Citation: Uddin, G. A., Alam, K., Gow, J. (2016). Estimating the major contributors to environmental impacts in Australia. *Journal of Ecological Economics and Statistics*, 37 (1): 1-14. ISSN 0973-1385 (print); 0973-7537 (online).

Estimating the Major Contributors to Environmental Impacts in Australia

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ABSTRACT

The 'Ecological Footprint' concept is used to measure the degree of environmental impacts caused by human activities. It is hypothesised that the driving forces of environmental impacts are population size, urban population concentration, non-dependent population ratio, affluence or gross domestic product (GDP) per capita, industry share of GDP, and carbon dioxide (CO_2) emissions per capita. This paper uses a consistent, well-known population-based framework, the refined STIRPAT model, to assess the sources of environmental impacts. The specific drivers of those impacts are not fully revealed, however, the STIRPAT model depicts a simple outline of non-proportionate impacts of human activities on the environment. Environmental impacts data was analysed using the STIRPAT model combined with the Ridge Regression (RR) method. This was because multicollinearity among the data sources could be a substantial problem, and the application of RR to the STIRPAT model enabled collinearity to be avoided. The results clearly showed that population has the most significant effect on ecological footprint, followed by GDP per capita and urbanisation. Thus, the impact of key driving forces on the environment revealed in this study should be taken into account in future planning and long-term strategies for environmental impact abatement.

Keywords: Affluence, Ecological Elasticity, Ecological Footprint, Population, Ridge Regression, STIRPAT

Mathematics Subject Classification: 62J05, 62J07

JEL Classification: Q15, Q51, Q57

1. INTRODUCTION

Human activities create a demand for resources to fulfil basic needs, such as food, water, clothing and shelter, among others. With a larger population, more resources are demanded. A number of theories state that the size of the population is one of the key variables that affects the environment (de Sherbinin et al., 2007). This statement is widely upheld by the work of Malthus, whose theory still causes strong reactions more than 200 years after it was first published (Malthus, 1967). The Malthusian idea is that environmental degradation occurs because of the pressure that the population puts on resources.

Another view on the population-environment scenario given by Boserup, (1981) is that population growth enhances technological innovation, which lessens the negative impact on the environment. Turner and Ali, (1996) made a comparison between the theories of Malthus and Boserup. Boserup considered technology as endogenous to the population and resources interaction, while Malthus saw it as exogenous. On the other hand, the followers of Malthus maintain the view that increased population naturally surpasses Earth's resources and capacity to cope, therefore eventually leading to ecological failure (de Sherbinin et al., 2007).

The supporters of Malthus have been criticised for overlooking cultural adaptation, technological developments, trade, and institutional arrangements (de Sherbinin et al., 2007). The widely cited IPAT formulation, introduced by Ehrlich and Holdren (1971), is framed through the neo-Malthusian terms. It explains the magnitude of the human-imposed impacts on the environment. However, the IPAT formula itself has been criticised due to there being no linear relationship among the variables (de Sherbinin et al., 2007). Thus, York et al., (2003) reshuffled the IPAT identity into the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, which harmonises non-proportionate impacts of population on the environment.

Environmental impacts threaten all humanity in both developed and developing countries. The main reason for this is that most people are directly dependent on basic economic activities for their survival and wellbeing (Madu, 2009). In Australia, for instance, many human activities including the use of natural resources have a direct impact on the environment. Australia ranks within the top 10 countries globally in respect to greenhouse gas (GHG) emissions per capita (National Sustainability Council 2013). Raupach (2007) estimate that CO_2 emissions from fossil fuels is the principal driver of climate change, and he also added that Australia, with only 0.32% of the global population, accounts for 1.43% of the world's carbon emissions.

Australia is reported to be one of the countries most at risk from the effect of climate change (Stern, 2006). The destruction of habitat by human activities – including land clearing, clearance of native vegetation, expansion of dryland salinity and intensification of resources in various sectors – is widely reported to contribute to environmental impacts in Australia (Glanznig, 1995). Literature suggests that human wellbeing can be improved without, or with minor impact on the environment. Dietz et al. (2007) found that although urbanisation, economic structure, age distribution and life expectancy are among the drivers of environmental impacts, they have little or no effect on the environment. GDP per capita or affluence does drive these environmental impacts, but at the same time it improves other aspects of human well-being without costing the environment (Madu, 2009).

Although the ecological footprint method has proved to be a useful tool to describe the environmental impacts caused by human activities, the specific forces driving those impacts are not yet fully understood (Wei et al., 2011). Despite there being the scientific consensus on the primary drivers of environmental impacts, little progress has been made in determining the precise relationship between drivers and impacts (Dietz et al., 2007). Researchers traced the environmental impacts using different dependent variables. For example, Madu (2009) measured environmental impact as a proxy for CO_2 emissions and rate of vegetation losses; whereas total energy consumption was used as the dependent variable in a study by Romero et al. (2009). A study by Liddle (2013) used private transport energy consumption as the dependent variable for measuring environmental impact.

A number of studies also utilised ecological footprint as a proxy for environmental impact, but most of them used cross-country data. Very few studies measured environmental impact using single-country data with the ecological footprint as a dependent variable. Especially in Australia, no studies have been identified which trace the driving forces of environmental impacts using ecological footprint as a proxy for the dependent variable. Thus, the purpose of this study is to find the key factors responsible for environmental impacts in Australia using ecological footprint as the dependent variable through the refined STIRPAT model along with ridge regression (RR).

This paper is organised as follows: Section 2 presents a brief overview of the literature on factors affecting environmental impacts; Section 3 describes the models; Section 4 presents the model specifications and justification; Section 5 describes the data and the construction of variables. The major findings are described in Section 6, and finally, conclusions are outlined in Section 7.

2. **LITERATURE REVIEW**

The most compelling issues that the world has been facing are rapid population growth and economic development, which have sharply increased global resource demand and exacerbated environmental deterioration (Mingquan et al., 2010). The World Wildlife Fund (2012) reported that the spiralling global population and over-consumption are threatening the health of the planet. Ying et al. (2009) similarly mentioned that the ecosystem faced the twofold impact of population growth and an increasing per capita resource consumption. Population, along with economic activities and technology, have also been theorised to be the key driving forces of environmental deterioration (Dietz and Rosa, 1994). Other studies reveal that population and affluence are critical indicators of a broad range of environmental impacts (Dietz et al., 2007).

Taking the Henan province of China as an example, Jia et al. (2009) computed and analysed the province's ecological footprint from 1983 to 2006. The results showed that the major drivers of Henan's ecological footprint are population size and GDP per capita. Employing the partial least square method for this study, the authors showed that the curvilinear relationship between economic development and ecological impact, i.e. the classical Environmental Kuznets Curve (EKC) hypothesis, did not exist in the Henan province. However, the EKC literature has shown mixed results in terms of empirical evidence (Tallarico and Johnson, 2010). Lin et al. (2009) showed that population size has the largest potential effect on environmental impacts, followed by urbanisation, industrialisation, GDP per capita and energy intensity. Similarly, Hobday and McDonald (2014) studied that the population growth is the contemporary drivers of environmental impact in Australia. The changes in the ecological footprint depend both on changes in per-capita consumption and the rate of growth of the population (Hanley et al., 1999).

Refining the methodology and updating the earlier ecological footprint estimates, and using recent data for NSW, Lenzen and Murray (2001) showed that the NSW community increased its total ecological footprint by 23% in the five years between 1993-94 and 1998-99. During this period, the population grew by 7%, implying that change in ecological footprint is associated with population changes. Analysing a sub-national area of Siena province in Italy, Bagliani et al. (2008) showed that urbanisation has an impact on ecological footprint. Using the lifecycle approach, Wood and Garnett

(2010) showed that the environmental impact of urban populations is generally higher than that of remote populations in northern Australia. The most fundamental assumption governing the demographic-environmental relationship is that the economically active population exerts a disproportionate force on environmental impacts (Roberts, 2012).

Madu (2009) showed that population size and affluence are the most important anthropogenic drivers of environmental impacts in Nigeria, while urbanisation or modernisation brings about a reduction in environmental impacts. Roberts (2012) used the STIRPAT framework to assess the strength of age-structure in driving US county-level CO_2 emissions. These estimates paint a complex picture of age-structure in respect to carbon emissions: countries with older working-age populations have higher emissions than their younger counterparts, while the size of the total dependent population illustrates no significant relationship. Knight and Rosa (2012) established a link between household dynamics and environmental impacts using a STIRPAT analysis. The results showed that nations with smaller average households consume more fuel wood per capita.

Wang et al. (2011) employed the STIRPAT model to reveal the factors that contribute to CO_2 emissions in the Minhang District, Shanghai, China. They found that population size, affluence and urbanisation level increase CO_2 emissions, while energy intensity decreases CO_2 emissions. Shi (2003) found that global population change over the last two decades is more than proportionally associated with growth in CO_2 emissions, and the impact of population change on emissions is much more pronounced in developing countries than it is in developed countries. Fan et al. (2006) revealed that the impact of population size, affluence and technology on the environment varies at different levels of development.

Cole and Neumayer (2004) showed that population increases are matched by proportional increases in CO_2 emissions, and a higher urbanisation rate and lower average household size also increase emissions. Madu (2009) measured environmental impact as a dependent variable by the rate of vegetation loss. She showed that this measurement assesses the cumulative effects of vegetation loss on soil, the water cycle and wildlife. Ping and Xinjun (2011) applied the ecological footprint and STIRPAT methods within the Yangtze Delta Region (YDR) and it’s 16 cities to assess their sustainability status and analysed the relevant driving factors. The research showed that the distribution pattern of the ecological footprint and the degree of sustainability development varied distinctly from city to city in the YDR. The driving factor that made the greatest change in ecological footprint was GDP per capita.

Fan et al. (2006) revealed both positive and negative impacts of working-age population on the environment, while Cole and Neumayer (2004) showed significant and positive impacts, but in both studies, the effects became non-significant when urbanisation was included in the model. Shi (2003) showed that economies whose GDP outputs are heavily derived from manufacturing are energy-intensive and will produce higher CO_2 emissions; whereas economies whose GDP is largely derived from services are less energy-intensive and will produce lower emissions.

The Ecological footprint measures the degree of environmental impact within a defined population in a country or region. The World Wildlife Fund (WWF 2012) estimated that Australia has the seventh biggest ecological footprint per capita in the world, and the ecological deficit is increasing daily. Both the per capita ecological footprint and biocapacity are gradually decreasing in Australia; however, the rate of decrease of ecological footprint is lower than biocapacity, indicating the gradual degradation of the environment in Australia. The report also revealed that the average household emits 14 tonnes of greenhouse gases each year, and 3.5 tonnes of that will still be trapping heat in the Earth's atmosphere in 500 years. Globally, a number of methodologies and indicators have been used for measuring the degree of environmental impacts. However, there is no literature which has attempted to reveal the major driving forces of these environmental impacts as a proxy for ecological footprint in Australia. Even the measurement of ecological footprint using the STIRPAT model has been rarely used in the context of Australia.

3. **METHODS**

It is generally assumed that every person and each populated area (e.g. a region, city or country) has an impact on the environment (van den Bergh and Verbruggen, 1999). Based on this generalisation, a lot of studies have been conducted to examine the consequences of the environmental impacts by employing an improvised form of the IPAT model. The I=PAT model has been employed since 1970 to assess the magnitude of human impacts on the environment, and was introduced by Ehrlich and Holdren (1971). The principal idea of an I=PAT model is that environmental impact (I) is the product of three key driving forces: population size (P); affluence (A), described as GDP per capita; and the level of environmental damage caused by technology (T), defined as production per unit.

Until 2005, a series of reformations of the I=PAT model had been conducted in the ecological literature. Waggoner and Ausubel (2002) added a variable into the I=PAT model, C, which represents consumption per unit of GDP, thus resulting in I=PACT. Subsequently, Schulze (2002) added another variable, behavioural decisions, into the I=PACT formula and argued that human behaviour is a key driving force of environmental impact. Xu et al. (2005) mentioned two additional variables, social development (S) and management (M), explaining social development and society's capability to decrease environmental impacts. Eventually, this explanation was considered by the notion that society and social development have proven difficult to quantify.

The IPAT identity, relabelled the 'Kaya' equation, lies at the heart of the efforts to project GHG emissions by the Intergovernmental Panel on Climate Change (Uddin et al., 2013). However, all the above models do not allow testing of the non-monotonic relationship of human-induced factors and environmental changes. In addition, Alcott (2009) argued that the success in lowering any of the right side factors of IPAT identity does not necessarily lower impact. To address these problems, York et al. (2003) reshuffled the IPAT identity into the STIRPAT model. Most of the STIRPAT model used different forms of dependent variables with cross-country data, but this study used single-country data with ecological footprint as a proxy for environmental impact, which harmonises non-proportionate impacts of population size on the environment in the following form: $I_i = aP_i^b A_i^c T_i^d e_i$, or in logarithmic form as:

$$\ln(I) = \mathrm{a} + \mathrm{b}\ln(P) + \mathrm{c}\ln(A) + \mathrm{d}\ln(T) + e \qquad (1)$$

Where *I* is environmental impact expressed by ecological footprint as the dependent variable. The subscript 'i' denotes the number of observations in the study. The constant 'a' scales the model, and the residual or error term 'e' possesses the effects of all other variables of I that are uncorrelated with *P*, *A* and *T*, while b, c and d are the exponents or coefficients of these independent variables that must be estimated from the regression. The coefficients are here used to represent the net effects of the variables and are referred to as the Ecological Elasticity (EE). EE is defined as the proportionate change in environmental impacts due to a change in any driving force (York et al., 2003). EE refers to the responsiveness or sensitivity of environmental impacts to a change in any of the driving forces. The coefficients b and c in equation (1) represent population and affluence elasticity of impacts respectively. No single operational measure of technology (*T*) is free from controversy (Fan et al. 2006), so technology elasticity of impact is not applied in the literature.

4. **MODEL SPECIFICATION**

The basic STIRPAT model consists of three driving forces: population (P), affluence (A) and technology (T). In addition to these basic factors of the STIRPAT model, any other variables that are conceptually compatible can be added into the model (York et al., 2003). In this study, all the models use ecological footprint as a dependent variable, which entails an index of the environmental impact. The specific and measurable driving forces which have influenced the environment (ecological footprint) include total population (P); affluence measured by GDP per capita (A_1) and the quadratic term of GDP per capita (A^2); percentage of people living in urban areas (T_1); percentage of GDP from the industry sector (T_2); energy use per capita; percentage of non-dependent population; energy intensity; and CO_2 emissions per capita. Six specifications of the STIRPAT model are estimated using the Ordinary Least Squares (OLS) and then the RR method to correct for multicollinearity.

Model 1 is known as the two factors (population and affluence) STIRPAT model, where T is included into the error term. In Model 2, an additional explanatory variable, affluence squared (A^2), is added for the assessment of the non-monotonic relationship between affluence and environmental impact. The basic STIRPAT model framed in Model 3 consists of three common variables – population (P), affluence (A) and technology (T) – where T refers to the rate of urbanisation. In Model 4, T is decomposed into two derivatives: the percentage of people living in urban areas (T_1) and percentage of GDP from the industry sector (T_2). Taking the percentage of GDP from industry as the T_2 variable, Model 5 was developed, and finally, Model 6 is called the saturated model comprising all previous independent variables.

The potential multicollinearity problem is assessed through the correlation coefficient matrix method. The values of the correlation coefficients among some explanatory variables were very high, which suggests multicollinearity exists amongst these independent variables. A high level of collinearity between GDP per capita and the quadratic term of GDP per capita was found to be problematic. This resulted in non-significant coefficients for each variable when included together, with each being significant and either positive/negative when included separately. In this stage of model specification, the multicollinearity problem is overcome through the application of the RR method.

5. DATA

Total population, GDP per capita, working-age population, industry share of GDP and urban population density are the most common metrics of control variables, while total ecological footprint (Dietz et al. 2007; Mingquan et al. 2010; Ping and Xinjun, 2011; Wei et al. 2011; Zhao, 2010); fuel consumption (Knight and Rosa, 2012; Madu, 2009); and rate of vegetation loss (Madu, 2009) are the most common units of environmental impacts of the dependent variable. Table 1 lists the definitions of variables used in the analysis. The data from 1960 to 2014 for the study were collected from various sources. The data on ecological footprint in terms of global hectares were obtained from the Global Footprint Network (GFN, 2012), and the missing data were imputed by multiplying per capita ecological footprint by total population.

The GDP per capita as current US dollars data were obtained from the World Development Indicators (World Bank 2014). The demographic data such as population size, the percentage of non-dependent population and percentage of urban population were obtained from the Australian Bureau of Statistics

(2014) and the World Bank (2014). The industry value added data (percentage of GDP) was sourced from the open data catalogue at the World Bank National Accounts (World Bank 2014). The industry value added comprises value added in mining, manufacturing, construction, electricity and water and gas. The CO_2 emissions per capita data in terms of metric tonnes came from the World Bank (2014) and United States Energy Information Administration (2014). CO_2 and energy intensity was measured as the amount of CO_2 or energy consumed in the production of each unit of economic output.

Table 1
Description of the variables

Variable	Description	Unit of measurement
Dependent Variable		
Ecological footprint	Land area required to support consumption of a nation	Hectare
Independent Variable		
Population	Population size (1960 to 2014)	Number
Non-dependent population	Percentage of population aged 15-65	Percent
GDP per capita	Per capita gross domestic product	USD per capita in current prices
Quadratic of GDP per capita	[log (GDP per capita)-Mean]^2	USD per capita in current prices
Percentage of non-service GDP	Percentage of GDP not in service sector	Percent
Urbanisation	Percentage of population living in urban areas	Percent
CO_2 emissions per capita	Emissions from industrial processing stemming from the burning of fossil fuels	Metric tonnes of carbon per year
Energy intensity	Energy consumed in the production of each unit of economic output	Ratio of GDP

The dependent variable is 'ecological footprint' in terms of hectares as an indicator of the environmental impacts. This measure allows comparison across types of impacts by estimating the quantity of land that would be required to support the material consumption of a nation. These data are logged to minimise excessive positive skewness. GDP per capita used as a measure of a nation's level of economic development, and the quadratic of GDP per capita used to allow for a non-monotonic relationship between development and impacts. These data have also been logged to minimise skewness.

Typically, GDP per capita has a positive effect on environmental impacts (Dietz et al., 2007; Roza et al. 2003). Similarly, it is predicted that GDP per capita will have a positive effect on ecological footprint. The percentage of the population living in urban areas is used as a general indicator of modernisation. Urbanisation sometimes improves environmental efficiencies; it may also produce changes in lifestyles and consumption patterns. Based on this assumption for Australia, urbanization is expected to have a positive effect on ecological footprint. As an indicator of economic structure, the percentage of GDP not in the service sector is included to test for predictions of the environmental impacts of a shift to a service economy.

6. RESULTS AND DISCUSSION

This study treated ecological footprint as the dependent variable and established the STIRPAT model. Firstly, it tested the correlation coefficient among all the variables then estimated the method using ordinary least squares. Table 2 shows the Ordinary Least Squares (OLS) regression estimates for STIRPAT Models 1 to 6 that analyses the effects of hypothesised drivers. The collinearity statistics in OLS results show that the Variance Inflation Factor (VIF) ranges between 8.59 and 129.53 among the Models 1 to 6. This is an indication that there is collinearity, since the rule is that collinearity is of much concern when the VIF is more than 10 (Wei et al. 2011). Here in the OLS results, the VIF value for most of the explanatory variables exceeded the acceptable standard. The RR model was applied to analyse the major drivers of the ecological footprint to mitigate the collinearity problem within independent variables.

The accuracy of the RR results relies on the selection of ridge parameter k. According to Hoerl and Kennard (1970), regression coefficients are to be obtained when the ridge parameter range ranges from 0 to 1. Assuming the ridge parameter's step-length is 0.05, the model was analysed using STATA 2012 version. The value of ridge parameter k was 0.05 in this study. Table 3 shows the RR results.

Table 2

OLS regression results

Variable	Symbol	UC	Standard error	t-test	Sig.	Collinearity Statistics Tolerance	VIF
Model 1							
Population	lnP	2.159	0.299	7.20	0.000	0.028	34.63
GDP per capita	lnA_1	-0.307	0.068	-4.48	0.000	0.028	34.63
Model 2							
Population	lnP	2.276	0.464	4.90	0.000	0.008	120.50
GDP per capita	lnA_1	-0.344	0.129	-2.66	0.010	0.012	81.84
(GDP per capita)^2	lnA^2	-0.007	0.022	-0.33	0.741	0.116	8.59
Model 3							
Population	lnP	2.564	0.329	7.79	0.000	0.010	99.35
GDP per capita	lnA_1	-0.530	0.110	-4.78	0.000	0.021	45.87
% Urban	lnT_1	2.191	0.0882	2.48	0.016	0.042	23.81
Model 4							
Population	lnP	2.794	0.365	7.66	0.000	0.017	57.42
GDP per capita	lnA_1	-0.485	0.114	-4.25	0.000	0.009	107.58
% Urban	lnT_1	1.271	1.091	1.17	0.249	0.026	37.10
% Industry GDP	lnT_2	0.256	0.182	1.41	0.165	0.103	9.72
Model 5							
Population	lnP	1.816	0.462	3.93	0.000	0.009	107.82
GDP per capita	lnA_1	-0.338	0.116	-2.92	0.005	0.007	129.51
(GDP per capita)^2	lnA^2	0.099	0.032	3.10	0.003	0.012	25.05
% Urban	lnT_1	4.736	1.505	3.15	0.003	0.039	82.81
% Industry GDP	lnT_2	0.255	0.167	1.52	0.135	0.102	9.72
Model 6							
Population	lnP	2.151	0.497	4.33	0.000	0.007	129.53
GDP per capita	lnA_1	-0.354	0.114	-3.10	0.003	0.007	130.59
(GDP per capita)^2	lnA^2	0.056	0.041	1.37	0.178	0.023	42.48
% Urban	lnT_1	4.314	1.501	2.87	0.006	0.011	85.30
% Industry GDP	lnT_2	0.188	0.169	1.11	0.273	0.024	41.19
CO_2 emissions per capita	lnC	-0.486	0.295	-1.65	0.106	0.096	10.31

Table 3

Ridge regression results

Variable	Symbol	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Population	lnP	2.147 (0.299)	2.243 (0.464)	2.537 (0.329)	2.767 (0.364)	1.792 (0.461)	2.117 (0.497)
GDP per capita	lnA_1	-0.305 (0.068)	-0.334 (0.129)	-0.521 (0.111)	-0.476 (0.114)	-0.329 (0.115)	-0.345 (0.114)
(GDP per capita)^2	lnA^2	---	-0.005 (0.021)	---	---	0.099 (0.032)	0.057 (0.041)
% Urban	lnT_1	---	---	2.137 (0.882)	1.224 (1.090)	4.709 (1.505)	4.304 (1.501)
% GDP from Industry	lnT_2	---	---	---	0.255 (0.181)	0.256 (0.167)	0.189 (0.169)
CO_2 emissions per capita	lnC	---	---	---	---	---	-0.479 (0.295)
Constant	a	-14.173 (4.342)	15.487 (6.504)	-28.076 (7.099)	-29.156 (7.072)	-29.904 (6.535)	-31.79 (6.531)
R^2	--	84.15%	83.87%	85.58%	85.85%	87.93%	88.34%
Root MSE	Sigma	0.0884	0.0892	0.0843	0.0835	0.0771	0.0758
N	---	55	55	55	55	55	55

GDP per capita was centred by subtracting their respective means in logarithmic form. Standard errors are in parentheses.

Population and GDP per capita were used in Model 1 to analyse the human impacts on the environment in Australia. Results indicated that a positive 1% change in the population factor, with the other factors remaining constant, would lead to a 2.15% increase in environmental pressure. A 1% increase in the per capita GDP would lead to a 0.31% decrease in environmental pressure. The results of model 1 showed that the net environmental impacts in Australia increase with the population and GDP per capita growth. The goodness of fit of model 1 was 0.84, which was high, showing that the population and affluence factors could explain almost 84% of all environmental pressures as measured in Australia.

On the basis of model 1, taking the quadratic term of GDP per capita (A^2), Model 2 was developed to test the non-monotonic relationship between affluence and environmental impacts. In this equation, the goodness of fit was 0.84, which is slightly lower than that for model 1. It showed that the three factors – population, per capita GDP and its square term – could explain 84% of all the environmental pressures measured in Australia. The coefficients of population and per capita GDP were 2.24 and -0.33 respectively, indicating that a 1% increase in population would lead to an increase of 2.24% in environmental pressure, and a 1% increase in GDP per capita would lead to a 0.33% decrease in environmental pressure. The p-value of the quadratic term of affluence is not significant, so this specified model is not well fitted with hypothesised independent variables.

Population, affluence, and urbanisation were selected in Model 3. The goodness of fit reached 0.86, indicating that these three factors are able to explain 86% of the impact on ecological footprint; and all coefficients were significant at 0.05 ($p<0.05$) levels, which indicates the model is perfectly fitted. The coefficients of lnP and lnA were 2.77 and -0.48 respectively in Model 4. These suggest that P and A represent elasticity of 2.77 and -0.48, which means a 1% change in population and affluence variables may lead to 2.77% and 0.48% changes in ecological footprint respectively.

In Model 5, the coefficient of population size was 1.79, suggesting that population had an elasticity of 1.79, and that a 1% change in population will lead to a 1.79% change in the ecological footprint in the study period in Australia. Similarly, A^2, T_1 and T_2 had an elasticity of 0.10, 4.71 and 0.26 respectively, indicating that a 1% change in each type of variable would induce 0.10%, 4.71% and 0.26% changes in environmental impacts respectively. In this model, only the industry share of GDP (T_2) was not significant. The model specification is not perfectly fitted for explaining the environmental impacts in Australia.

The rate of impact of population and urbanisation were similar to the other models. The variable with the highest impact was urbanisation followed by population and affluence. Therefore, population and urbanisation were the most important coefficients of environmental impacts in this model. On the other hand, the coefficient values of GDP square, industry share of GDP and CO_2 emissions per capita were not significant at the 95% confidence interval level. Therefore, this model is also not well fitted to explain the relationship between environmental impacts and repressors.

This study utilised ecological footprint as the index of environmental impacts and revealed the major driving forces of ecological footprint in Australia. So the study implies that the STIRPAT model is able to provide an appropriate analytical framework for decomposing the impact of human activities on the environment, quantitatively, for a single country. The OLS and RR results fully illustrate that the impact of population, economy, and technology on ecological footprint is different in different forms of models.

7. CONCLUSIONS

This study has firmly established that population, affluence and urbanisation are the influencing drivers of environmental impacts in Australia. The findings of this paper also clearly provide new evidence that population has the most significant effect on ecological footprint. However, the impact of population on the environment is more than proportional, i.e. a 1% increase in population size is associated with a 2.27% change in environmental impacts. This finding supports the Rosa et al. (2003) finding that population has long been hypothesised to be the primary driver of environmental stressors. There is growing evidence to support this hypothesis.

The regression coefficient of each model's specifications generally supports the Malthusian view that population size has had a severely adverse impact on the environment (Shi, 2003). It has also shown that affluence influences environmental change in Australia, although its effect is negative. The negative sign could be explained by the fact that affluence in Australia, as in most developed countries, leads to a change in lifestyle and standard of living of the people (Dietz et al., 2007), which has a reduction effect on the environment. Urbanisation also clearly affects the ecological footprint; this result is in accordance with the fact Australia is experiencing rapid urbanisation – from 1960 to 2014, the urbanisation rate in Australia increased from 73% to 90%. However, CO_2 emissions and industry share of GDP are not significant variables for defining ecological footprint in Australia.

The implication of the findings on the sustainability of the environment in Australia is that appropriate policy measures should be put in place to reduce the impact of the drivers on the environment.

Therefore, for easing the impacts of human activities on the environment, it is necessary to strengthen the study of population policy, the urbanisation process and economic growth pattern of Australia. In order to live in harmony with nature, ecological capacity needs to increase. To increase ecological capacity or reduce the ecological footprint, population impacts need to be controlled, a sustainable lifestyle promoted, and the efficiency of use of resources needs to be improved. The findings of this study will enable policymakers, environmental authorities and other stakeholders to fully appreciate environmental concerns and give them due weight. More importantly, the study is significant because it indicates the applicability of environmental impact models, particularly the STIRPAT model, to a single country's situation.

8. ACKNOWLEDGEMENT

This work is financially supported by the Brazil Family Foundation. We express our appreciation and thanks for their financial support.

9. REFERENCES

Alcott, B. 2009, Impacts Caps: Why population; affluence and technology strategies should be aboundoned. *Journal of Cleaner Technology*. 30, 1-9.

Australian Bureau of Statistics, 2014, Australian Demographic Statistics, cat. no. 3101.0, ABS Statistics, Canberra, Retrived from http://www.abs.gov.au/ausstats, Viewed 26 July 2014

Bagliani, M., Galli, A., Niccolucci, V., Marchettini, N., 2008, Ecological footprint analysis applied to a sub-national area: The case of the Province of Siena (Italy). *Journal of Environmental Management*. 86, 354-64.

Boserup, E. 1981, Population and Technological Change: A Study of Long-term Trends, University of Chicago Press, Chicago.

Cole, M. A., Neumayer, E., 2004, Examining the Impact of Demographic Factors on Air Pollution. *Population and Environment*. 26, 5-21.

de Sherbinin, A., Carr, D., Cassels, S., Jiang, L., 2007, Population and Environment. *Annual Review of Environment and Resources*. 32, 345-373.

Dietz, T., Rosa, E. A., 1994, Rethinking the Environmental Impacts of Population, Affluence and Technology. *Human Ecology Review*. 1, 427-300.

Dietz, T., Rosa, E., York, R,. 2007, Driving the Human Ecological Footprint. *Frontiers of Human Ecology*. 5, 13-18.

Ehrlich, P. R., Holdren, J. P., 1971, Impact of population growth. *Science*. 171, 1212-1217.

Fan, Y., Liu, L. C., Wu, G., Wei, Y. M., 2006, Analyzing Impact Factors of CO2 Emissions using the STIRPAT model. *Environmental Impact Assessment Review*. 26, 377-395.

Global Footprint Network, GFN, 2012, Australia Living Planet Report, Retrieved from http://www.wwf.org.au, Viewed 13 February 2014.

Glanznig, A., 1995, Native vegetation clearance, habitat loss and biodiversity decline. An overview of recent native vegetation clearance in Australia and its implications for biodiversity. http://www.deh.gov.au/biodiversity/publications/series/paper6/index.html, Viewed 31 October 2014.

Hanley, N., Moffatt, I., Faichney, R., Wilson, M., 1999, Measuring sustainability: A time series of alternative indicators for Scotland. *Ecological Economics*. 28, 55-73.

Hobday, A., McDonald, J. 2014, Environmental Issues in Australia. The Annual Review of Environment and Resources. 39, 1-28.

Hoerl, A. E., Kennard, R. W., 1970, Ridge regression: biased estimation for nonorthogonal problems. *Technometrics*. 12, 55-67.

Jia, J., Deng, H., Duan, J., Zhao, J., 2009, Analysis of the major drivers of the ecological footprint using the STIRPAT model and the PLS method - A case study in Henan Province, China. *Ecological Economics*. 68, 2818-2824.

Knight, K., Rosa, E., 2012, Household dynamics and fuelwood consumption in developing countries:a cross-national analysis. *Population and Environment*. 33, 365-378.

Lenzen, M., Murray, S. A., 2001, A modified ecological footprint method and its application to Australia. *Ecological Economics*. 37, 229-255.

Liddle, B., 2013, Urban Density and Climate Change: A STIRPAT Analysis using City-level Data. *Journal of Transport Geography*. 28, 22-29.

Lin, S., Zhao, D., Marinova, D., 2009, Analysis of the environmental impact of China based on STIRPAT model. *Environmental Impact Assessment Review*. 29, 341-347.

Madu, I. A., 2009, The environmental impacts of regional disparity in population and wealth distribution in Nigeria. *Environment, Development and Sustainability*. 11, 265-276.

Malthus, T. R., 1967, Essay on the Principle of Population. Seventh ed., Dent, London, UK.

Mingquan, W., Jingshuang, L., Jinda, W., Guangying, Z., 2010, Ecological Footprint and Major Driving Forces in West Jilin Province, Northest China. *Journal of Geographical Science*. 20, 434-441.

National Sustainability Council, 2013, Sustainable Australia Report, Conversations with the Future. Canberra, Retrieved from http://www.environment.gov.au

Ping, W., Xinjun, W., 2011 Spatiotemporal change of ecological footprint and sustainability analysis for Yangtze Delta Region. *Journal of Geographical Sciences*. 21, 859-868.

Raupach, M., 2007, CO2 Emissions Increasing Faster than Expected. Commonwealth Scientific and Industrial Research Organisation (CSIRO). Available at http://www.csiro.au/Organisation-Structure/Divisions/Marine--Atmospheric-Research/GlobalCarbonProject-PNAS.aspx

Roberts, T., 2012, Are macro-level relationships between demography, economy, and environmental impact significat at smaller scales of analysis? Identifying country-level age-specific drivers of CO_2 emissions in the US using age-structure and relative cohort size. Paper presented to the Population Association of America Annual Meeting, San Francisco, Viewed at http://www.paa2012.princeton.edu/papers/121274

Romero, P., Tribbia, J., Nychka, D., 2009, Testing theories to explore the drivers of cities atmosphere emissions. 38, 236-244.

Rosa, E. A., Dietz, T., York, R., 2003, Footprints on the earth: The environmental consequences of modernity. *American Sociological Review*. 68, 279-300.

Schulze, P., 2002, I=PBAT. *Ecological Economics*. 40, 149-150.

Shi, A., 2003, The impact of population pressure on global carbon dioxide emissions, 1975-1996: evidence from pooled cross-country data. *Ecological Economics*. 44, 29-42.

Stern, N., 2006, Stern Review on The Economics of Climate Change. Executive Summary. HM Treasury, London. Retrieved 31 October 2014.

Tallarico, C. D., Johnson, A. C., 2010, The Implications of Global Ecological Elasticities for Carbon Control: A STIRPAT Formulation. *Journal of Management Policy and Practice*. 11, 86-94.

Turner, B., Ali, S. A., 1996, Induced Intensification: Agricultural Change in Bangladesh. Proceedings of the National Academy of Sciences of the United States of America. 93, 14984-14991.

Uddin, G., Alam, K., Gow, J., 2013, Ecological Footprint and Regional Sustainability: A Review of Methodologies and Results. Australia and New Zealand Regional Science Association International: Proceedings of the Australia and New Zealand Regional Science Association International Meeting, Hervey Bay. 147-60.

United States Energy Information Administration, 2014, International Energy Statistics, Retrieved from http://www.eia.gov, Viewed 16 July 2014.

van den Bergh, J. C. J. M., Verbruggen, H., 1999, Spatial sustainability, trade and indicators: an evaluation of the ecological footprint. *Ecological Economics*. 29, 61-72.

Waggoner, P. E., Ausubel, J. H., 2002 A framework for sustainability science: A renovated IPAT identity. Proceedings of National Academy of Sciences of the United States of America. 99, 7860-7865.

Wang, M., Che, Y., Yang, K., Wang, M., Xion, L., Huang, Y., 2011, A local-scale low-carbon plan based on the STIRPAT model and the scenario method: The case of Minhang District, Shanghai, China. *Energy Policy*. 39, 6981-90.

Wei, T., Xianghao, Z., Shaoquan, L., 2011, Analysis of major driving forces of ecological footprint based on the STIRPAT model and RR method: a case of Sichuan Province, Southeast China. *Journal of Mountain Science*. 8, 611-618.

Wood, R., Garnett, S., 2010, Regional sustainability in Northern Australia-A quantitative assessment of social, economic and environmental impacts. *Ecological Economics*. 69, 1877-1882.

World Bank, 2014, World Development Indicators. http://data.worldbank.org/data-catalog/world-development-indicators Viewed 24 July 2014.

World Wildlife Fund, 2012, Earth Summit: WWF says over-consumption threatens planet, at http://articles.economictimes.indiatimes.com/2012-06-08/news/32124126_1_carbon-footprint-demand-on-natural-resources-biodiversity. Retrieved June 28, 2014.

Xu, Z., Cheng, G., Qiu, G., 2005 ImPACTS identity of Sustainable Assessment. *Geographical Sciences*. 60, 198-218.

Ying, L., Daming, H., Buchanan, S., Jiang, L., 2009, Ecological footprint dynamics in Yunnan, China. *Journal of Mountain Science*. 6, 286-292.

York, R., Rosa, E. A., Rosa, T., 2003, STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*. 46, 351-365.

Zhao, X. Y., 2010, Impacts of human activity on environment in the high cold pasturing area: A case of Gannan pasturing area. *Acta Ecologica Sinica*. 30, 141-149.