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Factors Affecting Emission Intensity of Pollutants Emitted from Agricultural Production

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Abstract

Energy products are the main sources of emissions for most of the pollutants in Iran. However, for some pollutants like Methane (CH_4) and Nitrous Oxide (N_2O), the production process, including the agricultural production process, plays a significant role. The aims of this study were to analysis the emissions intensity of the selected pollutants and to introduce the determinants in Iranian agricultural sector. The emission intensity in the agricultural sector was decomposed into its components using decomposition analysis. Then, the regression analysis was applied to investigate the emission intensity determinants. The selected pollutants are Carbon Dioxide (CO_2), CH_4, and N_2O emitted from agricultural production process. The applied data cover 1973-2016. The findings showed that CH_4 emission intensity has been decreasing over the study horizon by 3.9% annually. For N_2O, the corresponding value was 2.6%. Based on the results, output level in agricultural sectors is an important driving factor in the emission intensity. It was found that 1% increase in livestock output level is expected to increase CH_4 emission intensity by 0.9% while it will dampen the N_2O emissions intensity by more than 3.3%. By contrast, the same percentage of increase in the output level of agronomy and horticultural subsector will induce an increase of 3.3% in N_2O emission intensity and will reduce the CH_4 emission intensity more than 0.9%. Macroeconomic variables including urbanization and trade openness failed to affect the agricultural emission intensity significantly. The emission intensity of all pollutants, measured in CO_2 equivalent, has been decreasing over the study period by 3.5% annually. It was also found that, in terms of aggregated emission, output expansion in livestock and forestry sectors may induce higher emission intensity, while agronomy and horticultural output expansion can reduce the emissions intensity. Given that the output level plays a significant role in emission intensity while the macroeconomic variables have nothing to do with emission intensity, the measures taken to reduce the emission intensity in the agricultural sector should be sector-specific. Moreover, the measures should focus on each subsector individually.

Keywords: Agricultural sector, Emissions intensity, Methane, Nitrous oxide

Introduction

Global greenhouse gases emissions have grown by 2.5% annually over 1960-2014, reaching 34.6 billion tons. In other words, these emissions are 3.7 times of those in 1960. These changes may induce irreversible consequences (Manahan, 2010). Economic growth is accompanied by more energy use and more use of fossil fuels will result in higher emission of greenhouse gasses (Taylor *et al.*, 2014). More than 80% of Carbon Dioxide (CO_2) (as the main pollutant) is emitted from the consumption of energy products and the remaining part accounts for production process and final consumption . As for Methane (CH_4), more than

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۲- Energy consumption in Iranian economy has increased 7% annually over 1965-2016 while its GDP has grown by 3.9% (Iran's Energy Balance, 2016). The average energy use for USD 1000 of output is 234.72 Kg oil equivalent while the

84% of the emission accounts for the production process, and the corresponding value for energy is less than 1%. Although, energy products account for most of the pollutants, there are other sources for pollutants emission as well. There are three sources for pollutants emissions, including consumption of energy products, production process, and final consumption. The emissions from production are the part that is emitted in the production process and is not related to the consumption of the energy products[1]. The emissions from final consumption also include emissions from the consumption of the goods and services by households and institutions (Farajzadeh, 2012).

Emissions from production process are significant in some sectors like agriculture in the Iranian economy. The agricultural activities have not accounted for a significant part of energy use and pollution emissions from energy sources. However, they account for a significant part of some of the pollutants emitted from production process[2]. Accordingly, more than 90% of N_2O, around 55% of CO and more than 25% of NO_x emitted from production process. The corresponding value for CO_2 is more than 25% (Farajzadeh, 2012). Agricultural sector accounts for 9.6% of the Iranian GDP, and more than 25% of the population is dependent on agriculture (Central Bank of Iran, 2017). In addition, 4.1 out of 23.4 million active population of Iran are employed in agricultural sector (Central Bank of Iran, 2012; FAO, 2017).

The amount of emission with respect to the production level is measured by a concept known as emission intensity. It measures the emission per unit of production[3]. As literature shows, emissions from production process has not been considered enough due to the dominant role of emissions from energy, while agricultural activities account for a significant part of CH_4 and N_2O emissions. More than 84% of CH_4 emits from the production process and the agricultural sector accounts for around 20%, emitted mainly from livestock and agronomy subsectors. The corresponding values for N_2O are over 58 and 57%, respectively (Farajzadeh, 2012). Thus, as far as CH_4 and N_2O are considered, agricultural sector is important. During the last five decades, the total emissions of theses pollutants, measured in CO_2 equivalent[4], emitted from agronomy and horticultural and livestock subsectors has grown by 2.5 and 0.4%, respectively. The total emissions of the CH_4, N_2O, and CO_2, in terms of CO_2 equivalent, is more than 37 million tons. The corresponding value for the whole of the world is over 5410 million tons. In other words, Iran accounts for around 0.5% of the emissions while the corresponding value for agricultural output share is 1.1% (FAO, 2017). Although, the Iranian agricultural sector is less polluting compared to the world, the attempts to achieve less polluting agricultural output and lowering chemical inputs have been increasing. For instance, pistachio export from Iran to the EU area encountered challenges with respect to health problems (European Commission, 2010). Setting higher standards for agricultural and food products may restrict export. Thus, restricting chemical use and emission of pollutants should be considered.

We focus on intensity decomposition of emission from agricultural production process as well as examine the determinants. Accordingly, emission intensity of the selected pollutants was decomposed into the corresponding components. In addition, based on the current literature, more driving factors were introduced.

In the literature review, we have focused on the driving factors of emissions and emission intensity. However, most of the current literature has examined the emissions from energy products.

corresponding value for many countries is less than 100 and the global average is around 121 (World Bank, 2016).

۱- Globally, for the most of pollutants, energy products are account for the most part of emissions. Accordingly, 65% of greenhouses gases are assigned to energy consumption or production process (Marrero, 2010).

۲- Agricultural sector share of energy consumption has been decreasing over the decades, accounted for 8.5% and 3.7% in 1967 and 2016, respectively. However, the amount of energy products consumption has been rising, increasing from 4.4 to 50.7 million Barrel of oil equivalent over 1967-2016 with an annual growth of over 5.1% (Iran's Energy Balance, 2016). The reduction in agriculture share results from significant rise in the consumption of energy products in other sectors especially manufacturing activities.

۳- Considering this measure also shows that Iran's situation is not desired. CO_2 emission per income (measured in 2016 PPP$) has been 0.59 while the global average was 0.31 (World Bank, 2016). In other words, in terms of emissions intensity also the Iranian economy is more polluting compared to the world as a whole.

۴- The multiplication factor to aggregate N_2O and CH_4 into CO_2-equivalent are 310 and 21, respectively (United Nations, 2010).

While, the whole of the economy has been considered. Among the driving forces, urbanization has remarkably been at the central focus. For instance, Cramer (Cramer, 2002) showed that increased population is the main driver for air pollution. Some empirical works show that building in the developed countries induces a slowdown in the scale of carbon emissions from energy while it results in higher carbon intensity (Sadorsky, 2013). For example, building construction in the developed Europe may result in lower carbon emissions from energy products consumption (Kasman and Duman, 2015). On the other hand, Barrios *et al.* (Barrios *et al.,* 2006) suggest a significant relationship between rural and urban immigration and pollution in South Africa. Fan *et al.* (2006) believe that the extent of population effect on CO_2 emission depends on the income level of the countries and CO_2 emission is affected negatively in high-income countries, while the positive relation is expected for low-income ones. In the same vein, Shi *et al.* (2003) reported a higher effect of population for developing countries compared to those of the developed ones. Poumanyvong and Kaneko (2010) found the positive effect of population and urbanization on CO_2 emission for different levels of developing process. As for Iran, Behboodi *et al.* (2010) reported a positive relationship between urbanization and CO_2 emission. Shahbaz *et al.* (2016) found that urbanization effect on CO_2 emission depends on level of the emissions such that it dampens the emission primarily but after exceeding a threshold, it leads to higher CO_2 emission. Alam and Fatima (2007) suggested an emissions increasing effect for urbanization. Regarding the divergent findings for the empirical works, this conclusion may be driven; on the one hand, pollution emission may be increased with moving from agriculture-dominant economy to industrial economy. On the other hand, urbanization provides the chance of more efficient use ofinfrastructures, transportation systems, and energy, leading to lower emissions. Thus, the relationship between urbanization and pollution emissions can be positive or negative[1]. The effect of population on emissions is important since Iran has experienced an increasing trend of urbanization over the last decades, increasing from 47% in 1976 to around 75% in 2016 (Central Bank of Iran, 2017).

Production or income, the manufacturing output and trade liberalization are other driving forces considered in the literature. Fan *et al.* (2006) suggested the economic growth as the main driver of CO_2 emission. The same relationship was reported by York *et al.* (2003) for greenhouse gases. The positive effect of production on emissions intensity has been reported in many studies (Wu *et al.,* 2005; Wei *et al.,* 2008; Wang *et al.,* 2005). Lin *et al.* (2009) found that per capita income and population had the greatest effect on the environment, and industrialization was also significant. In Iran, Barghi Oskoei (2008) reported that the effects depend on the income level. He found that trade liberalization and per capita income lead to lower pollution in high and upper-middle-income countries, while those with income lower than average experience higher pollution. Hubler (2009) found that increasing FDI affects emission intensity significantly.

More attention to the pollutants emissions, especially carbon emissions from sources other than energy products, has been paid recently. This review of attention suggests agricultural activities. The corresponding literature can be divided into two groups. Some of them focus on technical aspects and pay more attention to production factors that contain pollutants at farm level. While other empirical works tend to address economic and political factors. From the first group, Li *et al.* (2014) investigated CO_2 emission intensity of Chinese agricultural sector and they determined the components using decomposition analysis. Also, Ma and Feng (2013) using the same approach concluded that in order to achieve low carbon agriculture in China, agricultural sector should decrease using chemical fertilizers and energy and more advanced technology should be applied. Natak *et al.* (2015) believe that to reduce the emission from crop growing activities, managerial attempts are needed. However, for emission from livestock activities the quality of foods and feeding management in pasture has more potential to reduce the emissions. In the agricultural studies, more attention have been paid to chemical fertilizers. Fisher *et al.* (2010), for agronomy activities, have suggested optimization in fertilizer production and improving agricultural production process. Wan *et al.* (2013) pointed out

١- In the case of positive effect of urbanization on pollution emission Jones (1991) has suggested two mechanisms. First, rising population increases the demand for electricity and transportation, leading to higher emissions of greenhouses gases. Second, higher population intensity increases demand for forestry and its products and leads to changes in forestry use like timber, which may destroy the forests.

increase in use of organic fertilizers and improved production technology of agricultural products in order to dampen CO_2 emissions. Monchuk *et al.* (2010) have investigated more deeply, and they reported the related industries as the sources of high emissions in agricultural sector. They have used Data Envelopment Analysis and concluded that inefficiency in heavy industries such as chemical and petrochemical have lead to increasing emission of CO_2 in agriculture. As mentioned before, the second group of studies addresses economic and political issues. For example, Xu and Lin (2017), while considered the importance of geographical differences in analyzing the emissions intensity of agriculture, suggested that the main driving forces of CO_2 emission in Chinese agriculture are output growth, urbanization and energy intensity. Moyen Uddin (2020), for a group of countries with different income levels showed that output or income is the determinant of CO_2 and CH_4 emission in agriculture; however, its effect is not the same for all countries. In addition, it was found that for some countries the degree of trade openness might result in lower emissions.

As discussed before, agricultural activities, compared to the other activities, play a significant role in pollution emitted from the production process rather than emissions from energy use. This fact has been illustrated in empirical works addressing emissions tax. For instance, Farajzadeh (2018) applying a dynamic CGE model, reported that levying emissions tax induces a rise in the agricultural output which mainly stems from the lower emissions of agricultural sector since it uses energy products much lower than non-agricultural sectors. Findings of Farajzadeh and Bakhshoodeh (2015) also conclude the same implicitly.

The aims of this study were to analysis the trend of selected pollutants emissions from production process in agricultural sector and to determine the driving forces. The distinguishing feature of the study from the current literature is that it examines the emission intensity in production process, while the emission from the consumption of the energy products has mainly been considered by scholars. In addition, the current empirical works have mainly focused on CO_2, while this study addresses N_2O and CH_4 as well. Examining the driving forces of emission intensity may contribute to policymakers to consider the emissions intensity in developing policies.

Method

Many cases of decomposition analysis in the literature apply the Logarithmic Mean Divisia Index (LMDI[1]) to examine the energy intensity. This approach provides an opportunity to determine the driving factors. Indeed, the aggregate emission of a pollutant is decomposed into its components using this method. Following index decomposition method, emission intensity of a pollutant can be presented as follows (Zhang *et al.*, 2019):

$$PI = \frac{\boldsymbol{C}}{\boldsymbol{Y}} = \sum_{\boldsymbol{i}} \frac{\boldsymbol{C_i}}{\boldsymbol{Y_i}} \times \frac{\boldsymbol{Y_i}}{\boldsymbol{Y}} \quad (1)$$

Where C is the total amount of pollution emissions from production process, $\mathbf{C_i}$ represents the pollution emitted from production process of sector i (including agriculture sectors), $\mathbf{Y_i}$ indicates output (value added) of production sector i, and Y is the total gross domestic production (total output).

Output expansion results from extensive use of resources and productivity growth. Thus, growth in productivity also may affect pollution emissions (Rodríguez and Pena-Boquete, 2017). To incorporate this fact in the analysis, we multiply Eq. 2 by $\frac{\boldsymbol{Y}}{\boldsymbol{L}} \times \frac{\boldsymbol{L}}{\boldsymbol{Y}}$:

$$PI = \frac{C}{Y} = \sum_i \frac{C_i}{Y_i} \times \frac{Y_i}{Y} \times \frac{Y}{L} \times \frac{L}{Y} \quad (2)$$

Population is another driving force examined in the literature that is expected to influence the emissions intensity. The emissions intensity equation including population (P) can be rearranged as follows:

$$PI = \frac{C}{Y} = \sum_i \frac{C_i}{Y_i} \times \frac{Y_i}{Y} \times \frac{Y}{P} \times \frac{P}{L} \times \frac{L}{Y} \quad (3)$$

Where $\frac{P}{L}$ is the inverse of employment rate and $\frac{L}{Y}$ is the inverse of labor productivity.

These variables have been applied in Zhang and Hao (Zhang and Hao, 2020) as well as Han *et al.* (2019). Analogue to Eq. 3 we may present the emissions intensity equation as follows:

$$PI = \frac{C}{Y} = \sum_i CY_i \times YY_i \times YP \times PL \times LY \quad (4)$$

Where i represents agriculture subsectors including agronomy and horticulture, livestock, and forestry and rangeland, which we name them as agricultural sectors. $YY_i \equiv \frac{Y_i}{Y}$ is the output share of sector i. $CY_i \equiv \frac{C_i}{Y_i}$ is the pollution-production factor or emissions intensity which indicates the emissions per unit of output.

1- Logarithmic Mean Divisia Index

Rodríguez and Pena-Boquete (2017) have applied a similar variable for pollution emitted from energy products. We examined different pollutants that have been aggregated into CO_2 equivalent using the multiplication factors. The main pollutants emitted from agricultural activities are N_2O and CH_4 presented in terms of CO_2 equivalent using the corresponding multiplication factors. Also, the emitted CO_2 from forestry and rangeland activities has been added to aggregated emissions of CH_4 and N_2O, forming the total emissions from the agricultural activities.

In the regression analysis applied to examine the driving forces of the emissions intensity in Iranian agriculture activities, in addition to the variables developed in the decomposition analysis (X variables), we further considered variables examined in the literature (Y variables). Thus, the general form of the estimated equation can be presented as follows (5):

$$lnPI_t = \beta_1 + \beta_2 lnX_t + \beta_3 lnY_t + u_t \quad (5)$$

The X-class of the variables includes those that are calculated based on the decomposition analysis (Zhang *et al.*, 2019) technique developed by Ang (2015):

$$\Delta PI = PI^t - PI^0 = \sum_i L_i \cdot ln\frac{CY_{i.t}}{CY_{i.0_i}} + \sum_i L_i \cdot ln\frac{YY_{i.t}}{YY_{i.0}} + \sum_i L_i \cdot ln\frac{YP_t}{YP_0} L_i + \sum_i L_i \cdot ln\frac{PL_t}{PL_0} + \sum_i L_i \cdot ln\frac{LY_t}{LY_0} \quad (6)$$

$$L_i = (PI_{i.t} - PI_{i.0})/(lnPI_{i.t} - lnPI_{i.0}) \qquad PI_{i.t} \neq PI_{i.0} \quad (7)$$

$$L_i = PI_{i.t} \; PI_{i.t} = PI_{i.0} \quad (8)$$

Output composition was also applied as determinant of Y-class of the explanatory variables. Zhu and Lin (Xu and Lin, 2017) examined the determinants of emissions intensity in Chinese agriculture using structural variables including energy consumption, urbanization, the population in the agricultural sector, per capita output, and energy intensity. In the same vein, Moyen Uddin (2020) applied agricultural output share, energy consumption, trade openness, and urbanization to examine the pollution emissions through a sample of countries. Regarding the empirical works reviewed, there are some points deserving to be noted. First, to the best of our knowledge, they examined the pollution emitted from the consumption of energy in the agricultural sector. While, emission from the chemical inputs is significant as well. However, due to the data limitation, we used the output level of agronomy and horticultural activities as a proxy for chemical inputs. A significant part of pollution emissions belongs to livestock activities. Thus, the output of these activities was considered in estimation as well. In addition, like the reviewed literature, the output composition and the production structure were taken into consideration using output share of livestock activities in total agricultural output. Moyen Uddin (2020) applied agricultural output share and its quadratic variable, which allow examining the non-linear effect of the variable:

$$lnPI_t = \beta_0 + \sum_{i=1}^{3} \beta_i \, lnCY_i + \beta_4 YYLv + \beta_5 (YYLv)^2 + \beta_6 lnYP + \beta_7 lnPL + \beta_8 lnLY + \beta_9 lnYAg + \beta_{10} lnYLv + \beta_{11} YFo + \beta_{12} U + \beta_{13} TO + u_t \quad (9)$$

In Eq. 9 only livestock output share ($YYLv$) has been included. It is worth noting that the output share of agricultural sectors including livestock and agronomy and horticultural subsectors are highly correlated (-0.98). Thus, we applied only livestock output share in estimated equation. Other explanatory variables are agronomy and horticultural activities output (YAg), livestock output (YLv), forestry and rangeland output (YFo), urbanization (U), and trade openness index (TO). In line with Malakootikhah and Farajzadeh (2020), trade openness was examined using Trade-GDP ratio. In other words, more openness of the economy has been considered as higher trade with respect to the GDP. Rao (2010) suggested a spillover effect for trade that induces technology and productivity improvement, leading to higher economic growth. Eq. 3 was estimated for CH_4, N_2O, and CO_2 equivalent separately.

Data

The applied data are time series of the introduced variables, relating to 1973-2016. The examined pollutants are CH_4, N_2O, and CO_2. The emissions date obtained from the database related to FAO (2017) and the other data are available in database related to the Central Bank of Iran (2017).

Results and Discussion

The results include decomposition analysis of the emission intensity into the components and regression analysis, presented for each pollutant separately. For all specifications, the data stationarity was tested using the Augmented Dickey Fuller test and Durbin-Wu-Hausman test was used to examine the variables erogeneity. Based on the results, all variables were found to be stationary. In addition, the null hypothesis of explanatory variables indigeneity was rejected. It is also worth noting that in all equations the first lag of dependent variable was used to dampen the autocorrelation problem. The lagged-dependent variables are correlated with error terms (Baltagi, 2008) which results in endogeneity problem, thus, the GMM[1] estimation method was applied.

CH_4

Emissions intensity of CH_4 has been decreased by over 3.9% annually. The emissions intensity components are illustrated in Fig. 1. Aggregate (total) emissions intensity has been decreasing over the study horizon, which has mainly been resulted from inverse labor productivity and subsectors emissions intensity. The output composition has contributed to dampen the emission intensity in the early years of the study horizon; however, its contribution has not changed significantly in the following years. Inverse productivity has induced an annual reduction of 1.4%, followed by subsectors' emission intensity by around 0.6% and output composition by 0.3%. Contrary to these components, output scale or per capita output shows a significant intensity increasing effect, leading to 0.75% annual increase in emissions intensity. Inverse employment also illustrates an insignificant but positive effect on emissions intensity. Table 1 presents the regression results for CH_4.

Most of the variables show a statistically significant effect on emissions intensity. Among the applied variables, the coefficients of livestock output share, urbanization and trade openness are not statistically significant. In addition, the non-linear relation for livestock output share was not confirmed.

As expected, an increase in emission intensity in agronomy and horticulture, and livestock induces an increase in aggregate emission intensity. However, there are significant differences in terms of their effects (coefficient). Accordingly, 1% increase in emission intensity of CH_4 in agronomy and horticultural sectors results in higher aggregate emission intensity of agriculture by 0.3% while the corresponding value for livestock sector is 0.8%. It is worth noting that livestock activities account for most of the CH_4 emission of agriculture. This significant role of the livestock activities in CH_4 emission intensity is observed via output level since a 1% rise in livestock activities output is expected to increase the CH_4 emission intensity by over 0.9%.

Inverse employment is another important variable that affects the CH_4 in agriculture significantly and positively. However, its coefficient's absolute value is not considerable. Based on the definition, the higher values for this variable mean higher dependency burden and the pressure imposed by a higher population, which is expected to put more pressure on natural resources and to raise the attempts to increase the output via using more polluting inputs.

As mentioned before, higher output in agronomy and horticultural sector may dampen the CH_4 emissions in agriculture since these activities are less emitting CH_4 compared to the livestock activities and have lower CH_4 emission intensity. According to the coefficient obtained, 1% increase in output of agronomy and horticulture sector is expected to decrease the CH_4 emission intensity of CH_4 in agriculture by over 0.9%. Per capita output also shows an emission intensity dampening effect; however, in terms of the absolute value, its effect is negligible. Higher per capita output may be accompanied by more efficient use of the production factors.

Urbanization and trade openness failed to have a statistically significant effect on the CH_4 emission intensity. In other words, CH_4 emission intensity is mainly derived from the agriculture sector itself. However, the lagged dependent variable also should be considered since it may include the delay effect of the variables. It is worth noting that this variable is applied to dampen the autocorrelation problem (Baltagi, 2008). It should also be noted that this variable may include the measuring errors (McKinnish, 2005), leading to downward bias in the estimated coefficients such that the corresponding value of the coefficient may not be appropriate to calculate the long run effect (Reed and Zhu, 2017).

The diagnostic statistics presented in Table 1 also confirm the appropriateness of the estimated equation. The applied explanatory variables can explain more than 99% of variations in the CH_4 emission intensity. The Ljung–Box Q-statistics also indicate that the residuals are not significantly correlated.

N_2O

N_2O emission intensity has been decreasing slightly over the study period by annual rate of 2.63%, reaching from 1.77 to 0.56 Kg/million Rials. However, the decreasing trend turned to be

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1- Generalized Method of Moments

more speeding in the last years and it has decreased by 8.4% annually over 2008-2016. Fig. 2 illustrates the general trend of N_2O emission and the corresponding components. The aggregate (total) emission intensity shows a decreasing trend with insignificant fluctuations. Among the components, inverse of labor productivity, emission intensity of sectors and output composition show negative effects on N_2O emission intensity, while inverse employment and output scale are expected to increase total emission intensity. In terms of the absolute value of the effects, emission intensity of sectors, output composition, and inverse employment rate affect by as low as 0.02% or lower, while the remaining components also have no significant effect since their corresponding values are less than 0.1%. As for CH_4, the most influencing factors of N_2O emission intensity are output scale and labor productivity. The former leads to higher emission intensity and the latter dampens it.

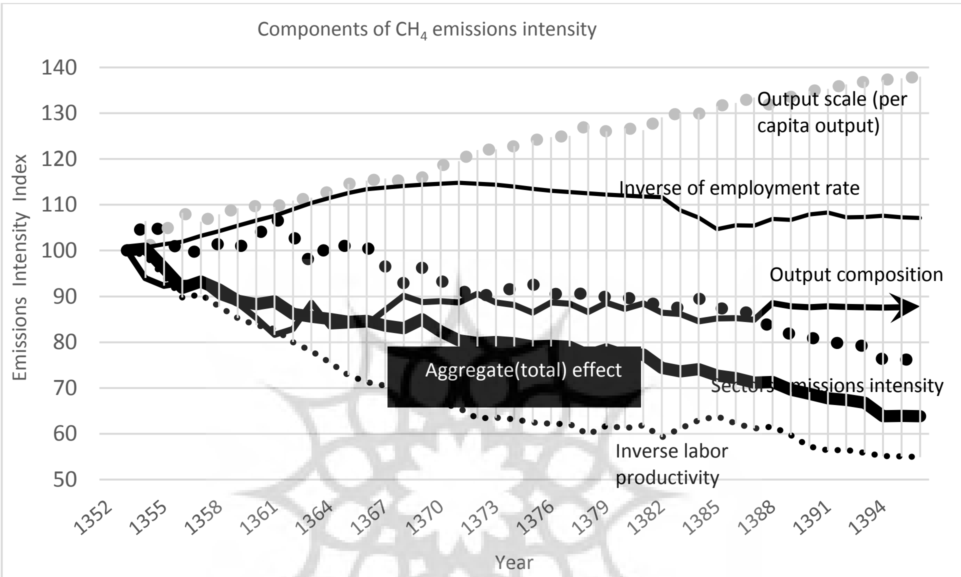

Fig. 1- CH_4 emissions intensity and its components over 1973-2016

Table 1- Regression results for CH_4 emissions intensity model over 1973-2016.

Variable	**Coefficient**	**Standard error**	**t-statistics**	
Constant	0.381	0.887	0.42	
CH_4 emissions intensity in agronomy and horticulture sector	0.257***	0.012	12.20	
CH_4 emissions intensity in livestock sector	0.824***	0.009	86.63	
Output share of livestock sector	-0.057	2.202	-0.026	
Squared of output share of livestock sector	-2.998**	1.136	-2.63	
Agriculture per capita output	-0.055*	0.028	-1.94	
Inverse of employment rate	0.028***	0.005	5.15	
Output of agronomy and horticulture sector	-0.912***	0.330	-2.75	
Output of livestock sector	-0.926***	0.323	2.85	
Urbanization	-0.014	0.060	-0.23	
Trade openness	-0.000	0.005	-0.09	
Lagged dependent variable	-0.017***	0.006	-2.53	
Statistics	Adjusted R^2	J-statistics	Q*(1)	Q(2)
	0.999	7.41(0.59)	).55(·0.34	).80(·0.42

The levels of statistical significance are denoted with ***, **, and * for 1%, 5%, and 10%, respectively.
*Q(p) is the significance level of the Ljung –Box statistics in which the first p of the residual autocorrelations is jointly equal to zero.

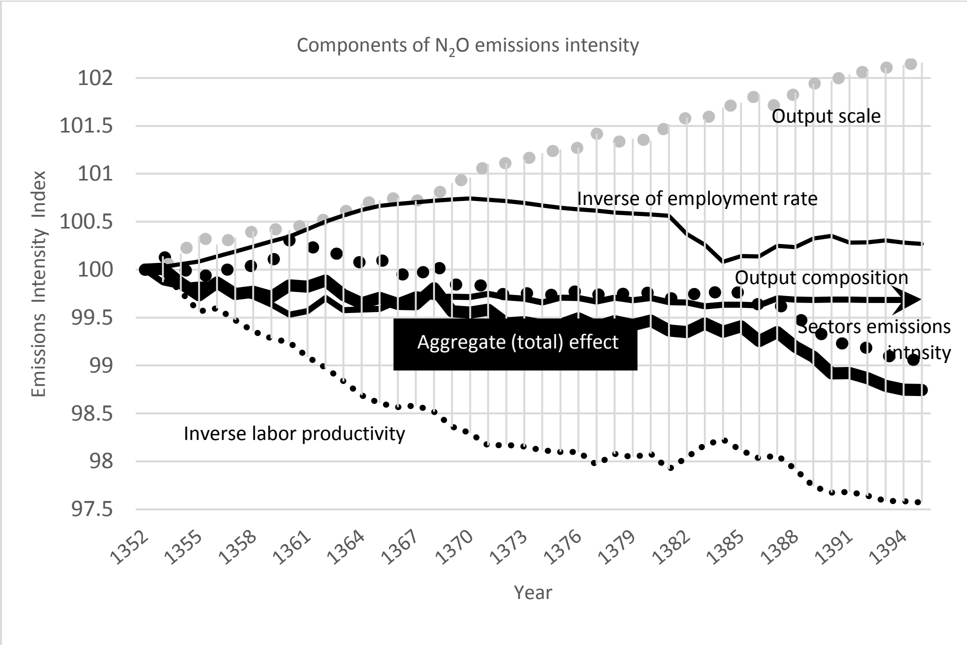

Fig. 2- N_2O emissions intensity and its components over 1973-2016

Agricultural per capita output is the only one that has failed to affect the N_2O emission intensity (Table 2). An inverse U-shaped non-linear relationship was also found between emission intensity and the output share of livestock sector. Based on the relationship, the turning point will occur in the value of 0.77 for emission intensity that regarding the current values of the emission intensity, the emission of N_2O is on the way of climbing up the path.

As the results show, 1% increase in N_2O emission intensity in agronomy and horticulture sector is as strong enough to raise the aggregate (total) emission intensity of agriculture by 0.47%. The corresponding value for livestock sector is around 0.5%. The interesting point is that, while emission intensity and the output share of livestock subsector affect the aggregate emission intensity positively, the corresponding output induces a reduction in emission intensity. Accordingly, 1% increase in livestock activities may reduce the aggregate emission intensity of N_2O by 3.34%. It should be noted that the estimated coefficient for output is interpreted while the effects of other variables are assumed to be unchanged. In other words, output increase in livestock sector should be examined while the output share of this subsector is assumed to be unchanged which is possible if the output of other subsectors increases. On the other hand, agronomy and horticultural sector have an intensity increasing effect and 1% increase in the output is expected to increase the emission intensity by 3.36%. Output expansion via more use of chemical inputs containing this pollutant may increase the N_2O emission intensity dramatically.

Contrary to CH_4, inverse employment has a negative relationship with N_2O emission intensity. In other words, higher dependency burden will dampen the emission intensity. However, its effect is slight. Trade openness reveals a statistically significant effect at 10% with a negligible coefficient. The estimation results showed that urbanization has a negative effect on emission intensity and 1% higher urban population will be accompanied by 0.26% lower emission intensity. However, it is worth noting that the current percentage of urban population is 75 (Central Bank of Iran, 2017), leaving not too much room for higher urbanization. The lagged dependent variable also shows a significant effect with slight value.

Total Agricultural Emissions

The total emission of agriculture including CH_4, N_2O, and CO_2 were aggregated into CO_2-equivalent[1]. As shown in Fig. 3, the general trend is decreasing and like CH_4 and N_2O, output scale plays the most significant role in increasing emission intensity. While, inverse labor productivity has a significant contribution in

١- The multiplication factor to aggregate N_2O and CH_4 into CO_2-equivalent are 310 and 21, respectively (United Nations, 2010).

lowering emission intensity. The intensity factor of sectors plays the role of intensity reducing effect. However, output composition and inverse employment rate (dependency burden) have no considerable effects

Table 2- Regression results for N_2O emissions intensity model over 1973-2016.

Variable	Coefficient	Standard error	t-statistics	
Constant	-9.804***	3.671	-2.67	
N_2O emissions intensity in agronomy and horticulture sector	0.472***	0.012	40.58	
N_2O emissions intensity in livestock sector	0.503***	0.016	30.72	
Output share of livestock sector	28.079***	9.982	2.81	
Squared of output share of livestock sector	-18.288***	5.297	-3.45	
Agriculture per capita output	-0.016	0.047	-0.34	
Inverse of employment rate	-0.021**	0.010	-2.02	
Output of agronomy and horticulture sector	3.363**	1.418	2.37	
Output of livestock sector	-3.335**	1.422	-2.34	
Urbanization	-0.265***	0.082	-3.22	
Trade openness	-0.012*	0.006	-1.85	
Lagged dependent variable	0.025***	0.006	4.22	
Statistics	Adjusted R^2	J-statistics	Q*(1)	Q(2)
	0.999	3.57(0.89)	0.24(1.37)	0.15(3.70)

The levels of statistical significance are denoted with ***, **, and * for 1%, 5%, and 10% respectively.
*Q(p) is the significance level of the Ljung –Box statistics in which the first p of the residual autocorrelations is jointly equal to zero.

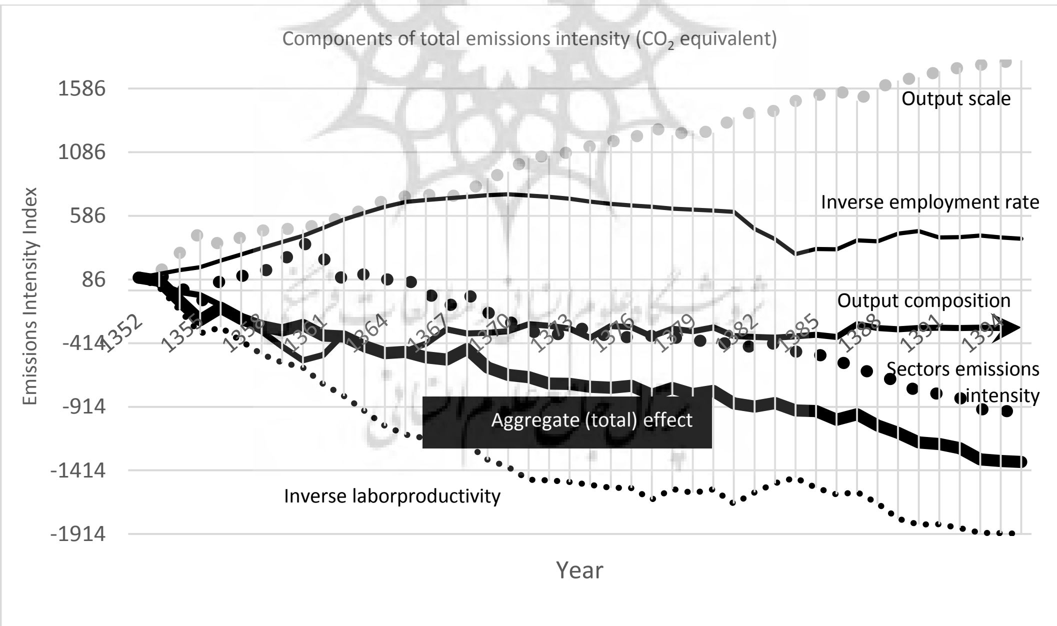

Fig. 3- Total emissions intensity (CO_2 equivalent) and its components over 1973-2016

The results of estimated equation are presented in Table 3. Per capita output is the only variable that has failed to affect emission intensity significantly. Increase in emission intensity of agronomy and horticulture sector by 1% will increase the emission intensity of CO_2 equivalent by around 0.24%. It is worth noting that this variable increases the emission intensity of both CH_4 and N_2O. The corresponding value for livestock sector's emission intensity is 0.6%. The significant contribution of livestock sector to CH_4 emissions is the underlying reason (Table 1). Forestry and rangeland have insignificant role in CO_2 emission. Accordingly, the corresponding coefficient is slight (0.16).

As shown in Table 3, there is an inverted U-shaped non-linear relationship between CO_2 equivalent emission intensity and livestock output share. The turning point value for this variable is 37 percent. Thus, the emission intensity will tend to dampen after approaching this value. The current output share of livestock sector is close to this value.

An increase in the output of agronomy and horticulture sector will induce a reduction in emission intensity, while higher output in livestock and forestry leads to higher emission intensity. This fact for livestock sector stems from its significant role in CH_4 emission. In the same vein, the lower contribution of agronomy and horticulture in CH_4 emission is why this sector induces a reduction in CO_2-equivalent emission intensity.

Among the variables with negative effects on emissions intensity, the inverse employment and trade openness, in terms of the magnitude of the coefficients, have slight effect. In addition, the effect of urbanization is not considerable.

This specification also shows an adjusted-R^2 as high as 99%. In addition, the Ljung–Box Q-statistics indicates that the residuals are not significantly correlated.

Table 3- Regression results for total emissions intensity model over 1973-2016.

Variable	Coefficient	Standard error	t-statistics	
Constant	-0.553***	0.457	-1.21	
Emissions intensity in agronomy and horticulture sector	0.236***	0.008	27.78	
Emissions intensity in livestock sector	0.586***	0.012	48.52	
Emissions intensity in forestry and rangeland sector	0.159***	0.026	6.05	
Output share of livestock sector	1.693***	0.582	2.90	
Squared of output share of livestock sector	-2.289***	0.448	-5.11	
Agriculture per capita output	-0.036	0.037	-0.96	
Inverse of employment rate	-0.040***	0.012	-3.13	
Output of agronomy and horticulture sector	-0.326***	0.090	-3.59	
Output of livestock sector	0.261***	0.082	3.16	
Output of forestry and rangeland sector	0.119***	0.027	4.34	
Urbanization	-0.112*	0.062	-1.79	
Trade openness	-0.014***	0.003	-4.31	
Lagged dependent variable	0.020**	0.008	2.33	
Statistics	Adjusted R^2	J-statistics	Q*(1)	Q(2)
	0.999	8.46(0.67)	)0.26(1.25	)0.41(1.76

The levels of statistical significance are denoted with ***, **, and * for 1%, 5%, and 10% respectively.

*Q(p) is the significance level of the Ljung –Box statistics in which the first p of the residual autocorrelations is jointly equal to zero.

Conclusion

As far as pollution emission has been considered, emission from energy use has received the most attention. However, the emission from production process also shouldn't be ignored. Among the pollutants, agriculture plays a significant role in CH_4 and N_2O emission from production process (Farajzadeh, 2012). This fact has been addressed by the current study in which the emission intensity of the pollutants and the corresponding determinants has been examined. Emission intensity was investigated using decomposition analysis in which the emission intensity of agricultural production process was decomposed into the related components. Then, the role of the components was examined using regression analysis. The considered pollutants are CH_4, N_2O, and CO_2. Livestock activities play significant role in CH_4 emission, while the contribution of agronomy and horticultural output to N_2O emission is more important than other activities (FAO, 2017). Over the study horizon, the emission of the mentioned pollutants has been increasing; however, the emission intensity shows a decreasing trend. In other words, the output of the agricultural activities has been expanded much further compared to the corresponding pollutants emission.

The aggregate emissions of the selected pollutants, measured in terms of CO_2 equivalent, increased by 0.8% annually over the study horizon; however, the emission intensity decreased around 3.5%. Thus, agriculture output has experienced a significant expansion with movement toward less polluting composition. Contrary to these results, there are empirical works showing the increasing emission intensity in Chinese agriculture, which mainly results from intensive use of chemical inputs (Fischer *et al.,* 2010; Li *et al.,* 2014; Nayak *et al.,* 2015). In Iran, chemical inputs also play a significant role in the emission of N_2O in agronomy and horticultural activities. However, livestock activities emit more than two times of agronomy and horticultural activities. Contrary to this fact, emission from livestock and other agricultural activities has not been significantly considered and the attempts are limited to development of strategies to reduce the pollutants emission at the farm level (Zhang *et al.,* 2017). Investigation of the pollutants emission at the sectoral level of agriculture is closely related to the literature at the macroeconomic level. Moyen Uddin (2020) is one of the rare empirical works that applies the macroeconomic variables such as income, urbanization, and trade openness to examine the emission intensity of agricultural activities.

The current study contributes to the literature since it examines the emission from production process. To the best of our knowledge, there are rare works dealing with the pollution emission in Iranian agriculture and some cases like Zibaei and Tarazkar (Zhang *et al.,* 2019) have only addressed the energy consumption in agriculture. Iranian agriculture accounts for only 3.5% of energy consumption, while produces 9% of GDP (Central Bank of Iran, 2017). While most of the current literature addresses the emissions from energy use at the whole of economy, decomposition analysis is useful to take further steps and examine other sources of pollutants emission. The advantage of this approach is that it helps to determine the driving forces of emission intensity (Zhang *et al.,* 2019). Based on this technique, the sectors' emission intensity, output composition, and output level were found to be determinants of emission intensity in agriculture. However, it was revealed that, in terms of the extent of the effect, there are some cases that decomposition analysis shows a slight inconsistency with regression analysis. A similar inconsistency has been reported by Dong *et al.* (Dong *et al.,* 2018). Specificantly, the variable per capita output shows an important increasing role in decomposition analysis, while in the regression analysis it fails to contribute to emission intensity. There are some possible reasons for this inconsistency. First, decomposition analysis applies limited variables compared to the regressions analysis. This point has been suggested as a limitation in Zhang *et al.* (Zhang *et al.,* 2019). In the current study we have used more driving forces like urbanization and trade openness in the regression analysis that are not applicable in the decomposition analysis. The second reason is related to the type of models applied. In the decomposition analysis whole of the dependent variable (emission intensity) changes are assigned to the applied variables, while in the regression analysis, a part of the changes is assigned to residual and constant terms which include those parts of changes that are not explained by explanatory or determinant variables. The third difference relates to the form of the variables applied. For instance, while the output composition factor is applied as an aggregated variable in decomposition analysis, in the regression analysis, a specific variable for each sector is used and three variables for agricultural sectors are defined. In addition, in order to address the possibility of non-linear relationship, some variables are applied in quadratic form in regression analysis. The current study also enjoyed this possibility in which output share of livestock sector was applied in quadratic form and was found to be highly significant. Moyen Uddin (2020) also confirms the contribution of these variables. Thus, it is worth noting that decomposition analysis is powerful in determining the driving forces; however, the variables developed by this technique are not enough necessarily. It assigns the whole of changes to a limited group of variables. However, the determined variables are useful for prediction of the dependent variable. In other words, it is possible to predict the dependent variable using a limited number of variables. The variables developed by decomposition analysis may include the effect of other variables applied in regression analysis. Therefore, we may rely more on regression results, while the contribution of decomposition analysis is also important and helpful especially in developing the driving forces.

Based on the regression results, output level of agricultural sectors is an important variable; however, the direction of their effects on the emission intensity of CH_4 and N_2O is not the same. Output expansion in agronomy and horticulture sector induces an increase in N_2O emission intensity, while it dampens the CH_4 emission intensity. The order is reversed for output rise in livestock sector. In other words, agronomy and horticulture sector is more involved in N_2O emission and livestock activities are more related to CH_4 emission. The sectors emission intensity coefficients also confirm these findings. Changes in output composition more inclined toward agronomy and horticultural (livestock) activities will raise emissions intensity of N_2O (CH_4). Macroeconomic variables like urbanization, trade openness and per capita output didn't reveal significant effects on emission intensity which is in line with findings of Moyen Uddin (2020). Therefore, the strategies developed to reduce the emission intensity can not be the same for livestock and agronomy and horticultural activities. There is a tradeoff between the pollutants emission and relying more on one sector to reduce the emission intensity will raise emission intensity in another sector. Placing restrictions on one sector will lead the production inputs to other sectors, resulting in higher emissions intensity in other sectors.

Based on the findings, the following policy implications are recommended:

1. In order to reduce CH_4 emissions intensity, the strategies should address the livestock activities, while for N_2O, agronomy and horticultural activities are more related. Thus, developing sector- or activity-specific strategies are recommended.
2. Macroeconomic variables have no significant effect on emission intensity of the selected pollutants in agriculture. Therefore, agriculture-specific strategies especially at the farm level are recommended.
3. Although trade openness failed to affect the emission intensity significantly, it is worth noting that it doesn't do with emission increase and trade openness has no more limitation from the emission point of view. This is important since the literature shows a significant potential of gains achievable from international trade.
4. The decomposition analysis and regression analysis are not rivals or substitutes and the weaknesses of decomposition analysis including limited variables and being numerical instead of statistical can be resolved. On the other hand, some estimation problems like the number of observations and multi collinearity bias are not the case in decomposition analysis. Thus, it is recommended to use both techniques simultaneously.

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عوامل مؤثر بر شدت انتشار آلاینده‌های تولید بخش کشاورزی

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چکیده

منشأ اصلی انتشار آلاینده‌ها در ایران حامل‌های انرژی است، اما در مورد اکسیددی‌نیتروژن و متان فرآیند تولید کشاورزی نقش مهمی دارد. در همین راستا، مطالعه حاضر با هدف تحلیل شدت انتشار آلاینده‌های منتخب در بخش کشاورزی و ارزیابی عوامل تعیین‌کننده آن صورت گرفت. برای این منظور ابتدا با استفاده از روش تحلیل تجزیه، شدت انتشار در بخش کشاورزی به اجزای آن تجزیه گردید. سپس با استفاده از تحلیل رگرسیون نقش عوامل تعیین‌کننده در شدت انتشار ارزیابی شد. آلاینده‌های منتخب در بخش کشاورزی شامل متان، اکسیددی‌نیتروزن و دی‌اکسیدکربن منتشرشده از فرآیند تولید و دوره مطالعه شامل ۹۵-۱۳۵۲ می‌باشد. یافته‌ها نشان داد شدت انتشار متان و اکسیددی‌نیتروژن در دوره مطالعه سالانه ۳/۹ و ۲/۶ درصد در حال کاهش بوده است. سطح تولید در زیربخش‌های کشاورزی عامل مهمی در شدت انتشار است. به این ترتیب که انتظار می‌رود یک درصد افزایش در سطح تولید زیربخش دام شدت انتشار متان را ۰/۹ درصد افزایش و شدت انتشار اکسیددی‌نیتروژن را بیش از ۳/۳ درصد کاهش دهد. از سوی دیگر همین میزان افزایش در سطح تولید زیربخش زراعت و باغبانی شدت انتشار متان را ۰/۹ درصد کاهش و شدت انتشار اکسیددی‌نیتروژن را بیش از ۳/۳ درصد افزایش خواهد داد. اثر متغیرهای کلان اقتصاد ایران شامل نرخ شهرنشینی و درجه بازبودن اقتصاد بر شدت انتشار در بخش کشاورزی چندان حایز اهمیت ارزیابی نشد. به این ترتیب سیاست‌های اتخاذشده برای کاهش شدت انتشار باید متمرکز بر متغیرهای بخش کشاورزی و بصورت مجزا در هر زیربخش دنبال شود.

واژه‌های کلیدی: اکسیددی‌نیتروژن، بخش‌کشاورزی، شدت انتشار، متان

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