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TIME-FREQUENCY IMPACT OF HUMAN WELL-BEING AND ECONOMIC GROWTH ON THE ECOLOGICAL FOOTPRINT:A VIETNAMESE PERSPECTIVE

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ABSTRACT

The nexus between natural resources and environmental degradation has significant implications. Nevertheless, this domain is insufficiently examined. This paper therefore a examines the time-frequency influence of economic growth, human development, and urbanisation on Vietnam's ecological footprint (EF) using wavelet analysis. The findings showed that the intercorrelation between EF and related variables is statistically significant at low, medium, and high frequencies. More importantly, the elationships between these variables occur at a high frequency, which means that EF, economic growth (GDP), human development index (HDI), and urbanisation (UB) have different fluctuations in the long run. These outcomes are also confirmed by the wavelet-based Granger causality test at various time scales, which supports our relationship results

Keywords: environmental degradation, natural resources, ecological footprint, wavelet analysis, Vietnam

INTRODUCTION

The definition of ecological footprint (EF) has attracted much attention among scholars studying environmental changes. The EF, introduced by Rees (1992) and developed by Wackernagel and Rees (1998), tackles the problem of resources in connection with productive human activities (Duro & Teixidó-Figueras, 2013). Human demands measure the ecological assets that a given population requires from the natural resources. Biocapacity is known as the productivity of those ecological assets. Additionally, human demands change the ecosystem by generating ecological pressures, such as land-use changes, resource extraction and depletion, emission of waste pollution, and the modification and movement of organisms (Rudolph & Figge, 2017). According to Kassouri and Altıntaş (2020), human beings are strongly connected with ecological conditions, therefore, good environmental management is important, leading to positive synergies between environmental conditions and human well-being. Pressures on the primary components of human development, including wealth, health, and education, are likely to rise due to rising human demands on ecological resources along with urban expansion, unsustainable pathways of consumption and production, and a growing population (Kassouri & Altıntaş, 2020).

Furthermore, enhancing human well-being and decreasing pressure on ecological resources is at the centre of sustainable development goals (SDGs) agenda (Nunan, 2015), in which determinants, such as educational quality, the status of women, human capital, and income inequality, make a significant contribution to rating the Human Development Index. Therefore, understanding the relationships between human development and environmental concerns is particularly urgent in Vietnam, where multiple economic and social drivers result in resource depletion.

Nations, whether developed or developing, face challenges with regards to the balance between economic development and the protection of the global environment. Nevertheless, the literature has almost entirely ignored how natural resources impact the EF (Hassan et al., 2019a). The abundance of natural resources is an essential element of the world economy, especially in developing countries that depend on extracting them contributing to their gross domestic product (Ansari et al., 2020).

This study contributes to the existing literature by exploring the relationship between the country's EF, economic growth, human development, and urbanisation. Due to its extensive natural resources and rising financial growth (Hung, 2021a), Vietnam is recognised as an important emerging economy. In recent years, the country has prioritised economic development over social development (Nathaniel, 2021; Hassan et al., 2019; Zeraibi et al., 2021). In this context, attention may be drawn to a widely held belief that the EF is caused by GDP and other related factors, which is a major source of concern for governments (Raza et al., 2021; Ullah et al., 2021; Solarin & Bello, 2018; Charfeddine & Mrabet, 2017).

Therefore, taking into consideration the complexity of the current socio-economic disparities in Vietnam, this paper looks at the interdependence between the EF, economic growth, human development, and urbanisation of the country. The exclusivity of this study is evident in its being a pioneer in examining the intercorrelation between selected indicators using the rigorous econometric framework of wavelet analysis. The novelty of this examination also lies in anticipating the influence of economic growth, human development, and urbanisation on Vietnam's EF across multiple frequencies and time scales. This paper employs a wavelet analysis because it is a powerful and robust methodology used in financial time series to examine their co-movements (Hung, 2020; Raza et al., 2019; Magazzino & Mutascu, 2019). These techniques outperform the traditional time-domain methods used in previous studies by a wide margin (Umar et al., 2020; Hung & Vo, 2021). Wavelet analysis transforms the fundamental time series into a time-frequency space, allowing the time series and frequency-varying information to be visualised highly intuitively. The interconnectedness and causalities between EF, economic growth, human development, and urbanisation co-vary across frequencies, and changes over time are achieved further in a time-frequency window. As a result, the short-term and long-term connectedness of the investigated variables, as well as possible structural changes and time-fluctuations in such a nexus, can be accurately observed (Hung, 2020; Hung, 2021b; Magazzino et al., 2021; Magazzino & Leogrande, 2021). Hence, the innovative findings obtained from such an advanced methodology may be free from biases and strive for greater insights into casual association by allowing the researchers to analyse the frequency elements of EF, economic growth, human well-being, and indicators of urbanisation without losing time information (Haseeb et al., 2020).

This article estimates the connectedness among economic growth, human development, urbanisation, and the EF in Vietnam in different time and frequency domains using wavelet analysis. Consequently, it tackles the following issues: How does the EF fluctuate with the duration of time horizons? What are the relationships between the EF and the variables under investigation? These issues may help policymakers explore the function and internal microstructure of the economy, environmental quality, and human well-being. This paper distinguishes itself from related studies by comprehensively considering the co-movement relationship under time-frequency conditions.

This work makes several different scientific contributions. To the best of the current researchers' knowledge, this is the first study in Vietnam to use wavelet analysis to investigate the relationship between EF, human development, urbanisation, and economic growth. Second, this research combines traditional time-domain causality analysis with time-frequency decomposition approaches in a unique way. Unlike traditional causality tools, this approach enables the analysis of causation between the specified variables at various frequency bands. In other words, this combined methodology demonstrates the direction of causality between the investigated indicators and their persistence over time. Third, this approach provides an understanding of the lead-lag association between these two variables across frequencies and over time. Finally, in order to increase the policy relevance of this paper, this inquiry asks whether economic growth, human development, and urbanisation are significant indicators affecting the EF in Vietnam.

LITERATURE REVIEW

The causal association between environmental protection and human well-being reveals that a fragile ecological environment and environmental pollution impair health and well-being (Lu & Chen, 2017; Charfeddine & Mrabet, 2017; Dogan et al., 2020). Ahmed et al. (2020) examined the impact of natural resource abundance, human capital, and urbanisation on China's EF. Based on the Bayer and Hack cointegration test and bootstrap causality approach, their findings suggest a long-run equilibrium association between variables, which means natural resource rent raises the EF. Specifically, urbanisation and economic growth contribute immensely to environmental degradation. In a similar fashion, Luo et al. (2018) shed light on the urbanisation-induced ecological pressure in Midwestern China. The authors indicated that urbanisation in China increased environmental pressure, and it is projected to rise until 2020. Uddin et al. (2017) explored the influence of real income, financial development, and trade openness on the EF of consumption. Their findings showed a positive and remarkable relationship between EF and real income and a negative and insignificant influence of trade openness on EF.

Solarin and Bello (2018) analysed the stationarity of the EF for 128 nations and provided evidence of a non-reversing mean in the series for 81% of the sample, which means that the EF is a nonstationary series. Charfeddine and Mrabet (2017) applied the Environment Kuznets Curve hypothesis in 15 Middle East and North African nations, applying the EF as a proxy for environmental degradation. They found that energy use worsens EF, while economic growth experiences an inverted U-shaped connectedness with the EF in oil-exporting countries. This nexus however, is U-shaped for non-oil-exported countries. Nathaniel and Khan (2020) focused on the impact of renewable and non-renewable energy consumption, economic growth, and urbanisation on EF between 1990 and 2016. The authors confirmed that economic growth, trade, and non-renewable energy contribute immensely to ASEAN countries' environmental degradation. Similarly, Wang et al. (2013) examined the nexus between economic growth and environmental influence on the indicators of EF. Their findings echoed Nathaniel and Khan (2020), indicating there was no evidence of an inverted U-shaped Environment Kuznets Curve. The authors suggested that the local EF of consumption is considerably impacted by the EF of consumption, income, and biocapacity in neighbouring nations.

Duro and Teixidó-Figueras (2013) analysed global inequalities in EF based on a two-factor decomposition and found that the interactive element explains the apparent pattern of stability observed in overall global inequalities. Verhofstadt et al. (2016) examined the interrelatedness between the EF and the subjective well-being at the individual level and suggested no significant correlation.

Hassan et al. (2019) studied the influence of economic growth and natural resources on Pakistan's EF using the autoregressive distributed lag (ARDL) approach. They showed that natural resources have a positive impact on an EF that leads to deterioration of environmental quality. More specifically, there is a bidirectional connectedness between natural resources and the EF, as well as a long-run relationship between biocapacity and EF. Kassouri and Altıntaş (2020) reveal the existence of a strong trade-off between the EF and human well-being as estimated by the human development index.

Magazzino et al. (2021) used wavelet analysis to investigate the relationship between energy consumption and economic growth in Italy; the study period covered 80 decades. They reported that all series are integrated into order one but showed no evidence of a long-run relationship between energy consumption and economic development. The frequency technique in particular, reinforces the causality from economic growth to energy consumption at longer time scales (8–32 years), but only at frequencies greater than 0.6 (more than 10.47 years). Magazzino and Mutascu (2019) also supported these outcomes. Based on the same approach, Magazzino et al. (2020) uncovered the absence of fiscal sustainability in the long run for Italy, reinforcing the need for a rebalancing of public accounts. Raza et al. (2021) examined the non-linear relationship between tourism development, economic growth, urbanisation, and environmental degradation, suggesting that the relationship between tourism development and environmental degradation is non-linear and regime-dependent. Similarly, Ullah et al. (2021) found a negative association between renewable energy consumption and EF and a positive relationship between natural resource rent and EF in both low and high regimes in

15 economies. Raza et al. (2019) also utilised the frameworks of wavelet to look into the influence of energy consumption and economic growth on environmental degradation in the US and showed that in the short, medium, and long run, energy consumption has a positive influence on carbon emissions.

The current study is different from existing literature in the following areas: First, the context of the study is Vietnam, which has been neglected in the literature. Second, the relationship between EF, human development index, economic growth, and urbanisation are analysed in the study. This provides policymakers with crucial information to achieve SDGs. Third, to the best of the current researcher's knowledge, there is a dearth of studies that estimate the EF's co-movement across different frequencies. This framework is employed to offer a detailed analysis of the co-movement between the examined variables across frequencies and over time, thereby contributing to this work's originality.

METHODOLOGY

Wavelet analysis is applied to decompose time series into several wavelet scales, which are stretched and translated functions of a given mother wavelet localised in both the time and frequency domains. As a result, the time series expands into a time-frequency space where its oscillations can be seen in a highly intuitive way. This study uses the wavelet framework in terms of continuous wavelets, and cross-wavelet transforms to explore how the local variance and covariance of two-time series make progress, and wavelet coherence and phase analysis to capture the interdependence between two series in the time-frequency domain. More importantly, wavelet filters offer a natural platform to address the time-varying characteristics found in most real-world time series, and the assumption of stationarity would be avoided.

The Continuous Wavelet Transform

The continuous wavelet transform $W_x(s)$ allow us to investigate the joint behaviour of time series for both frequency and time. The wavelet is defined as:

$$W_x(s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t}{s}\right) \tag{1}$$

where * denotes the complex conjugate and where the scale parameter s identifies whether the wavelet can detect higher or lower components of the series $x(t)$, possibly when the admissibility condition yields.

Wavelet Coherence

Three different ways to characterise the dependency between two time series in the time and frequency domains were used, including the wavelet power spectrum, cross-wavelet power, and cross-wavelet transform. Cross-wavelet power analyses the covariance contribution in the time-frequency space, whereas the wavelet power spectrum measures the series variance at each time scale. The cross-wavelet of two series $x(t)$ and $y(t)$ can be defined as:

$$W_n^{XY}(u,s) = W_n^{X}(u,s)\, W_n^{Y*}(u,s) \tag{2}$$

where u denotes the position, s is the scale, and * denotes the complex conjugate.

The wavelet coherence is defined by Torrence and Webster (1999) as the coefficient of the correlation of time frequency space. The squared wavelet coefficient is defined as:

$$R_n^2(u,s) = \frac{\left|S\left(s^{-1} W_n^{XY}(u,s)\right|^2\right)}{S\left(s^{-1}\left|W_X(u,s)\right|^2\right) S\left(s^{-1}\left|W_Y(u,s)\right|^2\right)} \tag{3}$$

where S is a smoothing parameter for both time and frequency. $R^2(u, s)$ is in the range $0 \leq R^2(u, s) \leq 1$, which is similar to correlation coefficient. Evidence of weak interdependence will be determined if its value is close to zero, and vice versa.

Phase Difference

The complete cycle of the time series for a function of frequency is referred to as a phase difference, and it informs us about a delay or synchronisation between two time series. It calculates negative and positive connections, as well as the lead-lag nexus, between two time series in time-frequency domains. As a result, the phase difference technique was employed to investigate the causation and dependency relationships between time series. Reboredo et al., 2017 defined the phase difference between $x(t)$ and $y(t)$ as follows:

$$\phi_{XY} = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1} W_{XY}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1} W_{XY}(u,s)\right)\right\}}\right) \tag{4}$$

where $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum respectively. In the coherence phase, arrows represent phase interrelatedness between two variables: (1) when the arrows point to the right (left), the correlation is positive (negative); and when the arrows point to down (up), the second (first) variable leads the first (second) variable by 90°.

Data

The study is based on annual data obtained from the World Bank and International Energy Agency databases spanning more than four decades, between 1970 and 2016. The GDP is gross domestic product per capita (constant 2010 prices in US dollars). The HDI is a human development index known as a ranking system to track and compare the national levels of human development. The urbanisation (UB) is the percentage of urban population, which is used to capture the impact of large-scale urbanisation process. The EF is a biophysical sustainability indicator that measures the set of impacts exerted by each country on its environment. It shows the critical natural capital requirements of a defined economy or population in terms of the related biologically productive region (Marti & Puertas, 2020). This is obtained from the Global Footprint Network and it is expressed in global hectares. The study period was between 1970 and 2016, and based on data availability. The variables were chosen with care, taking into account economic theory, data availability, and empirical literature. These indicators have been employed in recent study by Nathaniel (2021), Hassan et al. (2019), and Zeraibi et al. (2021). The indicators under consideration are expressed in logarithmic form.

Table 1
Descriptive statistics of variables

Variables	EF	GDP	HDI	UB
Mean	−0.054938	6.580189	0.649401	3.132228
Median	−0.257099	6.434226	0.569928	3.062783
Maximum	0.752534	7.692487	0.999169	3.541249
Minimum	−0.414023	5.780454	0.401564	2.906901
Std.Dev	0.356487	0.614014	0.167058	0.201494
Skewness	0.856959	0.335831	0.656723	0.636536
Kurtosis	2.277954	1.738309	2.270644	1.989604
Jacque-Bera	6.773611***	4.000866***	4.420159***	5.173161***

Note: *** denotes significance at the 1% level.

Table 1 contains descriptive statistics for all the variables under examination. The EF’s mean was negative while the mean for GDP, HDI, and UB was positive. The standard deviation of GDP exceeded that of the other indicators. The skewness and kurtosis measures indicated that most series are skewed and leptokurtic with regard to normal distribution. The significant Jarque-Bera (JB) test statistics suggested that the data had a non-normal distribution; Figure 1 provides us with further insight into the data distribution and correlation structure of the four variables. Specifically, Figure 1 describes significant cross-correlations between variables. The EF exhibits a higher level of correlation with GDP, HDI, and UB, revealing the results' partial robustness. Therefore, the non-normal distribution characteristics of the examined time series recommend the usage of wavelet analysis. Linear correlation-based frameworks may not reliably estimate non-linear or frequency-interdependent relationships between two variables. Cautious interpretation of outcomes is needed to draw reasonable conclusions.

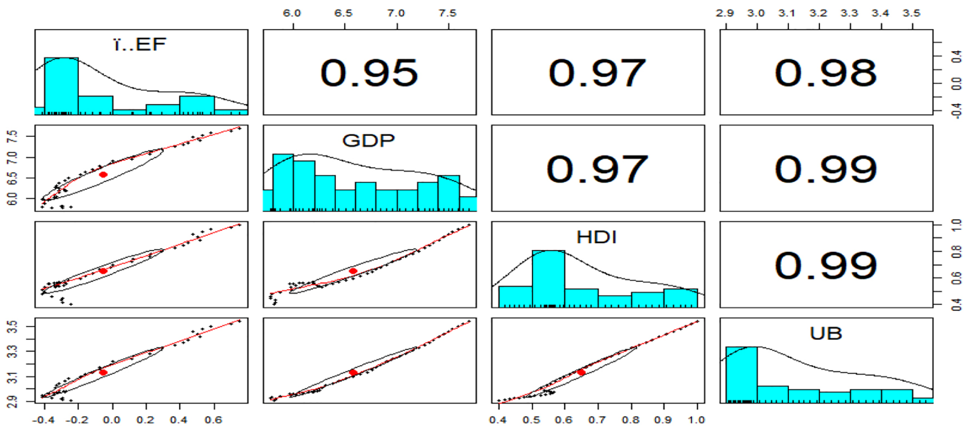

Figure 1. Scatter plots, histograms, and Pearson correlation of variables

EMPIRICAL RESULTS

Wavelet analysis was employed to assess the time-frequency connectedness between EF and GDP, HDI, and UB in Vietnam. These techniques are powerful enough to allow us to capture co-movement between the selected series quickly. First, continuous wavelet analysis provides a better understanding than the linear association framework of the interdependence between examined variables and localised volatility through time and frequency domains simultaneously. Second, wavelet coherence was used to examine co-movement and the lead-lag relationship structures between EF and GDP, HDI, and UB in Vietnam. Finally, the analysis shed light on the causal association between these variables based on the time-frequency band of the wavelet transform using a wavelet-based Granger causality test.

In this study, the continuous wavelet method was used to decompose the original data into four levels. The EF, GDP, HDI, and UB data were decomposed into four time scales, namely D1, D2, D3, and D4, which provide information about the original data. S4 is the trend element. Table 2 further divides these levels into three holding periods, namely 2- to 4-year scales based on the wavelet scale D1, which represents the short-run horizon. The estimated outcomes rely on the wavelet scale D2, which refers to the medium run horizon, corresponding to the fluctuation in EF, GDP, HDI, and UB due to shocks in the period ranging between four and eight years. In this paper, the wavelet scale D3, D4 shows the long-run horizon associated with the variation in periods of 8–16 and 16–32 years. Finally, S4 is linked with very long-term dynamics corresponding to the period above 32 years.

Table 2
Time interpretation of wavelet scales

Detail	Wavelet Scale	Frequency (years)
D1	1	2−4
D2	4	4−8
D3	8	8−16
D4	16	16−32
S4	> 32	> 32

The outcome of the continuous wavelet power spectrum of all pairs of variables in Figure 2, is reported which shows that Vietnam's EF, GDP, HDI, and UB experience significant volatility at a 5% significant level. The continuous power spectrum measures the variance of examined variables, estimating both time and frequency elements. The colour code for power ranges from blue (low power) to yellow (high power). The intensity levels gradually rose from blue to yellow. Based on the calculation of Monte Carlo simulations with randomised surrogate time series, a black contour indicates a 5% significant level. Furthermore, a solid curving line indicating the cone of influence (COI) depicts the zone influenced by edge effects, while blue beyond the COI denotes that intercorrelation between the variables at different time-frequency domains is not significant (Bilgili et al., 2020; Bilgili et al., 2021; Kassouri et al., 2022). In Figure 2, there are patterns of low volatility in high and low-frequency bands over the period 1970−2016. Around 2000, power slightly increased in the long term in the selected indicators in Vietnam. In addition, the power distributions for indicators are the same across frequencies as well as overtime. No strong volatility at different scales during the period shown was observed. In short, all series variances are relatively low volatility for different time scales.

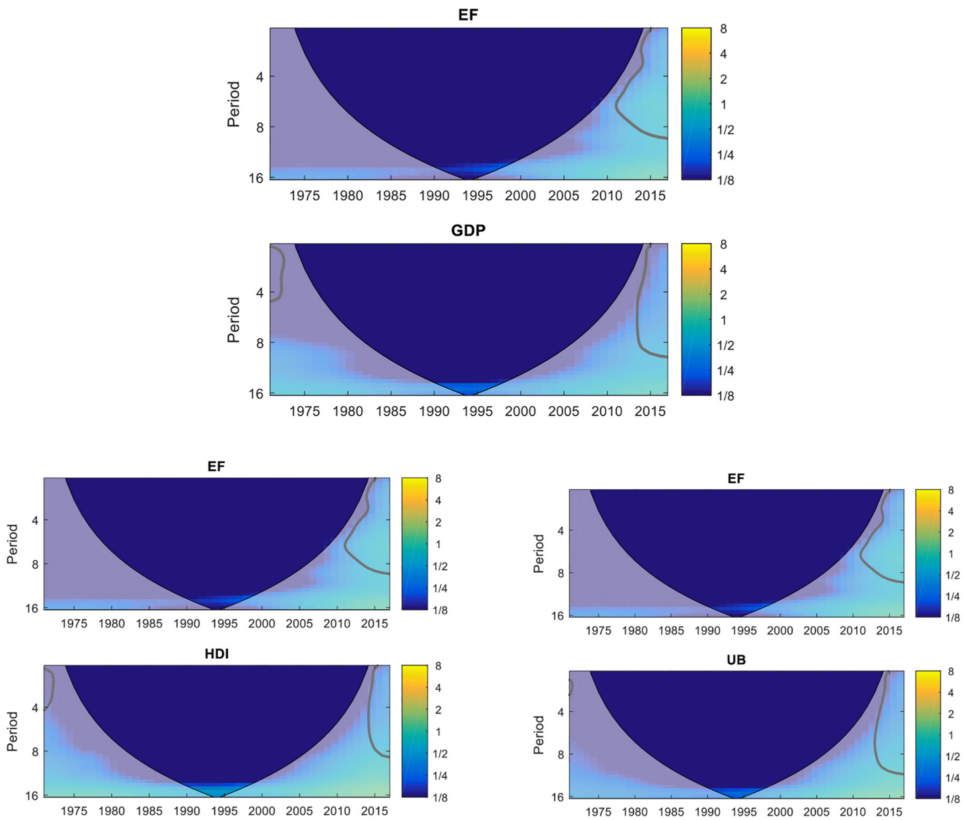

Figure 2. Continuous wavelet power spectra of EF, GDP, HDI, and UB
Notes: The vertical axis is the frequency element whereas the horizontal axis is time element. The thick black contour presents a significant region at 5% level, and cured black line denotes a cone of effect, which shows areas impacted by edge effects.

Figure 3 illustrates the cross wavelet transform results, which are similar to the continuous wavelet transform power spectrum plots in Figure 2. The cross-wavelet transform measures the local covariance between EF and other variables at different frequencies and periods. The cross-wavelet transform reveals that the interconnectedness between EF and GDP, HDI, UB is significant at low and high frequency scales, suggesting that the two variables have similar variation in the long run in Vietnam. Additionally, the arrows show both cyclic and anti-cyclic effects over the sample period shown. This indicates that the variables exhibit both in-phase and out-phase associations. More precisely, phase differences illustrate that the interdependence between EF and other indicators is not homogeneous across time and frequencies, as indicated by arrows that point up, down, right, and left through various time and scales.

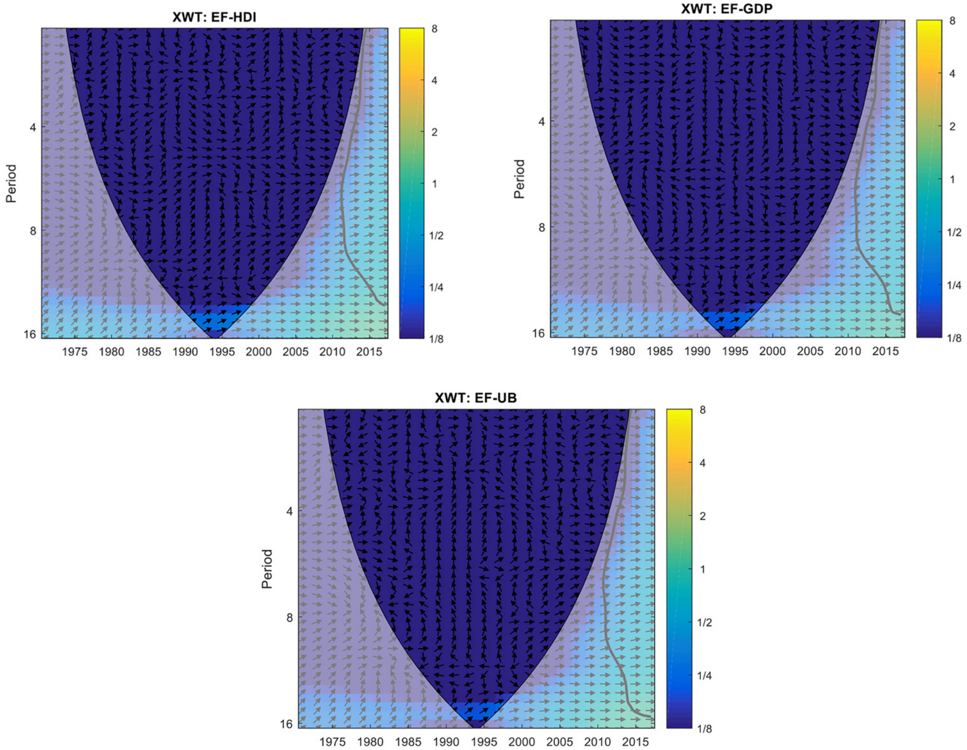

Figure 3. Cross-wavelet transforms for EF, GDP, HDI and UB
Notes: The vertical axis is the frequency element whereas the horizontal axis is time element. The thick black contour presents a significant region at the 5% level, and cured black line denotes a cone of effect, which shows areas impacted by edge effects. Right up and down represents in-phase, while left up and down shows out of phase.

The findings of wavelet coherence are shown in Figure 4. The wavelet coherence transform detects the regions where the two-time series co-vary in the time and frequency domain. The outcomes of wavelet coherence for EF-GDP indicate that the arrows are right side upward, suggesting that the EF and GDP are in-phase and present cyclic effects where GDP is leading. This means that EF has a positive impact on GDP. Similarly, the results of wavelet coherence of EF-HDI show that in the period of the 0−4-year cycle between 2000 and 2005, the arrows are right up, suggesting that the variables are in-phase with EF lagging. However, arrows are left down, indicating that EF is leading in 1980−1985.

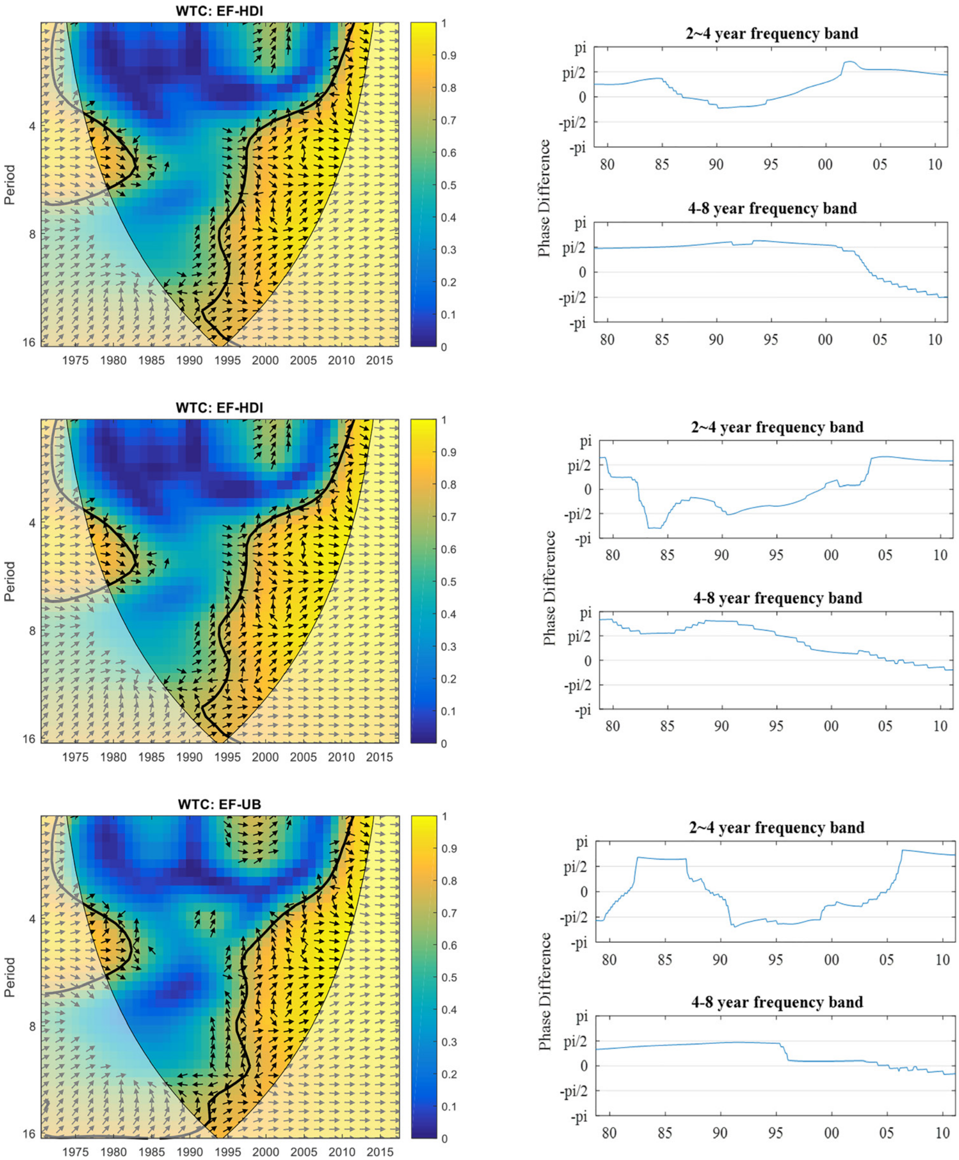

Figure 4. Wavelet coherence and Phase difference in EF, GDP, HDI, and UB

Notes: The vertical axis is the frequency element whereas the horizontal axis is time element. The thick black contour presents a significant region at 5% level, and cured black line denotes a cone of effect, which shows areas impacted by edge effects. Right up and down represents in-phase, while left up and down shows out of phase.

For almost the entire studied period on a long scale, the study evidences a strong coherence between both EF and HDI. The most interesting part of this coherence is the persistence of a unidirectional relationship from EF to HDI in the whole sample period. The connectedness between EF and UB reveals that significant intercorrelation exists at all scales, namely, the short, medium, and long-run, over 1970−2016. Specifically, the highest level of co-movement was recorded on scales ranging from eight to 16-year scales from 1995 to 2016. In addition, the downward right arrows suggested that the causality nexus between EF and UB is positive; in this case, EF leads UB in Vietnam.

The phase-difference scalograms in the right panels of Figure 4 are also instructive. The phase differences are used in this study to focus on the lead-lag relationship between EF, HDI, and UB variables in Vietnam. The phase diagrams for all analysed pairs reveal a distinct pattern, with values of phase difference ranging from pi/2 to −pi/2 at all frequency bands over the whole period under examination, implying that the EF, HDI, and UB indicators are in-phase and out-of-phase at the specific time and move together. In the long run, it appears that the indicators have a lead-lag relationship.

The plot pairs of wavelet coherence indicate that EF and HDI, GDP, and UB show significant co-movement over time and frequency domain in Vietnam. More importantly, the index pair's coherence increased at a higher frequency band, and it existed from 1990–2016. These empirical results are consistent with those obtained by the continuous wavelet transform. They are also reported by Ahmed et al. (2020), Luo et al. (2018) and Uddin et al. (2017) for China, and Hassan et al. (2019) and Kassouri and Altıntaş (2020) for Pakistan.

The Granger causality test on wavelet decomposed data was carried as the final step. Table 3 contains the outcomes of Granger causality across frequency ranges and time scales. The analysis offers an opportunity to identify whether EF causes changes in low, medium, and high frequencies of the examined variables. The findings show the persistence of bidirectional causal interaction between EF and GDP, HDI, and UB in the medium and long term. Therefore, the dependence of GDP, UB, and HDI on EF indeed changes in the time-frequency space from the time dimension. The current results echoed those of Hassan et al. (2019), and Kassouri and Altntaş (2020).

Table 3
Results of wavelet-based Granger causality test at different time scales

Time Domain	Result	Null hypothesis			
		EF does not related variables		Related variables do not cause EF	
		F-test	*P*-Value	F-test	*P*-Value
EF-GDP					
D1	$EF \rightarrow GDP$	2.51158	0.0939	1.64266	0.2062
D2	$EF \leftrightarrows GDP$	6.07429	0.0050	4.44914	0.0180
D3	$GDP \rightarrow EF$	2.47736	0.1261	2.47736	0.0968
D4	$GDP \rightarrow EF$	2.06821	0.1397	4.23419	0.0215
S4	$EF \leftrightarrows GDP$	5.91961	0.0056	5.10535	0.0106
EF-HDI					
D1	No causality	0.93475	0.1577	1.38375	0.2624
D2	$EF \leftrightarrows HDI$	15.7199	0.0000	12.0982	0.0000
D3	$EF \leftrightarrows HDI$	8.24394	0.0010	7.28666	0.0020
D4	$EF \leftrightarrows HDI$	35.9963	0.0000	36.7001	0.0000
S4	$EF \leftrightarrows HDI$	48.5958	0.0000	59.2716	0.0000
EF-UB					
D1	No causality	1.93912	0.1571	1.30985	0.2812
D2	$EF \leftrightarrows UB$	11.1605	0.0001	8.09019	0.0011
D3	$EF \leftrightarrows UB$	3.71013	0.0333	3.72623	0.0328
D4	$EF \leftrightarrows UB$	35.9963	0.0000	36.7001	0.0000
S4	$EF \leftrightarrows UB$	2.67193	0.0814	2.53511	0.0919

Robustness Checks

The wavelet cohesion was utilised to check the robustness of the current results. Wavelet cohesion is a time-frequency approach developed by Rua (2013), which estimates the cross wavelet transform correlation to provide robust insights into casual nexus between the selected indicators. The correlation intensity measure $\rho_{x,y}$ as the real number on $[-1,1]$ and it can be expressed as:

$$\rho_{x,y} = \frac{\Re(W_n^x W_n^y)}{\sqrt{|W_n^x|^2 |W_n^y|}} \tag{5}$$

This method considers both positive and negative interdependence between the two variables. The wavelet Rua's connection between EF, GDP, and UB is plotted in Figure 5. Wavelet coherence, continuous wavelet spectrum, and cross wavelet transform outcomes are all reinforced by the spectra. Positive co-movements between EF, GDP, and UB are shown in yellow at all frequencies from 1970 to 2016. However, the vivid blue colour suggests a negative nexus at high frequency from 1990 to 2000. It can be concluded that multivariate analysis is critical when investigating the lead-lag relationship between EF, GDP, and UB in Vietnam. The robust empirical estimations revealed a considerable intercorrelation between the variables under study.

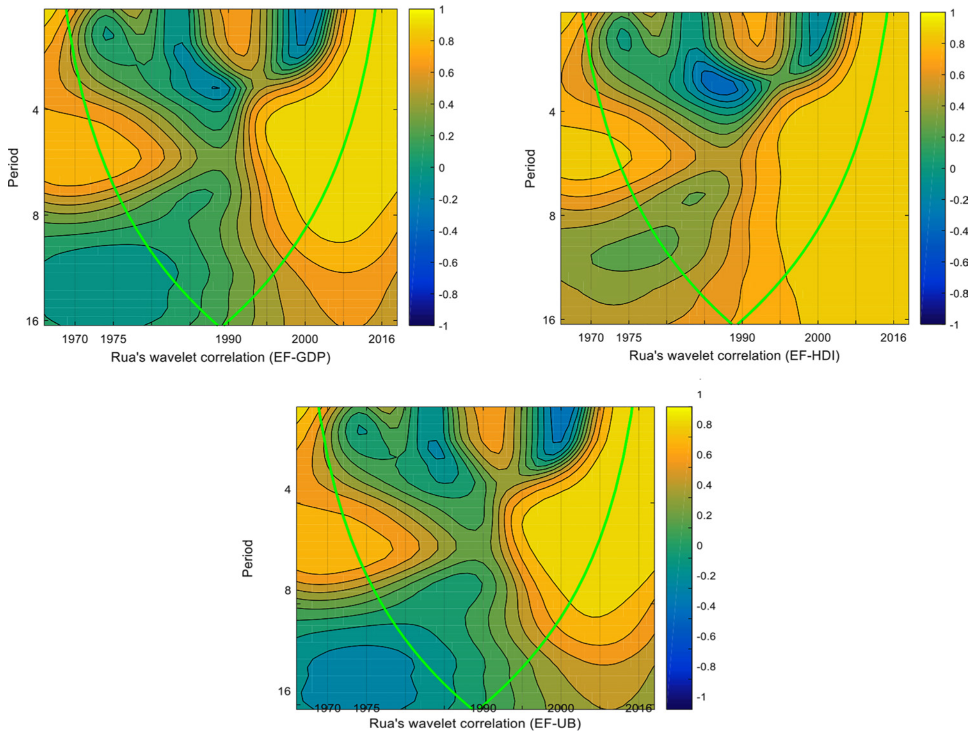

Figure 5. Wavelet-based correlations. The colour code indicates the degree of correlation, which goes from the blue (negative correlation) to yellow colour (positive correlation)

CONCLUSION

This paper discusses the interdependence between EF, GDP, HDI, and UB in Vietnam. The aim is to shed light on the lead-lag effect and mutual coherence function between the examined variables using wavelet analysis. The wavelet transform method allows various variables in a time series to be decomposed at different time frequencies. Annual data between 1980 and 2016 was used to analyse the relationship between the variables. The wavelet-based Granger causality test, the coherence spectrum, and the continuous power spectrum were among the approaches used on the dataset.

The pairwise nexus results showed that interconnectedness between EF and concerned variables is statistically significant at low, medium, and high frequencies in Vietnam. More specifically, the nexus between these variables occurred at a high frequency, which means that EF and GDP, HDI, and UB have different fluctuations in the long run. These outcomes were also officially confirmed by wavelet-based Granger causality test at various time scales, which provides additional support for the relationship results.

The study shows that EF and HDI have a substantial relationship. The most intriguing aspect of this coherence is the unidirectional relationship between EF and HDI's persistence over the whole study period. Over the period 1970−2016, considerable intercorrelation occurred between EF and UB at all scales, namely the short, medium, and long-run. From 1995 to 2016, the highest levels of co-movement were observed at scales ranging from 8 to 16 years. Furthermore, downward right arrows are visible, implying that the causality nexus between EF and UB is positive; in this situation, EF precedes UB in Vietnam.

For a variety of reasons, the aggregate findings showed that Vietnamese authorities are focused on growing the economy and human capital. First, the government must maintain the country's economic growth path, which is not in the proper direction in terms of its impact on the environment. Rising income in Vietnam has prompted people to invest in property, the country's only profitable source of revenue, resulting in an unequal distribution of resources. The enormous number of housing developments has resulted in the conversion of agricultural and forestland to housing, which has a negative impact on the environment. By raising land and environmental-impact levies, Vietnam's government can control the rapid growth of housing complexes. The dangers of global environmental change to people and ecosystems are becoming more apparent. Second, policymakers must grasp the implications of economic growth and resource use on ecosystems and the complex interplay between economic development, biodiversity, ecosystem services, and human well-being, which are still poorly understood and disregarded.

Third, the lack of a role for human capital in lowering environmental stress shows that the country's citizens are unaware of environmental issues. The Vietnamese government should encourage universities and institutes to implement environmental quality awareness programme to expose students on the impact of human actions on the environment, as human capital can be a powerful weapon in the fight against environmental degradation.

This study recommends policymakers focus on negative energy consumption shocks to maintain environmental quality. Similarly, disintegrated forms of energy consumption can be examined when developing environmental policies. The government should encourage the use of clean energy to meet the country's energy needs. In fact, economic growth can be achieved by adopting an environmentally friendly growth strategy. Because Vietnam is an agrarian economy, the country may emphasise agricultural sector development, which will ultimately aid in meeting economic growth targets. It may invest in pollution-free modern technologies and manufacturing equipment, thereby protecting environmental quality. The ongoing COVID-19 crisis has a negative impact on travel, industrialisation, and other economic activities, reducing the environmental burden. However, lower energy demand may have a negative impact on efforts to transition to clean energy sources. In this scenario, the government must support decarbonisation projects by focusing solely on environmentally friendly capital formation projects. This can be accomplished by employing cutting-edge capital formation technology to ensure environmental sustainability.

Due to data limitations, this study's analysis was limited to Vietnam. It also reduced analysis time. As a result, a country-specific study was not possible. This study could be expanded in the future by examining the effects of economic growth, renewable power generation capacity, technical innovation, financial development, and population expansion on the various components of EF.

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