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Explore Associations between Subjective Well-Being and Eco-Logical Footprints with Fixed Effects Panel Regressions

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Abstract: As environmental degradations constantly and directly threaten human well-being, it is imperative to explore the environmental impacts on people's happy life. This research investigates the association between subjective well-being (SWB) and ecological footprints (EF) through space-time fixed effects panel regressions. EF, as a vital indicator of environmentally sustainable development, plays a vital role in ecological balance. SWB determines the subjective quality of life for humanity. EF-related factors and socio-economic indexes referring to GDP, urbanization rate, income, education, health, political stability, and political voice accountability in 101 countries were captured. Compared with ordinary least square (OLS), stepwise regression (SR) and fixed effects panel regression models (FEPR) exhibited good fitness regardless of the cross-section or longitudinal models due to R2 beyond 0.9. The finding also discloses that EF and health were positively significant to SWB, while income was negatively significant to SWB. EF was an invert u-shaped link to SWB, which met the assumption of EKC. This research provided a model-driven quantitative method to address environmental impacts on people's quality life of happiness, and opened shared doors for further research of carbon balance and circular economy.

Keywords: fix effects regression; ecological footprint; subjective well-being; a panel data

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1. Introduction

Environmental degradations constantly threaten human well-being. According to the Intergovernmental Panel on Climate Change (IPCC)'s data (see: https://www.ipcc.ch/ accessed on 31 August 2021), diverse environmental metrics are dramatically tended to negative impacts with different levels [1,2], not to mention COVID-19, as a global social, environmental, and economic comprehensive crisis, intangibly deprived human life, public health [3]. The research of environmental deterioration in the world triggering problematical environmental health has far-reaching effects, not only facilitating both countries environment and health head for the right direction but also finding out the best way to realize the goal of higher well-being with lower consumption. Therefore, exploring spatio-temporal associations between ecological footprint and subjective well-being (SWB) in the world is significant and worthy for understanding gaps in environment mitigations and adaptions.

Subjective well-being (SWB), a longstanding concern in the west, is a synonym of the term "happiness" by a single score representing an aggregate of a person/country's satisfaction. SWB is an interdisciplinary perspective, which refers to ethical, theological, political, economic, and psychological terms [4]. In a nutshell, it is used as an approach of the subjective quality of life to widen the measures of the objective living criteria that have dominated welfare research in social science for a long time. Life satisfaction (LS) is defined as the degree of that individual estimates their life-as-a-whole quality, involving an affective aspect and cognitive contentment [5]. The happiness survey in the U.S had been reported since 1957 by the frequency of positive intuition, instead of the measurement of affect intensity [6]. Interestingly, SWB is abided by the principle of dynamic equilibrium regardless of stocks and flows frameworks. Paralleling previous studies, LS was explored in association with depression and various psychosocial variables [7–9].

Ecological footprint (EF) is used to measure humans' consumption and natural supply [10]. It is also an important orientation of environment research [11–17]. Proposed by Wackernagel et al. in 1996 [18], EF has constantly been well reported from 1961–2016 by the free public platform of the global footprint network. Admittedly, the EF research aims to realize Environmentally Sustainable Development (ESD). When the topic of environment is permanent research, accordingly, EF research also turns into an international consensus of creating systems of indicators that can be compared and lead to subsequent policies and actions [19]. Current EF research just considered physical disasters impairment, not combine intangible factors such as mental health requirements. Hence, EF corresponds with SWB measurement could estimate human life quality in uniformed and judicial criteria in the world.

This study devotes to delve the interplay between consumption and happiness, which is literally related to the Easterlin paradox. Easterlin (1974) first proposed empirical evidence that pointed out life satisfaction taken from country-level surveys and per capita income data show only a positive relationship until per capita income reaches a certain level of development [20]. After a turning point, the relationship between income and reported life satisfaction across countries is zero. Such a relationship between income, consumption, and happiness would infer that most microeconomic models leave out a key dynamic in consumption behavior. If increased income does not give rise to increased happiness, happiness is not the only factor driving the consumption decisions. Moreover, it would doubt the focus on growth for developed countries. If more income and thus more consumption is not making people happier, the focus of governments in developed countries should be concerns rather than growth—especially given the many negative externalities, such as global warming and co-pollutants, created by economic activity. However, the fact that happiness does increase as a result of increased income until a point would also infer that the development of low- and middle-income countries and increasing the income of those in poverty in developed countries is still an immensely important purpose [21–23]. Sarkodie (2021) advanced overarching environmental convergence questions between developed and developing countries, which is a new adaption of ESD [24]. From an environmental efficiency perspective, ES is to determine the balance between economic growth, social equality, and environmental protection. The idea of "double dividend" is increasingly prevailing, meaning there is entropy in their relationship, beyond entropy, the growth GDP or income has not played a role in well-being, happiness, or life satisfaction [25,26]. It aims to minimize environmental impacts and maximize human well-being, as studied by Knight et al., who addressed environmental consumption with the environmental efficiency of well-being (EWEB) through computing maximum likelihood (MLE) routine of the multivariate regression model in the cross-national analysis [27]. The weakness is that the EF statistical period was 2005, not in accord with life satisfaction from 2006–2009 [28,29]. Happy planet index (HPI) is a good indie to measure EWEB, but HPI corrected EF shortcoming as a ratio, not sustained over time. There was a 2016 report about 140 countries estimation of EWEB without time series and straightforward ratio. Yew-Kwang advanced a new national success indicator of Environmentally Responsible Happy Nation Index (ERHNI), which means adjusted happiness life year minors per capita external costs (PCEC) [30–32]. It avoided the limitation of HPI and GDP estimation. Nonetheless, it still belongs to interval assessment, instead of considering constant estimation [33–36]. As matter of fact, it is an estimation of HPI, making HPI more reasonable. Hence, it is worth noting that constantly sustainable and dynamic models in the long run will contribute to an account for the debate regarding environment consumption and social well-being, just like a resolution of the paradox "income and subjective well-being" needs cross-section and longitudinal panel data analysis. This research focuses on original ecological footprint changes with spatio-temporal dimensions affecting well-being, preventing bias, or interval estimation.

Spatio-temporal semantic explanation of environmental impacts on subjective well-being is better to understand the trajectory of happiness and environment irreversible process [37,38]. Panel regression models can be measured with serial correlation or spatial dependence so that the model control for spatio-temporal dependence and heterogeneity can be determined [39]. We set forth the use of time differencing and spatial differencing transformations to handle space-time non-stationarity in estimation in this research. In order to eliminate endogenous or exogenous problems, we investigated panel data regression models based on previous research of partial correlations [8].

2. Materials and Methods

2.1. Data

In the previous research, The World Bank, the World Value Survey, the global footprint network, and the Gallup World Poll were used to explore the association between SWB and EF with partial correlation analysis. Via partial correlation, EF impacts on SWB were examined and separated in synergistic coupling between EF and other social-economic indexes [8]. The same datasets are used in this research. To find out the fixed effects panel regression model of correlation between SWB and EF on 101 countries data (2006–2016), representation of SWB changes with the components of EF is employed by a panel data. SWB is a dependent variable, GDP per capita, urbanization rate, literacy rate, youth life expectancy, wage and salaried workers, political stability, voice accountability are control variables. Bio-capacity, carbon footprint, cropland footprint, fishing land footprint, built-up land footprint, forestland footprint, grazing-land footprint, EF consumption per capital are independent variables. The EF dataset has been extracted from the global footprint network dataset. Control variables are extracted from the World Bank and World Value Survey. LS is an alternative to SWB, collected from the Gallup World Poll. More details were listed in Supplementary Materials Table S1: Variable abbreviation list.

2.2. Study Framework

In order to figure out the association between SWB and EF-related factors to substitute traditional SWB survey, through data observation, a unit root test was initially conducted to make sure variables pass the test, then a simple OLS regression model and detect *t*-test were conducted. Multicollinearity and endogeneity were found out as the reasons without passing the *t*-test. Facing multicollinearity, stepwise regression was set forth, and the results showed biased R-square. Facing endogeneity, a fixed-effects panel regression model in cross-section and time-series was elucidated, respectively. The modeling framework in Figure 1 is as follows.

2.3. Methods

2.3.1. Panel Unit Root Test

Panel unit root test is the common feature of panel data analysis. The early panel unit root test meant Dickey-Fuller (ADF) tests, the Phillips-Perron tests, and the Iwiatkowski et al. (1992) tests [40]. The first-generation panel unit root test is called the Levin-Lin-Chu (LLC) [41]. Im-Pesaran-Shin [42] and the Hadri [43] are the second-generation panel unit root tests. They minimized the size distortions and increased the power. A theoretical description of these tests is presented as follows: The data-producing process of the series y, in its different form, be:

$$\Delta y\_it = \alpha y_{it-1} + \sum_{j=1}^{pi} \beta i_j \Delta y_{it-j} + X'\delta + \varepsilon_{it} \quad (1)$$

where $i = 1, 2, 3, \cdots, N$ representing cross-sections and $t = 1, 2, 3, \cdots, T$ meaning period observations, X_it are the exogenous variables such as individual effects and linear trends, $\alpha = (\rho - 1)$ and ρ_i are the autoregressive coefficients. The LLC assumes that the autoregressive coefficients in (2) are identical across the panel (common unit root process), while in the IPS test, they are different. In the LLC test, the null hypothesis is the presence of a unit root for all i, and the alternative hypothesis requires that the individual process is stationary for all i, and when the null hypothesis is the same, the alternative in the IPS test is illustrated to include a non-zero fraction of individual process as stationary. IPS statistic equation as:

$$t\_IPS = \frac{\sqrt{N}\left(\bar{t} - \frac{1}{N}\sum_{i=1}^{N} E[t_i T|\rho_i = 0]\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} V_{ar}[t_i T|\rho_i = 0]}} \quad (2)$$

In Equation (2), according to the simple Lindberg-Levy theory, the test statistic is asymptotically distributed as N (0,1) as the number of observations is extremely large. Im et al. (2003) exhibited values of the mean and variance for standardizing the test statistic [44].

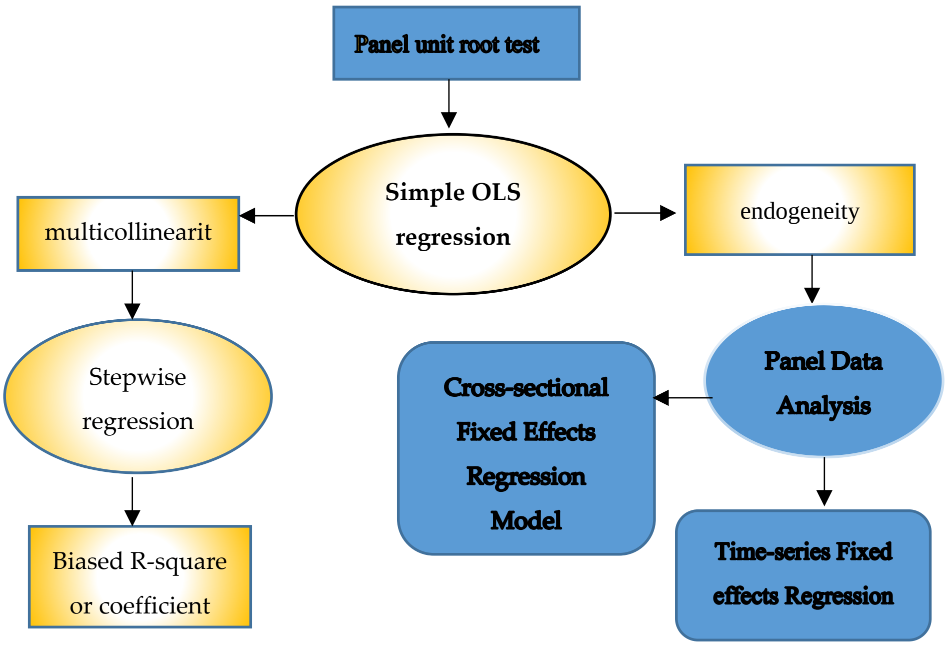

Figure 1. Modeling study framework.

2.3.2. Stepwise Regression (SR)

SR is an automatic variable selection procedure that selects from a couple of candidates the explanatory variables, which are the most related. We used the unidirectional forward methods. Forward selection begins with no variables in the model, examining each variable with a chosen model-fit criterion until none of the remaining variables improves the model to a statistically significant extent [45].

2.3.3. Fixed Effect Panel Model

In order to eliminate the endogenous or exogenous problems, we investigated panel data regression models based on previous research of partial correlations [8]. Panel data typically mean "data containing time series observations of a number of individuals" [46]. They contain independently pooled panels, random-effects models, and fixed effects models. Fixed effects panel regression models (FEPR) have two-dimensional data, referring to cross-sectional fixed effects models and longitudinal fixed-effects models. It is a widespread regression model in macros spectrum analysis due to the impact disparity of spatio-temporal heterogeneity. Panel data have many strengths in either cross-sectional or time-series data, including: (1) more accurate model parameters; (2) more widely available in the international spectrum; (3) more intensive capacity for collecting the complication of human behavior than a single angle; (4) more simplified computation and statistical inference (Hsiao, 2007); (5) minimize the effects of aggregation bias, from aggregating firms into large scale; (6) better measure the impacts that can be detected in neither cross-section nor time-series data; (7) more reliable estimates and test more sophisticated behavioral models with less restrictive assumptions; (8) control for individual heterogeneity [47,48].

The below equation is used to model SWB on various dimensions of EF.

$$SWB_{it} = \beta_{0i} + \beta_{1i} \times EF_{si} + \beta_{2i} \times Controls_i + u_{it} \quad (3)$$

where the dependent variable SWB is the subjective well-being level for country i in year t. The explanatory variables EF_{si} are a set of environmental indices, which measure the different types of resources consumption including EF, BC, CBF, CLF, FIF, BLF, GLF, and FLF. $Controls_i$ are variables that may relatively affect SWB including GDP, URB, WSW, LR, YLE, PS, and VA. u_{it} is the disturbance term.

3. Results

3.1. Panel Unit Root Tests

To keep stability-based time-series data and avoid pseudo regression models, unit root tests were emphasized to examine the association between variables. Panel unit root test is a conventional method to examine variable rationality in panel data analysis. The result of panel unit root with SWB variable is shown in Table 1. p-value is 0, qualified cross-section records are 99, observation records are 826 cases. The result of panel unit root of TEF variable of p-value is 0, qualified cross-section records are 99, observation records are 826 cases. The result of panel unit root with TBC variable of p-value is 0.0001, qualified cross-section records are 99, observation records are 826 cases. The result of panel unit root of SWB with control variable of P-value is 0, qualified cross-section records are 4, and observation records are 4655 cases. All variables passed unit root tests owing to p-value less than 0.05.

Table 1. The result of panel unit root of variables.

Variables	Method	Coef.	Prob.**	Cross-Sections Obs.	Records
Null: unit root (assumes common unit root process)					
SWB	Levin, Lin & Chu t*	173.355	0.000	99	826
TEF	Levin, Lin & Chu t*	−14.698	0.0000	99	826
TBC	Levin, Lin & Chu t*	−3.793	0.0001	99	826
Control variables	Levin, Lin & Chu t*	−19.288	0.0000	4	4651
Null: unit root (assumes individual unit root process)					
SWB	Im, Pesaran and Shin W-stat	−69.319	0.0000	99	826
	ADF—Fisher Chi-square	1013.71	0.0000	99	826
	PP—Fisher Chi-square	1340.59	0.0001	99	900
TEF	Im, Pesaran and Shin W-stat	−2.390	0.0084	99	826
	ADF—Fisher Chi-square	262.865	0.0014	99	826
	PP—Fisher Chi-square	357.207	0.0000	99	900
TBC	Im, Pesaran and Shin W-stat	−0.054	0.4785	99	826
	ADF—Fisher Chi-square	221.116	0.1246	99	826
	PP—Fisher Chi-square	387.289	0.0000	99	900
Control variables	Im, Pesaran and Shin W-stat	−75.9524	0.0000	4	4655
	ADF—Fisher Chi-square	987.895	0.0000	4	4655
	PP—Fisher Chi-square	899.930	0.0000	4	4673

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.
Note: Above data were computed by EViews software that belongs to IHS Global Inc., Englewood, CO, USA.

3.2. Regression Analysis

By 965 observation records over a decade, we performed four regression models in Table 2 such as ordinary least square (OLS), stepwise regressions, cross-sectional fixed effects regressions, and time-series fixed effects regressions. In the OLS, we partitioned SWB-control variables OLS (model 1), SWB-EF OLS without control variables (model 2), and SWB-EF OLS with control variables (model 3). The 0.77 R^2 of model 3 is higher than others, implying multicollinearity might cause pseudo regressions. The stepwise regression aimed to eliminate multicollinearity negative inventions. Without doubt, EF coefficients were reduced in the step-wise model while the coefficients of control variables were the same as the model 3, including the coefficient of TEF was reduced from −16.17 to −0.026, the coefficient of BLF was reduced from 1.252 to 17.4, the coefficient of CLF was reduced from 0.185 to 16.33, the coefficient of FIF was reduced from −0.22 to 15.93, the coefficient of FLF was reduced from −0.055 to 16.09, the coefficient of GLF was reduced from 0.204 to 16.35.

Table 2. Comparison of four regression models.

Variables Parameters	**OLS OLS OLS**			**Stepwise Regression**	**Cross-Sectional Fixed Effects Regression**	**Time-Series Fixed Effects Regression**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
TBC		0.051	0.022	0.023	−0.001	0.022
TEF		−49.810	−16.170	−0.026	0.048	−0.022
BLF		56.190	17.400	1.252	2.148	1.611
CBF		50.080	16.150	0.000	0.000	0.000
CLF		50.280	16.330	0.185	0.000	0.000
FIF		51.280	15.930	−0.217	0.000	0.000
FLF		49.670	16.090	−0.055	0.000	0.000
GLF		50.170	16.350	0.204	0.231	0.212
YLE	0.036		0.039	0.039	0.011	0.000
GDP	1.370		1.500	1.490	1.600	1.560
PS	−0.003		−0.002	−0.002	0.002	−0.002
WSW	−0.043		−0.04	−0.040	−0.041	−0.037
VA	0.006		0.005	0.005	−0.001	0.004
UBR	0.016		0.014	0.014	−0.010	0.014
LR	0.007		0.007	0.007	0.009	0.006
C	1.221	3.910	0.943	0.942	4.144	0.852
R^2	0.759	0.575	0.771	0.770	0.922	0.770
N	965.000	965.000	965.000		965.000	965.000
F	430.900	161.779	213.040		91.220	154.470
Prob	0.000	0.000	0.000		0.000	0.000

In the cross-section fixed effects panel regression (model 5) of Table 2, the result shows that BC is negatively related to SWB, based on the coefficient of −0.001, meaning natural supply over time did not impact SWB due to its stationary characteristic, but EF is positive related to SWB due to the coefficient of 0.048, indicating human consumption positively impacts SWB change with time. In particular, the coefficient of BLF was 2.48, the highest value beyond the impacts of control variables and the other explanatory variables, portraying a rise of built-up land consumption in a decade dramatically increased life satisfaction. GLF was positively related to SWB owing to the coefficient of 0.231, depicting grazing-land consumption enhancing people's happy feelings. Among the control variables, the coefficients of Health, GDP, stability, and education are positive, meaning they have positive impacts on happiness. In other words, an increase in health, GDP, PS, and LR will facilitate more people's pleasure. In contrast, WSW, VA, and URB have negative coefficients, which means an increase in these coefficients caused losses of people's safety and indirectly caused SWB shrinking.

Time-series fixed effects panel regression (model 6) of Table 2 is considered spatial disparity without time differencing. The results show that BC is positively related to SWB, based on the coefficient of 0.022, meaning bio-capacity on geographical differences positively increased happiness recognition, but EF is negatively related to SWB due to the coefficient of −0.022, indicating human consumption with spatial heterogeneity inhibits happiness identity. Only interpretation can we imagine that geographical disparity is dominated by culture and religions in a region, and over-sufficient material hedonism induced spirit vacuity. Fixed effect parameters are influenced on discrepancy of geographical location, as shown in Table 3. The coefficients of BLF and GDP (1.611 and 1.56) were the number one and two impacts on SWB spatial dependence, demonstrating that personal spatio-occupation and individual income directly support happiness growth. GLF was positively related to SWB owing to the coefficient of 0.212, which means individual grazing-land consumption can improve people's happy feelings. Despite the coefficients of WSW and PS are negative, GDP, VA, URB, and LR are positive, meaning their increases will promote more people's pleasure.

From the time-series fixed effects regression model to the cross-sectional fixed effects regression model, the reliability of the model increased due to an increase in the R-squared value from 0.77 to 0.92. The results also indicated that the stepwise regression model could eliminate multicollinearity. Similarly, Table 2 shows that impacts of cross-section differences in SWB are more striking than time series in several dimensions, including: (1) the effect degree of longitudinal fixed-effects panel regression is in a small range from −0.12 to 0.14, while the effect degree of cross-sectional fixed effects is in a large range from −2.09 to 1.75. (2) R-square values in the longitudinal model are less likely than that in the cross-sectional model (0.77 versus 0.92). (3) Spatial distribution impacts map of cross-section fixed-effects model 5 is exhibited reasonably in different development levels of each country. (4) Time-series fixed effects panel regression model 6 has a low volatility value with different periods of the same countries. (5) Model 6 was not considered a health factor, compared to Model 5.

According to the spatial distribution impacts map of the cross-section fixed effects model, fixed effects in each country are generated in Table 3. We also established a cross-section fixed effects map whose impacts are categorized into five classes with different colors in Figure 2. Green color represents negatively high effects, the values range from −2.09 to −0.98, those countries are distributed in the second-most-populous continent. In these areas, most countries are mainly poor countries with poor health care such as Congo, Niger, and Afghanistan. Tender green colors represent negatively low effects, the values are in the range from −0.98 to −0.03, those countries are distributed in the most populous continent such as Asia. In these areas, most countries are mainly developing countries with fair health care such as China, India, and Mali. The yellow color represents mediate effects. The values are the range from −0.03 to 0.73, those countries are distributed in Europe. In these areas, most countries belong to developed countries with good health care such as France, Germany, and Italy. The red color represents the highest positive effects. The values are in the range from 0.73 to 1.75, those countries are in North America, Europe, and South America. In these areas, most countries belong to the most developed countries with very good health care such as U.S., Denmark, and Sweden. The blue color represents no data.

Table 3. The effect value of divergent countries in the same period.

COUNTRY	Effect	COUNTRY	Effect	COUNTRY	Effect
Afghanistan	−1.51088	Lebanon	−0.180311	Estonia	−0.090499
Albania	0.045380	Lithuania	0.277951	Ethiopia	−1.07871
Angola	−0.619248	Luxembourg	−0.271843	France	0.582562
Argentina	0.923528	Macedonia	0.584715	Germany	0.586486
Armenia	−0.436922	Madagascar	−1.670047	Ghana	−0.537327
Australia	0.910666	Malawi	−1.132996	Greece	0.429039
Austria	0.728967	Malaysia	0.355872	Haiti	−0.665673
Azerbaijan	−0.466232	Mali	−1.145177	India	−0.711663
Bahrain	0.101220	Mexico	1.530931	Indonesia	−0.036024
Bangladesh	−0.689438	Montenegro	0.389134	Israel	1.725349
Belarus	0.304442	Myanmar	−1.222246	Italy	0.403465
Belgium	0.894801	Nepal	−1.098227	Japan	−0.033037
Benin	−1.783677	Netherlands	1.272200	Jordan	0.616101
Bhutan	−0.976775	Nicaragua	0.173986	Kazakhstan	0.313510
Bolivia	−0.13884	Niger	−1.55483	Kenya	−0.823037
Bosnia and Herzegovina	0.545076	Norway	0.579930	Kuwait	0.156473
Botswana	−0.672194	Pakistan	−0.125697	Latvia	−0.059265
Brazil	1.248360	Panama	1.219165	Sri Lanka	−1.253539
Burkina Faso	−1.374199	Paraguay	−0.284495	Sweden	1.014358
Burundi	−1.96029	Peru	0.103869	Switzerland	0.853278
Cameroon	−0.74744	Philippines	−0.295956	Tanzania	−1.802745
Canada	1.242624	Poland	0.393796	Thailand	0.532577
Chad	−1.650706	Portugal	−0.187612	Togo	−2.091407
Chile	0.925958	Romania	−0.198973	Tunisia	0.163915
China	−0.600853	Russia	0.320365	Turkey	0.259620
Colombia	1.101339	Rwanda	−1.840178	Uganda	−1.173354
Congo	−1.143827	S Korea	0.210454	United Arab Emirates	0.931038
Costa Rica	1.749141	Saudi Arabia	1.125122	United Kingdom	0.786135
Croatia	0.286016	Serbia	0.236301	United States	1.037721
Czech Republic	0.602562	Sierra Leone	−1.002086	Uzbekistan	0.314745
Denmark	1.048223	Singapore	0.544174	Venezuela	1.414359
Dominican Republic	−0.100939	Slovenia	0.218718	Vietnam	−0.472808
El Salvador	0.613418	Spain	1.408133	Yemen	−0.835204
Zimbabwe	−1.095074	Zambia	−0.341393		

Note: 101 countries were computed by EViews software that belongs to IHS Global Inc., Englewood, CO, USA https://www.eviews.com/general/about_us.html (accessed on 31 August 2021).

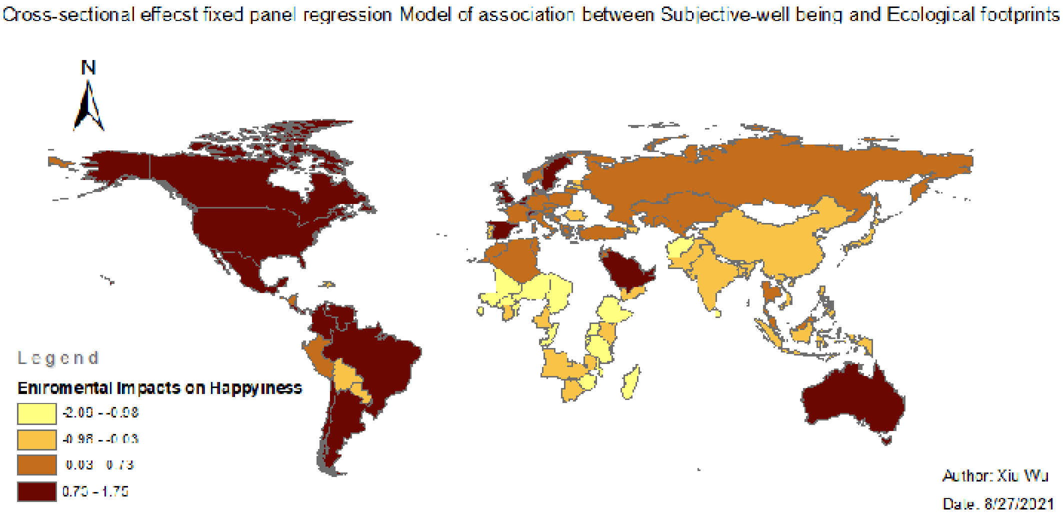

Figure 2. Cross-sectional fixed effects panel regression model map. Note: The above map was created by ArcMap software from Esri. Co.

4. Discussion

According to fixed effects panel regression analysis, the results portrayed that the cross-sectional model was more remarkable than the time-series model. However, in reality, the time-series model is more available than the cross-sectional model in the association between SWB and EF-related factors. First, R-squared values could not determine whether the model is good or not. R-square (R^2) is a statistical measure of model fit that indicates how much variation of a dependent variable is explained by the independent variable(s) in a regression model. Indeed, high R-square does not mean good models. In other words, R-square could neither convey the reliability of the model, nor whether the right regression had been chosen. R-square is not a unique standard to examine the reliability of the model. A good model might have a low R-square, a poorly fitted model might have a high R-square, and vice versa. Second, effects values' range could not determine whether the model is good or not. In the context of the fixed effect models, effects values are constants, which are less important than variables, just like residuals. They just influence the model's movements but could not change the tendency or directions of the models. Hence, the value of the effects is not a key point when good models or bad models were estimated. Third, correlation coefficients are not reliable in the cross-sectional fixed effects panel regression model. Gehlke and Biehl (1934) argued that correlation coefficients go up with the level of geographic aggregation by census data [49]. In 1950, Robinson found out that the correlation between race and illiteracy increased with the level of geographic aggregation [50]. In other words, what is significant at one spatial scale may not be significant at another. The reason is heteroscedasticity, which is common in spatial regression analysis. Accordingly, correlation coefficients in the cross-sectional fixed effects panel regression model are not available in this research. Last but most importantly, the time-series fixed effects panel regression model supported PC analysis, i.e., SWB is significantly positively related to TBC. In the cross-sectional fixed effects panel regression model (Table 4), SWB has no significant impacts on TBC due to p-value (0.337) beyond 0.05, but SWB has significantly positive impacts on TEF in that coefficient is 0.059 and p-value (0.006) is less than 0.05. On the contrary, in the time-series fixed effects panel regression model, SWB is significantly positively related to TBC for the reason that coefficient is 0.022 and p-value is 0.002, but not significantly related to TEF since coefficient is -0.023 and p-value is 0.143. Hence, it is evident that the time-series fixed effects panel regression model reveals the same result as previous PC analysis.

Table 4. Cross-section fixed effects panel regression model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BC	−0.032131	0.033433	−0.961042	0.3368
EF	0.059125	0.021677	2.727521	0.0065
BLF	1.072607	0.826403	1.297923	0.1947
GLF	0.083497	0.121051	0.689768	0.4905
VA	−0.001739	0.001819	−0.955970	0.3394
UPR	−0.004341	0.008171	−0.531263	0.5954
WSW	−0.044785	0.005499	−8.144363	0.0000
PS	0.001496	0.001118	1.338161	0.1812
GDP	6.31×10^{-6}	7.39×10^{-6}	0.854006	0.3933
LR	0.003451	0.009830	0.351046	0.7256
YLE	0.022598	0.010068	2.244603	0.0250
C	3.867909	0.859549	4.499930	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Weighted Statistics				
R-squared	0.964015	Mean dependent var		7.787289
Adjusted R-squared	0.959332	S.D. dependent var		4.854981
S.E. of regression	0.337928	Sum squared resid		97.40874
F-statistic	205.8665	Durbin-Watson stat		1.621291
Prob (F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.921740	Mean dependent var		5.498159
Sum squared resid	99.34218	Durbin-Watson stat		1.431227

Note: The above table was created by EViews software that belongs to IHS Global Inc., Englewood, CO, USA https://www.eviews.com/general/about_us.html accessed on 31 August 2021.

With respect to the map shown in Figure 2, big disparity of SWB between developed countries and developing countries can be seen. EF has a statistically insignificant impact on the SWB gap, but the economic and demographic structure and GDP growth contribute to the underlying SWB growth. Therefore, environmental improvement is not a determinant of SWB development. However, their correlations might be two folds.

On the one hand, EF is related to individual SWB improvement. For example, we chose 12 countries to represent debtor countries and creditor countries, respectively. In the ranking table of between total EF and EF per capital (Table 5), EF in developed countries is higher than that in developing countries. Resources consumption per person is highly related to the degree of own property. The increasing of the population is the main reason for environmental degradation in developing countries, which leads to low EF producing bad feeling of happiness. In other words, EF might indirectly generate causality with SWB. It probably gets the consequence that individual about environmental improvement benefits individual happiness in a certain time by hedonic treadmill [51], instead, SWB of each country is restricted by multiple factors such as economic and demographic structure, and GDP per capita growth.

On the other hand, even though EF has not had a causality with SWB, EF is an inverted u-shaped link to SWB in correlation analysis using the Weka machine learning in Figure 3. That is in accord with a Kuznets curve, which means environmental improvement has increased from the beginning of SWB growth to a turning point [52,53]. After that, the SWB development benefits environmental degradation with excessive carbon emission, taking up over 60% of TEF [50]. As far as environmental quality increasing, the low-carbon circular economy model might be an underlying, sustainable development trend in future.

Table 5. The ranking between TEF and EF per capital.

Country	Debtor Countries Hierarchy			Creditor Countries Hierarchy		
	Total EF Rank	**EF per Capital Rank**	**SWB (2017) Rank**	**Total EF Rank**	**EF per Capital Rank**	**SWB (2017) Rank**
China						
USA						
India	1	65	90			
Japan	2	6	19			
Germany	3	162	133			
The U.K.	4	43	56			
Afghanistan	5	38	15			
Brazil	7	42	14	1	86	33
Canada	71	5th last	1st last	2	7	7
Russia				3	32	73
Australia				4	11	12
Congo Demo				5	183	97

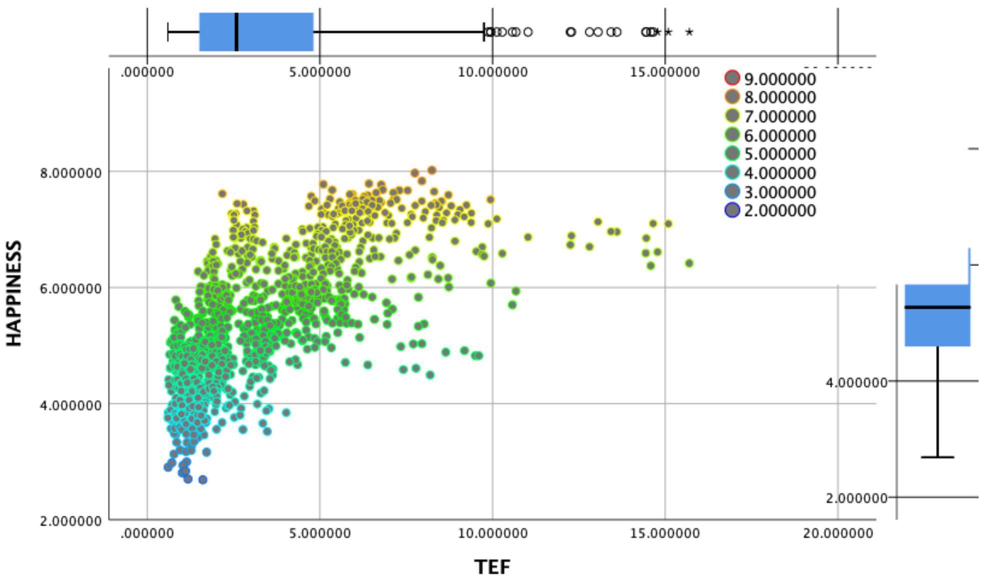

Figure 3. Correlation Between EF and SWB. Note: Above picture was taken by IBMSPSS Statistics, IBM Corp. Released 2020. IBM SPSS Statistics for Windows, Version 27.0. Armonk, NY, USA: IBM Corp. to the University of Waikato, New Zealand.

5. Conclusions

Within the continuous improvement of the human development index and the popularity of the concept of environmental protection, the low-carbon circular economy model will be an underlying, sustainable development trend to mitigate environment pressure and improve happiness satisfaction from being enforced by the government to people's subjective consciousness. Space-time fixed effects regression model based on a panel data analysis provided an effective way to study those imbalanced problems.

5.1. Implication

This research provided an underlying quantitative method to measure SWB using socio-economic and environmental impact factors. It not only compensates weakness of qualitative SWB research but also sets forth the feasibility of model-dominated SWB calculation. Because the shortcoming of SWB calculation endows weights to partition ranks from 1 to 10 [54], the fixed-effect model is a supplement through regression analysis, especially missing data in qualitative research. Besides, with increasing environmental awareness and government emission policies, shrinking EF targets carbon emission reduction and end-of-life products supply [55]. This research provides public and transparent platform for exploring carbon-footprint tracking and carbon balance [56]. Resource scarcity is a common tendency around the globe so that circular economy [57] and zero-waste policy is not a surprise for environmental austerity consideration at the local government level. Lastly, a circular economy is just as important for a healthy environment as the balance of natural supply and demand. Nevertheless, the traditional linear model that resources are extracted from the nature and eventually discarded as waste to landfill, caused resource overconsumption and hampered environmental sustainability [58]. A circular economy aims to move away from the model in the context of stretching the life of material resources while minimizing pressures to ensure environmental benefits [59]. This research gave data-driven support in favor of circular economy.

5.2. Limitation

This paper just addressed the model-based interpretation of environmental, political, social-economic impacts on SWB, and there are still unperfect considerations to be improved. First, some essential culture-related factors should be encompassed in the model, such as religion, social media, the tradition of wisdom, and tourism [60–65]. Sometimes those entities predominate developed countries or undeveloped countries in intangible or tangible stimulations of human life. Second, the model presents different ways without fixed equations and coefficients, showing that the model has more potential requirements to be improved in the future. EF concept himself should offer detailed components in terms of structures. For example, carbon footprint takes up beyond 70% of total footprints, which disguise the influence of other footprints, especially built-up land sprawls due to global urbanization overwhelming. Lastly, environmental impacts on SWB need an unfolded process, thus, it is important to draw attention to individual EF in our daily lifestyle. Future research of calculating individual EF impacts should focus on the ecological research agenda.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/land10090931/s1, Table S1: Variable abbreviation list.

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