

# A quantitative approach on environment-food nexus: integrated modeling and indicators for cumulative impact assessment of farm management practices (#77196)

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# A quantitative approach on environment-food nexus: integrated modeling and indicators for cumulative impact assessment of farm management practices

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**Background.** Farm management strategies in a basin can simultaneously affect pollution exports and nutrition production. This study develops a combined methodology to introduce and calculate the state-of-the-art indicator of food's environmental footprint (FEF).

**Methods.** The methodology integrates water quality and quantity simulation by the SWAT model in basin with the indicators of ReCiPe, a life cycle impact assessment (LCIA) method. Accordingly, the effectiveness of management practices (BMPs) on pollution loads, production yields, and water footprints (WFs) are evaluated and converted as equivalent environmental damages. FEF is then accounted by the aggregated environmental damages of nutrition production. This method is verified in Zrebar Lake, an agricultural basin in western Iran. Here, water consumption and Eutrophication were main midpoint indicators that converted WF and pollutions into equivalent units, respectively. The endpoint indicators then turned midpoints into equivalent health and ecosystem damages. Two methods based on entropy and environmental performance index (EPI) were also used for weighting normalized endpoints.

**Results.** Results showed that 25-50% fertilizer and irrigation reduction combined with vegetated filter strips reduce N and P pollution exports about 34-60% and 8-21%, respectively. These abatements reduce damages on ecosystem and health about 5-9% and 7-14%, respectively. Thus, FEF can be reduced between 4% and 9% regarding BMPs and weighting methods. Here, freshwater Eutrophication is identified as the most significant ecosystem damage by farmlands. It is also concluded that combined SWAT-ReCiPe can provide a quantitative framework for environment-food nexus, FEF assessment, and comparing different management strategies.

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## Abstract

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## Introduction

Best management practices (BMPs) are promising solutions for controlling pollution discharges from non-point sources (NPS), including agricultural activities (Y. Liu et al., 2017). Phosphorous (P) and nitrogen (N) compounds are typical pollutants transported in basins from farmlands (Hanief & Laursen, 2019). Water quality degradation and Eutrophication are possible consequences of these emissions. Filter strips (FS) (Merriman et al., 2019), fertilizer reduction (FR) (Geng et al., 2019), no-tillage farming (Plunge et al., 2022), tracing and fencing (Sheshukov et al., 2016), constructed wetlands (CWs) (Li et al., 2021), straw mulching (Jang et al., 2017), or changing crop patterns and land-uses (LUs) (Plunge et al., 2022) are recommended solutions as BMPs that have different impacts regionally on pollution transport (Stubbs, 2016). However, these strategies might have secondary impacts on other ecosystems (Čuček et al., 2015), farmers income (Imani et al., 2017) or even nutrition production. Hence, assessing the effectiveness of BMPs requires detailed studies in basin scale at least with combined methods.

Recently, the effectiveness of BMPs have been evaluated and determined in some researches. In The Great Lakes and by considering flow, total phosphorus (TP) and total nitrogen (TN), it was concluded that multiple BMPs combined with FS can reduce nutrients and sediment more significantly than single BMPs. Here, TP and TN were estimated to be reduced about 20% (Merriman et al., 2019). Liu et al. (2019) similarly concluded that combined BMPs with FS are more effective on pollution load abatement than individual BMPs. They recommended that modeling tools for cost-effective analysis can create a more sustainable framework for water quality enhancement in agricultural basins (Y. Liu et al., 2019). This approach was also recommended by Imani et al. (2019) in which BMPs in critical areas (CAs) were prioritized according to their TN and TP reduction and related costs (Imani et al., 2019). Based on modeling and field surveys, it was verified that BMPs can reduce nutrient pollution 25% in a basin while sediment entrapment in the riparian zone can develop organic nutrient removal to about 60% (Sheshukov et al., 2016). Similar to the above-mentioned researches, FS was identified as an effective BMP with 20% TP removal. Nonetheless, some BMPs may reduce the runoff and adversely concentrate pollutants downstream (Jang et al., 2017). It should be considered that farmers may be reluctant to apply some BMPs mainly due to economic reasons. Therefore, a mix of knowledge about farmer and farm characteristics with environmental attitudes might be required prior to adopting BMP schemes (H. Liu & Brouwer, 2022). Dai et al. (2018) proposed a combined model to generate a series of BMPs placement schemes based on nutrients reduction and related costs. They concluded that nutrient load discharged into the lake and tributaries could be dropped to an acceptable level with a proper tradeoff between costs and risks (Dai et al., 2018). During climate change, the effectiveness of 171 BMPs on TN and TP reduction were also analyzed (Chiang et al., 2012). However, their secondary impacts on food production or

environment were the missing subjects. Recent studies imply that pollution reduction, applicability, and economic issues are the main concerns in BMP assessment, while their probable impacts on larger ecosystems and nutrition production are neglected.

In the most of literature and above-mentioned studies, soil and water assessment tool (SWAT) was used for integrated basin modeling. Here, the direct impacts of BMPs on pollution reduction can be evaluated in hydrological response units (HRUs) and receiving water bodies (Jamshidi et al., 2020). However, this simulation cannot account both direct and indirect cumulative environmental impacts (CIAs) of BMPs. For instance, the secondary impact of FS, after TN reduction, on terrestrial or aquatic ecosystem is not clear. A question is that which BMP has the least overall impacts on the ecosystem. For answering this question, life cycle assessment (LCA) has this potential to use data inventory for the quantification of main environmental indicators, such as aquatic ecosystem as midpoint indicators, which can translate simulation outcome into ecological damages. It provides a framework for comparing strategies quantitatively based on their CIAs. For example, the impacts of different sludge-dredging methods in Baiyangdian Lake, northern China (Zhou et al., 2021), low impact development BMPs (LID-BMP) as treatment systems (Xu et al., 2017), implementing treatment systems such as CWs for Yangtze River rehabilitation, Eastern China (Yao et al., 2021), or sea water desalination (Mannan et al., 2019) were recently compared and evaluated by LCA. Accordingly, it is revealed that hydropower systems, in contradiction with their renewable energy production, can be the significant sources of GHG emissions due to their long-term secondary limnology and ecological impacts (Gemechu & Kumar, 2022). This implies that direct short-term water quality rehabilitation, such as TN and TP reduction, may not necessarily ends into a sustainable strategy with the perspective of integrated environmental management (IEM). By this point of view, on-farm intervention

strategies may have by-effects due to terrestrial pollution, water consumption, or changing LUs (McAuliffe et al., 2022). Eutrophication is also a critical subject among the midpoint indicators in life cycle impact assessment (LCIA) (Cosme & Hauschild, 2017; Rosenbaum et al., 2017). This phenomenon is directly affected by TN and TP concentrations (Chapra, 2008), while other parameters such as water consumption can also be effective on freshwater ecosystems, aquatic habitat or Eutrophication intensification (Damiani et al., 2019). It is claimed that accounting the Eutrophication potential of agricultural systems is complicated. Therefore, a combined methodology is required to evaluate the impacts of nutrients release from agricultural systems on freshwater Eutrophication and ecosystem (Ortiz-Reyes & Anex, 2018). It is also recommended that using LCA methods based on its related footprints, such as water footprint (WF), carbon footprint (CF), biodiversity footprint (BF), ecological footprint (EF), etc. can help to account the environmental footprint of productions (Čuček et al., 2015). Nonetheless, an applicable method was missing.

The main purpose of this study is to develop a combined methodology based on SWAT-LCIA to evaluate and compare the CIAs of BMPs in a basin. The developed framework also introduces a state-of-the-art indicator for quantifying food environmental footprint (FEF). This approach accounts related environmental damages of nutrition production in a basin and develops water-food nexus into a more comprehensive environmental perspective. For these purposes, a lake basin is used as the study area to verify the proposed methodology. Here, the SWAT outcomes are used as the main inventory for related midpoint indicators in LCIA. Health, Eutrophication, water consumption, aquatic and terrestrial ecosystems are emphasized as affected environments. CIA is then normalized and evaluated by endpoint indicators as ecological and health damages. The midpoint and endpoint indicators are quantified according to ReCiPe (M. Huijbregts et al.,

2016), a developed LCIA method. In addition, this research considers WF as the driving indicator for water consumption in LCIA and also uses two different methods in calculations for weighting indicators.

## Materials & Methods

### METHODOLOGY

This study follows a 4-step combined methodology. In the first two steps, data is gathered and a basin is simulated by the SWAT model with the perspective of water quality and quantity. Here, the effectiveness of different farm management practices (BMPs) on exporting pollution loads (kg/ha), pollutants concentration in lake (mg/L), crop production yields (ton/ha), nutrition production (Kcal/yr), and water footprint ( $m^3$ ) are evaluated. Hence, the modeling provides a quantitative framework for further environmental-food analysis in basin. In this study, the first two steps, except the nutrition production, follows the previously developed SWAT model by Jamshidi et al. (2020) as explained in sections 2.2-2.5.

In the third step and in order to quantify the CIAs of BMPs, a combined methodology is developed to convert the modeling outputs into equivalent environmental damages. For this purpose, an excel-base LCIA method according to ReCiPe (2016 v1.1) is used including related characterization midpoints (water consumption and Eutrophication) and endpoints (human health and ecosystem damages) with normalization coefficients as explained in section 2.6. In this step, some new approaches are also considered to develop LCIA analysis. For example, the embedded water consumption directly analyzed by the SWAT model (WF) is introduced as a more reliable water consumption indicator in LCIA of food crops. This is due to the fact that WF of food crops includes both consumed (blue and green) and polluted (grey) water which fit more to life cycle

assessment of available water in the ecosystem. In addition, this step considered two different weighting approaches for integrating health and ecosystem damages (endpoints) under a single index. The entropy analysis uses a mathematical equation to calculate the weights of health and ecosystem, while EPI uses predefined weights for these two indicators. This is explained in section 2.7.

In final step, a state-of-the-art indicator is introduced in section 2.8 as “environmental footprint of food production” (FEF) that calculates the accumulated environmental damages of nutrition production in basins. This new index can be used for quantifying the equivalent environmental damages related to food production and comparing the impacts of BMPs and farm management practices with multiple perspectives including WF, pollution emissions, crop nutrition, and ecosystem protection. Therefore, the main innovation of this research is in its methodology, particularly the third and fourth steps. Here, an environment-food nexus analysis compares the accumulated impacts of BMPs in a basin. The steps of methodology are illustrated in Figure 1. Figure 1.

It should also be noted that this methodology is verified in Zrebar Basin, western Iran, which it doesn't mean this method is developed for a specific basin. The combined method of SWAT-ReCiPe is applicable in any basin for comparing farm management strategies. Nonetheless, the midpoint indicators can be different regarding the basin specifications. For example, in addition to water consumption or Eutrophication, other environmental issues like global warming, LU change, and even air pollution can be simply considered in LCIA step (M. A. J. Huijbregts et al., 2017).

## STUDY AREA

The proposed methodology is verified in Zrebar Lake basin, western Iran, for quantifying FEF and the CIA of BMPs based on environmental indicators and food production. Zrebar basin encompasses 90 km<sup>2</sup> including 20 km<sup>2</sup> of irrigated and rain-fed farmlands (22%). Its lake encounters Eutrophication problem mainly due to the agricultural discharges, particularly irrigated farmlands (Imani et al., 2019). Main rain-fed (RF) crops in this area are wheat, barley, grape and peas with average nutrition values of 3640, 3540, 670 and 420 Cal/kg, respectively. The irrigated crops include tomato, tobacco, alfalfa, apple with average nutrition values of 180, 0, 230, and 520 Cal/kg, respectively in addition to wheat and barley. The dominant LUs in the study area with geographical condition of the study area are shown in Figure 2.

### *SIMULATION-CALIBRATION*

In this integrated methodology, using the SWAT model for basin simulation is proposed prior to accounting environmental damages and footprints of agricultural productions. This is due to the fact that this model can simulate complicated systems by considering management practices in farmlands, interactions between water quality and quantity, pollution transport and cycles, and production yields (Abbaspour et al., 2015; J. G. Arnold et al., 2012; Rivas-Tabares et al., 2019). Therefore, required data such as topography, soil properties, LU type, management practices, and weather/climate were inputted to the model and calibrated based on lake inflow volume and nutrients concentrations in lake (nitrate and phosphate) simultaneously. It is noteworthy that the main idea of this research is to develop an integrated methodology for accounting environment-food nexus and FEF. Accordingly, authors used the outcomes of the already calibrated SWAT model previously developed for BMP and WF assessment in the study area (Jamshidi et al., 2020). In order to focus more on the main purpose and outcomes of current

research, the details of simulation-calibration are skipped here but it was fully described in Jamshidi et al. (2020). In this model, the simulation was carried out in 26 sub-basins with 1100 HRUs. The regression coefficient ( $R^2$ ) and RMSE-observations standard deviation ratio (RSR) index were calculated as Table 1.

# *BMP SCENARIO*

This study uses the SWAT outcomes for BMP analysis in 3 scenarios as defined in Table 2. Base is the scenario without using any BMPs. In BMP1 and BMP2, the application of fertilizers, manure and chemical, and water for irrigation is reduced 25% and 50% for all farmlands, respectively. In these two BMP scenarios, FS is assumed to be implemented in the vicinity of lake. Slim FS represents 10-12 m width, while moderate FS has 20-25 m width.

# *WATER FOOTPRINT*

The WFs of agricultural productions are accounted by the standard method and include the three main elements of green, blue and grey water (Franke et al., 2013; Hoekstra et al., 2011). It should be noted that WFs calculate the direct embedded water of farmlands and exclude indirect water embodied in further processing of agricultural productions.

$$WF = GnWF + BWF + GWF \quad (1)$$

$$GnWF = 10ET_a \quad (2)$$

$$BWF = 10(ET_b - ET_a) \quad (3)$$

$$GWF = \max \left( \frac{L}{C_{max} - C_{nat}} \right)_i \quad (4)$$

In these equations,  $GnWF$ ,  $BWF$  and  $GWF$  are green, blue and grey WFs ( $m^3$ ), respectively.  $ET_a$  refers to the evapotranspiration from soil and vegetations in times when there is no irrigation

(mm), while  $ET_b$  includes the accumulated evapotranspiration in times of irrigation ( $ET_b > ET_a$ ).  $L$  is the exported pollution loads (ton/ha) of pollutant  $i$  to the receiving water body,  $C_{max}$  is the maximum allowable concentration of pollutants, and  $C_{nat}$  equals the concentration of pollutants in the receiving water on the condition that the interferences of human activities are eliminated. Here, the  $C_{max}$  of TN and TP are assumed constant as 1.5 and 0.035 mg/L, respectively with respect to the global limits for controlling the trophic state of lakes (Jamshidi, 2021).  $C_{nat}$  of TN and TP are also assumed 0.4 and 0.01 mg/L, respectively (Jamshidi et al., 2022).

## ENVIRONMENTAL IMPACT ASSESSMENT

The method for quantifying environmental damages in basin is developed by internationally coded indicators exhibited in LCIA. In the current research, LCIA characterization coefficients are derived according to the ReCiPe method, which was presented by a series of collaborations in Europe (M. A. J. Huijbregts et al., 2017). In this method, normalized data at the European and global level are available for 16 midpoint and 3 endpoint indicators. In later ReCiPe updates, several conversion coefficients are considered which represent the global scale instead of the European scale, while maintaining the possibility of using these coefficients on the continental and country scale. Another feature of ReCiPe is that this method expands environmental consequences and evaluates the impacts of water consumption on human health, aquatic and terrestrial ecosystems to consider related damages (M. A. J. Huijbregts et al., 2017). However, the current study proposes of using the WF as the water consumption of food crops due to its comprehensiveness in both water quality and quantity. In this method, all the effective environmental factors are converted into the equivalent operating units. Accordingly, the simulated concentrations of pollutants in lake, such as  $\text{NO}_3$ ,  $\text{NO}_2$ ,  $\text{NH}_3$

and  $\text{PO}_4$ , derived in different BMP scenarios from the SWAT model, are initially converted to equivalent environmental indicators by Eutrophication midpoint coefficients (Table 3). For water consumption midpoint in aquatic, terrestrial and marine ecosystems, the average WF of crops in each scenario is considered ( $\text{m}^3$ ). These conversions are carried out as Equation 5.

$$Q_j = (T \times M)_j \quad (5)$$

$Q$  is the midpoint indicator,  $T$  represents the output of the SWAT model such as water footprint or pollutant concentration,  $M$  is the conversion coefficients, and  $j$  is environmental component such as aquatic, terrestrial, and marine. By this equation, it is possible to calculate the equivalent environmental effects of each pollutant in the life cycle period of the product or activity. It should be noted that these coefficients are on average and do not need supplementary conversion coefficients for shallow or deep waters, with vegetation or different trophic conditions. In addition, pollutant discharges to any environment may ultimately have impacts on aquatic and marine ecosystems in long-term and nutrient cycles. Thus, marine impacts are also considered even the pollution is not directly discharged to the sea.

Since the midpoint indicators are calculated based on equivalent units, such as  $\text{kgN-eq}$  or  $\text{m}^3$  water consumed, it is necessary to accumulate these environmental impacts with different units under a single indicator. This is the most challenging step in conventional CIA methods. ReCiPe uses equivalent damage-based indicators for integrating midpoints into endpoints by Equation 6.

$$D_j = (Q \times E)_j \quad (6)$$

Here, the calculated midpoint indicators ( $Q$ ) are converted into endpoint damage-based indices ( $D$ ) according to related conversion coefficient of  $E$  as Table 4. Endpoint indicators are classified as 1) human health and 2) ecosystem (non-human) damages. In a nutshell, all midpoint indicators with different equivalent units are now converted to two categories of health damage based on

disability-adjusted life years (DALY) and ecosystem damages based on probable number of harmed species in year (species.yr).

As shown in Table 4, the conversion coefficients turn each equivalent midpoint indicators into two parameters of health damage in terms of DALY and ecosystem damage in terms of Species. In this method, the DALY shows the equivalent years of human life lost by death or being disabled due to illness caused by existing pollutants in the environment. On the other hand, the unit of measuring ecosystem damage is the total number of species lost over time. Based on the ReCiPe, it is recommended that endpoints ( $D$ ) should be normalized by specific coefficients that turn the calculated damages into dimensionless indicators per person per year (Sleeswijk et al., 2008) which is explained in next section.

# *NORMALIZATION AND WEIGHTING*

Calculated endpoints are finally normalized (Equation 7) on a global scale regarding reference coefficients (Table 4) and aggregated according to their weights by Equation 8. Here, two approaches of Entropy and EPI are considered for weighting normalized indicators.

$$R = \frac{D}{N} \tag{7}$$

$$C = \sum(W \times R) \tag{8}$$

Where,  $C$  is the annual environmental damage per person,  $W$  is the weight of each endpoint indicator,  $N$  represents the normalization value and  $R$  is the normalized endpoint. Weights can be calculated based on different mathematical methods, such as entropy or fuzzy (J. Chen et al., 2019; Zeng et al., 2022), or based on expert opinions and references (Z. Chen et al., 2022). In this study, EPI determines health and ecosystem weights as 0.4 and 0.6, respectively (Hsu &

Zomer, 2016), whereas the weights of endpoint indicators by Entropy method ( $W_{En.}$ ) are calculated through a probabilistic function by Equation 9.

$$W_{En.} = -\frac{1}{\ln(t)} \sum_{z=1}^t (R \times \ln R)_z \quad (9)$$

In which,  $t$  is the number of available data. In entropy analysis, factor with more data dispersion gains higher weights (Imani et al., 2019). Since this study evaluates  $C$  from 2007-2013 for each BMP scenario, the variations of both endpoint indicators ( $R$ ) can be calculated. Based on evaluations, the weights of ecosystem and health endpoints by entropy method are 0.44 and 0.56, respectively.

# ENVIRONMENTAL-FOOD INDEX

According to the environmental damages calculated by SWAT-ReCiPe, a new footprint index can now be quantified for food and nutrition production in farmlands. This indicator accounts the CIA per food production in any area as Equation 10.

$$FEF = \frac{C}{S} \quad (10)$$

In this equation,  $FEF$  is a dimensionless indicator that represents the CIA of food production. In other words,  $FEF$  is the environmental footprint of nutrition production. This indicator can be calculated by the proposed methodology for comparing major environmental concerns in food production, including water-food nexus. Low  $FEF$  ( $\sim 0$ ) means that strategies used for food production is rather clean, while higher  $FEF$  ( $> 1$ ) indicates their destructive mode.  $C$  was defined earlier and notes the environmental damages (CIA) and  $S$  is calculated by Equation 11.

$$S = \frac{T_{Cal}}{B \times P} \quad (11)$$

In which  $T_{Cal}$  is the daily total nutrition (calories) of food production in the study area,  $B$  equals the malnutrition baseline of humans assumed 2000 cal/day (D. Liu et al., 2022), and  $P$  is the global population (7.75 billion) to convert and normalize  $S$  per person in global scale.

## Results and discussions

### *SWAT OUTCOMES*

According to the basin simulation by the SWAT model in different management scenarios, the annual pollution loads exported by different HRUs are calculated. Figures 3 and 4 illustrate the accumulated N and P loads discharged by RF and irrigated farmlands in three scenarios, respectively. On an average for 2007 to 2013, BMP1 can reduce 33.8%N and 7.7%P pollution exports from agricultural LUs. BMP2 can improve these reductions to 59.9% and 20.9% for N and P, respectively. These reductions may have different ecological impacts on marine, aquatic and terrestrial systems which are accounted through the combined methodology. Yet, BMPs are also effective on crops production yields and consequently WF and nutrition production (Table 5).

### *ENVIRONMENTAL IMPACTS*

For base scenario, the environmental midpoint impact ( $Q$ ) of farming activities in Zrebar basin is calculated by the proposed methodology. Figure 5 shows that freshwater Eutrophication is the most critical item during the study period. The embedded water consumed is also significant for damaging the terrestrial ecosystem and human health. Figure 6 implies that the above conclusion remains unchanged in BMP1 and BMP2 as well despite 25%-50% fertilizer reduction. This is due to the fact that eutrophication in freshwater by the combined methodology is mainly affected

by TP concentration in lake which can be hardly improved with ammonium-based fertilizer reduction in short term. Controlling erosion and sediment transport by filter strips from upstream is more efficient for TP reduction.

Figure 7 shows that the cumulative ecological damages are relatively larger than health problems in all management scenarios. This is due to the fact that human health is mostly influenced by toxins and heavy metals which were excluded in this study. The results indicate that the average ecological impact reduces from  $1.41\text{E-}6$  to  $1.34\text{E-}6$  (4.9%) and  $1.28\text{E-}6$  (9.2%) for BMP1 and BMP2, respectively. Likewise, human health risk reduces from  $2.58\text{E-}7$  to  $2.4\text{E-}7$  (6.8%) and  $2.22\text{E-}7$  (13.9%) for BMP1 and BMP2, respectively. It means that 50% reduction in fertilizers in this area may ultimately reduce 9% ecological and 14% health risks (Figure 8). Here, the cumulative impacts are low but not negligible as they range  $1\text{E-}6$  and  $1\text{E-}7$  per person. Nonetheless, these values seem to be meaningless unless they are used as a quantitative tool of comparative analysis.

In Figure 8, in addition to normalized environmental impacts (per person), food production ( $S$ ) is also illustrated in different BMPs. Since nutrition production is a positive activity, the impacts are shown as negative. The overall environmental impact of farming activities and related management practices should be finally calculated by the weighted average of normalized ecosystem and health damages. This step is carried out with different weighing methods described in section 2.7. Since EPI allocates higher weights to ecological items, the related result are relatively more than entropy method. Despite different weighting, the overall  $C$  reduction for BMP1 ranges between 5-8%, while it ranges between 10-13% for BMP2. It implies that using strict BMPs may not necessarily have significant improvement. On the contrary,  $S$  is reduced 1.66% and 3.73% by BMP1 and BMP2, respectively. It points to the fact that using some farm

management practices may reduce environmental damages in one hand, while it can also reduce the nutrition production on the other hand. This fact emphasizes on an environment-food nexus index for more comprehensive understanding of management impacts.

Figure 9 indicates that malnutrition reduction by agricultural productions in Zrebar Basin with its conventional crop pattern can quantitatively generate 0.61 (Entropy) and 0.78 (EPI) combined environmental impacts (FEF). In other words, 0.61-0.78 environmental units would be damaged by the consumed water and Eutrophication originated by agricultural activities. Using BMP1 and BMP2 can reduce FEF 6.5-9.1% (entropy) and 4-6.4% (EPI), respectively. It means that 50% FR combined with FS (BMP2) can reduce 6.4-9.1% of FEF in Zrebar basin. Obviously, this new indicator is more helping for policy makers rather than conventional analysis on pollution reductions in a basin. For example, this indicator may present criteria to compare implementing vegetated FS or changing crop patterns in a basin. The first alternative only reduces pollution loads and consequently environmental impacts, while the second alternative may focus more on nutrition improvement despite pollution discharges.

What signifies this research and makes it different with previous literature is the combination of SWAT-ReCiPe, for accounting the damage-based FEF. In previous studies, this approach has not been achieved or verified in a basin. In addition, this method can find a quantitative solution how to include water quality issues in water-energy-food nexus problems (Heal et al., 2021).

## Conclusions

This study developed a combined methodology with simulation basin by the SWAT model and LCIA by ReCiPe. This integrated framework, founded on modeling-indicators, could account the aggregated environmental damages of BMPs and eventually the FEF index. Therefore, SWAT-

LCIA is recommended as a reliable tool for the quantification of farm management cumulative impacts. In addition, FEF is introduced and recommended as a referencing index for comparing these BMPs under environment-food nexus.

It is also concluded that pollution reduction is only one pillar of a sustainable BMPs while their impacts in larger ecosystems, environmental components, and food production are also necessary for integrated decision-making. Embedded water consumption and Eutrophication are typical midpoint indicators and health and ecosystem damages are typical endpoint indicators. Yet, this method has the potential of including other footprints such as CB within LCIA.

BMPs are rather effective on pollution reduction but they may have secondary positive or negative impacts on larger ecosystems, human health, and food production that should be considered in decision-making. In spite of this fact, in the study area, it is found that FR combined with FS has not considerable negative impacts. In addition, these scenarios can finally reduce FEF.

It is also implied that accounted FEF is reliant on a wide range of indicators and coefficients according to the LCIA method, pollutants (TN, TP, toxins, heavy metals, etc.) and their transport according to basin specification, farm management practices, SWAT modeling assumptions and accuracy, WF assumptions and factors ( $C_{max}$ ,  $C_{nat}$ , and  $ET$ ), weighting and normalization methods. All these uncertainties support this idea as a tool for comparing strategies relatively instead of reporting absolute results. Yet, it has the potential of being upgraded by future achievements on the accuracy of coefficients or regionally developed indicators in LCIA.

## References

- Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology*, 524, 733–752. <https://doi.org/10.1016/j.jhydrol.2015.03.027>
- Chapra, S. C. (2008). *Surface water quality modelling*. Waveland Press.
- Chen, J., Wang, Y., Li, F., & Liu, Z. (2019). Aquatic ecosystem health assessment of a typical sub-basin

- of the Liao River based on entropy weights and a fuzzy comprehensive evaluation method. *Scientific Reports*, 9(1), 14045. <https://doi.org/10.1038/s41598-019-50499-0>
- Chen, Z., Zhong, P., Liu, M., Ma, Q., & Si, G. (2022). An integrated expert weight determination method for design concept evaluation. *Scientific Reports*, 12(1), 6358. <https://doi.org/10.1038/s41598-022-10333-6>
- Chiang, L.-C., Chaubey, I., Hong, N.-M., Lin, Y.-P., & Huang, T. (2012). Implementation of BMP Strategies for Adaptation to Climate Change and Land Use Change in a Pasture-Dominated Watershed. *International Journal of Environmental Research and Public Health*, 9(10), 3654–3684. <https://doi.org/10.3390/ijerph9103654>
- Cosme, N., & Hauschild, M. Z. (2017). Characterization of waterborne nitrogen emissions for marine eutrophication modelling in life cycle impact assessment at the damage level and global scale. *International Journal of Life Cycle Assessment*, 22(10), 1558–1570. <https://doi.org/10.1007/s11367-017-1271-5>
- Čuček, L., Klemeš, J. J., & Kravanja, Z. (2015). Overview of environmental footprints. In *Assessing and Measuring Environmental Impact and Sustainability* (pp. 131–193). Elsevier. <https://doi.org/10.1016/B978-0-12-799968-5.00005-1>
- Dai, C., Qin, X. S., Tan, Q., & Guo, H. C. (2018). Optimizing best management practices for nutrient pollution control in a lake watershed under uncertainty. *Ecological Indicators*, 92, 288–300. <https://doi.org/https://doi.org/10.1016/j.ecolind.2017.05.016>
- Damiani, M., Lamouroux, N., Pella, H., Roux, P., Loiseau, E., & Rosenbaum, R. K. (2019). Spatialized freshwater ecosystem life cycle impact assessment of water consumption based on instream habitat change modeling. *Water Research*, 163, 114884. <https://doi.org/https://doi.org/10.1016/j.watres.2019.114884>
- Franke, N. A., Boyacioglu, H., & Hoekstra, A. Y. (2013). Grey Water Footprint Accounting: Tier 1 Supporting Guidelines, Value of Water Research Report Series No. 65. In *UNESCO-IHE Institute for Water Education* (Issue November). Unesco-Ihe Delft.
- Gemechu, E., & Kumar, A. (2022). A review of how life cycle assessment has been used to assess the environmental impacts of hydropower energy. *Renewable and Sustainable Energy Reviews*, 167, 112684. <https://doi.org/https://doi.org/10.1016/j.rser.2022.112684>
- Geng, R., Yin, P., & Sharpley, A. N. (2019). A coupled model system to optimize the best management practices for nonpoint source pollution control. *Journal of Cleaner Production*, 220, 581–592. <https://doi.org/10.1016/j.jclepro.2019.02.127>
- Hanief, A., & Laursen, A. E. (2019). Meeting updated phosphorus reduction goals by applying best management practices in the Grand River watershed, southern Ontario. *Ecological Engineering*, 130, 169–175. <https://doi.org/https://doi.org/10.1016/j.ecoleng.2019.02.007>
- Heal, K. V., Bartosova, A., Hipsey, M. R., Chen, X., Buytaert, W., Li, H.-Y., McGrane, S. J., Gupta, A. B., & Cudennec, C. (2021). Water quality: the missing dimension of water in the water–energy–food nexus. *Hydrological Sciences Journal*, 66(5), 745–758. <https://doi.org/10.1080/02626667.2020.1859114>
- Hoekstra, A. Y., Chapagain, A. K., Mekonnen, M. M., & Aldaya, M. M. (2011). *The water footprint assessment manual: Setting the global standard*. Routledge.
- Hsu, A., & Zomer, A. (2016). Environmental Performance Index. In *Wiley StatsRef: Statistics Reference Online* (pp. 1–5). Wiley. <https://doi.org/10.1002/9781118445112.stat03789.pub2>
- Huijbregts, M. A. J., Steinmann, Z. J. N., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., & van Zelm, R. (2017). ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. *The International Journal of Life Cycle Assessment*, 22(2), 138–147. <https://doi.org/10.1007/s11367-016-1246-y>
- Huijbregts, M., Steinmann, Z. J. N., Elshout, P. M. F. M., Stam, G., Verones, F., Vieira, M. D. M., Zijp, M., & van Zelm, R. (2016). ReCiPe 2016 - A harmonized life cycle impact assessment method at midpoint and endpoint level. Report I: Characterization. *National Institute for Public Health and the Environment*, 194.

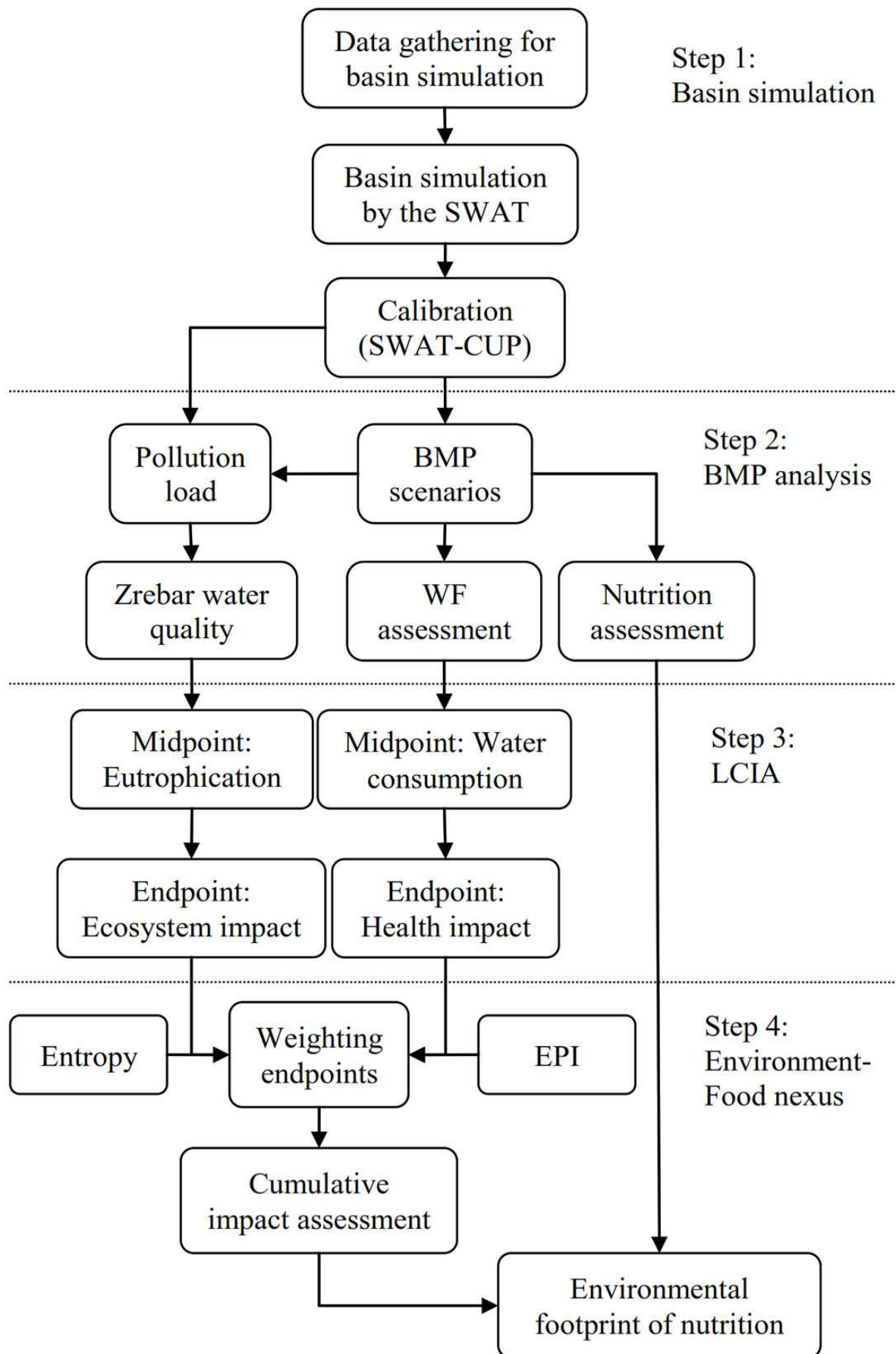
- Imani, S., Delavar, M., & Niksokhan, M. H. (2019). Identification of Nutrients Critical Source Areas with SWAT Model under Limited Data Condition. *Water Resources*, 46(1), 128–137. <https://doi.org/10.1134/S0097807819010147>
- Imani, S., Niksokhan, M. H., Jamshidi, S., & Abbaspour, K. C. (2017). Discharge permit market and farm management nexus: an approach for eutrophication control in small basins with low-income farmers. *Environmental Monitoring and Assessment*, 189(7), 346. <https://doi.org/10.1007/s10661-017-6066-4>
- J. G. Arnold, D. N. Moriasi, P. W. Gassman, K. C. Abbaspour, M. J. White, R. Srinivasan, C. Santhi, R. D. Harmel, A. van Griensven, M. W. Van Liew, N. Kannan, & M. K. Jha. (2012). SWAT: Model Use, Calibration, and Validation. *Transactions of the ASABE*, 55(4), 1491–1508. <https://doi.org/10.13031/2013.42256>
- Jamshidi, S. (2021). Grey Water Footprint Accounting, Challenges, and Problem-Solving. In *Agroecological Footprints Management for Sustainable Food System* (pp. 247–271). Springer Singapore. [https://doi.org/10.1007/978-981-15-9496-0\\_8](https://doi.org/10.1007/978-981-15-9496-0_8)
- Jamshidi, S., Imani, S., & Delavar, M. (2020). Impact Assessment of Best Management Practices (BMPs) on the Water Footprint of Agricultural Productions. *International Journal of Environmental Research*, 14(6), 641–652. <https://doi.org/10.1007/s41742-020-00285-y>
- Jamshidi, S., Imani, S., & Delavar, M. (2022). An approach to quantifying the grey water footprint of agricultural productions in basins with impaired environment. *Journal of Hydrology*, 606, 127458. <https://doi.org/10.1016/j.jhydrol.2022.127458>
- Jang, S. S., Ahn, S. R., & Kim, S. J. (2017). Evaluation of executable best management practices in Haeen highland agricultural catchment of South Korea using SWAT. *Agricultural Water Management*, 180, 224–234. <https://doi.org/10.1016/j.agwat.2016.06.008>
- Li, J., Zheng, B., Chen, X., Li, Z., Xia, Q., Wang, H., Yang, Y., Zhou, Y., & Yang, H. (2021). The Use of Constructed Wetland for Mitigating Nitrogen and Phosphorus from Agricultural Runoff: A Review. *Water*, 13(4), 476. <https://doi.org/10.3390/w13040476>
- Liu, D., Huang, Y., Huang, C., Yang, S., Wei, X., Zhang, P., Guo, D., Lin, J., Xu, B., Li, C., He, H., He, J., Liu, S., Shi, L., Xue, Y., & Zhang, H. (2022). Calorie Restriction with or without Time-Restricted Eating in Weight Loss. *New England Journal of Medicine*, 386(16), 1495–1504. <https://doi.org/10.1056/NEJMoa2114833>
- Liu, H., & Brouwer, R. (2022). Incentivizing the future adoption of best management practices on agricultural land to protect water resources: The role of past participation and experiences. *Ecological Economics*, 196, 107389. <https://doi.org/10.1016/j.ecolecon.2022.107389>
- Liu, Y., Engel, B. A., Flanagan, D. C., Gitau, M. W., McMillan, S. K., & Chaubey, I. (2017). A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. *Science of The Total Environment*, 601–602, 580–593. <https://doi.org/10.1016/j.scitotenv.2017.05.212>
- Liu, Y., Wang, R., Guo, T., Engel, B. A., Flanagan, D. C., Lee, J. G., Li, S., Pijanowski, B. C., Collingsworth, P. D., & Wallace, C. W. (2019). Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. *Journal of Hydrology*, 577, 123965. <https://doi.org/10.1016/j.jhydrol.2019.123965>
- Mannan, M., Alhaj, M., Mabrouk, A. N., & Al-Ghamdi, S. G. (2019). Examining the life-cycle environmental impacts of desalination: A case study in the State of Qatar. *Desalination*, 452, 238–246. <https://doi.org/10.1016/j.desal.2018.11.017>
- McAuliffe, G. A., Zhang, Y., & Collins, A. L. (2022). Data, and sample sources thereof, on water quality life cycle impact assessments pertaining to catchment scale acidification and eutrophication potentials and the benefits of on-farm mitigation strategies. *Data in Brief*, 108505. <https://doi.org/10.1016/j.dib.2022.108505>
- Merriman, K. R., Daggupati, P., Srinivasan, R., & Hayhurst, B. (2019). Assessment of site-specific agricultural Best Management Practices in the Upper East River watershed, Wisconsin, using a field-scale SWAT model. *Journal of Great Lakes Research*, 45(3), 619–641.

- 496 <https://doi.org/https://doi.org/10.1016/j.jglr.2019.02.004>
- 497 Ortiz-Reyes, E., & Anex, R. P. (2018). A life cycle impact assessment method for freshwater
- 498 eutrophication due to the transport of phosphorus from agricultural production. *Journal of Cleaner*
- 499 *Production*, 177, 474–482. <https://doi.org/https://doi.org/10.1016/j.jclepro.2017.12.255>
- 500 Plunge, S., Gudas, M., & Povilaitis, A. (2022). Effectiveness of best management practices for non-point
- 501 source agricultural water pollution control with changing climate – Lithuania’s case. *Agricultural*
- 502 *Water Management*, 267, 107635. <https://doi.org/https://doi.org/10.1016/j.agwat.2022.107635>
- 503 Rivas-Tabares, D., Tarquis, A. M., Willaarts, B., & De Miguel, Á. (2019). An accurate evaluation of
- 504 water availability in sub-arid Mediterranean watersheds through SWAT: Cega-Eresma-Adaja.
- 505 *Agricultural Water Management*, 212, 211–225. <https://doi.org/10.1016/j.agwat.2018.09.012>
- 506 Rosenbaum, R. K., Hauschild, M. Z., Boulay, A. M., Fantke, P., Laurent, A., Núñez, M., & Vieira, M.
- 507 (2017). Life cycle impact assessment. In *Life Cycle Assessment: Theory and Practice*.
- 508 [https://doi.org/10.1007/978-3-319-56475-3\\_10](https://doi.org/10.1007/978-3-319-56475-3_10)
- 509 Sheshukov, A. Y., Douglas-Mankin, K. R., Sinnathamby, S., & Daggupati, P. (2016). Pasture BMP
- 510 effectiveness using an HRU-based subarea approach in SWAT. *Journal of Environmental*
- 511 *Management*, 166, 276–284. <https://doi.org/10.1016/j.jenvman.2015.10.023>
- 512 Sleeswijk, A. W., van Oers, L. F. C. M., Guinée, J. B., Struijs, J., & Huijbregts, M. A. J. (2008).
- 513 Normalisation in product life cycle assessment: An LCA of the global and European economic
- 514 systems in the year 2000. *Science of The Total Environment*, 390(1), 227–240.
- 515 <https://doi.org/10.1016/j.scitotenv.2007.09.040>
- 516 Stubbs, M. (2016). Irrigation in U.S. Agriculture: On-Farm Technologies and Best Management
- 517 Practices. *Congressional Research Service (CRS) Report R44158*, 10-13.
- 518 Xu, C., Hong, J., Jia, H., Liang, S., & Xu, T. (2017). Life cycle environmental and economic assessment
- 519 of a LID-BMP treatment train system: A case study in China. *Journal of Cleaner Production*, 149,
- 520 227–237. <https://doi.org/10.1016/j.jclepro.2017.02.086>
- 521 Yao, X., Cao, Y., Zheng, G., Devlin, A. T., Yu, B., Hou, X., Tang, S., Xu, L., & Lu, Y. (2021). Use of
- 522 life cycle assessment and water quality analysis to evaluate the environmental impacts of the
- 523 bioremediation of polluted water. *Science of The Total Environment*, 761, 143260.
- 524 <https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.143260>
- 525 Zeng, Q., Luo, X., & Yan, F. (2022). The pollution scale weighting model in water quality evaluation
- 526 based on the improved fuzzy variable theory. *Ecological Indicators*, 135, 108562.
- 527 <https://doi.org/10.1016/j.ecolind.2022.108562>
- 528 Zhou, H., Zhang, W., Li, L., Zhang, M., & Wang, D. (2021). Environmental impact and optimization of
- 529 lake dredged-sludge treatment and disposal technologies based on life cycle assessment (LCA)
- 530 analysis. *Science of The Total Environment*, 787, 147703.
- 531 <https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.147703>
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# Figure 1

Flow diagram of methodology and research steps

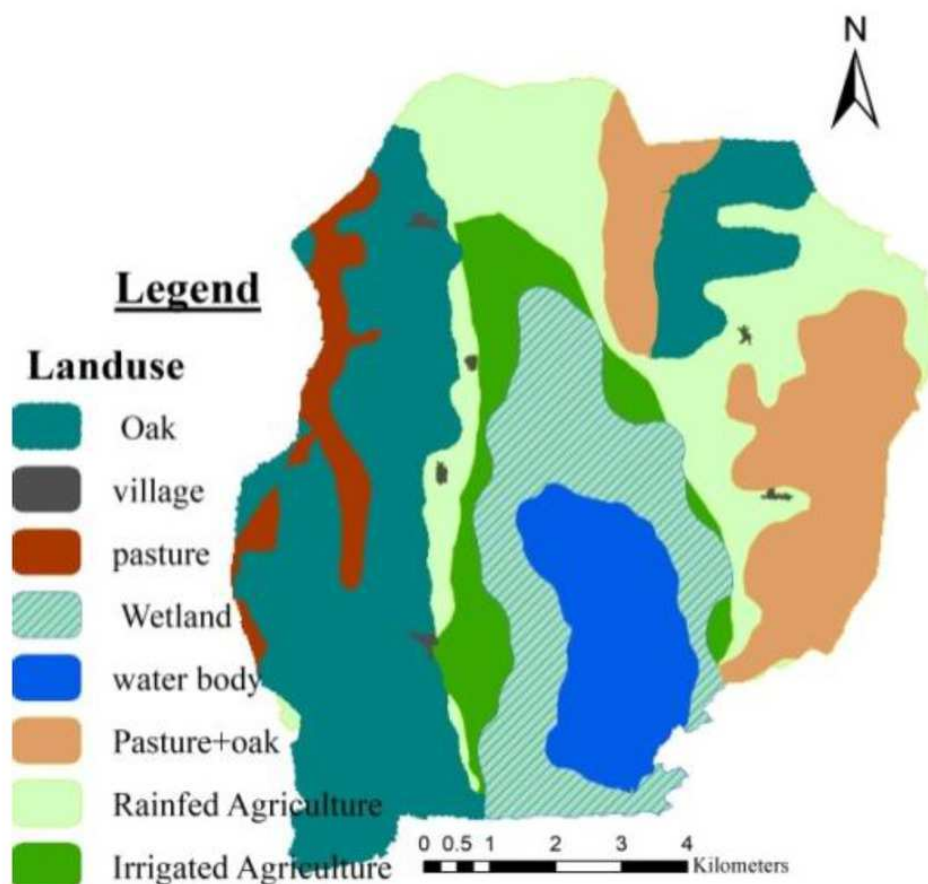
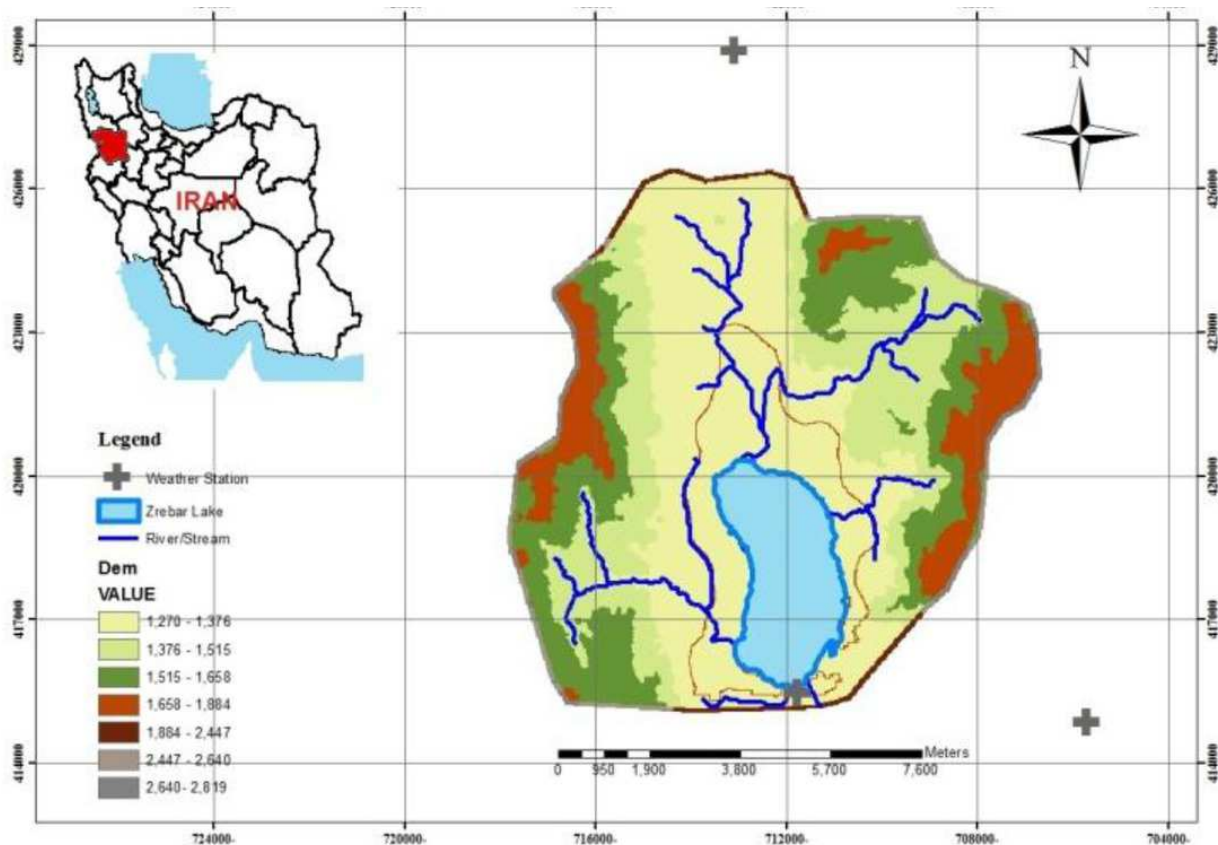
Each box introduces the main activity in the proposed methodology and markers join boxes with their previous and next activities. The methodology is divided in four main steps.



# Figure 2

Geographical status of Zrebar Lake basin with its land-uses

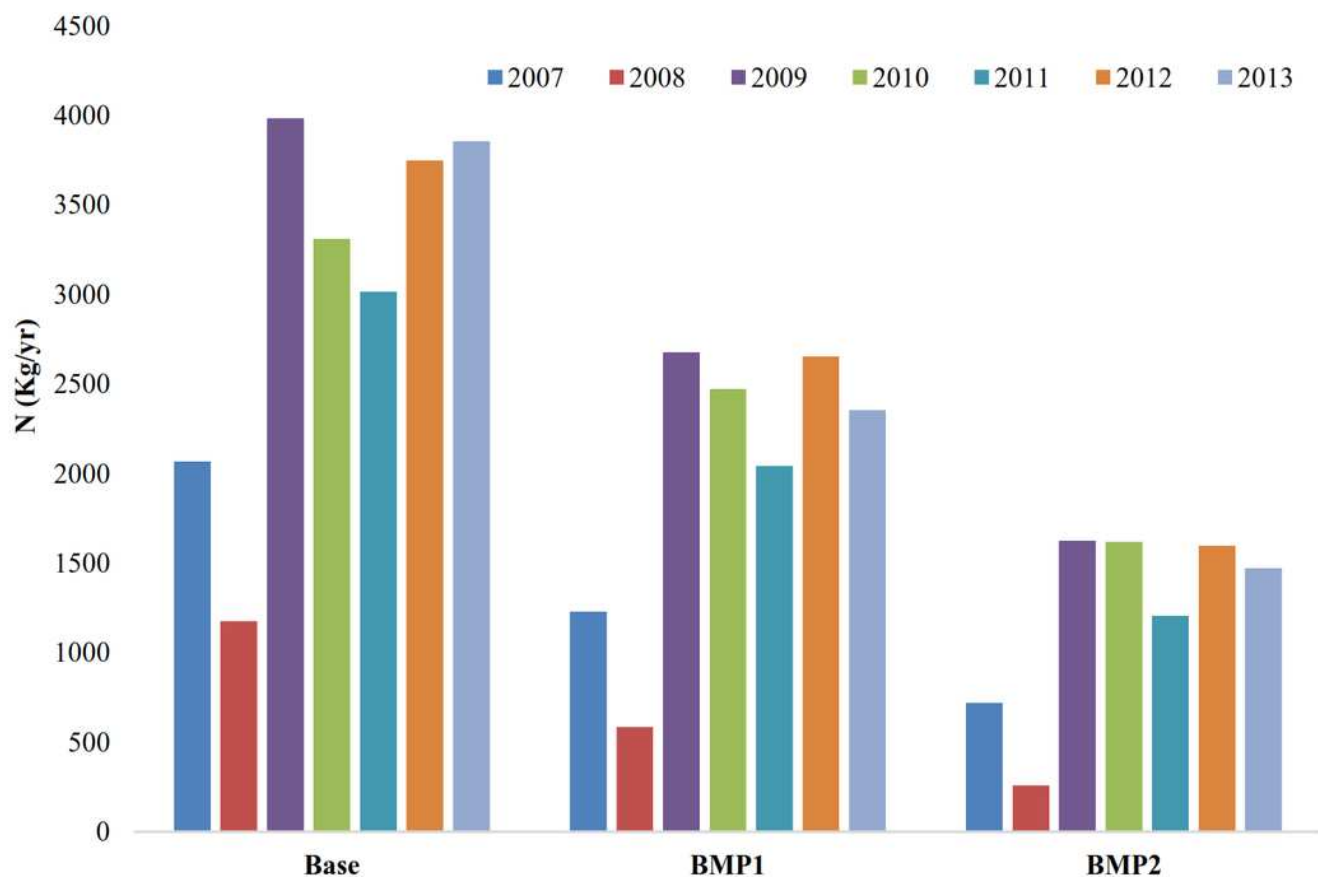
This figure shows the location of study area near the west borders of Iran and illustrates the main land-uses in different colors.



# Figure 3

Accumulated annual N pollution exported by farmlands in management scenarios

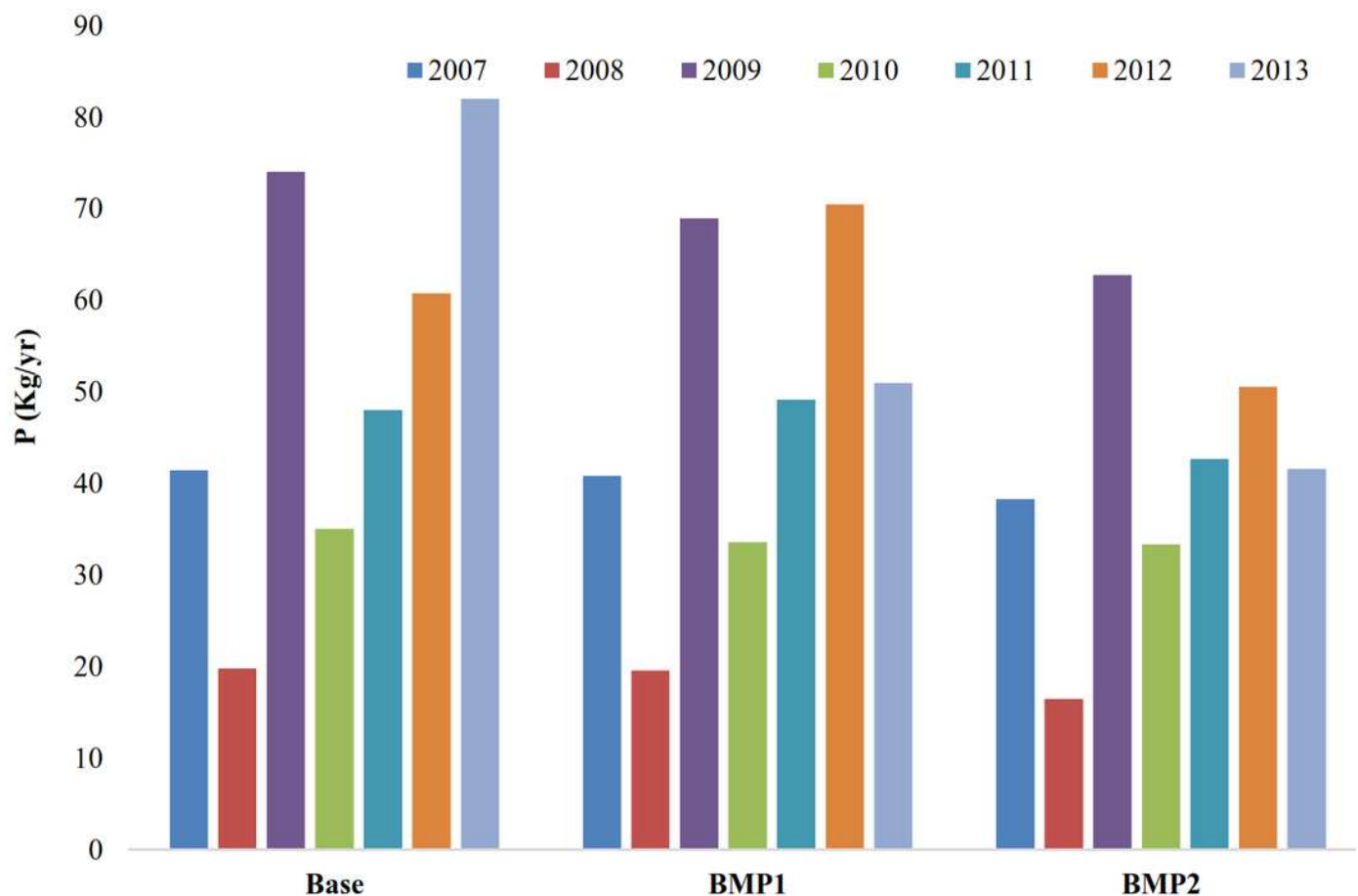
The total nitrogen pollution loads discharged to the lake from all HRUs. Each column represents a year of simulation in the three scenarios of BMPs



# Figure 4

Accumulated annual P pollution exported by farmlands in management scenarios

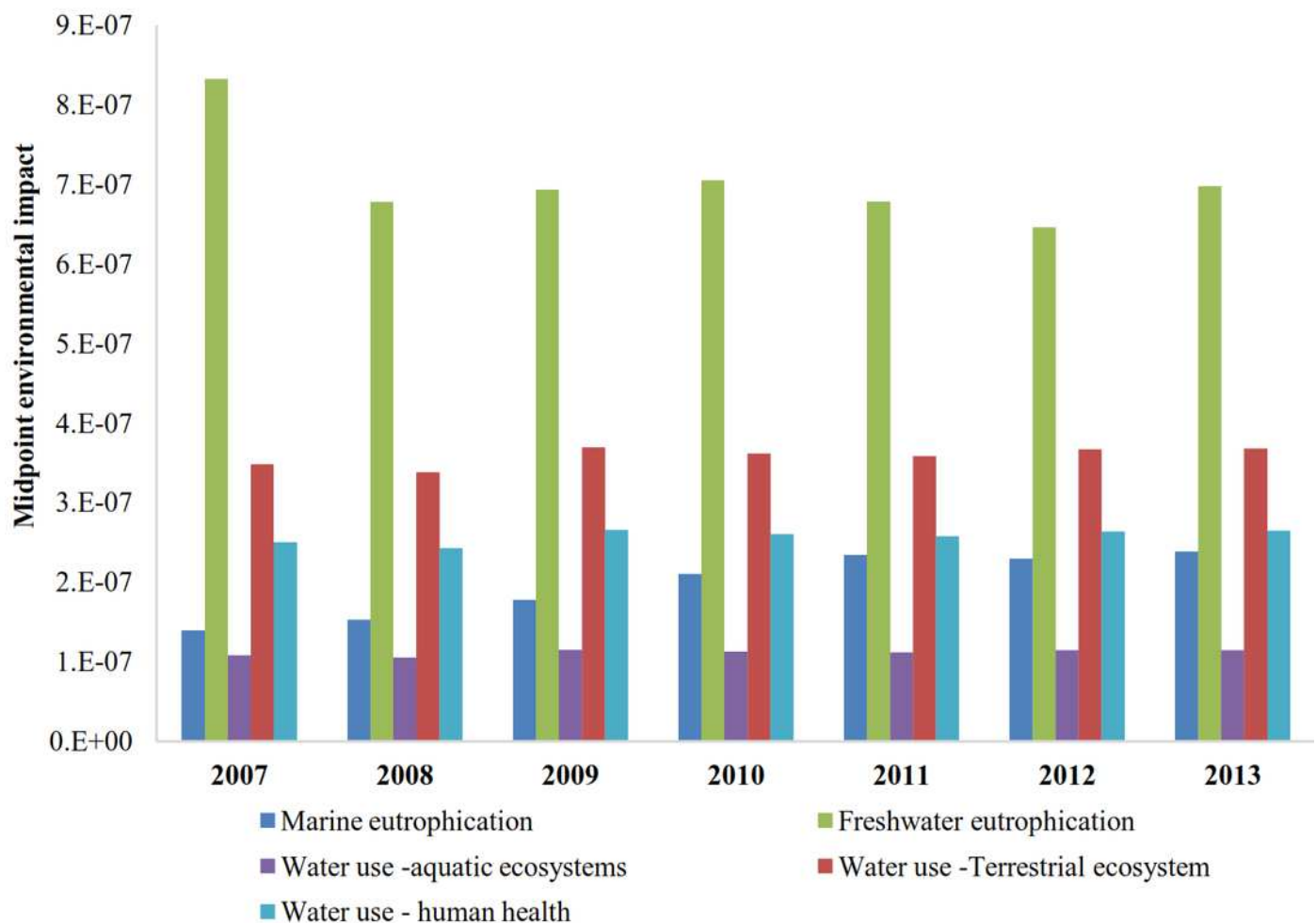
The total phosphorous pollution loads discharged to the lake from all HRUs. Each column represents a year of simulation in the three scenarios of BMPs



# Figure 5

Environmental impact of farming activities based on midpoints without using BMPs

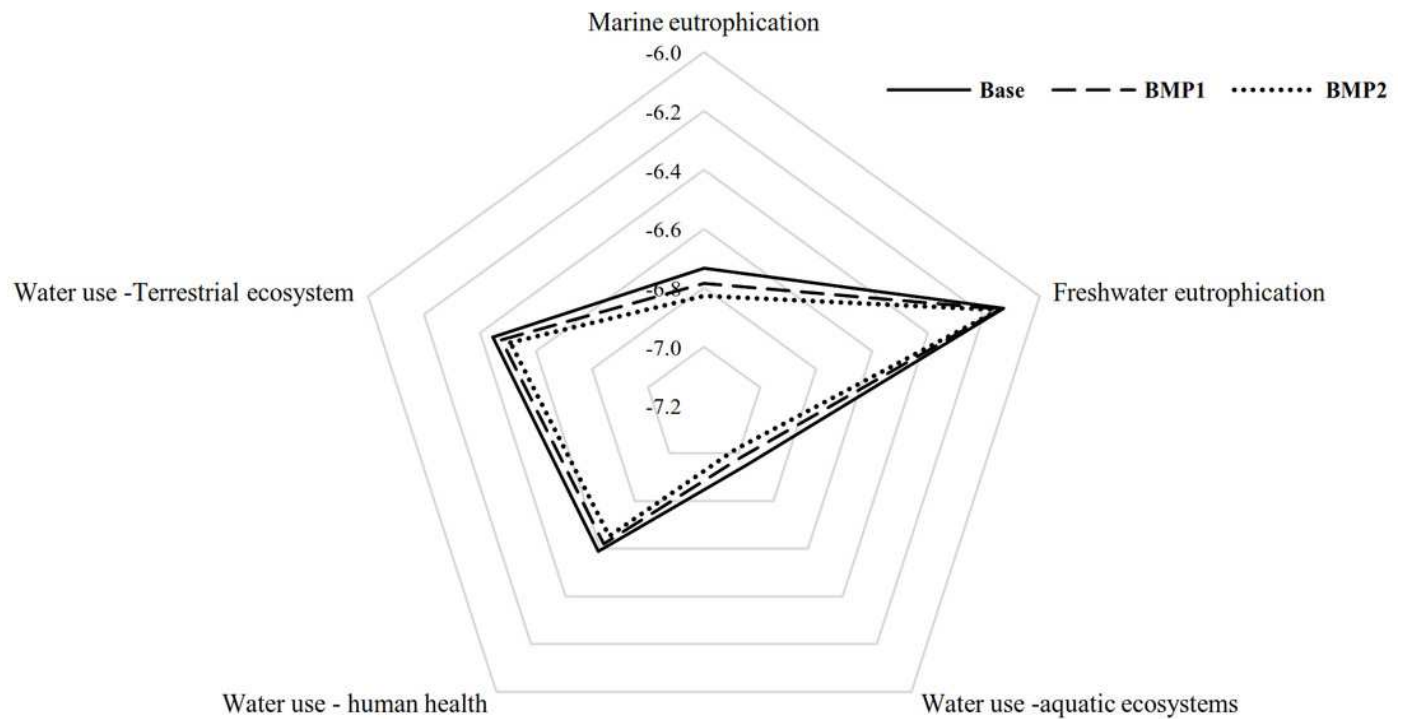
In base scenario, the 5 main midpoints of this study are calculated by the SWAT model outcomes in different simulation years.



# Figure 6

Comparative environmental impact of management practices based on five midpoints

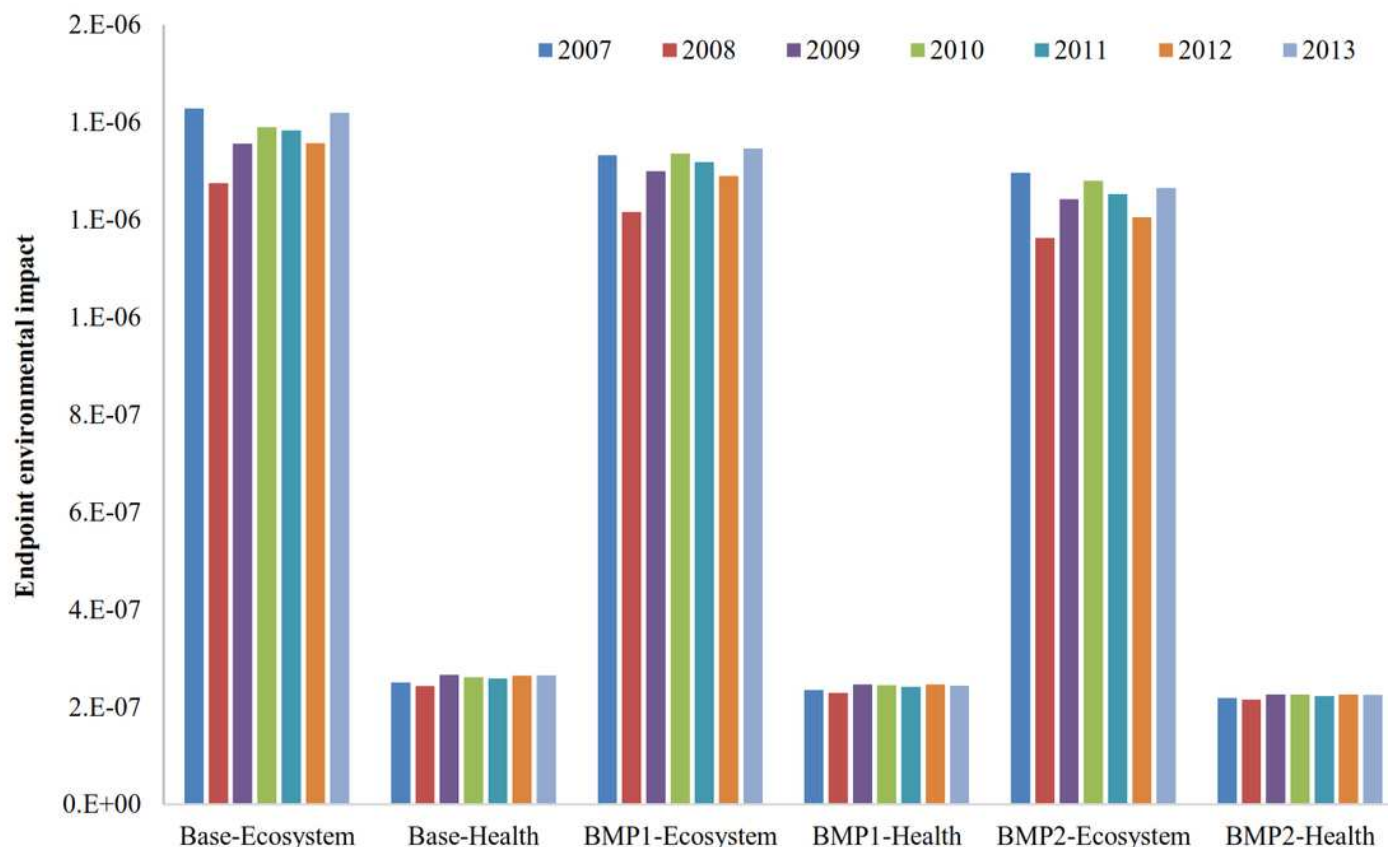
The sharpest corner of diagram points to the highest midpoint in three BMP scenarios.



# Figure 7

Comparative annual endpoint environmental impacts of management practices

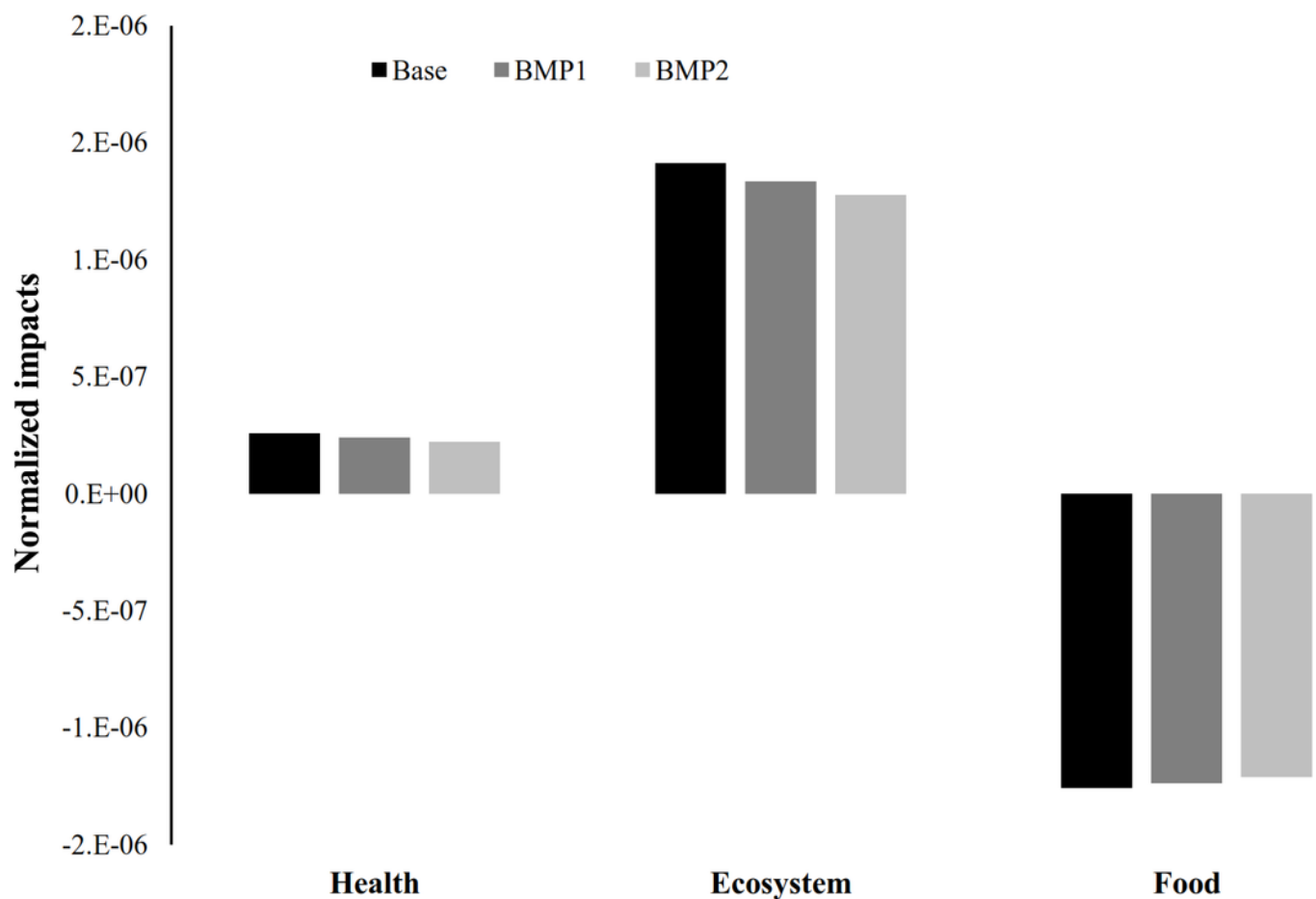
Calculated endpoints of ecosystem and health per BMP scenarios and simulation years



# Figure 8

The average impact of management practices on endpoints (*R*) and food production (*S*)

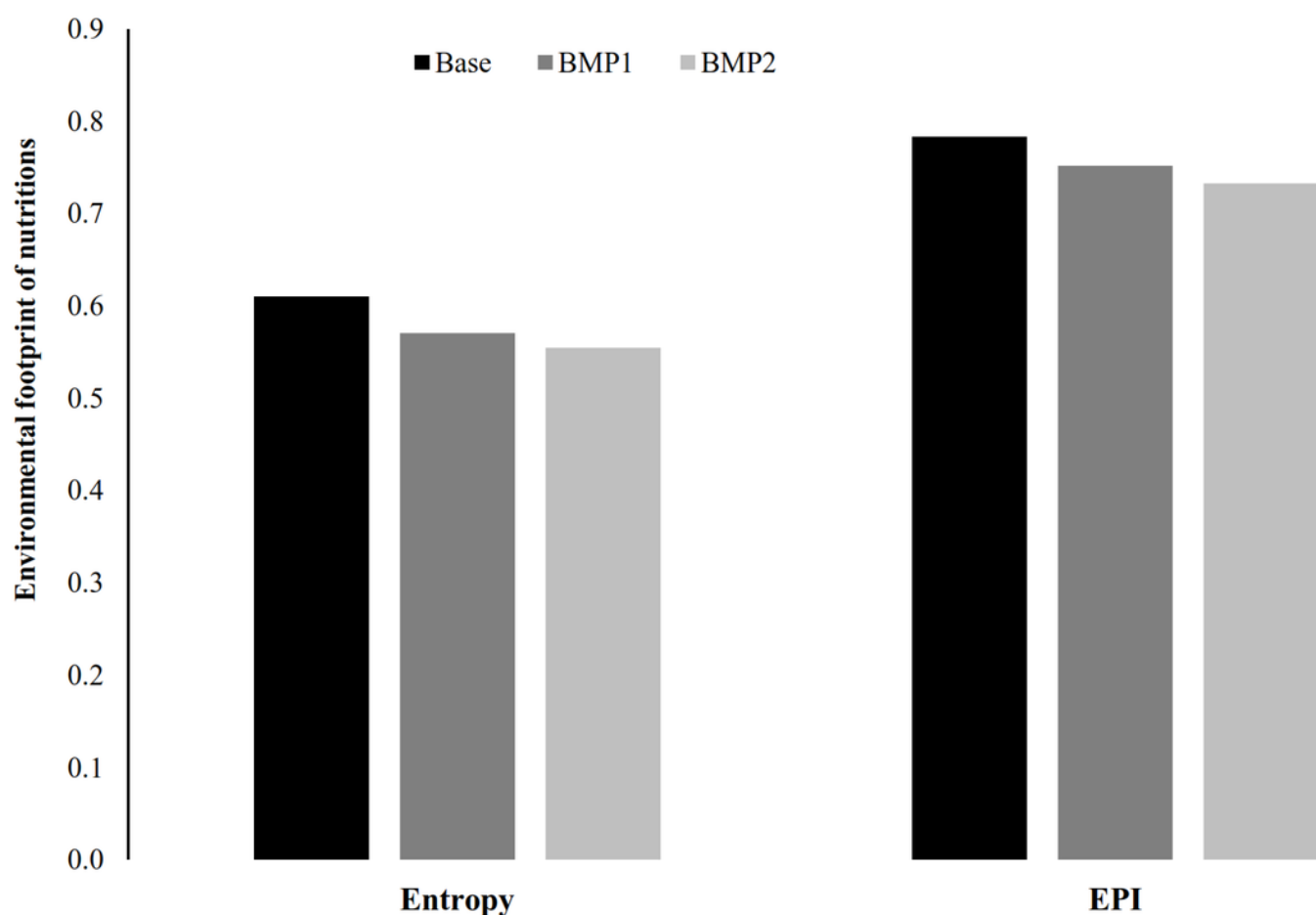
Agricultural productions in this area have adverse impacts on ecosystem and health, while have constructive impacts on food and nutrition values.



# Figure 9

Environmental footprint of food production in different BMPs and weighting methods

The overall negative and positive impacts of agricultural productions on environment and food production is combined within a footprint value. Two weighting methods present different values for this footprint.



**Table 1**(on next page)

Model performance in simulating the water quality and quantity of Lake Basin (Jamshidi et al., 2020)

1

Parameter	Calibration		Validation	
	R <sup>2</sup>	RSR	R <sup>2</sup>	RSR
Lake inflow (m <sup>3</sup> /s)	0.64	0.41	0.76	0.22
Nitrate (mg/L)	0.89	0.62	0.70	0.70
Phosphate (mg/L)	0.64	0.34	0.30	0.38

2

## **Table 2**(on next page)

BMP scenarios and their specifications

BMP scenario	Management strategies
Base	Without BMP
BMP1	25% reduction of fertilizers and water for irrigation, with slim vegetated filter strip
BMP2	50% reduction of fertilizers and water for irrigation with moderate vegetated filter strip

1

# **Table 3**(on next page)

Midpoint coefficients considering Eutrophication in different environments

Environment	Effective ecosystem	Midpoint conversion coefficients (M)				equivalent unit
		Nitrate	Nitrite	phosphorus	Phosphate	
Fresh water	fresh water	-	-	1	0.33	kg P-eq. to freshwater/kg
	marine	0.07	0.09	-	-	kg N-eq to marine water/kg
Marine water	fresh water	-	-	0	0	kg P-eq. to freshwater/kg
	marine	0.23	0.3	-	-	kg N-eq to marine water/kg

1

2

**Table 4**(on next page)

Endpoint coefficients to convert midpoints into equivalent environmental damages

Environment	Midpoint indicator	Endpoint conversion coefficient (E)	equivalent unit	Normalization index (N)
Human health	Water consumption	2.22E-06	Daly/m <sup>3</sup> consumed	1.96E-04
Terrestrial ecosystems	Water consumption	1.35E-08	species.yr/m <sup>3</sup> consumed	3.48E-06
Freshwater ecosystems	Eutrophication	6.71E-07	Species.yr/kg P to freshwater eq.	4.90E-07
	Water consumption	6.04E-13	species.yr/m <sup>3</sup> consumed	6.16E-10
Marine ecosystems	Eutrophication	1.70E-09	Species.yr/kg N to marine water eq.	6.12E-09

1

2

# **Table 5**(on next page)

Outputs of the SWAT model in different BMP scenarios

LU	Base			BMP1			BMP2		
	Yield (ton/ha)	WF (m <sup>3</sup> /ton)	Nutrition (MCal/yr)	Yield (ton/ha)	WF (m <sup>3</sup> /ton)	Nutrition (MCal/yr)	Yield (ton/ha)	WF (m <sup>3</sup> /ton)	Nutrition (MCal/yr)
Alfalfa	4.5	2699.7	91	3.93	2673.5	79	3.4	2529.3	68
Apple	11.2	1065.8	431	9.28	1114.1	357	7.4	1144.9	284
RF Barley	0.9	3521.0	464	0.90	3499.3	464	0.9	3451.3	464
Barley	2.1	2095.1	200	2.10	2048.8	200	2.1	1953.1	200
RF Pea	0.5	8497.6	61	0.50	8479.7	61	0.5	8477.3	61
RF Grape	4.0	939.5	536	4.00	936.1	536	4.0	927.7	536
Tobacco	1.9	4149.6	0	1.67	4221.0	0	1.5	4075.8	0
Tomato	11.1	974.3	27	9.10	1028.1	22	3.7	2077.4	9
RF Wheat	1.1	2926.1	4004	1.10	2909.0	4004	1.1	2872.6	4004
Wheat	2.8	2206.7	1303	2.74	2196.1	1275	2.6	2173.0	1224

1