Gorgan University of Agricultural Sciences and Natural Resources

Environmemtal Resources Research (ERR)

Print ISSN: 2783-4832
Online ISSN: 2783-4670

The relationship between sustainability development, environmental performance and agro-economic indicators in EU and ME countries: A Bayesian network based model

Somayeh Naghavi[1], Ali Firoozzare[2*], Mehdi Ahmadyousefi[3]

[1]Assistant Professor, Department of Agricultural Economics, Faculty of Agriculture, University of Jiroft, Kerman, Iran, Email: somnaghavi@ujiroft.ac.ir
[2]Assistant Professor, Department of Agricultural Economics, Faculty of Agriculture, Ferdowsi University of Mashhad, Khorasan Razavi, Iran, Email: firooz@um.ac.ir
[3]Ph.D. Departments of Plant Physiology, Faculty of Agriculture, University of Jiroft, Kerman, Iran, Email: m.ahmadyousefi1@gmail.com

Article Info

Article type:
Research Article

Article history:
Received: October 2021
Accepted: February 2022

Corresponding author:
firooz@um.ac.ir

Keywords:
Agro-environmental-economic indicators
Agriculture area certified organic
Agricultural value added
Bayesian Network
Environmental Performance Index
Land productivity

Abstract

Agricultural sector has a key role in poverty reduction and improving food security. One of the important challenges in the agriculture sector is to feed the increasing global population. Agriculture has both significant positive and negative impacts on environment and is a significant contributor to pollution which in turn restricts expansion of the agriculture production. Climate change has also attracted attentions in agricultural-environmental interactions. Bayesian networks are relatively well recognized and employed in different types of environmental modeling efforts. In this study a Bayesian network model was designed to investigate the relationship between agro-economic-environmental indicators and Environmental Performance Index (EPI) in the EU countries compared to Middle East (ME) countries that face many challenges for sustainable development. Scarcity of water, population growth and degradation of natural ecosystems are a few of these challenges. In this study, we showed the relationships between influential variables on EPI based on expert interview and available data. The results indicated land productivity was directly affected by organic agriculture area. It is found that with expansion of the organic and conservation agriculture area, productivity can be increased in EU Countries. Our findings also showed that with decreasing N_2O and CH4 emissions, EPI in EU countries increased but it decreased in ME countries. Therefore, EU countries have been able to improve the EPI and achieve sustainable development objectives due to improved agricultural practices and optimum applications of pesticides and fertilizer. However, ME countries did not achieve such status. Modeling of agro-environmental indicators can help policymakers to evaluate the changes of agro-ecosystem and apply them even at international scales.

Cite this article: Somayeh Naghavi, Ali Firoozzare, Mehdi Ahmadyousefi. 2022. The Rlation between Sustainability Development, Environmental Performance and Agri-Economics Indicators in EU and ME countries: A Bayesian Network Based Model. *Environmental Resources Research*, 10 (1), 51-70. DOI: 10.22069/IJERR.2022.6031

DOI: 10.22069/IJERR.2022.6031
Publisher: Gorgan University of Agricultural Sciences and Natural Resources

Introduction

The COVID-19 pandemic has threatened human health and made the food security vulnerable at critical stage in the world (United Nations, 2020). Agricultural sector has a key role in relation to poverty reduction and improving food security. Expansion of agricultural productions has also caused higher pollution which in turn has restricted increase in production of agricultural sector (Li et al., 2019). Agricultural sector has an important role in sustainability issues (Pretty, 2008; UN, 2015). Increasing the food production requires higher application of chemical pesticides and fertilizers (Chakraborty et al., 2014). Pesticides and fertilizers exposure, can endanger human and environmental health. Under such situation, sustainable agriculture has become a vital issue (Punith Kumar and Indira, 2017). Population growth and the associated increase in food demand has put pressure on water resources and environment (Liu et al., 2017; Falkenmark et al., 1989; Alcamo et al., 2000; Verosmarti et al., 2000). Therefore, preventing the degradation of the environment (Pretty, 2008) and avoiding the application of agrochemicals, with regard to sustainable development is vital (Sulewski et al., 2018). Organic farming is an agricultural practice aiming to achieve the sustainable development, improving food security and reducing the agrichemicals use (WHO & Food and Agricultural Organization, 2015). Organic farming can increase the natural fertility and potential of agricultural soil productivity, especially in communities with food poverty. Muller et al. (2017) showed that organic agricultural practices decreased N-surplus and chemical pesticides use.

Agricultural management factors are vital for higher production but inappropriate application levels of these factors always pose a risk on the environment. Improving farming practices can help protect the environment and public health (FAO of the United Nations, 2011). Agricultural sector growth has considerable effects on the environment, so protection of environmental quality is a major issue in sustainable development. Environmental performance index (EPI) considers two major goals for environmental protection, including increasing environmental health and ecosystem vitality (Shahabadi et al., 2017; Zarandi Motasadi and Bebaran, 2009). The environmental performance index is a very important indicator that identifies goals to achieve environmental efficiency and measures the current position of each of the components of this index and evaluates the position of each country in achieving the desired goals. The EPI also provides an effective and valid tool to guide policymakers for environment. This index is one of the major indicators applied in many countries.

There are few studies on the relationship between agro-economic-environmental and EPI indicators using Bayesian Network (BN). Grotkiewicz (2017) applied Bayesian network to investigate the relation between sustainability and agriculture. Carpani & Giupponi (2010) designed Bayesian network to investigate agricultural and environmental indicators. Viikari et al. (2007) evaluated agro-environmental indicators at national level. Mohammadian et al. (2020) investigated economic and environmental effects of crop diversification in Mahidasht plain in Iran. Russell et al. (2018) investigated spatial assessment of environmental indicators in Kazakhstan. Alishah and Longsheng (2020) investigated new environmental performance indicators for measuring environmental performance in major sectors in Pakistan. Volkov et al. (2020) investigated economic and environmental performance of the agricultural sectors of the selected EU countries. Their results showed that the new EU member states have higher performance compared to the old member states. Dkhili (2019) investigated the relationship between EPI and economic growth in Middle East and North Africa. Widatat et al. (2019) examined the relationship between EPI and agricultural productivity. Jafari Samimi et al. (2010), investigated the relation between economic growth and EPI in developing countries. Their results showed a positive relationship between EPI and economic growth. Safarelizadeh et al. (2017) investigated situation of the Middle East in terms of sustainable development indices. Results indicated that more than 60% of the Middle East countries had a moderate performance level in regard to sustainable development indicators from 2009 to 2012. Kaikkonen et al. (2020) applied BN model for environmental assessment across a range of ecosystem types and scales. Batary et al. (2015) examined the role of agricultural-environmental programs in protection and environmental management.

Considering the previous studies and the importance of environmental management and governments' interest in improving environmental performance, there is a gap for comparison of the predictions of the impacts of environmental indicators on agricultural economic indicators and also the impact of pollution on environmental performance improvement indicators in the Middle East and the European Union. The environmental situation and its changes is one of the important issues of the new era. In the Middle East, there is a growing emphasis on investigating the institutional requirements of technological modernization, expanding local energy consumption, and monitoring the pollution due to governments' functions and non-state actors (Maleki, 2018). Agriculture imposes many hazards on the environment which needs a complete assessment. Common Agricultural Policy (CAP) in regard to agro-environment policy was considered in the European Union in the mid-1980s for declining environmental standards. Agro-environmental schemes (AES) help in agricultural management (Batary, 2015). Sustainable development is a major goal for the European Union in line with environmental protection and social justice (Radermacher, 2009). Despite their many natural resources, Middle Eastern countries also have faced many challenges in the path of sustainable development. The scarcity of water, high population growth and degradation of natural ecosystems are some of these issues.

In this study we investigate the answers to likely the relationships between agro-economic and sustainability development indicators in the EU countries compared to Middle Eastern countries and the impact of agricultural pollution on the EPI. Hence, policymakers and researchers can target the most important impacts and select Middle Eastern and the European Union countries that have done better to improve environmental performance. Therefore, a Bayesian network model was used to investigate a general review of the agro-environmental indicators and pollution impacts on agro-economic indicators in Middle East and EU. We also assessed factors affecting environmental performance and provided tips to be used for decision makers in the Middle East and EU in 2018. Bayesian network is a probabilistic model that displays the relationship between various variables and is able to combine agricultural-economic and environmental indicators. Modeling of agro-environmental indicators can provide policymakers with insight on the changes of agro-ecosystem useful at the international scale.

Materials and Methods

Data

The major objective of our study is the assessment of relationships between agro-economic-environmental indicators and EPI in the selected EU and Middle Eastern countries using Bayesian Network (BN) modeling. Figure 1 shows the agro-environmental indicators and the relations between agriculture and the environment. A summary description of the methodology is also shown in Figure 2.

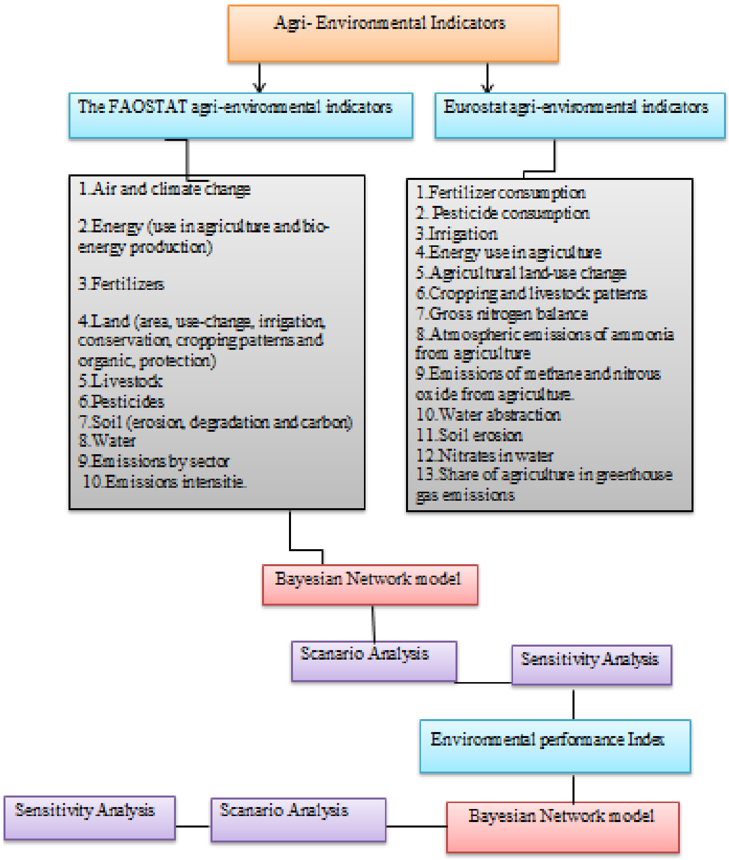

Figure 1. Flowchart of the study for predicting agro-economic indicators using Bayesian Network

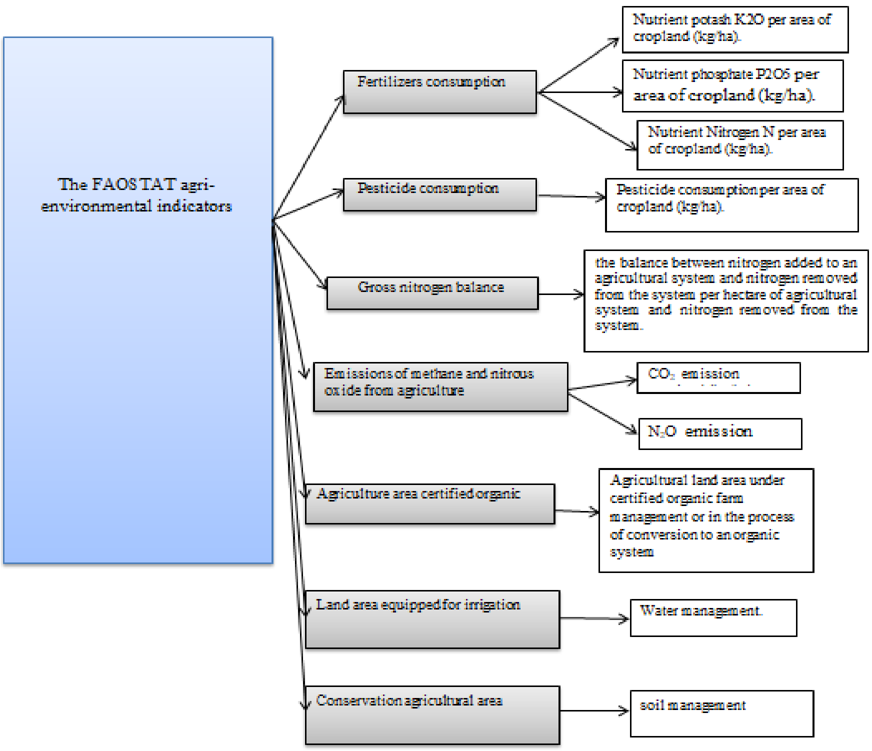

Figure 2. Flowchart of the study for FAOSTAT agro-environmental indicators, 2018

Geographical location of the study is shown in Figure 3 for European union and Middle Eastern countries.

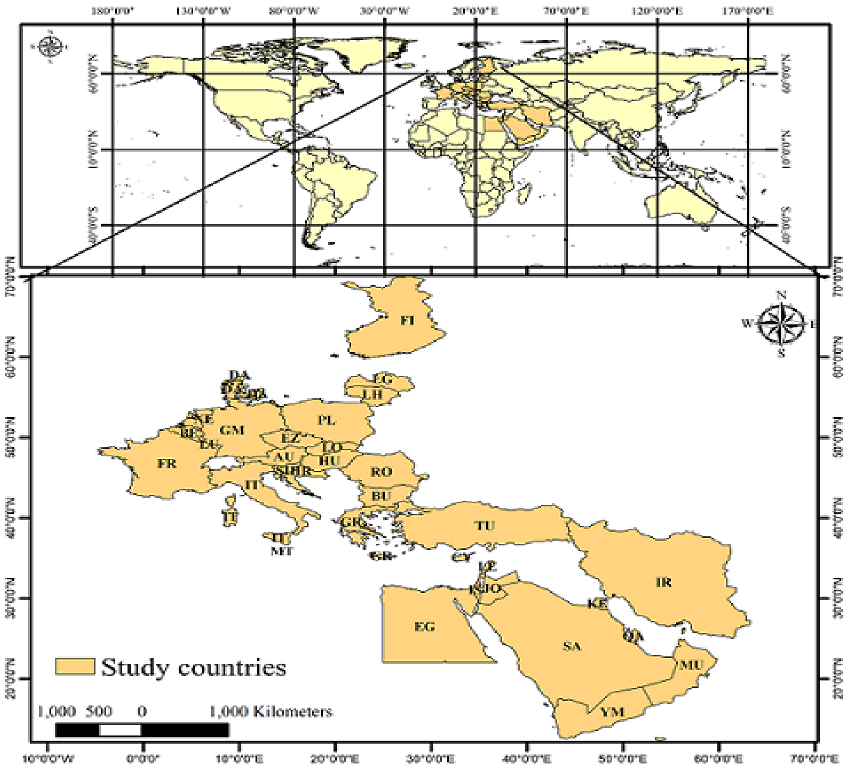

Figure 3. Geographical location of the study

Map of countries based on consumption of potash (K_2O), nitrogen (N) and phosphate (P_2O_5) and agricultural area as certified organic, respectively using GIS software are shown in Figures 4-5.

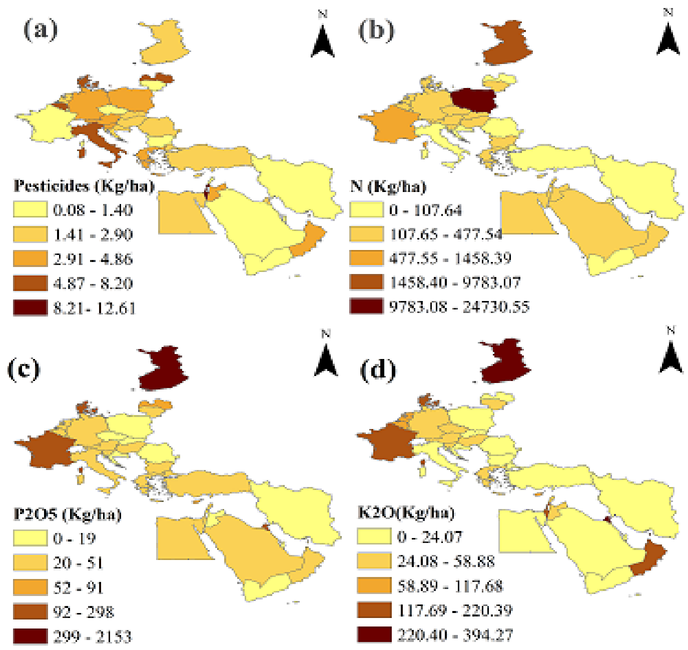

Figure 4. Consumption of pesticides, N, P_2O_5 and K_2O, respectively

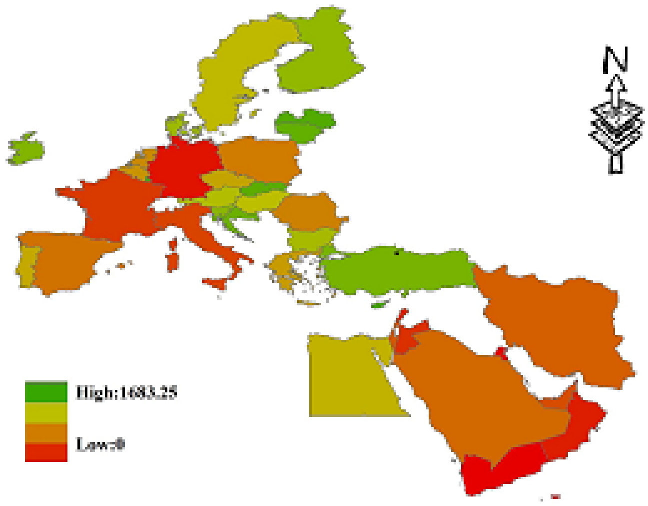

Figure 5. Agricultural area for certified organic

In 2018, 69 million hectares of land area in the world were under organic farming. In EU in 2017, 7% of the total land was under organic farming. The growth of organic production by 70% over the past ten years indicates the importance of organic products (EU, 2019). In 2018, in EU countries, 13.4 million hectares of agricultural lands were under organic agriculture. Figure 1 shows that the area under organic farming is more highlighted in Spain, Germany, Italy, and France. The highest level of agricultural area as certified organic is concentrated in Egypt (Figure 1). Use of fertilizers in agriculture is the key source for greenhouse gas emissions from agricultural soils. Mineral fertilizers, such as nitrogen (N) and phosphorus (P), are widely used in agriculture to optimize production. A surplus of nitrogen and phosphorus can lead to environmental pollution. In 2018, 10.2 million tons of nitrogen fertilizer was used in EU agriculture, a slight increase of 1.9% since 2008 (Eurostate, 2018). Based on the analysis from FAOSTAT (2017), in the considered EU countries (left side of the map) the highest level of consumption of N, K_2O, and P_2O_5 per hectare occurred in Slovakia, Lithuania and Latvia. Among the considered Middle Eastern countries, the highest level of consumption of these mineral fertilizers were recorded in Egypt and Jordan.

Environmental Performance Index

The environmental performance index (EPI) is a method of ranking and scoring the environmental performance of a country toward the sustainable development objectives (Shahabadi et al., 2017). In this regard, EPI considers two major goals of environmental protection, including decreasing environmental health and ecosystem vitality (Shahabadi et al., 2017; Zarandi Motasadi and Bebaran, 2009). The components of EPI in 2018 are shown in Figure 6.

Figures 7 illustrates the EPI Score for the selected countries as the performance of countries in environmental degradation prevention.

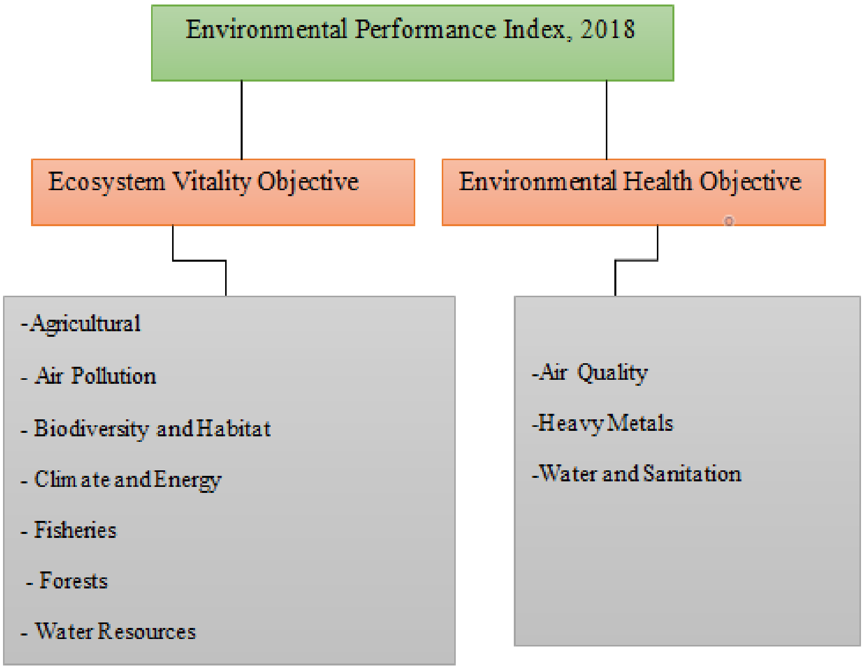

Figure 6. Environmental performance index (EPI), Yale University, 2018

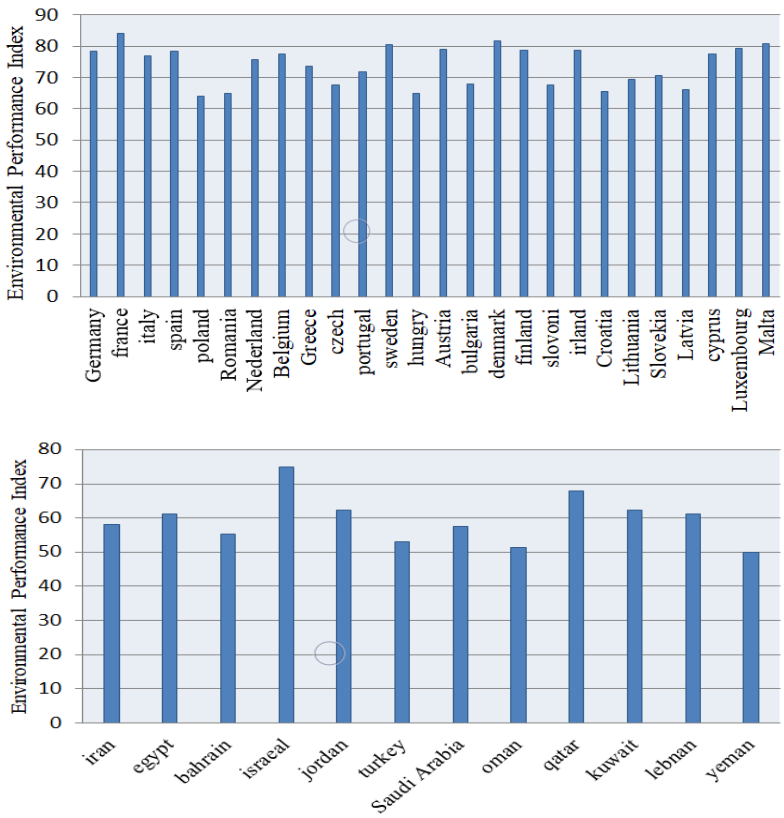

Figure 7. Environmental performance index (EPI) in EU and ME countries, 2018

In 2018, in EU countries, France had higher EPI score than other countries and in Middle East, Israel had higher EPI score than other countries (Figure 7). Therefore, these two countries have performed better than other countries in preventing environmental degradation.

Bayesian Network

The Bayesian networks are a class of probabilistic models (Kaikkonen, 2020) that can be applied to decision making under uncertainty (Levontin et al., 2011) and represent a set of variables without a clear causal structure (Carriger, 2021). The objective of the Bayesian Network (BN) is to represent the independent relationships between effective variables and the uncertainty associated with these variables (Arnaldo Valdés, 2018). The BN provides a framework for representing the uncertainty of variables in the network and consists of three parts: nodes, links and conditional probability tables. The nodes are variables, and links represent causal relationships between nodes (Mamitimin et al., 2015). The BN consists of three steps: (1) to identify the nodes 2) to create link between the nodes; 3) to estimate the probabilities for each node (Chai et al., 2020). In this study Netica package was employed for BN modeling. The BN that was developed here is based on major variables and links identified through expert knowledge. The conditional probability based on Bayesian theorem is:

$$\mathrm{P(A|B)} = \frac{\mathrm{P(A)P(B|A)}}{\mathrm{P(B)}} \quad (1)$$

Where A and B are the two random occurrences (Mamitimin et al., 2015), "$P(A)$" shows the probability of occurrences i, and "$P(B)$" indicates the probability of occurrences of B (Mamitimin et al., 2015). "$P(B|A)$" is the conditional probability of occurrences of A when occurrences of B is occurred" (Mamitimin et al., 2015; Pearl, 1988; Koski and Noble, 2011; Blitzstein and Hwang, 2014).

Results and Discussion

Discrete values are required in the BN and for discretization of constant values analytical methods can be used (Grotkiewicz, 2017). In this study we used two-step cluster approach for grouping variables. Therefore, 14 variables were selected to represent agro-economic and agro-environmental indicators and create BN structure in the EU countries and 12 variables for Middle East. Data was obtained from the FAOSTAT of 2018. We designed various BN models using multi-scenario approach to investigate the relationship between indicators. The BN contained 14 nodes and 28 links in the EU countries and 12 nodes and 23 links in the Middle Eastern countries. Table 1 shows variables that were included in the final BN for EU countries.

Economic indicators

Economic indicators and their changes are examined by considering environmental scenarios. Here 3 economic indicators were chosen for the in EU and Middle Eastern countries including agricultural value added, labor productivity and land productivity (Grotkiwicz, 2017).

Agro-Environmental indicators

Agro-Environmental indicators were extracted from FAOSTAT. In this study 11 agro-environmental indicators, agricultural area as certified organic, conservation agricultural area, nitrogen, potash, phosphate, pesticides, balance per hectare, N_2O emissions, CH4 emissions, livestock units per agricultural land area, and land area equipped for irrigation (FAOSTAT, 2018) in EU counties. Similarly, 10 agro-environmental indicators including agricultural area as certified organic, nitrogen, potash, phosphate, pesticides, N_2O emissions, CH4 emissions, livestock units per agricultural land area, and land area equipped for irrigation (FAOSTAT, 2018) were used for the Middle Eastern countries. In this study, land productivity and labor productivity were calculated as:

$$\text{Labor Productivity} = \frac{\mathrm{GDP_A}}{\mathrm{L_A}} \quad (2)$$

$$\text{Land Productivity} = \frac{GDP_A}{AL_A} \quad (3)$$

Where, GDP_A is Gross Domestic Product in agriculture (USD) in the EU and ME countries, L_A is Labor force in agricultural sector in EU and ME countries, AL_A is the area of agricultural land (ha) in EU and ME countries. In Tables 1-2 variables used in the final BN for EU and ME countries are shown.

Table 1. Variables of the final BN for EU countries, 2018

Variable (node)	Prior Probability (Node states)
Agricultural area as certified organic	Low (58.6%), Medium (20.7%), High (20.7%)
Conservation agricultural area	Low (75.7%), Medium (10.8%), High (13.4%)
Nutrient nitrogen N	Low (66.6%), Medium (11.2 %), High (22.2%)
Nutrient potash K2O	Low (63.6%), Medium (20%), High (16.4%)
Nutrient phosphate P2O5	Low (72.4%), Medium (13.9%), High (13.7%)
Pesticides	Low (46.2%), Medium (28.7%), High (25.1%)
Balance per hectare	Low (33.7%), Medium (44.3%), High (22%)
Land productivity	Low (39.7%), Medium (30.2%), High (30.1%)
N2O emissions	Low (43.6%), Medium (28.4%), High (28%)
CH4 emissions	Low (43%), Medium (29. %), High (28%)
Agricultural value added	Low (53.4%), Medium (46.6%)
Livestock units per agricultural land area	Low (82.1%), Medium (17.9%)
Land area equipped for irrigation	Low (72.4%), Medium (6.90%), High (20.7%)
Labor productivity	Low (30%), Medium (26.7 %), High (26.7%), Very High (16.7%)

Table 2. Variables of the final BN for ME countries, 2018

Variable	Definition/Prior Probability
Agricultural area as certified organic	Low (80%), High (20%)
Nutrient nitrogen N	Low (65.1%), Medium (15.4 %), High (19.4%)
Nutrient potash K2O	Low (42.3%), Medium (26.9%), High (30.9%)
Nutrient phosphate P2O5	Low (59.4%), Medium (26.9%), High (13.7%)
Pesticides	Low (70.4%), High (29.6%)
Land productivity	Low (55.4%), High (44.6%)
N2O emissions	Low (35.7%), Medium (32.6%), High (31.8%)
CH4 emissions	Low (34.7%), Medium (32.7%), High (32.7%)
Agricultural value added	Low (57.3%), High (42.7%)
Livestock units per agricultural land area	Low (53.3%), Medium (46.7%)
Land area equipped for irrigation	Low (73.3%), High (26.7%)
Labor productivity	Low (68.8%), Medium (18.8 %), High (12.5%)

Figures 8 and 9 illustrate BN with the probability distribution of variables in the EU and ME countries. The relation between variables was built based on expert interview and literature reviews.

In this structure, nodes represent variables of BN model. As shown in Figure 1, conservation agricultural area is directly affected by the node agriculture area as certified organic, N, K_2O, P_2O_5, and pesticides, and balance per hectare are directly affected by node conservation agricultural area. Agricultural value added is also affected by nodes land productivity, livestock units per agricultural land area and labor productivity. Nitrogen, K_2O, P_2O_5, pesticides are directly affected by node agriculture area as certified organic (Figure 2). Agricultural added value is also affected by nodes land productivity, livestock units per agricultural land area, labor productivity and indirectly by node agricultural area for certified organic.

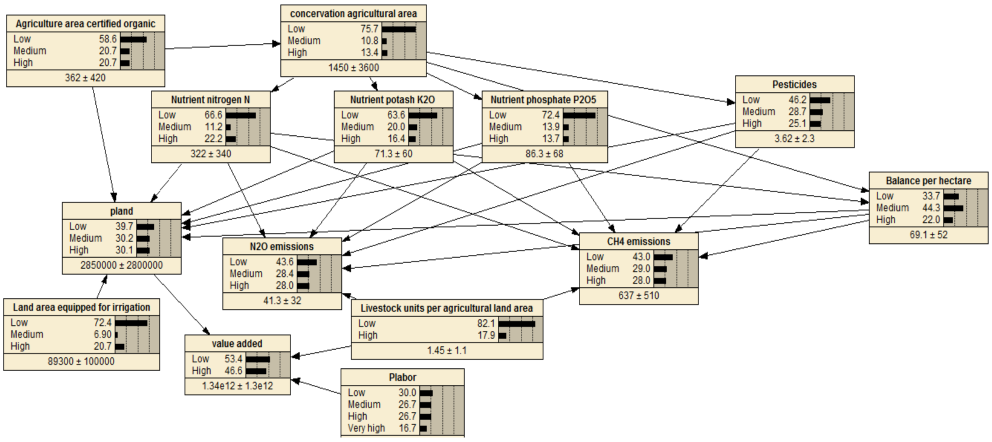

Figure 8. Bayesian network with the probability distribution of variables, EU countries

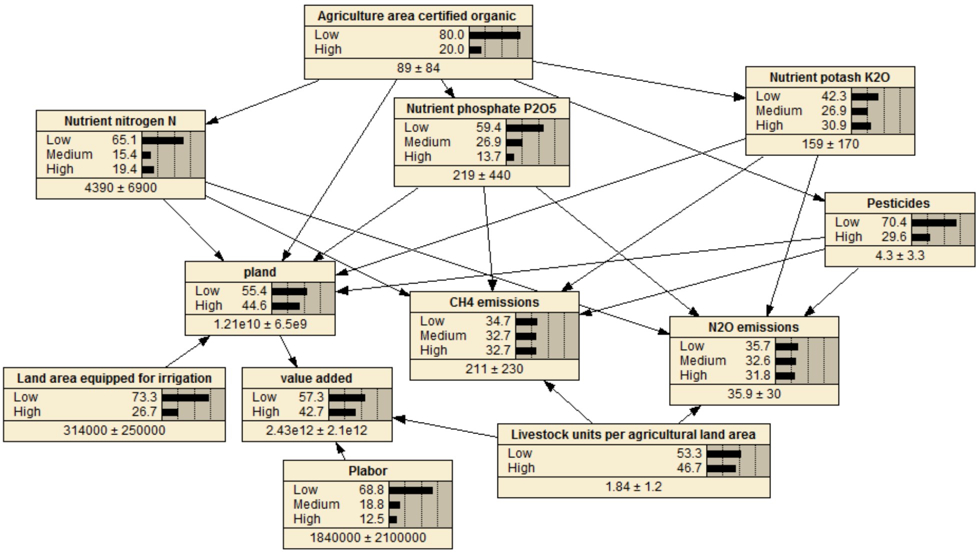

Figure 9. Bayesian network with the probability distribution of variables, Middle East countries

Scenario Analysis

Table 2 shows different scenarios and posterior probability distribution for predicting agro-environmental indicators impacts on agro-economic indicator in EU and ME countries, in 2018.

Agricultural area for certified organic scenario

This section discusses the impact of agricultural area as certified organic from environmental aspect. The results are shown in Table 3.

Table 3 illustrates that agricultural area as certified organic (Aaco) and conservation agricultural area (Caa) influence nodes N, K_2O, P_2O_5, pesticides and balance per hectare. Calculated parameters in this Table are: $P(\mathrm{N}|\mathrm{Aaco.Caa})$, $P(\mathrm{K2O}|\mathrm{Aaco.Caa})$, $P(\mathrm{P2O5}|\mathrm{Aaco.Caa})$, $P(\mathrm{pesticides}|\mathrm{Aaco.Caa})$, $P(\text{balance per hectare}|\,P(\mathrm{pesticides}|\mathrm{Aaco.Caa}))$

As an example, when (Aaco=high, Caa=high) or (Aaco=high, Caa=medium) or (Aaco=medium, Caa=high) or (Aaco=medium, Caa=medium) or (Aaco=low, Caa=high) or (Aaco=low, Caa=medium) Balance per hectare = high. When (Aaco=high, Caa=low) or (Aaco=medium, Caa=low) or (Aaco=low, Caa=low) balance per hectare N= medium. However, balance per hectare can be high if agricultural area as certified organic is at high, medium and low states and conservation agricultural area is at high state.

Table 3. Results of posterior probability distribution (%) agri-environmental indicators in EU countries, 2018.

Aaco*	Caa*	P(Nutrient nitrogen N)			P(Nutrient potash K2O)			P(Nutrient phosphate P2O5)			Pesticides			Balance per hectare		
		L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
high	high	20%	20%	60%	20%	20%	60%	20%	20%	60%	20%	20%	60%	25.3%	25.3%	49.3%
high	medium	25%	25%	50%	25%	25%	50%	25%	50%	25%	25%	25%	50%	29.2%	29.2%	41.6%
high	low	80.8%	7.69%	11.5%	76.9%	19.2%	3.85%	88.5%	7.69%	3.85%	53.8%	30.8%	15.4%	35.8%	49.9%	14.3%
medium	high	20%	20%	60%	20%	20%	60%	20%	20%	60%	20%	20%	60%	25.3%	25.3%	49.3%
medium	medium	25%	25%	50%	25%	25%	50%	25%	50%	25%	25%	25%	50%	29.2%	29.2%	41.7%
medium	low	80.8%	7.69%	11.5%	76.9%	19.2%	3.85%	88.5%	7.69%	3.85%	53.8%	30.8%	15.4%	35.8%	49.9%	14.3%
low	high	20%	20%	60%	20%	20%	60%	20%	20%	60%	20%	20%	60%	25.3%	25.3%	49.3%
low	medium	25%	25%	50%	25%	25%	50%	25%	50%	25%	25%	25%	50%	29.2%	29.2%	41.6%
low	low	80.8%	7.69%	11.5%	76.9%	19.2%	3.85%	88.5%	7.69%	3.85%	53.8%	30.8%	15.4%	35.8%	49.9%	14.3%

Aaco*, Agriculture area as certified organic
Caa*, Conservation agricultural area

Table 4. Results of posterior probability distribution for agro-environmental indicators in Middle East countries in 2018.

Agricultural area certified organic	P (Nutrient nitrogen N)			P (Nutrient potash K2O)			P (Nutrient phosphate P2O5)			Pesticides	
	L	M	H	L	M	H	L	M	H	L	M
High	40%	20%	40%	40%	20%	40%	40%	20%	40%	75%	25%
Low	71.4%	14.3%	14.3%	42.9%	28.6%	28.6%	64.3%	28.6%	7.14%	69.2%	30.8%

Table 5. Results of posterior probability distribution (%) for economic indicators in EU countries, 2018

Aaco	Caa	P (Land productivity)			P (Agricultural value added)	
		L	M	H	L	H
high	high	33%	33.6%	33.4%	52.2%	47.8%
high	medium	33.2%	33.5%	33.3%	52.2%	47.8%
high	low	33.3%	33.3%	33.3%	52.3%	47.75
medium	high	33.4%	33.3%	33.3%	52.3%	47.7%
medium	medium	33.4%	33.3%	33.3%	52.3%	47.7%
medium	low	35.9%	32%	32%	52.7%	47.3%
low	high	33.4%	33.3%	33.3%	52.3%	47.7%
low	medium	33.4%	33.3%	33.3%	52.3%	47.7%
low	low	44.8%	27.6%	27.6%	54.2%	45.8%

As shown in Table 5, (Aaco=high, Caa=high) or (Aaco=high, Caa=medium), Land Productivity= medium and Agricultural value added= low, when (Aaco=high, Caa=high) or (Aaco=medium, Caa=medium) or (Aaco=medium, Caa=low) or (Aaco=low, Caa=high) or (Aaco=low, Caa=medium) or (Aaco=low, Caa=low), Land Productivity= medium and Agricultural value added= low and when (Aaco=low, Caa=low), Land Productivity= low and Agricultural value added= low. When Agricultural area certified organic and conservation agricultural area are at high state in EU countries, Land Productivity is medium with highest probability of 33.6% and when Agricultural area certified organic and conservation agricultural area are at low state in EU countries, Agricultural added value and land Productivity at low state with highest probability of 54.2% and 44.8%, respectively.

Results of scenarios analysis in the Middle East countries in 2018 are shown in Table 4. The results shown in Table 5 indicate when Aaco=high or low, N is low. Therefore, when agricultural area as certified organic is at low state in Middle East countries, N is at low state with the highest probability of 71.4%.

As shown in Table 6, when Aaco=high, land productivity=low or high and agricultural value added= low. When Aaco=low, land productivity= low and agricultural value added= low. When agricultural area as certified organic is at low state in Middle East countries, land productivity and agricultural value added are at low state with the highest probability of 56.8% and 57.5%, respectively.

Table 6. Posterior probability distribution (%) for economic indicators in East Middle countries, 2017.

Agricultural area certified organic	P (Land Productivity)		P (Agricultural value added)	
	Low	High	Low	High
High	50%	50%	56.6%	43.4%
Low	56.8%	43.2%	57.5%	42.5%

Results of increasing the impact of balance per hectare on agro-economic-environmental aspects are also shown below.

The results of analysis in Table 7 indicate that if balance per hectare =high, N2O emissions would be high. When balance per hectare=medium or, low, N_2O emissions=low. However, N_2O emissions can be low if balance per hectare is at medium state.

Table 7. Results of posterior probability distribution for agro-environmental indicators in EU countries, 2018

Balance per hectare	P (N2O emissions)			P (CH4 emissions)		
	L	M	H	L	M	H
high	33%	33.5%	33.5%	33%	33.5%	33.5%
medium	48.8%	26%	25.25%	47.3%	27.5%	25.2%
low	43.7%	28.1%	28.1%	43.7%	28.1%	28.1%

The results shown in Table 8 indicate that when (balance per hectare =high), land productivity is equal to medium and agricultural value added is low. When balance per hectare is medium, then land productivity= low and agricultural added value added= low. When (balance per hectare =low), land productivity= low and agricultural value added= low. However, agricultural added value added can be low if balance per hectare be at medium state. Land productivity can also be low if balance per hectare is at medium state.

Table 8. Results of posterior probability distribution for economic indicators in EU countries, 2018

Balance per hectare	P(Land productivity)			P(Agricultural value added)	
	L	M	H	L	H
high	33.2%	33.5%	33.3%	52.2%	47.8%
medium	43%	28.5%	28.5%	53.9%	46.1%
low	39.7%	30.2%	30.2%	53.4%	46.6%

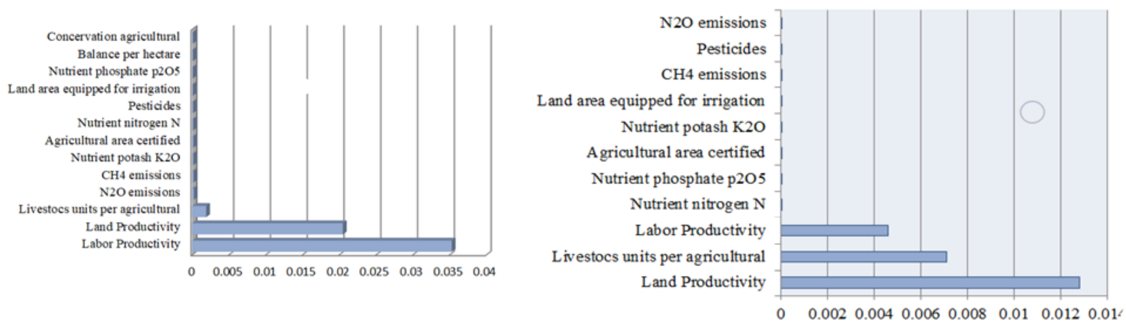

Figure 10. Results of sensitivity analysis of BN for agricultural added value, EU and ME, respectively.

Sensitivity analysis

For validating BN two techniques were used: 1) interview with experts 2) sensitivity analysis (Korb and Nicholson, 2011; Sule et al., 2018). Results of the sensitivity analysis of BN for agricultural added value and land productivity in EU countries are shown in Figs. 11 and 12. In this study we applied Netica software for sensitivity analysis. The variance reduction is used to rank the variables from highest to lowest importance in terms of impacts on the target node. Larger variance reduction values indicate highest impact. In Figure 11, target node is agricultural added value in EU countries.

As shown in Figures 10 and 11, agricultural added value is the target variable. The sensitivity analysis indicated that the labor productivity variable is the most influential variables in EU and ME countries.

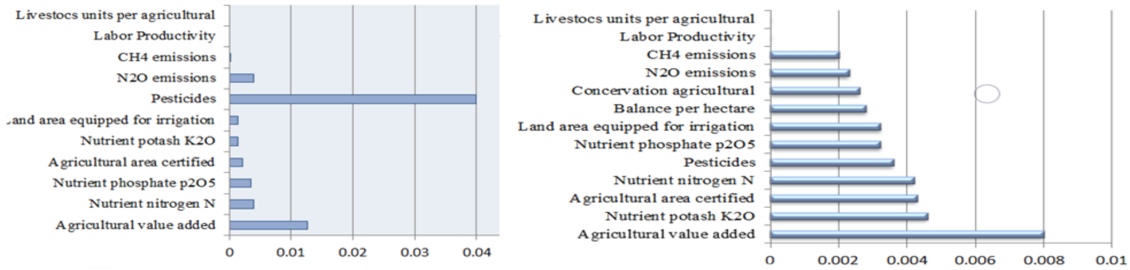

Figure 11. Results of the sensitivity analysis of BN for land productivity, EU and ME, respectively.

Bayesian Network Model for EPI

In this section, we assessed risk of agro-environmental indicators on EPI. Table 14, shows the impact of agro-environmental indicators on EPI. It should be noted that impacts of scenario N_2O and CH_4 emission on EPI was analyzed and used for EPI calculation. We also investigated the scenario of agricultural added value impact on EPI. Figures 12 and 13 show the prior probability distribution of variables in BN for EU and ME countries.

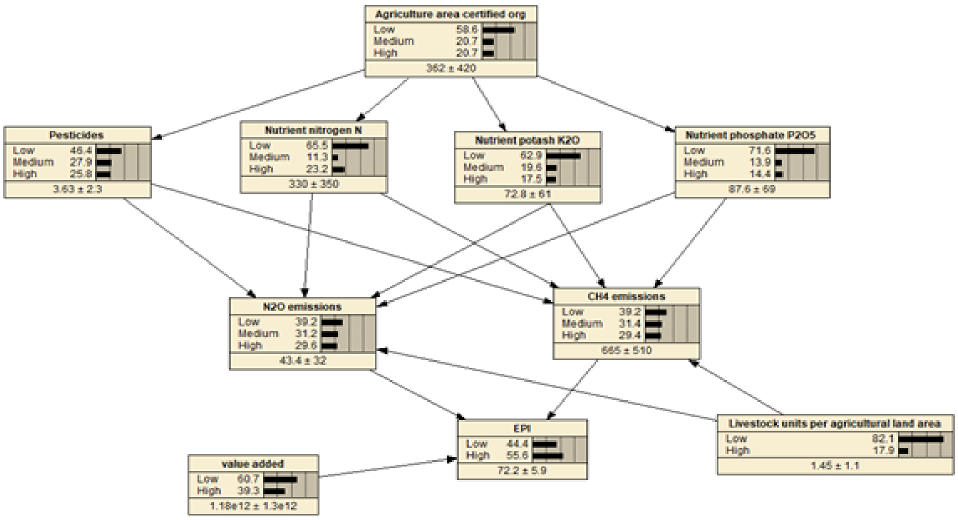

Figure 12. Bayesian network with the probability distribution of variables, EU countries

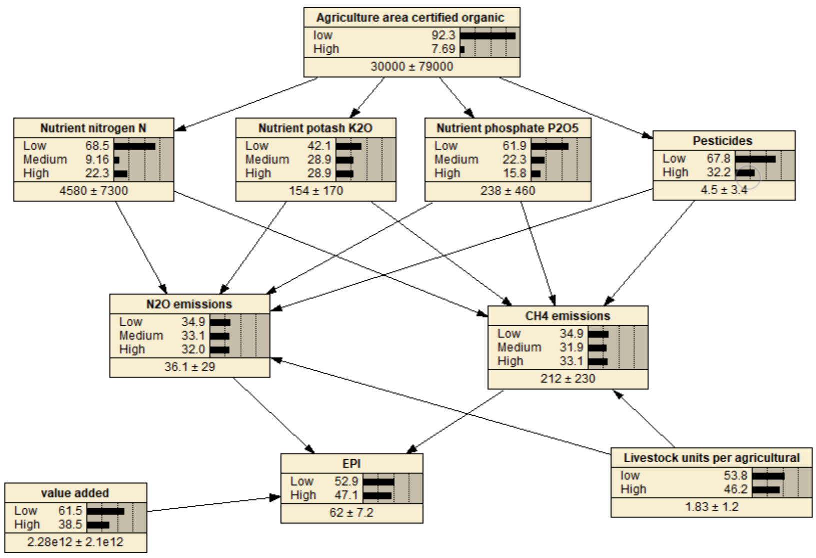

Figure 13. Bayesian network with the probability distribution of variables, Middle East countries

The results of N2O and CH_4 emissions impact scenario on EPI in the EU and ME countries are shown in Tables 9 and10.

Table 9. Results of posterior probability distribution EPI in the EU and ME countries, 2018

Variable		EU countries			
		N_2O emissions		CH_4 emissions	
		LOW 100%	High -	LOW 100%	High -
EPI	Low	32.9%			
	High	**67.1%**			

Table 10. Results of posterior probability distribution (%) EPI in the EU and ME countries, 2018

Variable		ME countries			
		N2O emissions		CH_4 emissions	
		LOW 100%	High -	LOW 100%	High -
EPI	Low	**53.4%**			
	High	46.6%			

According to Table 9, in EU countries N_2O and CH4 emissions lowered EPI increases with high probability of 67.1%. This issue indicates these countries have improved agricultural practices and pesticides and fertilizer applications in agricultural sector. Therefore, the resulted pollution from pesticides and fertilizer applications have been highly reduced. In ME countries, when N_2O and CH4 emissions decreased, EPI decreased with high probability of 53.4%. Therefore these countries have not been successful in improving the environmental performance index and sustainable development objectives.

Table 11. Results of posterior probability distribution (%) for EPI in EU and Middle East countries, 2017.

Variable		EU countries	
		Agricultural value added	
		LOW 100%	High -
EPI	Low	40.7%	
	High	**59.3%**	

Table 12. Results of posterior probability distribution for EPI in EU and Middle East countries, 2017.

Variable		ME countries	
		Agricultural value added	
		LOW 100%	High -
EPI	Low	**56.3%**	
	High	43.7%	

Agricultural added value impacts on EPI in EU and ME countries are shown in Tables 11 and 12. The results indicate that in EU countries when agricultural added value increased, EPI increased with high probability of 59.3%. In ME countries with increase of agricultural added value, EPI with high probability of 56.3% decreased. Therefore, agricultural growth in ME countries could not improve EPI. Agriculture plays an important role in majority of the Middle Eastern countries economies, but policymakers have not paid much attention to this sector.

Sensitivity analysis results are shown in Figure 14, and according to this figure, in EU countries, N_2O emissions is highest on EPI and in ME countries, the agricultural added value is the highest variable on EPI.

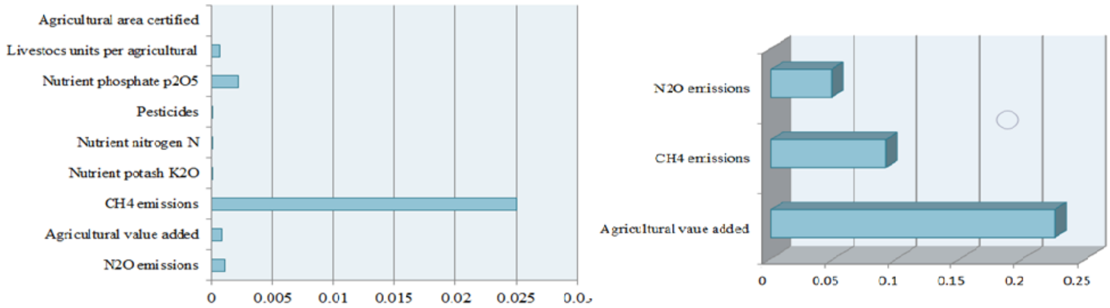

Figure 14. Bayesian network with the probability distribution of variables, EU and ME, respectively.

Conclusion

It is important to assess the relationship between agro-environment and economic indicators that reflect sustainable development. In this study, a Bayesian network model was applied to investigate the relationship between agro-economic-environment indicators in the EU countries in comparison with ME countries. We showed relationships between variables of model based on expert interviews and previous studies. Then K-means cluster analysis for classification of variables in the EU and ME countries was applied. Finally, we analyzed the scenarios resulting from changing the agricultural area as certified organic, conservation agriculture, balance per hectare in EU and ME. Our findings showed when agricultural area as certified organic and conservation agricultural area are high in EU countries, land productivity is medium with the highest probability of 33.6%. Therefore, it is predicted that with increasing agricultural area as certified organic and conservation agricultural area, at 100% probability, land productivity can be increased with a probability of 33.6% in EU Countries. The results also indicated that with increasing agricultural area as certified organic and conservation agricultural area at 100% probability, land productivity and agricultural added value can be increased with a probability of 56.8% and 57.5%, respectively in ME Countries. This indicates that organic farming has the potential for improvement of food security. Organic farming should be considered as a strategy for community development and sustainable food systems for food security improvement. The results of sensitivity analysis showed that in EU countries, labor productivity and land productivity have the highest impact on agricultural added value and in ME countries land productivity has the highest impact on agricultural added value. The results also showed that decreasing pesticide, nitrogen, phosphate, and potash consumption, can improve EPI in the EU and ME countries. The ME region faces a wide array of environmental stresses that include water scarcity and air pollution. Therefore, ME countries should employ different approaches to reform agricultural policy to achieve the sustainable development objectives. The results suggest that agricultural area as certified organic creates more added value in agricultural sector. Organic farming lead to minimal use of fertilizers and pesticides, and can result in lower input costs. Organic farming also can increase land productivity that has the highest impact on agricultural added value. The EU and ME countries should seek better management and control of agrochemicals use. Pollution emission due to pesticides and fertilizer use can significantly decrease the level of EPI. In summary, based on this study, Bayesian networks could be applied in more studies for investigating agro-environmental impacts and environmental management modelling.

References

Alcamo, J., Henrichs, T., and Rösch, T. 2000. World water in 2025-global modeling and scenario analysis for the World Commission on Water for the 21st Century, Kassel World Water Series, Univ. of Kassel, Kassel, Germany.

Ali Shah, S.A., and Longsheng, C. 2020. New environmental performance index for measuring sector-wise environmental performance: a case study of major economic sectors in Pakistan. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-020-10145-z

Arnaldo Valdés, R., Liang Cheng, S., Gómez Comendador, V., and Sáez Nieto, F. 2018. Application of Bayesian Networks and Information Theory to Estimate the Occurrence of Mid-Air Collisions Based on Accident Precursors. Entropy. 20, 969.

Batary, P.V., Dicks, L., Kleijn, D.J., and Sutherland, W. 2015. The role agri-environmental schemes in conservation and environmental management. Conservation Biology. 29(4), 1006-1016.

Carpani, M., and Giupponi, C. 2010. Construction of a Bayesian Network for the Assessment of Agri-Environmental Measures – The Case Study of the Venice Lagoon Watershed. Italian Journal of Agronomy. 3, 265-274.

Carriger, J.F., and Parker, R.A. 2021. Conceptual Bayesian networks for contaminated site ecological risk assessment and remediation support. Journal of Environmental Management 278, 1-11.

Chai, J., Shi, H., Lu, Q., and Hu, Y. 2020. Quantifying and predicting the Water-Energy-Food-Economy-Society-Environment Nexus based on Bayesian networks - a case study of China. Journal of Cleaner Production. 256,1-27.

Chakrabarty, T., Akter, A., Saifullah, A.S.M., Sheikh, Md.S., Bhowmick, A.C. 2014. Use of fertilizer and pesticide for crop production in agrarian area of Tangail District Bangladesh. Environment and Ecology Research. 2 (6), 253–261.

Dkhili, H. 2019. Environmental Performance and Economic Growth in Middle East and North Africa Countries. Journal of Health & Pollution. 9 (24), 1-9.

Falkenmark M.J., Lundqvist, C., and Widstrand, C. 1989. Macro-scale water scarcity requires micro-scale approaches, Natural Resources Forum. 13, 258–267.

Food and Agricultural Organization of the United Nations, 2011. The state of the world's land and water resources for food and agricultural- managing systems at risk (1st ed). Rome and Earthscan, London.

Grotkiewicz, K. 2017. Analysis of economic and agricultural indicators under sustainable agriculture conditions with the use of bayesian modelling. Technical Sciences. 20(3), 209-225.

High Level Panel of Experts on Food Security and Nutrition (HLPE/FSN) 2016. Sustainable agricultural development for food security and nutrition: what roles for livestock? A report by the High Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security, Rome.144 pp. Available at: http://www.fao.org/fileadmin/user_upload/hlpe/hlpe_documents/HLPE_Report

Jafari Samimi, A., Esmaeili Erami, N., and Mehnatfar, Y. 2010. Environmental Performance Index and Economic Growth: evidence from some Developing Countries. Australian Journal of Basic and Applied Sciences. 4(8), 3098-3102.

Kaikkonen, L., Parviainen, T., Rahikainen, M., Uusitalo, L., and Lehikoinen, A. 2020. Bayesian Networks in Environmental Risk Assessment: A Review. Integrated Environmental Assessment and Management. 17(5), 1-17.

Korb K.B. and Nicholson, A.E. 2011. Bayesian artificial intelligence. Chapman & Hall/CRC, London, UK.

Levontin, P., Kulmala, S., Haapasaari, P. and Kuikka, S. 2011. Integration of biological, economic, and sociological knowledge by Bayesian belief networks: the interdisciplinary evaluation of potential management plans for Baltic salmon. ICES Journal of Marine Science. 68(3), 632–638.

Li, S., Gong, Q., and Yang, S. 2019. Analysis of the Agricultural Economy and Agricultural Pollution Using the Decoupling Index in Chengdu, China. International Journal of Environmental Research and Public Health. 16, 1-11.

Liu, J., Yang, H., Gosllng, S.N., Kummu, M., florke, M., Pfister, S., Hanasaki, N., Wada, Y., Zhang, X., Zheng, C., Alcamo, J., and Oki, T. 2017. Water scarcity assessments in the past, present, and future. Agu publications Earth's Future. 5, 545-559.

Maleki, A. 2018. Environmental Pollution in the Middle East. Strategics Studies of Public Policy.Strategic Studies of Globalization Journal. 8(27), 349-359.

Mamitimin, Y., Feike, T., Doluschitz, R. 2015. Bayesian network modeling to improve water pricing practices in northwest China. Water. 7(10), 5617-5637.

Mitchell, T.M. 1997. Machine Learning. McGraw-Hill.

Mohammadian, F., Yazdani, S., and Fehresti-sani, M. 2020. The Role of Diversity in Improving Environmental Indicators: A Case Study in Mahidasht Plain, Iran. International Journal of Environmental Research 1-14, doi.org/10.1007/s41742-020-00288-9.

Muller, A., Schader, C., El-Hage Scialabba, N., Judith Brüggemann, J., Isensee, A., Erb, K.H., Smith, P., Peter Klocke, P., Leiber, F., Stolz, F., Niggli, U. 2017. Strategies for feeding the world more sustainably with organic agriculture. Nature Communications | DOI: 10.1038/s41467-017-01410-w

Pretty, J. 2008. Agricultural sustainability: Concepts, principles and evidence. Philos. Trans. R. Society of London, Biological Sciences. 363, 447-465.

Punith Kumar, L.M., and Indria, M. 2017. Trends in Fertilizer Consumption and Food Grain Production in India: A Co-Integration Analysis. SDMIMD Journal of Management. 2,45-50.

Radermacher, W. 2009. Sustainable development in the European Union. Monitoring report of the EU sustainable development strategy.

Russell, A., Chalaieny, M., Gazdiyeva, B., Sara Zhumabayeva, S., Kurmanbayeva, A., Akhmetov, K.K., Mukanov, Y., McCann, M., Ali, M., Tucker, A., Vitolo, C., and Althonayan, A. 2018. A Spatial Survey of Environmental Indicators for Kazakhstan: An Examination of Current Conditions and Future Needs. International Journal of Environmental Research. 12, 735-748.

Safarelizadeh, E., Hosseinzadeh, R., and Akbari, M. 2017. The Analysis of the Relative Performance of the Middle East in Terms of Sustainable Development Indices. Journal of Regional Planning. 8(29), 1-11.

Sharma, N., and Singhvi, R. 2017. Effects of chemical fertilizers and pesticides on human health and environment: a review. Int. J. Agric. Environ. Biotechnol. 10 (6): 675–679.

Sule, I., Khan, F., Butt, S., and Yang, M. 2018. Kick control reliability analysis of managed pressure drilling operation. Journal of Loss Prevention in the Process Industries. 52, 7–20.

Sulewski, P., and Kloczho-Gajewska Sroka, W. 2018. Relations between Environmental, Economic and Social Dimensions of Farms' Sustainability.sustainability.10,1-23.

United Nations 2015. Population Pyramids of the World from 1950 to 2100. World Population Prospects. Retrieved from. https://un.org

United Nations. 2020. Policy Brief: The Impact of COVID-19 on Food Security and Nutrition.

United Nations. 2015. Resolution Adopted by the General Assembly on 25 September 2015. Transforming Our World: The 2030 Agenda for Sustainable Development; Seventieth Session; Distr. General 21; United Nations: New York, NY, USA.

Vikari, A., Hietala, R., Huusela-Veistola, E., and Hyvönen, T. 2007. Evaluating agri-environmental indicators (AEIs)--Use and limitations of international indicators at national level. Ecological Indicators. 7(1), 150-163.

Volkov, A., Morkunas, M., Balezentis, T. and Sapolaite, V. 2020. Economic and Environmental Performance of the Agricultural Sectors of the Selected EU Countries. Sustainability. 12, 1-17.

Vörösmarty C.J., Green, P., Salisbury, J., Lammers, R.B. 2000. Global water resources: Vulnerability from climate change and population growth, Science. 28, 284-288.

Widayati, T., Waridin, W., and Mafruhah, L. 2019. Between Environmental Performance and Agricultural Productivity: Assessing the Convergence and Divergence of Demand-Driven

Agricultural Extension," International Journal of Energy Economics and Policy. 9(4), 158-165.
World Health Organization (WHO); Food and Agriculture Organization of the United Nations (FAO). Organically Produced Foods. Available online: http://ftp.fao.org/docrep/fao/010/a1385e/a1385e00.pdf (accessed on 14 October 2015).
Zarandi Motasadi, S., and Bebaran, S. 2009. Strategies of the environmental sector to achieve the goals of the 20-year vision document of the country. Strategy Quarterly. 48, 101-122.