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

Shervin Jamshidi [Corresp., 1] , **Anahita Naderi** [1]

[1] Department of Civil Engineering, University of Isfahan, Isfahan, Iran

Corresponding Author: Shervin Jamshidi
Email address: sh.jamshidi@eng.ui.ac.ir

Background. Best management practices (BMPs) are promising solutions that can partially control pollution discharged from farmlands. These strategies, like fertilizer reduction and using filter strips, mainly control nutrient (N and P) pollution loads in basins.. However, they have secondary impacts on nutrition production and ecosystem. This study develops a method to evaluate the cumulative environmental impacts of BMPs. It also introduces and calculates food's environmental footprint (FEF) for accounting the total environmental damages per nutrition production.

Methods. This study combines the soil and water assessment tool (SWAT) for basin simulation with the indices of ReCiPe, a life cycle impact assessment (LCIA) method. By these means, the effectiveness of BMPs on pollution loads, production yields, and water footprints (WFs) are evaluated and converted as equivalent environmental damages. This method is verified in Zrebar Lake, western Iran. Here, water consumption, as WFs, and eutrophication are the main indices that are converted into equivalent health and ecological impairments. Two methods, entropy and environmental performance index (EPI), are used for weighting normalized endpoints in last step.

Results. Results showed that using 25-50% less fertilizer and water for irrigation combined with vegetated filter strips reduce N and P pollution about 34-60% and 8-21%, respectively. These can decrease 5-9% ecosystem damages and 7-14% health risks. Here, freshwater eutrophication is relatively a more critical damage in ecosystem. However, using less fertilizer adversely reduces 1.7-3.7% total nutrition production. It means that BMPs can decline total ecological damages and health risks, while threaten nutrition production. FEF presents a tool to solve this dilemma about the sustainability of BMPs. In the study area, 4-9% decrease in FEF means that BMPs are more environmental friendly than nutrition menacing. Finally, this study concludes that SWAT-ReCiPe with FEF provides a quantitative framework for environment-food nexus assessment. However, due to the uncertainties, this method is recommended as a tool for comparing management strategies instead of reporting certain values.

A quantitative approach on environment-food nexus:

integrated modeling and indices for cumulative impact

assessment of farm management practices

Shervin Jamshidi[1], Anahita Naderi[1]

1- Department of Civil Engineering, University of Isfahan, Isfahan, Iran.

Corresponding Author:

Shervin Jamshidi

Hezar Jerib Ave, Azadi Sq., Isfahan, PO Code: 81746-73441, Iran.

Email: sh.jamshidi@eng.ui.ac.ir

Abstract

Background. Best management practices (BMPs) are promising solutions that can partially

control pollution discharged from farmlands. These strategies, like fertilizer reduction and using

filter strips, mainly control nutrient (N and P) pollution loads in basins.. However, they have

secondary impacts on nutrition production and ecosystem. This study develops a method to

evaluate the cumulative environmental impacts of BMPs. It also introduces and calculates

food's environmental footprint (FEF) for accounting the total environmental damages per

nutrition production.

Methods. This study combines the soil and water assessment tool (SWAT) for basin simulation

with the indices of ReCiPe, a life cycle impact assessment (LCIA) method. By these means, the

effectiveness of BMPs on pollution loads, production yields, and water footprints (WFs) are

24   evaluated and converted as equivalent environmental damages. This method is verified in

25   Zrebar Lake, western Iran. Here, water consumption, as WFs, and eutrophication are the main

26   indices that are converted into equivalent health and ecological impairments. Two methods,

27   entropy and environmental performance index (EPI), are used for weighting normalized

28   endpoints in last step.

29   **Results.** Results showed that using 25-50% less fertilizer and water for irrigation combined with

30   vegetated filter strips reduce N and P pollution about 34-60% and 8-21%, respectively. These

31   can decrease 5-9% ecosystem damages and 7-14% health risks. Here, freshwater

32   eutrophication is relatively a more critical damage in ecosystem. However, using less fertilizer

33   adversely reduces 1.7-3.7% total nutrition production. It means that BMPs can decline total

34   ecological damages and health risks, while threaten nutrition production. FEF presents a tool to

35   solve this dilemma about the sustainability of BMPs. In the study area, 4-9% decrease in FEF

36   means that BMPs are more environmental friendly than nutrition menacing. Finally, this study

37   concludes that SWAT-ReCiPe with FEF provides a quantitative framework for environment-food

38   nexus assessment. However, due to the uncertainties, this method is recommended as a tool

39   for comparing management strategies instead of reporting certain values.

Introduction

42   Best management practices (BMPs) are promising solutions for controlling pollution discharged

43   from non-point sources (NPS), including agriculture (Y. Liu et al., 2017). Phosphorous (P) and

44   nitrogen (N) compounds are typical pollutants transported in basins from farmlands (Hanief &

45   Laursen, 2019). Water quality degradation and eutrophication are the possible results of these

46   emissions. Filter strips (FS) (Merriman et al., 2019), fertilizer reduction (FR) (Geng et al., 2019),

47   no-tillage farming (Plunge et al., 2022), tracing and fencing (Sheshukov et al., 2016), constructed

48   wetlands (J. Li et al., 2021), straw mulching (Jang et al., 2017), or changing crop patterns and

49   land-uses (LUs) (Plunge et al., 2022) are some examples of BMPs. Although these strategies

50   have positive regional impacts on pollution transport (Stubbs, 2016), they may affect other

51   ecosystems (Čuček et al., 2015), farmers' income (Imani et al., 2017), and even nutrition

52   production. Therefore, assessing the effectiveness of BMPs needs detailed studies in basin scale

53   with combined methods.

54   Some research has recently evaluated the effectiveness of BMPs. In The Great Lakes, Merriman

55   et al. (2019) concluded that multiple BMPs combined with FS can reduce nutrients and sediment

56   more significantly than single BMPs. Here, total phosphorus (TP) and total nitrogen (TN)

57   removal could reach about 20% (Merriman et al., 2019). The results of Liu et al. (2019) similarly

58   showed that combined BMPs with FS are more effective on reducing pollution load than

59   individual BMPs. They recommended that modeling tools for cost-effective analysis can create a

60   more sustainable framework for water quality improvement in agricultural basins (Y. Liu et al.,

61   2019). Imani et al. (2019) also recommended to set priorities for BMPs in critical areas

62   according to their TN and TP reduction and related costs (Imani et al., 2019). Modeling with

63   field surveys verified that BMPs can reduce 25% nutrient pollution in a basin while sediment

64   entrapment in the riparian zone can develop organic nutrient removal to about 60%. FS can

65   solely act as an effective BMP with 20% TP removal (Sheshukov et al., 2016). Nonetheless,

66   BMPs may reduce the runoff and adversely concentrate pollutants downstream (Jang et al.,

67   2017). Farmers may also be reluctant to apply BMPs due to economic reasons. Therefore, an

68   integrated knowledge about farm characteristics and the environmental attitudes of farmers is

69   required before adopting BMPs (H. Liu & Brouwer, 2022). Dai et al. (2018) proposed a

70   combined model to create a series of BMPs placement schemes based on nutrients reduction and

71   related costs. They concluded that nutrient load discharged into the lake and tributaries could be

72 decreased to an acceptable level with a proper tradeoff between costs and risks (Dai et al., 2018).

73 In a brief, recent studies imply that pollution reduction, applicability, and economic issues are

74 the main concerns in BMP assessment. Nonetheless, their probable impacts on larger ecosystems

75 and nutrition production require further evaluations.

76 In the most of literature, soil and water assessment tool (SWAT) was the main technique for

77 integrated basin modeling. By this tool, the direct impacts of BMPs can be evaluated in

78 hydrological response units (HRUs) and receiving water bodies (Jamshidi et al., 2020). However,

79 this simulation tool cannot account both direct and indirect cumulative environmental impacts

80 (CIAs). A question remains that which BMP has the least total impacts on the ecosystem and

81 food production? Life cycle assessment (LCA) has the potential of answering this question

82 through a data inventory that quantifies main ecological indices. These indices can translate data

83 into ecological damages. It provides a framework for comparing strategies quantitatively based

84 on their CIAs. For example, Xu et al. (2017) compared the CIAs of different low impact

85 development BMPs as treatment systems (Xu et al., 2017). Comparing sludge-dredging methods

86 in Baiyangdian Lake, northern China (Zhou et al., 2021), treatment systems for Yangtze River

87 rehabilitation (Yao et al., 2021), and sea water desalination (Mannan et al., 2019) are other

88 applications of LCA in water quality management. Eutrophication is also a critical subject

89 among the midpoint indices in life cycle impact assessment (LCIA) (Cosme & Hauschild, 2017;

90 Rosenbaum et al., 2017). TN and TP concentrations in water directly affect this problem

91 (Chapra, 2008), while other features, such as water consumption, are also effective on freshwater

92 ecosystems, aquatic habitat or eutrophication intensification (Damiani et al., 2019). Since it is

93 difficult to evaluate the eutrophication potential of agricultural systems, a combined method is

94 required for the CIA of nutrients release from farmlands (Ortiz-Reyes & Anex, 2018).

95   The main purpose of this study is to develop a combined method based on SWAT-LCIA to

96   evaluate and compare the CIAs of BMPs in a basin. The developed framework also introduces a

97   state-of-the-art index for quantifying food environmental footprint (FEF). This approach

98   accounts related environmental damages of nutrition production in a basin and develops

99   environmental perspective in water-food nexus problems. For these purposes, a lake basin is

100   used as the study area to verify the proposed methodology. Here, the SWAT outputs are the main

101   inventory of related midpoint indices in ReCiPe, a developed LCIA method (M. Huijbregts et al.,

102   2016). Health, eutrophication, water consumption, aquatic and terrestrial ecosystems are the

103   affected environments. Their CIA is normalized afterwards and evaluated by endpoint indices as

104   ecological and health damages in ReCiPe. In addition, this research considers WF as the driving

105   index for water consumption in LCIA and uses two different methods in calculations for

106   weighting indices.

107

Materials & Methods

109   *METHODOLOGY*

110   This study follows a 4-step combined methodology. In the first two steps, data is gathered and a

111   basin is simulated by the SWAT model with the perspective of water quality and quantity. Here,

112   the effectiveness of different BMPs on exporting pollution loads (kg/ha), pollutants

113   concentration in lake (mg/L), crop production yields (ton/ha), nutrition production (Kcal/yr), and

114   water footprint (m^3) are evaluated. Thus, the modeling provides a quantitative framework for

115   further environmental-food analysis in basin. In this study, the first two steps, except the

116   nutrition production, follows the previously developed SWAT model by Jamshidi et al. (2020).

117   In the third step and to quantify the CIAs of BMPs, a combined method is developed to convert

118   the modeling results into equivalent environmental damages. An excel-base LCIA method

119   according to ReCiPe (2016 v1.1) is used including related characterization midpoints (water

120   consumption and eutrophication) and endpoints (human health and ecosystem damages) with

121   normalization coefficients. In this step, some new approaches are considered to develop LCIA

122   analysis. For example, the embodied water consumption, directly analyzed by the SWAT model

123   (WF), is introduced as a reliable water consumption index for the LCIA of food crops. This is

124   due to the fact that food crop's WF includes both consumed (blue and green) and polluted (grey)

125   water. These items fit to life cycle assessment of available water in the ecosystem (Bigdeli

126   Nalbandan et al., 2022). In addition, this step considered two different weighting approaches for

127   integrating health and ecosystem damages (endpoints) as a single index. The entropy analysis

128   uses a mathematical equation to calculate the weights of health and ecosystem, while

129   environmental performance index (EPI) applies predefined weights for the two endpoints.

130   In final step, a state-of-the-art index is introduced as "environmental footprint of food

131   production" (FEF) that calculates the cumulative environmental damages of nutrition production

132   in basins. This new index is applicable for quantifying the equivalent environmental damages

133   related to food production. It also compares the cumulative impacts of BMPs and farm

134   management practices by considering different perspectives like WF, pollution emissions, crop

135   nutrition, and ecosystem protection. The main contribution of this research is in its combined

136   method, particularly the third and fourth steps. Here, an environment-food nexus analysis

137   compares the cumulative impacts of BMPs in a basin. The methodology steps are illustrated in

138   Figure 1.

139   Authors have chosen Zrebar Basin, western Iran, to verify the method. It doesn't mean this

140   approach is developed for a specific basin. On the contrary, the SWAT-ReCiPe is applicable in

141   any basin for comparing farm management strategies.

142

143   *STUDY AREA*

144   The proposed methodology is verified in Zrebar Lake basin, western Iran. Zrebar basin

145   encompasses 90 km^2 including 20 km^2 of irrigated and rain-fed farmlands (22%). Its lake meets

146   eutrophication problem mainly due to the agricultural discharges, particularly irrigated farmlands

147   (Imani et al., 2019). Main rain-fed (RF) crops in this area are wheat, barley, grape and peas with

148   average nutrition values of 3640, 3540, 670 and 420 Cal/kg, respectively. The irrigated crops

149   include tomato, tobacco, alfalfa, apple with average nutrition values of 180, 0, 230, and 520

150   Cal/kg, respectively in addition to irrigated wheat and barley. Figure 2 shows the dominant LUs

151   in the study area with its geographical conditions.

152

153   *SIMULATION-CALIBRATION*

154   In the proposed methodology, the SWAT model is used for basin simulation before accounting

155   environmental damages and footprints of agricultural productions. This model can simulate

156   complicated systems by considering management practices in farmlands, interactions between

157   water quality and quantity, pollution transport, and production yields (Abbaspour et al., 2015;

158   Arnold, Moriasi, et al., 2012; Rivas-Tabares et al., 2019). Therefore, required data such as

159   topography, soil properties, LU type, management practices, and weather/climate were inputted

160   to the model (Table 1). The basin was split into 26 sub-basins and 1100 HRUs. This model was

161   calibrated and validated based on available data (2006-2013) of monthly lake inflow, nitrate and

162 phosphate concentrations simultaneously. Production yields and evapotranspiration rates were

163 also controlled with the observation data (Jamshidi et al., 2020). Table 2 outlines the calculated

164 regression coefficient (R^2) and RMSE-observations standard deviation ratio (RSR) in the

165 calibrated model.

166 It is noteworthy that the main idea of this research is to develop an integrated method for

167 accounting environment-food nexus. Accordingly, authors used the outputs of the already

168 calibrated SWAT model previously developed for BMP and WF assessment in the study area

169 (Jamshidi et al., 2020). Thus, simulation-calibration details are skipped here as they can be fully

170 retrieved in the cited reference.

171

172 *BMP SCENARIO*

173 This study uses the SWAT outcomes for BMP analysis in 3 scenarios as defined in Table 3. Base

174 is the scenario without using any BMPs. In BMP1, the application of fertilizers, manure and

175 chemical, and water for irrigation are reduced 25% for farmlands. In BMP2, the reduction equals

176 50%. In both BMP scenarios, FS is assumed to be implemented in the vicinity of lake. Slim FS

177 represents 10-12 m width, while moderate FS has 20-25 m width. All scenarios are analyzed by

178 the SWAT model in the same period from 2007-2013.

179

180 *WATER FOOTPRINT*

181 The WFs of agricultural productions are accounted by the standard method and include the three

182 main elements of green, blue and grey water (Franke et al., 2013; Hoekstra et al., 2011). It

183 should be noted that WFs calculate the direct embedded water of farmlands and exclude indirect

184 water embodied in further processing of agricultural productions.

185    $WF = GnWF + BWF + GWF$ (1)

186    $GnWF = 10ET_a$ (2)

187    $BWF = 10(ET_b - ET_a)$ (3)

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

189   In these equations, *GnWF, BWF* and *GWF* are green, blue and grey water footprints (m³),

190   respectively. ET_a refers to the evapotranspiration from soil and vegetations when there is no

191   irrigation (mm). ET_b includes the total evapotranspiration during irrigation ($ET_b > ET_a$). Thus,

192   the SWAT models evapotranspiration twice with and without irrigation. It uses the climatic data

193   of minimum and maximum daily temperature with precipitation as mentioned in Table 1.

194   Afterwards, it estimates the actual evapotraspiration for crops by Hargreaves equation (Kisi,

195   2007; Majidi et al., 2015). *L* is the exported pollution loads (ton/ha) of pollutant *i* to the receiving

196   water body. In modeling, output.hru file shows the pollution loads per each HRU and sub-basin.

197   *L* is the net pollution loads transported from LUs into the 26th sub-basin, the Zrebar Lake in this

198   study (Arnold, Kiniry, et al., 2012). C_{max} is the maximum allowable concentration of pollutants.

199   C_{nat} equals pollutants concentration in the receiving water on the condition there is no human

200   interference. Here, the C_{max} of TN and TP are assumed constant according to the global limits for

201   controlling the trophic state of lakes (Jamshidi, 2021) and they equal 1.5 and 0.035 mg/L,

202   respectively. C_{nat} of TN and TP are also assumed 0.4 and 0.01 mg/L, respectively (Jamshidi et

203   al., 2022).

204

205   *ENVIRONMENTAL IMPACT ASSESSMENT*

206   The quantification method of environmental damages in basin is compatible with the indices of

207   LCIA. In the current research, LCIA characterization coefficients are derived according to the

208   ReCiPe method, which was previously developed by some collaborations in Europe (M. A. J.

209   Huijbregts et al., 2017). In this method, normalized data at the European and global level are

210   available for 16 midpoint and 3 endpoint indices. In later updates, ReCiPe considered several

211   conversion coefficients based on global scale, instead of the European scale. However, it

212   preserved the possibility of using these coefficients on the continental and country scales.

213   Another feature of ReCiPe is to expand environmental damages for evaluating the impacts of

214   water consumption on human health, aquatic and terrestrial ecosystems (M. A. J. Huijbregts et

215   al., 2017). However, the current study proposes to use WF for accounting the water consumption

216   of food crops in LCIA. This is due to the ability of WF in calculating water consumption

217   including both water quality and quantity.

218   In this method, all effective environmental factors derived from the SWAT model are initially

219   converted into the equivalent units. Table 4 illustrates eutrophication midpoint coefficients that

220   convert NO_3, NO_2, NH_3 and PO_4 to the equivalent environmental damages. The average WFs of

221   crops are considered (m^3) for water consumption midpoint in aquatic, terrestrial and marine

222   ecosystems. Equation 5 shows how conversions are carried out.

223    $Q_j = (T \times M)_j$ $\hspace{8cm}$ (5)

224   Q is the midpoint index, T represents the output of the SWAT model such as water footprint or

225   pollutant concentration, M is the conversion coefficients, and j is environmental component such

226   as aquatic, terrestrial, and marine. By this equation, it is possible to calculate the equivalent

227   environmental effects of each pollutant in the life cycle period of the product or activity. It

228   should be noted that these coefficients represent average values. It means that they do not need

229   supplementary conversion coefficients for shallow or deep waters as they are free from

230   adjustment for the conditions with different vegetation or trophic state. Moreover, pollution

231   discharge to freshwater has indirect impacts on other ecosystems in long-term. Thus, marine

232   impacts are also considered in calculation even the pollution is not directly discharged to the sea.

233   Since the midpoint indices are calculated based on equivalent units, such as kgN-eq or m^3 water

234   consumed, it is necessary to accumulate these environmental impacts with different units under a

235   single index. This is the most challenging step in conventional CIA. ReCiPe uses equivalent

236   damage-based indices for integrating midpoints into endpoints by Equation 6.

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

238   Here, the calculated midpoint indices (Q) are converted into endpoint damage-based indices (D)

239   according to conversion coefficient of E (see Table 5). Here, human health and ecosystem (non-

240   human) damages are two endpoint indices. The former is based on disability-adjusted life years

241   (DALY) and the latter is based on probable number of harmed species in year (species.yr).

242   DALY represents the equivalent years of human life lost by death or being disabled due to illness

243   caused by existing pollutants in the environment. On the other hand, the unit of measuring

244   ecosystem damage is the total number of species lost over time. Table 5 shows the conversion

245   coefficients that turn each equivalent midpoint indices into the two endpoints. ReCiPe model

246   also recommends that endpoints (D) should be normalized by specific coefficients that turn the

247   calculated damages into dimensionless indices per person (Sleeswijk et al., 2008).

248

249   *NORMALIZATION AND WEIGHTING*

250   Calculated endpoints are normalized by Equation 7 on a global scale based on reference

251   coefficients (Table 5). They are finally aggregated according to their weights by Equation 8. In

252   this study, entropy and EPI are the weighting methods of normalized endpoints.

253    $R = \dfrac{D}{N}$ (7)

254    $C = \sum(W \times R)$ (8)

255   Where, C is the annual environmental damage per person, W is the weight of each endpoint, N

256   represents the normalization value and R is the normalized endpoint. Weights can be calculated

257   based on different mathematical methods, such as entropy or fuzzy (J. Chen et al., 2019; Zeng et

258   al., 2022), or based on expert opinions and references (Z. Chen et al., 2022). In this study, EPI

259   determines health and ecosystem weights as 0.4 and 0.6, respectively (Hsu & Zomer, 2016),

260   whereas entropy method ($W_{En.}$) calculates the weights of endpoints through a probabilistic

261   function as Equation 9.

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

263   In which, t is the number of available data. In entropy, factors with more data dispersion gain

264   higher weights (Imani et al., 2019). Here, the weights of endpoints (R) are evaluated based on C

265   variations from 2007-2013 in each BMP scenario. Accordingly, the ecosystem and health

266   endpoints weigh 0.44 and 0.56, respectively in the entropy method.

267

268   *ENVIRONMENTAL-FOOD INDEX*

269   This study introduces a new index for food and nutrition production in farmlands. It is quantified

270   based on the environmental damages calculated by the SWAT-ReCiPe. This index quantifies the

271   CIA per food production in any area or BMP as Equation 10.

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

273   In this equation, *FEF* is a dimensionless index that represents the CIA of food production. In

274   other words, *FEF* is the environmental footprint of nutrition production. It can be calculated by

275   the proposed method for comparing major environmental concerns in food production, including

276   water-food nexus. Low *FEF* (~0) means that strategies used for food production is rather clean,

277   while higher *FEF* (>1) indicates their destructive condition. *C* is defined earlier that notes

278   environmental damages (CIA), and *S* is calculated by Equation 11.

279    $S = \dfrac{T_{Cal}}{B \times P}$ (11)

280   In which T_{Cal} is the daily total nutrition (calories) of food production in the study area, *B* equals

281   the malnutrition baseline of humans assumed 2000 cal/day (D. Liu et al., 2022), and *P* is the

282   global population (7.75 billion) to convert and normalize *S* per person in global scale.

283

Results and discussions

285   *SWAT OUTCOMES*

286   The basin simulation by the SWAT model could calculate the annual pollution loads exported by

287   HRUs in different management scenarios. Figures 3 and 4 respectively show the cumulative N

288   and P loads discharged by farmlands in three scenarios. Here, the annual variations are due to 1)

289   the precipitation variation influencing pollution transport from RF farms, and 2) temporary water

290   transfers from upstream for irrigation development. The average N pollution of all irrigated and

291   RF farms ranges between 1176 and 3985 kg yr^{-1}. This value for P is between 20 and 82 kg yr^{-1}.

292   For 20 km^2 farming area, the average export coefficients for N and P are 0.6-2 kg ha^{-1} yr^{-1} and

293   0.01-0.04 kg ha^{-1} yr^{-1}, respectively. This range implies that nutrient export coefficients can

294   increase 3-4 times greater than dry periods in the study area. On an average for 2007 to 2013,

295   BMP1 can reduce 33.8%N and 7.7%P pollution exported from all agricultural LUs. BMP2 can

296   improve these removals to 59.9% and 20.9% for N and P, respectively. It implies that basin

297   response to BMPs' is not linear. In addition, P removal requires stricter BMPs than N removal.

298   Yet, nutrient pollution reduction may have different ecological impacts on marine, aquatic and

299   terrestrial systems which are accounted through the combined method. BMPs are also effective

300   on crops production yields, WFs and nutrition productions (Table 6).

301

302   *ENVIRONMENTAL IMPACTS*

303   For the base scenario, the combined method calculates the environmental midpoint impact (Q) of

304   farming in Zrebar basin as Figure 5. It shows that freshwater eutrophication is the most critical

305   item during the study period. The embodied water consumed is also significant for damaging the

306   terrestrial ecosystem and human health. This conclusion remains unchanged in BMP1 and BMP2

307   despite 25%-50% FR (Figure 6). Since TP concentration in lake is the main driver of freshwater

308   eutrophication, consuming less ammonium-based fertilizer can hardly solve eutrophication

309   problem in short term in the combined method. On the contrary, controlling erosion and

310   sediment transport by FS from upstream is more efficient for TP mitigation in the lake.

311   Figure 7 shows the cumulative ecological damages. Their values in Zrebar basin are relatively

312   larger than health problems in all management scenarios. It is noteworthy that human health

313   indices are mostly reliant on toxins and heavy metals. These pollutants were hardly traced in the

314   study area. The results present that farm management strategies can mitigate the average

315   ecological impacts from 1.41E-6 to 1.34E-6 (4.9%) for BMP1 and 1.28E-6 (9.2%) for BMP2.

316   Likewise, these strategies can diminish human health risk from 2.58E-7 to 2.4E-7 (6.8%) for

317   BMP1 and 2.22E-7 (13.9%) for BMP2. It means that using 50% less fertilizer with a FS in this

318   area may totally reduce 9% ecological and 14% health risks (Figure 8). Here, the cumulative

319   impacts are low but not negligible as they range between 1E-6 and 1E-7 per person. However,

320   these values are meaningless unless they are used as quantitative tools for comparative analysis.

321   Figure 8 summarizes the impacts of BMPs on food production (S) in addition to normalized

322   environmental impacts (per person) on the ecosystem and health. Since nutrition production is

323 intrinsically a favorable action with environmental perspective, their related impacts are

324 negative. The overall environmental impact of farming and related management practices are

325 finally calculated by the weighted average of normalized ecosystem and health damages. The

326 weighing step is carried out with different methods. Since EPI gives higher weights to ecological

327 items, the related results are relatively more than entropy method. Despite different weighting

328 approaches, the overall CIA (C) reduction for BMP1 ranges between 5-8%, while it ranges

329 between 10-13% for BMP2. It implies that using strict BMPs may not necessarily have

330 significant improvement. On the contrary, S is reduced 1.66% and 3.73% by BMP1 and BMP2,

331 respectively. It points an important conclusion that although farm management practices may

332 reduce environmental damages, they can adversely reduce the nutrition production. This

333 conclusion highlights an environment-food nexus index for more comprehensive understanding

334 of management impacts.

335 Figure 9 draws the environmental footprint of nutrition production (FEF) in Zrebar Basin. Here,

336 the conventional pattern (base scenario) can quantitatively generate 0.61 (Entropy) and 0.78

337 (EPI) environmental impacts. In other words, 0.61-0.78 environmental units would be damaged

338 for one unit nutrition production. This is a footprint mainly accounted by the impacts of

339 consumed water and eutrophication in the study area originated by the agriculture. Using BMP1

340 and BMP2 can reduce FEF 6.5-9.1% (entropy) and 4-6.4% (EPI), respectively. It means that

341 50% FR combined with FS (BMP2) can reduce 6.4-9.1% of FEF in Zrebar basin. Obviously, this

342 new index is more helping for policy makers rather than conventional approach on pollution

343 reductions in a basin. For example, this index can present criteria to compare two alternatives of

344 implementing vegetated FS or changing crop patterns in a basin. The first alternative only

345 reduces pollution loads and consequently environmental impacts, while the second option

346 emphasizes nutrition improvement despite pollution discharges.

347

348 *DISCUSSION*

349 What stands out this research and makes it different with previous literature is combining

350 SWAT-ReCiPe for accounting the new damage-based index of FEF. This idea provided a

351 quantitative solution to include water quality issues within water-energy-food nexus problems

352 (Heal et al., 2021). It is verified in a lake basin with different irrigated and rain-fed farming.

353 Results showed that N and P pollution removal by BMPs in Zrebar lake basin varies between 34-

354 60% and 8-21%, respectively. These ranges are comparable with recent literature. For example,

355 Venishetty and Parajuli (2022) estimated 25%N and 10%P removal by FS and riparian buffer

356 zone (Venishetty & Parajuli, 2022). In another study, the minimum impact of FS on TN and TP

357 removal was 29% and 42%, respectively (Risal & Parajuli, 2022). In a river basin with 20000

358 km^2 area, P export coefficient was 0.63 kgha^{-1}yr^{-1} and FS could reduce 4-20% of its pollution

359 (Almendinger & Ulrich, 2017). Ricci et al. (2022) also estimated TN and TP export coefficients

360 about 49 kg ha^{-1}y^{-1} and 0.044 kg ha^{-1}y^{-1}, respectively in a river basin. Here, BMPs could remove

361 20% nutrient pollution loads from farmlands (Ricci et al., 2022).

362 The current study also implied that BMPs may have secondary impacts due to long-term

363 terrestrial and aquatic pollution transport, water consumption, or changing LUs. Similar

364 conclusion has been recently achieved by McAuliffe et al. (2022). They highlighted that direct

365 short-term water quality rehabilitation, such as TN and TP reduction, may not necessarily ends

366 into a sustainable strategy. With the perspective of integrated environmental management, on-

367 farm intervention strategies have by-effects that should be considered in decision-making

368   (McAuliffe et al., 2022). The proposed method can more or less consider these impacts via

369   LCIA. However, midpoint indices can be different on the subject of basin specifications. For

370   example, water consumption and eutrophication are the main environmental issues in the current

371   study. In different regions, other environmental issues like global warming, LU change, and even

372   air pollution have related indices in ReCiPe (M. A. J. Huijbregts et al., 2017). Variety in

373   midpoint indices may not limit SWAT-ReCiPe and FEF application. On the contrary, its

374   multidisciplinary specification develops its purpose to calculate broader range of environmental

375   damages for integrated monitoring and problem solving. For example, it is conventionally

376   believed that hydropower systems in water reservoirs are a renewable energy source and

377   environmental friendly. Nevertheless, it is recently noted that these systems can be the

378   significant sources of greenhouse gas emissions due to their long-term secondary limnology and

379   ecological impacts (Gemechu & Kumar, 2022). Čuček et al. (2015) recommended LCA method

380   for environmental assessment because of the chance of using footprints, such as carbon footprint,

381   biodiversity footprint, ecological footprint, etc. (Čuček et al., 2015). These indices can help to

382   account cumulative environmental footprint of productions within LCIA similar to the method

383   used for WF in this study. It is noteworthy that recent literature has also focused on developing

384   social LCA indices (Bouillass et al., 2021; Siebert et al., 2018). This perspective aims on

385   integrating social with environmental-based LCA indices. In other words, the safe and healthy

386   living conditions of farmers, their employment, social fairness, and public commitment to

387   sustainability would also be important in decision-making (Kühnen & Hahn, 2017). Thus, we

388   recommend future studies to assess the cumulative impacts of BMPs based on the combined

389   social-environmental indices of LCIA before FEF evaluation.

390 This study also applied the SWAT model for basin simulation. It could present a reliable

391 framework for integrated LCIA, WF and water quality assessment in different BMPs. It is

392 noteworthy that using WF is more efficient in LCIA than typical water consumption. It has two

393 reasons: 1) WF is the embodied water in production. Thus, it is compatible with other LCA

394 indices as both consider indirect impacts, 2) WF includes equivalent water pollutions in form of

395 GWF within the consumed water. GWF is an exceptional index for LCIA as it bridges water

396 pollution to unavailable water for health or ecosystem consumption. It means that GWF is the

397 only functional index that enables LCIA to include the indirect impacts of water pollution on

398 destroying water resources. Recent studies could even develop the understanding about GWF. In

399 new definition, regional ecological impairments are decisive for GWF calculations (Jamshidi et

400 al., 2022). The interactions between water resource and ecological assessment does not limit to

401 WF assessment. A recent study used environmental Kuznets curves with the SWAT model.

402 Researchers assessed the relationship between environmental degradation and developing

403 agriculture (Golzari et al., 2022). However, the current study could develop a quantifiable

404 method for integrated water and environmental assessment based on WF, LCIA and FEF indices.

405 The proposed method can also be applicable for climate change. Delavar et al. (2022) showed

406 the applicability of the SWAT model for water accounting during both wet and dry periods of

407 climate change (Delavar et al., 2022). On the other hand, the effectiveness of 171 BMPs on

408 reducing TN and TP were previously analyzed by LCA approach (Chiang et al., 2012). Despite

409 the abilities of the SWAT model for basin water quality modeling (Bigdeli Nalbandan et al.,

410 2022; W. Li et al., 2021), this method has limits on accurate simulation of some pollutants.

411 Toxins, heavy metals, and microbial pollution require accurate simulation as their impacts on

412 health and ecological midpoint indices are critical in LCIA. However, they are sensitive to

413   contamination transports and environmental conditions. Erosion, sediment adsorption and re-

414   suspension, biomass accumulation, and volatilization are different transports that increase the

415   uncertainties of both field samples and simulated results (Du et al., 2019; Ouyang et al., 2018).

416   Further studies can focus on finding proper tools for simulating these pollutants in combination

417   with LCIA. Since uncertainty is the main drawback of the proposed method, authors recommend

418   it as an applicable tool for comparing the effectiveness of different strategies respecting their

419   CIAs and FEFs.

420

Conclusions

421

422   Pollution control is only one pillar of BMPs' sustainability assessment. Their impacts in larger

423   ecosystems are also crucial for integrated decision-making. This study developed a method that

424   combines basin simulation and life cycle impact assessment (LCIA). The soil and water

425   assessment tool (SWAT) simulates the basin, while ReCiPe uses the modeling results as an

426   inventory for LCIA. This approach has some advantages for the sustainability assessment of

427   BMPs:

428   • It is a quantitative tool based on various environmental indices. The cumulative

429   environmental impact accounts possible aquatic, terrestrial and marine impairments.

430   Thus, it can simplify integrated evaluations and comparing BMPs.

431   • It is flexible to include new or integrated indices. Food environmental footprint (FEF) is a

432   state of the art index that quantifies the total environmental damages of one unit nutrition

433   production. In a nutshell, FEF can add environmental footprint in water-food-energy

434   nexus problems.

435 In the study area, fertilizer reduction and filter strip were effective on controlling nutrient

436 pollution without notable negative impacts. BMPs reduced FEF and water footprint (WF)

437 and improved eutrophication problem. However, uncertainties were the main limits and

438 drawbacks. These uncertainties are mainly reliant on LCIA coefficients and modeling

439 pollution transports. Thus, this idea is recommended as a tool for comparing strategies

440 instead of reporting certain results. Future studies can focus on upgrading this method.

441 Developing indices, variable midpoints and footprints, besides social indices are some

442 possible research areas.

References

444 Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A
445   continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a
446   high-resolution large-scale SWAT model. *Journal of Hydrology*, *524*, 733–752.
447   https://doi.org/10.1016/j.jhydrol.2015.03.027

448 Almendinger, J. E., & Ulrich, J. S. (2017). Use of SWAT to Estimate Spatial Scaling of Phosphorus
449   Export Coefficients and Load Reductions Due to Agricultural BMPS. *JAWRA Journal of the*
450   *American Water Resources Association*, *53*(3), 547–561. https://doi.org/10.1111/1752-1688.12523

451 Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., & Neitsch, S. L. (2012). *Soil &*
452   *Water Assessment Tool: Input/Output Documentation*.

453 Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C.,
454   Harmel, R. D., van Griensven, A., Van Liew, M. W., Kannan, N., & Jha, M. K. (2012). SWAT:
455   Model Use, Calibration, and Validation. *Transactions of the ASABE*, *55*(4), 1491–1508.
456   https://doi.org/10.13031/2013.42256

457 Bigdeli Nalbandan, R., Delavar, M., Abbasi, H., & Zaghiyan, M. R. (2022). Model-based water footprint
458   accounting framework to evaluate new water management policies. *Journal of Cleaner Production*,
459   135220. https://doi.org/10.1016/j.jclepro.2022.135220

460 Bouillass, G., Blanc, I., & Perez-Lopez, P. (2021). Step-by-step social life cycle assessment framework: a
461   participatory approach for the identification and prioritization of impact subcategories applied to
462   mobility scenarios. *The International Journal of Life Cycle Assessment*, *26*(12), 2408–2435.
463   https://doi.org/10.1007/s11367-021-01988-w

464 Chapra, S. C. (2008). *Surface water quality modelling*. Waveland Press.

465 Chen, J., Wang, Y., Li, F., & Liu, Z. (2019). Aquatic ecosystem health assessment of a typical sub-basin
466   of the Liao River based on entropy weights and a fuzzy comprehensive evaluation method. *Scientific*
467   *Reports*, *9*(1), 14045. https://doi.org/10.1038/s41598-019-50499-0

468 Chen, Z., Zhong, P., Liu, M., Ma, Q., & Si, G. (2022). An integrated expert weight determination method
469   for design concept evaluation. *Scientific Reports*, *12*(1), 6358. https://doi.org/10.1038/s41598-022-
470   10333-6

471 Chiang, L.-C., Chaubey, I., Hong, N.-M., Lin, Y.-P., & Huang, T. (2012). Implementation of BMP
472   Strategies for Adaptation to Climate Change and Land Use Change in a Pasture-Dominated
473   Watershed. *International Journal of Environmental Research and Public Health*, *9*(10), 3654–3684.
474   https://doi.org/10.3390/ijerph9103654

475 Cosme, N., & Hauschild, M. Z. (2017). Characterization of waterborne nitrogen emissions for marine

476   eutrophication modelling in life cycle impact assessment at the damage level and global scale.
477   *International Journal of Life Cycle Assessment*, *22*(10), 1558–1570. https://doi.org/10.1007/s11367-
478   017-1271-5

479   Čuček, L., Klemeš, J. J., & Kravanja, Z. (2015). Overview of environmental footprints. In *Assessing and*
480   *Measuring Environmental Impact and Sustainability* (pp. 131–193). Elsevier.
481   https://doi.org/10.1016/B978-0-12-799968-5.00005-1

482   Dai, C., Qin, X. S., Tan, Q., & Guo, H. C. (2018). Optimizing best management practices for nutrient
483   pollution control in a lake watershed under uncertainty. *Ecological Indicators*, *92*, 288–300.
484   https://doi.org/https://doi.org/10.1016/j.ecolind.2017.05.016

485   Damiani, M., Lamouroux, N., Pella, H., Roux, P., Loiseau, E., & Rosenbaum, R. K. (2019). Spatialized
486   freshwater ecosystem life cycle impact assessment of water consumption based on instream habitat
487   change modeling. *Water Research*, *163*, 114884.
488   https://doi.org/https://doi.org/10.1016/j.watres.2019.114884

489   Delavar, M., Eini, M. R., Kuchak, V. S., Zaghiyan, M. R., Shahbazi, A., Nourmohammadi, F., &
490   Motamedi, A. (2022). Model-based water accounting for integrated assessment of water resources
491   systems at the basin scale. *Science of The Total Environment*, *830*, 154810.
492   https://doi.org/10.1016/j.scitotenv.2022.154810

493   Du, X., Shrestha, N. K., & Wang, J. (2019). Incorporating a non-reactive heavy metal simulation module
494   into SWAT model and its application in the Athabasca oil sands region. *Environmental Science and*
495   *Pollution Research*, *26*(20), 20879–20892. https://doi.org/10.1007/s11356-019-05334-4

496   Franke, N. A., Boyacioglu, H., & Hoekstra, A. Y. (2013). Grey Water Footprint Accounting: Tier 1
497   Supporting Guidelines, Value of Water Research Report Series No. 65. In *UNESCO-IHE Institute*
498   *for Water Education* (Issue November). Unesco-Ihe Delft.

499   Gemechu, E., & Kumar, A. (2022). A review of how life cycle assessment has been used to assess the
500   environmental impacts of hydropower energy. *Renewable and Sustainable Energy Reviews*, *167*,
501   112684. https://doi.org/https://doi.org/10.1016/j.rser.2022.112684

502   Geng, R., Yin, P., & Sharpley, A. N. (2019). A coupled model system to optimize the best management
503   practices for nonpoint source pollution control. *Journal of Cleaner Production*, *220*, 581–592.
504   https://doi.org/10.1016/j.jclepro.2019.02.127

505   Golzari, S., Abyaneh, H. Z., Dinan, N. M., Delavar, M., & Wagner, P. D. (2022). Modeling the effects of
506   human influences on water quality and quantity in the Zarrineh River Basin, Iran. *Journal of Hydro-*
507   *Environment Research*, *40*, 51–63. https://doi.org/10.1016/j.jher.2021.11.001

508   Hanief, A., & Laursen, A. E. (2019). Meeting updated phosphorus reduction goals by applying best
509   management practices in the Grand River watershed, southern Ontario. *Ecological Engineering*,
510   *130*, 169–175. https://doi.org/https://doi.org/10.1016/j.ecoleng.2019.02.007

511   Heal, K. V., Bartosova, A., Hipsey, M. R., Chen, X., Buytaert, W., Li, H.-Y., McGrane, S. J., Gupta, A.
512   B., & Cudennec, C. (2021). Water quality: the missing dimension of water in the water–energy–food
513   nexus. *Hydrological Sciences Journal*, *66*(5), 745–758.
514   https://doi.org/10.1080/02626667.2020.1859114

515   Hoekstra, A. Y., Chapagain, A. K., Mekonnen, M. M., & Aldaya, M. M. (2011). *The water footprint*
516   *assessment manual: Setting the global standard*. Routledge.

517   Hsu, A., & Zomer, A. (2016). Environmental Performance Index. In *Wiley StatsRef: Statistics Reference*
518   *Online* (pp. 1–5). Wiley. https://doi.org/10.1002/9781118445112.stat03789.pub2

519   Huijbregts, M. A. J., Steinmann, Z. J. N., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M., Zijp, M.,
520   Hollander, A., & van Zelm, R. (2017). ReCiPe2016: a harmonised life cycle impact assessment
521   method at midpoint and endpoint level. *The International Journal of Life Cycle Assessment*, *22*(2),
522   138–147. https://doi.org/10.1007/s11367-016-1246-y

523   Huijbregts, M., Steinmann, Z. J. N., Elshout, P. M. F. M., Stam, G., Verones, F., Vieira, M. D. M., Zijp,
524   M., & van Zelm, R. (2016). ReCiPe 2016 - A harmonized life cycle impact assessment method at
525   midpoint and endpoint level. Report I: Characterization. *National Institute for Public Health and the*
526   *Environment*, 194.

527 Imani, S., Delavar, M., & Niksokhan, M. H. (2019). Identification of Nutrients Critical Source Areas with
528   SWAT Model under Limited Data Condition. *Water Resources*, *46*(1), 128–137.
529   https://doi.org/10.1134/S0097807819010147
530 Imani, S., Niksokhan, M. H., Jamshidi, S., & Abbaspour, K. C. (2017). Discharge permit market and farm
531   management nexus: an approach for eutrophication control in small basins with low-income
532   farmers. *Environmental Monitoring and Assessment*, *189*(7), 346. https://doi.org/10.1007/s10661-
533   017-6066-4
534 Jamshidi, S. (2021). Grey Water Footprint Accounting, Challenges, and Problem-Solving. In
535   *Agroecological Footprints Management for Sustainable Food System* (pp. 247–271). Springer
536   Singapore. https://doi.org/10.1007/978-981-15-9496-0_8
537 Jamshidi, S., Imani, S., & Delavar, M. (2020). Impact Assessment of Best Management Practices (BMPs)
538   on the Water Footprint of Agricultural Productions. *International Journal of Environmental*
539   *Research*, *14*(6), 641–652. https://doi.org/10.1007/s41742-020-00285-y
540 Jamshidi, S., Imani, S., & Delavar, M. (2022). An approach to quantifying the grey water footprint of
541   agricultural productions in basins with impaired environment. *Journal of Hydrology*, *606*, 127458.
542   https://doi.org/10.1016/j.jhydrol.2022.127458
543 Jang, S. S., Ahn, S. R., & Kim, S. J. (2017). Evaluation of executable best management practices in
544   Haean highland agricultural catchment of South Korea using SWAT. *Agricultural Water*
545   *Management*, *180*, 224–234. https://doi.org/10.1016/j.agwat.2016.06.008
546 Kisi, O. (2007). Evapotranspiration modelling from climatic data using a neural computing technique.
547   *Hydrological Processes*, *21*(14), 1925–1934. https://doi.org/10.1002/hyp.6403
548 Kühnen, M., & Hahn, R. (2017). Indicators in Social Life Cycle Assessment: A Review of Frameworks,
549   Theories, and Empirical Experience. *Journal of Industrial Ecology*, *21*(6), 1547–1565.
550   https://doi.org/10.1111/jiec.12663
551 Li, J., Zheng, B., Chen, X., Li, Z., Xia, Q., Wang, H., Yang, Y., Zhou, Y., & Yang, H. (2021). The Use of
552   Constructed Wetland for Mitigating Nitrogen and Phosphorus from Agricultural Runoff: A Review.
553   *Water*, *13*(4), 476. https://doi.org/10.3390/w13040476
554 Li, W., Zhe, C., Hui-ying, L., & Dun-qiu, W. (2021). Simulation of nitrogen and phosphorus pollution in
555   typical agricultural and forested basins as well as relevant reduction effect based on SWAT model.
556   *Water Supply*, *21*(3), 992–1004. https://doi.org/10.2166/ws.2020.237
557 Liu, D., Huang, Y., Huang, C., Yang, S., Wei, X., Zhang, P., Guo, D., Lin, J., Xu, B., Li, C., He, H., He,
558   J., Liu, S., Shi, L., Xue, Y., & Zhang, H. (2022). Calorie Restriction with or without Time-
559   Restricted Eating in Weight Loss. *New England Journal of Medicine*, *386*(16), 1495–1504.
560   https://doi.org/10.1056/NEJMoa2114833
561 Liu, H., & Brouwer, R. (2022). Incentivizing the future adoption of best management practices on
562   agricultural land to protect water resources: The role of past participation and experiences.
563   *Ecological Economics*, *196*, 107389. https://doi.org/https://doi.org/10.1016/j.ecolecon.2022.107389
564 Liu, Y., Engel, B. A., Flanagan, D. C., Gitau, M. W., McMillan, S. K., & Chaubey, I. (2017). A review on
565   effectiveness of best management practices in improving hydrology and water quality: Needs and
566   opportunities. *Science of The Total Environment*, *601–602*, 580–593.
567   https://doi.org/10.1016/j.scitotenv.2017.05.212
568 Liu, Y., Wang, R., Guo, T., Engel, B. A., Flanagan, D. C., Lee, J. G., Li, S., Pijanowski, B. C.,
569   Collingsworth, P. D., & Wallace, C. W. (2019). Evaluating efficiencies and cost-effectiveness of
570   best management practices in improving agricultural water quality using integrated SWAT and cost
571   evaluation tool. *Journal of Hydrology*, *577*, 123965. https://doi.org/10.1016/j.jhydrol.2019.123965
572 Majidi, M., Alizadeh, A., Vazifedoust, M., Farid, A., & Ahmadi, T. (2015). Analysis of the Effect of
573   Missing Weather Data on Estimating Daily Reference Evapotranspiration Under Different Climatic
574   Conditions. *Water Resources Management*, *29*(7), 2107–2124. https://doi.org/10.1007/s11269-014-
575   0782-0
576 Mannan, M., Alhaj, M., Mabrouk, A. N., & Al-Ghamdi, S. G. (2019). Examining the life-cycle
577   environmental impacts of desalination: A case study in the State of Qatar. *Desalination*, *452*, 238–

578   246. https://doi.org/10.1016/j.desal.2018.11.017

579   McAuliffe, G. A., Zhang, Y., & Collins, A. L. (2022). Data, and sample sources thereof, on water quality
580   life cycle impact assessments pertaining to catchment scale acidification and eutrophication
581   potentials and the benefits of on-farm mitigation strategies. *Data in Brief*, 108505.
582   https://doi.org/https://doi.org/10.1016/j.dib.2022.108505

583   Merriman, K. R., Daggupati, P., Srinivasan, R., & Hayhurst, B. (2019). Assessment of site-specific
584   agricultural Best Management Practices in the Upper East River watershed, Wisconsin, using a
585   field-scale SWAT model. *Journal of Great Lakes Research*, *45*(3), 619–641.
586   https://doi.org/https://doi.org/10.1016/j.jglr.2019.02.004

587   Ortiz-Reyes, E., & Anex, R. P. (2018). A life cycle impact assessment method for freshwater
588   eutrophication due to the transport of phosphorus from agricultural production. *Journal of Cleaner
589   Production*, *177*, 474–482. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.12.255

590   Ouyang, W., Wang, Y., Lin, C., He, M., Hao, F., Liu, H., & Zhu, W. (2018). Heavy metal loss from
591   agricultural watershed to aquatic system: A scientometrics review. *Science of The Total
592   Environment*, *637–638*, 208–220. https://doi.org/10.1016/j.scitotenv.2018.04.434

593   Plunge, S., Gudas, M., & Povilaitis, A. (2022). Effectiveness of best management practices for non-point
594   source agricultural water pollution control with changing climate – Lithuania's case. *Agricultural
595   Water Management*, *267*, 107635. https://doi.org/https://doi.org/10.1016/j.agwat.2022.107635

596   Ricci, G. F., D'Ambrosio, E., De Girolamo, A. M., & Gentile, F. (2022). Efficiency and feasibility of
597   Best Management Practices to reduce nutrient loads in an agricultural river basin. *Agricultural
598   Water Management*, *259*, 107241. https://doi.org/10.1016/j.agwat.2021.107241

599   Risal, A., & Parajuli, P. B. (2022). Evaluation of the Impact of Best Management Practices on
600   Streamflow, Sediment and Nutrient Yield at Field and Watershed Scales. *Water Resources
601   Management*, *36*(3), 1093–1105. https://doi.org/10.1007/s11269-022-03075-7

602   Rivas-Tabares, D., Tarquis, A. M., Willaarts, B., & De Miguel, Á. (2019). An accurate evaluation of
603   water availability in sub-arid Mediterranean watersheds through SWAT: Cega-Eresma-Adaja.
604   *Agricultural Water Management*, *212*, 211–225. https://doi.org/10.1016/j.agwat.2018.09.012

605   Rosenbaum, R. K., Hauschild, M. Z., Boulay, A. M., Fantke, P., Laurent, A., Núñez, M., & Vieira, M.
606   (2017). Life cycle impact assessment. In *Life Cycle Assessment: Theory and Practice*.
607   https://doi.org/10.1007/978-3-319-56475-3_10

608   Sheshukov, A. Y., Douglas-Mankin, K. R., Sinnathamby, S., & Daggupati, P. (2016). Pasture BMP
609   effectiveness using an HRU-based subarea approach in SWAT. *Journal of Environmental
610   Management*, *166*, 276–284. https://doi.org/10.1016/j.jenvman.2015.10.023

611   Siebert, A., Bezama, A., O'Keeffe, S., & Thrän, D. (2018). Social life cycle assessment indices and
612   indicators to monitor the social implications of wood-based products. *Journal of Cleaner
613   Production*, *172*, 4074–4084. https://doi.org/10.1016/j.jclepro.2017.02.146

614   Sleeswijk, A. W., van Oers, L. F. C. M., Guinée, J. B., Struijs, J., & Huijbregts, M. A. J. (2008).
615   Normalisation in product life cycle assessment: An LCA of the global and European economic
616   systems in the year 2000. *Science of The Total Environment*, *390*(1), 227–240.
617   https://doi.org/10.1016/j.scitotenv.2007.09.040

618   Stubbs, M. (2016). Irrigation in U.S. Agriculture: On-Farm Technologies and Best Management
619   Practices. *Congressional Research Service (CRS) Report R44158, 10-13.*

620   Venishetty, V., & Parajuli, P. B. (2022). Assessment of BMPs by Estimating Hydrologic and Water
621   Quality Outputs Using SWAT in Yazoo River Watershed. *Agriculture*, *12*(4), 477.
622   https://doi.org/10.3390/agriculture12040477

623   Xu, C., Hong, J., Jia, H., Liang, S., & Xu, T. (2017). Life cycle environmental and economic assessment
624   of a LID-BMP treatment train system: A case study in China. *Journal of Cleaner Production*, *149*,
625   227–237. https://doi.org/10.1016/j.jclepro.2017.02.086

626   Yao, X., Cao, Y., Zheng, G., Devlin, A. T., Yu, B., Hou, X., Tang, S., Xu, L., & Lu, Y. (2021). Use of
627   life cycle assessment and water quality analysis to evaluate the environmental impacts of the
628   bioremediation of polluted water. *Science of The Total Environment*, *761*, 143260.

629   https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.143260

630   Zeng, Q., Luo, X., & Yan, F. (2022). The pollution scale weighting model in water quality evaluation

631   based on the improved fuzzy variable theory. *Ecological Indicators*, *135*, 108562.

632   https://doi.org/10.1016/j.ecolind.2022.108562

633   Zhou, H., Zhang, W., Li, L., Zhang, M., & Wang, D. (2021). Environmental impact and optimization of

634   lake dredged-sludge treatment and disposal technologies based on life cycle assessment (LCA)

635   analysis. *Science of The Total Environment*, *787*, 147703.

636   https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.147703

637

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.

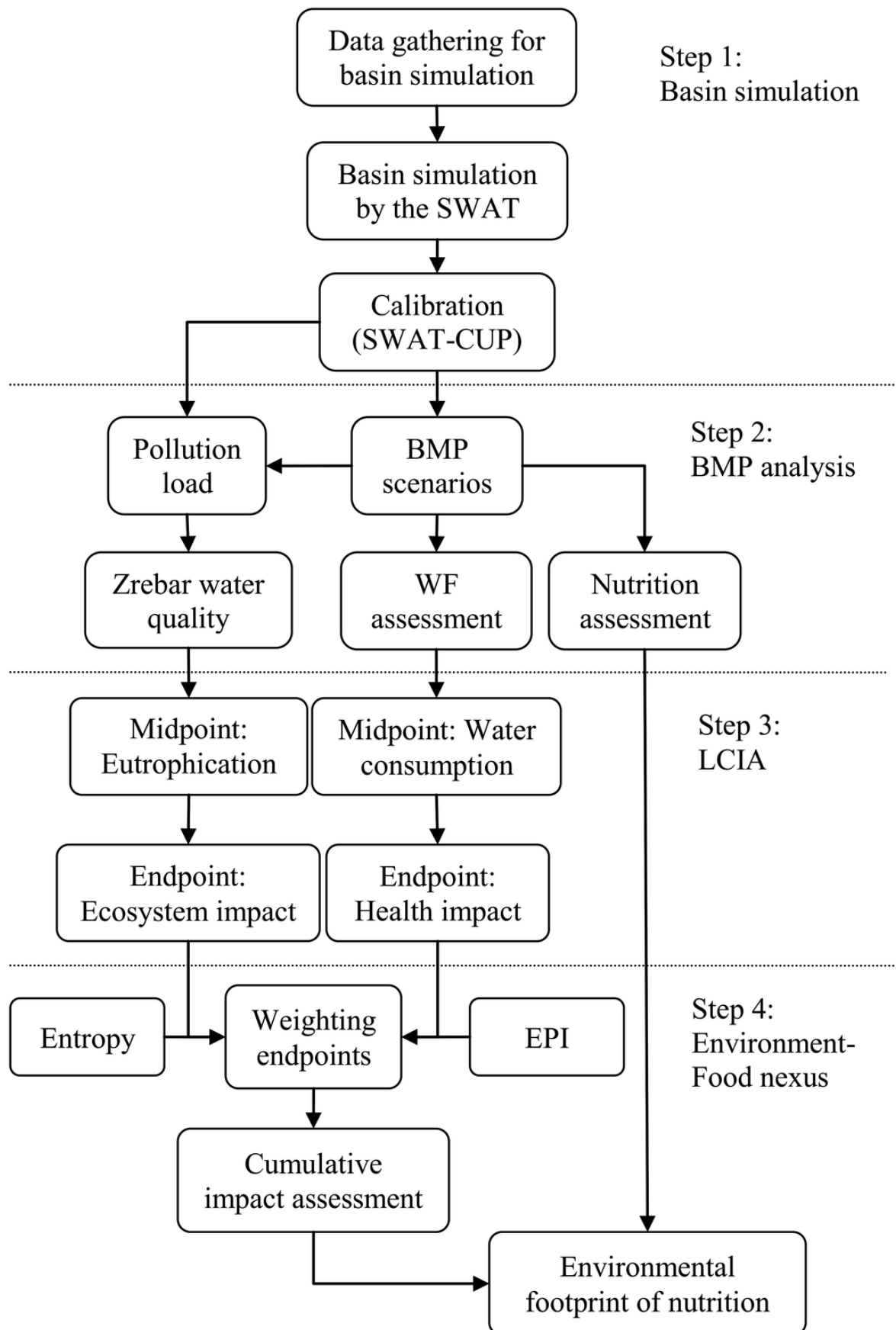



Figure 2

Geographical status of Zrebar Lake basin with its land-uses

This figure shows the DEM with main land-uses of the study area.

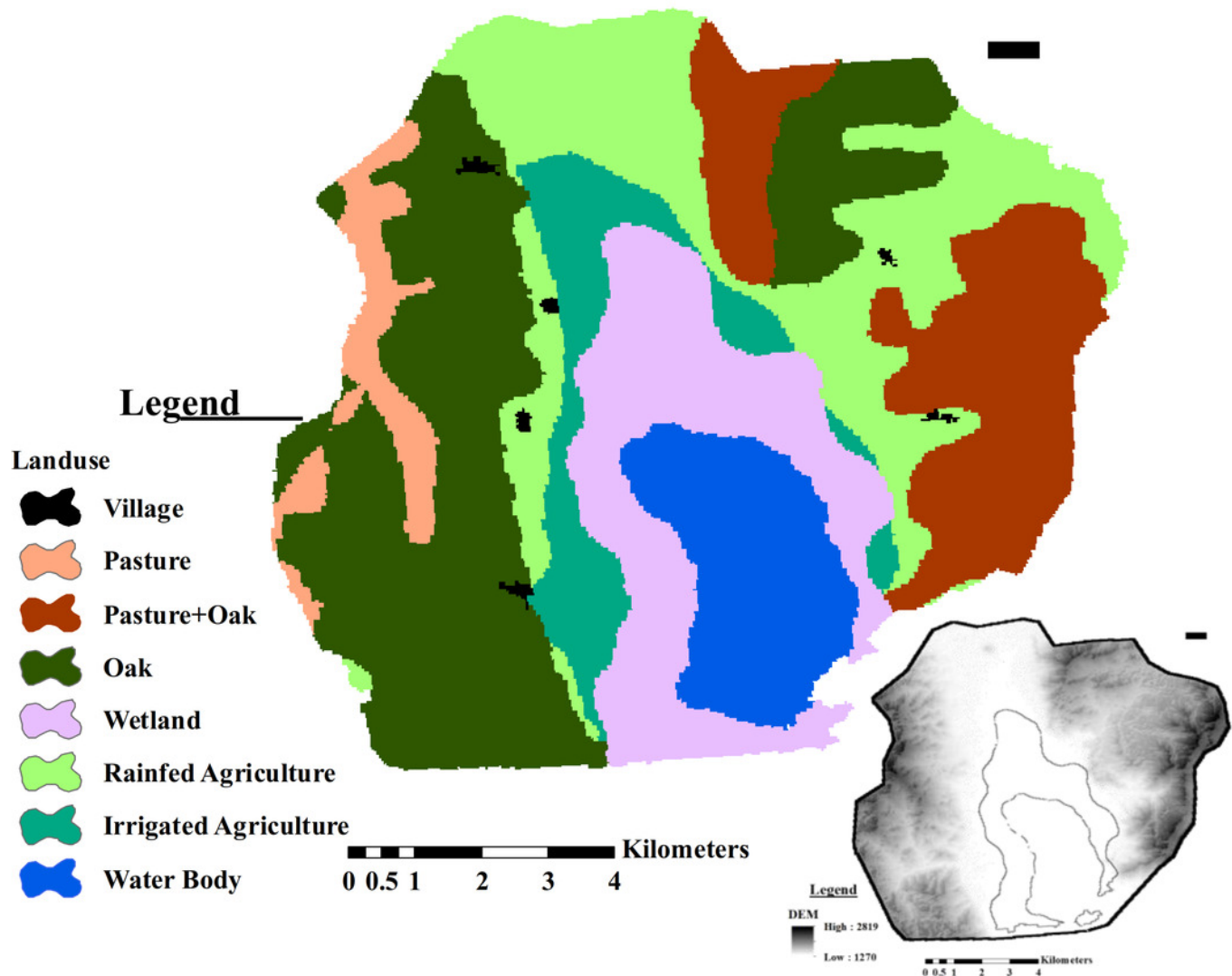



Figure 3

Accumulated annual N pollution exported by farmlands in management scenarios (2007-2013)

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

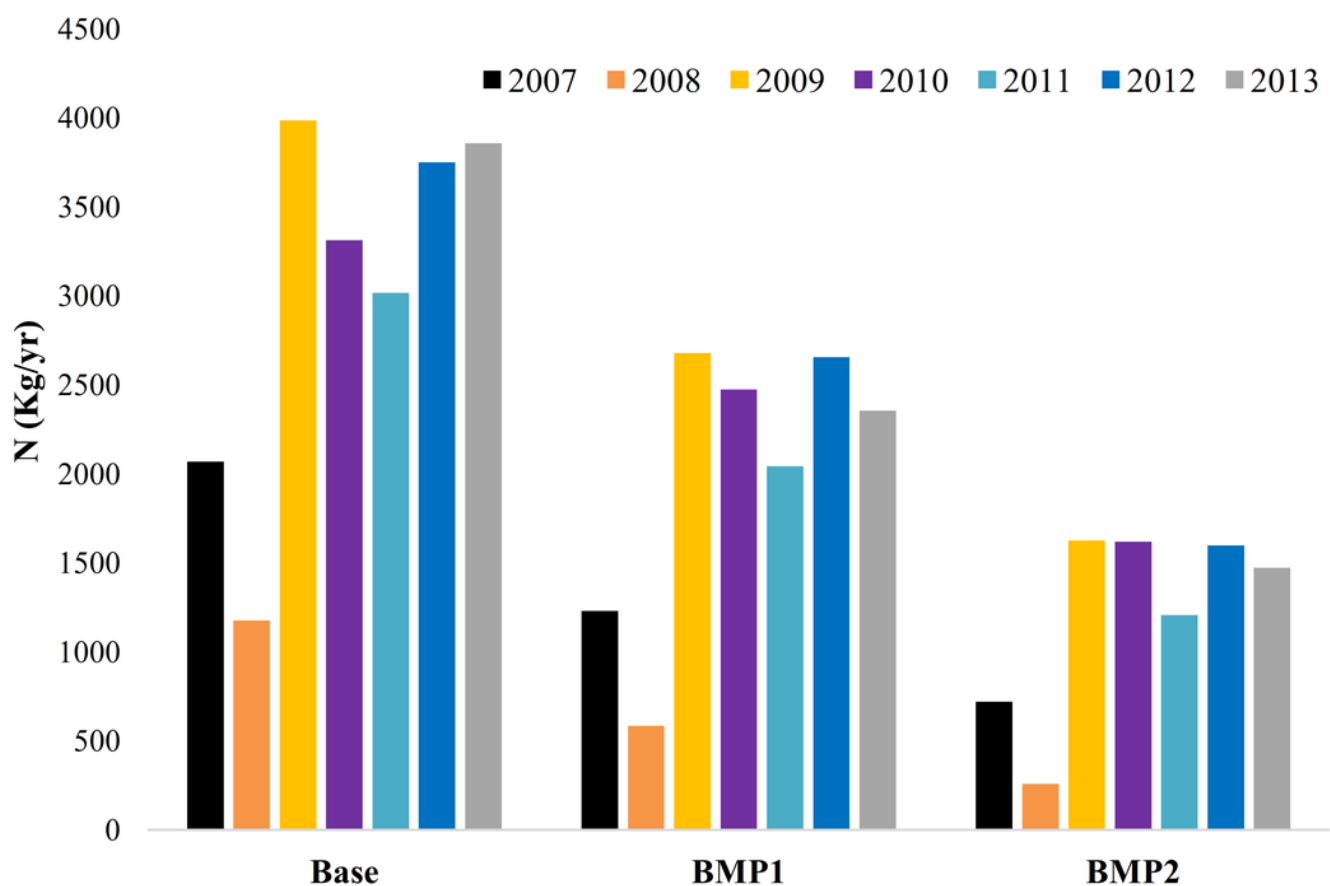



Figure 4

Accumulated annual P pollution exported by farmlands in management scenarios (2007-2013)

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

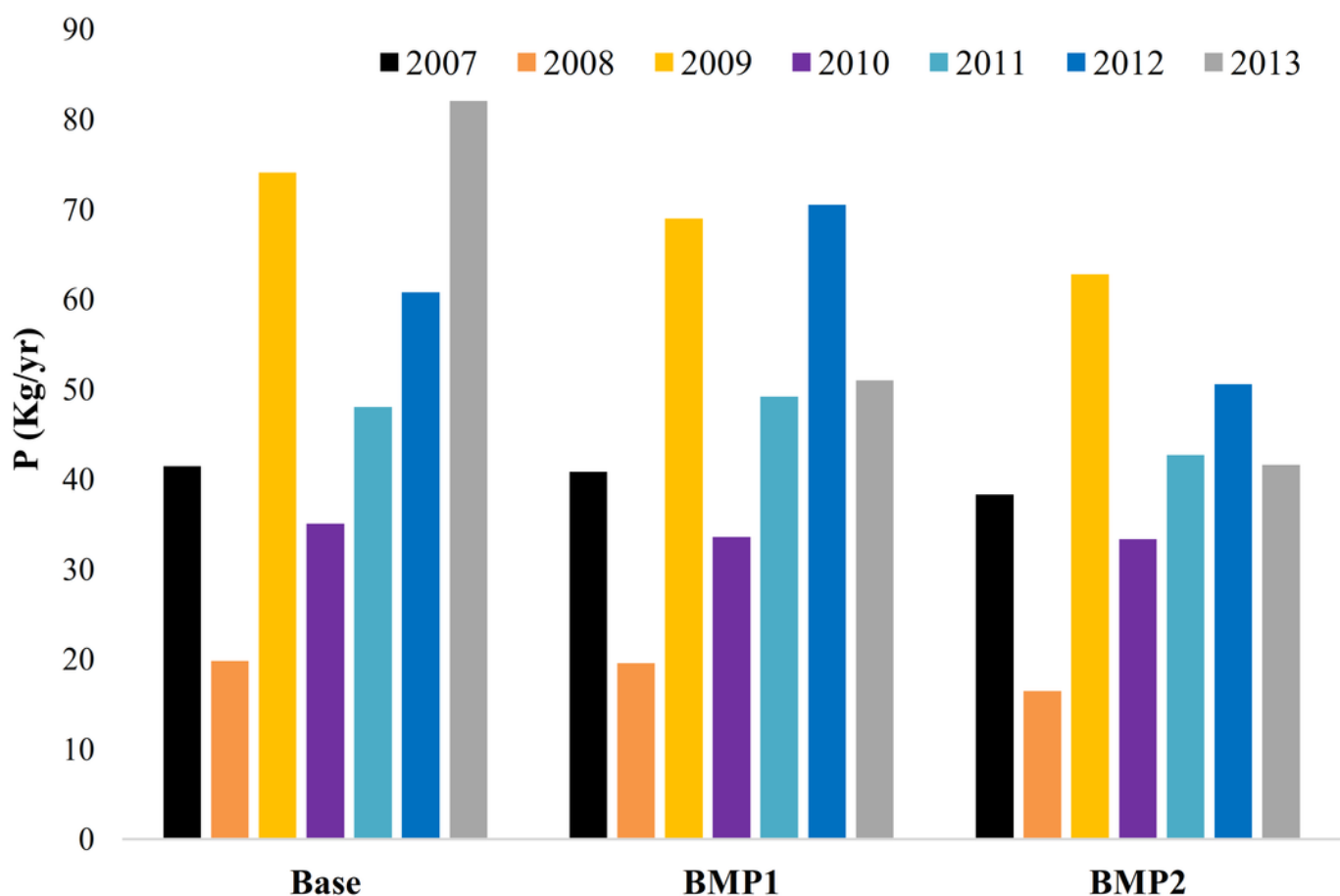



Figure 5

Environmental impacts of farming based on midpoints without using BMPs (base scenario)

In base scenario, the 5 main midpoints of this study are calculated by the SWAT model seperately for each simulation year (2007-2013).

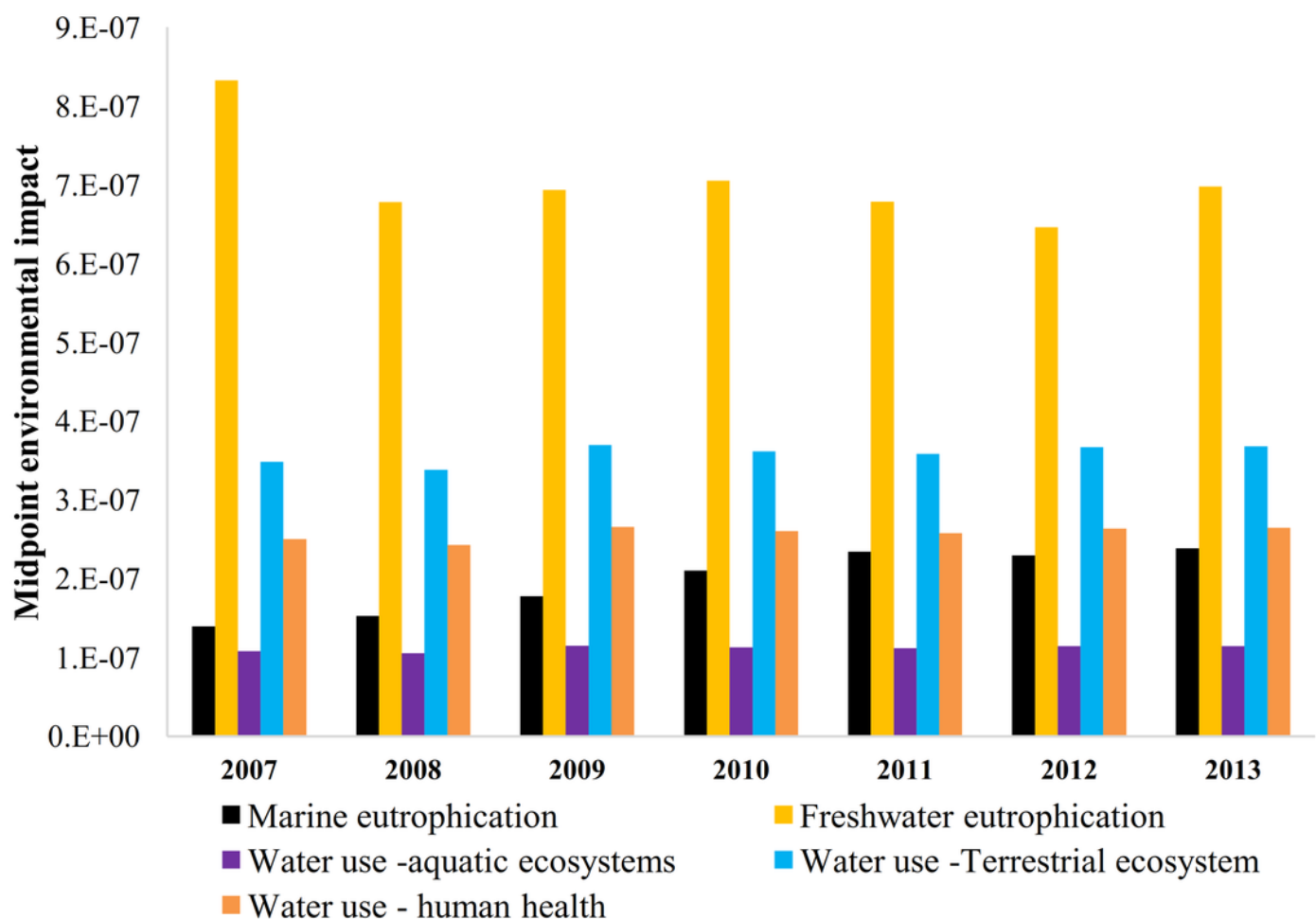



Figure 6

The environmental impacts of management practices based on five midpoints on average for study period (2007-2013)

The sharpest corner of diagram points to the highest midpoint (impact) in BMP scenarios.

Data are based on average results of 2007-2013.

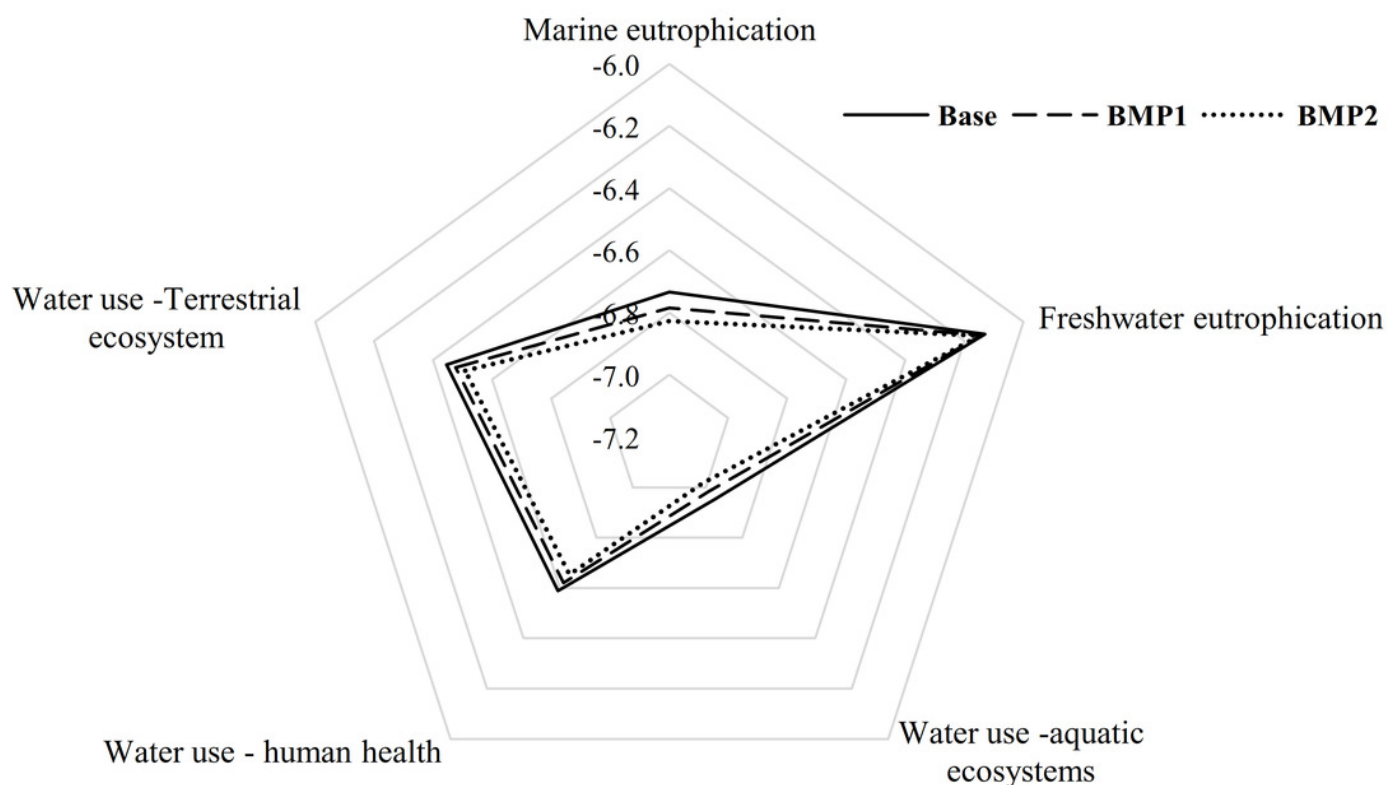



Figure 7

The annual endpoint environmental damages of management practices

Calculated endpoint indices of ecosystem and health per BMP scenarios and simulation years (2007-2013)

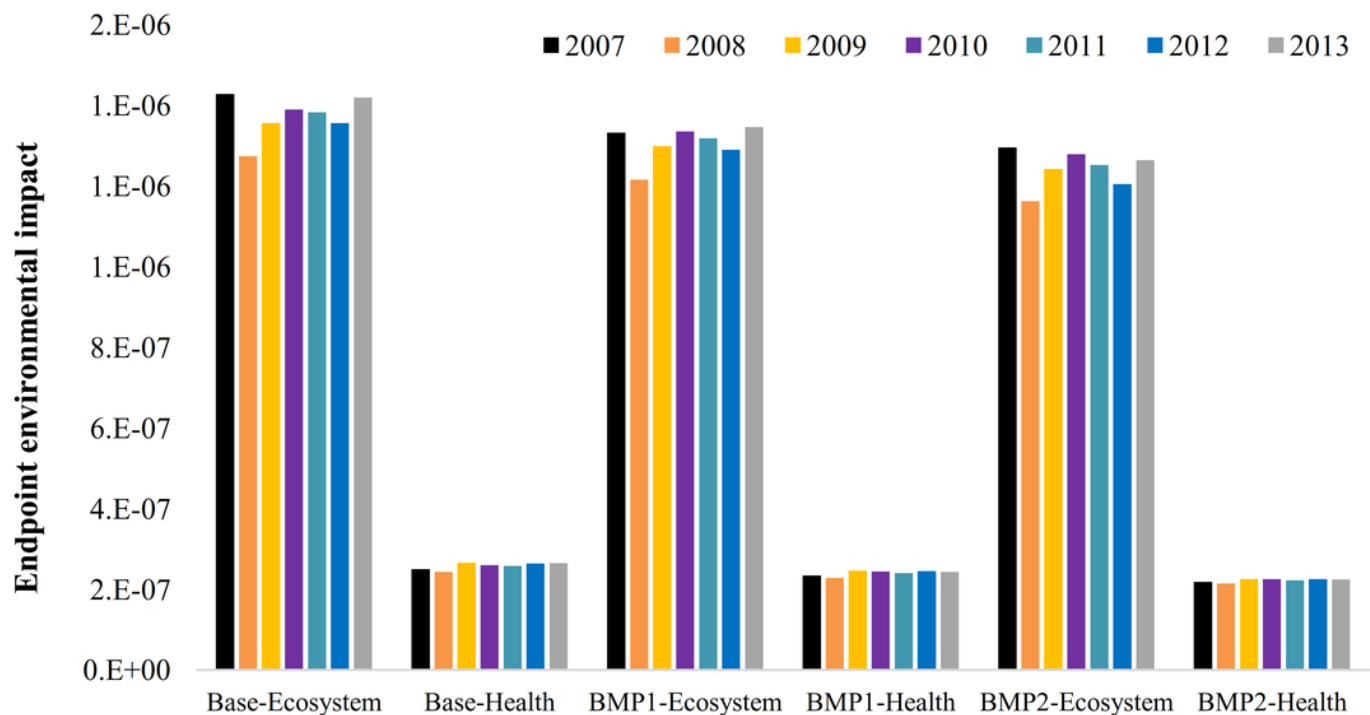



Figure 8

The impacts of management practices on endpoints and food production on average for study period (2007-2013)

Agricultural productions in this area have adverse impacts on ecosystem and health, while have constructive impacts on food and nutrition values. BMPs reduce adverse impacts but lose some nutrition production.

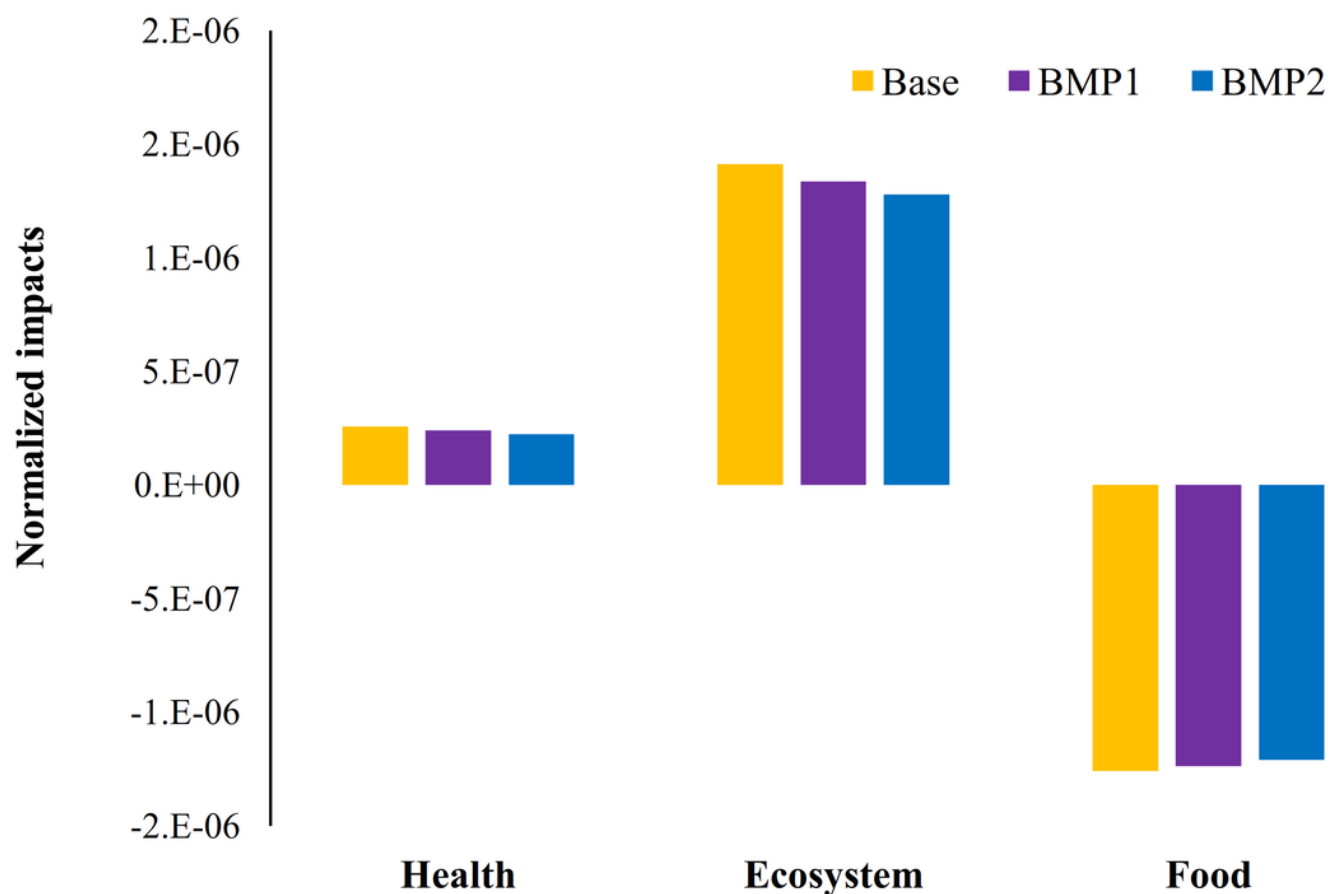
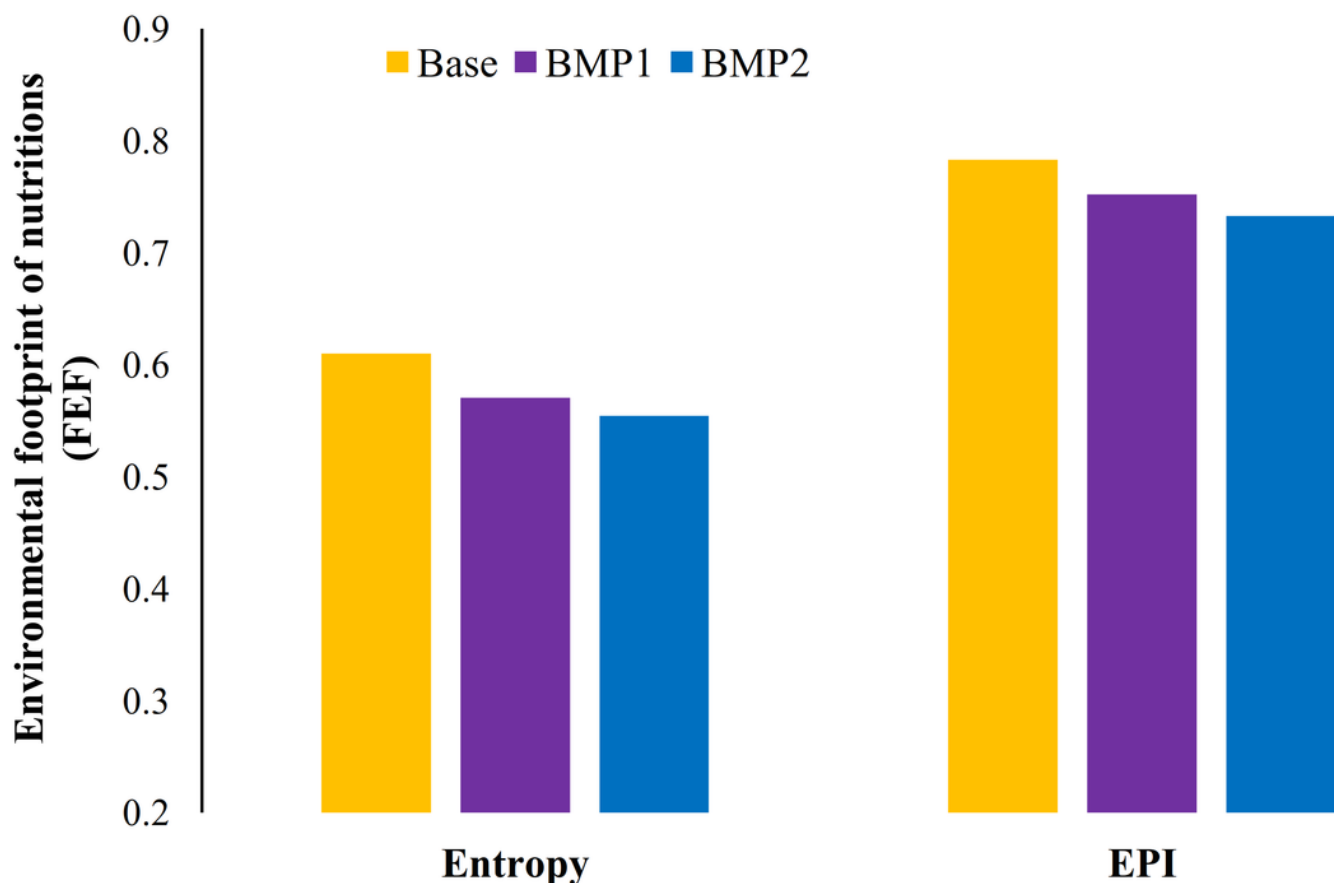



Figure 9

Average environmental footprint of food production in different BMPs and weighting methods for study period (2007-2013)

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

Required datasets of SWAT and their sources

Theme	Data basis	Source and scale
Topography	Digital Elevation Model (DEM)	National Aeronautics and Space Administration (NASA) database of the United States, 30m resolution grid
Land use data	Land-use maps	Iranian Forests and Farms Organization (2006); 1000m resolution grid
Soil data	Soil properties, soil layers	Global soil map of Food and Agriculture Organization (FAO, 1995); 1:500000
Climatic data	Minimum and maximum daily temperature, mean monthly and daily precipitation, relative humidity, wind velocity	Iran Meteorological Organization (IRIMO) (2000-2014)
Hydrological data	Monthly flow rates, Lake water level, dam operation	Kurdistan regional Water Authority, Ministry of Energy (2006-2013)
Water quality	TN and TP concentrations of Lake	Department of Environment, Kurdistan province (2007 and 2010-2013), export coefficients for point sources (Chapra, 2008)
Management practices	Planting types, tillage, harvesting, grazing, fertilizers application and their types, irrigation	Ministry of Agriculture, Kurdistan province (2000-2014)
Crop yields	Typical yields and evapotranspiration data	Ministry of Agriculture- Kurdistan province (2014)

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

Parameter	Calibration		Validation	
	R^2	RSR	R^2	RSR
Lake inflow (m³/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

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

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

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^3 consumed	1.96E-04
Terrestrial ecosystems	Water consumption	1.35E-08	species.yr/m^3 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^3 consumed	6.16E-10
Marine ecosystems	Eutrophication	1.70E-09	Species.yr/kg N to marine water eq.	6.12E-09

Outputs of the SWAT model in different BMP scenarios

LU	Base			BMP1			BMP2		
	Yield (ton/ha)	WF (m³/ton)	Nutrition (MCal/yr)	Yield (ton/ha)	WF (m³/ton)	Nutrition (MCal/yr)	Yield (ton/ha)	WF (m³/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