Impact of Agricultural Factors on Carbon Footprints for GHG Emission Policies in Asia

Jayasooriya, Sujith

19 September 2021

Impact of Agricultural Factors on Carbon Footprints for GHG Emission Policies in Asia

S.P. Jayasooriya[1]

Abstract

Climate change becomes one of the most severe problems in the World. Notably, carbon footprints are one of the key factors for the climate change. The important question is that how to mitigate the climate change by adapting the mitigation practices in the agricultural sector in Asia. The rationale for the study is to understand the determining factors for the emission of carbon dioxide in the agricultural sector with robust analysis. In terms of policy perspectives as the main emission gases are carbon dioxide, methane and nitrous oxide. This study is only considered the CO2 emissions from agricultural sector. The data was obtained from USDA website supplemented by the WDI of the World Bank in 46 Asian countries from 1970 to 2016. The study applied random and fixed effect models in the panel data analysis to predict the factors affecting the CO2 emission in the agricultural sector. Furthermore, the generalized estimation of equations was also applied to avoid the endogeneity issue while obtaining robust estimates. The agricultural factors like feed, fertilizer, labour, livestock, irrigation and machinery were significant and positive predictors of the carbon footprints. Thus, the management of sustainable agricultural factors to control the CO2 emission can be proposed for the GHG emission policies in the Asian region.

Keywords: Agriculture, Carbon footprint, GEE, GHG policies

JEL: C2, Q22, Q54

[1] Chartered Economist (Economic Policy), Sri Lanka

1. Introduction

Climate change is one of the most severe environmental issues in today's world because of excessive emission of Green House Gases (GHG) into the atmosphere. Carbon dioxide is the most dominant GHG, which accounts for more than 60% of total contribution to the greenhouse effect (IPCC, 2000). Agricultural sector of the many developing countries also produces considerable amount of the carbon dioxide. Agriculture, forestry and other land use sector contributions to climate change data (IPCC, 2014). According to the distribution of Global GHG emissions by sector, Agriculture, Forestry and Other Land Use (AFOLU) 24%, 35% Energy, 6% Building, 14% transport and 21% in industries are prominent (IPCC, 2014; FAOSTAT, 2016).

A carbon footprint is a measure of the total amount of carbon dioxide emissions caused by an activity or accumulates both directly and indirectly in daily life (Geng, et. al., 2011). The concept of carbon footprint has been well known in recent decades as an indicator of greenhouse gas emissions originating from human activities (Salo et. al., 2019). The concept of carbon footprint is divided into two; primary carbon footprint and secondary carbon footprint. The primary carbon footprint is a measure of CO2 emissions resulting from direct use of fuel such as oil or LPG for cooking (Donglan et. al., 2010), and transportation fuel oil while the secondary carbon footprint is indirect carbon dioxide emissions. Secondary carbon footprint is generated from household electronic equipment where the electronic equipment can be used by using electrical power sourced from power plants with fossil fuels so that consumers of electric power users indirectly have burned fossil fuels to obtain electricity. This certainly shows that there is a relationship between the secondary carbon footprint and the primary carbon produced. The carbon footprint unit is tons of CO2 equivalent (tCO2e) or kg-equivalent-CO2 (kgCO2e) (Han et. al., 2015).

2. Literature Review

According to the UN definition, the agriculural sector causes 10-15 percent of global anthropogenic GHG emissions (Baumert et al. 2005; Smith et al. 2007; Bellarby et al. 2008; EC 2010a). Including the indirect sources, this percentage increases to more than 30 percent (Bellarby et al. 2008). This makes agriculture the second largest emitter after fossil energy use (US-EPA 2006a). Agriculture is also the largest producer of both methane and nitrous oxide, which together make up about 22 percent of global emissions (Baumert et al. 2005).

Agricultural practices are each associated with certain level of emissions. CO_2 is directly released as a result of agricultural activities in addition to the methane and nitrous oxide. Counted as direct agricultural emissions under the IPCC categorization are only CO_2 emissions from microbial decay or burning of plant litter and soil organic matter, and not the emissions from fossil fuel use in machinery and input production (IPCC 2006). Indirect emissions occur also in the form of methane, nitrous oxide and CO_2. Besides from land use change, CO_2 is also released from fossil fuel use for irrigation, agricultural machinery and the heating of greenhouses. This corresponds to about 10 percent of direct agricultural emissions although not counted in the agricultural sector by the IPCC categorization (Bellarby et al. 2008). Overall global agricultural emissions, for which are counting direct agricultural emissions plus input production and energy use (Bellarby et al., 2008).

As a result of this increasing attention towards global carbon emissions, researchers have begun quantifying the carbon emissions (Liu and Liang, 2017). While some of these studies focused on quantifying the carbon emissions on a national scale, some studies have quantified the carbon emissions on a global scale. Wang et al. (2017) applied decomposition method to decompose aggregate environmental indicators, while Voigt et al. (2014) studied the energy intensity. Moreover, Lan et. al. (2016) explored the energy footprint and Xu et al. (2012) investigated the industrial carbon emissions. Global scaled carbon emission quantification studies revealed China as the largest carbon emitter since 2008 (Zhao, 2014). According to Zhang and Da (2013), China accounts for 27% of the global carbon emissions and as indicated by Michaelowa and Michaelowa (2015), emission value of China has increased by 174% during 1990–2010, while it has been doubled during 2001–2010. Moreover, these carbon exploration studies identified countries such as the USA, UK, and Australia as significant contributors to global carbon emissions. Therefore, it is evident that all the countries are responsible for the global carbon emissions in different scales. Carbon emissions of a country are influenced not only by its development demand but also by the production demand of other countries (Jiang, 2019). Therefore, decision makers across the globe have relied on research outcomes to understand the current situation of carbon emissions and derive future plans to reduce GHG emissions.

3. Data and Variable Definition

The annual data was gathered for 46 Asian countries from 1970 to 2016. The data was gathered from https://www.ers.usda.gov/data-products/international-agricultural-productivity/. The agricultural total factor productivity index was also collected from this web. It was prepared by USDA economic research services. These data were supplemented by the WDI of the World Bank.

Agricultural Land: 1000 hectares of rainfed-cropland-equivalents (rainfed cropland, irrigated Cropland and pasturement pasture, weighted by relative quality - Land Weights)
Cropland: 1000 hectares of land
Irrigation: 1000 hectares of irrigation land
Labour: 1000 persons economically active in agriculture, 15+ yrs, male & female
Livestock: 1000 head of cattle-equivalents
Machinery: Number of 40-CV tractor-equivalents of farm machinery in use (includes tractors, harvester-threshers, milking machines, water pumps)
Fertilizer: Metric tonnes of fertilizer
Feed: 1000 Mcal of Metabolizable Energy (ME)
Total greenhouse gas emissions (kt of CO2 equivalent): composed of CO_2 totals excluding short-cycle biomass burning (such as agricultural waste burning and savanna burning) but including other biomass burning (such as forest fires, post-burn decay, peat fires and decay of drained peatlands), all anthropogenic CH4 sources, N_2O sources and F-gases (HFCs, PFCs and SF6).

4. Empirical method

(i) Fixed and Random Effect Model

In the fixed effects model, μ_i and λ_t are assumed to be fixed parameters and $v_{it} \sim IID(0, \sigma_v^2)$. This model can be estimated by the least squares dummy variable (LSDV) method, by adding N-1 and T-1 country and time period dummy variables. The resulting estimated parameters would be consistent and unbiased.

The model may also be estimated by "within" estimators, transforming the Y and X variables into deviations from individual and time period means. The model is then estimated by least squares on:

$$Y_{it}^w = X_{it}^w \beta + u_{it}^w \qquad (1)$$

where the within-transformed variables and residuals are obtained: $Y_{it}^{w} = (Y_{it} - \bar{Y}_{i.} - \bar{Y}_{.t} + \bar{Y}_{..})$, $X_{it}^{w} = (X_{it} - \bar{X}_{i.} - \bar{X}_{.t} + \bar{X}_{..})$, and $u_{it}^{w} = (u_{it} - \bar{u}_{i.} - \bar{u}_{.t} + \bar{u}_{..})$. The slope coefficients would be consistent and unbiased. A disadvantage of the within estimation method is that the observable time-invariant and country-invariant effects are not estimated.

In the random effect model, the unobservable country-specific and time-specific effects and the random error term are assumed randomly distributed, $\mu_i \sim IID(0, \sigma_\mu^2)$, $\lambda_i \sim IID(0, \sigma_\lambda^2)$, and $v_{it} \sim IID(0, \sigma_v^2)$. and independent of *x* and of each other. The model can be estimated using the generalized least squares (GLS) estimation method. The model may be written as:

$Y_{it}^{*} = \alpha + X_{it}^{*}\beta + u_{it}^{*}$ ……………………………………………………………………….....*(2)*

where the within-transformed *Y* and *X* variables are obtained as:

$Y_{it}^{*} = (Y_{it} - \theta_1 \bar{Y}_{i.} - \theta_2 \bar{Y}_{.t} + \theta_3 \bar{Y}_{..})$, $X_{it}^{*} = (X_{it} - \theta_1 \bar{X}_{i.} - \theta_2 \bar{X}_{.t} + \theta_3 \bar{X}_{..})$, and the parameters $\theta_1, \theta_2, \theta_3$ are transformation parameters. If they are equal to 0, the model is reduced to pooled OLS; if they are equal to 1, the model is a within model; and if they are between 0 and 1, it is a case of GLS. Four different feasible GLS (FGLS) have been developed following Wallace and Hussain (1969), Amemiya (1971), Nerlove (1971) and Swamy and Arora (1972). The methods differ by the way different unobservable effects' variances are estimated.

(ii) Generalized Estimating Equation Model

The generalized estimating equations (GEEs) methodology, introduced by Liang and Zeger (1986), enables you to analyze correlated data that otherwise could be modeled as a generalized linear model. GEEs have become an important strategy in the analysis of correlated data. These data sets can arise from longitudinal studies, in which subjects are measured at different points in time, or from clustering, in which measurements are taken on subjects who share a common characteristic.

To estimate the statistical relationship between carbon footprints and agricultural factors, we use the GEE approach. The GEE requires three components including mean response, variance, and a working correlation assumption [21]. Given the GLM estimation with conditional expectation, $E(Y_{it}|X_{it}) = \mu_{it}$, the link function G (·) (a non-linear function that links predicted values and independent variables) can be expressed as:

$\mu_{it} = G(X_{it}\beta)$ ……………………………………………………………………………………(3)

Then the conditional variance of the response variable Y_{it}, given the independent variables, is:

$Var(Y_{it}) = \phi v(\mu_{it})$ ……………………………………………………………………………..*(4)*

where ϕ is a known parameter that depends upon the distribution of the response variable; and $v(\mu_{it})$ is the variance function of mean $E(Y_{it}|X_{it}) = \mu_{it}$. The GEE is defined by substituting the variance term in the GLM with the following variance-covariance matrix (Hardin, and Hilbe, 2012).

$V(\mu_{it}) = [D(V(\mu_{it}))^{\frac{1}{2}} R(\alpha)_{(ni \times ni)} D(V(\mu_{it}))^{\frac{1}{2}}]_{ni \times ni}$ ……………………………………………….....*(5)*

α = the correlation parameter;

where: D = the diagonal matrix; $V(\mu_{it})$ = the variance of marginal mean μ_{it} ; $R(\alpha)_{(ni\times ni)}$ = the working correlation matrix.

We define CO_2 emission as a dependent variable which explains the variation of the GHG emission. As such, we adopt a non-linear factional response model in this study. The most often used fractional response models are fractional probit and fractional logit. Here, we use the fractional probit model because the probit function is computationally simple in the presence of unobserved heterogeneity. For the panel data form, which usually includes many cross-sectional units observed at a few time points, the GEE has an advantage over the GLM by separating the nuisance variation due to the population-wide behavior from the variation related to time trends (Gibbons, et al, 2010). The fractional probit model with unobserved effect can generally be written as:

$$E(y_{it}|X_{i1}X_{i2\ldots\ldots}X_{iT}) = \Phi(X_{it}\beta + c_i)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where i = 1, 2, ..., N for cross-sectional units; t = 1, 2, ..., T for time; y = the response variable; X = the K ×1 vector of explanatory variables; β = the K ×1 vector of constants; c_i = the unobserved effect which is defined as $c_i|\ (X_{i1}X_{i2\ldots\ldots}X_{iT})$~Normal $(\psi + \bar{X}_i\xi, \sigma_a^2)$. A simple way to express c_i is that $c_i = \psi + \bar{X}_i\xi + a, where\ a_i|X_i \sim N(0, \sigma_a^2)$.

5. Results and Discussion

This section provides the results of the empirical analysis on what agricultural factors determine the emission of CO_2 (carbon footprints) in Asian countries. Initially the panel data model is estimated and then generalized estimation of equations-population averaged model was estimated to improve the robustness and consistency. The table 1 provides the summary statistics of the variables used in the analysis.

Table 1: Summary Statistics of the Variables

Variables	Means	Standard deviation	Observations
Carbon footprints	223981.20	734672.30	1806
Cropland	8640.78	25078.94	1806
Feed	1.88e+07	6.56e+07	1856
Fertilizer	761643.60	3180886	1856
Labour	18436.44	52001.95	1856
Livestock	10304.45	31648.78	1856
Machinery	188276.40	688166.30	1806
Total Factor Productivity	94.21	38.72	1806
Irrigation	1499.43	6122.79	1856
Agricultural Land	11836.49	37101.28	1856

Source: Author's estimation

The table 2 and 3 provide the results of the panel data analysis model which includes the random effect and fixed effect estimations.

Table 2: Results of the Random Effect

Dependent variable: log of carbon footprints	RE 1	RE 2	RE 3
Log of crop land	-	-	-0.399 (-0.47)
Log of feed	0.008*** (51.63)	0.007*** (52.15)	0.006*** (50.34)
Log of fertilizer	0.009*** (3.21)	0.006*** (2.26)	0.007*** (3.12)

Log of labour	0.623** (2.41)	0.492** (1.74)	0.542** (2.12)
Log of livestock	0.061*** (3.01)	0.345*** (2.88)	0.426*** (2.99)
Log of machinery	0.397*** (10.34)	0.334*** (30.34)	0.386*** (12.20)
Log of Total Factor Productivity	-	80.496 (0.90)	33.47 (0.73)
Log of irrigation	-	-	16.542***(-2.80)
Log of agricultural land	-	-	4.025 (1.36)
Constant	9112.32*** (0.48)	-327.892 (-0.02)	-420.21 (-0.01)
No of observations	1856	1856	1856
No of groups	46	46	46
Wald chi2	28653.31***	27764.46***	22467.86***
R2	40.2	92.2	54.9

Note: Panel data model – random effects GLS regression; z values are in the brackets

Source: Author's estimation

The random effect model 1 (RE 1) shows that feed, fertilizer, labour, livestock and machinery are significant positive factors that affect the GHG emissions. All agricultural factors are positive implying that these factors are resulted the emission of the carbon dioxides. The second equation (RE 2) is inclusion of total factor productivity in to the panel data equation. Random effect model predicts that the total factor productivity is not an indicator of supporting the emission of carbon dioxides. The third equation (RE 3) consists of all factors that predicts the emission of carbon dioxides shows that feed, fertilizer, labour, livestock and machinery are significant positive factors while irrigation is a significant positive factor that increases the emission of carbon dioxides into the atmosphere. It also predicts that the total factor productivity is not a significant determinant for CO_2 emissions. The coefficient of determinant for the final equation is around 55% means that the model predicts the 55 percentage of variability. Further, the coefficients are the elasticities of the model equation.

Table 3: Results of the Fixed Effect

Dependent variable: log of carbon footprints	FE 1	FE 2	FE 3
Log of crop land	-	-	0.287*** (6.20)
Log of feed	0.008*** (7.23)	0.021*** (15.44)	0.010*** (5.09)
Log of fertilizer	0.009*** (4.32)	0.009*** (5.11)	0.263**(3.75)
Log of labour	0.623**(2.51)	0.597**(2.61)	2.071***(8.68)
Log of livestock	2.061***(6.61)	2.009***(4.38)	0.300***(5.75)
Log of machinery	0.397***(31.72)	0.359***(30.30)	0.278*** (5.21)
Log of Total Factor Productivity	-	-12.001*** (-10.63)	-12.060***(-9.90)
Log of irrigation	-	-	0.397***(31.72)
Log of agricultural land	-	-	0.047*** (4.27)
Constant	9112.32*** (106.48)	89633.24*** (109.33)	80234.21***(121.95)
No of observations	1856	1856	1856
No of groups	46	46	46
R2	0.74	0.79	0.64

Note: Panel data model – fixed effects regression; t values are in the brackets

Source: Author's estimation

The table 3 above shows the results of fixed effect estimation of the panel data model. In equation 1 (FE 1), the results shows that the feed, fertilizer, labour, livestock, and machinery are significant predictors of the carbon footprint at 5 percentage of significant level. The equation 2 (FE 2) of the results shows that additionally new variable, total factor productivity, is also significant predictor of the carbon footprints at 5 percentage significant level. However, increase of total factor productivity reduces carbon dioxide emissions in the agricultural activities. In equation 3 (FE 3), which includes all variables predict that all the determinants of the model are significant factors in deciding the emission of carbon footprints in the agriculture. Notably, total factor productivity of the model is negatively significant indicating that increase of the productivity reduces the carbon footprints. These coefficients of the factors in the model shows the elasticities of each independent variables.

The table 4 shows the estimated results of the generalized estimation of equations. In order to achieve a higher robustness and consistency avoiding the endogeneity the generalized estimation equation is used in the following table 4.

Table 4: Results of the Generalized Estimation of Equations

Dependent variable: log of Carbon Footprints	GEE 1	GEE 2	GEE 3
Log of feed	0.008*** (55.46)	0.007***(56.72)	0.007***(54.04)
Log of fertilizer	0.009** (1.98)	0.008***(2.72)	0.007***(2.62)
Log of labour	0.623**(1.86)	0.574**(2.24)	0.531**(1.72)
Log of livestock	2.061***(3.85)	1.667***(3.56)	1.640***(3.42)
Log of machinery	0.397***(31.21)	0.343*** (32.70)	0.342***(31.79)
Log of Total Factor Productivity	-	78.476(0.92)	81.366 (0.95)
Log of irrigation	-	13.980***(-5.87)	15.381**(-2.51)
Log of agricultural land	-	-	2.604**(2.84)
Log of crop land	-	-	-0.783 (-0.07)
Constant	9112.32(0.48)	9318.346 (0.53)	9432.510 (0.54)
No of observations	1856	1856	1856
No of groups	46	46	46
Wald chi2	28653.31***	28805.32***	28794.64***
Exchangeable	40.2	40.2	40.2

GEE population-averaged model; t values are in the brackets

Source: Author's estimation

The equation 1 (GEE 1) shows the feed, fertilizer, labour, livestock, and machinery are significant predictors of the carbon dioxide emissions at 5 percentage of significant level. Similarly, the GEE 2 equation also predicts the model and the variables feed, fertilizer, labour, livestock, and machinery are significant predictors of the model; irrigation included in the model is positively significant while total factor productivity is not significant. The GEE 3 equation in the table shows that all variables included in the model is significant except the total factor productivity. The coefficients of the model present the elasticities of the independent variables that predict the changes of the carbon footprints.

6. Conclusion

GHG emission policies are mainly concerned with the emission reduction and mitigation for the climate change. Since agriculture is key sector that generate GHG emission, it is important to study how the agricultural factors affecting the CO_2 emission in Asia. The study intends to understand the causal relationship between the agricultural determinant on the CO_2 emission. The study applied fixed and random effect models followed by the generalized estimation of equation approaches. The results of the fixed and random effect models support the idea that GHG emission policies can be designed with understanding the factors affecting the carbon footprints in agricultural sector. Further, the application of generalized estimation of equation model shows that the factors like feed, fertilizer, labour, livestock, irrigation and machinery were significant and positive predictors of the carbon footprints. This implied that the GHG emission can be controlled with sustainable use of these factors in the agricultural sector.

7. References

Amemiya T (1971) The estimation of the variance in a variance-components model. Int Econ Rev 12(1):1–13

Donglan, Z., Z. Dequn, Z. Peng, Energy Policy, 38, 7, 3377–3383, (2010).

Fuglie, Keith O. (2012). "Productivity Growth and Technology Capital in the Global Agricultural Economy." In: Fuglie K., Wang, S.L. and Ball, V.E. (eds.) *Productivity Growth in Agriculture: An International Perspective.* CAB International, Wallingford, UK, pp. 335-368.

Fuglie, Keith O. (2015). "Accounting for Growth in Global Agriculture," *Bio-based and Applied Economics* 4(3): 221-54.

Geng, Y., C. Peng, M. Tian, Energy Procedia, 5, 370–376 (2011).

Gibbons, R.D.; Hedeker, D.; DuToit, S. Advances in analysis of longitudinal data. Annu. Rev. Clin. Psychol. 2010, 6, 79–107.

Han, L., X. Xu, L. Han, J. Clean. Prod*.,* 103, 219–230 (2015).

Hardin, J.W.; Hilbe, J.M. Generalized Estimating Equations, 2nd ed.; Chapman and Hall/CRC: Boca Raton, FL, USA, 2012.

IPCC. *Special Report on Emissions Scenarios, Working Group III, Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2000.

IPCC, Intergovernmental Panel on Climate Change, 2006. Guidelines for national greenhouse gas inventories. In: Eggleston, S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), Volume 4: Agriculture, Forestry and Other Land Use. OECD Press, Paris Available from. http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.htm, Accessed date: 9 September 2019.

IPCC, Intergovernmental Panel on Climate Change, 2013. Climate change 2013: the physical science basis. In: Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Jiang, M.; An, H.; Gao, X.; Liu, S.; Xi, X. Factors driving global carbon emissions: A complex network perspective. *Resour. Conserv. Recycl.* 2019, *146*, 431–440.

Lan, J.; Malik, A.; Lenzen, M.; McBain, D.; Kanemoto, K. A structural decomposition analysis of global energy footprints. *Appl. Energy* 2016, *163*, 436–451.

Liu, L.-J.; Liang, Q.-M. Changes to pollutants and carbon emission multipliers in China 2007–2012: An input-output structural decomposition analysis. *J. Environ. Manag.* 2017, *203*, 76–86.

Michaelowa, A.; Michaelowa, K. Do rapidly developing countries take up new responsibilities for climate change mitigation? *Clim. Chang.* 2015, *133*, 499–510.

Nerlove M (1971) Further evidence on the estimation of dynamic economic relations from a time-series of cross-sections. Econometrica 39(2):359–382

Salo, M., M. K. Mattinen-yuryev, A. Nissinen, J. Clean. Prod*.,* 207, 658–666, (2019).

Swamy PAVB, Arora SS (1972) The exact finite sample properties of the estimators of coefficients in the error components regression models. Econometrica 40(2):261–275

Voigt, S.; De Cian, E.; Schymura, M.; Verdolini, E. Energy intensity developments in 40 major economies: Structural change or technology improvement? *Energy Econ.* 2014, *41*, 47–62.

Wallace TD, Hussain A (1969) The use of error components models in combining cross-section and time-series data. Econometrica 37(1):55–72

Wang, H.; Ang, B.; Su, B. A Multi-region Structural Decomposition Analysis of Global CO_2 Emission Intensity. *Ecol. Econ.* 2017, *142*, 163–176.

Xu, J.-H.; Fleiter, T.; Eichhammer, W.; Fan, Y. Energy consumption and CO_2 emissions in China's cement industry: A perspective from LMDI decomposition analysis. *Energy Policy* 2012, *50*, 821–832.

Zhao, Z.-Y.; Chang, R.-D.; Zillante, G. Challenges for China's energy conservation and emission reduction. *Energy Policy* 2014, *74*, 709–713.