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Mitigating degradation and emissions in China: The role of environmental sustainability, human capital and renewable energy

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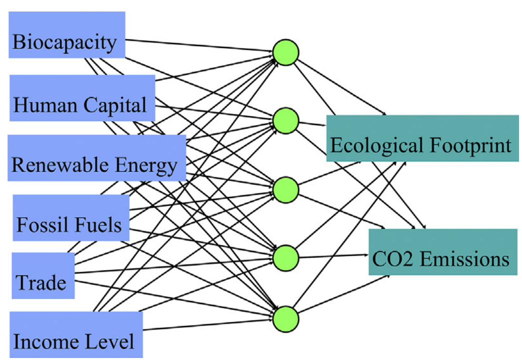
HIGHLIGHTS

- We developed conceptual tools for mitigating climate change and its impacts.
- Fossil fuel energy spurs environmental degradation by 1.93% and emissions by 1.58%.
- The penetration of renewables in the energy mix declines emissions by 0.38% and degradation by 0.21%.
- Increasing human capital is conducive for the escalation of emissions and environmental degradation.
- The study shows that the Chinese economy is sustained through pollution-embedded trade.

GRAPHICAL ABSTRACT



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ABSTRACT

China's carbon-embedded growth trajectory is gradually becoming a burden to environmental sustainability, hence, requires much attention. The complexity of human capital attributed emissions coupled with fossil fuel inclined energy utilization for industrialization underscores the failure of China to meet its mitigation target. We developed a policy-driven conceptual tool based on disaggregate energy utilization, human capital, trade, income level and natural resource exploitation in a carbon and environmental degradation function. Using a battery of statistics and econometric techniques such as neural network, SIMPLS, *U* test, dynamic ARDL Simulations, and Prais-Winsten first-order autoregressive [AR(1)] regression with robust standard errors, we examined the theme based on a data spanning 1961–2016. The study demonstrates that fossil fuel energy consumption and human capital are conducive catalysts for climate change. The instantaneous increase in renewable energy, environmental sustainability and income level has a diminishing effect on emissions and environmental degradation. The environmental Kuznets curve (EKC) hypothesis is validated in both emissions and degradation function — at a turning point of US$ 5469.79 and US$ 5863.70, respectively. The study highlights that the over-dependence on fossil fuel energy and natural resources for economic development, carbon-intensive trade and carbon-embedded human capital, thwart efforts to mitigating climate change and its impacts. Thus, the onus of responsibility for achieving a cleaner environment in China depends majorly on governmental policies that favour or dampens environmental sustainability.

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1. Introduction

The Chinese economy has experienced robust growth in the last three decades with concomitant environmental degradation due to excessive carbon dioxide (CO_2) emissions. It is reported that the global energy production and consumption accounted for 25% (49 Gt CO_2-eq, 2010) of the overall global carbon emissions (Blanco et al., 2014). It is in this light that energy consumption has shifted from being purely an environmental issue to one that has a political economy and sociocultural global implication (Liu et al., 2018). The Chinese government has therefore implemented many strategies including carbon taxes to reduce emissions, but success has been limited and in certain cases resulted in distortions (Salim et al., 2017a).

The China Energy Statistical Yearbook shows energy annual growth rate of 8.1 over the period 1991–2013, with a total energy consumption of around 3123 Mtoe, which makes up 22.97% of the world's total energy consumption (Ouyang and Li, 2018; Liu et al., 2018; CESY, 2013). It is reported for the 17th consecutive year that China is the largest growth market for energy (BP Energy Statistics, 2018). CO_2 emissions from energy consumption increased by 1.6%, after little or no growth for the three years from 2014 to 2016. As the Chinese economy continues to reform and develop, the problems associated with rapid growth in energy demand and severe environmental pollution have become increasingly critical, contributing nearly one-third of global greenhouse gas (GHG) emissions. Data show that China's per capita CO_2 emissions were 6.6 t/person, 49% above the world average but 59% below that of the United States, even as China accounted for over half of the world's total coal consumption (China Energy Statistics, 2016). It is not surprising that China's "13th Five-Year Plan", launched in 2016, requires all regional government divisions to reduce energy consumption and primary pollution (Liu et al., 2018). A key strategy to reduce environmental pollution has been an agenda towards the use of renewable energy. The combination of renewable energy and energy efficiency is estimated to provide over 90% of the necessary energy-related CO_2 emission reductions (IRENA, 2018). The renewable energy agenda in China reports that renewable energy and energy efficiency policies have far-reaching effects for energy security, climate change economic performance, and human livelihoods and therefore need to become a national priority for the Chinese government (Lo, 2014). This means that strategies for mitigating environmental pollution and consequent climate change are critical to the economy, an act which motivates our study.

Similarly, the high rate of environmental degradation and the subsequent climate change and the need for energy justice have become key human rights issues across the world. The International Renewable Energy Agency has noted that renewable resources and technologies are key to a sustainable future (IRENA, 2018). However, the big question is how growth in renewable energy impacts environmental quality in China. This question drives the study and is relevant because, an understanding of the energy – environmental pollution nexus provides the desired information for climate change mitigation and the basis for evidence-informed energy policy (Li et al., 2016).

It is worth mentioning that many studies have looked at the energy consumption and environmental degradation link, but the results have been inconsistent (Bekun et al., 2019; Adams and Nsiah, 2019; Apergis, 2019). With the debate on environmental degradation deepening, many analysts report (World Economic Forum, 2017) that the inconsistency in the result could be attributed to the omission of human capital, however, not much has been done about the role of education or human capital in the energy consumption – environmental degradation link. This study contributes to the literature in filling this gap. This is consistent with the view that human capital development or sustainable education becomes a critical factor in mitigating climate change (Ponce et al., 2019; Hassan et al., 2019; Bashir et al., 2019; Lan et al., 2012). The methodology employed allows the examination of both direct and indirect effects of human capital on climate change. Contrary to previous attempts in extant literature, we develop conceptual tool for policy direction based on novel estimation techniques.

Empirically, many studies have investigated the renewable energy and environmental pollution relationship, however, very few studies have examined the effect of human capital and environmental sustainability in mitigating climate change, especially in China. An examination of energy consumption and carbon emissions for ten Asian economies over the period 1980–2010 reports that while fossil fuel energy increases carbon emissions, renewable energy has the opposite effect (Salim et al., 2017a). In a study that forecasted the impact of renewable energy on environmental pollution in 2050 for China, renewable energy was found to promote economic growth while reducing the emissions of CO_2 and air pollutants such as NO_x, and SO_2 (Dai et al., 2016). However, renewable energy must reach a minimum threshold before it can have a positive impact on environmental quality (Chiu and Chang, 2009). It is reported that the shift to renewable energy could lead to a reduction of between 17 and 57% for the Chinese economy by 2030 with huge financial implications (Urban et al., 2009). In a study of OECD[1] countries, renewable energy supply is predicted to account for over 8% of total energy supply before any impact on mitigating CO_2 emissions could be observed. Similar results have been reported for Pakistan, India, and Bangladesh over the period 1978–2011 (Irfan and Shaw, 2017). Other studies, however, are not so optimistic about the role of renewable energy. For example, renewable energy is reported to escalate CO_2 emissions in developed and developing countries although nuclear energy has a positive effect on environmental quality (Apergis et al., 2010; Bölük and Mert, 2014). Meanwhile, renewable energy is reported to have no significant effect on CO_2 emissions (Al-Mulali et al., 2015).

There has been a growing debate on the role of human capital in mitigating the incidence of environmental degradation and climate change impacts (Balaguer and Cantavella, 2018; Sapkota and Bastola, 2017; Salahodjaev, 2018). Education, a fibre of human capital, causes people to be more concerned about social welfare and therefore behave in a more environmentally-friendly manner (World Economic Forum, 2017). Hence, people with formal education were found to be more likely to exhibit more environmentally-oriented behaviours (Meyer, 2016). Human capital was used as a variable in identifying the determinants of environmental degradation and to reduce omitted variable bias (Balaguer and Cantavella, 2018). The findings show that higher education has a significant positive impact on environmental quality. In the case of 94 countries, higher social cognitive capital within a democratic state was found to radically increase the commitment to adopt environmental policies (Obydenkova and Salahodjaev, 2017). In another instance of the role of human capital on environmental awareness in 119 countries, it is reported that cognitive capability is positively related to climate change awareness, thus, increasing environmental quality (Salahodjaev, 2018). In a survey of 3900 adults to investigate the nexus between human capital and environmental degradation, it was reported that women and individuals with higher education are more likely than others to worry about global warming and more likely to act or adopt behavioural and technical changes (Muttarak and Chankrajang, 2015). People with higher education had a greater probability of taking knowledge-based environmentally-friendly actions, but not cost-saving pro-environmental actions (Chankrajang and Muttarak, 2017). In contrast, no significant relationship between human capital and environmental quality was found in 181 countries (Williamson, 2017) while the impact of human capital on pollution emission was found inconsistent across countries (Sapkota and Bastola, 2017).

However, not much has been done in the Chinese contexts though a few studies have examined the nexus between human capital and energy consumption (Salim et al., 2017b; Broadstock et al., 2016;

[1] Organization for Economic Co-operation and Development.

Démurger and Fournier, 2011). It is reported that human capital reduces energy consumption between 0.18 and 0.45%. Strong accumulation of post-school human capital in eastern China is identified as a key driver for energy efficiency consumer behaviour (Salim et al., 2017b). Increasing education is positively related to pro-environmental behaviour especially in Northern China when dealing with energy source switching behaviour (Démurger and Fournier, 2011).

The literature on renewable energy, environmental sustainability and human capital in a carbon and degradation function is limited in the case of China. Thus, examining the role of environmental sustainability, human capital and renewable energy consumption in mitigating climate change has policy implications for China in terms of prioritization of strategies employed in reducing the environmental pollution.

2. Materials & method

2.1. Data

This study collated an annual frequency data series spanning 1961–2016 based on existing theories and the United Nations guidelines and methodologies for Sustainable Development (DiSano, 2002). The selected data comprising of Human Capital Index [Abbreviated as HCPI (measured in index)], CO_2 emissions [CO2E (metric tons per capita]), Renewable energy consumption [RECON (% of total final energy consumption)], Fossil fuel energy consumption [FECON (% of total)], Trade [TRADE (% of GDP)] and GDP per capita [GDPPC (constant 2010 US dollar)] were extracted from the Quality of Government Insitute Standard Dataset (Teorell et al., 2018), while data for Ecological footprint [ECOFT (gha per person)] and Biocapacity [BIOCP (gha per person)] were mined from Global Footprint Network (Global Footprint Network, 2017). The databases follow World Bank and United Nations guidelines to ensure data quality. The human capital index captures the workforce, education and employment dynamics of a country to examine capacity, deployment, know-how and development. Thus, a useful indicator for assessing the Sustainable Development Goal (SDG) 8 that ensures sustained and productive employment. The ecological footprint measures natural resources exploited, consumed and waste generated from land and water productivity, hence, a useful indicator for assessing environmental degradation. Hereafter, ecological footprint is used as a proxy for *environmental degradation*, as it comprises built-up land, land used for grazing, carbon footprint, forest products, land used for cropping and fishing grounds. Biocapacity measures the regenerative capacity of available natural resources embedded ecosystem to meet human demand regardless of carbon footprint, waste generation and the use of extractive technologies. Because the ratio of biocapacity and ecological footprint underlies either ecological deficit (ecological footprint exceeds biocapacity) or ecological reserve (biocapacity exceeds ecological footprint), it appears a useful indicator for assessing *environmental sustainability*. Using disaggregate energy consumption (renewable and fossil fuels) individually rather than aggregated form is useful for investigating the decoupling effect of energy consumption from a policy perspective.

2.2. Variable selection & pre-modelling techniques

Traditional forms of variable selection are always not comprehensive enough to warrant the importance of data series captured in model estimation techniques. Thus, most studies based on theoretical rather than statistical variable selection may have exaggerated *a priori* expectations. In line with Sarkodie and Adom (2018); Sarkodie and Ozturk (2020), we employed the variable importance in projection (VIP) based on a statistically inspired modification of partial least squares (SIMPLS) (De Jong, 1993) to examine the predictive power of the independent variables to the target variables. Fig. 1 presents the VIP of predictors in carbon and environmental degradation function. It can be observed that GDP per capita and renewable energy

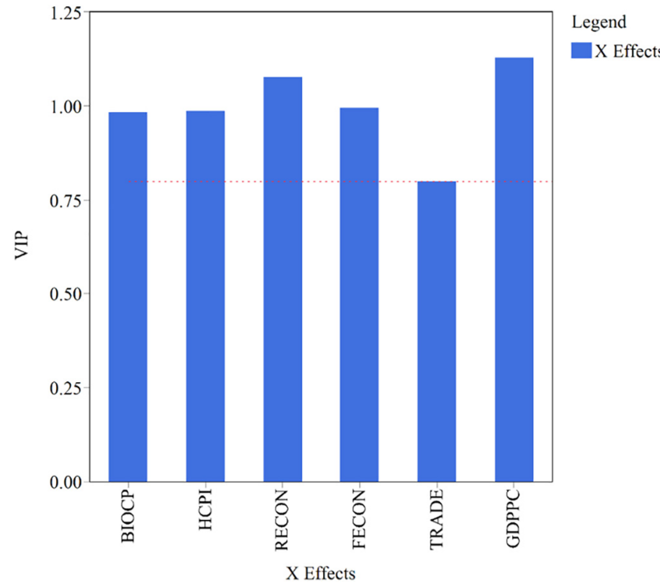

Fig. 1. VIP of predictors in carbon and environmental degradation function. **Legend**: HCPI represents Human Capital Index, CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, ECOFT signifies Ecological footprint and BIOCP means Biocapacity, a proxy for environmental sustainability.

consumption are highly influential predictors (VIP > 1.00) while the remaining variables are moderately influential in predicting the target variables.

After the selection of important variables for the model estimation, a descriptive statistical analysis to examine the characteristics of the data series was performed, with subsequent results presented in Appendix A. The Jarque-Bera test statistic in Appendix A shows that all the variables are normally distributed except for CO2E, ECOFT and GDPPC, thus, underscores the log-transformation applied to the variables used in the econometric-based model estimation technique.

The presence of structural breaks in data series affects parameter stability of a series over time, hence, the application of the novel cumulative sum test statistics from recursive and ordinary least squares residuals (Brown et al., 1975; Ploberger and Krämer, 1992). The null hypothesis of no structural break is rejected when the cumulative sum process falls outside the 95% confidence band. The recursive cumulative sum plot in Fig. 2 reveals that all the variables are within the 95% confidence band, hence, have no issues with structural break, thus, produce coefficient stability over time.

After examining the presence of possible structural breaks, we proceeded to test for the presence of unit root and cointegration using Phillips-Perron (PP), Augmented-Dickey Fuller (ADF) and Pesaran, Shin and Smith (PSS-Bounds) tests presented in Appendix B. Appendix B confirms a mixture of the order of integration and cointegration.

2.3. Model estimation techniques

The proposed model can be expressed as a linear relationship in a carbon and degradation function, expressed statistically as:

$$\begin{aligned} &CO2E \mid ECOFT \\ &\quad \sim f\left(BIOCP, HCPI, RECON, FECON, TRADE, GDPPC|GDPPC^2\right) \end{aligned} \tag{1}$$

The model estimation first utilized the Prais-Winsten transformed regression with robust standard errors to correct residuals with first-order autoregressive [AR(1)] serial correlation, expressed as (Prais and

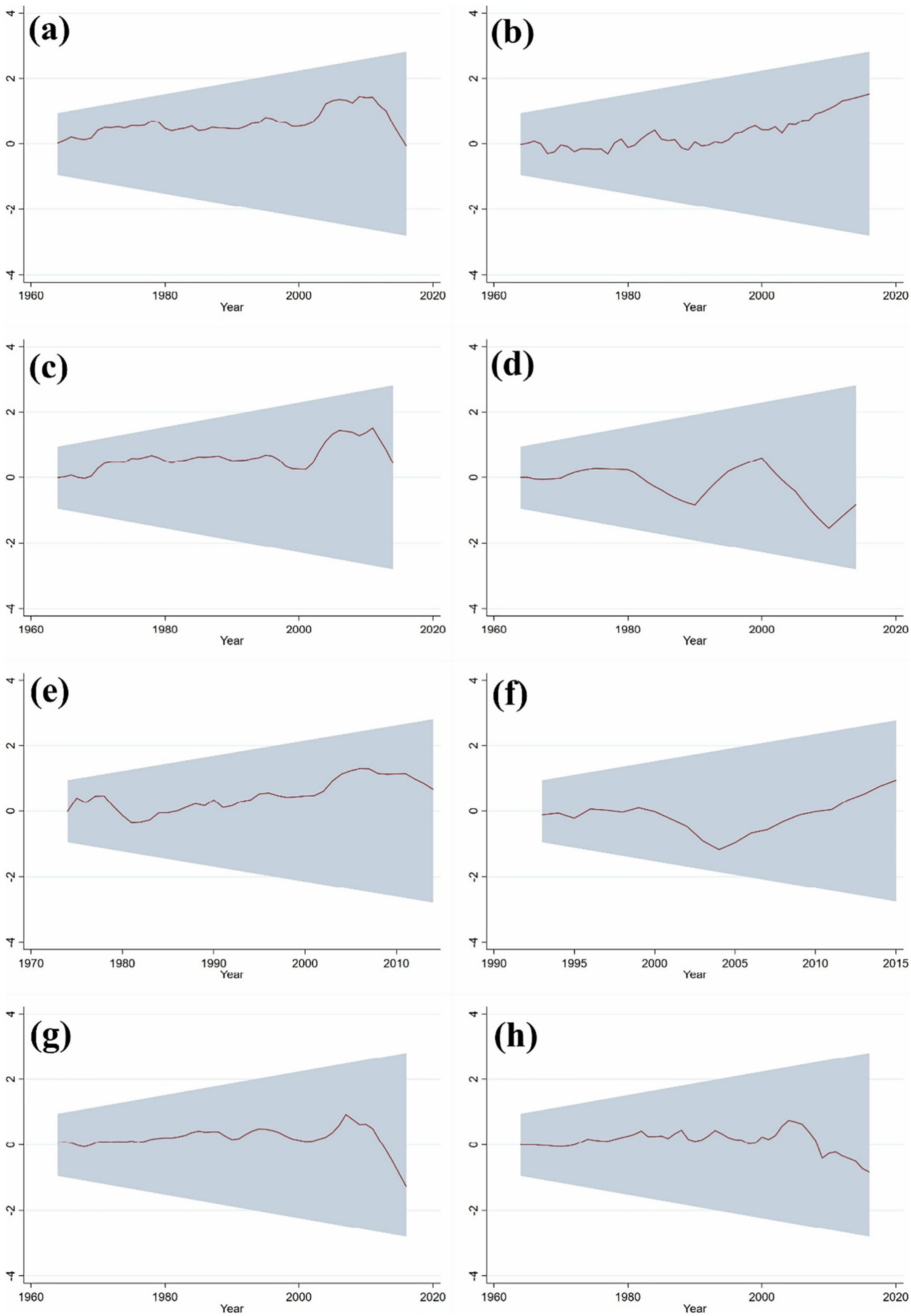

Fig. 2. Recursive Cusum plot (a) ECOFT (b) BIOCP (c) CO_2 (d) HCPI (e) FECON (f) RECON (g) GDPPC and (h) TRADE. **Legend**: HCPI represents Human Capital Index, CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, ECOFT signifies Ecological footprint and BIOCP means Biocapacity, a proxy for environmental sustainability.

Winsten, 1954):

$$CO2E_t \mid ECOFT_t = \beta_1 BIOCP_t + \beta_2 HCPI_t + \beta_3 RECON_t + \beta_4 FECON_t + \beta_5 TRADE_t + \beta_6 GDPPC_t + \beta_7 GDPPC^2{}_t + u_t \quad (2)$$

where the error term $u_t = \rho u_{t-1} + e_t$ and e_t follows an independent and identical distribution. The Prais-Winsten transformed regression is based on the generalized least-squares estimator, which preserves the initial observation.

Second, based on the attributes of the data series through pre-modelling estimation techniques such as unit root and cointegration tests, we adapted the dynamic autoregressive distributed lag (ARDL) simulations proposed by Jordan and Philips (2018) for structural policy modelling, expressed as:

$$\Delta y_t = \alpha + \phi_0 lny_{t-1} + \beta_1 \Delta lnBIOCP_t + \phi_1 lnBIOCP_{t-1} + \beta_2 \Delta \ lnHCPI_t + \phi_2 lnHCPI_{t-1} + \beta_3 \Delta \ lnRECON_t + \phi_3 lnRECON_{t-1} + \beta_4 \Delta \ lnFECON_t + \phi_4 lnFECON_{t-1} + \beta_5 \Delta \ lnTRADE_t + \phi_5 lnTRADE_{t-1} + \beta_6 \Delta \ lnGDPPC_t + \phi_6 lnGDPPC_{t-1} + \varepsilon_t \quad (3)$$

where y denotes $lnCO2E_t$ and $lnECOFT_t$, ln represents logarithmic transformation, α is the intercept, Δ is the difference operator, $\phi_0, \ldots, \phi_6$ and $\beta_1, \ldots, \beta_6$ are the parameters to be estimated, ε_t denotes the white noise in time t. Using the outlined model specification, we made predictions with the dynamic ARDL stochastic simulations (Sarkodie et al., 2019). The output enables the examination and visualization of how a counterfactual shock in one predictor while holding other predictors constant at a point in time has policy implications in a carbon and environmental degradation function. It is noteworthy that the novel dynamic simulations are only applicable after assessing the order of integration using unit root test, testing for a structural break for parameter stability, cointegration testing and diagnosing the estimated model such that the residuals are independent. The dynamic simulations based on 1000 draws from a multivariate normal distribution among other stochastic processes facilitate the creation of new predicted emissions and degradation over the forecast period. For simplicity, we applied $\pm$ 1% shock to the individual regressors to trigger a counterfactual change in the target variables; 20 scenario time to observe the applied shock; and a range of 100 to ascertain the length of the simulation scenario of the estimated ARDL in equilibrium.

After applying the dynamic ARDL simulations for structural policy modelling, we applied a nonlinear modelling technique to add complexity and turning points of development important to the estimated model. All the regressors were subjected to nonlinearity expressed as:

$$y_t = \alpha + \beta_1 x_t + \beta_2 x^2{}_t + \varepsilon_t \quad (4)$$

where x represents the regressors and x^2 is the quadratic form of the regressors. To validate the nonlinear model aka Kuznets curve hypothesis, we employed the novel U test algorithm expounded in Lind and Mehlum (2010). The U test algorithm allows the type of structure of the curve and turning point to be known.

The final step of the model estimation utilized the predictive power of the neural network algorithm specified in Bishop (1995) to develop conceptual tools using the prediction profiler. The study utilized a multilayer perceptron with hyperbolic tangent ($TanH$) activation function. The sigmoid function used in this model fits the neural network based on one hidden layer with five hidden nodes. For brevity, the neural network algorithm can be expressed as (Bishop, 1995):

$$y_j = TanH\left(\alpha_j + \sum_i \beta_{i,j}\, x_i\right) \quad (5)$$

where y_j is the activation of the hidden layer, α_j denotes the bias of jth hidden unit, $\beta_{i,\,j}$ represents the weight that connects the ith predictor to the jth hidden unit, and x_i is the ith predictor. The model specification of Eq. (1) for the proposed model is expressed as:

$$CO2E_j \mid ECOFT_j = TanH(0.5 * (\alpha + \beta_{1,j} BIOCP + \beta_{2,j} HCPI + \beta_{3,j} RECON + \beta_{4,j} FECON + \beta_{5,j} TRADE + \beta_{6,j} GDPPC)) \quad (6)$$

To validate the estimated model based on the trained data set, we employed the Random K-fold technique with 5 (K) subsets. Thus, the 5 subsets of the original data are used as cross-validation of the remaining data. The optimal model with the best validation statistic is then selected.

The limitation of the study stems from the availability of data and its periodicity utilized in the model estimation. This explains the inconsistencies reported in extant literature on similar studies.

3. Results

Based on over two decades of historical data, the equilibrium relationship in a carbon and degradation function presented in Table 1 has policy implications. The estimated model based on Prais-Winsten AR (1) regression with robust standard errors in a degradation function (lnECOFT) has a goodness of fit (R-squared) approximately 93% compared to 79% in a carbon function (lnCO2E). All the estimated models are statistically significant (p-$value$ < 0.01), free from conditional heteroskedasticity (archlm) and first-order serial correlation (bgodfrey), thus, validating the independence of the residuals. The coefficient of human capital (lnHCPI) is positive in both models, but statistically significant (p-$value$ < 0.05) in the emissions model. This infers that China's intensive human capital exacerbates emissions (by ~1.17%) rather than environmental degradation. Biocapacity, a variable used as a proxy for environmental sustainability seems to have no significant impact on environmental degradation but rather emissions. Evidence from model 2 in Table 1 shows that a regeneration of the ecosystem absorbs carbon, hence, decreases emissions by ~0.37%. The coefficient of trade (lnTRADE) in both models produces varying outcomes. While trade in model 1 is negative and insignificant, it turns positive and statistically significant (p-$value$ < 0.01) in model 2. An increase in trade appears to have a significant impact on China's emission levels, increasing it by 0.15%. To examine the economic impact on degradation and emissions, income level in both level and quadratic form was added to the

Table 1
Prais-Winsten AR(1) regression with robust standard errors.

Variable	Model 1: lnECOFT	Model 2: lnCO2E
lnBIOCP	−0.1884	−0.3691*
	[0.3218]	[0.2073]
lnHCPI	0.5215	1.1728**
	[0.3356]	[0.4515]
lnRECON	−0.2060***	−0.3838***
	[0.0617]	[0.0850]
lnFECON	1.9341***	1.5757**
	[0.5435]	[0.7360]
lnTRADE	−0.0032	0.1542***
	[0.0634]	[0.0491]
lnGDPPC	0.2382***	0.4223***
	[0.0643]	[0.1191]
$lnGDPPC^2$	−0.0266***	−0.0495***
	[0.0086]	[0.0116]
rho	−0.1802	0.4741
R^2	0.9257	0.7857
Prob > F	0.0000***	0.0000***
archlm[a]	0.7028	0.4781
bgodfrey[b]	0.6853	0.4157

Notes: [] represents standard error; **, *** denote statistical significance at 1% and 5% level; [a]Engle's Lagrange multiplier test and [b]Breusch-Godfrey test. **Legend**: HCPI represents Human Capital Index, CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, ECOFT signifies Ecological footprint and BIOCP means Biocapacity, a proxy for Environmental Sustainability.

model. The coefficient of income level (lnGDPPC) in both degradation and emission function is positive and statistically significant (*p-value* < 0.01) but turns statistically (*p-value* < 0.01) negative in its quadratic form ($\mathrm{lnGDPPC}^2$). Using the approximation of Eq. (2), $\Delta\hat{y}/\Delta\hat{x} = \widehat{lnGDPPC} + 2 * \widehat{lnGDPPC^2}$, thus, income level initially spurs environmental degradation and emissions by ~0.24% and 0.42% in the first year but declines to 0.21% and 0.37%, respectively in the second year of income level. In terms of turning point interpreted in the light of $x^* = -\widehat{lnGDPPC}/(2 * \widehat{lnGDPPC^2})$, China's growth in income initially exacerbates both degradation and emissions but subsequently declines environmental degradation by 8.95% and emissions by 4.27%. This implies that income level has a diminishing effect on both environmental degradation and emissions. To account for the decoupling effect of energy consumption, we used disaggregate energy consumption, specifically fossil fuel and renewable energy consumption in the estimated model. While the coefficient of fossil fuel energy consumption (lnFECON) is positive and statistically significant (*p-value* < 0.05), the coefficient of renewable energy is negative (*p-value* < 0.01) in both models. Implying that, increasing the share of fossil fuel energy technologies in the energy mix spurs environmental degradation by 1.93% and emissions by 1.58%. In contrast, increasing the penetration of renewable energy sources in the energy portfolio declines emissions by 0.38% and degradation by 0.21%.

After testing the long-run equilibrium and partial effects of income level in a carbon and degradation function, we estimated the response of emissions and environmental degradation to a counterfactual change in individual predictors while holding other regressors constant. Using the dynamic ARDL simulations estimation technique selected after testing the importance of variables (Fig. 1), structural breaks (Fig. 2), unit root (Appendix B), cointegration (Appendix B) and the equilibrium relationship with its corresponding diagnostic tests (Appendix C), the resulting plots are depicted in Figs. 3–6. The plots of the dynamic ARDL simulations are response from emissions and degradation based on ±1% shock to the individual regressors in 20 scenario time and over a range of 100 to determine the length of the simulation scenario. All the simulated plots shown in Figs. 3–6 are within the red short-dash dot-dot outline pattern — representing the 95% confidence interval, thus, the estimated models are statistically significant and stable to make unbiased inferences. The dynamic ARDL simulations in Figs. 3–6 reveal that a –1% shock to environmental sustainability, human capital and renewable energy consumption escalate emissions and degradation, however, −1% change in fossil fuel energy consumption and income level decline CO_2 emissions and environmental degradation. In contrast, a 1% change in human capital, renewable energy consumption and environmental sustainability mitigate CO_2 emissions and environmental degradation, while growth in income and fossil fuel energy consumption exacerbate emissions and degradation. Though a –1% change in trade hampers both long term emissions and degradation while 1% shock on trade spurs CO_2 emissions and environmental degradation, but the trend appears wiggly along the horizon (see Figs. 3c & 5c).

Contrary to the standard technique based on quadratic term, we utilized the nonlinear (second degree polynomial of the regressor) estimation and *U* test algorithm to examine the shape and turning point of the environmental Kuznets curve (EKC) hypothesis. The nonlinear estimation in emissions and degradation function based on Eq. (4) is depicted in Fig. 7 while the EKC Hypothesis using *U* test estimation technique is presented in Table 2. The predictive power (R-squared) of the nonlinear relationship between environmental degradation and regressors are: renewable energy consumption (97.7%), fossil fuel energy consumption (95.2%), and income level (98.4%). Similarly, the predictive power of the nexus between emissions and nonlinear predictors are: renewable energy (98.3%), fossil fuel energy (93.2%), and income level (97.8%).

The *U* test estimation in Table 2 (columns 2–4) reveals that the shape and turning point of the regressors in a degradation function are: human capital (Monotone) at a turning of 1.05 index, renewable energy consumption (Monotone) at a turning of 51.01%, trade (Monotone) at a turning of 66.95% of GDP, environmental sustainability (U shape) at a turning of 0.94 gha/person, fossil fuel energy consumption (U shape) at a turning point of 60.11% and income level (inversed-U shape) at a turning point of 5863.70 constant 2010 USD. The shape of the nexus between degradation and income level in China validates the EKC hypothesis.

Likewise, the structure and turning point of the regressors in an emission function presented in Table 2 (columns 5–7) are: human capital (Monotone) at a turning of 0.41 index, renewable energy consumption (Monotone) at a turning of 43.37%, trade (Monotone) at a turning of 66.95% of GDP, fossil fuel energy consumption (U shape) at a turning point of 56.11%, environmental sustainability (inversed-U shape) at a turning of 0.93 gha/person, and income level (inversed-U shape) at a turning point of 5469.79 constant 2010 USD. The structure of the relationship between emissions versus environmental sustainability and income level confirms the EKC hypothesis in China.

To develop conceptual tools for policy direction, the study utilized the predictive power of neural network algorithm-based prediction profiler to examine the impact of regressors on the predicted values. Based on a TanH activation function with a single hidden layer and five hidden nodes, a predictive model was developed for both degradation and emissions. The predictive model was then validated based on the training dataset using the Random 5-fold cross-validation technique. The corresponding training and validation of the predictive model based on the neural network are depicted in Fig. 8. The R-square of the estimated model in both emissions and degradation function shows a predictive power of about 100% for the training and validation sets. Using the prediction profiler, a sensitivity analysis of the neural network of the estimated model is depicted in Fig. 9. A visual inspection of the sensitivity indicator (violet triangle) shows that human capital and fossil fuel energy consumption has a positive profile while environmental sustainability, renewable energy consumption, trade and income level have a negative profile in both degradation and emission function. The profiler indicates that the predicted median value of 0.90 gha per person (for environmental sustainability), 1.85 index (human capital), 22.90% (renewable energy consumption), 76.18% (fossil fuel energy consumption), 26.87% of GDP (trade), and 1587.10 constant 2010 USD (income level) spur environmental degradation and emissions by 1.51 gha per person and 2.83 metric tons per capita, respectively. This implies that higher human capital and fossil fuel energy consumption in China escalate environmental degradation and emissions whereas environmental sustainability, trade, income level and renewable energy consumption decline degradation and emissions, corroborating the equilibrium model.

4. Discussion

The empirical results show that increasing human capital is conducive for the escalation of emissions and environmental degradation. The EKC hypothesis for human capital with a monotonic structure in a carbon and degradation function corroborates these results. This infers that China's historical human capital is embedded with emissions, which may be due to the use of cheap labour to achieve economic development and attract foreign direct investment (FDI) from countries with stringent environmental policies. In support of this view, it is reported that human capital plays a moderating role in the FDI-environment relationship such that in regions with high human capital, FDI has a positive effect on environmental quality and vice versa (Lan et al., 2012). Additionally, the use of environmental and energy resources in a society significantly depends on the level of education (Balaguer and Cantavella, 2018). A host country's absorptive capacity is highly related to its human capital, which determines how technology is diffused in dealing with environmental pollution (Fu, 2008). Thus, the extent of this effect depends on the workforce, education and employment

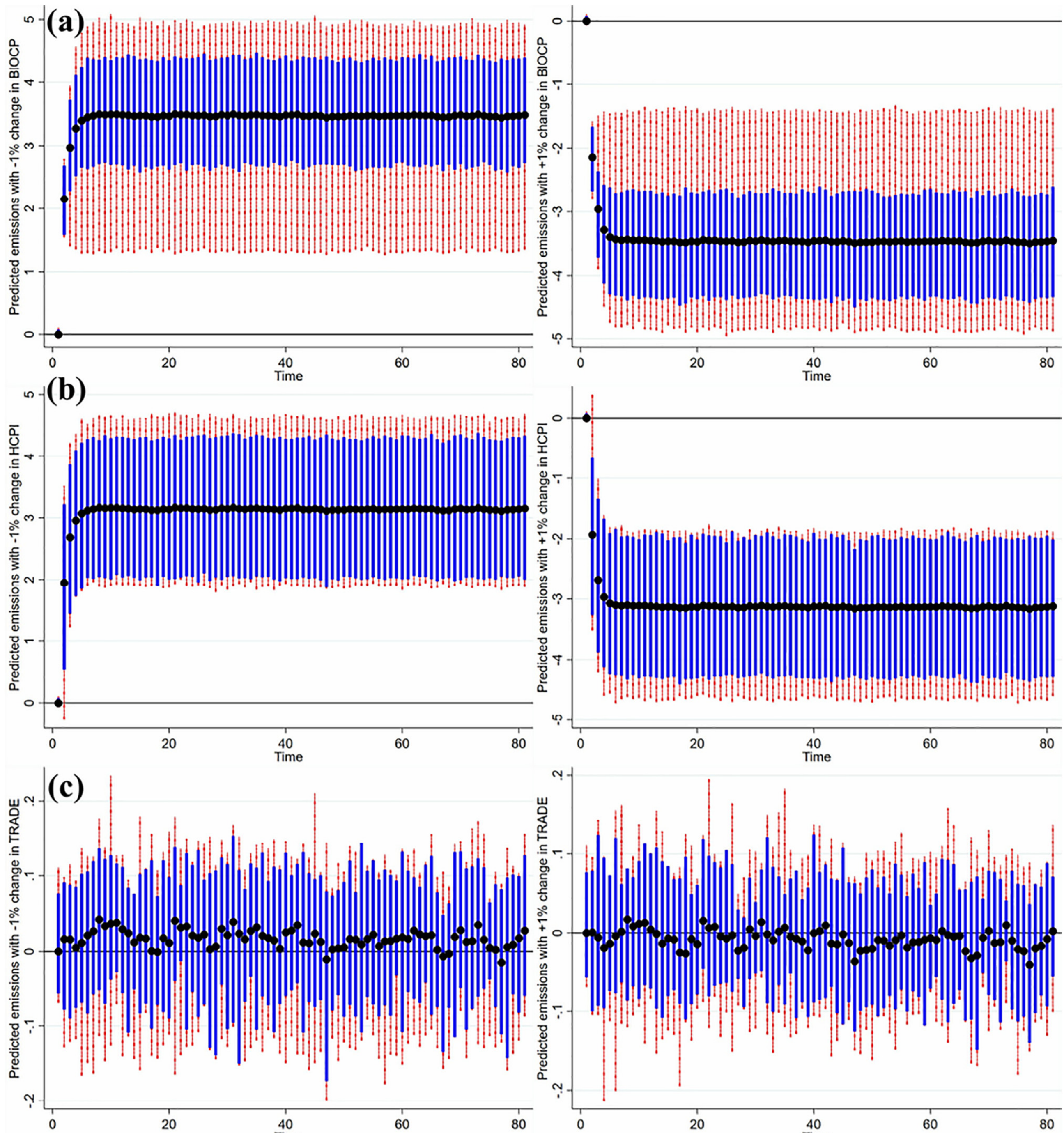

Fig. 3. Dynamic ARDL simulations — predicted emissions with % change in (a) BIOCP (b) HCPI (c) TRADE. **Legend**: HCPI represents Human Capital Index, and BIOCP means Biocapacity, a proxy for environmental sustainability.

dynamics of the country. This explains why countries that have deployed a broad share of their labour force with educational attainment in skill-intensive jobs have achieved high-income status (World Economic Forum, 2017). Aside from the historically-based model estimation, the prediction of the dynamic ARDL simulations indicates that a positive future shock to human capital has a diminishing effect on emissions and degradation. Meaning that improvement in human capital through capacity, deployment, know-how and development across economic sectors spurs environmental sustainability.

Trade has a significant positive effect on emission while no significant impact on environmental degradation, yet, the relationship exhibits a monotonic shape for both functions. This implies that the Chinese economy is sustained through pollution-embedded trade from the production process of goods and services rather than natural resource extraction. This is evident in the sensitivity indicator of the neural network predictor profiler for environmental degradation (Fig. 9). It is reported that pollution-embedded goods and services from China are more compared to countries with stringent environmental regulations (Yunfeng and Laike, 2010). Thus, the Chinese economy supports the trade-evolution hypothesis — which posits that energy-intensive attributable emissions increase with increasing trade. The counterfactual change in trade projects that future trade in China will be volatile to external shocks, which will affect both emissions and environmental degradation. When such volatility occurs in trade,

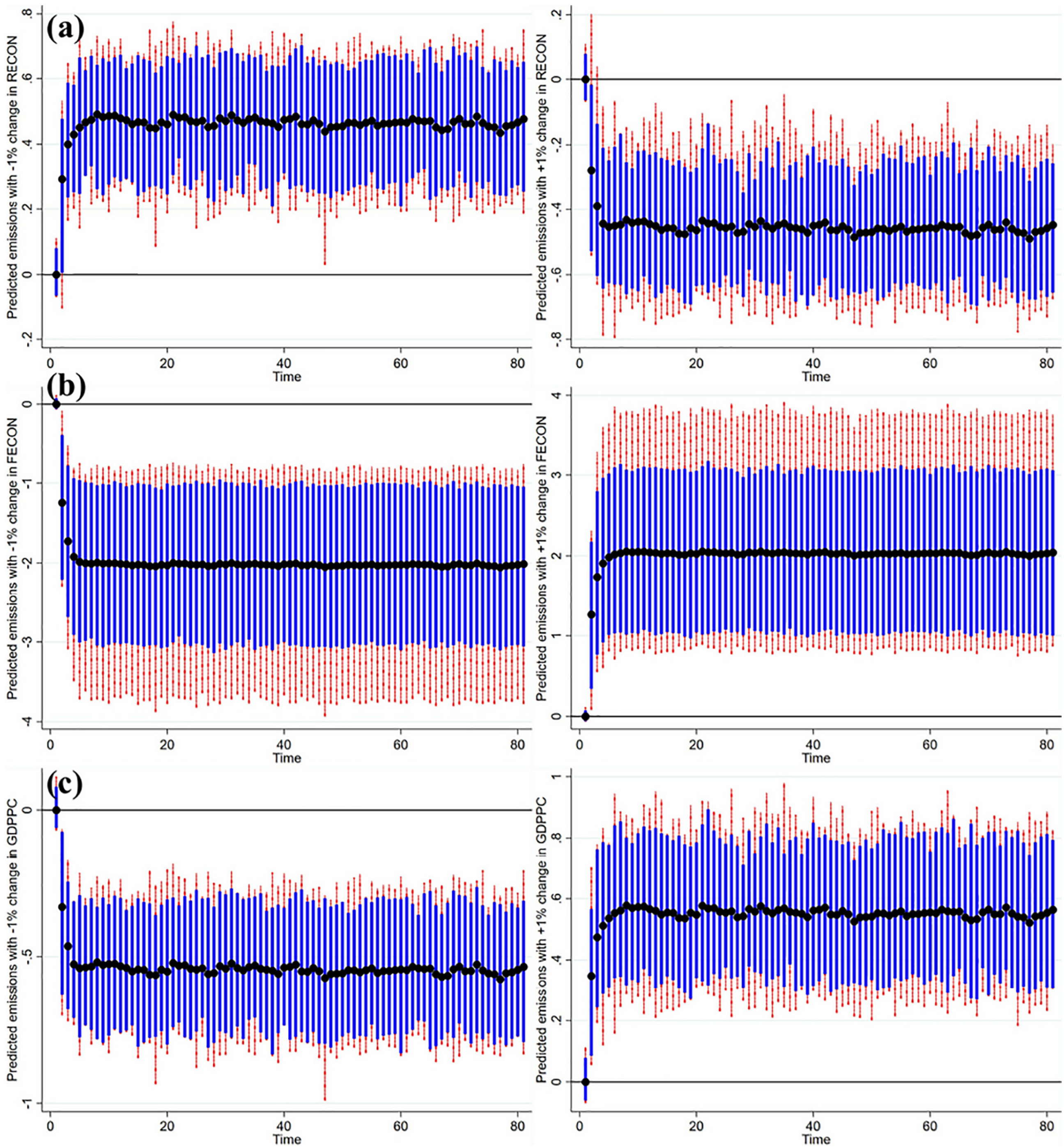

Fig. 4. Dynamic ARDL simulations — predicted emissions with % change in (a) RECON (b) FECON (c) GDPPC. **Legend**: RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, and GDPPC means GDP per capita/income level.

the magnitude of this effect depends on the technique effect of the economy.

The inversed-U shape at a turning of 0.93 gha/person of the relationship between emissions and environmental sustainability confirms the EKC hypothesis in China while the *U* test estimation finds a U shape at a turning of 0.94 gha/person in a degradation function. The inversed-U shape means that the Chinese economy is initially characterized by energy and carbon-intensive production based on natural resource exploitation and waste generation (Yunfeng and Laike, 2010). But as economic and technology advance, pressure on natural resource depletion declines at a turning point in environmental sustainability, limiting resource depletion and promoting regeneration, recycling and reusing. The U-shape infers a “hand-to-mouth” Chinese economy dependent on natural resources for the production of goods and services, leading to an ecological deficit. In contrast, the dynamic ARDL simulations predict that a positive change in environmental sustainability declines both emissions and environmental degradation. The regeneration of the ecosystem above the demand for natural resources and the absorption of carbon improves the ecological reserve, therefore, limits the detrimental effect of emissions and degradation.

Income level is positive in both emissions and degradation function, signifying both carbon-intensive and natural resource dependent economy. China's economic development initially exacerbates both degradation and emissions but subsequently declines environmental

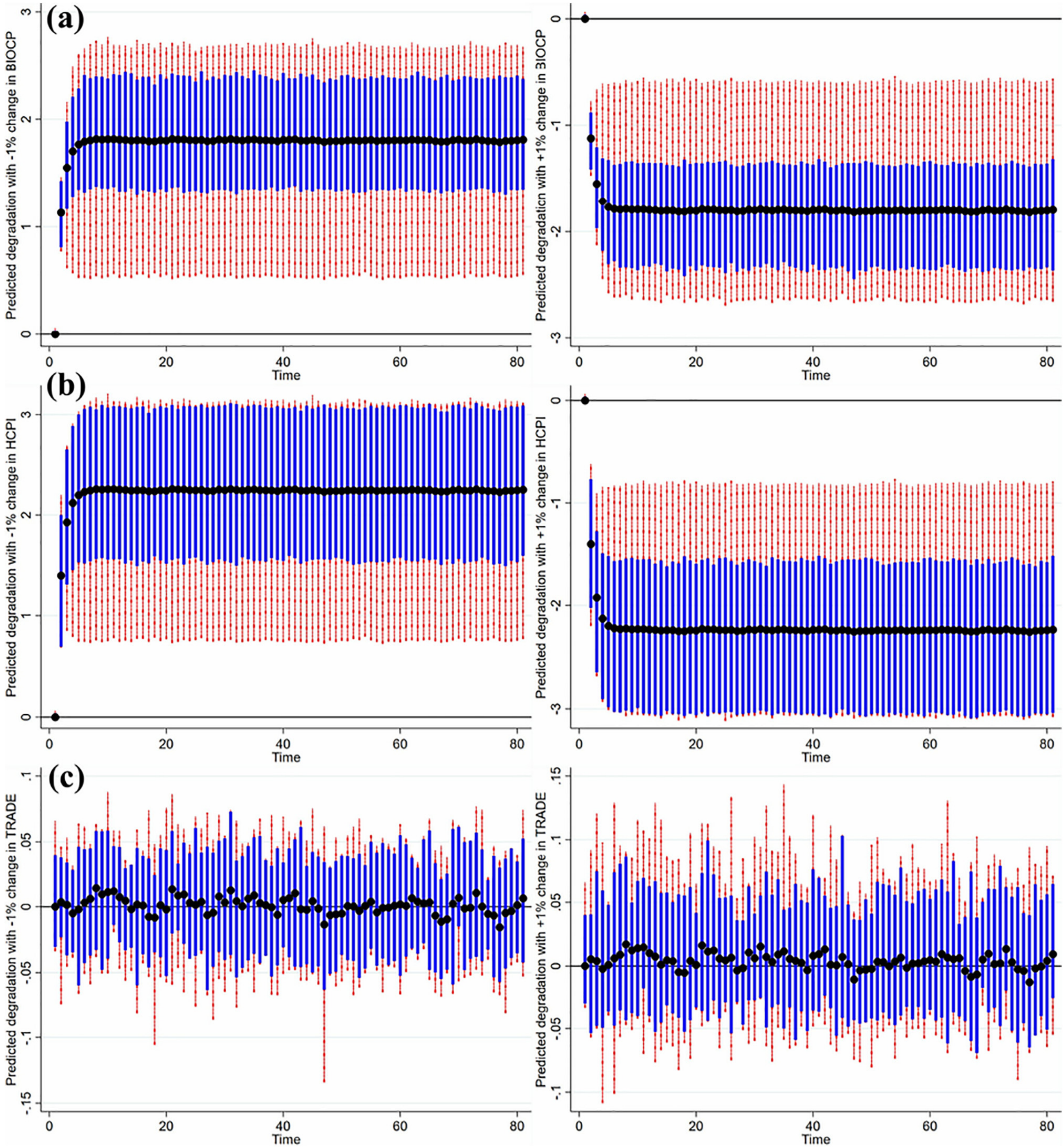

Fig. 5. Dynamic ARDL simulations — predicted degradation with % change in (a) BIOCP (b) HCPI (c) TRADE. **Legend**: HCPI represents Human Capital Index, and BIOCP means Biocapacity, a proxy for environmental sustainability.

degradation by 8.95% and emissions by 4.27%. The report of the EKC hypothesis at a turning point of US$ 5863.70 and US$ 5469.79 indicates that China has already attained the minimum threshold that negates degradation and emissions. The instantaneous change (positive) in income level implies a diminishing effect on both environmental degradation and emissions.

While fossil fuel energy consumption increases both degradation and emissions, renewable energy consumption safeguards environmental quality. Implying that, increasing the share of fossil fuel energy consumption in the energy mix spurs environmental degradation by 1.93% and emissions by 1.58%. In contrast, increasing the penetration of renewable energy sources in the energy portfolio declines emissions by 0.38% and degradation by 0.21%. A study that forecasted factors driving renewable energy and its impact on the environment and development in China for the period 2020–2030, found that the continuation of renewable energy policies underpins sustainable energy development in China (Wang et al., 2018). An earlier study for the period 1957–2005 in China found that fuel switching, especially to renewable energy sources, contributed to the reduction of CO_2 emissions (Wang et al., 2005). The empirical results explain the importance of accounting for the decoupling effect of energy consumption. The prediction profiler indicates that China's over-dependence on fossil fuel energy amounts to 76.2% compared to 22.9% of renewable energy penetration. It is reported

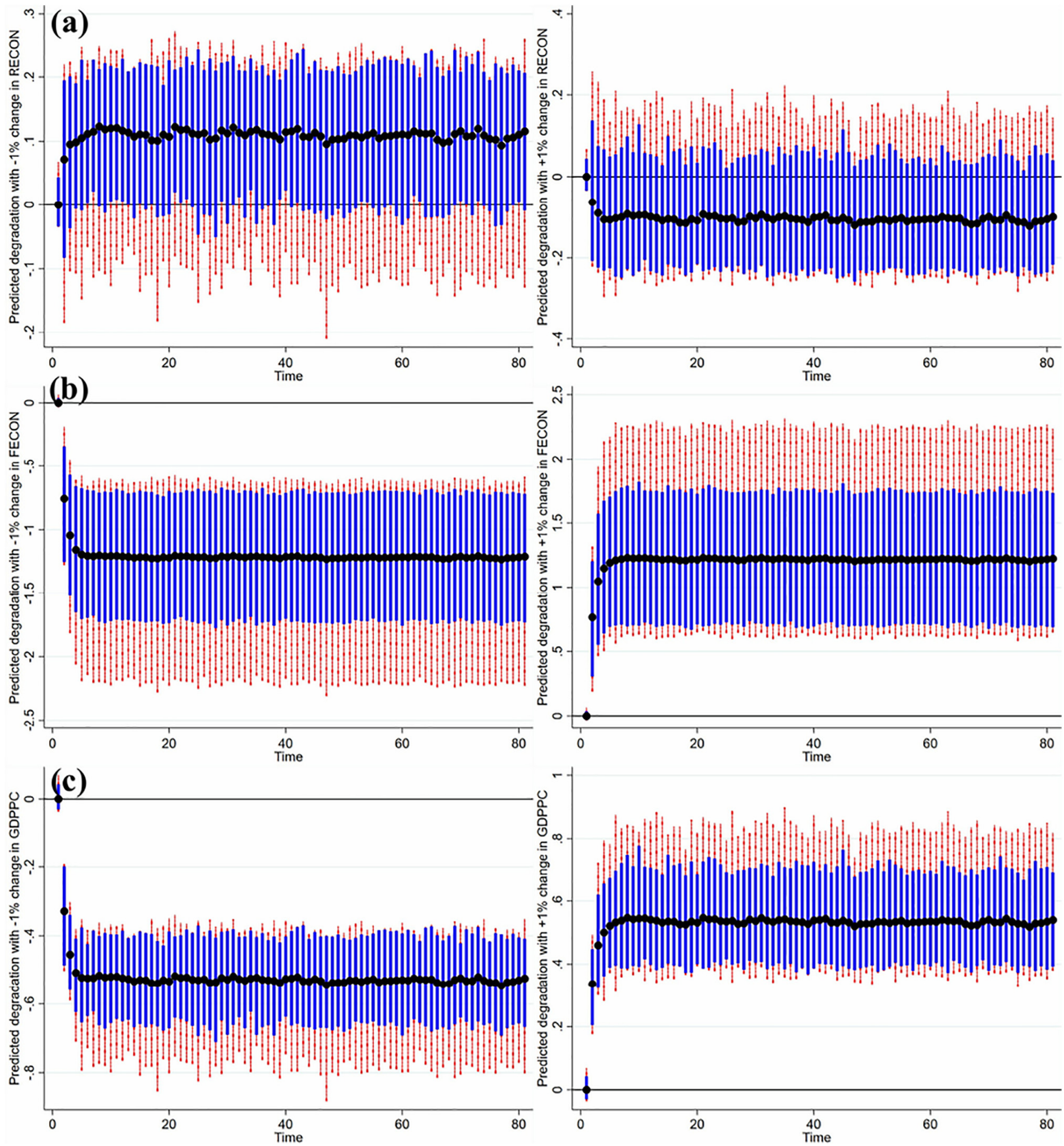

Fig. 6. Dynamic ARDL simulations — predicted degradation with % change in: (a) RECON (b) FECON (c) GDPPC. **Legend**: RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, and GDPPC means GDP per capita/income level.

that renewable power generation grew by 17%, higher than the 10-year average and the largest increment on record (69 mtoe). Renewable power generation in China rose by 25 mtoe – a country record, and the second-largest contribution to global primary energy growth from any single fuel and country, behind natural gas in China. China remains the largest investor in renewables with US$78 billion, doubled its solar capacity to a cumulated 78 GW and added 20 GW of wind power capacity to reach just under 150 GW in total, more than all of Europe combined (Schneider and Froggatt, 2017). However, diversification of the 76.2% share of fossil fuel with clean and modern energy technologies is critical for achieving the emission targets.

5. Conclusion

In this era of robotics, human capital remains the panacea for mitigating human-attributable climate change and its impacts via innovation, technological advancement, research and development. In view of this, we examined the contemporaneous effect of renewable energy, trade, income, environmental sustainability and human capital on environmental degradation and emissions. The empirical results showed that environmental sustainability, renewable energy consumption, and income level have a negative profile in both degradation and emission function. Income level exacerbates both degradation and emissions but subsequently declines environmental degradation by 8.95% and

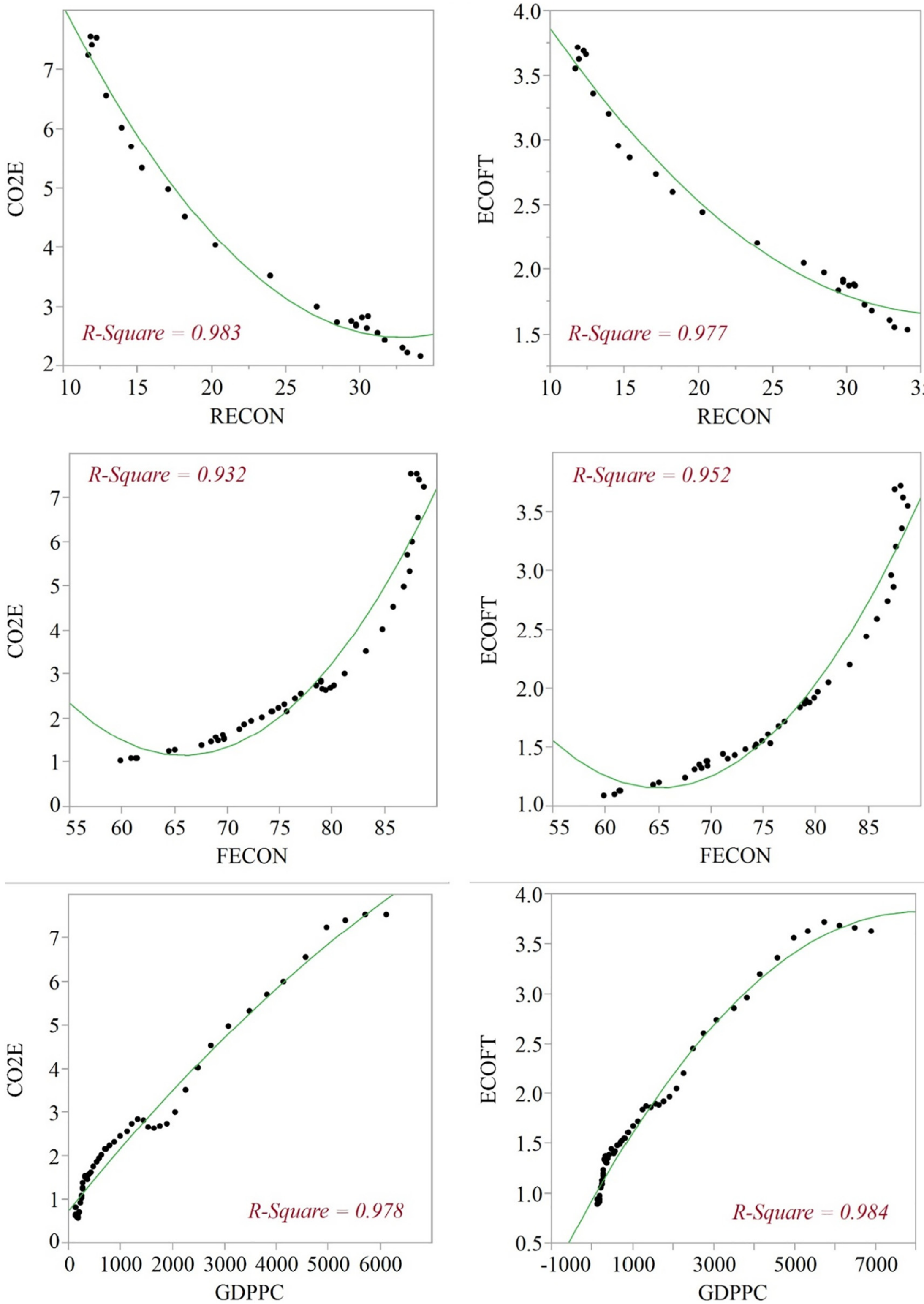

Fig. 7. Nonlinear estimation in an emission and degradation function. **Legend**: CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, and ECOFT signifies Ecological footprint.

emissions by 4.27%. While increasing the share of fossil fuel energy technologies spurs environmental degradation by 1.93% and emissions by 1.58%, the penetration of renewable energy sources declines emissions by 0.38% and degradation by 0.21%. This suggests that the diversification of the energy portfolio through fuel-switching technologies from fossil fuel to clean and renewable modern energy is essential to improve environmental quality. An inverted U-shaped relationship in a carbon and degradation function confirms the EKC hypothesis — at a turning point of US$ 5863.70 and US$ 5469.79, indicating China's achievement of the minimum threshold that negates degradation and emissions. The counterfactual change predicted the volatility of future trade to external shocks in China, which will affect both emissions and environmental degradation. The neural network-based predictive profiler demonstrated that human capital and fossil fuel energy consumption

Table 2
The EKC hypothesis using *U* test estimation technique.

Variable	Turning point	Interpretation	Verdict: achieved	Turning point	Interpretation	Verdict: achieved
Dependent	ECOFT			CO_2E		
BIOCP $BIOCP^2$	0.9403	U shape	Yes	0.9302	Inverse U shape	Yes
HCPI $HCPI^2$	1.0544	Monotone	Yes	0.4120	Monotone	Yes
RECON $RECON^2$	51.007	Monotone	Not yet	43.3721	Monotone	Not yet
FECON $FECON^2$	60.1070	U shape	Yes	56.1084	U shape	Yes
TRADE $TRADE^2$	66.95	Monotone	Not yet	64.8018	Monotone	Not yet
GDPPC $GDPPC^2$	5863.696	Inverse U shape	Yes	5469.787	Inverse U shape	Yes

Legend: HCPI represents Human Capital Index, CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, ECOFT signifies Ecological footprint and BIOCP means Biocapacity, a proxy for Environmental Sustainability.

has a positive profile with a predicted median value of 1.85 and 76.18%. A U-shaped relationship is found for fossil fuel consumption in emissions and degradation, at a turning point of 56.11% and 60.11%. This confirmed the dominance of fossil fuel energy in the production of goods and services, at the expense of the environment. The results found that higher human capital and fossil fuel energy consumption in China escalate environmental degradation and emissions. Human capital comprises of knowledge and skills that add value to economic development. Hence, formal education and skilling do not solely underpin human capital, but the enhancement and use of knowledge and skill over time across the lifetime. This suggests that human capital depreciates over time when not in use, thus, a higher unemployment rate of a

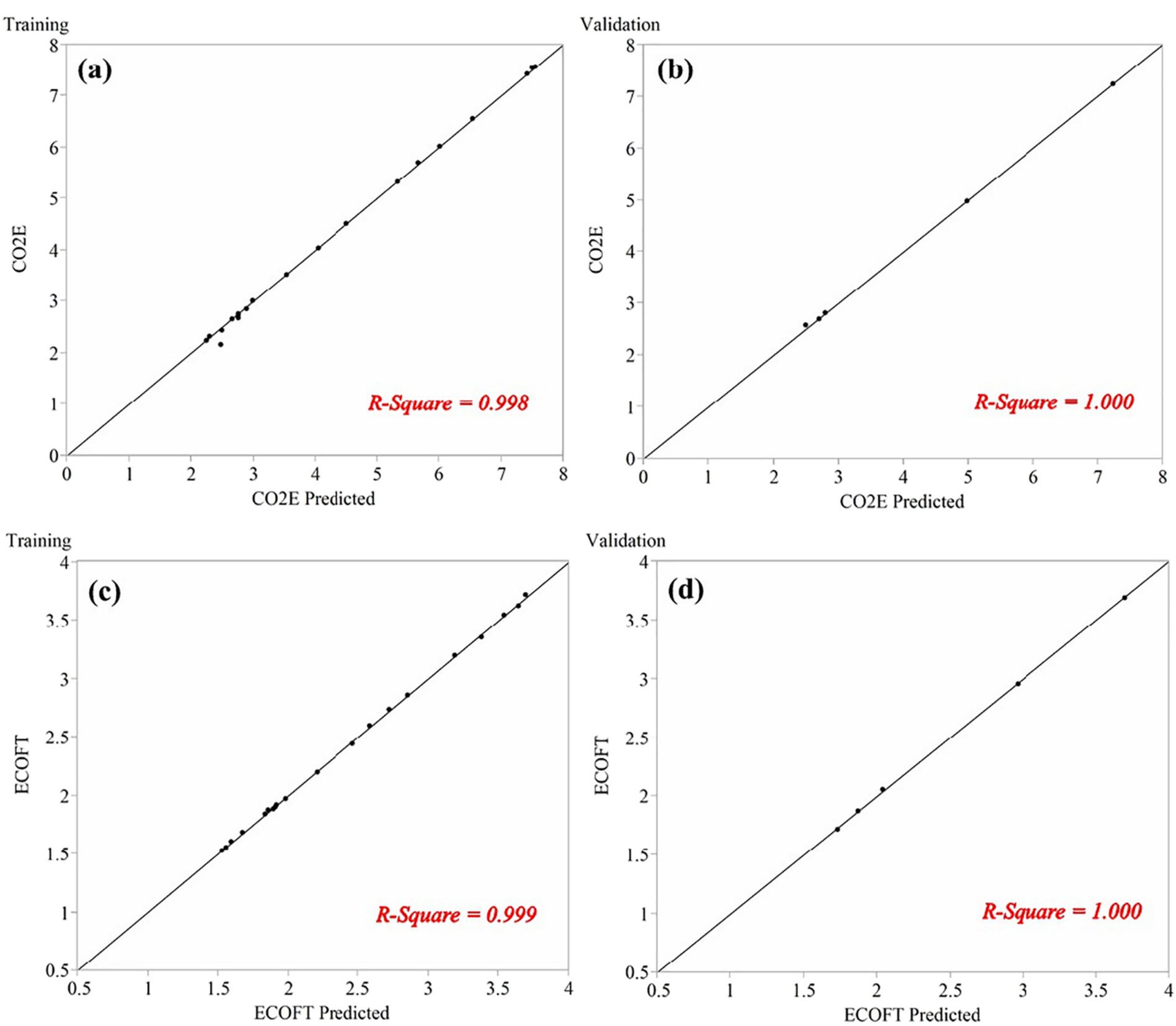

Fig. 8. Training and validation based on neural network: (a)–(b) emissions (c)–(d) environmental degradation. **Legend**: CO2E means CO_2 emissions, and ECOFT signifies Ecological footprint.

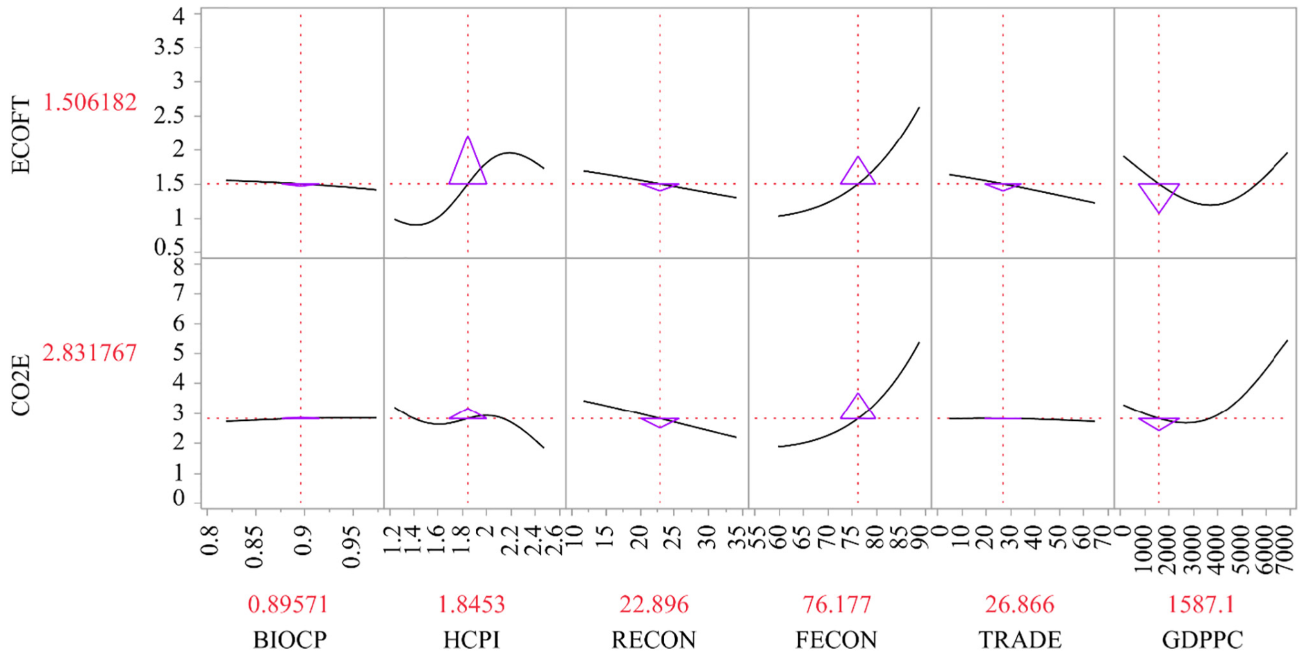

Fig. 9. Sensitivity analysis of neural network using prediction profiler. Note: the violet triangle signifies the sensitivity indicator. **Legend**: HCPI represents Human Capital Index, CO2E means CO_2 emissions, RECON denotes Renewable energy consumption, FECON represents Fossil fuel energy consumption, GDPPC means GDP per capita/income level, ECOFT signifies Ecological footprint and BIOCP means Biocapacity, a proxy for environmental sustainability. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

country's educated population predicts the collapse of environmental sustainability. A policy cycle that enhances the capacity and development of education, deployment and know-how improves human capital, which accelerates the agenda towards achieving environmental security specified in the Sustainable Development Goals.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing - review & editing.**Samuel Adams:**Writing - original draft.**Phebe Asantewaa Owusu:**Writing - original draft.**Thomas Leirvik:**Supervision, Writing - review & editing.**Ilhan Ozturk:**Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.137530.

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