Dynamic linkages between tourism, transportation, growth and carbon emission in the USA: evidence from partial and multiple wavelet coherence

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Abstract: The present paper endeavors to analyze and provide fresh insights from the dynamic association between tourism, transportation, economic growth and carbon emission in the United States. The analysis employs a novel Morlet's Wavelet Approach. Precisely, the paper implements Partial and Multiple Wavelet Coherence techniques to the monthly data spanning from 2001-2017. From the frequency domain point of view, the study discovers remarkable wavelet coherence and robust lead and lag linkages. The analysis discovers significant progress in variables over frequency and time. The variables display strong but inconsistent associations between them. There exist a strong co-movement among the variables considered, which is not equal across the time scales. The study may help the policymakers and regulars to devise strategies and formulate policies pertaining to tourism development, which can contribute towards environmentally sustainable economic growth.

Keywords: Tourism; Transportation; CO_2 Emissions; Partial Wavelet Coherence; Multiple Wavelet Coherence

1. Introduction

Since last few decades, Tourism has earned the distinction of being a major socio-economic activity in the global economic scenario (Sharif et al. 2017; Raza et al. 2017). Being a major service sector, tourism is having a far-reaching contribution towards economic growth, trade, investments, employment generation, and development of society, and therefore, researchers designate it as a panacea for unemployment and economic decline (Isik and Shahbaz, 2015; Ertrugul et. al. 2016; Isik et. al. 2017a, 2017b). The decreasing travel costs and easy availability of information about the destinations have led the tourism industry to become one of the rapidly growing industries in the world. The development of tourism sector has now been recognized as a significant driving force for the global economic growth.

Driven by this growth in tourism sector, energy and environmental economists have turned their attention towards discovering the possible link between tourism development, energy consumption, and climate change (Katircioglu et al. 2014; Raza et al. 2017; Sharif et al. 2017). Researchers have identified various channels through, which tourism stimulates the increase in energy demand (Becken et al., 2003, 2011). From transportation to accommodation, growth in each aspect of tourism and allied activities, energy is consumed through both direct and indirect forms. The World Tourism Organization (UNWTO) postulated that 4.6% of global warming and 5% of global CO_2 emissions is due to the tourism sector. Peeters et al. (2007) and Nielsen et al. (2010) have identified the same for the European countries and Switzerland, respectively. Apart from increasing the level of CO_2 emissions in ambient atmosphere, tourism industry also contributes to environmental degradation through construction of hotels and tourist facilities, and thereby, encroaching green space (Gossling, 2002; Day et al. 2012). Development of tourism infrastructure might also lead to significant land alteration process, which also leads to deterioration of environmental quality (IPCC, 2001).

Despite being one of the top three tourist destinations in the world, the tourism industry in the United States of America (USA) is also facing these issues. During last decade, the USA has experienced two contradicting scenarios in the tourism industry. On one hand, the recessionary pressure in the economy led to slump in the tourist footfall, and on the other, the share of ecotourism in the USA tourism industry has grown to nearly 60 percent (Fetters, 2017). This rise in the ecotourism has led to the changes in ecosystems and faster depletion of natural resources, thereby, causing more harm to the ecological quality. Moreover, even at the time of slump, the USA has accounted the world's highest carbon footprint from tourism, and this very phenomenon can be characterized by the dependence of tourism on transportation (Lenzen et al., 2018). In this view, sustainability of the tourism industry in the USA might be questioned, within the purview of its present outlook. Therefore, from the perspective of sustainable tourism, we intend to assess the interaction between tourism development, transportation, economic growth, and climate change in the context of the USA, in the present study.

Methodologically speaking, in the present study, we have employed the partial and multiple wavelet coherence method by Aguiar-Conraria et al. (2008, 2012) to investigate the association between tourism development, transportation, economic growth, and CO_2 emissions.[1] Following Dima et al. (2015), Balli et al. (2018), Das and Kumar (2018) and Singh et al. (2018), This approach allows to examine the wavelet coherence of different time series, while controlling for their mutual related factors described by the effect of multiple predictor variables (Ng and Chan, 2012). Assuming the possible complication of the hypothesized association, this method can suggest inclusive outcomes about the interactions both in time and frequency realm.

Given the present issues being faced by the tourism industry in the USA, this study has its contributions both theoretically and methodologically. As the world has ushered in the regime of Sustainable Development Goals (SDGs), it is the responsibility of every nation to look into the

[1] Kumar et al. (2018) and Suresh and Tiwari (2018) are the earliest ones to apply wavelet analysis in the area of tourism, and our methodology is adopted from their studies.

contributing sectors and assure the sustainability of that sector in keeping with the global socio-ecological balance. From the perspective of sustainable tourism, assessment of the linkage between tourism development, transportation, economic growth, and CO_2 emissions might turn out to be important for the USA, as the futuristic sustainable policy design should incorporate not only the tourism sector, but also the demand and supply sides of the sector in augmenting the level of environmental degradation. Methodologically, multiple wavelet analysis offers full and distinct consideration to the time and frequency domain association among the model parameters, while discovering undisclosed information through frequency-level disintegration (Aguiar-Conraria et al. 2008). Additionally, the partial and multiple wavelet analysis have noteworthy power during the standard time series models, predominantly when the time series in research are not stationary (Roueff and Von-Sach, 2011).[2] Lastly, through wavelet analysis, we can visualize the degree of association among the model parameters, how such a connection progress with the time, and the lead-lag position of variables in short, medium and long-run.

The rest of the paper is set as follows: section 2 elaborates the literature review of the study, section 3 discusses the methodology of partial wavelet coherence and multiple wavelet coherence, section 4 explains and discusses outcomes and findings, and the final section provides the conclusions and major policy implications of our findings.

2. Literature Review

A number of researchers have endeavored to examine the relationship between energy consumption and tourism. Becken et al. (2003) observed how different transport choices add up the total energy bill of international and domestic tourists in New Zealand. The authors found energy usage by international tourists to be four times greater than that of their domestic counterparts. Lai et al. (2011) assessed the relationship between electricity consumption, tourism and other control variables in China. The authors employed Johansen cointegration and Granger

[2] The motivation for selecting Morlet wavelet is "yields information on the amplitude and phase, both essential to study synchronism between different time-series" (Aguiar-Conraria and Soares, 2011).

Causality Test to assess the relationship and failed to found any significant role of tourism in China's electricity consumption. Tiwari et al. (2013) examined the association between energy consumption, tourism and CO_2 emissions in a trivariate panel Vector Auto Regression setup for OECD countries, and found significant positive impact of tourism on energy consumption. This result contradicts the findings of Lai et al. (2011).

In Turkey, Katircioglu (2014a) adopted Bounds Testing Approach to Cointegration, Impulse Response Function, and Variance Decomposition Analysis to analyze the relationship between energy consumption, tourism, CO_2 emission and economic growth. Besides observing cointegration among the variables, the authors found unidirectional causality running from tourism to energy consumption. Similar findings were also obtained in Singapore by Katircioglu (2014b) which was further substantiated by the analysis done by Yorucu and Mehmet (2015) in Turkey. Katircioglu (2014) employed a similar approach to examine whether tourism development stimulates energy consumption and/or CO_2 emissions in Cyprus and found long run relationship among the variables under study. The author's analysis further observed bidirectional causality between tourism and energy consumption and found tourism having a direct influence on long-term energy consumption in Cyprus. In India, Tang et al. (2016) on Bounds Test Approach and Gregory-Hansen Test for Cointegration with Structural Break observed cointegration among energy consumption, tourism and economic growth. The authors found tourism and economic growth strongly affecting energy consumption in India.

During the last few years, many researchers have examined the tourism on CO_2 emission. Lee and Brahmasarene (2013) employed Im-Pesaran-Shin (IPS) and Levin-Lin-Chu (LLC) Panel Unit Root Test, along with Johansen Cointegration and OLS estimator on a panel of European Union countries to examine the impact of tourism for the period 1988-2009. In their study, the authors observed a negative influence on tourism on CO_2 emission. On the contrary, in Cyprus, Katricioglu (2014) statistically positive influence of tourism on CO_2 emission along with energy.

Katricioglu (2015) also observed the significant role of tourism on environmental degradation in Turkey. While analyzing the linkage between tourism development and CO_2 emission in Malaysia, Solarin (2014) observed the long-run relationship between the variables under study. The author found the existence of positive unidirectional causality running from tourism development to the level of CO_2 emission. In Mauritius, Durbarry and Seetanah (2014) on employing Autoregressive Distributed Lag (ARDL) approach confirmed tourist arrivals having a significant positive influence on CO_2 emission both in a long and short run. Dogan et al. (2015) used cross-sectionally augmented IPS (CIPS) and cross-sectionally augmented Dickey-Fuller (CADF) unit root tests, Lagrange multiplier (LM) Bootstrap cointegration test, dynamic ordinary least square (OLS), and Dumitrescu-Hurlin causality test to analyze the long-run relationship between tourism, CO_2 emission, energy consumption and real GDP for OECD countries over 1995-2010. In their study, the authors observed from tourism to CO_2 emission, tourism to energy consumption and from tourism to economic growth. Similarly, Zaman et al. (2016) on employing two-stage technique and Dumitrescu- Hurlin Causality Method observed unidirectional causality running from tourism to CO_2 emission and energy consumption to CO_2 emission in East Asia and Pacific, The European Union, and high income OECD and non-OECD economies. Sharif et al. (2017) on investigating the relationship between CO_2 emission and growth of tourism in Pakistan confirmed the existence of unidirectional causality running from tourist arrival to CO_2 emission.

Many researchers have also examined the influence of tourism arrival and departure on pollution caused by transportation industry termed to be the major mode of tourism movement (Byrnes and Wanken, 2006; Gossling, 2002; Howitt et al., 2010; Scott et al., 2010). Gossling (2002) termed the transportation sector to be responsible for nearly 94% of the total contribution of tourism towards greenhouse gas emission. In Australia, Byrnes and Warnken (2006) found total greenhouse gas emitted by tour boat operations to be 0.1% of the transport industry.

However, Peeters et al. (2007) found intercontinental and air transportation tourism to be responsible for enhanced air pollution. In Switzerland. Perch-Nielsen et al. (2009) found a share of air transport at 80% to be highest in Greenhouse Gas emission. Howitt et al. (2010) while analyzing the cause and effect relationship between CO_2 emission and to-and-fro journey by cruise ship in New Zealand found a ship to travel to be the more greenhouse gas emitting approach of international travel as compared to a flight. Lin (2010) while investigating the CO_2 emission of five different national parks in Taiwan to examine the role of road vehicles in greenhouse gas emission found CO_2 emitted by tourist using private cars to be extraordinarily high. Wei et al. (2012) in his study observed a significant increase in CO_2 emissions due to China's tourism transport during the last three decades.

Limited studies have also employed Wavelet methodology to investigate the causality between tourism development, energy consumption, and CO_2 emission. Raza et al. (2017) employed a wavelet approach to analyzing the causality between tourism development and environmental degradation in the United States. In their study, the authors concluded that tourists' arrival exerts a significant positive impact on CO_2 emission in short, medium and long run. The authors also suggested the existence of unidirectional causality between tourism development and CO_2 emission in the United States.

The review of the literature has elucidated us about the studies conducted on the association between tourism development, transportation, economic growth, and CO_2 emissions. However, any definitive direction regarding the sustainable future of the tourism industry in the USA has not emerged out of the review, and there lies the focus of our study. By means of the wavelet coherence method, we have analyzed the short-run, medium run, and long run scenarios for the aforementioned association in the USA. From the perspective of sustainable tourism policy design, this study contributes to the literature by addressing the recent issues being faced by the USA and recommending the suitable policies for the same.

3. Data and Variables

The present study employs monthly observations of tourism development, transportation service index, energy consumption and CO_2 emissions of the USA for 2001 (M1)-2017 (M12). The data of tourist arrivals have been collected from the National Travel and Tourism Office[3]. The data on CO_2 emissions are collected from U.S. Energy Information Administration. Data of transportation service index and industrial production index are collected from FRED| ST. LOUIS FED[4]. The data have been converted into a logarithmic difference series for obtaining the return series and ensure its stationarity.

4. Methodology

4.1. The Wavelet Coherence

The present paper employs Wavelet Coherence to encircle the relationship between Tourism Development, transportation service index, economic growth and CO_2 emission across the time scales. The Wavelet Coherence approach is popularly used irrespective of time series. Initially, we need to define cross wavelet transform and cross-wavelet power. According to Torrence and Compo (1998), the framework for cross wavelet transform between two-time sequences x(t) and y(t) can be formulated as follows:

$$W_{xy}(m,n) = W_x(m,n)\, W_y^*(m,n) \tag{2}$$

$W_x(m,n)$ and $W_y(m,n)$ represent cross wavelet transform of *x(t)* and *y(t)* separately. The location index is represented by m and n denotes the measure. The sign * represents the composite conjugate. The cross-wavelet power is calculated by cross wavelet to transform as $|W_x(m,n)|$. In the time-frequency domain, the regions of intense energy concentration defined as cumulus of confined variance relative to the considered time series are isolated by the cross-wavelet power spectra.

[3] https://travel.trade.gov/research/monthly/arrivals/index.asp
[4] https://fred.stlouisfed.org/series/TSITTL

The wavelet coherence in a particular time-frequency domain identifies those areas where abrupt and significant variations happen in the co-movement pattern of the given time series. Torrence and Webster (1999) formulated the coefficient for adjusted wavelet coherence as follows:

$$R^2(m,n) = \frac{\left|N(N^{-1}W_{xy}(m,n)\right|^2}{N(N^{-1}|W_x(m,n)|^2)N(N^{-1}\left|W_y(m,n)\right|^2)} \tag{3}$$

The range of squared wavelet coherence coefficient is represented as follows:

$$0 \leq R^2(m,n) \leq 1 \tag{4}$$

The value close to zero signifies the absence of correlation. On the contrary, when the value is close to unity, it implies the presence of a high level of correlation. The Wavelet Coherence in the present study is examined through Monte Carlo methods.

4.2. The Partial Wavelet Coherence

The partial wavelet coherence is a unique approach that can be utilized in a simple correlation theory. Using the wavelet approach, we can attain this with the support of partial wavelet coherence. The method lets one detect the wavelet coherence among two time series x_2 and x_1 after eliminating the influence of another time series y. Therefore, coherence among x_1 and x_2, x_1 and y and x_2 and y is transcribed as:

$$R(x_1,x_2) = \frac{S\,[\,W\,(x_1,x_2)]}{\sqrt{S\,[W\,(x_1)].S[W(x_2)}}\,; \tag{5}$$

$$R^2(x_1,x_2) = R\,(x_1,x_2).\ R\,(x_1,x_2)^*; \tag{6}$$

$$R(\mathrm{x}_1,\mathrm{y}) = \frac{\mathrm{S\,[\,W\,(x_1,y)]}}{\sqrt{\mathrm{S\,[W\,(x_1)].S[W(y)}}}\,; \tag{7}$$

$$R^2(x_1,y) = R\,(x_1,y).\ R\,(x_1,y)^*; \tag{8}$$

$$R(\mathrm{x}_2,\mathrm{y}) = \frac{\mathrm{S\,[\,W\,(x_2,y)]}}{\sqrt{\mathrm{S\,[W\,(x_2)].S[W(y)}}}\,; \tag{9}$$

$$R^2(x_2,y) = R\,(x_2,y).\ R\,(x_2,y)^*; \tag{10}$$

4.3. The Multiple Wavelet Coherence

The Multiple Wavelet Coherence (MWC) is similar to multiple correlations and is suitable when we need to analyze the coherence of multiple dependent variables on the dependent variable. The framework for MWC can be formulated as follows:

$$RM^2(y, x_2, x_1) = \frac{R^2(y,x_1)+R^2(y,x_2)-2Re[R(y,x_1).R(y,x_2)^{*}.R(x_2,x_1)^{*}]}{1-R^2(x_2,x_1)} \quad (11)$$

Eq. (11) represents the resulting wavelet coherence squared that derives the proportion of wavelet power of dependent time series y understood by two independent time series x_1 and x_2 at a given frequency domain. The Monte Carlo methods are employed to estimate the significance level of MWC. The significance tests are derived from the generated from the huge set of surrogate data having the same AR(1) coefficients as the input datasets. The Cone of Influence (COI) represented by lighter shade splitting the high-power region from the rest is the region of the wavelet spectrum with important edge effects (Torrence and Compo, 1998). The values outside the COI ascertains the significance level of each scale of Wavelet Coherence.

5. Empirical Analysis

5.1. Stationarity test and cointegration

The present paper endeavors to analyze the time-frequency causality between Tourism development, economic growth, Transportation service index and CO_2 emission. Prior to the empirical analysis, Descriptive Statistics is conducted to understand and analyze the univariate characteristics of the variables under study. Apart from descriptive statistics, the stationarity properties of the data under study are also ascertained by employing Ng and Perron (2001) unit root test. Descriptive statistics and the results of unit root test are presented in Table 1.

<Insert Table 1 here>

From the information on descriptive statistics presented in Table 1, it can be observed that mean value of CO_2 emission is maximum experiencing the highest degree of volatility owing to maximum standard deviation as compared to other variables under study. The Jarque Bera Test reveals the non-normal nature of all the variables under study.

The results of unit root test show that the variables are stationary at first order difference. Therefore, it can be said that the variables under study are integrated to first order, i.e. I (1).[5] Further, the long run relationship between the variables is estimated with the Johansen and Juselius (1990) cointegration test. Results are presented in Table 2, and they show the presence of cointegrating vectors is visible for both the cases of trace and maximum eigenvalue. It denotes the presence of cointegrating association among tourism development, transportation, economic growth, and CO_2 emissions.

<Insert Table 2 here>

5.2. Wavelet Decomposition

From the literature, it can be observed that a very limited number of researchers have worked on analyzing the relationship between the variables under study, within the wavelet framework. The dataset comprising of a number of different variables has several periods, and all are needed to explain the proper time scales in the specific analysis (Gallegati et al. 2011). This necessitates analyzing the relationship between the variables at various time horizons in different time series data sets with time frequency-based methods, generally referred to "Wavelets". The Wavelets method considers nonstationarity as the intrinsic property of data and is not required to be sorted out with pre-processing of the data. The Multiresolution analysis (MRA) of the pattern, J=6 for all the time series data under study, viz. IPI, TOR, CO_2 and TSI employing the MODWT based Daubechies (1992) Least Asymmetric (LA) Wavelet Filter is illustrated in Figure 1(a-d). According to Daubechies (1992), the LA Wavelet Filter is the widely used wavelet, as it provides the most accurate time-alignment between wavelet coefficients at various scales and the original time series, and it is applicable to wide variety of data types. In Figures 1 (a-d), we plot the orthogonal components (D1, D2 …, D6) which details the different frequency components of the original series and a smoothed component (S6). From the figures, we observe high

[5] Hylleberg et al. (1990) seasonal unit root test results (see Appendix 2) show no unit root in various frequencies.

frequencies in the short period of the time series under study, with the variations becoming stable in the longer periods.

<Insert Figure 1 here>

After decomposing the wavelet time series data of the variables under study, we examine the association between the variables, by employing MODWT based wavelet covariance analysis, which analyses the covariance between two variables in a particular timescale. Apart from Wavelet Covariance Analysis, we also employ Wavelet Correlation Analysis to analyze the correlation between the variables under study. Figure 2 illustrates the outcome of the Wavelet Covariance and Correlation between Industrial Production Index, Tourism, Transportation Index and CO_2 emission in the United States. From Figure 2, we can observe positive covariance and correlation between Industrial Production Index and Tourism development in the United States in very short, short, medium and long run. Similarly, there exists a positive covariance and correlation between Industrial Production Index and Transportation Index and CO_2 emission. The tourism development also has a positive influence on Transportation level in the United States as observed from the Wavelet Correlation and Covariance Analysis. However, Tourism development is not having a significant influence on CO_2 emission. In short and medium run, there exists a negative correlation between Tourism Development and CO_2 emission. In a medium, long and very long run, there does not exist any covariance between Tourism Development and CO_2 emission in the United States. There exist a positive correlation and covariance between CO_2 emission and Transportation Index in the United States as observed from Wavelet Correlation and Covariance analysis between the variables under study.

The present paper further employs Continuous Wavelet Analysis on the relationship between the variables under study to evaluate the findings of MODWT based approach. The Continuous Wavelet Power Spectrum of all the time series under study is presented in Figure 3. The Continuous Wavelet Power Spectrum illustrates the movement of the series in a threedimension contour plot i.e. time, frequency and color code. From Figure 3, we can very well witness the different characteristics of IPI, TOR, CO_2, and TSI in different time-frequency domains. The figure indicates that for tourism, there exists a stable variance in a long and very long run as compared short and medium run. In case of CO_2 emission, the variances remain stable for medium, long and very long run. There exists a strong variance in short and medium and run for tourism and short run for CO_2 emission. The variances remain strong in short and very long run but remain stable in a medium run for Industrial Production Index. However, for the Transportation Index, the variances remain strong enough across all time periods.

<Insert Figure 2 here>

<Insert Figure 3 here>

5.3. Wavelets Coherence Transform (WTC)

The outcome of the Wavelet Coherence Transform illustrating the sectors where the two-time series exhibit co-movement in time and frequency domain is presented in Figure 4. The WTC for IPI-TOR (Figure 4a) shows that in the period 1-4 and 4-8 months' cycle during the year 2000 to the year 2012, the arrows are either right side up or left side down, indicating that IPI and TOR are in phase presenting the cyclic effect with TOR leading. However, during the year 2013 and 2014, the arrows are in anti-phase. Similarly, during the medium period cycle of 8 to 16 months also, we find TOR leading during the years of 2005, 2006 and 2010.

<Insert Figure 4 here>

However, in 2014 and 2015, we observe IPI leading. In the long period of 16-32 months' cycle, TOR leads from the year 2004 to 2007. From the year 2008 to the year 2012, the arrows point towards the right direction showing the time series data in phase. In the very long period of 32-64 months' cycle also, the give time series data are in phase. The outcome of WTC for IPI with CO2 emission (Figure 4b) show that during the year 2013 and 2014, with arrows right side up, CO_2 emission leads in 1-4 months' cycle. A similar scenario is also observed during the months of 2001, 2002 2003 and 2004. In the short period of 4 to 8 months' cycle, IPI lags during the months of the year 2004. In the long period and very long period of 16 to 32 months' and 32 to 64 months' cycle, the time series data remain in phase and IPI leading. Also during the very long period, CO_2 emission leads suggesting that in the case of IPI-CO_2 emission, both the variables are leading each other. In many instances during the long and very long period, we find strong co-movement between the variables.

For WTC results of IPI-TSI (Figure 4c), we observe both the variables i.e. IPI and TSI leading each other in the very short period of 0 to 4 months' cycle. Similarly, in the short period and medium period also, both the variables are leading each other. During the long and very long period, we do find strong co-movement between IPI-TSI variables. In the case of TOR-CO_2 emission (Figure 4d), TOR leads during 0 to 4 months' cycle during whole time span under study. On the contrary, the CO_2 emission is observed to be leading in the medium period of 8 to 16 months' cycle. In the months of the year 2008, 2009, 2010 and 2012, the TOR is observed to be leading and CO_2 emission lagging in the long period of 16 to 32 months' cycle. In the long run period, with the arrows pointing towards the right, the variables are observed in phase with strong co-movement among the variables.

For TOR-TSI, we observe both TOR and TSI (Figure 4e), leading each other, in the very short period of 1-4 months. In the short period, during the months of the year 2004, we observe TOR leading and TSI lagging. In the long and very long run period, the variables exhibit strong co-movements among them. A similar situation is also observed in WTC for CO_2 emission and TSI during the very long period (Figure 4f). In the long period, the CO_2 emission is observed to be leading and TSI lagging. No significant relationship is observed among the variables during the medium period. In the short and very short period of 1-4 months' cycle and 4-8 months' cycle, we observe CO_2 emission and TSI leading other.

5.4. Partial and Multiple Wavelet Coherence

The outcome of Partial and Multiple Wavelet Coherence explaining the coherence plots between IPI, TOR, CO_2, and TSI in the United States presented in Figure 5. The results of Partial Wavelet Coherence (PWC) is presented on the left-hand side, whereas that of Multiple Wavelet Coherence (MWC) in Right Hand Side. Figure (5a) presents the partial wavelet coherence among CO_2 emission and Industrial Production Index (IPI) after canceling out the Tourism (TOR). The correlation is observed to be weak with very few numbers of small red color significant islands identified across the different horizons. We observe one small island in a very short period of 0 to 4 months' cycle in between 2008 and 2012 and one during the months of 2015 and 2016. One small red color significant island is observed in the short period of 4-8 months' cycle during 2015. Similarly, very few significant islands are observed in medium, the long and very long horizon of 8-16 months' cycle, 16-32 months' cycle and 32 to 64 months' cycle respectively during the respective months of 2007-2008, 2013-2014 and 2005-2006. When TOR is considered in the relationship between CO_2 emission and IPI, a strong co-movement among the variables is observed in 1-4 months' cycle and 4-8 months' cycle with a remarkable number of the red color significant island across different time horizons from 2004 to 2016. The correlation ranges from 0.8 to 1. In the medium run, on the island for a whole 8 - 16 months' cycle stretching from 2004 to 2015 with correlation range 0.9 to 1 is observed. For the long and very long period, one red color significant island of correlation ranges 0.7 to 0.9 stretch from, the year 2005 to the year 2013. From figure 5(a) and 5(b) illustrating the PWC and MWC between, CO_2, IPI, and TOR, we can observe the robust effect of Tourism in examining the relationship between CO_2 emission, Industrial Production Index, and Tourism.

Figure 5(c) illustrates the Partial Wavelet Coherence between CO_2 emission and TOR after canceling out the Transportation Index (TSI). In the frequency bands of 1-4 months' cycle and 4-8 months' cycle, we observe significant red color islands with correlation ranging from 0.8 to 0.9 during the sub-period ranging from 2004 to 2007, 2008 to 2010 and 2012. In the medium frequency band of 8-16 months' cycle, we observe one significant red color island as a whole stretching from 2004 to 2016. The correlation at this medium period ranges from 0.8 to 1. In MWC, when we consider TSI in examining the relationship between CO_2 and TOR, along with low and medium frequency band, we observe significant red color island in a high-frequency band covering a long period of 16 – 32 months' cycle and very long period of 32-64 months' cycle. In very short, short and medium period, the correlation ranges from 0.8 to 1. However, in the long and very long period, the correlation ranges from 0.7 to 0.9.

<Insert Figure 5 here>

The Partial Wavelet Coherence between CO_2 and TSI on canceling out IPI is shown in Figure 5(e). From the given PWC, we observe three significant red color islands depicting the strong co-movement in the frequency band of the very short period 1-4 months' cycle during 2004, 2009 and 2015. Here the correlation ranges from 0.9 to 1. In a short period of 4-8 months' cycle, we observe islands during the sub-period of 2004 and 2010. However, the correlation with a range between 0.6 and 0.7 is not much significant. On considering IPI, in explaining the relationship between CO_2 and TSI (Figure 5f), we observe significant red color islands in the frequency band of very short period 1-4 months' cycle during the sub-period of 2003 to 2004, 2005, 2008, 2010 to 2012, and 2015 to 2016. Here the correlation ranges from 0.9 to 1. In a short period of 4-8 months' cycle, few islands could be observed, but the correlation ranges from 0.6 to 0.8. In the frequency band of medium period 8 to 16 months, one island is observed in the sub-period of 2009. Here the correlation is about 0.6. In the long and very long period of 16-32 months' cycle and 32-64 months' cycle respectively, we observe one red color significant island stretching from the sub-period 2004 to 2012 with the correlation ranging from 0.8 to 1.

Figure 5g and figure 5k depicts the partial wavelet coherence between IPI and CO_2 emission and IPI and TOR respectively, canceling out TSI from both. In IPI-CO_2 relation we observe small significant red color island depicting strong correlation during sub-period of 2005, 2008, 2010 and 2015. In the frequency band of 4-8 months' cycle, we observe one significant island with a correlation of about 0.7 during the sub-period of 2006. In the PWC of IPI and TOR, we observe three significant red color islands formed during the sub-period of 2004-2005 in the frequency band of 1-4 months' cycle. Here the correlation ranges between 0.8 to 1. One small island is formed in the frequency band of 16-32 months' cycle with the correlation range between 0.7-0.9. When we consider TSI, the scenario in the relationship between IPI and CO_2 emission and IPI and TOR (Figure 5h and Figure 5l) becomes different. We detect a strong co-movement in the short, medium and long run of IPI-CO_2-TSI and IPI-TOR-TSI. In figure 5h we observe significant red color islands formed in 2003, 2004, between 2008 and 2011, 2012, and between 2014 and 2016. The correlation ranges from 0.8 to 1. In the frequency band of 4-8 months' cycle islands with correlation range from 0.7 to 0.8 are formed between 2008 and 2008 and during 2009. In the frequency band of 8-16 months' cycle, one island of correlation of about 0.8 is formed in 2004. Apart from them, a single island covering the frequency bands of 8-16 months', 16-32 months' and 32-64 months' cycle is formed which spans from the period 2004 to 2016. Here the correlation ranges from 0.7 to 1. The similar scenario is also observed in figure 5l. The presence of islands formed in frequency bands of 1-4 months' cycle between 2004 to 2012 in MWC for IPI-TOR-TSI we strong co-movements between the time series. In 4-8months' cycle islands with correlation range between 0.7 to 0.9 suggest co-movements between the variables during 2003, between 2004 and 2008 and between 2015 and 2016. A single island with correlation range between 0.9 and 1 covering all the sub-periods stretches from frequency band 8-16 months' cycle to 32-64 months' cycle.

The PWC depicting the relationship between IPI and TOR, TOR and TSI, and TSI and IPI on canceling the CO2 emission is illustrated in figure 5i, figure 5o and figure 5u. In PWC between IPI and TOR, as observed in figure 5i, the co-movement between the variables exist with the formation of islands in the frequency band of 4-8 months' cycle between 2004 and 2008 and 2012 and 2016. Here the correlation is within the range of 0.7 to 0.9. A very small island bearing the correlation of about 0.7 is formed in the frequency band of 8 to 16 months' cycle and 16 to 32 months' cycle during 2004. Apart from that formation of the single significant red color island of correlation between 0.9 and 1 in the frequency band of 16-32 months' cycle indicates strong co-movement in the long period between 2008-2012. A similar scenario is also observed in the PWC between TOR and TSI (figure 5o). Here few significant red color islands in the frequency bands of 4-8 months' and 8-16 months' of correlation of about 0.8 indicate strong movement between the variables between 2004 and 2008. In the frequency band of 32-64 months' cycle, the red color significant island of correlation about 0.9 is formed between 2012-2016 showing the co-movement between the variables. In case of PWC between TSI and IPI (figure 5u), strong co-movement between the variables is observed with the formation of significant red color islands bearing correlation in the range of 0.8 to 1 in the frequency bands of 1-4 months' cycle, 4-8 months' cycle and 8-16 months' cycle between 2012-2016. Strong co-movements between the variables also exist between the sub-period 2004 and 2012 in the frequency band of 16-32 months' cycle and 32-64 months' cycle due to presence island bearing the correlation of the range 0.9 to 1. When CO2 emission is considered in analyzing the relationship between IPI-TOR-CO2, TOR-TSI-CO2 and TSI-IPI-CO2, the scenario is significantly different. In case of IPI-TOR-CO2 (figure 5j), due to the formation of significant red color islands in the very short and short period of 1-4 months' cycle and 4-8 months' cycle respectively, the significant co-movement among the variables is observed between the sub-period 2004-2008 and 2012-2016. Here the correlation ranges between 0.8 and 1. In between the sub-period 2004 and 2005, two islands bearing the correlation of range 0.7 to 0.9 are formed in the frequency band of 16-32 months' cycle. In the frequency bands of 16-32 months' cycle and 32-64 months' cycle, two significant red color islands are formed of correlation ranging between 0.9-1 indicating significant co-movement between the variables in the sub-period between 2004 and 2012. Similarly, when CO_2 emission is considered in analyzing the relation between TOR and TSI (Figure 5p), with the formation of islands between 2003 and 2015, a strong correlation between the variables exist in the frequency band of 1-4 and 4-8 months' cycle. Here the correlation is between 0.9 and 1. Similarly, strong correlation of range 0.8-1 exists between the time range between 2003 and 2013, in frequency bands of 8-16 months' cycle, 16-32 months' cycle, and 32-64 months' cycle. In the case of MWC between TSI-IPI-CO_2 (Figure 5v), strong correlation ranging between 0.9-1 exist across time horizon in all the frequency bands.

Figure 5m and figure 5q analyses the PWC between TOR and CO_2, and TOR and TSI on canceling the influence of IPI on it. In the PWC analysis of TOR-CO_2 as observed in figure 5m strong correlation of range 0.9-1, exist between the variables in the short period of 1-4 months' cycle with the presence of islands in the time period between 2004 and 2006, 2008, 2012 and 2015. In the frequency band of 4-8 months' cycle islands of correlation, range 0.8-1 are formed during 2004, 2007 and 2012. In the frequency band of 8-16 months' cycle and the single island is formed of correlation range 0.9-1 across the time horizon of 2004 to 2016. However, when we consider the influence of IPI and analyze the relation between TOR-CO_2-IPI, we find a strong correlation among the variables across the time period in all the frequency bands. In the case of PWC between TOR-TSI, we find a strong correlation between the variables, with only three small islands formed during 2005, 2009 and 2015 in the frequency band of 1-4 months' cycle. In the frequency band of 4-8 months' cycle, we observe only two small islands of correlation range 0.9-1 formed between 2003 and 2005. When we consider the influence of IPI and analyze the relation between TOR-TSI-IPI (figure 5r), we observe the formation of islands of correlation range 0.8-1 between 2003 and 2005, 2008 and between 2010 and 2012 in the short period of 1-4 months' cycle. We observe very few significant islands formed in the frequency band of 4-8 months' cycle formed during 2004 and 2008. However, in the frequency band stretching between

16-32 months' cycle and 32-64 months' cycle we observe a significant island of correlation range 0.9-1 formed across the time period 2004-2012.

Figure 5s and figure 5w analyze the PWC between TSI-CO_2 and TSI-IPI respectively on canceling the influence of TOR. In the PWC of TSI-CO_2 (figure 5s) we observe only one island of strong correlation formed in the frequency band of 1-4 months' cycle in the sub-period between 2008 and 2012. Similarly, in the frequency bands of 8-16 months' cycle, 16-32 months' cycle and 32-64 months' cycle only one island of correlation range 0.9-1 is formed between 2004 and 2006. When we consider the influence of TOR in analyzing the TSI-CO_2-TOR relation (figure 5t), we observe few islands of correlation range 0.8-1 formed between 2004-2006, 2008-2012 and 2012-2015 in the very short period of 1-4 months' cycle. In the frequency band of 4-8 months' cycle and 8-16 months' cycle, we find few small significant red color islands formed between 2004 and 2008. However, in the frequency band stretching from 16-32 months' cycle and 32-64 months' cycle, we find a single significant red color island formed across the time period 2004-2012. Here the correlation ranges between 0.8-1. The presence of this single island indicates the existence of strong co-movement between the variables in the long and very long period. Figure 5w illustrates the PWC between TSI-IPI on canceling the effect of TOR. In the figure 5w, we observe significant red color islands of correlation 0.9-1, formed between 2012-2016 in the frequency band of 1-4 months' cycle. In the frequency band of 8-16 months', 16-32 months, and 32-64 months' cycle we observe a strong correlation among the variables between the time period 2006-2012. When we consider the influence of TOR in analyzing TSI-IPI-TOR relation (Figure 5x), we observe with the presence of small islands formed in the frequency band of 1-4 months' cycle between the period 2001-2004 and 2015 indicating the correlation of range 0.8-1. In the frequency band of 4-8 months' cycle, we few islands formed between the period 2004-2006, 2008-2010 and 2013-2016. Here the correlation ranges between 0.8-1. In the frequency band stretching from 16-32 months' cycle to 32-64 months', the cycle we observe a single significant red color island formed across 2004-2012. Here the correlation range is 0.9-1. This indicates the presence of intense co-movement between the variables in the long and very long period.

As a final step of the analysis, following Lehkonen and Heimonen (2014), Mensi et al. (2016) and Gupta et al. (2018), we have conducted the Granger causality tests on the original and wavelet-decomposed data. The causality test results on the original data show the existence of bidirectional causal association between CO_2 emissions and tourism development. Alongside this, industrial production and transportation service are found to have respective causal impacts on tourism development. However, the results of causality results on frequency-decomposed data reveal the existence of the bidirectional casual associations between CO_2 emissions and tourism development, industrial production and tourism development, and transportation service and tourism development, respectively. In light of this new evidence, we can conclude that the co-movements among the model parameters discovered through the wavelet coherence analysis are subsequently validated by the results of causality analysis. Therefore, we can infer that in the short run, while having a co-movement among the variables, significant causal association among the variables can also be found.

6. Conclusion and Policy Recommendations

The present paper employs wavelets transform approach to analyze the relation between tourism development, transportation, economic growth, and CO_2 emissions. The approach decomposes the time series into a number of time frequencies and presents the outcomes specific to these frequencies based on very short, short, medium, long and very long run. The study employs MODWT, wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence transform, partial and multiple wavelet coherence, and wavelet-based Granger causality tests to analyze the association between the variables in the USA. The paper uses the monthly data from January 2001 to December 2017.

The wavelet approach employed in the present study explains the way the association between the model variables develops over time and frequencies. The wavelet decomposition analysis indicates the frequency of the variables becoming stable in the long run, whereas wavelet covariance and correlation analysis indicate positive correlation and covariance between them. As revealed by the wavelet coherence transform, wavelet coherence and robust lead-lag relationship exist among the variables. For the temporal domain, we observe a heterogeneous association between the variables. Co-movements of the variables are observed to be unequal across the time periods. Partial and multiple wavelet coherence analysis divulge significant association among the model variables. Moreover, the results of wavelet-based Granger causality analysis divulge bidirectional causal links between CO_2 emissions and tourism development, industrial production and tourism development, and transportation service and tourism development, respectively.

The outcome of the analysis calls for significant policy implications for the sustainable tourism development in the USA. As the ecotourism in the USA is on a rise, the policymakers should invest the revenue generated from tourism in educating the tourists about maintaining the ecological quality, so that ecosystem can remain unharmed. Along with investing for increasing the awareness among the tourists, the policymakers should also preserve the natural resources, while limiting the expansion in the ecotourism activities. Soft ecotourists should be encouraged more over the hard ecotourists, as the engagement of soft ecotourists with the environment is less, and therefore, the possibility and volume of environmentally degrading activities reduce. Rising level of environmental awareness will also make the hard ecotourists inherently comply with the directives for the preservation of ecological quality, and it will eventually help the USA to earn more revenue from ecotourism.

While saying this, it should also be mentioned that the mode of transportation used in the tourism industry needs a thorough reassessment. The mode of transportation used in the tourism sector is not only responsible for the ambient air pollution, but also the shift in ecological balance through displacement of the wildlife. Owing to the negative impact of transportation sector on environmental quality, policymakers need to promote clean energy policies, which might help the US in promoting sustainable tourism. In this pursuit, policymakers may promote hybrid engines, electrical transport or carbon neutral transport solutions for land transport. At the same time, it is also needed to enhance their investment in R&D activities towards development fuel efficient and cleaner technologies especially thriving upon the renewable sources of energy, which will help in reducing pollution in the long-run. Now, shifting the fuel sources from nonrenewable to renewable at one go might harm the economic growth pattern significantly, as well as the growth in tourism sector. Owing to the high implementation cost of renewable energy solutions, the policymakers need to carry out a phase-wise shift of fuel sources. Alternate fuels for transport might be implemented in the places with low tourist penetration to start with, and with graduation of acceptance among the users and communities, implementation might be carried out towards the areas with high tourist penetration. While carrying this out, the policymakers should also think of encouraging the people-public-private partnerships for making the transition smoother. Along with these policies, the policymakers should also need to be careful about the use of transportation in the deeper regions of the forests, as the increased use of transportation by hard ecotourists might create ecological imbalance. Therefore, while carrying out cleaner energy policies, the policymakers should also think about restricting the use of transportation in the deep forest areas.

As future scope of research, the study could also employ daily and weekly data to get a more detailed outcome. Moreover, from the contextual perspective, scope of the study could be further extended to other nations like France, China, Germany, Spain etc. which have not only witnessed huge tourism development but also experienced economic growth.

Appendix

Appendix 1: Results of Seasonal unit root test at level

	3 Months	*6 Months*	*12 Months*
IPI	-2.606[c]	-5.990[a]	-4.637[a]
TOR	-2.795[c]	-6.747[a]	-3.895[a]
CO_2	-3.088[b]	-10.001[a]	-5.453[a]
TSI	-2.179[b]	-5.217[a]	-4.080[a]

a significant value at 1%, b significant value at 5%, c significant value at 10%

Tables

Table 1: Descriptive statistics and Unit root test

	Mean	*Min.*	*Max.*	*Std. Dev.*	*Jarque-Bera statistics*			
IPI	98.285	87.069	106.663	4.860	10.976[a]			
TOR	4.456	2.096	8.365	1.380	10.550[a]			
CO_2	470.196	383.660	557.625	37.925	15.774[a]			
TSI	110.156	93.900	124.800	7.728	18.544[a]			
Results of Unit Root test								
	With Intercept				*With Trend and Intercept*			
	MZa	*MZt*	*MSB*	*MPT*	*MZa*	*MZt*	*MSB*	*MPT*
IPI	-2.0218	-0.8408	0.4159	10.5685	-5.8570	-1.7113	0.2922	15.5584
TOR	-4.6511	-1.5487	0.3479	5.2830	-11.3550	-2.4091	0.2062	7.0556
CO_2	-0.3984	-0.3966	0.9954	50.017	-1.1884	-0.5573	0.4690	46.9662
TSI	0.9199	0.5956	0.6475	32.8792	-6.2513	-1.7311	0.2769	14.5709
ΔIPI	-78.9106[a]	-6.2627[a]	0.0794[a]	0.3500[a]	-83.0250[a]	-6.4174[a]	0.0773[a]	1.2033[a]
ΔTOR	-20.0393[a]	-7.0849[a]	0.0706[a]	0.2441[a]	-30.1461[a]	-7.1220[a]	0.0702[a]	0.9003[a]
ΔCO_2	-67.1622[a]	-5.6385[a]	0.0840[a]	0.7164[a]	-81.6436[a]	-6.3390[a]	0.0776[a]	1.3244[a]
ΔTSI	-93.2216[a]	-6.8260[a]	0.0732[a]	0.2653[a]	-95.6451[a]	-6.9119[a]	0.0723[a]	0.9662[a]

a significant value at 1%

Table 2: Results of cointegration test

Trace (TR) test				*Maximum Eigenvalue (ME) test*			
Null	*Alternate*	*TR Statistic*	*Critical value*	*Null*	*Alternate*	*ME Statistic*	*Critical value*
Without Intercept and Trend							
$r \leq 0$	$r > 0$	45.5771[a]	40.1749	$r \leq 0$	$r > 0$	28.8707[a]	24.1592
$r \leq 1$	$r > 1$	16.7064	24.2760	$r \leq 1$	$r > 1$	10.2825	17.7973
$r \leq 2$	$r > 2$	6.4239	12.3209	$r \leq 2$	$r > 2$	6.0215	11.2248
With Intercept and Trend							
$r \leq 0$	$r > 0$	102.9253[a]	55.2458	$r \leq 0$	$r > 0$	65.6408[a]	30.8151
$r \leq 1$	$r > 1$	37.2845[b]	35.0109	$r \leq 1$	$r > 1$	22.1973	24.2520
$r \leq 2$	$r > 2$	15.0872	18.3977	$r \leq 2$	$r > 2$	10.5906	17.1477

r is the number of cointegrating vectors

a significant value at 1%, b significant value at 5%

Table 3: Results of Wavelet-based Granger Causality tests

Frequency Domains	*Dependent Variables*	*Independent Variables*			
		IPI	TOR	CO_2	TSI
D1	IPI	-	16.9273[b]	1.2567	21.9575[a]
	TOR	31.3103[a]	-	21.0715[a]	19.5302[a]
	CO_2	26.3759[a]	15.8762[a]	-	10.2930[b]
	TSI	7.2386[c]	3.5154[c]	11.8731[b]	-
D2	IPI	-	3.1974[c]	0.3839	7.7511[a]
	TOR	23.8193[a]	-	21.0857[a]	16.2776[a]
	CO_2	17.9916[b]	7.9488[a]	-	15.2727[b]
	TSI	13.1979[a]	2.6391	8.7834[c]	-
D3	IPI	-	15.1958[b]	1.8753	28.4359[a]
	TOR	21.9815[a]	-	24.1255[a]	16.4274[a]
	CO_2	23.5337[a]	215.3583[a]	-	22.7770[a]
	TSI	14.3971[a]	12.8440[b]	13.7680[a]	-
D4	IPI	-	18.8371[b]	5.4995[b]	6.0557[b]
	TOR	16.6077[a]	-	5.9843[b]	21.4189[a]
	CO_2	15.0956[a]	54.0960[a]	-	32.1816[a]
	TSI	4.2164[b]	21.2484[a]	13.5562[a]	-
D5	IPI	-	7.1338[b]	9.2638[a]	18.7076[a]
	TOR	74.6382[a]	-	24.4549[a]	3.7064[c]
	CO_2	12.3198[a]	23.3502[a]	-	25.2039[a]
	TSI	6.3580[b]	27.7620[a]	15.9180[a]	-
D6	IPI	-	16.7368[a]	26.3779[a]	96.5913[a]
	TOR	41.3161[a]	-	6.0611[b]	32.4846[a]
	CO_2	73.6162[a]	52.5378[a]	-	22.7352[a]
	TSI	119.2425[a]	26.4918[a]	13.2017[b]	-
Original	IPI	-	2.2588	0.0837	15.1129[a]
	TOR	24.0120[a]	-	13.1949[a]	20.0705[a]
	CO_2	0.2335	22.0946[a]	-	18.5468[b]
	TSI	9.6929[a]	3.9371	1.8737	-

Note: Asymptotic Chi-square values are reported

a significant value at 1%, b significant value at 5%, c significant at 10%

Figures

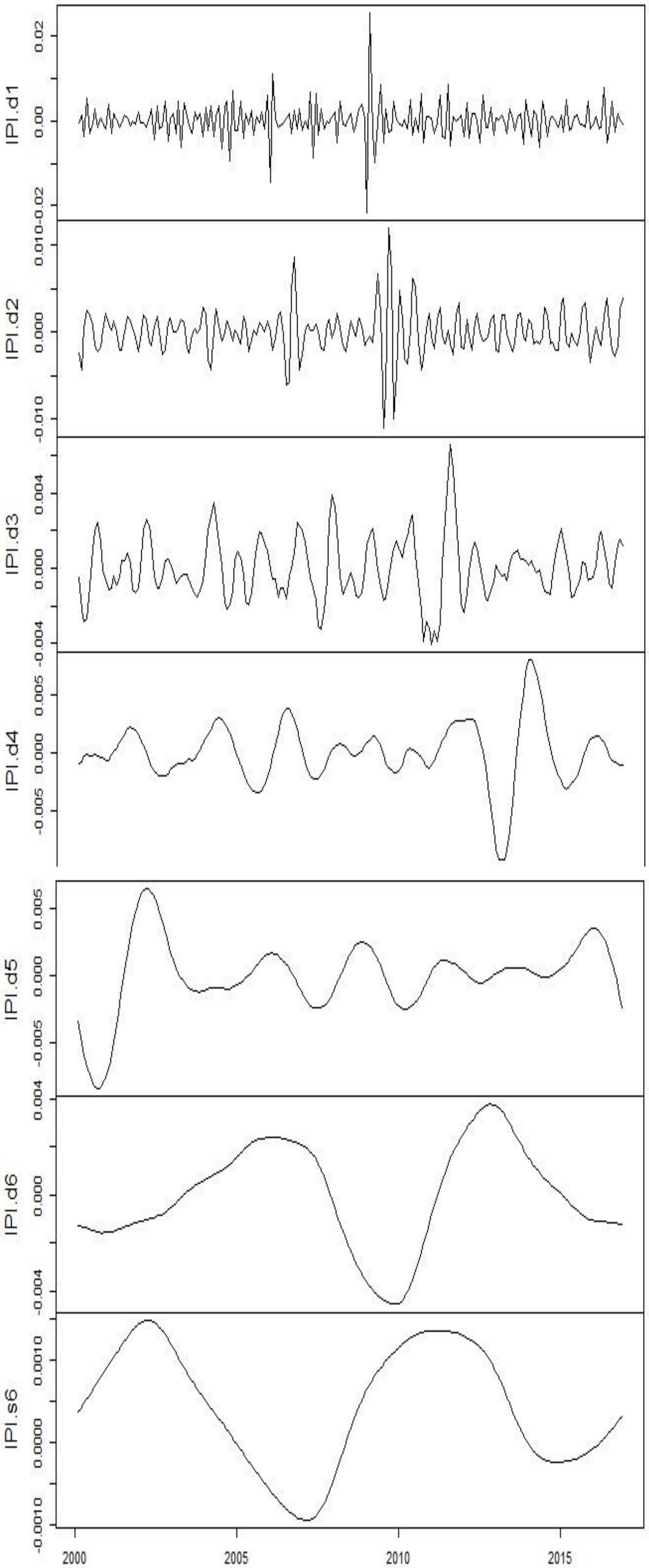


Figure 1(a)

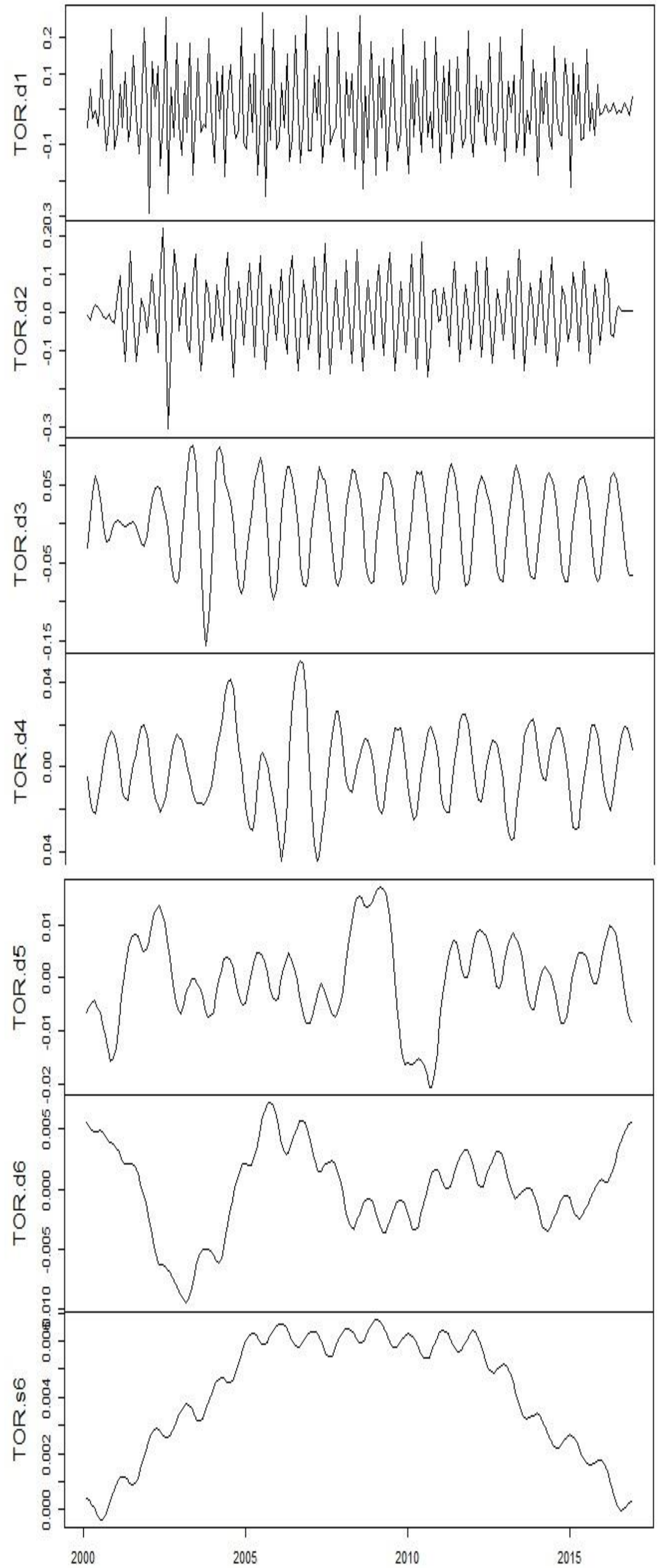


Figure 1(b)

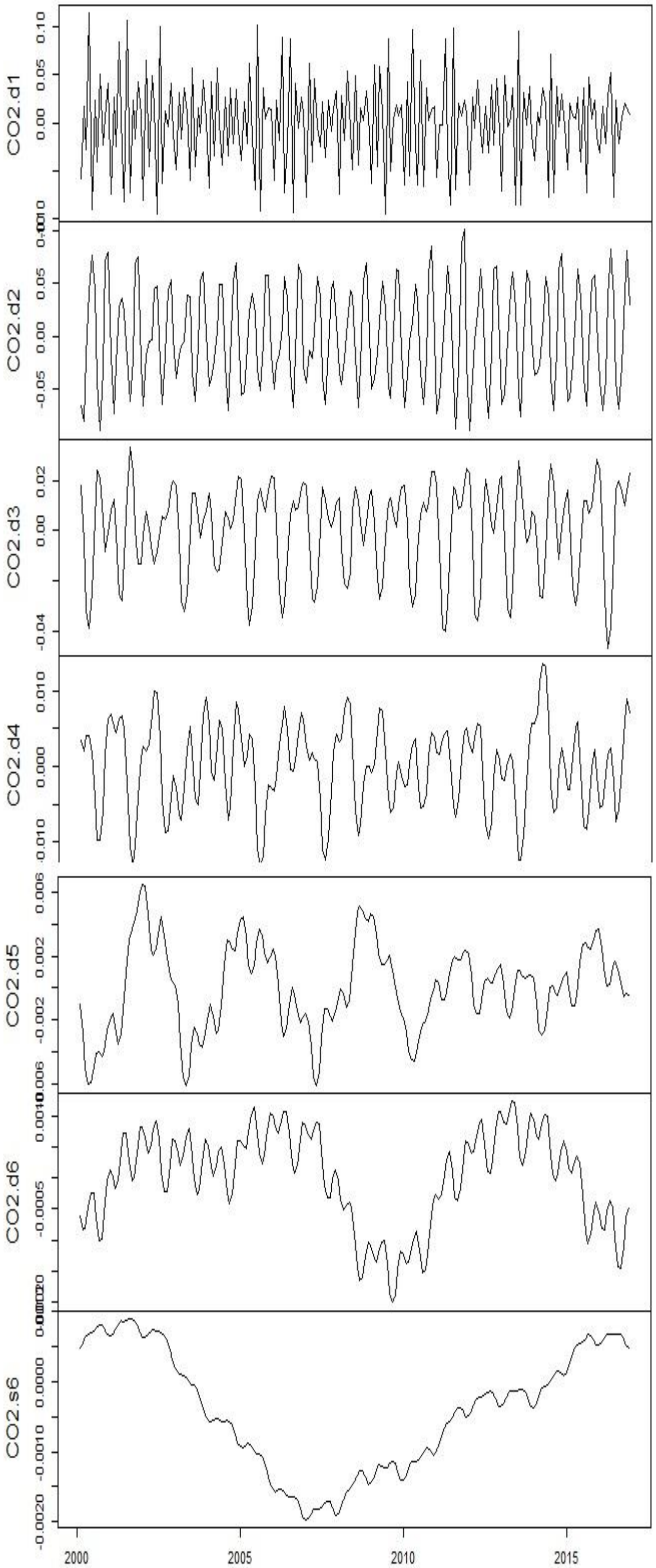


Figure 1 (c)

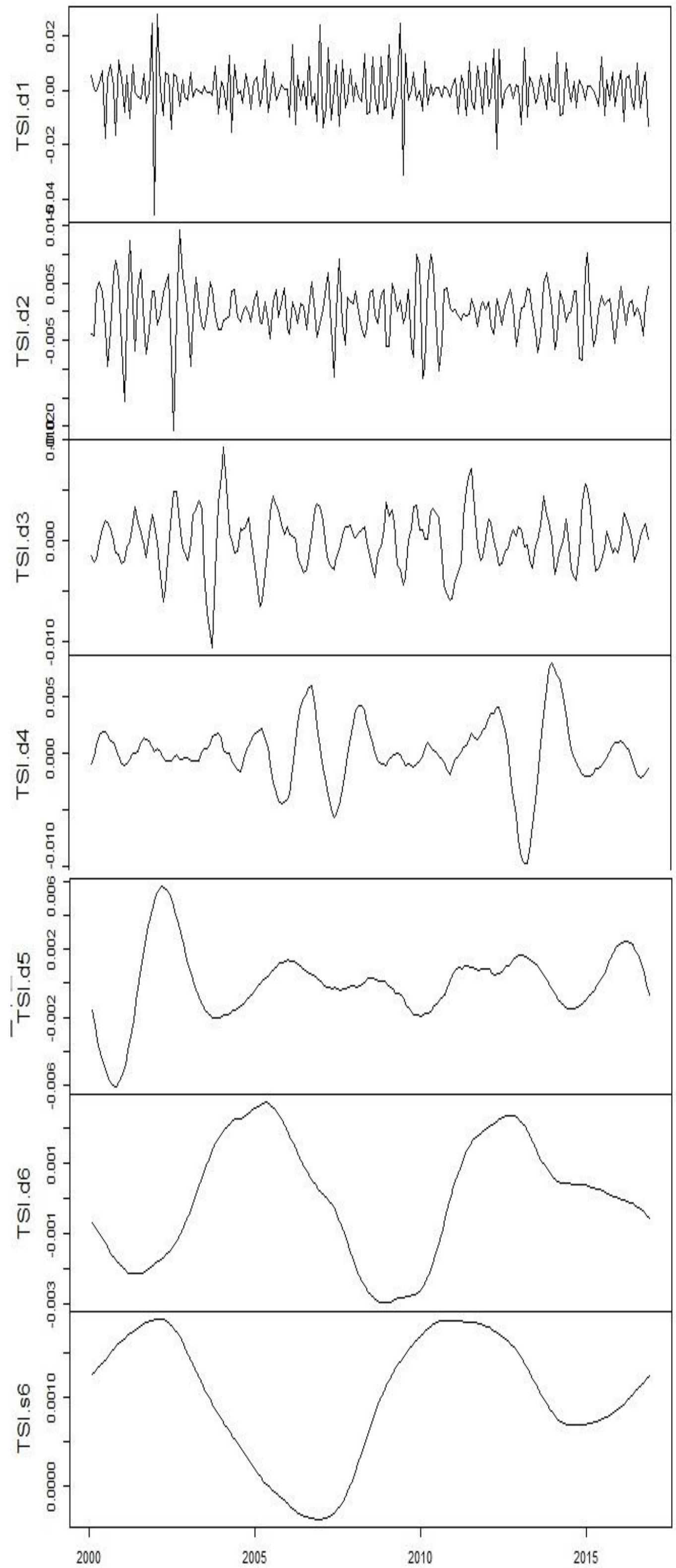
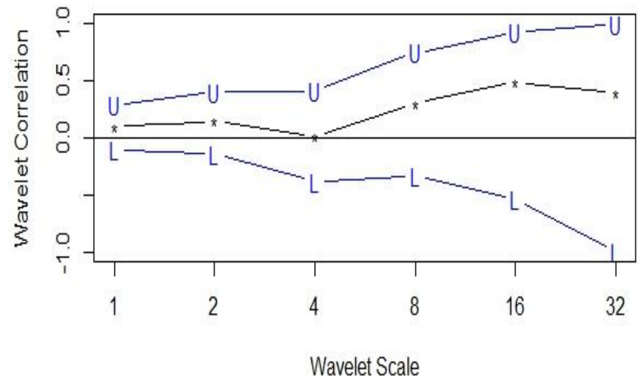


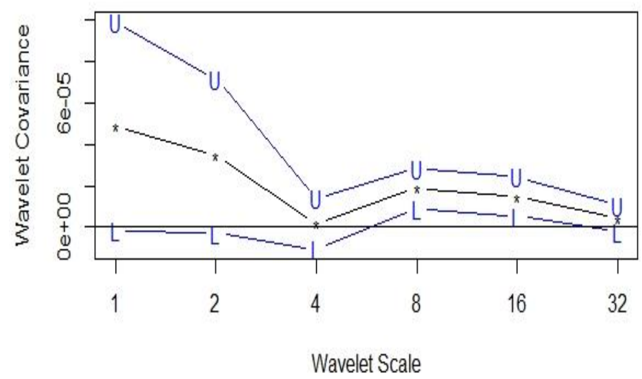
Figure 1(d)

Figure 1: MODWT decomposition of variables on J = 6 Wavelet Levels

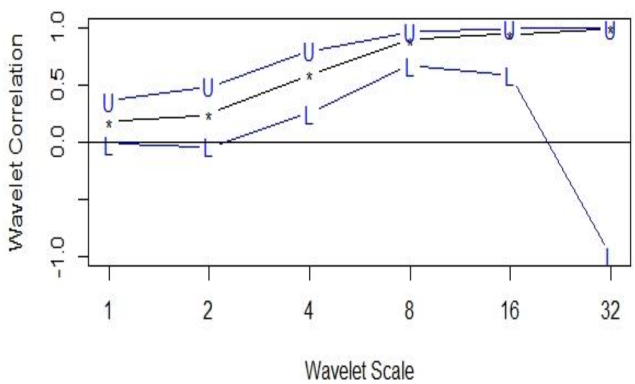
Wavelet Correlation between IPI-TOR



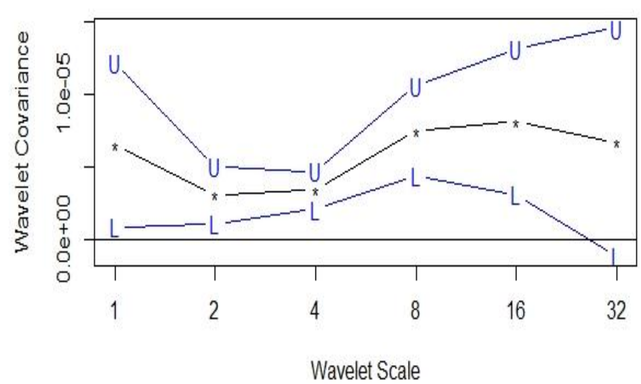
Wavelet Covariance between IPI-TOR



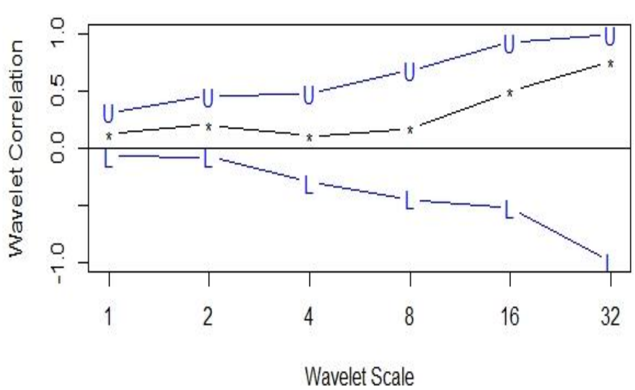
Wavelet Correlation between IPI-TSI



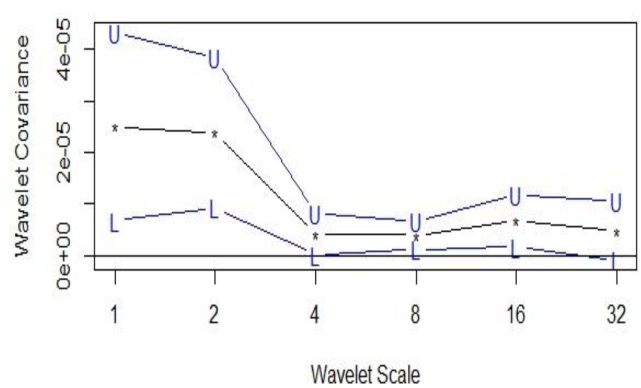
Wavelet Covariance between IPI-TSI



Wavelet Correlation between IPI-CO_2



Wavelet Covariance between IPI-CO_2



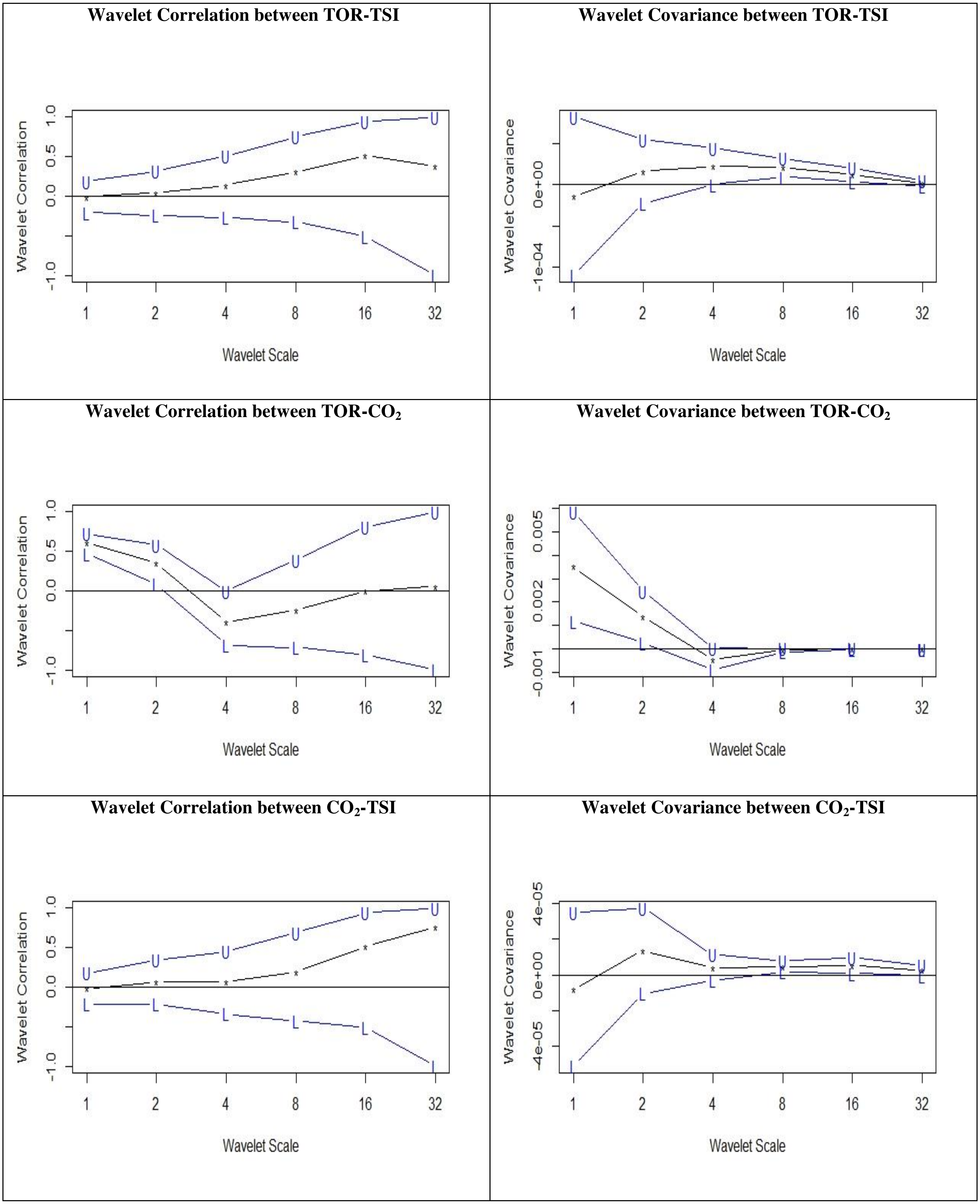


Figure 2: Wavelet Correlation and Covariance Analysis between IPI, TOR, TSI and CO2 emission in the United States

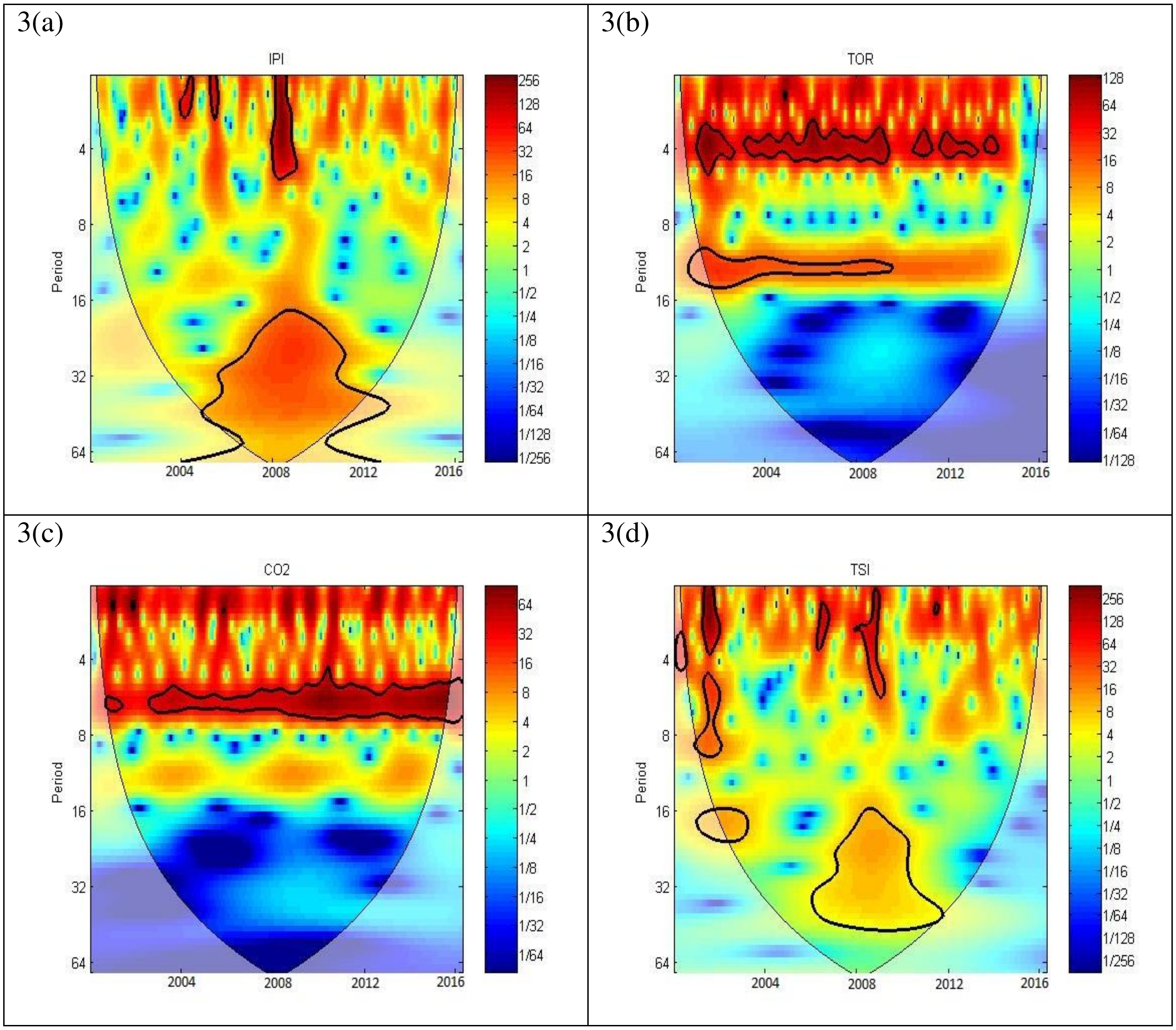


Figure 3: Continuous Wavelet Transform of IPI, TOR, CO_2 & TSI

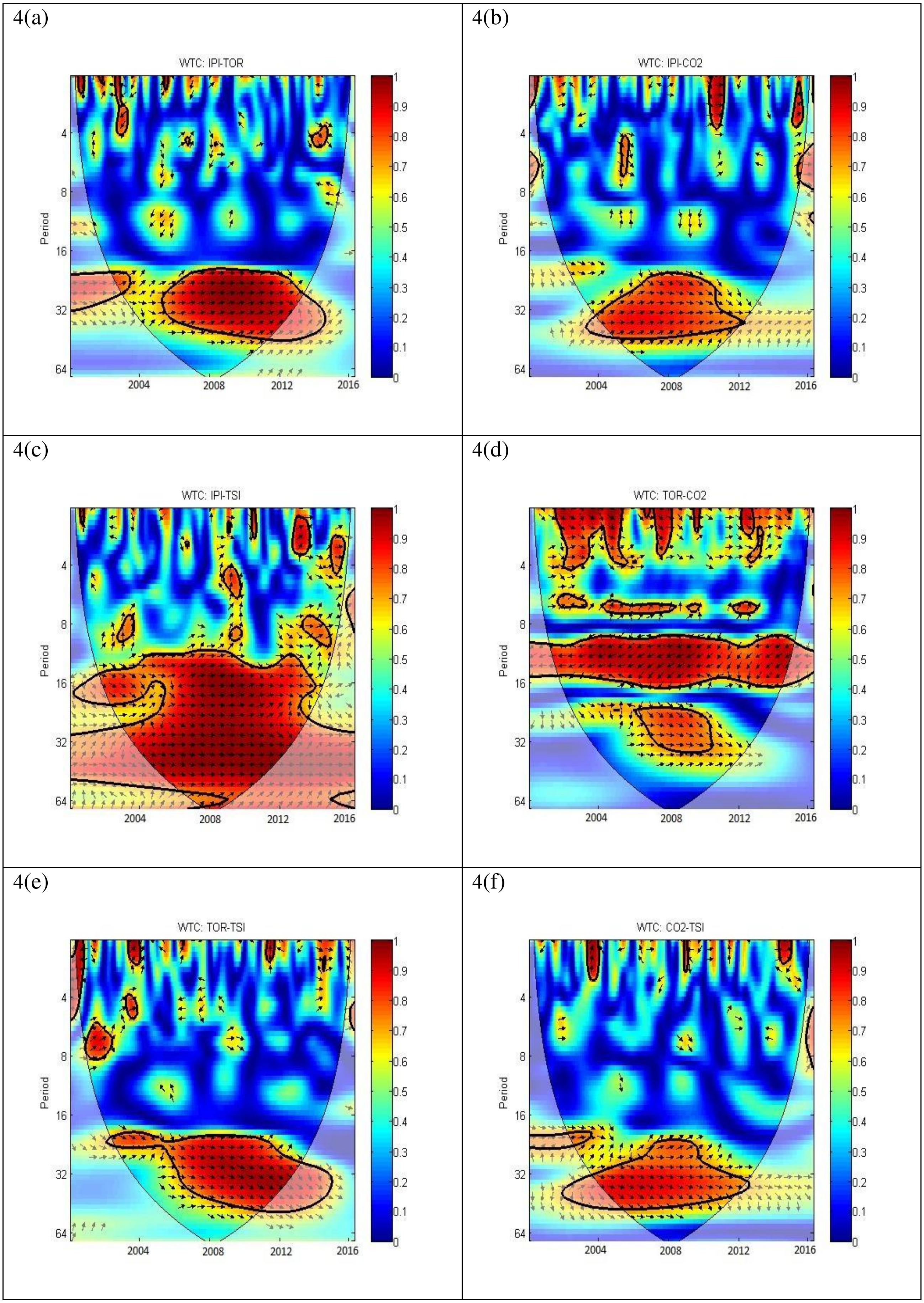
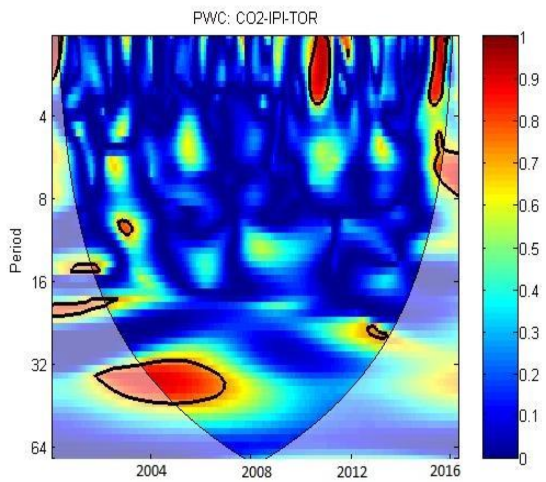
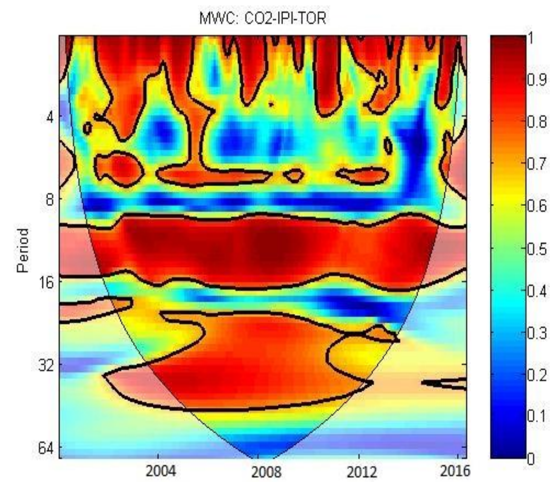


Figure 4: Wavelet Coherence of IPI, TOR, CO2 & TSI

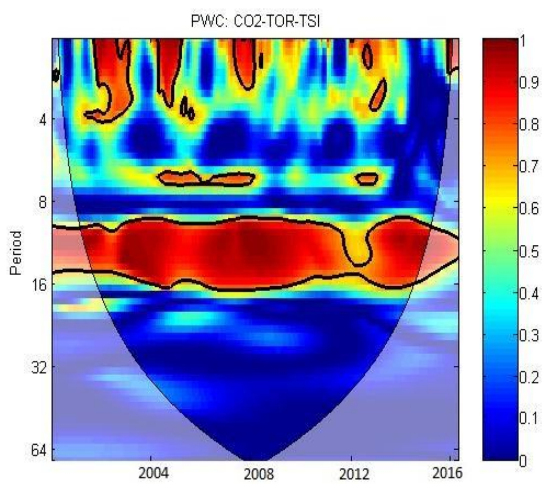
5(a)



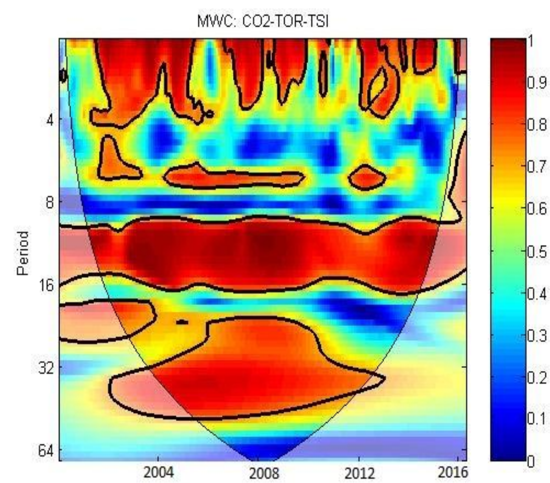
5(b)



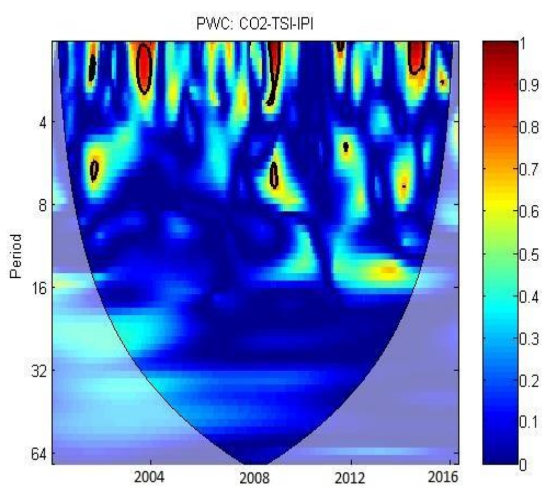
5(c)



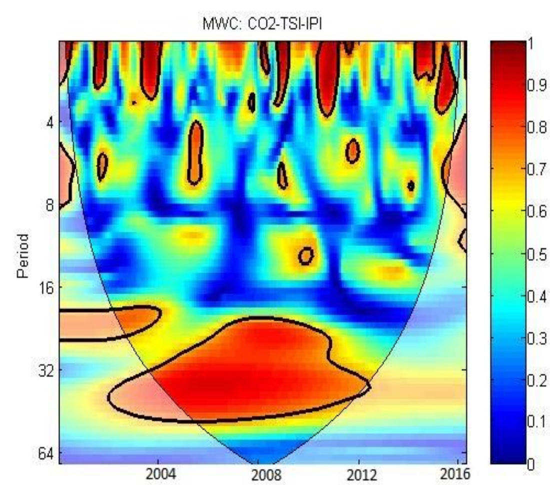
5(d)



5(e)



5(f)



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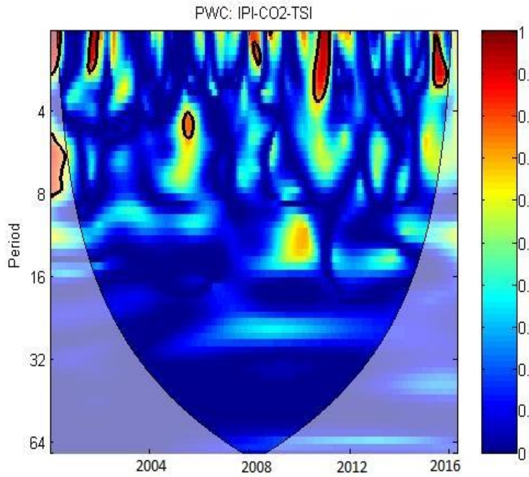

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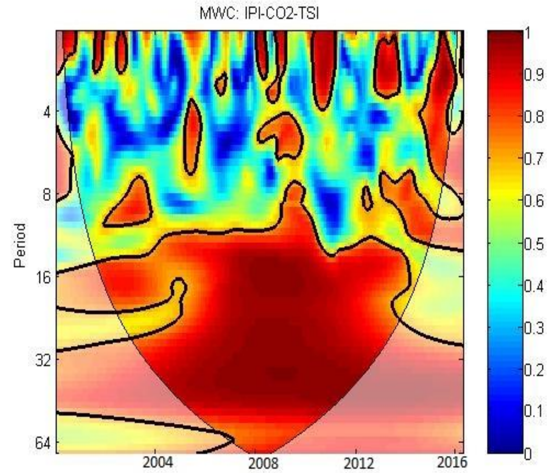

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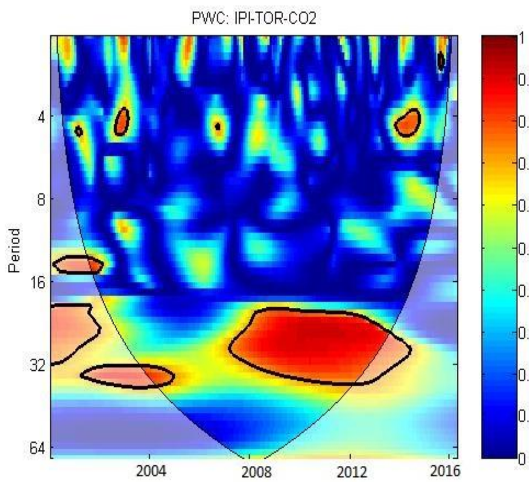

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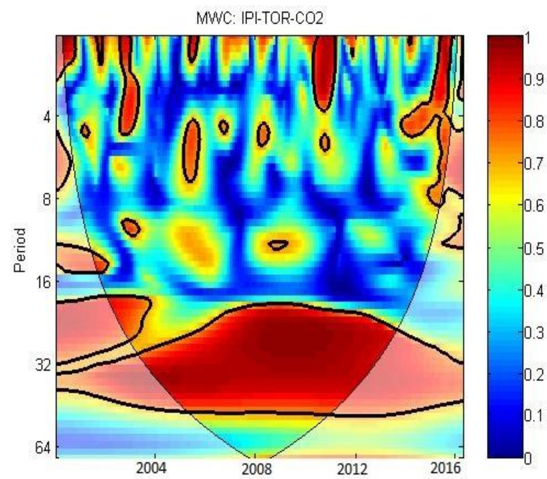

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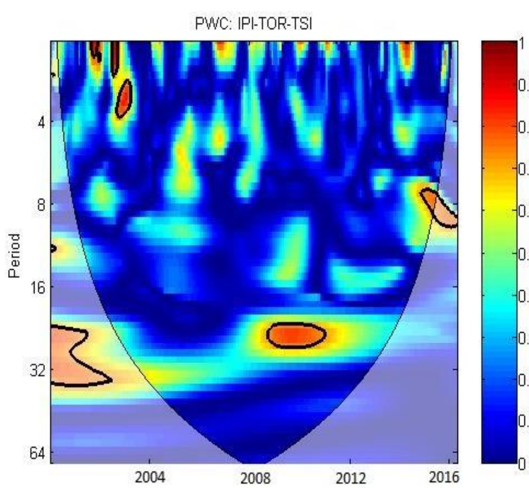

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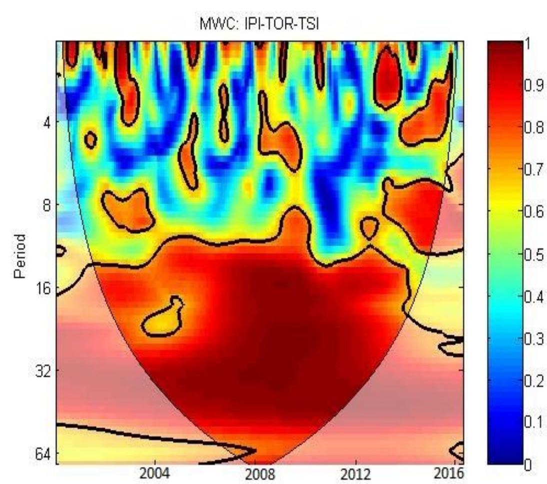

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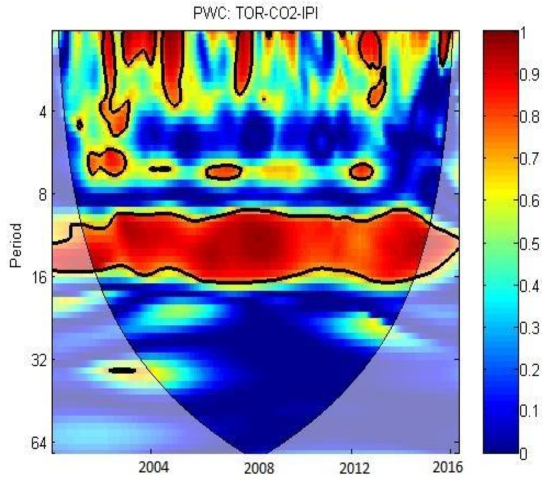

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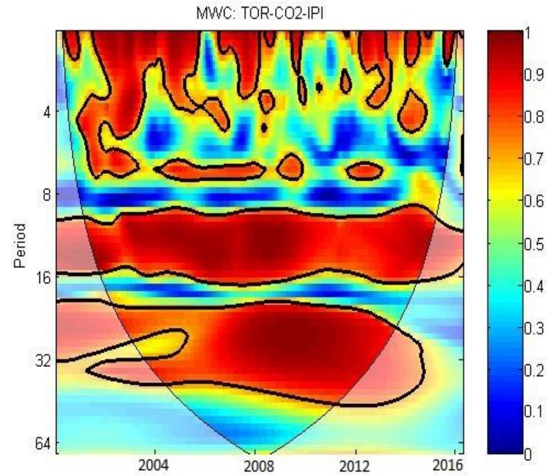

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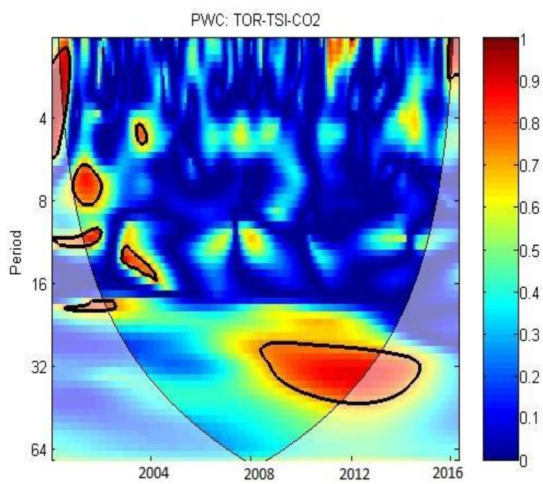

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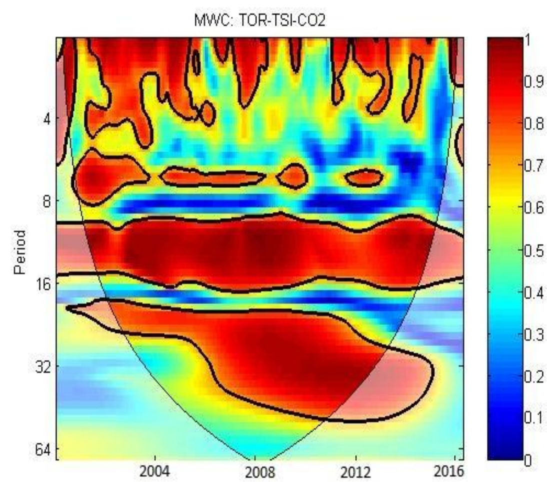

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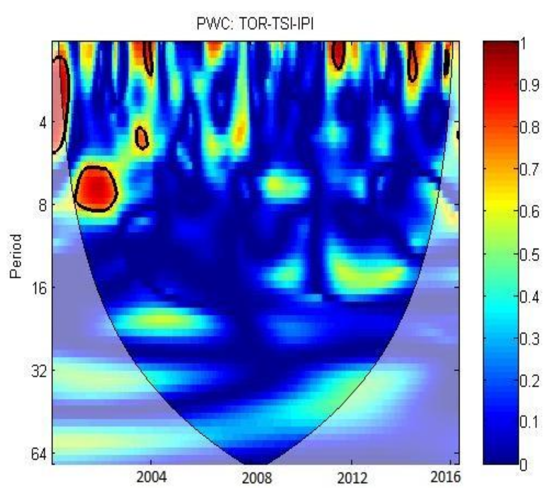

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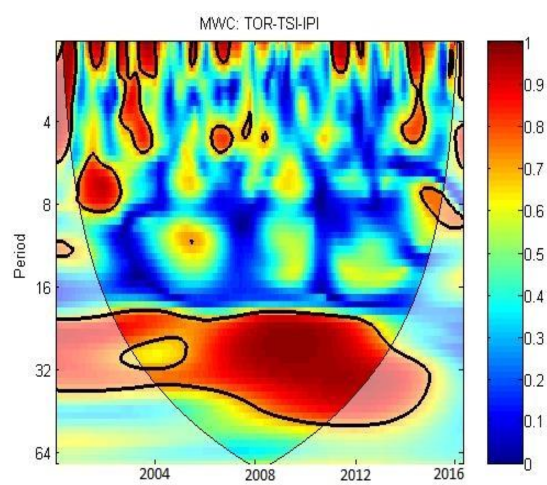

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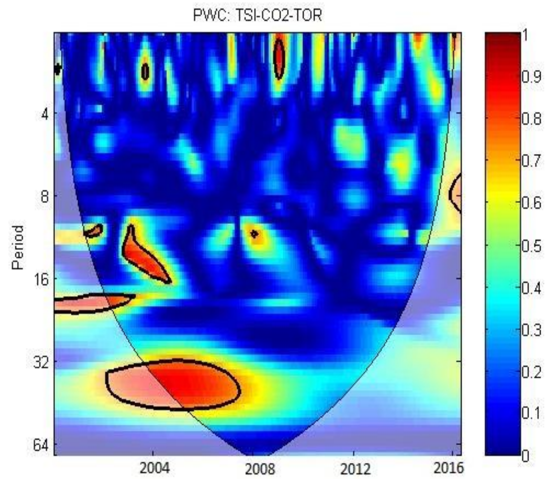

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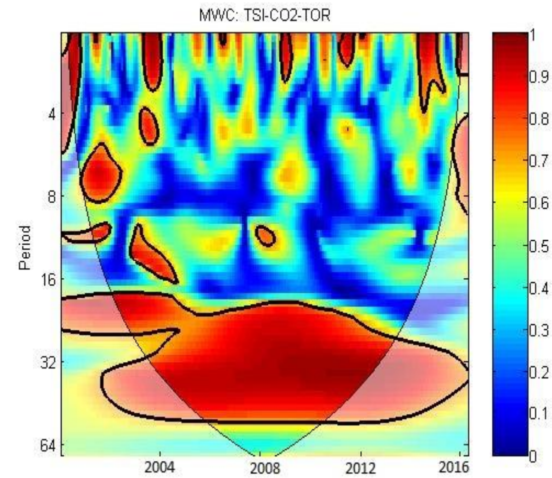

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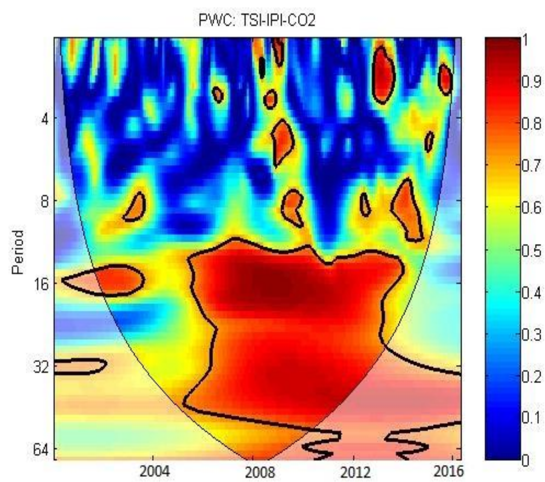

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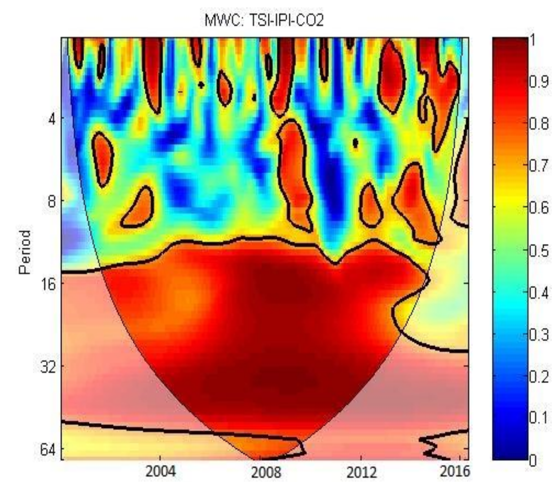

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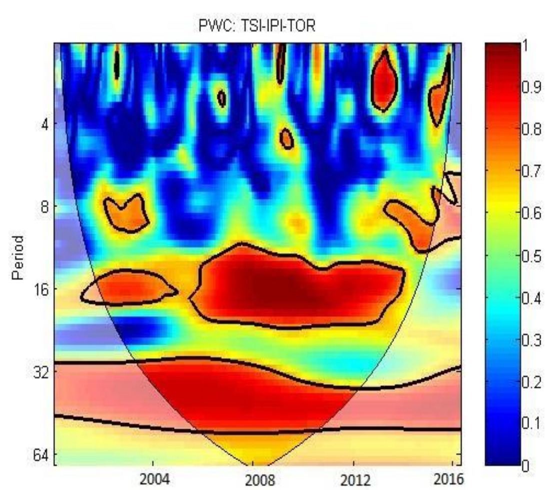

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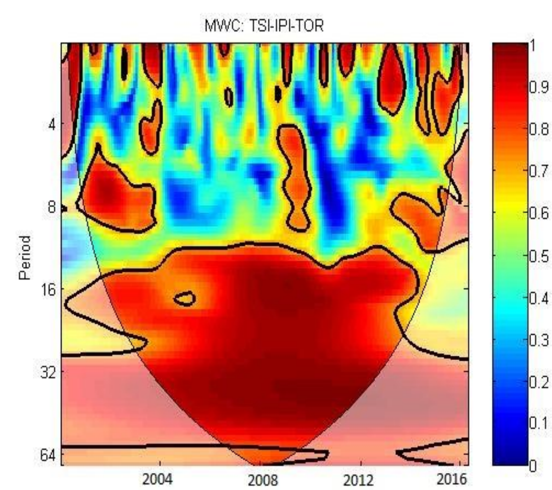

Figure 5: Partial and Multiple Wavelet Coherence of IPI, TOR, ENG and CO_2

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