Investigating the interdependence between non-hydroelectric renewable energy, agricultural value added, and arable land use in Argentina

Ben Jebli, Mehdi and Ben Youssef, Slim

University of Jendouba, FSJEG de Jendouba, Tunisia, Univ. Manouba, ESCT, QUARG UR17ES26, Campus Universitaire Manouba, 2010, Tunisia

13 March 2017

Investigating the interdependence between non-hydroelectric renewable energy, agricultural value added, and arable land use in Argentina

Mehdi Ben Jebli
University of Jendouba, FSJEG de Jendouba, Tunisia
Univ. Manouba, ESCT, QUARG UR17ES26, Campus Universitaire Manouba, 2010, Tunisia
benjebli.mehdi@gmail.com
Slim Ben Youssef
Univ. Manouba, ESCT, QUARG UR17ES26, Campus Universitaire Manouba, 2010, Tunisia
slim.benyoussef@gnet.tn

Abstract: We examine the dynamic relationships between per capita carbon dioxide (CO_2) emissions, real gross domestic product (GDP), non-hydroelectric renewable energy (NHRE) consumption, agricultural value added (AVA), and agricultural land (AGRL) use for the case of Argentina over the period 1980-2013 by employing the autoregressive distributed lag (ARDL) bounds approach to cointegration and Granger causality tests. The Wald test confirms the existence of a long-run cointegration between variables. There are long-run bidirectional causalities between all considered variables. The short-run Granger causality suggests bidirectional causality between AVA and agricultural land use; unidirectional causalities running from AGRL to NHRE and from NHRE to AVA. Long-run elasticity estimates suggest that increasing AVA increases GDP and reduces both pollution and NHRE; increasing NHRE reduces AVA and AGRL. Thus it seems that agriculture and renewable energy are substitute activities and compete for land use. We recommend that Argentina should continue to encourage agricultural production. The substitutability between agricultural and non-hydroelectric renewable energy productions, and their competition for agricultural land use,

should be at least reduced or even stopped by encouraging R&D in second-generation (or even in third-generation) biofuels production and in new renewable energy technologies more efficient in land use.

Keywords: Autoregressive distributed lag; Granger causality; non-hydroelectric renewable energy; agricultural value added; agricultural land; Argentina.

JEL classifications: C32; O54; Q15 ; Q42 ; Q54.

1. Introduction

Argentina is considered among the top countries for biofuel production. Indeed, its fuel ethanol and biodiesel production was 3 billion litres in 2011 ranking it fourth in the world after the USA, Brazil, and Germany (REN21). In 2012, the share of renewable energy (RE) in the total primary energy supply is 7.3%, the share of renewables in total electricity generation was 23.8%, and the shares in total renewable energy were: wind (0.5%), liquid biofuels (16.4%), solid biomass (40.1%), and hydropower (43%) (International Renewable Energy Agency, 2015). Many projects related to the use of solar and wind energy are encouraged. As part of the national program of rural electrification, 12000 electrification systems are planned and 170 have been realized in 2011 in the Argentina province of Neuquén. It has the ambitious program of 20% renewable energy in 2025 (Navia et al., 2016).

Argentina continues to encourage renewable energy production mainly through its fiscal policies. Indeed, the 2006 Law 26190 provided 15-year feed-in tariffs for all renewable energy sources (International Renewable Energy Agency, 2015). This was funded from a Fiduciary Fund for Renewable Energy, which is financed by a tax on electricity imposed on wholesale companies of electricity. In addition, Federal laws on renewable energy recommend provinces to apply the legislation and to develop proper province-level incentives. Argentina gives particular fiscal encouragements to the production and exportation of biofuels, and especially biodiesel, as differentiated export taxes have been established. It is obvious that the production of bio-energy is closely related to agriculture.

In 2014, agricultural value added (AVA) represents 7.95% of gross domestic product (GDP) and employment in agriculture represents 0.5% of total employment in Argentina (World Bank, 2017). This shows the economic importance of the agricultural sector which is more and more mechanized and employs less people. Argentina has taken advantage of the technical progress to improve energy efficiency in agriculture. Energy-saving techniques are commonly used and include genetically improved livestock and plants to increase yield, to resist pests and diseases, and to ameliorate the tolerance to drought (Viglizzo and Frank, 2014). In addition, energy-efficient machinery and irrigation systems, reduced or zero tillage, improved efficiency of the inputs used, water management improvement, and site-specific nutrient and pesticide application are used in Argentina. Due to political incentives, energy-saving strategies are also oriented to the use of renewable energies and particularly bio-energies aiming the substitution or reduction of fossil fuels use. Indeed, bio-energies can be easily promoted through livestock manure use, energy crops cultivations, the use of plant residues and other byproducts obtained from the processing industry of farming.

By reducing its greenhouse gas (GHG) emissions from fossil energy use in agriculture, Argentina reinforces its internal energy security and contributes to combat climate change despite not being among the top carbon dioxide (CO_2) emissions countries. Authorities are conscious that decreases in GHG emissions will still need specific policies requiring incentive fiscal policies, investments in research and development (R&D), and green oriented education. However, governmental authorities should give a special attention to potential emissions that might come from land-use change particularly in areas where the rapid expansion of the agricultural frontier caused important deforestation. Indeed, the principal changes that occurred in land use in Argentina consisted in the expansion of agricultural areas at the expense of forests (World Bank; CIAT; CATIE., 2014). In the last three to four decades, cropland area has increased two-fold, while crop production has increased five-fold. This country produces now more crops with higher yields. At the same time, livestock productions have been reduced and limited to areas less suitable for crop activities such as the semiarid areas of San Luis and Mendoza.

The preceding paragraphs show the interdependence between renewable energy, agricultural production, agricultural land, and CO_2 emissions in Argentina. To the best of our knowledge, no econometric research has been reported on Argentina and interested by renewable energy and agriculture or land use. Our paper is closely related to that of Ben Jebli and Ben Youssef (2017c) study on Morocco and differs from it mainly by the fact that the present paper concerns Argentina, and agricultural value added and agricultural land (AGRL) are used in the same model in the current study, while in Ben Jebli and Ben Youssef (2017c) these two variables are used in two different models.

Our paper has the following structure. Section 2 is a literature review. Section 3 is for data and descriptive statistics. Section 4 is designed for the empirical methodology, econometric results and their discussion. Section 5 concludes with policy implications.

2. Literature review

To the best of our knowledge, Omri et al. (2015) is the unique research that brought causal relationships results about renewable energy in Argentina. These authors consider a panel of 17 developed and developing countries and show that there is a unidirectional causality running from economic growth to renewable energy consumption for the case of Argentina and for the whole panel. However, there are few studies interested by renewable energy in Argentina. Diogo et al. (2014) present a land-use modeling framework to evaluate the economic potential of biofuel production avoiding indirect land-use changes (iLUC) resulting from land competition. Their framework is applied for the case of Argentina to evaluate the development of biofuel potential from soy and switch grass until 2030. They find that if current trends continues, no surplus land is expected to become available for agricultural and livestock productions. Di Sbroiavacca et al. (2016) use simulation models to evaluate the impact of specific climate change control policies on energy consumption and CO_2 emissions savings in Argentina in the period 2010–2050. The results of the LEAP (Long-Range Energy Alternatives Planning System Model) model indicate that if Argentina implements some recommended mitigation measures this will leads to a 16% decrease in GHG emissions compared to a business-as-usual scenario. With the LEAP model, a low CO_2 price scenario leads to the replacement of coal by wind energy and nuclear in electricity expansion, while a high CO_2 price leads to more investments in hydropower.

There is a rich literature, not concerned by the Argentina case, dealing with the causal relationships between renewable energy and other economic variables as the emission of pollution, GDP, and international trade (Al Mulali et al., 2016a; Apergis and Payne, 2010a, 2010b, 2011; Ben Jebli, 2016; Ben Jebli and Ben Youssef, 2015; Dogan, 2016; Menyah and Wolde-Rufael, 2010; Pao and Fu, 2013a, 2013b; Sadorsky, 2009; Tugcu et al., 2012). Most of these studies agree on the existence of a causal relationship between renewable energy consumption and economic growth and on the positive impact of renewable energy on both economic growth and the environment.

Several econometric papers, not concerned by Argentina, have studied the relationship between energy consumption and agriculture (Dogan et al., 2016; Karkacier et al., 2006; Mushtaq et al., 2007; Qureshi et al., 2016; Rafiq et al., 2016; Sebri and Abid, 2012; Shahbaz et al., 2016; Tang and Shahbaz, 2013; Turkeful and Unakitan, 2011). We conclude from these researches on the existence of a causal relationship between energy consumption and agricultural value added and that energy is needed for agricultural production. Recently, some studies have investigated the relationship between renewable energy consumption and agriculture (Ben Jebli and Ben Youssef, 2016, 2017a, 2017b). They conclude to the existence of a causal relationship between renewable energy consumption and agricultural production and that renewable energy consumption helps to combat global warming.

The first econometric study on the relationship between renewable energy production and land use is that of Al Mulali et al. (2016b). They evaluate the impact of renewable energy production on water and land footprint by considering a panel of 58 developed and developing countries. Their study come to the conclusion that economic growth, urbanization, and trade openness increase the water and land footprint and thus have a harmful impact on water and land use. They also show that renewable energy production increases water and land inefficiency, and that renewable energy production will continue to increase water and land footprint in the future. These countries are advised to replace current renewable energy technologies with new ones that ameliorate water and land use efficiency. The second study is that of Ben Jebli and Ben Youssef (2017c) which investigate the relationships between renewable energy consumption, emissions, GDP, agricultural value added, and arable land use (LUSE) in Morocco. They use two models: the first with the AVA variable, while the second is with the LUSE variable. Their long-run estimates show that an increase in agricultural production or in land use increases renewable energy consumption. Their Granger causality tests conclude to the existence of a short-run unidirectional causality running from LUSE and from AVA to renewable energy consumption. In addition, there is a long-run unidirectional causality running from land to RE, and a long-run bidirectional causality between agriculture and renewable energy. These authors advise Moroccan authorities to continue encouraging renewable energy use because it is not in competition with agricultural production for the use of land. The present research differs from this last cited paper by the fact that agricultural value added and agricultural land variables are used in the same model.

3. Data and descriptive statistics

The annual data selected for the empirical analysis are from 1980 to 2013 and include CO_2 emissions per capita (e) measured in metric tons. Real GDP per capita (y) measured in constant 2010 US dollars. Non-hydroelectric renewable energy consumption per capita (NHRE, *nhre*) measured in billion kilowatt hours (kWh) concerns renewable electricity consumption from solar, wind, geothermal, biomass and waste, tide and wave. Agricultural value added (AVA, *ava*) measured in constant 2010 US dollars. Agriculture comprises livestock production, forestry, hunting, fishing, and cultivation of crops. The value added of a sector is its net output after adding up all outputs and subtracting intermediate inputs. Agricultural land (AGRL, *agrl*) measured in square kilometers (sq.km). Agricultural land comprises land under temporary crops, temporary meadows for pasture or for mowing, land under market or kitchen gardens, and land temporarily fallow. Land for growing trees for wood is excluded. All data, including population number, are collected from the World Bank (2017) except those on non-hydroelectric renewable energy which are obtained from Energy Information Administration (2017). AVA variable comprises forestry, hunting, fishing, cultivation of crops, and livestock production. We tried to optimize the collection of data in order to obtain the maximum information according to their availability. The data on NHRE, AVA, and AGRL are divided by population number in order to get the per capita unit. All time series are transformed to natural logarithms before starting the empirical study. Eviews 9.0 is used as basic software for all estimates.

Insert Figure 1 and Table 1 Here

The descriptive statistics of the selected time series are presented in Table 1 and Figure 1. In Table 1, some descriptive estimates (means, maximum, minimum…) are done to evaluate the trend of per capita CO_2 emissions, real GDP, non-hydroelectric renewable energy consumption, agricultural value added, and agricultural land over the considered period of time. The tendencies of our selected variables have been reported in Figure 1 and indicate that all series have an upward trend and periodic fall over time, except for agricultural land plot which shows downward tendency across time. Some perturbations were documented, over the selected period of time, and a sharp decrease was recorded in 2002 followed by a fast increase in 2008. The evolution of economic growth is greatly instable and realized important falls in 1990 and 2002. The highest value of economic growth was equal to 10853.26 US dollars in 2011. Regarding the per capita AVA plot, its trend is upward with a serious fall in 2009 and its highest level is 749.2640 US dollars realized in 2007. A continued decrease was observed for per capita AGRL until 2002 where the lowest level of 0.033970 sq. km was reached. The maximum level of per capita AGRL is equal to 0.045549 sq. km reached in 1980. An approximately continuous stagnation during the first fifteen years was observed for the per capita consumption of non-hydroelectric renewable energy. In 1996, the consumption starts to rise and reached a higher level of $7.26*10^{-8}$ billion kWh in 2006. The evolution of per capita CO_2 emissions was instable across the selected period with an upward tendency. The minimum value of 3.291541 metric tons per capita CO_2 emissions was reached in 2002 and the maximum value of 4.682974 metric tons was reached in 2008.

4. Empirical methodology, econometric results and discussion

The principal aim of the present paper is to examine whether there is competition for agricultural land use between renewable energy production and agricultural production. Additionally, this empirical investigation tries to evaluate the interdependence between per capita CO_2 emissions, real GDP, non-hydroelectric renewable energy consumption, agricultural value added, and agricultural land using the autoregressive distributed lag (ARDL) bound approach to cointegration and Granger causality tests for the case of Argentina. Our empirical methodology follows four steps: *i)* we test the integration order of each time series by using the Zivot and Andrews (1992) unit root test with structural break; *ii)* examine the cointegration relationship between variables by using the test of Wald which is based on the Fisher (F) statistics; *iii)* we investigate the short and long-run estimates of the dependent variables and we test the stability of the estimated coefficients for each equation; *iv)* we inspect the directions of short and long-run causalities between our variables by using the Granger causality method.

4.1. Stationary tests

The integration order is measured to check whether variables are integrated of order zero (I(0)) or of order one (I(1)). To do that, the employment of a unit root test with structural break proposed by Zivot and Andrews (1992) is considered in the present investigation. This unit root test seems to be more powerful than other traditional tests, such as the augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) tests, because it gives more information about structural change. Zivot and Andrews (1992) unit root test with structural change suggests three models to check for stationary proprieties. The first model assumes that there is one-time change in the variable at level, while the second model suggests that there is one-time change in the trend coefficient. The third model allows that, in both intercept and deterministic trends, there is one-time change. The Zivot and Andrews unit root test advises that series contain unit root with one-time change for the null hypothesis, while the alternative hypothesis suggests that the series is stationary with one-time change. In this case, stationary tests are done for the case with intercept and deterministic trend.

Insert Table 2 Here

The results from the Zivot and Andrews's unit root test with structural change are reported in Table 2. This test is examined at level and after first difference for all considered variables. At level, all the variables are non-stationary except for non-hydroelectric renewable energy consumption which is estimated to be stationary at level. After first difference, the t-student estimated statistics mentioned that all variables are integrated of order one, i.e. are I(1).

4.2. ARDL cointegration test

The employment of the ARDL bounds approach to cointegration is considered in this study because of its advantages compared to other econometric techniques such as Pesaran and Pesaran (1997) and Pesaran and Smith (1998). In fact, this method is relatively a recent technique which has been developed by Peasran et al. (2001) and gives further advantages in terms of sample size, integration order (stationary), endogeneity, and estimated coefficients. These advantages can be summarized as follow: *i)* time series can be stationary at level, or stationary after first difference, or fractionally stationary; *ii)* the estimate of the short and long-run elasticities can be done with the same specified model; *iii)* it provides good results even with a small sample; and *iv)* it resolves the problem of endogeneity.

The ARDL equations are presented as follows:

$$\Delta e_t = \alpha + \sum_{i=1}^{q}\alpha_{1i}\Delta e_{t-i} + \sum_{i=1}^{q}\alpha_{2i}\Delta y_{t-i} + \sum_{i=1}^{q}\alpha_{3i}\Delta nhre_{t-i} + \sum_{i=1}^{q}\alpha_{4i}\Delta ava_{t-i} + \sum_{i=1}^{q}\alpha_{5i}\Delta agrl_{t-i} + \alpha_6 e_{t-1} + \alpha_7 y_{t-1} + \alpha_8 nhre_{t-1} + \alpha_9 ava_{t-1} + \alpha_{10} agrl_{t-1} + \varepsilon_{1t} \tag{1}$$

$$\Delta y_t = \beta + \sum_{i=1}^{q}\beta_{1i}\Delta e_{t-i} + \sum_{i=1}^{q}\beta_{2i}\Delta y_{t-i} + \sum_{i=1}^{q}\beta_{3i}\Delta nhre_{t-i} + \sum_{i=1}^{q}\beta_{4i}\Delta ava_{t-i} + \sum_{i=1}^{q}\beta_{5i}\Delta agrl_{t-i} + \beta_6 e_{t-1} + \beta_7 y_{t-1} + \beta_8 nhre_{t-1} + \beta_9 ava_{t-1} + \beta_{10} agrl_{t-1} + \varepsilon_{2t} \tag{2}$$

$$\Delta nhre_t = \delta + \sum_{i=1}^{q}\delta_{1i}\Delta e_{t-i} + \sum_{i=1}^{q}\delta_{2i}\Delta y_{t-i} + \sum_{i=1}^{q}\delta_{3i}\Delta nhre_{t-i} + \sum_{i=1}^{q}\delta_{4i}\Delta ava_{t-i} + \sum_{i=1}^{q}\delta_{5i}\Delta agrl_{t-i} + \delta_6 e_{t-1} + \delta_7 y_{t-1} + \delta_8 nhre_{t-1} + \delta_9 ava_{t-1} + \delta_{10} agrl_{t-1} + \varepsilon_{3t} \tag{3}$$

$$\Delta ava_t = \gamma + \sum_{i=1}^{q}\gamma_{1i}\Delta e_{t-i} + \sum_{i=1}^{q}\gamma_{2i}\Delta y_{t-i} + \sum_{i=1}^{q}\gamma_{3i}\Delta nhre_{t-i} + \sum_{i=1}^{q}\gamma_{4i}\Delta ava_{t-i} + \sum_{i=1}^{q}\gamma_{5i}\Delta agrl_{t-i} + \gamma_6 e_{t-1} + \gamma_7 y_{t-1} + \gamma_8 nhre_{t-1} + \gamma_9 ava_{t-1} + \gamma_{10} agrl_{t-1} + \varepsilon_{4t} \tag{4}$$

$$\Delta agrl_t = \lambda + \sum_{i=1}^{q}\lambda_{1i}\Delta e_{t-i} + \sum_{i=1}^{q}\lambda_{2i}\Delta y_{t-i} + \sum_{i=1}^{q}\lambda_{3i}\Delta nhre_{t-i} + \sum_{i=1}^{q}\lambda_{4i}\Delta ava_{t-i} + \sum_{i=1}^{q}\lambda_{5i}\Delta agrl_{t-i} + \lambda_6 e_{t-1} + \lambda_7 y_{t-1} + \lambda_8 nhre_{t-1} + \lambda_9 ava_{t-1} + \lambda_{10} agrl_{t-1} + \varepsilon_{5t} \tag{5}$$

where Δ, ε, and q denote the first difference operator, the error term, and the number of lags, respectively.

In the first step, the ARDL bound approach proposed by Pesaran et al. (2001) requires fixing the number of lag length for the vector autoregressive (VAR) model which is based on several criteria such as Log likelihood (LogL), Log likelihood ratio (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQ).

Insert Table 3 Here

Based on the previous statistical criteria, we run the unrestricted VAR model to check for the number of lags, which is practically based on the AIC criterion. The results from these statistics are reported in Table 3 and indicate that most criteria confirm that the number of lags is equal to 2. Thus, the optimal number of lag length in our investigation is equal to 2.

In the second step, the ARDL equations (1-5) reported above will be estimated by using the Ordinary Least Squares (OLS) method. To check for long-run cointegration among the variables for each equation, the joint significance of the estimated coefficients is tested by using the significance of the Fisher statistics of the Wald test. The null hypothesis of no cointegration is $\alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$; $\beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = 0$; $\delta_6 = \delta_7 = \delta_8 = \delta_9 = \delta_{10} = 0$; $\gamma_6 = \gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = 0$; $\lambda_6 = \lambda_7 = \lambda_8 = \lambda_9 = \lambda_{10} = 0$, against the alternative hypothesis which assumes that $\alpha_6 \neq \alpha_7 \neq \alpha_8 \neq \alpha_9 \neq \alpha_{10} \neq 0$; $\beta_6 \neq \beta_7 \neq \beta_8 \neq \beta_9 \neq \beta_{10} \neq 0$; $\delta_6 \neq \delta_7 \neq \delta_8 \neq \delta_9 \neq \delta_{10} \neq 0$; $\gamma_6 \neq \gamma_7 \neq \gamma_8 \neq \gamma_9 \neq \gamma_{10} \neq 0$; $\lambda_6 \neq \lambda_7 \neq \lambda_8 \neq \lambda_9 \neq \lambda_{10} \neq 0$. Pesaran et al. (2001) suggest that the computed Fisher-statistic of the Wald test should be compared to two terminal critical values: the lower critical value assumes that series are integrated of order zero, i.e. are I(0), and the upper critical value assumes that series are integrated of order one, are i.e. I(1). Thus, if the estimated value of the Fisher-statistic is greater than the upper critical value, then the null hypothesis of no cointegration is rejected. If the computed Fisher-statistic is between the lower and upper critical values, then the result is inconclusive. Is this case, the existence of cointegration between the variables can be tested through the significance of the error correction term (ECT) by running the vector error correction model (VECM). The last case suggests that if the computed value of the Fisher-statistic is weaker than the lower critical value, then the null hypothesis of no cointegration is not rejected. The choice of the optimal number of lag length which is used for the Fisher statistic is based on AIC and SIC criteria. The estimated Fisher statistics are done for the case of unrestricted intercept and trend. Diagnostic tests are then estimated to check for autocorrelation of residues (Breusch-Godfrey LM test), residual heteroscedasticity (ARCH test), and normality distribution tests (Jarque-Bera statistic).

Insert Table 4 Here

The results from the ARDL cointegration tests are reported in Table 4. With respect to Eq. (1), the calculated Fisher-statistic (2.5489) seems to be higher than the lower critical value but is too smaller than the upper critical value. Thus, the result is inconclusive and the VECM should be run to check for long-run cointegration between variables through the significance of the ECT corresponding to Eq. (1). For Eq. (2)-(5), the estimated Fisher statistics are higher than the upper critical value at mixed levels indicating the existence of long-run cointegration between variables when GDP, NHRE, AVA, and AGRL is defined as the dependent variable , respectively. For all these equations a maximum number of four lags can be considered. Finally, the diagnostic tests approve that there is no residues autocorrelation, no heteroscedasticity, and residues are well normally distributed.

4.3. ARDL estimates

The estimate of the short and long-run elasticitites are done by running the ARDL representation of Eqs.(1-5) for each considered model. The ARDL estimates are reported in Table 5 which shows that all long-run estimated coefficients are statistically significant at mixed levels except for the CO_2 emissions coefficient when NHRE is the dependent variable (Eq. (3)).

Insert Table 5 Here

When per capita CO_2 emissions is a dependent variable, the lagged ECT corresponding to Eq. (1) is negative, comprised between -1 and 0, and is statistically significant at the 5% level prouving the existence of long-run cointegration between variables. Economic growth increases CO_2 emissions because it needs more fossil energy use. Non-hydroelectric renewable energy consumption has a positive and weak impact on emissions because some of these renewable resources, such us biofuels, are polluting but by far less than fossil fuels. An increase in agricultural production seems to reduce CO_2 emissions. This result might be due to the more renewable energy use and/or more efficient energy use of agriculture in comparison to the other economic sectors in Argentina. This result is similar to that of Rafiq et al. (2016) and that of Ben Jebli and Ben Youssef (2017b), but it is contrary to the finding of Ben Jebli and Ben Youssef (2017a) study on Tunisia. Interestingly, increasing agricultural land use reduces CO_2 emissions. This could be explained by the fact that when more land is used farmers are less incited to increase its productivity by using more polluting inputs such us industrial fertilizers or fossil energy. To the best of our knowledge, this constitutes a new result because no preceding research has evaluated the impact of agricultural land use on pollution.

The results concerning Eq. (2) show that all the independent variables have a positive and beneficial impact of economic growth. Our long-run estimates show that economic growth increases NHRE consumption because GDP increase needs more energy for production and consumption purposes. This finding is similar to that of Sadorsky (2009). In addition, economic growth increases AVA because it enables to acquire the necessary investments and inputs for agricultural production. Agricultural production and non-hydroelectric renewable energy consumption seem to play substitute roles because increasing AVA reduces NHRE consumption, and increasing NHRE consumption reduces AVA. This result is in accordance with that of Ben Jebli and Ben Youssef (2016) study on Brazil. This substitutability is reinforced by the fact that an increase in agricultural land reduces non-hydroelectric renewable energy consumption. This finding is opposite to that reached by Ben Jebli and Ben Youssef (2017c) study on Morocco. Interestingly, less agricultural land use increases agricultural production, and an increase in AVA reduces

AGRL use. The reason is that less agricultural land use incites to produce more efficiently. This constitutes a new result not addressed by previous literature. Finally, an increase in non-hydroelectric renewable energy consumption reduces the lands used for agriculture purposes because several renewable energy resources, from which is excluded hydroelectric renewable energy, need lands for production. This result is in accordance with that of Al-Mulali et al. (2016) concerned by a panel of 58 countries.

Insert Figures 2-6 Here

The stability of the computed short and long-run coefficients should be examined. To do that, the cumulative sum (CUSUM) and the CUSUM of Squares techniques developed by Brown et al. (1975) are employed. These statistical tests are based on the recursive regression on residuals and incorporate the short-run dynamics to the long-run through residuals. Both of these tests are reported graphically. If the plots representations of these statistics fall inside the critical bounds of 5% significance, we can conclude that the short and long-run elasticity of a given regression are stable. The graphical representations of these estimated statistics are reported in Figures 2-6. These representations indicate that the computed short and long-run elasticity are well within the critical bounds except for the CUSUM of Squares of recursive residuals for per capita AVA signifying that the estimated coefficients might be instable when per capita AVA is the dependent variable.

4.4. Granger causality tests

The two steps procedure of Engle and Granger (1987) are considered to investigate the directions of the short and long-run causal relationships between per capita CO_2 emissions, real GDP, NHRE consumption, AVA and AGRL. The first step estimates the long-run coefficients and recuperates the residuals, while the second step estimates the parameters concerning the short-run adjustment. The short-run interaction between the considered variables is studied by using the pairwise Granger causality and its significance is measured by the Fisher-statistic. The significance of the long-run interdependence between our variables is assessed by using the t-student statistic. The vector error correction model is given as follows:

$$\Delta e_t = \phi_1 + \sum_{i=1}^{p} \phi_{11i} \Delta e_{t-i} + \sum_{i=1}^{p} \phi_{12i} \Delta y_{t-i} + \sum_{i=1}^{p} \phi_{13i} \Delta nhre_{t-i} + \sum_{i=1}^{p} \phi_{14i} \Delta ava_{t-i} + \sum_{i=1}^{p} \phi_{15i} \Delta agrl_{t-i} + \tau_1 ECT_{t-1} + \zeta_{1t} \tag{6}$$

$$\Delta y_t = \phi_2 + \sum_{i=1}^{p} \phi_{21i} \Delta e_{t-i} + \sum_{i=1}^{p} \phi_{22i} \Delta y_{t-i} + \sum_{i=1}^{p} \phi_{23i} \Delta nhre_{t-i} + \sum_{i=1}^{p} \phi_{24i} \Delta ava_{t-i} + \sum_{i=1}^{p} \phi_{25i} \Delta agrl_{t-i} + \tau_2 ECT_{t-1} + \zeta_{2t} \tag{7}$$

$$\Delta nhre_t = \phi_3 + \sum_{i=1}^{p} \phi_{31i} \Delta e_{t-i} + \sum_{i=1}^{p} \phi_{32i} \Delta y_{t-i} + \sum_{i=1}^{p} \phi_{33i} \Delta nhre_{t-i} + \sum_{i=1}^{p} \phi_{34i} \Delta ava_{t-i} + \sum_{i=1}^{p} \phi_{35i} \Delta agrl_{t-i} + \tau_3 ECT_{t-1} + \zeta_{3t} \tag{8}$$

$$\Delta ava_t = \phi_4 + \sum_{i=1}^{p} \phi_{41i} \Delta e_{t-i} + \sum_{i=1}^{p} \phi_{42i} \Delta y_{t-i} + \sum_{i=1}^{p} \phi_{43i} \Delta nhre_{t-i} + \sum_{i=1}^{p} \phi_{44i} \Delta ava_{t-i} + \sum_{i=1}^{p} \phi_{45i} \Delta agrl_{t-i} + \tau_4 ECT_{t-1} + \zeta_{4t} \tag{9}$$

$$\Delta agrl_t = \phi_5 + \sum_{i=1}^{p} \phi_{51i} \Delta e_{t-i} + \sum_{i=1}^{p} \phi_{52i} \Delta y_{t-i} + \sum_{i=1}^{p} \phi_{53i} \Delta nhre_{t-i} + \sum_{i=1}^{p} \phi_{54i} \Delta ava_{t-i} + \sum_{i=1}^{p} \phi_{55i} \Delta agrl_{t-i} + \tau_5 ECT_{t-1} + \zeta_{5t} \quad (10)$$

Where Δ denotes the first difference operator; p designates the VAR lag length; ECT_{t-1} indicates the lagged ECT corresponding to each equation; τ indicates the speed of adjustment from the short to the long-run equilibrium; ζ_t denotes the residual term.

Insert Table 6 Here

The results from the short and long-run Granger causalities interdependencies between our variables are reported in Table 6. All the error correction terms are statistically significant and are comprised between -1 and 0 implying the existence of long-run bidirectional causalities between all our considered variables.

There is short and long-run bidirectional causality between agricultural land and agricultural production. This can be explained by the remarkable progress of land productivity realized by the agricultural sector in Argentina. Indeed, between 1980 and 2013, per capita agricultural land has decreased from 0.045 to 0.035 square kilometers, while per capita agricultural value added has increased from 515.680 to 673.175 constant 2010 US dollars (see Fig. 1). This constitutes a new and an interesting result because the causal relationships between agricultural production and land use have not been evaluated by previous studies.

There is a short-run unidirectional causality running from AGRL to NHRE, and long-run bidirectional causality between these two variables. This can be explained by the remarkable progress in productivity realized by agricultural lands for biofuels production in Argentina. Indeed, from

1980 to 2013, per capita non-hydroelectric renewable energy consumption has increased from 3.56 to 69.4 kWh, while per capita agricultural land has decreased from 0.045 to 0.035 square kilometers (see Fig. 1). Our short-run causality finding is similar to that of Ben Jebli and Ben Youssef (2017c) study on Morocco. However, these authors find only a long-run unidirectional causality running from arable land use to renewable energy consumption.

We also have a short-run unidirectional causality running from NHRE to AVA, and long-run bidirectional causality between these two variables which are due to the substitutability existing between agricultural and non-hydroelectric renewable energy productions in Argentina. These long-run results are in accordance with those of Ben Jebli and Ben Youssef (2016, 2017a). Short-run unidirectional causalities running from agricultural land to economic growth and to CO_2 emissions are found. Finally, there are short-run unidirectional causalities running from non-hydroelectric renewable energy consumption to GDP and to carbon emissions. These last results differ from those reached by Apergis et al. (2010) because these authors prove the existence of short and long-run bidirectional causalities between RE, GDP and CO_2 emissions for a panel of 19 developed and developing countries.

5. Conclusion and policy implications

The main objective of this study is to examine whether there is competition for agricultural land use between non-hydroelectric renewable energy and agricultural productions in the cased of Argentina. We have excluded hydroelectric renewable energy because it does not need land in consistent amount for energy production. We estimate the long-run elasticity and the causal relationships between per capita CO_2 emissions, economic growth, non-hydroelectric renewable energy consumption, agricultural value added, and agricultural land by using the ARDL bounds approach to cointegration and Granger causality tests. The existence of long-run relationships between variables has been demonstrated for each equation.

We show the existence of long-run bidirectional causalities between all our variables. Lon-run estimates highlight that agricultural production and agricultural land use are beneficial for both economic growth and the environment. There is a short and long-run causality running from NHRE to CO_2 emissions. In addition, our long-run estimates prove that NHRE increases carbon dioxide emissions because some of these renewable resources, such us biofuels, are polluting but by far less than fossil fuels.

There is a short-run unidirectional causality running from NHRE to AVA, and long-run bidirectional causality between these two variables. Long-run elasticities show that non-hydroelectric renewable energy and agricultural productions are substitutes because an increase in one variable reduces the other one. Moreover, there is a competition for land use between renewable energy and agricultural productions in Argentina. Indeed, there is a short-run causality running from AGRL to NHRE in addition to a long-run bidirectional causality, and increasing agricultural land reduces renewable energy consumption in the long-run, and vice versa.

Interestingly, there is short and long-run bidirectional causality between AGRL and AVA denoting a strong causal relationship. Moreover, reducing agricultural lands increases agricultural production and vice versa, which reflects the remarkable improvements realized by agricultural land yield in Argentina during the last decades. This constitutes a new result not addressed by previous literature.

Our econometric results and the actual state of agriculture in Argentina push us to recommend continuing the encouragement of agriculture because of its positive impact on both economic growth and the environment. The substitutability between agricultural production and non-hydroelectric renewable energy production, and their competition for agricultural land use, should be at least reduced or even stopped by: *i)* investing in R&D to get new renewable energy technologies more efficient in land use; *ii)* transforming agricultural and biofuels productions as complementary activities. This might be realized by boosting second-generation biofuels production and discouraging first-generation biofuels production by using appropriate fiscal policies. Let us notice that first-generation biofuels are considered as substitutes to agricultural production because they are derived from sources such as sugarcane and corn starch. Second-generation biofuels are considered complementary to agricultural production because they use non-food-based biomass sources such as municipal and agricultural wastes. Regrettably, this promising alternative still faces technological difficulties; *iii)* Argentina should encourage R&D in renewable energy and particularly in second-generation (or even in third-generation) biofuels production, and should offer competitive credits for investing in the necessary production capacities. Several strategies for helping second-generation biofuels, the cellulosic ethanol, to become major biofuels in the world are proposed by Tan et al. (2008).

References

Al-Mulali, U., Solarin, S.A., Ozturk, I., 2016a. Biofuel energy consumption-economic growth relationship: an empirical investigation of Brazil. Biofuels, Bioproducts & Biorefining, 10, 753–775.

Al-Mulali, U., Solarin, S.A., Sheau-Ting, L., Ozturk, I., 2016b. Does moving towards renewable energy causes water and land inefficiency? An empirical investigation. Energy Policy, 93, 303–314.

Apergis, N., Payne, J.E., 2010a. Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. Energy Policy, 38, 656-660.

Apergis, N., Payne, J.E., 2010b. Renewable energy consumption and growth in Eurasia. Energy Economics, 32, 1392-1397.

Apergis, N., Payne, J.E., 2011. The renewable energy consumption–growth nexus in Central America. Applied Energy, 88, 343-347.

Apergis, N., Payne, J.E., Menyah, K., Wolde-Rufael, Y., 2010. On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. Ecological Economics, 69, 2255-2260.

Ben Jebli, M., 2016. On the causal links between health indicator, output, combustible renewables and waste consumption, rail transport, and CO_2 emissions: The case of Tunisia. Environmental Science and Pollution Research, 22, 16699–16715.

Ben Jebli, M., Ben Youssef, S., 2015. The environmental Kuznets curve, economic growth, renewable and non-renewable energy, and trade in Tunisia. Renewable and Sustainable Energy Reviews, 47, 173-185.

Ben Jebli, M., Ben Youssef, S., 2016. Combustible renewables and waste consumption, agriculture, CO_2 emissions and economic growth in Brazil. MPRA Paper No. 69694. Accessed at: https://mpra.ub.uni-muenchen.de/69694/.

Ben Jebli, M., Ben Youssef, S., 2017a. Renewable energy consumption and agriculture: evidence for cointegration and Granger causality for Tunisian economy. International Journal of Sustainable Development & World Ecology, 24, 149-158.

Ben Jebli, M., Ben Youssef, S., 2017b. The role of renewable energy and agriculture in reducing CO_2 emissions: Evidence for North Africa countries. Ecological Indicators, 74, 295-301.

Ben Jebli, M., Ben Youssef, S., 2017c. Renewable energy, arable land, agriculture, CO_2 emissions, and economic growth in Morocco. MPRA Paper No. 76798.

Brown, R.L., Durbin, J., Evans, J.M., 1975. Techniques for testing the constancy of regression relations over time.Journal of the Royal Statistical Society, Series B, 37, 149–63.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, 427-431.

Diogo, V., Hilst, F.V.D., Eijck, J.V., Verstegen, J.A., Hilbert, J., Carballo, S., Volante, J., Faaij, A., 2014. Combining empirical and theory-based land-use modelling approaches to assess economic potential of biofuel production avoiding iLUC: Argentina as a case study. Renewable and Sustainable Energy Reviews, 34, 208–224.

Di Sbroiavacca, N., Nadal, G., Lallana, F., Falzon, J., Calvin, K., 2016. Emissions reduction scenarios in the Argentinean energy sector. Energy Economics, 56, 552–563.

Dogan, E., 2016. Analyzing the linkage between renewable and non-renewable energy consumption and economic growth by considering structural break in time-series data. Renewable Energy, 99, 1126-1136.

Dogan, E., Sebri, M., Turkekul, B., 2016. Exploring the relationship between agricultural electricity consumption and output: New evidence from Turkish regional data. Energy Policy, 95, 370–377.

Energy Information Administration, 2017. International Energy Outlook. Accessed at: www.eia.gov/forecasts/aeo.

Engle, R.F., Granger C.W.J., 1987. Co-integration and error correction: Representation, estimation, and testing. Econometrica, 55, 251-276.

International Renewable Energy Agency, 2015. Renewable Energy Policy Brief: Argentina. Accessed at: http://www.irena.org/DocumentDownloads/Publications/IRENA_RE_Latin_America_Policies_2015_Country_Argentina.pdf.

Karkacier, O., Goktolga, Z.G., Cicek, A., 2006. A regression analysis of the effect of energy use in agriculture. Energy Policy, 34, 3796-3800.

Menyah, K., Wolde-Rufael, Y., 2010. CO_2 emissions, nuclear energy, renewable energy and economic growth in the US. Energy Policy, 38, 2911–2915.

Mushtaq, K., Abbas, F., Ghafour, A., 2007. Energy use for economic growth: Cointegration and causality analysis from the agriculture sector of Pakistan. The Pakistan Development Review, 46, 1065–1073.

Navia, T., Sewell, A., Avila, J., 2016. Argentina launches innovative renewables program. Accessed at: http://www.renewableenergyworld.com/articles/2016/06/argentina-launches-innovative-renewables-program.html.

Omri, A., Daly, S., Nguyen, D.K., 2015. A robust analysis of the relationship between renewable energy consumption and its main drivers. Applied Economics, 47, 2913-2923.

Pao, H.T., Fu, H.C., 2013a. Renewable energy, non-renewable energy and economic growth in Brazil. Renewable and Sustainable Energy Reviews, 25, 381-392.

Pao, H.T., Fu, H.C., 2013b. The causal relationship between energy resources and economic growth in Brazil. Energy Policy, 61, 793-801.

Pesaran, M.H., Pesaran, B., 1997. Working With Microfit 4.0: Interactive Econometric Analysis. Oxford University Press, Oxford.

Pesaran, M.H., Smith, R.P., 1998. Structural analysis of cointegratingVARs. Journal of Economic Survey, 12, 471–505.

Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16, 289–326.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regressions.Biometrika, 75, 335-346.

Qureshi, M.I., Awan, U., Arshad, Z., Rasli, A.M., Zaman, K., Khan, F., 2016. Dynamic linkages among energy consumption, air pollution, green house gas emissions and agricultural production in Pakistan: Sustainable agriculture key to policy success. Nat Hazards, DOI: 10.1007/s11069-016-2423-9.

Rafiq, S., Salim, R., Apergis, N., 2016. Agriculture, trade openness and emissions: An empirical analysis and policy options. Australian Journal of Agricultural and Resource Economics, 60, 348-365.

REN21, 2012. Renewables 2012 Global Status Report. Accessed at: www.ren21.net.

Sebri, M., Abid, M., 2012. Energy use for economic growth: A trivariate analysis from Tunisian agriculture sector. Energy Policy, 48, 711-716.

Shahbaz, M., Islam, F., Butt, M.S., 2016. Finance–growth–energy nexus and the role of agriculture and modern sectors: Evidence from ARDL bounds test approach to cointegration in Pakistan. Global Business Review, 17, 1037–1059.

Sadorsky, P., 2009. Renewable energy consumption and income in emerging economies. Energy policy, 37, 4021-4028.

Tan, K.T., Lee, K.T., Mohamed, A.R., 2008. Role of energy policy in renewable energy accomplishment: The case of second-generation bioethanol. Energy Policy, 36, 3360– 3365.

Tang, C.F., Shahbaz, M., 2013. Sectoral analysis of the causal relationship between electricity consumption and real output in Pakistan. Energy Policy, 60, 885–891.

Tugcu, C.T., Ozturk, I., Aslan, A., 2012. Renewable and non-renewable energy consumption and economic growth relationship revisited: Evidence from G7 countries. Energy Economics, 34, 1942-1950.

Turkekul, B., Unakitan, G., 2011. A co-integration analysis of the price and income elasticities of energy demand in Turkish agriculture. Energy Policy, 39, 2416–2423.

Viglizzo, E.F., Frank, F.C., 2014. Energy use in agriculture: Argentina compared with other countries (Chapter 4). In: Energy Consumption: Impacts of Human Activity, Current and Future Challenges, Environmental and Socio-Economic Effects (S. Reiter, Editor). NOVA Science Publishers, Inc. N York Pp 77-98.

World Bank, 2017. World Development Indicators.Accessed at: http://www.worldbank.org/data/onlinedatabases/onlinedatabases.html.

World Bank; CIAT; CATIE, 2014. Supplementary material to climate-smart agriculture in Argentina. CSA country profiles for Latin America series. Washington D.C.: The World Bank Group.

Zivot, E., Andrews D., 1992. Further evidence of great crash, the oil price shock and the unit root hypothesis. Journal of Business and Economic Statistics, 10, 251-270.

Tables

Table 1. Descriptive statistics of the selected variables

Variables	Per capita CO_2 emissions	Real GDP per capita	NHRE consumption per capita	AVA per capita	AGRL per capita
Mean	3.861547	8093.550	2.13E-08	586.3826	0.037827
Median	3.740313	7845.545	1.25E-08	574.8176	0.036107
Maximum	4.682974	10853.26	7.26E-08	749.2640	0.045549
Minimum	3.291541	5955.651	2.86E-09	470.3141	0.033970
Std. Dev.	0.417252	1355.575	2.32E-08	77.62627	0.003463
Skewness	0.647480	0.642441	1.073896	0.648504	0.908840
Kurtosis	2.099651	2.441078	2.821976	2.334665	2.498512
Jarque-Bera	3.524028	2.781366	6.580000	3.010273	5.036885
Probability	0.171699	0.248905	0.037254	0.221987	0.080585

Table 2. Zivot and Andrews's unit root results

Zivot-Andrews unit root test						
Variables	**level**			**first difference**		
	t-statistic	**decision**	**time break**	**t-stat**	**decision**	**time break**
e	-3.869474 (1)	non-stationary	2003	-5.387792 (2)	stationary	2003
y	-3.719574 (1)	non-stationary	2001	-4.751465 (0)	stationary	1990
nhre	-6.616901 (0)	stationary	1996	-6.145645 (0)	stationary	1995
ava	-5.522402 (0)	non-stationary	1994	-8.167090 (1)	stationary	2007
agrl	-3.246735 (1)	non-stationary	1998	-5.789980 (0)	stationary	2002

Notes: Lag length are presented in parenthesis. All time series are examined after logarithmic transformation.

Table 3. Lag selection for the VAR model

Number of Lags	LogL	LR	FPE	AIC	SIC	HQ
0	127.8374	NA	3.19e-10	-7.677340	-7.448319	-7.601426
1	276.4394	241.4782	1.44e-13	-15.40246	-14.02834*	-14.94698
2	309.5177	43.41529*	9.83e-14*	-15.90736*	-13.38812	-15.07230*

Notes: Log likelihood (LogL), Log likelihood ratio (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQ).

Table 4. ARDL cointegration results

Estimated model	Bounds testing to cointegration	Lag criteria		F-statistics	Conclusion
	optimal lag length	AIC	SIC		
F(e/y,nhre,ava,agrl)	(4,4,4,4,4)	-4.039644	-2.871980	2.548937 (4)	Inconclusive
F(y/e,nhre,ava,agrl)	(4,4,4,4,3)	-3.729558	-2.608600	4.584440 (4)	Cointegration
F(nhre/e,y,ava,agrl)	(4,4,4,4,4)	-0.441407	0.726257	6.750942 (4)	Cointegration
F(ava/e,y,nhre,agrl)	(1,1,2,0,2)	-2.925587	-2.421740	12.23211 (4)	Cointegration
F(agrl/e,y,nhre,ava)	(1,4,4,2,4)	-7.685810	-6.751678	14.07239 (4)	Cointegration
Critical values	Lower bounds I(0)			Upper bounds I(1)	
10%	2.45			3.52	
5%	2.86			4.01	
2.5%	3.25			4.49	
1%	3.74			5.06	
Diagnostic tests					

	Residuals correlation test (Breusch-Godfrey LM Test)	Probability	Heteroscedasticity test (ARCH statistic)	Probability	Normality test (Jarque-Bera statistic)	Probability
F(e/y,nhre,ava,agrl)	F(2,8)=5.3061	0.1035	F(1,27)=2.8670	0.1020	0.695736	0.70619
F(y/e,nhre,ava,agrl)	F(2,8)=1.8480	0.7201	F(1,27)=0.1010	0.7530	0.345876	0.84119
F(nhre/e,y,ava,agrl)	F(2,8)=5.1852	0.1063	F(1,27)=0.0784	0.7815	2.271011	0.32126
F(ava/e,y,nhre,agrl)	F(2,8)=0.4461	0.6466	F(1,29)=1.8628	0.1828	0.455026	0.79691
F(agrl/e,y,nhre,ava)	F(2,8)=0.1755	0.8422	F(1,27)=0.8186	0.3736	0.097117	0.95260

Table 5. ARDL estimates

Long and short-run estimates										
Dependent variable	*e=f(y,nhre,ava,agrl)*		*y=f(e,nhre,ava,agrl)*		*nhre=f(e,y,ava,agrl)*		*ava=f(e,y,nhre,agrl)*		*agrl=f(e,y,nhre,ava)*	
Regressors	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Long-run estimates										
e	-	-	2.481851	[5.27564]***	2.903407	[1.18748]	0.436287	[3.426130]***	0.475233	[8.219286]***
y	12.93731	[2.72574]**	-	-	2.867669	[1.95688]*	0.590476	[15.53959]***	0.484443	[11.08091]***
nhre	0.081437	[5.17683]***	0.186963	[3.85305]***	-	-	-0.014465	[-1.95373]*	-0.016337	[-2.26326]**
ava	-0.491182	[-2.63541]**	0.863727	[2.10869]**	-4.619777	[1.8925]*	-	-	-0.835765	[-11.1040]***
agrl	-0.271419	[-3.24686]**	0.482329	[1.95128]*	-4.429364	[-2.9729]***	-1.144661	[-10.9996]***	-	-
c	54.67974	[2.72748]**	9.199788	[2.54377]**	-46.09601	[-6.5046]***	-3.108411	[-5.10877]***	-2.861367	[-7.02362]***
Short-run estimates										
d(e)	-	-	-0.328647	[-0.91699]	2.611677	[1.95219]*	-1.153714	[-9.41189]***	0.087723	[2.61040]**
d(y)	0.128360	[0.69468]	-	-	-2.808348	[-1.9139]*	1.115608	[-9.02347]***	-0.050515	[-1.90524]*
d(nhre)	-0.051208	[-1.06730]	0.068460	[1.95557]*	-	-	0.052885	[2.70622]**	-0.010410	[-2.40183]**
d(ava)	0.039091	[0.25412]	-0.071688	[-0.56724]	-1.355155	[-1.06549]	-	-	-0.038462	[-2.53026]**
d(agrl)	0.482025	[0.21081]	4.476183	[2.33237]**	-0.785074	[-0.51717]	6.382834	[4.00726]***	-	-

c	0.010033	[0.57178]	0.064875	[2.84240]**	0.027248	[0.26057]	0.000744	[0.03386]	-0.002657	[-1.38947]
ECT	-0.491327	[-2.06619]**	-0.343402	[-2.8618]**	-0.344687	[-2.70652]**	-0.953099	[-5.70125]***	-0.019250	[-3.41717]***

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; ECT denotes the error correction term corresponding to each equation; t-statistics are presented in brackets.

Table 6. Granger causality results

	Short-run					**Long-run**
Variables	***Δe***	***Δy***	***Δnhre***	***Δava***	***Δagrl***	**ECT**
Δe	-	1.54931	2.96165	1.44304	3.82866	-0.491327
		(0.2307)	(0.0687)*	(0.2539)	(0.0344)**	[-2.06619]**
Δy	0.40013	-	3.37474	0.78047	3.52912	-0.343402
	(0.6741)		(0.0492)**	(0.4683)	(0.0435)**	[-2.86182]**
Δnhre	5.4E-05	0.83962	-	0.95486	2.54343	-0.344687
	(0.9999)	(0.4428)		(0.3975)	(0.0973)*	[-2.70652]**
Δava	0.33697	0.65949	7.15557	-	13.7103	-0.953099
	(0.7169)	(0.5252)	(0.0032)***		(0.0000)***	[-5.701251]***
Δagrl	0.61815	2.03992	0.06098	6.28039	-	-0.019250
	(0.5464)	(0.1496)	(0.9410)	(0.0058)***		[-3.41717]***

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Probability values are reported in parenthesis and t-statistics are presented in brackets.

Figures

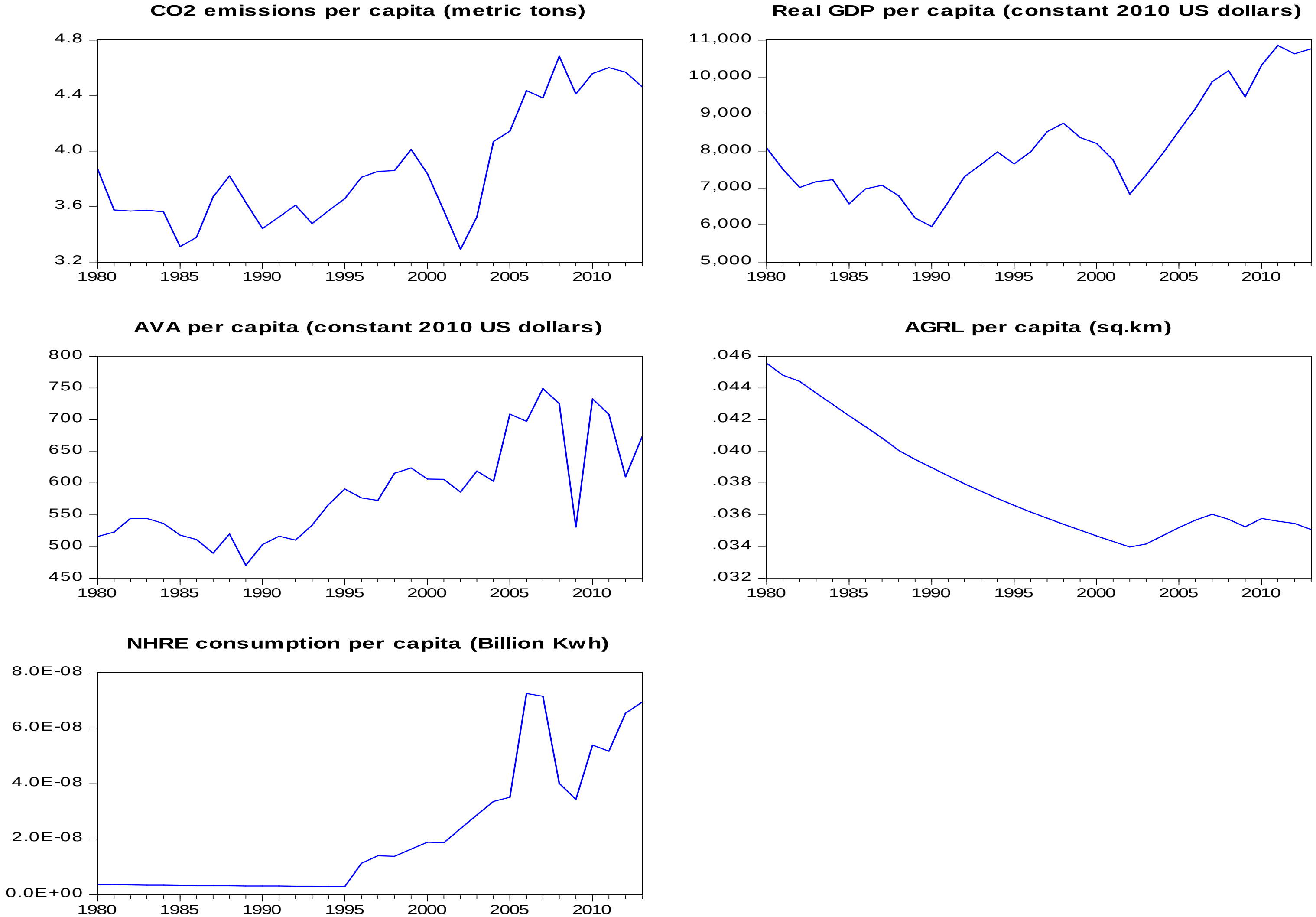

Fig.1. Representation plots of the selected variables

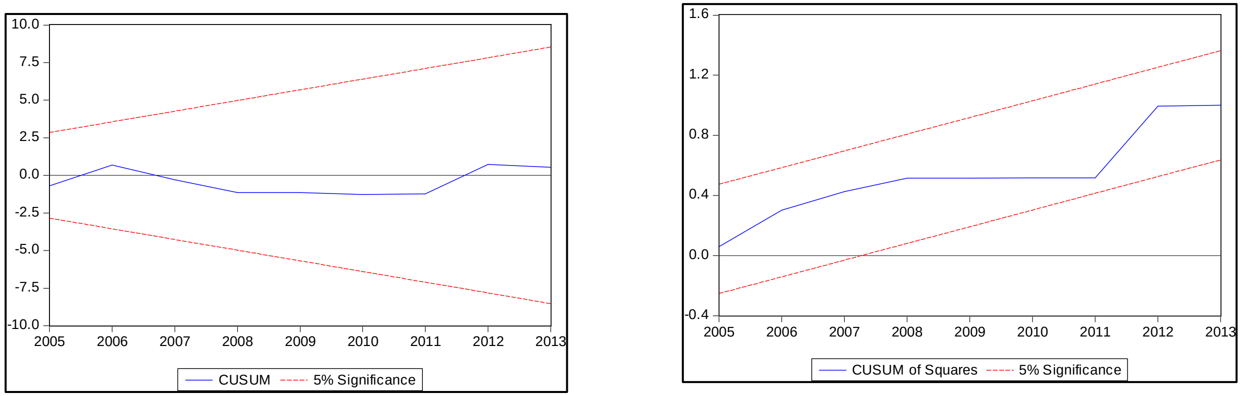

Fig.2. CUSUM and CUSUM of Squares of recursive residuals for per capita CO_2 emissions

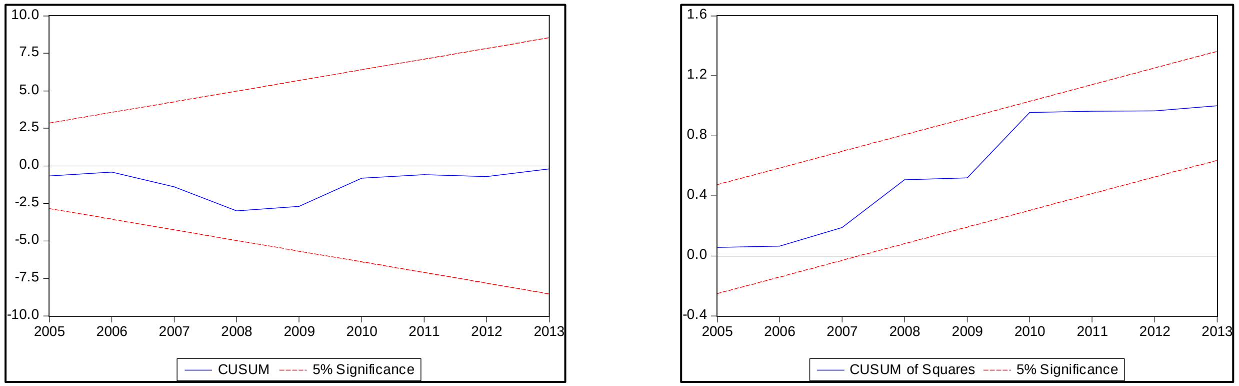

Fig.3. CUSUM and CUSUM of Squares of recursive residuals for per capita real GDP

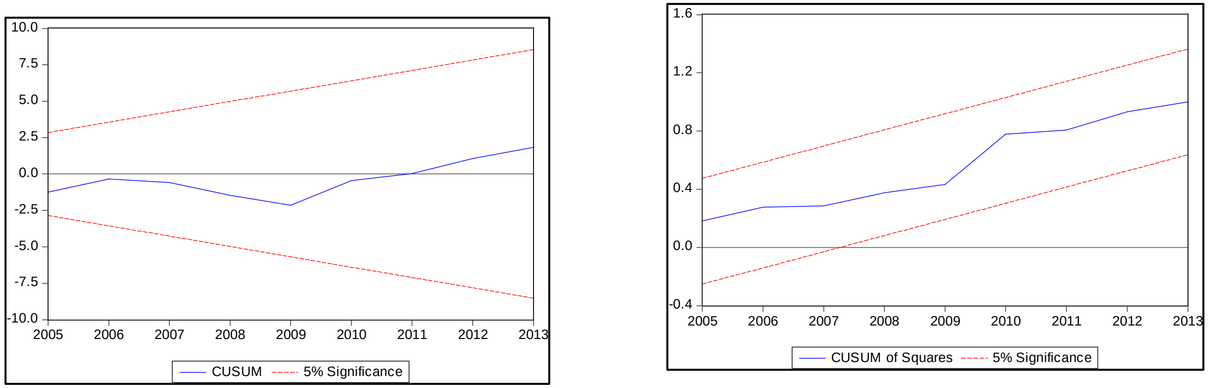

Fig.4. CUSUM and CUSUM of Squares of recursive residuals for per capita NHRE

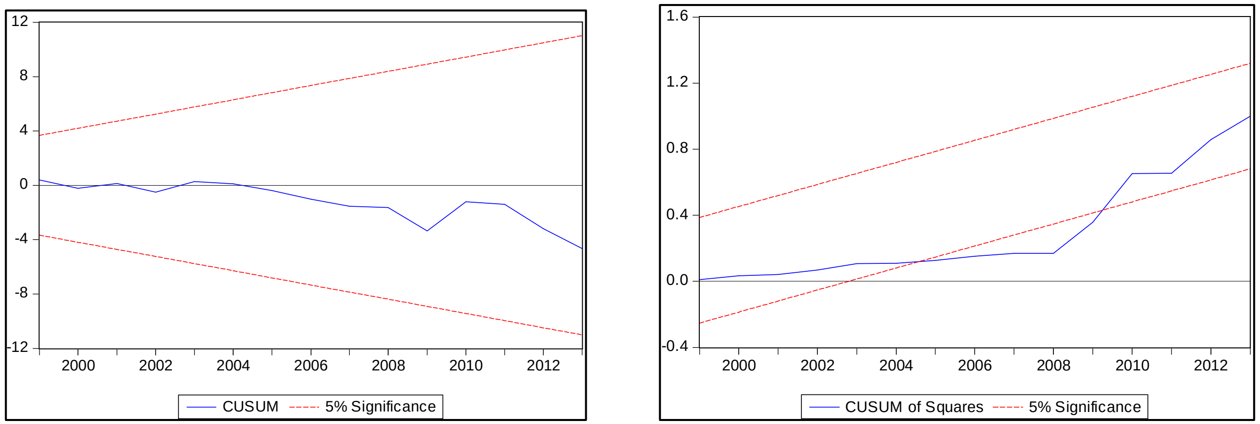

Fig.5. CUSUM and CUSUM of Squares of recursive residuals for per capita AVA

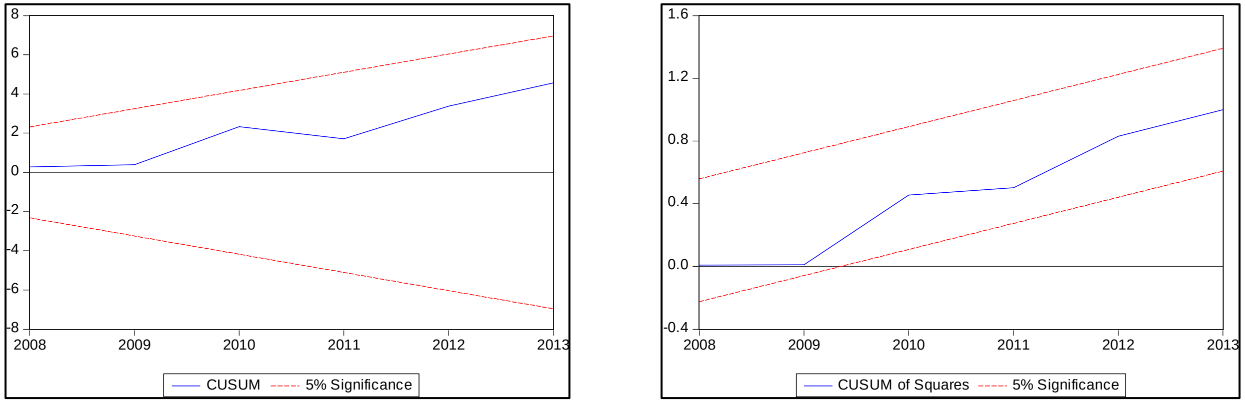

Fig.6. CUSUM and CUSUM of Squares of recursive residuals for per capita AGRL