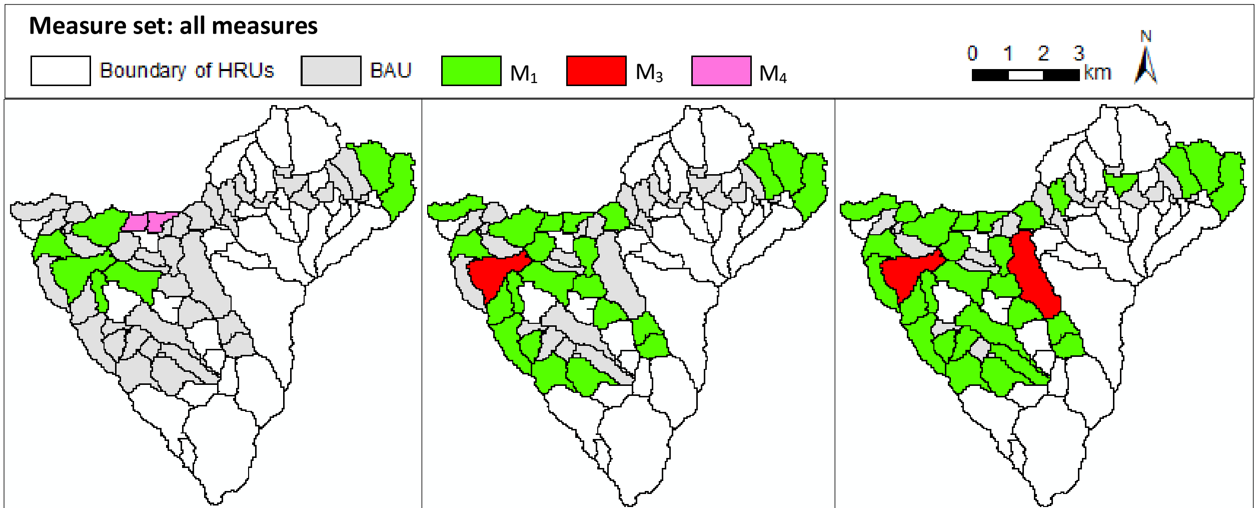
4. Results and analysis

For the optimization analysis, we have to make choices with respect to (I) the weights of the mitigation targets of N and P, (II) the selection of measures, and (III) the budget levels. (I) The weights of the mitigation targets should be set from an economic perspective such that they reflect the monetary benefits of the unit reduction of the different pollutants (Arabi *et al.*, 2006). Alternatively, they may be based on the (local) decision makers' preferences (Chen *et al.*, 2015). As we have neither relevant information on monetary benefits of N and P mitigation nor on decision makers' preferences for the case study area, we attach equal weights (50%) to the pollutants of N and P. (II) We consider two sets of measures. One set includes all nine identified measures (Table 1), while the other set excludes the three structural measures of filter strips. The reason for excluding the structural measures is that they change cropland into permanent grassland, which might be unpopular with farmers (they lose cropland in the long-term) and governments (due to food security considerations). (III) It has been shown that the budget level may have an influence on the cost-effective design of AES (e.g. Wätzold and Drechsler, 2014). Therefore, we investigate three budget levels (100,000, 300,000 and 500,000 RMB) for the two sets of measures.

Figure 4 shows the results with all nine measures for the three budget levels. For all budget levels, the predominantly selected measure is M_1 (filter strip with a width of 5 meters, cf. Table 1). This can be explained by a combination of the low costs of M_1 and, in particular, a high mitigation impact. Of the other selected measures, M_3 (filter strip with a width of 15 meters) has a higher

adopted.

mitigation impact than M_1 but is substantially more costly in the majority of HRUs, and M_4 (chemical fertilizer reduction by 25%) has only a limited mitigation impact but is a low cost measure.



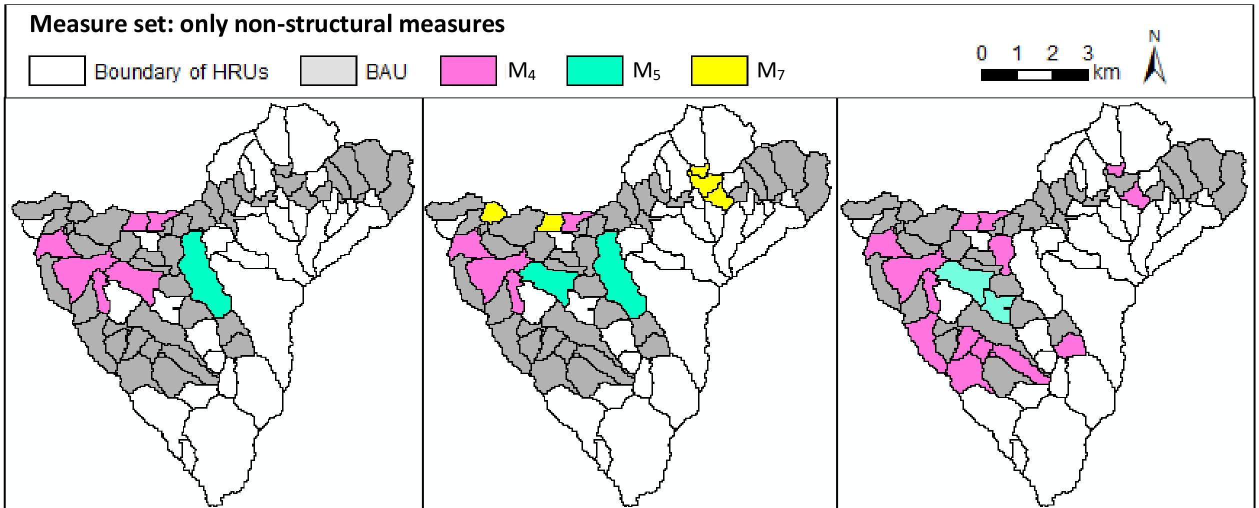
$B_0 = 100{,}000$ (RMB) $SP_{AES} = 90{,}177$(RMB) $p^{M_1} = 134$ (RMB) $p^{M_4} = 88$ (RMB)			$B_0 = 300{,}000$ (RMB) $SP_{AES} = 293{,}153$ (RMB) $p^{M_1} = 186$ (RMB) $p^{M_3} = 268$ (RMB)			$B_0 = 500{,}000$ (RMB) $SP_{AES} = 489{,}822$ (RMB) $p^{M_1} = 220$ (RMB) $p^{M_3} = 312$ (RMB)		
	mitigated amount (kg)	mitigated percentage		mitigated amount (kg)	mitigated percentage		mitigated amount (kg)	mitigated percentage
N	7,240	6.9%	N	22,378	21.3%	N	31,065	29.6%
P	1,850	7.8%	P	7,000	29.6%	P	9,783	41.4%

B_0 is the available budget, SP_{AES} the total amount of AES payments, and p^{M_j} the compensation payment of measure M_j. Conversion rate (1st May, 2020) 1 Euro = 7.7 RMB. The original pollution loads in the whole watershed under BAU are 104,953 kg for N and 23,630 kg for P.

Figure 4: AES design results with all measures under three budget levels

Figure 5 provides the results with the six non-structural measures for the three budget levels. The dominant measure is M_4, especially for the budget levels of 100,000 RMB and 500,000 RMB. This is mainly due to the low costs of M_4. They can be explained by a general overuse of chemical fertilizer in China, which implies that a moderate fertilizer reduction leads to a small decrease in yield but some decrease in fertilization costs. It is reasonable to assume that there is also an overuse of fertilizer in the study region as recommendations for the optimal chemical fertilizer application in northern China (Zhang *et al.*, 2018) are lower than the amount applied in the

Baishahe watershed under BAU. As to the other selected measures, M_5 (chemical fertilizer reduction by 40%) has a slightly better mitigation impact than M_4 in the majority of HRUs for N and in some HRUs for P, but is substantially more costly than M_4 in all HRUs. M_7 (chemical fertilizer reduction by 50% plus additional sheep manure application of 1000kg/ha) has a slightly better mitigation impact for N than M_4 in some HRUs but is more costly than M_5 in all HRUs.



B_0 = 100,000 (RMB)
B_{AES} = 97,335 (RMB)
p^{M_4} = 78 (RMB)
p^{M_5} = 386 (RMB)

	mitigated amount (kg)	mitigated percentage
N	4,950	4.7%
P	238	1.0%

B_0 = 300,000 (RMB)
B_{AES} = 298,783 (RMB)
p^{M_4} = 78 (RMB)
p^{M_5} = 421 (RMB)
p^{M_7} = 1,164 (RMB)

	mitigated amount (kg)	mitigated percentage
N	5,580	5.3%
P	270	1.1%

B_0 = 500,000 (RMB)
B_{AES} = 499,644 (RMB)
p^{M_4} = 481 (RMB)
p^{M_5} = 551 (RMB)

	mitigated amount (kg)	mitigated percentage
N	6,423	6.1%
P	483	2.0%

B_0 is the available budget, SP_{AES} the total amount of AES payments, and p^{M_j} the compensation payment of measure M_j. Conversion rate (1st May, 2020) 1 Euro = 7.7 RMB. The original pollution loads in the whole watershed under BAU are 104,953 kg for N and 23,630 kg for P.

Figure 5: AES design results with only non-structural measures under three budget levels

Comparing Figure 4 and Figure 5, we find that the mitigation impact for N and P for identical budget levels is much stronger if not only non-structural but also structural measures are considered. This finding is in line with results from previous studies which have shown the high mitigation impacts of vegetative filter strips (Borin et al., 2005), and also their higher level of cost-effectiveness compared to other measures (Lescot et al., 2013).

A common feature of the results of both sets of measures is that there is one dominant measure across the different budget levels (M_1 in Figure 4 and M_4 in Figure 5). This is not surprising as our study region is small and homogeneous with only one uniform climate and two soil types. If conditions were more heterogeneous, this may also result in a more heterogeneous set of measures. However, research has shown that even in a more heterogeneous environment, filter strips and fertilizer reduction are cost-effective (Balana *et al.*, 2015).

Regarding the relationship between budget size and resulting pollution mitigation, one would expect that budget increases also lead to more mitigation, but with mitigation increases decreasing with rising budget levels (positive but decreasing marginal pollution reduction benefits). This is also what we observe in Figures 4 and 5 except for a budget rise from 100,000 RMB to 300,000 RMB for all measures (Figure 4), and a budget rise from 300,000 RMB to 500,000 RMB for only non-structural measures (Figure 5).

Two reasons might explain the increasing marginal pollution reduction benefits. The first relates to the different sizes of the HRUs. During the process of AES simulation, the HRUs with the lowest unit area costs are selected first. However, a HRU with low unit area costs may have a very large area, resulting in a high total payment for this HRU. This triggers a possible situation in which, especially for low budget sizes, such a large HRU cannot be selected. The second reason is that profit-maximizing farmers (and thus the simulation procedure) select a specific measure according to costs – independent of its mitigation impact. This implies that for a specific measure a HRU with lower costs but also a lower benefit/cost ratio is selected before a more costly HRU, which, however, may have a higher benefit/cost ratio.

5. Discussion and conclusion

We develop a novel integrated hydro-economic modelling procedure which is able to design cost-effective AES to incentivize cropland management measures targeted at the mitigation of water pollution from N and P. The modelling procedure considers spatial heterogeneity not only with respect to the pollution mitigation impacts of the implemented measures but also regarding their costs. The modelling procedure is generic and can be applied to other agricultural watersheds provided adequate data is available. Compared to other hydro-economic models in the field of cost-effective mitigation of water pollutants from agricultural sources (e.g. Geng *et al.*, 2019; Hasler *et al.*, 2014; Konrad *et al.*, 2014), our procedure explicitly considers the decisions of farmers being confronted with different cropland management measures and respective payments in the context of an AES.

We apply the modelling procedure to the Baishahe watershed in China for demonstration purposes. Given a lack of data reliability for the watershed, which is a problem in many areas in the world, the developed recommendations for an AES should be taken with caution. However, our main results that – depending on the policy context – either the measure of "pennisetum filter strip of 5 meters" or the measure of "chemical fertilization reduction by 25%" are cost-effective is in line with research in other study areas (Balana *et al.*, 2015).

We made some simplifying assumptions, which deserve mentioning. We assumed that farmers are well-informed about the costs of implementing the different cropland management measures. In reality, not all farmers would have this information, as they may not be familiar with some measures that are uncommon in the study area (in particular, filter strips with different widths). We further assumed that profit-maximization is the only criterion determining how farmers select measures. However, we know from research that other factors may also be important (Bartkowski and Bartke, 2018) like the wealth of the farmers, income sources other than farming, and the emotional connection of farmers to different cropland patches, for example due to the locations of family graves in China. Furthermore, transaction costs also play an important role for farmers' participation in AES (McCann, 2013; Mettepenningen *et al.*, 2009; Schöttker and Wätzold, 2018). We leave it to further research to investigate to what extent more realistic assumptions about the participation decision of farmers in AES have an impact on the design of cost-effective AES.

Regarding data collection, we acknowledge that a sample size of 40 farmers is insufficient to generate representative cost data. However, given that our primary aim is not providing a policy recommendation for the Baishahe watershed but method development, we consider the sample size sufficient for this purpose. Data constraints were also present when setting up the SWAT model. For example, the resolution of the obtained soil data (1x1 km^2) is much coarser than that of the available land use data (30x30 m^2), which may not adequately reflect the level of soil heterogeneity in the watershed. For the model calibration and validation, stream flow and sediment indices were available for four years only. We would have preferred to calibrate and validate the indices of N and P with data from much longer periods of 10 or 20 years.

A further important simplification is that we assumed the HRUs derived from the SWAT model to be individual farms. We did this because no information about the spatial location of individual farms and the corresponding fields was available. The justification for our approach is that the soil quality, the land use and the climate are similar in the area represented by a HRU.

Generally, we see several avenues for further research based on the developed modelling procedure. First, we applied our modelling procedure to the case study area for demonstration purposes. In order to develop more policy-relevant recommendations for cost-effective AES, the above-mentioned data limitations should be overcome, and the procedure should be applied to an area with an existing AES in order to compare its impacts with the results from the modelling procedure and to investigate the extent of possible cost-effectiveness improvements. However, as AES are usually designed for large areas, the challenge of increasing computational time needs to be addressed for the optimization as larger areas will have substantially more spatial units.

A further step towards policy relevance would be to turn the developed modelling procedure into a user-friendly decision support software to support environmental agencies in designing cost-effective AES for mitigation of water pollution. This would enable agencies to simulate potential AES of their choice and consider suggestions for optimized cost-effective AES. Based on the same idea, the ecological-economic modelling procedure to design cost-effective AES for conserving grassland species (Wätzold *et al.*, 2016) has been used as the basis to develop the decision support software DSS-Ecopay (Sturm *et al.*, 2018). Alternatively, cost, simulation and optimization components could be integrated into existing tools such as the SWAT model to turn them from purely hydrological tools into tools that adopt a perspective that integrates hydrological and economic concerns.

Finally, the presented research focused on the pollutants N and P. However, the procedure can easily be applied to other pollutants such as sediments. Further research may address such an extension. This would also make it possible to investigate which measures generate trade-offs, and which measures create synergies between the mitigation of different pollutants through AES. Moreover, cost-effectiveness losses could be investigated if different AES are developed to address different mitigation goals separately (as is often the case in the real world) rather than if a single-optimized AES is designed that considers different mitigation goals jointly (Drechsler and Wätzold, 2017).

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Appendix

Table A1: Manual calibration of crop parameters for winter wheat

No.	parameter	definition	original value	calibrated value
1	BLAI	maximum potential leaf area index	4	8
2	BIO_E	radiation-use efficiency or biomass-energy ratio	30	40
3	HVSTI	harvest index for optimal growing conditions	0.4	0.68
4	T_OPT	optimal temperature for plant growth (ºC)	18	15

Table A2: Parameters for calibration of streamflow and sediment load

No.	parameter	absolute Value range	calibrated value range	original value	calibrated value
1	USLE_K(1).sol	0~0.65	0.06~0.13	0.1 (B); 0.17 (C)	0.0896
2	USLE_K(2).sol	0~0.65	0.06~0.13	0.12 (B); 0.18 (C)	0.0815
3	SOL_AWC(1).sol	0~1	0.03~0.07	0.05 (B); 0.14 (C)	0.0435
4	SOL_AWC(2).sol	0~1	0.03~0.07	0.06 (B); 0.14 (C)	0.0631
5	SOL_K(1).sol	0~2000	5~8	53 (B); 9.2 (C)	6.3455
6	SOL_K(2).sol	0~2000	1~7	26.05 (B); 6.75 (C)	1.999
7	SOL_BD(1).sol_B	0.9~2.5	1.5~2.2	1.59	1.7167
8	SOL_BD(1).sol_C	0.9~2.5	1.8~2.5	1.52	2.5538
9	USLE_P.mgt_AGRL	0~1	0.75~0.85	1	0.8012
10	CN2.mgt_FRST	35~98	64~75	70	73.1795
11	CN2.mgt_PAST	35~98	80~93	79	86.2595
12	CN2.mgt_AGRL	35~98	66~83	83	78.1295
13	SPCON.bsn	0.0001~0.01	0.0001~0.003	0.0001	0.0004
14	ALPHA_BF.gw	0~1	0.02~0.05	0.048	0.0457
15	GWQMN.gw	0~5000	0~0	1000	0
16	REVAPMN.gw	0~1000	1000~1000	750	1000
17	SLSUBBSN.hru	10~150	10~14	9.146341	13.85
18	OV_N.hru_FRST	0.01~30	1~7	0.1	5.611
19	OV_N.hru_PAST	0.01~30	1~7	0.15	4.309
20	OV_N.hru_AGRL	0.01~30	1~7	0.14	6.601
21	CH_K2.rte	-0.01~500	-0.01~100	0	29.643
22	CH_N2.rte	-0.01~0.3	-0.01~0.007	0.014	0.0033

Table A3: Calculation of crop yield revenue and variable costs of measures

<table>
<tr><th colspan="2">categories</th><th>activities/items involved</th><th>formulas for changed revenue and costs comparing BAU-scenario and a measure</th></tr>
<tr><td>revenue</td><td>yield benefits</td><td>· grain selling</td><td>$\sum_{i_1}^{n_1}(y_{ref,i_1} - y_{m,i_1}) \cdot p_{y,i_1}$</td></tr>
<tr><td rowspan="5">variable costs</td><td>material input costs</td><td>· seeds
· fertilizers
· herbicide
· pesticide/fungicide</td><td>$\sum_{i_2}^{n_2}(q_{ref,i_2} - q_{m,i_2}) \cdot p_{m,i_2}$</td></tr>
<tr><td>mechanical operation costs</td><td>· plowing
· harrowing
· seeding</td><td>$\sum_{i_3}^{n_3}(o_{ref,i_3} - o_{m,i_3})$</td></tr>
<tr><td>labor costs</td><td>· land cleaning
· top-dressing
· weeding
· trimming
· pest/disease controlling</td><td>$\sum_{i_4}^{n_4}(l_{ref,i_4} - l_{m,i_4}) \cdot p_{l,i_4}$</td></tr>
<tr><td>transport costs</td><td>· labor transport
· fertilizer and grain transport</td><td>$\frac{2D\cdot n_t\cdot s_w}{t_{wd}} \cdot \sum_{i_4}^{n_4}(l_{ref,i_4} - l_{m,i_4}) \cdot p_{l,i_4} + \frac{\sum_{i_1}^{n_1}(y_{ref,i_1} - y_{m,i_1}) + \sum_{i_2}^{n_2}(q_{ref,i_2} - q_{m,i_2})}{w_t} \cdot c_t$</td></tr>
<tr></tr>
<tr><td colspan="4">$\left(r_{y,ref}^{H_i} - r_{y}^{H_i,M_j}\right) = \sum_{i_1}^{n_1}(y_{ref,i_1} - y_{m,i_1}) \cdot p_{y,i_1}$
$c_{v,ref}^{H_i} = \sum_{i_2}^{n_2} q_{ref,i_2} \cdot p_{m,i_2} + \sum_{i_3}^{n_3} o_{ref,i_3} + \sum_{i_4}^{n_4} l_{ref,i_4} \cdot p_{l,i_4} + \frac{2D\cdot n_t\cdot s_w}{t_{wd}} \cdot \sum_{i_4}^{n_4} l_{ref,i_4} \cdot p_{l,i_4} + \frac{\sum_{i_1}^{n_1} y_{ref,i_1} + \sum_{i_2}^{n_2} q_{ref,i_2}}{w_t} \cdot c_t$
$c_{v}^{H_i,M_j} = \sum_{i_2}^{n_2} q_{m,i_2} \cdot p_{m,i_2} + \sum_{i_3}^{n_3} o_{m,i_3} + \sum_{i_4}^{n_4} l_{m,i_4} \cdot p_{l,i_4} + \frac{2D\cdot n_t\cdot s_w}{t_{wd}} \cdot \sum_{i_4}^{n_4} l_{m,i_4} \cdot p_{l,i_4} + \frac{\sum_{i_1}^{n_1} y_{m,i_1} + \sum_{i_2}^{n_2} q_{m,i_2}}{w_t} \cdot c_t$</td></tr>
<tr><td colspan="4">In these formulas, y_{ref} , q_{ref} , o_{ref} and l_{ref} are the quantity of yield, input material, mechanical operation fees and labor time respectively under BAU-scenario in a HRU; y_m, q_m, o_m and l_m are the quantity of them respectively for applying a measure in the corresponding HRU. p_y, p_m and p_l are the market price of grain, input material and labor price respectively. i_1, i_2, i_3, i_4 and n_1, n_2, n_3, n_4 refer to the different activities/items (like, i_1 refers to different kinds of crops) and the total numbers of these activities/items (like, n_1 refers to two if there are two kinds of crops planted in a HRU) under each category respectively.
Transport costs include costs for labor transport and costs for material transport. Labor transport costs are heterogeneous based on the different distances from different HRUs to the corresponding villages. Labor transport costs are estimated according to the transport time of famers between HRUs and villages, as represented by $\frac{2D\cdot n_t\cdot s_w}{t_{wd}} \cdot \sum_{i_4}^{n_4}(l_{ref,i_4} - l_{m,i_4}) \cdot p_{l,i_4}$, where D is the distance between a HRU and its corresponding village, n_t is the number of trips of farmers in a full time manual workday, s_w is the speed of walking of farmers, t_{wd} is the number of hours farmers work per day. Material transport costs are only considered for the material of fertilizer and grain (Iton, 2012), as the weight of these materials is much higher than of other materials. Material transport costs are represented by $\frac{\sum_{i_1}^{n_1}(y_{ref,i_1} - y_{m,i_1}) + \sum_{i_2}^{n_2}(q_{ref,i_2} - q_{m,i_2})}{w_t} \cdot c_t$, where w_t indicates the carrying capacity of applied</td></tr>
</table>

transportation facility and c_t is the fee per time material delivery by the transportation facility in each village. $\left(r_{y,ref}^{H_i} - r_y^{H_i,M_j}\right)$ refers to the changed crop yield revenue. $c_{v,ref}^{H_i}$ and $c_v^{H_i,M_j}$ represent the total variable cost in a HRU under BAU-scenario and a measure implementation respectively.
Note: In the Baishahe watershed the mechanical operation costs refer to the trusteeship fees between agricultural machine operators and farmers. Cropland is taken care by the needed specialized machine operators with their machines, and farmers pay the mechanical operation costs (as the trusteeship fee) according to the activity type and cropland area worked by the machine operator.

Table A4: Cost data without heterogeneity

	crop types		
	wheat	corn	soybean
grain price (RMB/kg)	2.347	1.733	4.4*
seed cost (RMB/ha)	681.875	735.91	675
herbicide cost per weeding (RMB/ha)	262.279	278.036	262.279
number of times of weeding under BAU	1.015	1.129	1.015
number of times of weeding under no-till**	3	3	3
pesticide/fungicide cost per pest/disease control (RMB/ha)	169.934	203.75	169.934
number of times of pest/disease control under BAU	0.275	0.303	0.275
labor time for per weeding or per pest/disease control (day)	0.277	0.277	0.277
labor time for top-dressing (day)	0.33	0.816	----
cost for whole harvest (RMB)	1452.857	1906.25	1452.857

fertilizer price (RMB/kg)		mechanical operation cost (RMB/ha)			manual labor time (day)	
nitrophosphate	urea	plowing + harrowing	seeding under BAU	seeding with No-till planter	spreading fresh manure	land cleaning
2.825	2.133	734.375	520.588	1200	0.35	13.667

Irrigation	pennisetum (filter strip)		material transport	labor transport	
total labor time for each crop (day)	cost per cutting (RMB/ha)	seed cost*** (RMB/ha)	cost per delivery (RMB)	walking speed (min/km)	number of trips per full manual work day
1.542	2139.845	7200	30	14.233	2.565

In Eq. 2, for filter strip the ratio rm is evaluated as 1% based on Arabi *et al.* (2006) and Maringanti *et al.* (2011), and the number of cuts for mowing the vegetative filter strip per year N is taken as two times according to Xiao *et al.* (2010).

In Eq. 4, the discount rate r is calculated as 3.2%, based on the average value of the real interest rates in the last five year of AES design from 2013 to 2017 in China (World Bank, 2018).

Note: Data in this table are from the questionnaire survey (except for data with *, ** and ***), where the figures are average results from all respondents with five valid samples obtained in each of the eight villages in the Baishahe watershed (Figure 1).

*As soybean is rarely planted in the watershed, this data results from the combination of answers of three farmers and a survey in the local farm producer fair.

**This number is a combination of farmer's responses to the questionnaire and experts' recommendation from the government official website (http://www.mldw.gov.cn/content/detail/55ee7b15672a1094189f378e.html).

***Data for the seeding rate and the price of pennisetum was obtained from Chinese online store information.

Table A5: Cost data with heterogeneity among villages

<table>
<tr><th colspan="2"></th><th colspan="3">data from SWAT</th><th colspan="3">data from questionnaire*</th></tr>
<tr><th rowspan="2">villages</th><th rowspan="2">sub-basins belonged (code in SWAT)</th><th rowspan="2">area (ha)</th><th rowspan="2">length of river way (km)</th><th rowspan="2">distance (km)</th><th colspan="2">carrying capability of transportation facility (kg)</th><th rowspan="2">market labor price (RMB/day)</th></tr>
<tr><th>fertilizer/grain</th><th>manure</th></tr>
<tr><td rowspan="5">Damiao (大庙)</td><td>24</td><td>66.709</td><td>1.226</td><td>0.314</td><td>565</td><td>1062.5</td><td>55</td></tr>
<tr><td>27</td><td>30.608</td><td>0.964</td><td>0.938</td><td>565</td><td>1062.5</td><td>55</td></tr>
<tr><td>31</td><td>32.491</td><td>1.087</td><td>0.689</td><td>565</td><td>1062.5</td><td>55</td></tr>
<tr><td>37</td><td>6.043</td><td>0.417</td><td>0.988</td><td>565</td><td>1062.5</td><td>55</td></tr>
<tr><td>52</td><td>61.686</td><td>1.550</td><td>1.311</td><td>565</td><td>1062.5</td><td>55</td></tr>
<tr><td rowspan="6">Shentouling (神头岭)</td><td>38</td><td>27.939</td><td>1.124</td><td>0.462</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td>39</td><td>99.907</td><td>2.004</td><td>0.699</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td>41</td><td>29.823</td><td>1.185</td><td>1.004</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td>42</td><td>13.185</td><td>0.954</td><td>1.248</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td>45</td><td>47.556</td><td>1.628</td><td>1.432</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td>48</td><td>47.089</td><td>1.072</td><td>0.966</td><td>950</td><td>1200</td><td>55</td></tr>
<tr><td rowspan="5">Jiandihe (涧底河)</td><td>28</td><td>37.514</td><td>1.191</td><td>0.894</td><td>700</td><td>806.25</td><td>60</td></tr>
<tr><td>33</td><td>40.261</td><td>1.475</td><td>0.680</td><td>700</td><td>806.25</td><td>60</td></tr>
<tr><td>34</td><td>21.661</td><td>1.000</td><td>0.392</td><td>700</td><td>806.25</td><td>60</td></tr>
<tr><td>36</td><td>47.795</td><td>1.244</td><td>0.558</td><td>700</td><td>806.25</td><td>60</td></tr>
<tr><td>43</td><td>29.901</td><td>1.267</td><td>0.975</td><td>700</td><td>806.25</td><td>60</td></tr>
<tr><td rowspan="12">Guojiahe (郭家河)</td><td>2</td><td>12.792</td><td>0.636</td><td>0.737</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>6</td><td>37.436</td><td>1.199</td><td>0.513</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>8</td><td>105.557</td><td>2.039</td><td>2.764</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>9</td><td>111.443</td><td>2.266</td><td>3.311</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>10</td><td>20.562</td><td>0.941</td><td>1.290</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>13</td><td>31.549</td><td>1.126</td><td>0.729</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>14</td><td>37.043</td><td>1.454</td><td>1.725</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>15</td><td>74.008</td><td>1.870</td><td>2.124</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>17</td><td>5.180</td><td>0.495</td><td>2.300</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>20</td><td>4.160</td><td>0.309</td><td>1.752</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>21</td><td>27.233</td><td>1.108</td><td>0.965</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td>22</td><td>16.952</td><td>0.849</td><td>0.373</td><td>500</td><td>600</td><td>60</td></tr>
<tr><td rowspan="2">Peipeiling (裴裴岭)</td><td>66</td><td>47.010</td><td>1.132</td><td>0.874</td><td>470</td><td>480</td><td>55</td></tr>
<tr><td>74</td><td>45.205</td><td>1.202</td><td>1.447</td><td>470</td><td>480</td><td>55</td></tr>
<tr><td rowspan="2">Houpo</td><td>44</td><td>51.484</td><td>1.379</td><td>0.985</td><td>550</td><td>580</td><td>60</td></tr>
<tr><td>59</td><td>47.246</td><td>1.226</td><td>0.265</td><td>550</td><td>580</td><td>60</td></tr>
</table>

(后坡)	61	176.504	3.193	0.587	550	580	60
	64	53.210	1.388	0.771	550	580	60
Jingcao (井曹)	49	26.998	1.098	0.591	570	587.5	60
	50	25.506	1.432	0.337	570	587.5	60
	55	120.233	1.957	1.780	570	587.5	60
	56	36.494	1.266	1.266	570	587.5	60
	57	68.200	2.282	2.529	570	587.5	60
	58	98.965	2.014	0.272	570	587.5	60
Shaling (沙岭)	62	57.370	1.670	1.714	600	750	70
	65	21.896	1.052	0.718	600	750	70
	67	39.319	1.121	0.699	600	750	70
	68	117.722	3.643	0.652	600	750	70
	69	88.527	2.020	1.183	600	750	70
	71	40.339	1.207	0.223	600	750	70
	72	26.919	0.945	0.504	600	750	70
	75	67.337	2.184	1.563	600	750	70
	78	83.818	1.899	1.410	600	750	70
	79	83.269	1.926	1.057	600	750	70
Note: *The data are the averaged results from respondents in each village in the questionnaire.							

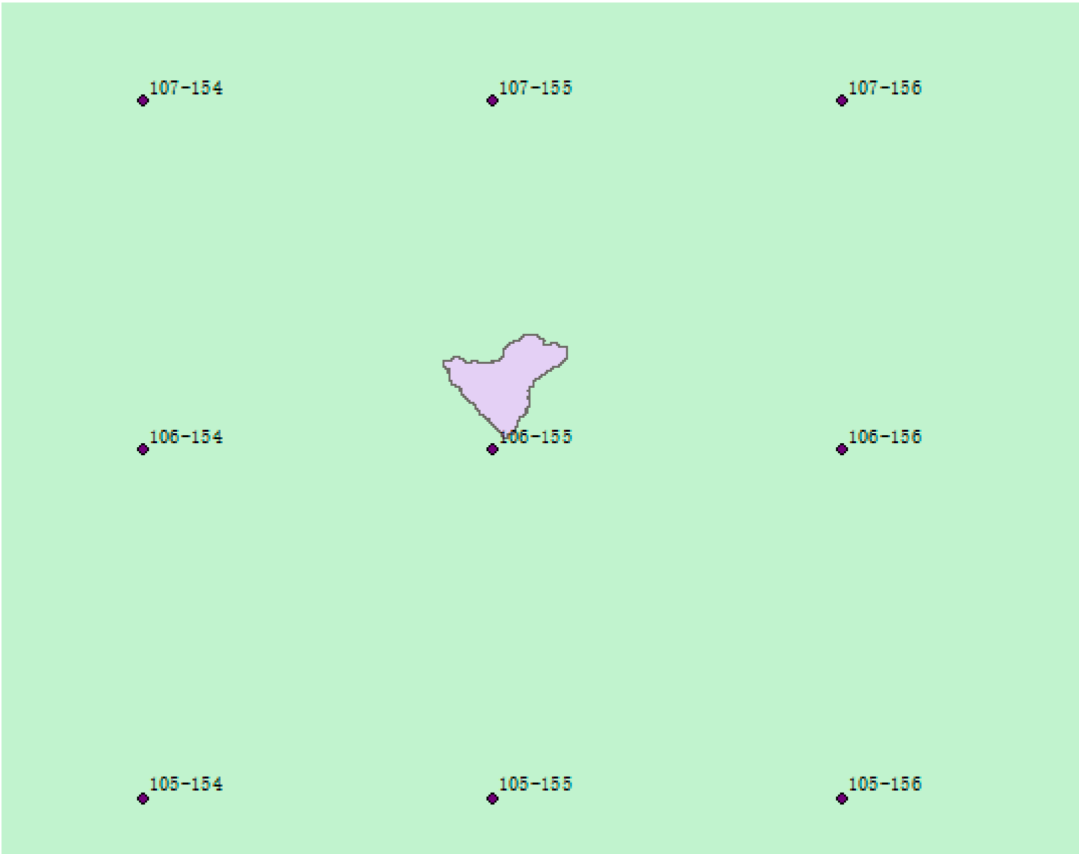


Figure A1: Location of CMADS climate stations and study watershed

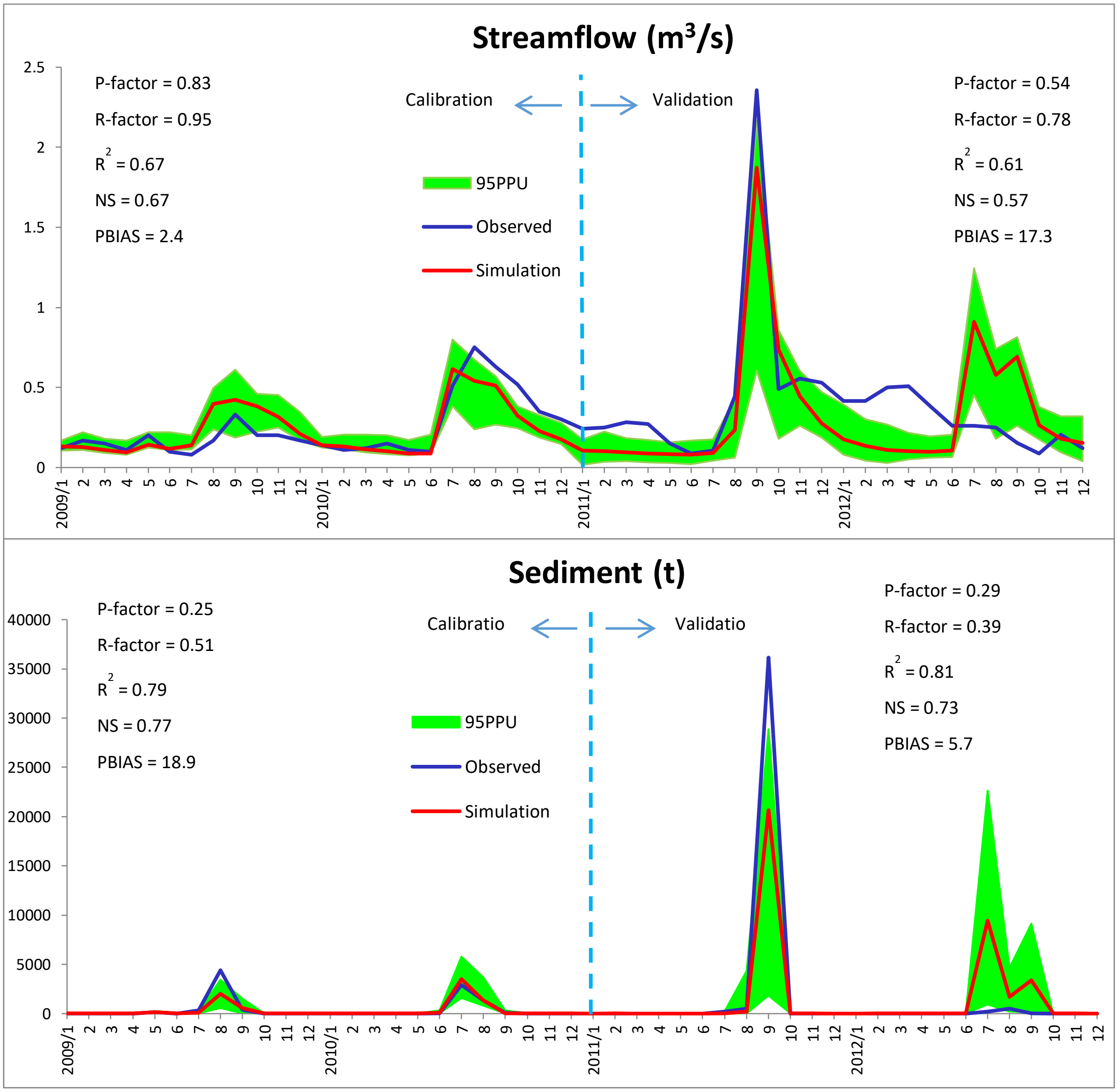


Figure A2: Calibration and validation results for streamflow and sediment load

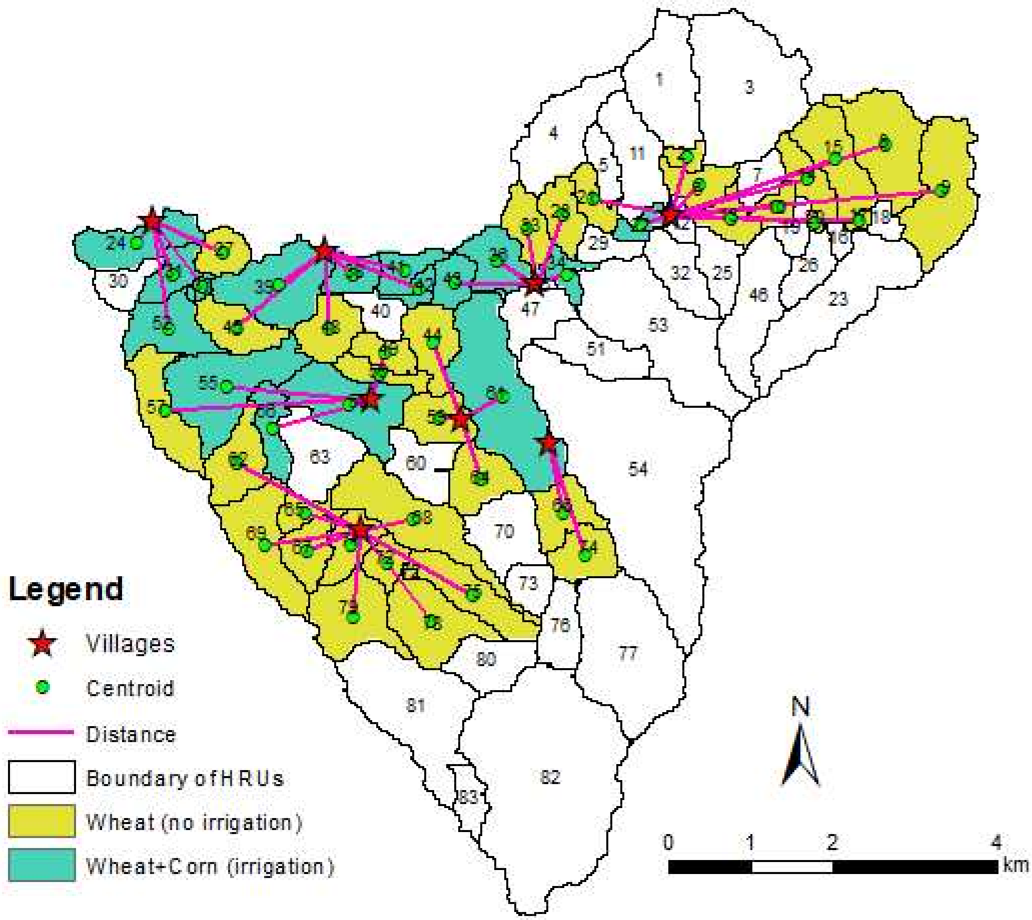


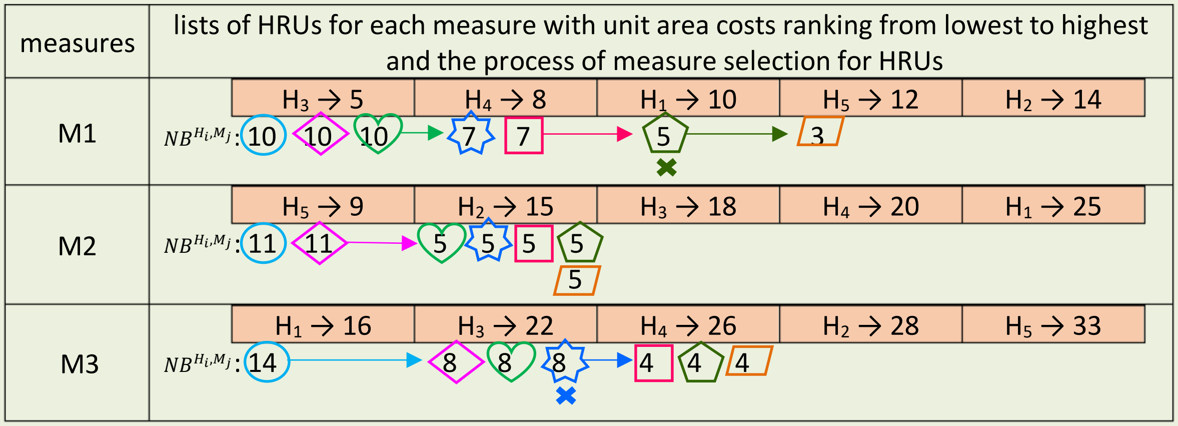
Figure A3: Distance of each HRU to its corresponding village

A

payments	measures	unit area costs of measures in each HRU				
15	M_1	$H_1 \rightarrow 10$	$H_2 \rightarrow 14$	$H_3 \rightarrow 5$	$H_4 \rightarrow 8$	$H_5 \rightarrow 12$
20	M_2	$H_1 \rightarrow 25$	$H_2 \rightarrow 15$	$H_3 \rightarrow 18$	$H_4 \rightarrow 20$	$H_5 \rightarrow 9$
30	M_3	$H_1 \rightarrow 16$	$H_2 \rightarrow 28$	$H_3 \rightarrow 22$	$H_4 \rightarrow 26$	$H_5 \rightarrow 33$

Note: M_1, M_2, M_3 represent measures, H_1, H_2, H_3, H_4, H_5 refer to HRUs; values of unit area costs and payments of measures are for illustrational purposes and have no relationship to the real values of this study.

B



Note: NB^{H_i,M_j} refers to net economic benefits of farmers (Eq. 5). For NB^{H_i,M_j}, values within the same shape are in the same round of comparison, with the one linked with the arrow being the one identified for selecting the corresponding measure to the corresponding HRU. However, the shape with both arrows linked and a cross below it refers to an invalid selection in a round, as the corresponding HRU is already selected earlier with a measure.

C

selected measures for HRUs in each round					
spatial units	H_1	H_5	H_3	H_4	H_2
attached measures	M3	M2	M1	M1	M2

Note: The shapes attached to the selected measures correspond to the comparison rounds in the previous step respectively.

Figure A4: Illustration of the principle for the simulation of AES with a made up example

Note: To illustrate the simulation principle, a made up example is shown in this figure, with three measures and five HRUs. First, based on the heterogeneous costs of measures, a list of HRUs is generated for each measure with their unit area costs ranking from lowest to highest (Figure A4-B). As under uniform payment for each measure (Figure A4-A), the lowest cost generates the highest net economic benefit NB^{H_i,M_j} for farmers. Second, within the generated lists, the first ranked HRUs in each of the lists are considered to get their NB^{H_i,M_j} for comparison (Figure A4-B), with the maximum NB^{H_i,M_j} being identified, resulting in the corresponding measure being selected for the corresponding HRU (Figure A4-C). After this round, the HRU being selected with a measure is taken out, with the former second HRU in the list acting as the first ranked HRU to repeat the previous process for the second round. This repeated process would continue until either all HRUs are selected with measures, or NB^{H_i,M_j} of all left HRUs are negative, or the given budget of AES is not affordable for a further HRU being selected with a measure.

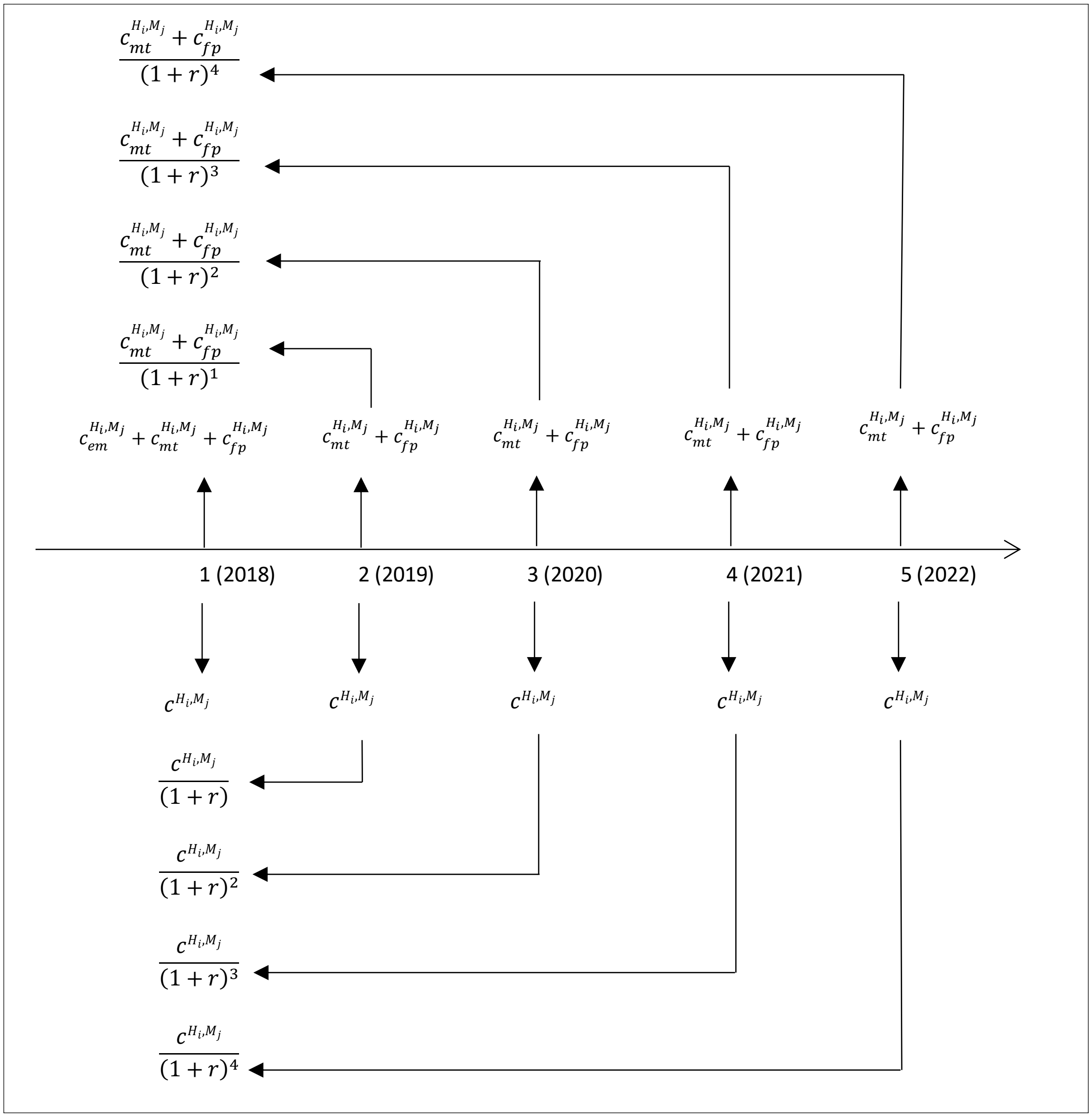


Figure A5: Different costs over time and their present values

Note: r is the discount rate. The sum of the present value of costs in five years calculated by real cost items ($c_{em}^{H_i,M_j}$, $c_{mt}^{H_i,M_j}$, $c_{fp}^{H_i,M_j}$) in each year equals the sum of the present value of total cost in five years calculated by the average annual cost (c^{H_i,M_j}) in each year. Therefore, we form the equation $c_{em}^{H_i,M_j} + c_{mt}^{H_i,M_j} + c_{fp}^{H_i,M_j} + \sum_{i=2}^{n=5} \frac{c_{mt}^{H_i,M_j} + c_{fp}^{H_i,M_j}}{(1+r)^{i-1}} = \sum_{i=1}^{n=5} \frac{c^{H_i,M_j}}{(1+r)^{i-1}}$ which is the basis for Eq. 4.

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