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Environment-Related Technological Innovation and Ecological Footprint in India: Aggregate and Component-Wise Time–Frequency Analysis

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ABSTRACT

This study investigates the time-frequency dynamics between environment-related technological innovation and environmental quality using the ecological footprint as a comprehensive measure of environmental quality and its components for India. To capture time-varying and frequency-dependent relationships, the study adopts a wavelet coherence framework, which allows simultaneous analysis of short-, medium-, and long-run dynamics between environment-related technological innovation and environmental quality for the period between 1990Q1 to 2022Q4. The results indicate that the relationship between environment-related technological innovation and environmental quality is strongly time-varying and scale-dependent. In the aggregate ecological footprint, the significant coherence is concentrated on the short and medium horizons, while the long-run interactions are weak and non-persistent. The phase dynamics show that the rise in ecological footprint precedes the adoption of environment-related technological innovation. In components analysis, it shows a strong short-term coherence between technological innovation in the environmental field and single parts of the ecological footprint. At the same time, the medium-run effects are intermittent, and the long-run relationships are mostly insignificant or driven by boundary effects. The results suggest that the environmental benefits from environment-related technological innovation are gradual and uneven in ecological dimensions. Therefore, policymakers should complement technology-promotion strategies with regulatory and demand-side measures to avoid overreliance on long-term technological solutions and to better address short-term ecological footprint.

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Research Highlights

- It examines the relationship between environment-related technological innovation and ecological footprint components.
- Applies wavelet coherence to 1990Q1–2022Q4 data for India.
- Identifies strong, time-varying short- and medium-term coherence.
- Reveals heterogeneous relationships across ecological footprint components.
- Supports integrated technology, regulatory, and demand-side policies.

1. Introduction

Technological advancement is recognised as one of the important means of promoting more responsible consumption and production [1]. In terms of environment, technological innovation can facilitate the transition towards cleaner production processes, improved resource efficiency, and reduced pollution [2, 3]. However, maintaining environmental quality while sustaining economic growth remains a major global challenge, which requires a better understanding of the environmental consequences of technological progress [2].

Although some of the technological innovations aim to reduce emissions and resource intensity, others may indirectly intensify environmental degradation through rebound effects, increased consumption, or shifts in production patterns [4]. Moreover, the overall technology is considered in most of the existing studies [5, 6], while leaving the precise measurement of environmentally specific innovation. Environment-related technological innovation generally refers to technological developments toward reducing ecological footprint, improving resource efficiency, and mitigating pollution [7]. In empirical research, such innovation measures using environment-related patent indicators and established classifications of environmental technologies [8–11]. Hence, it argued that environmental-related technologies should be preferred while assessing the environmental sustainability of technology [1].

Environmental technological innovation is increasingly recognized as a potentially important determinant of environmental sustainability, but its ecological consequences are insufficiently understood. In particular, evidence based on general technological innovation may not adequately capture the environmental implications of innovations specifically intended to reduce ecological footprint. Moreover, the extent to which environment-related technological innovation translates into improvements in overall ecological sustainability remains uncertain, as its effects may depend on changes in production, consumption, and resource use, including potential rebound effects [12, 13]. Although recent empirical studies have examined the relationship between environmental innovation and ecological footprint, the findings also point to the possibility that environmental innovation may not consistently reduce ecological footprint [14]. This uncertainty raises an important question regarding whether, and to what extent, environment-related technological innovation contributes to improvements in ecological sustainability.

The ambiguous relationship between environment-related technological innovation and environmental quality can be explained by competing theoretical mechanisms. On the one hand, as part of environment-related technology innovation, there is a possibility for reducing energy prices due to cleaner energy discovery and its availability, in addition to having energy efficiency and other economic benefits, thereby increasing consumption and production [15, 16]. On the other hand, some arguments favor the beneficial role of environment-related technology, as it minimizes production and consumption-related emissions through faster clean energy adoption, better waste management, and improves energy efficiency [17–20]. Therefore, it is important to assess the relationship between environment-related technology innovation and environmental quality. Understanding this relationship requires an empirical assessment that considers the possibility of both environmental improvements and offsetting the ecological footprint.

Adding to this ambiguity about the relation between environmental-related technologies and environmental quality, which is further compounded by differences in the measurement of environmental quality. At the same time, some studies rely on conventional indicators [21, 22], which overlook the broader ecological pressures by focusing on the narrow dimension of environmental degradation. Thus, the ecological footprint gains prominence in literature as a more comprehensive measure reflecting the combined pressure of human activities [23–30]. However, even when the ecological footprint is employed, empirical results remain inconclusive as the environment-related technology innovation–environment nexus may vary across contexts and methodological approaches [31, 32], which suggests that the environmental implications of ERT may not be adequately understood through conventional environmental indicators alone and highlights the importance of examining its relationship with a broader measure of ecological pressure.

Another limitation concern is the treatment of environmental quality as a single aggregate outcome [33–35]. The ecological footprint consists of multiple dimensions (i.e., "carbon footprint, built-up land, cropland, fishing grounds, forest products, and grazing land"), each of which may respond differently to environmental-related technological innovation; therefore, aggregating these components may conceal heterogeneous effects and lead to misleading conclusions regarding the overall environmental impact of environment-related technologies, in addition to this there is little attention given to dynamic evolution these componentsh over time in response to the environmnt related technology. Furthermore, limited attention to the temporal evolution of these component-specific relationships restricts our understanding of whether the environmental implications of ERT vary across different dimensions of ecological pressure and over time. A component-wise analysis is therefore important for identifying patterns that may remain obscured in aggregate measures.

Methodologically, most empirical studies rely on conventional time-domain econometric techniques that focus on average or long-run relationships [4, 6, 18, 20, 33–37]. Such approaches may fail to capture short-run adjustments, transitional dynamics, and structural shifts arising from changing environmental regulations, technological diffusion, and economic cycles. Time–frequency methods, particularly wavelet analysis, provide an alternative framework by decomposing the relationship between time series simultaneously across time and frequency domains [38, 39]. Wavelet coherence is particularly useful for identifying localized co-movements and phase relationships between two non-stationary series across different frequency bands [40]. Accordingly, the extent to which the relationship between ERT and ecological sustainability varies over time and across frequency scales remains an important empirical question, particularly when the aggregate ecological footprint and its individual components are considered separately.

While a growing body of literature has adopted wavelet-based techniques to study the drivers of ecological footprint, existing wavelet studies predominantly focus on aggregate technological innovation or general energy variables, often treating technological progress as a single, time-invariant factor. Furthermore, prior wavelet applications frequently evaluate the ecological footprint strictly at the aggregate level [41, 42], leaving the scale-dependent, time-varying interactions between environment-specific innovations and individual ecological sub-components (such as built-up land, carbon, cropland, fishing grounds, forest products, and grazing land) unexplored—particularly in the context of major emerging economies like India.

These research gaps are particularly relevant to India, where economic development and environmental sustainability must be pursued simultaneously. The environmental consequences of technological innovation in this context cannot be assumed to be uniformly beneficial, as changes in production, consumption, energy use, and resource demand may influence different dimensions of ecological pressure in distinct ways. Government initiatives, environmental regulations, and international commitments also form part of the broader policy context shaping the adoption and diffusion of environmentally oriented technologies [3, 6, 43]. These considerations render India a relevant setting to examine whether ERT is associated with improvements in aggregate ecological footprint and whether such relationships vary across ecological footprint components and time horizons. A country-specific investigation can thus shed light on the degree to which aggregate indicators are able to capture the environmental implications of environment-related technological innovation and whether such implications differ across different components of the ecological footprint.

In the backdrop of this, the present study attempts to analyze the nexus between ERT and environmental quality in India using aggregate ecological footprint and its underlying components, wherein the study uses wavelet time-frequency analysis to investigate how this relationship changes across time and different frequency scales. The component-wise analysis further explores whether the relation between ERT and ecological sustainability varies across different components of the ecological footprint. By integrating an India-specific focus, disaggregated ecological footprint measures, and a time–frequency perspective, this study extends the existing literature beyond an exclusively aggregate and time-invariant assessment of the ERT–environment nexus. The findings can provide policy-relevant insights into the ecological dimensions and time horizons over which ERT is associated with changes in environmental quality, thereby informing the design of more effective environmental and innovation policies.

The rest of the study consists of the literature review in Section 2, data and methodology in Section 3 and Section 4 consists of the results and discussion and the final section for conclusion and policy implications.

2. Literature Review

The role of environment-related technologies and environmental quality measures has been extensively studied in the literature. Although the empirical findings remain inconsistent, this divergence largely stems from differences in environmental indicators and econometric methodologies [1]. Therefore, existing studies can be distinguished by the environmental indicators employed, the analytical approaches adopted, and the extent to which environmental degradation is measured in aggregate or disaggregated terms.

A substantial strand of the literature relies on various measures of environmental quality while assessing the nexus between environmental-related technology and environmental quality. For instance, a few studies use the CO_2 emissions [17, 21, 22, 44]. However, CO_2 emissions capture only one dimension of environmental pressure, prompting researchers to advocate the ecological foot-

print as a broader indicator that accounts for multiple dimensions of resource use and environmental degradation [23, 31, 32, 45]. Nevertheless, even within the ecological footprint literature, empirical evidence remains mixed with regard to environmental-related technology and ecological footprint. For example, Ref. [31] uses the ecological footprint to gauge the environmental quality and found that eco-friendly innovation degrades the environment for 38 countries. Conversely, by using "Driscoll-Kraay standard errors for long-run estimation and feasible generalized least squares (FGLS) and panel-corrected standard errors (PCSE)", the study by [32] underscores that eco-friendly innovation improves the environmental quality by reducing the ecological footprint for the ten largest ecological footprint countries. Although the ecological footprint is employed as an indicator of environmental quality in both studies, a counterintuitive perspective emerges on the relationship between the environment and environment-related technology. These contrasting findings indicate that differences in environmental indicators alone may not explain the observed inconsistencies, highlighting the need to investigate how the innovation–environment relationship evolves over time.

Although CO_2 emissions are widely used to measure environmental degradation, they primarily capture the carbon-emission dimension of environmental pressure. The ecological footprint provides a broader assessment by accounting for human demand on biologically productive land and resources. Examining its individual components—built-up land (BL), carbon (CB), cropland (CL), fishing grounds (FG), forest products (FP), and grazing land (GL)—further helps identify whether the relationship between environment-related technological innovation and environmental sustainability varies across different components of ecological footprint. This disaggregation is important because changes in one component may not necessarily be accompanied by similar changes in others. Therefore, analysing both aggregate and component-wise ecological footprints can provide a more nuanced assessment of the environmental implications of technological innovation than relying exclusively on conventional emissions indicators.

One potential explanation for these mixed findings is that the relationship between environment-related technological innovation and environmental quality may vary across time horizons and frequency domains. Most existing studies rely on conventional time-domain econometric techniques that assume constant long-run effects and homogeneous adjustment processes [21, 23, 31, 32, 45, 46]. In particular, such approaches may provide limited insight into how the relationship evolves across different frequencies and periods in response to technological diffusion, environmental regulation, and economic fluctuations. Accordingly, the literature calls for analytical frameworks that are capable of capturing both time- and frequency-domain dynamics, for which wavelet coherence analysis attracts much attention in recent literature [47]. This approach provides an opportunity to investigate whether the relationship between environment-related technological innovation and environmental quality differs across short-, medium-, and long-term horizons.

Moreover, despite the growing use of the ecological footprint as a comprehensive indicator, the majority of empirical studies treat it as an aggregate measure [23, 32, 33, 35, 45] which may conceal heterogeneous responses across its underlying components such as "built-up land (BL), carbon (CB), cropland (CL), fishing grounds (FG), forest products (FP), and grazing land (GL)." Although few studies have assessed determinants of the ecological footprint components [34], the time–frequency relationships between environment-related technological innovation and these individual components remain insufficiently explored in the context examined here. Component-wise analysis is therefore important for determining whether the relationship observed for the aggregate ecological footprint also characterizes its constituent environmental pressures.

In India, many studies assess the role of total technology innovation on environmental quality. For instance, Ref. [48] find that total technology innovation improves environmental quality by using "autoregressive distributed lag (ARDL), fully modified ordinary least square (FMOLS), and dynamic ordinary least square (DOLS)" methods for the period range 1981 to 2018, which has been further underlined by [18]. In contrast, Ref. [6] observes by using the "autoregressive distributed lag (ARDL)" model that environmental quality degradation due to technological innovation, which in turn is consistent with other studies [37, 43]. Specifically, eco-friendly innovation collaboration on environmental quality is assessed by [3] for the period between 1985 and 2016 using the ARDL model, which finds that both eco-friendly innovation and total innovation collaborations improve the environmental quality. These studies indicate that the environmental implications of technological innovation in India remain empirically inconclusive, reinforcing the need to examine the relationship using alternative environmental indicators and analytical approaches.

Given the importance of India's environmental policy and technological development context, examining this relationship over time may provide additional insights into how environment-related technological innovation is associated with environmental sustainability [49]. Despite the mixed findings of existing India-specific studies, the combined examination of environment-related technological innovation and both aggregate and component-wise ecological footprints across time and frequency domains remains insufficient. Accordingly, the present study employs wavelet coherence analysis to investigate the time–frequency relationships between environment-related technological innovation and aggregate as well as component-wise ecological footprints in India, which extends the existing literature by examining whether these relationships vary across ecological footprint components and evolve across different time and frequency domains.

3. Data and Methodology

A couple of sources are used for collecting the data for each variable in this study. First, the data for the environment-related technology innovation (ERT) are proxied by an index of patents related to the development of environment-related technologies for India, which is sourced from the OECD data explorer under the technology domain. Patent-based indicators are widely used to represent technological innovation because they capture documented inventive activity and provide a measurable indicator of efforts to develop environment-related technologies. This measure is particularly relevant to the present study because it enables the examination of the relationship between technological innovation and ecological footprint over an extended period. However, patent counts do not necessarily reflect the commercialisation, adoption, or diffusion of patented technologies, nor do they directly measure their realised environmental benefits. Furthermore, patents may differ in their technological significance, and not all environment-related inventions necessarily result in improvements in environmental quality. Therefore, the ERT indicator should be interpreted as a proxy for environment-related inventive activity rather than a direct measure of the actual deployment or environmental effectiveness of technological innovation.

Second, the Global Footprint Network (GFN) is used for collecting data related to total ecological footprint (EF) and its components i.e., "built-up land (BL), carbon (CB), cropland (CL), fishing grounds (FG), forest products (FP), and grazing land (GL)," which are the indicators of consumption-based ecological footprint and are measured in global hectares per person (gha per person). The study spanned between 1990Q1 and 2022Q4, which was primarily due to the availability of data for environment-related technological innovation. Although the respective sources give the data in annual frequencies for all the variables, the study quarterizes all variables under consideration by using the Denton–Cholette temporal disaggregation method [50, 51].

3.1. Methodology

The wavelet coherence is applied to study how two variables interact with each other by analyzing their relationship through time and frequency variations. Unlike traditional methods that maintain constant dependency throughout the study period, this method identifies both synchronized and opposing movements through its ability to track changing relationship patterns at different frequencies [47, 52, 53]. Moreover, this approach demonstrates its main advantage through its capability to identify directional connections while separating short-term movements from long-term patterns and evaluating how different variables react to unexpected external events and planned policy modifications, which conventional econometric models fail to capture [47]. It is worth noting that the analytical foundation of wavelet coherence uses a bivariate continuous wavelet transform, which combines the coherence properties with the cross-wavelet transform [53].

Against this backdrop, the cross-wavelet transform (CWT) of two time series $x(t)$ and $y(t)$ is defined as in Equation (1), which follows the approach of [39].

$$"W_n^{xy}(u,s) = W_n^x(u,s) * W_n^y(u,s) \tag{1}$$

where: $W_x^n(u,s)$ and $W_y^n(u,s)$ denote the continuous wavelet transforms of $x(t)$ and $y(t)$, respectively. The asterisk $(*)$ indicates the complex conjugate, s denotes the scale (frequency-related) parameter, and u represents the time (location)" parameter. The cross-wavelet transform finds areas where two time series show a higher interaction in both time and frequency by measuring how the variations of $x(t)$ and $y(t)$ align at each period and across different scales. In essence, the method tracks how the two series evolve through time while showing their periods of co-movement at different frequency ranges. However, Equation (2) defines the wavelet squared coherence.

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W^{xy}(u,s)\right)\right|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)}. \tag{2}$$

Here, the operator S provides data smoothing across both time dimensions and different scale dimensions to create stable calculation results, which leads to the wavelet coherence through $R^2(u,s)$ values that range from 0 to 1, as higher values indicate stronger interaction between two series at a specific time and frequency. Values approaching 1 (typically highlighted by warmer colors on a heat map) indicate strong local co-movement, whereas values near 0 signify weak or negligible association.

However, the output of the wavelet coherence plot is further interpreted along two primary dimensions. First, frequency scales, which are on the vertical axis of the coherence spectrum, where lower scales correspond to high frequencies (short time horizons) and higher scales represent low frequencies (long time horizons). Specifically, high-frequency or short-term scales represent rapid fluctuations, noise, transient market shocks, or immediate short-run reactions to external events. In contrast, medium-frequency or medium-term scales capture cyclical dynamics, intermediate policy adjustments, and medium-term business cycle patterns, while low-frequency or long-term scales reflect persistent macroeconomic trends, structural changes, and long-run equilibrium relationships. Second, the phase differences, because $R^2(u,s)$ strictly non-negative, it cannot distinguish whether the series moves together or in opposite directions. Therefore, the phase difference technique from [39] provides a method to determine the alignment or inverse movement of the time series data using directional arrows on the coherence map. In-phase relationships indicate arrows pointing to the right $(\rightarrow)$, i.e., a positive correlation where variables move in the same direction. In contrast, anti-phase relationships represent the arrows pointing to the left $(\leftarrow)$, i.e., a negative

correlation where variables move in opposite directions. Additionally, the representation of lead/lag relationships using the arrows pointing upward ($\nearrow, \nwarrow$) or downward ($\searrow, \swarrow$), i.e., specific series leads or lags the other in time.

4. Results and Discussion

Descriptive statistics of the study variables are reported in Table 1, in which the total observations are 132 for each. The mean (median) value of ERT is 0.214 (0.208), whereas EF has an average value of 0.211. Among the components of the EF, CB records the highest mean value (0.108), followed by CL with a mean of 0.054. BL, FP, FG, and GL show relatively low mean values. The standard deviation values indicate moderate variability for ERT, EF, and CB, while BL, FG, FP, and GL exhibit comparatively lower dispersion. Skewness values for most variables are positive, except for FP, which shows slight negative skewness.

In contrast, the kurtosis values indicate that ERT is highly leptokurtic, whereas the remaining variables are either mesokurtic or slightly platykurtic. Overall, the descriptive statistics reveal notable heterogeneity across environmental indicators, which suggests that ERT, EF and components of EF are time-varying and scale-dependent. Therefore, tatic, time-averaged measures fail to capture these dynamics, thereby motivating the use of wavelet coherence analysis as it allows simultaneous examination of the strength and direction of co-movements across short-, medium-, and long-run horizons. Further, visual inspection of the trend plots in Figure 1 supports these statistical properties, which show early-period spikes in ERT with a subsequent stabilization. At the same time, total EF exhibits a steady upward trajectory with brief contractions around the 2008 financial crisis and the 2020 pandemic. Among the EF components, CB and BL show strong upward trends, whereas FP and GL decline persistently, while CL and FG display cyclical fluctuations over 1990–2022.

Following the trand analysis, Pearson correlation results in Figure 2 indicate that ERT is significantly and negatively associated with total EF, particularly through CB and BL, which suggests a potential mitigation effect on carbon and built-up land pressure. In contrast, FP shows a significant positive association with ERT, while CL, FG, and GL exhibit weak and insignificant relationships, indicating that static correlations may not capture their underlying dynamics.

The results of the Pearson correlations provide evidence of the general linear association between ERT and EF and its components, but they are not informative on the time-varying nature of these relationships. Thus, the wavelet coherence between environment-related technology innovation (ERT) and ecological footprint (EF) is shown in Figure 3, in which results reveal a clear time and scale varying relationship across various economic and policy regimes in India. During the period 1990–2000, coherence was focused on short scales (around scale 4, corresponding to about 1-year horizons). This pattern is consistent with the post-1991 period of economic liberalization in India, which experienced rapid industrialization, infrastructure development and resource extraction, in which early environmental technologies operated largely as short-term reactive adjustments to immediate environmental pressures.

Table 1. Descriptive statistics.

Statistic	ERT	EF	BL	CB	CL	FG	FP	GL
Mean	0.2140	0.2110	0.0080	0.1080	0.0540	0.0040	0.0340	0.0030
Median	0.2080	0.1950	0.0070	0.0970	0.0530	0.0040	0.0340	0.0030
Maximum	0.4610	0.2800	0.0100	0.1780	0.0620	0.0040	0.0400	0.0040
Minimum	0.1330	0.1630	0.0060	0.0580	0.0450	0.0030	0.0280	0.0020
Std. Dev.	0.0560	0.0370	0.0010	0.0370	0.0040	0.0002	0.0030	0.0004
Skewness	2.2760	0.3560	0.2830	0.2370	0.0400	0.3930	−0.1740	0.0860
Kurtosis	9.8940	1.6520	1.8280	1.6480	3.0770	2.6750	2.5060	2.0680
Observations	132	132	132	132	132	132	132	132

Note: ERT denotes environment-related technology innovation; EF represents ecological footprint and its components—BL (built-up land), CB (carbon footprint), CL (cropland), FG (fishing grounds), FP (forest products), and GL (grazing land).

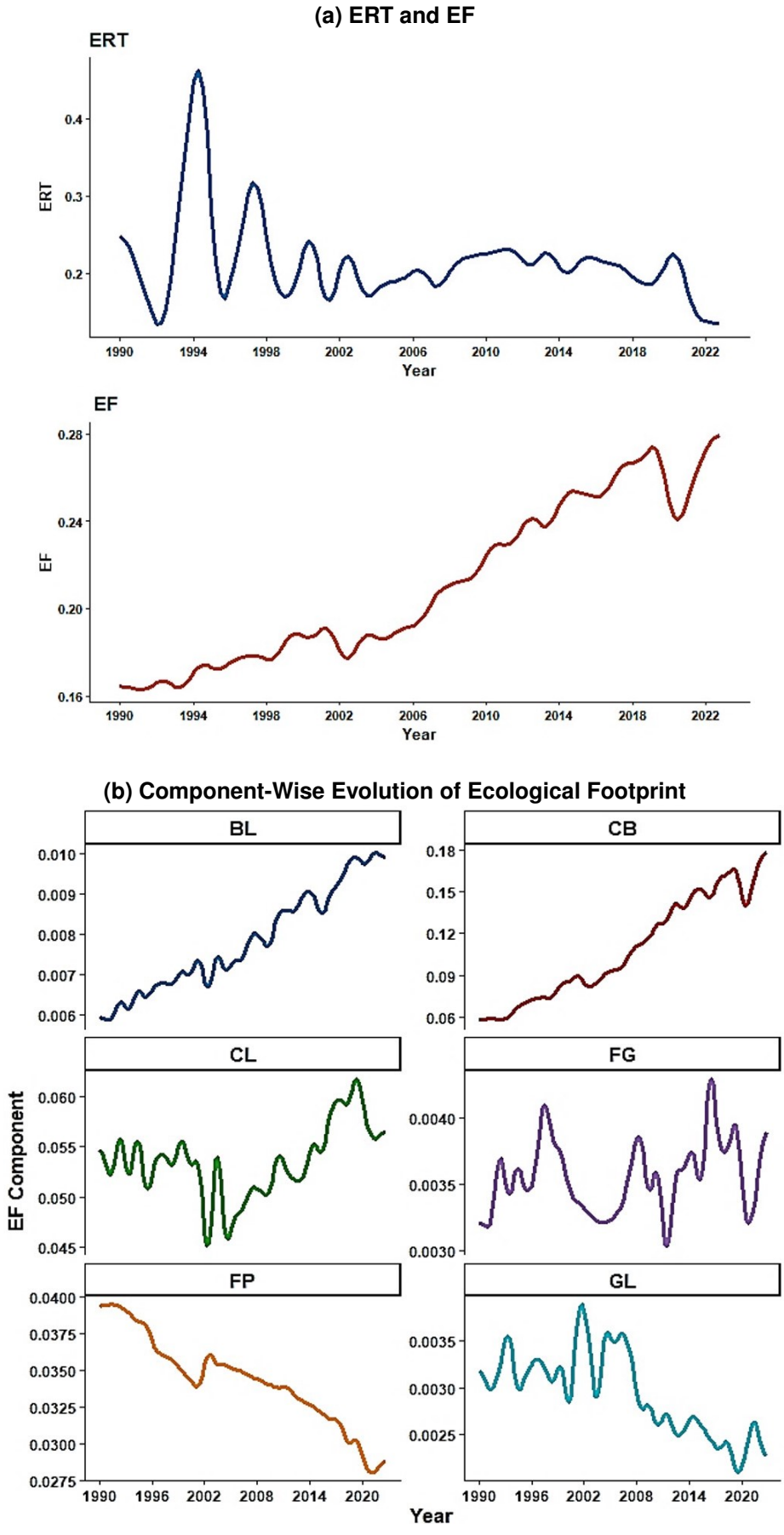


Figure 1. EF, ERT and EF component-wise trends.

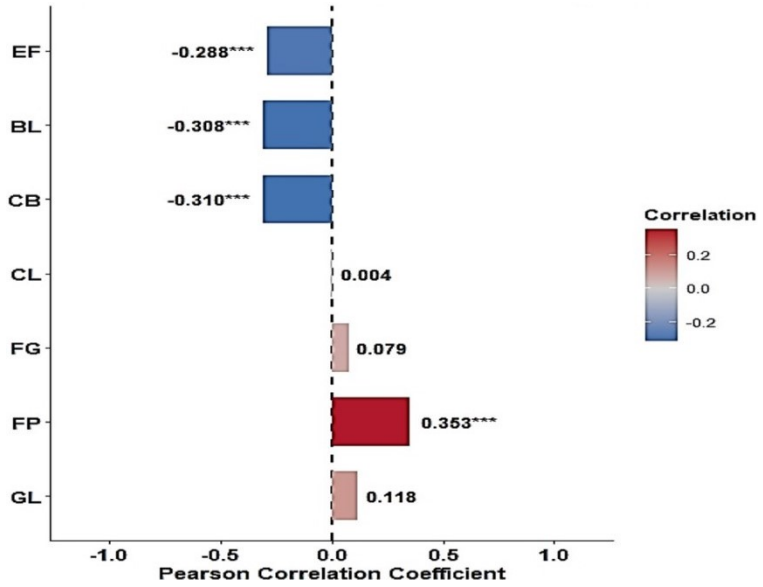


Figure 2. Correlation of ERT with EF and all EF components. Note: *** indicate significance at 1% level.

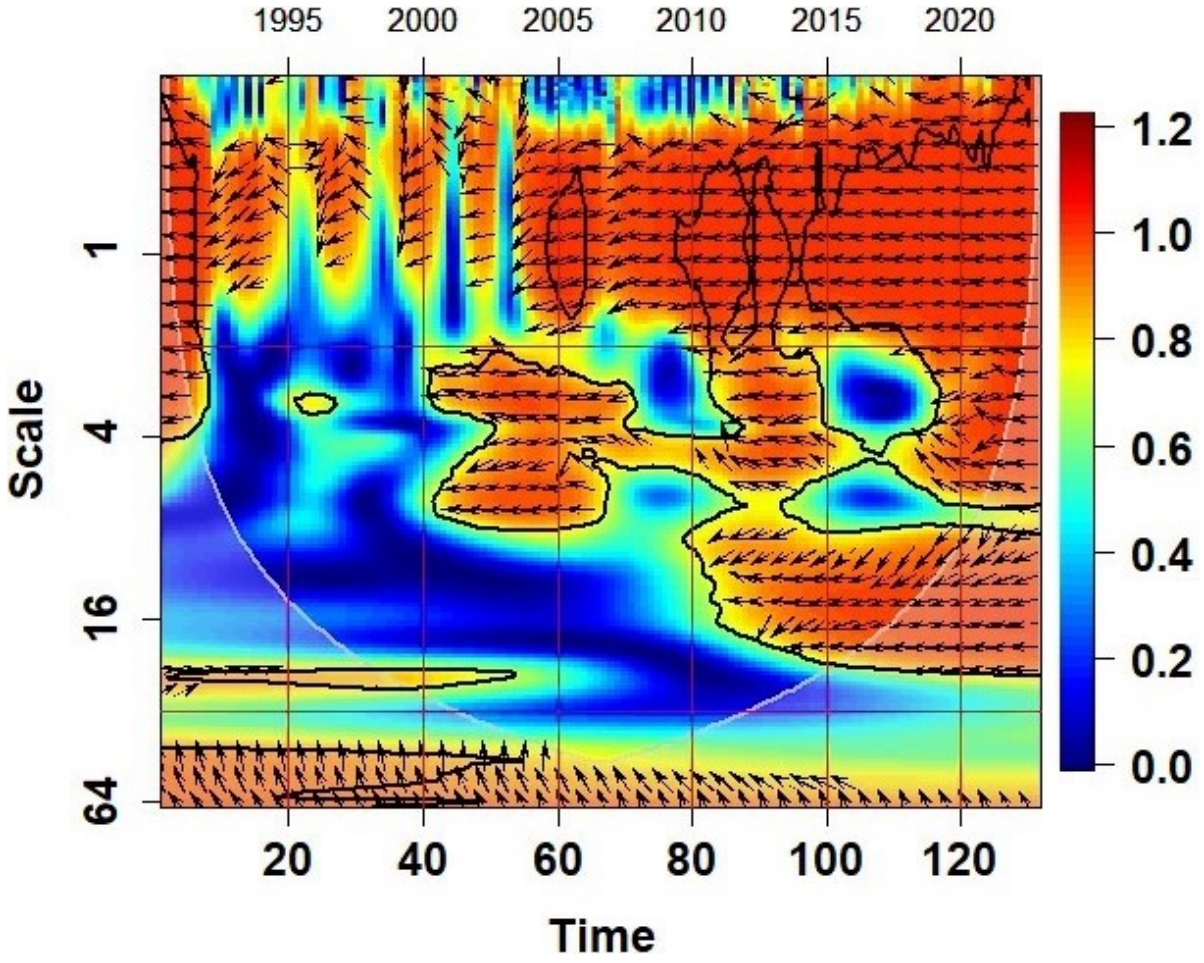


Figure 3. ERT vs. EF.

In the following decade (2000–2010), coherence was moved to the scale 10 (approximately 2.5-year horizon) with phase arrows mainly pointing leftwards (out-of-phase), suggesting that ecological pressures were followed by eco-friendly innovation adoption in a medium-short horizon. The change is a sign of the rapid growth of India's GDP, and institutional policy developments such as the National Environment Policy of 2006 and the National

Action Plan on Climate Change of 2008. Since 2010, coherence has extended to scales 16–20 (approx. 4–5-year horizon), revealing how technology adoption has increasingly acquired a structured, medium-term lag as green technology policies (e.g., energy efficiency mandates and renewable energy targets) take years to mature and manifest at the aggregate level.

Crucially, long-run interactions (scale 64) remain weak or non-persistent. From an environmental economics perspective, this confirms that efficiency gains from ERT do not automatically yield permanent aggregate reductions in EF. Instead, the expansion of production and consumption in a growing economy triggers a rebound effect (Jevons Paradox), where macroeconomic scaling offsets the environmental gains achieved through technological innovation.

In the case of components of EF, the study finds from Figure 4a that ERT responds to changes in built-up land (BL) mostly in short horizons. At the same time, low coherence (blue region) indicates weak correlation in medium terms. In the short-term (scale around 4), in most years, there are significant interactions between ERT and BL with arrows mostly pointing right, suggesting ERT and BL move in phase, i.e., ERT moves in phase with short-term urbanization pressures or land-use changes. Around 2017, onwards, the scale is extending to 16, while there is no significant relationship in the long run. This emerging medium-term coherence aligns with India's aggressive urban infrastructure push, including the Smart Cities Mission, housing initiatives, and industrial corridor development [54]. As expanding cities demand extensive capital investment and material inputs, the environmental benefits of green construction and smart infrastructure take several years to materialize, illustrating the operational lag between urban policy implementation and localized footprint mitigation.

Figure 4b shows that the relationship between ERT and carbon (CB) footprint is significant for only a very short-term horizon (mostly scale 1). Medium-term scales (4–16) are mostly blue, indicating low coherence. Long-term scales (64) show no significant coherence. This lack of persistent medium- and long-term coherence highlights a structural decoupling failure between technological innovation and aggregate emissions. In India, rapid expansion in industrial production, transport electrification demands, and overall electricity consumption continues to offset per-unit energy efficiency gains. This outcome exemplifies a macroeconomic Rebound Effect, where thermal energy remains the baseline power source despite aggressive renewable capacity deployment under the National Solar Mission. As highlighted by the International Energy Agency [55], the operational necessity of coal-fired generation to meet base-load power limits the capacity of short-term efficiency innovations to achieve sustained reductions in aggregate carbon pressure.

This finding is consistent across the other components, such as ERT and cropland (CL) footprint (Figure 4c), there is a strong coherence at very short-term scales (scale 1–4) across most of the sample period, consisting of dominant red and yellow regions. Moreover, there is a short-term in-phase relationship where ERT displays a slight lead phase relative to cropland pressures, which is evident from the arrows at these scales mostly point to the right and downward after 2005. At medium-term scales (approximately 4–16), the coherence is largely insignificant, in addition to having no long-term meaningful impact, as the regions of coherence lie outside the cone of influence. This pattern reflects the structural dynamics of India's agricultural sector under the Green Revolution legacy, where technological advancements in micro-irrigation, mechanization, and high-yield crop management have raised productivity [56]. However, subsidized energy and excessive, imbalanced fertilizer usage have generated localized land degradation. Consequently, technological efficiency improvements fail to yield sustained reductions in cropland footprint, as yield-enhancing innovations simultaneously encourage agricultural intensification and expanded cultivation scales.

Similarly, Figure 4d shows that a strong and persistent coherence is evident at short-term scales (scale 1) with a mostly in-phase relationship between ERT and the fishing ground footprint. At medium-term scales (approximately 4–16), the coherence is largely weak or insignificant. Although some areas of higher coherence appear at long-term scales (around scale 64), these regions are located outside the cone of influence. Technological improvements in fishing equipment, vessel efficiency, and resource monitoring can enhance productivity and management. However, greater harvesting capacity may also intensify pressure on aquatic resources when regulatory controls are inadequate. From an environmental economics perspective, this illustrates a potential rebound mechanism: technological improvements that reduce the cost or increase the efficiency of harvesting may also encourage greater fishing activity, limiting the environmental benefits of innovation. Whether such efficiency gains translate into lower ecological pressure, therefore, depends on the effectiveness of resource-management institutions and harvesting restrictions.

Further, ERT and forest product (FP) footprint (Figure 4e) shows strong and persistent coherence in short-term scales (scale 1–4), in addition to having an in-phase relationship between ERT and forest product footprint, as the arrows at these scales predominantly point to the right. At medium-term scales (approximately 4–16), particularly around the mid-sample period, several localized islands of statistically significant coherence emerge with arrows mostly pointing to the right and right-downward with a medium-run in-phase relationship, with a slight lead–lag structure. It is worth noting that coherence exists as an intermittent phenomenon, which demonstrates that medium-term interactions fail to maintain their effects throughout the study duration. The relationship between ERT and forest products at high long-term scales (64 scale) exists outside the cone of influence, which indicates that the relationship cannot be accurately understood because of boundary effects. Technological innovation can reduce

forest-resource requirements through recycling, material substitution, and efficient processing. However, expanding construction and industrial production may sustain demand for forest products and offset these efficiency gains. The relationship, therefore, depends not only on the availability of resource-saving technologies but also on whether material substitution, recycling, and improvements in production efficiency are sufficient to offset rising demand. This distinction is particularly important in a growing economy, where infrastructure development and industrial expansion can increase demand for materials even as production processes become more efficient.

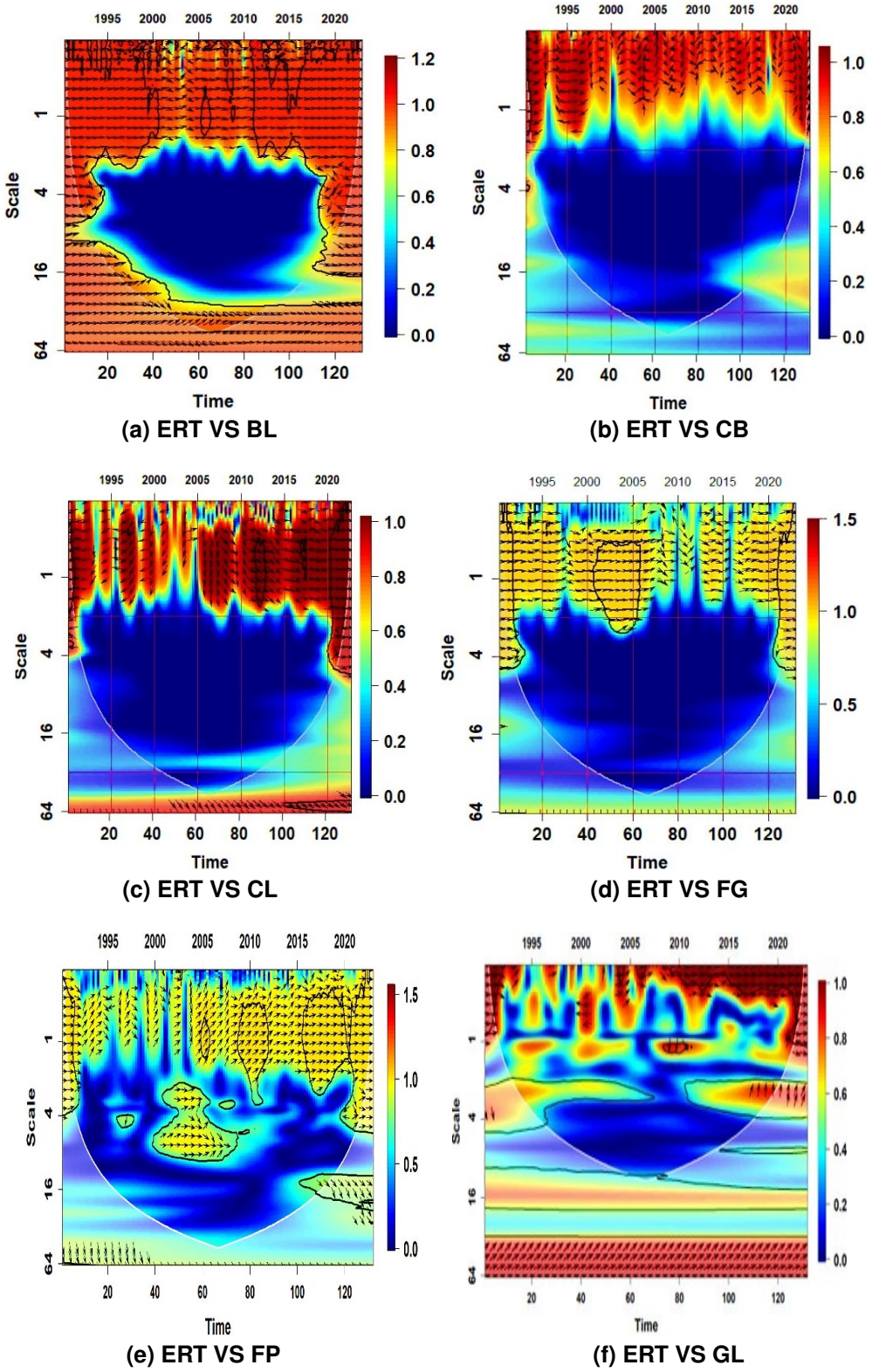


Figure 4. ERT vs. components of EF.

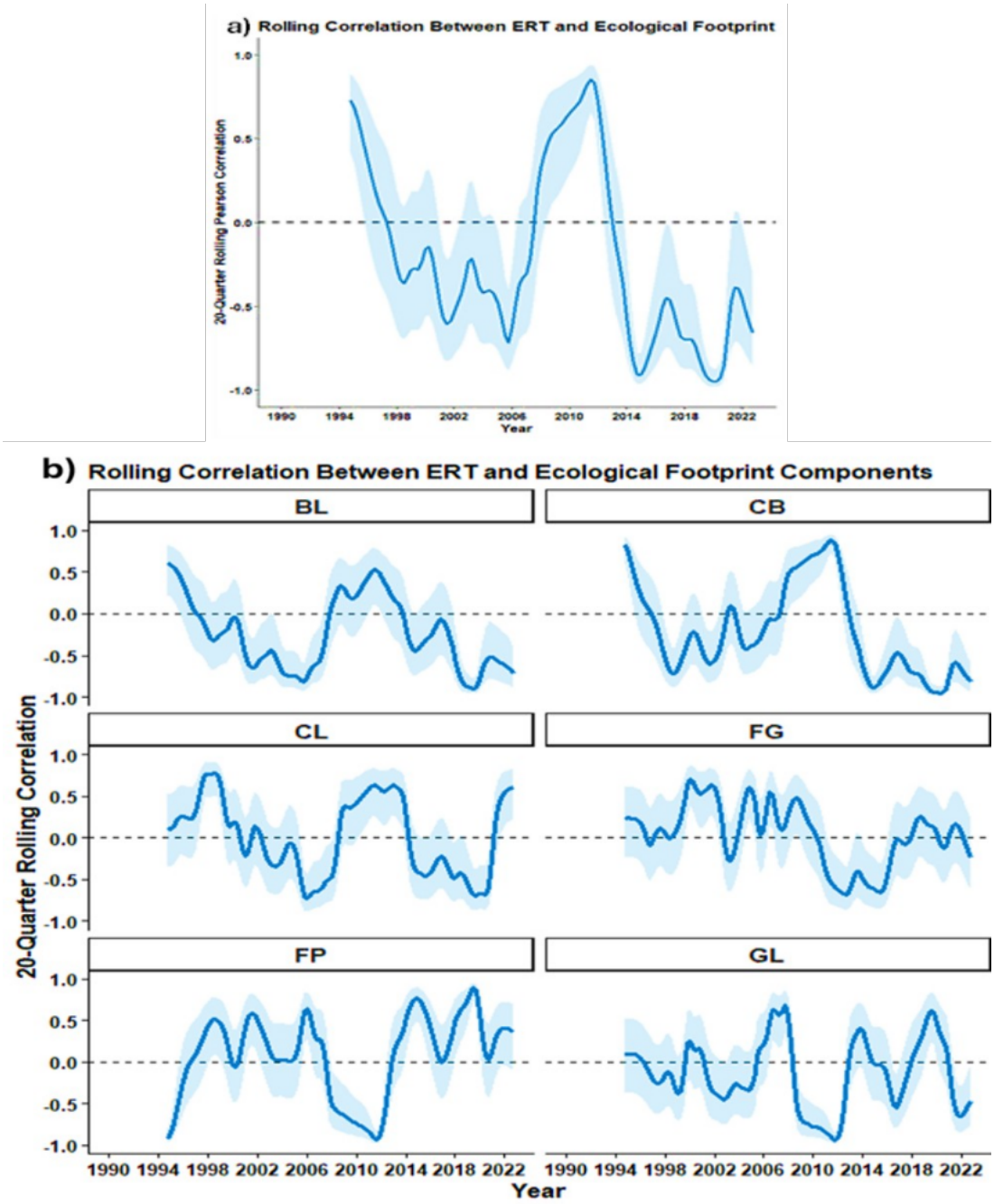


Figure 5. Rolling-window correlation: ERT with each EF component in 95% CI.

Similarly, ERT and grazingland (GL) footprint (Figure 4f) shows that strong and persistent coherence is evident throughout much of the sample period (within scale 1) with a slight lead–lag structure since the phase arrows at these scales predominantly point to the right and right-downward, however, with large blue regions dominating means that coherence is generally weak and intermittent in medium-term scales (approximately 4–16). The high coherence lies outside the cone of influence on the long-term scale, suggesting the possibility of edge effects in the formation of any apparent long-run association. In India, technological improvements in livestock management, animal health, and feed efficiency may reduce resource requirements per unit of output. However, expanding livestock production can offset these gains and sustain grazingland pressure, which suggests that improvements in livestock productivity and resource efficiency should be distinguished from changes in the overall scale of livestock production. Even if technological improvements reduce resource requirements per unit of output, total grazingland pressure may remain substantial when production expands or feed, and grazing practices remain resource-intensive.

This dynamic perspective helps reconcile Indian evidence showing both improvement [18, 48] and deterioration [6, 43] in environmental quality due to environment-

related technological innovation. Given that environment-related innovation in India is largely policy-induced, the results support the view that the innovation–environment nexus is inherently dynamic, non-linear, and sensitive to time horizons.

Following the wavelet coherence analysis, the 20-quarter rolling Pearson correlations with 95% confidence intervals (Figure 5a,b) reveal substantial temporal variation in ERT–EF relationships. ERT generally shows strong negative associations with total EF, CB, and BL, whereas the 2007–2012 period exhibits a marked positive shift; FP maintains prolonged positive associations, while CL, FG, and GL display pronounced oscillations that indicate considerable temporal and component-specific heterogeneity.

Finally, cross-correlation analysis in Figure 6a,b identifies the lead–lag dynamics between ERT and EF indicators, which reveals the significant negative associations for total EF, CB, and BL across multiple lags, with the strongest effects occurring around the contemporaneous and subsequent periods. In contrast, FP shows positive lagged associations, while CL, FG, and GL remain largely within the confidence bounds, indicating weaker and less persistent lead–lag relationships.

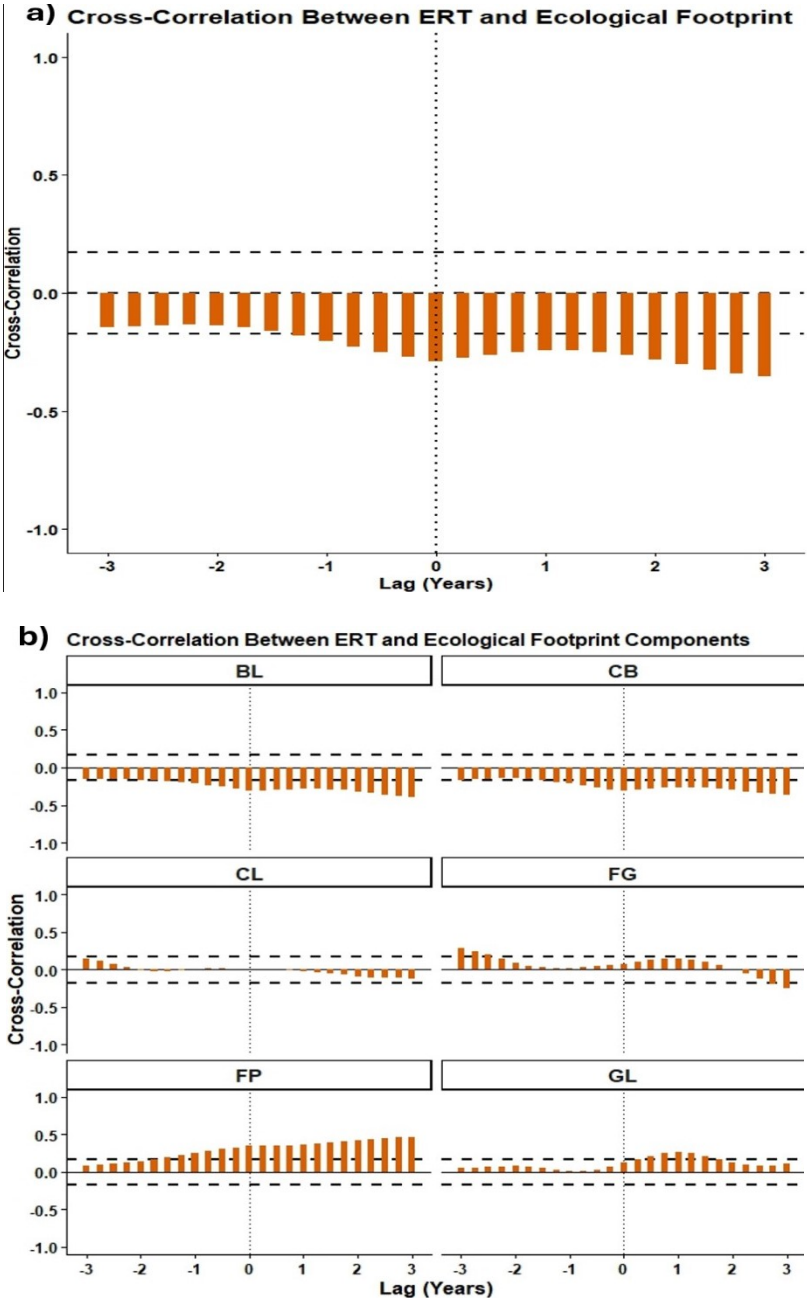


Figure 6. Cross-correlation of ERT with each EF component in 95% CI.

5. Conclusion and Policy Implications

In this study, the relationship between time and frequency of environment-related technological innovation (ERT) and ecological footprint (EF) in India during 1990Q1 to 2022Q4 is explored using wavelet coherence analysis (WCA). The results show that ERT is scale- and time-varying and that the relationships between ERT and environmental pressure tend to be stronger at shorter time horizons. Meaningful coherence in the aggregate EF is seen at short to medium term scale only, while long-run coherence is weak or non-existent. The phase patterns represent the relative lead–lag relationships between the variables in both the time and frequency domains, and the relative lead–lag relationships are not uniformly the same in time and frequency domains throughout the sample period, meaning that environmental pressure and technological innovation are not necessarily synchronously evolving. Such patterns should, however, be considered as time–frequency associations and not as evidence of causality.

The component-wise analysis also yields significant differences between the relationships of ERT and environmental pressure. The coherence pattern of built-up land, carbon footprint, cropland, fishing grounds, forest products, and grazing land varies over time and frequency. There are increasing short-term coherence trends found in some of its components, for instance, in land use (cropland), biological resources (fishing grounds, forest products, and grazing land).

Stronger short-term coherence is observed across several components, particularly those associated with land and biological resources, including cropland, fishing grounds, forest products, and grazing land. In contrast, medium-term coherence is generally weaker or intermittent, while apparent long-scale coherence in several figures lies outside the cone of influence and therefore cannot provide reliable evidence of persistent long-run relationships. By comparison, in most results, the medium-term coherence is either weak or absent, and apparent long-scale coherence in several of the results is outside the cone of influence and is not sufficient to demonstrate a persistent long-run coherence. In summary, the results indicate that the environmental consequences of innovation in technology vary for various components of the ecological footprint and time scales. Also, the lack of long-run coherence in most of the relations suggests that technological innovations cannot be relied on to bring about continued environmental pressure reductions.

Thus, the theoretical implications of the study are that it adds to the environment-related innovation literature by spotting the significance of time- and frequency-dependent relationships in the study of the relationship between innovation and the environment. The findings validate the assumption that technology innovation in the environmental domain results in uniform and constant improvements in the environment. Rather, the fact that the patterns observed are consistent with the idea that technological innovation is linked to economic growth, resource demand and sector-specific production processes in a time-varying manner. Efficiency gains can go hand in hand with growing environmental pressure, if the pressure of production and consumption is increasing and resource savings are diminishing. The results also show that assessing ecological footprints by components can mask significant variations in the nature and extent of the environmental pressures on land, on carbon, and on resources. The study, therefore, emphasizes the use of the analytical power of the integration of aggregate and component-wise environmental indicators and of time–frequency methods to gain a finer-grained knowledge of the relationship between technological innovation and environmental sustainability.

The results have a few policy implications relating to environmental policy in India. First, the short-term links observed and the different lags and leads indicate the need not only for reactive but also for anticipatory environmental governance. Incorporating forward-looking environmental standards, ecological monitoring systems, and proactive regulatory measures can help identify new environmental pressures and help develop and adopt cleaner technologies. Second, policy tools like targeted innovation grants, tax incentives, green public procurement and well-designed subsidies should be assessed on multiple time horizons—not assuming that the spillovers of technology will automatically lead to long-term environmental gains. Third, the diversity of the components of the ecological footprint requires sectoral approaches. In agriculture, policies may assist in resource-efficient irrigation, sustainable use of inputs and better crop husbandry. In order to support the technological upgrading in fisheries and forestry, resource monitoring, harvesting controls, sustainable resource management practices, and material substitution and recycling incentives must be in place. Urban development and built-up land must be planned and built taking into account environmental factors. Fourth, the lack of strong or consistent medium and long-term links highlights the need for complementary actions such as sound environmental regulation, institutional capacity, policy stability and behaviour change to promote sustainable production and consumption. A coordinated strategy that integrates technological innovation with these other actions will be more likely to yield continued environmental progress than will a strategy focused solely on innovation.

Despite this, there are a few limitations in this study, which can serve as a basis for further research. First, the analysis is limited to India, and the identified relationships may not be generalisable to economies with varying technological capabilities, industrial structure, energy system, environmental institutions and so on. Future research might be able to use the same approach for other emerging economies, or a cross-country comparison could be conducted to see if the patterns identified are country-specific or more widespread. Second, wavelet coherence finds time-varying associations and relative phase relationships, but not causal effects. Future studies may use time–frequency analysis in conjunction with other econometric techniques to explore the causal relationships identified. Third, the ecological footprint and its elements reflect key

elements of environmental pressure, but do not reflect all aspects of environmental quality. Future studies may include other indicators (such as pollutant emissions, biodiversity indicators and resource-depletion indicators) to determine if results are similar under other indicators. Finally, the coherence observed in the larger scales could be influenced by the edge effects and the limited number of longer-horizon fluctuations within the sample. The continued relationship between innovation and the environment may be further substantiated from future empirical studies with more data, different measures of innovation, and other combinations of time–frequency specifications. Such extensions would assist in elucidating the conditions under which environment-related technological innovation can make contributions to sustainable environmental aspects.

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Informed Consent Statement

Not applicable. This study does not involve human participants.

Data Availability Statement

The data used in this study are derived from publicly available sources. All data sources and relevant details are provided in the manuscript.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Use of AI and AI-assisted Technologies

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References

1. Chu, L.K. Determinants of ecological footprint in OCED countries: Do environmental-related technologies reduce environmental degradation? *Environ. Sci. Pollut. Res.* **2022**, *29*, 23779–23793. https://doi.org/10.1007/s11356-021-17261-4
2. Kasioumi, M. The environmental kuznets curve in the 21st century: Future projections under socioeconomic and climate change scenarios. *J. Clean. Prod.* **2026**, *541*, 147522. https://doi.org/10.1016/j.jclepro.2026.147522
3. Villanthenkodath, M.A.; Mahalik, M.K. Does overseas eco-friendly innovation collaboration matter for environmental quality sustainability in India? *OPEC Energy Rev.* **2022**, *46*, 250–284. https://doi.org/10.1111/opec.12232
4. Ozkan, O.; Iormom, B.I.; Usman, O.; et al. Fossil fuel efficiency as a pathway to decarbonisation and the role of international trade: A perspective of the LCC hypothesis. *Environ. Dev. Sustain.* **2025**. https://doi.org/10.1007/s10668-025-06351-9
5. Khattak, S.I.; Ahmad, M.; Khan, Z.U.; et al. Exploring the impact of innovation, renewable energy consumption, and income on CO_2 emissions: New evidence from the BRICS economies. *Environ. Sci. Pollut. Res.* **2020**, *27*, 13866–13881. https://doi.org/10.1007/s11356-020-07876-4
6. Villanthenkodath, M.A.; Mahalik, M.K. Technological innovation and environmental quality nexus in India: Does inward remittance matter? *J. Public. Aff.* **2022**, *22*, e2291. https://doi.org/10.1002/pa.2291
7. Rennings, K. Redefining innovation — Eco-innovation research and the contribution from ecological economics. *Ecol. Econ.* **2000**, *32*, 319–332. https://doi.org/10.1016/S0921-8009(99)00112-3
8. Wang, Q.; Qu, J.; Wang, B.; et al. Green technology innovation development in China in 1990–2015. *Sci. Total Environ.* **2019**, *696*, 134008. https://doi.org/10.1016/j.scitotenv.2019.134008
9. Johnstone, N.; Haščič, I.; Poirier, J.; et al. Environmental policy stringency and technological innovation: Evidence from survey data and patent counts. *Appl. Econ.* **2012**, *44*, 2157–2170. https://doi.org/10.1080/00036846.2011.560110
10. Haščič, I.; Migotto, M. *Measuring Environmental Innovation using Patent Data*; OECD Environment Working Papers 89; ECD Publishing: Paris, France, 2015. https://doi.org/10.1787/5js009kf48xw-en
11. OECD Environmental Policy. *Technological Innovation and Patents*. OECD Studies on Environmental Innovation; OECD Publishing: Paris, France, 2008. https://doi.org/10.1787/9789264046825-en
12. Font Vivanco, D.; Freire-González, J.; Galvin, R.; et al. Rebound effect and sustainability science: A review. *J. Ind. Ecol.* **2022**, *26*, 1543–1563. https://doi.org/10.1111/jiec.13295
13. Font Vivanco, D.; McDowall, W.; Freire-González, J.; et al. The foundations of the environmental rebound effect and its contribution towards a general framework. *Ecol. Econ.* **2016**, *125*, 60–69. https://doi.org/10.1016/j.ecolecon.2016.02.006
14. Aydin, C.; Esen, Ö.; Çetintaş, Y. Nexus between environmental innovation and ecological footprint in OECD countries: Is there an environmental rebound effect? *J. Environ. Stud. Sci.* **2025**, *15*, 113–123. https://doi.org/10.1007/s13412-024-00901-9
15. Ali, U.; Li, Y.; Yánez Morales, V.P.; et al. Dynamics of international trade, technology innovation and environmental sustainability: Evidence from Asia by accounting for cross-sectional dependence. *J. Environ. Plan. Manag.* **2021**, *64*, 1864–1885. https://doi.org/10.1080/09640568.2020.1846507
16. Wang, H.; Wei, W. Coordinating technological progress and environmental regulation in CO_2 mitigation: The optimal levels for OECD countries & emerging economies. *Energy Econ.* **2020**, *87*, 104510. https://doi.org/10.1016/j.eneco.2019.104510
17. Ahmed, K. Environmental policy stringency, related technological change and emissions inventory in 20 OECD countries. *J. Environ. Manag.* **2020**, *274*, 111209. https://doi.org/10.1016/j.jenvman.2020.111209
18. Destek, M.A.; Pata, U.K. Carbon efficiency and sustainable environment in India: Impacts of structural change, renewable energy consumption, fossil fuel efficiency, urbanization, and technological innovation. *Environ. Sci. Pollut. Res.* **2023**, *30*, 92224–92237. https://doi.org/10.1007/s11356-023-28641-3
19. Hussain, M.; Mir, G.M.; Usman, M.; et al. Analysing the role of environment-related technologies and carbon emissions in emerging economies: A step towards sustainable development. *Environ. Technol.* **2022**, *43*, 367–375. https://doi.org/10.1080/09593330.2020.1788171
20. Zameer, H.; Yasmeen, H.; Zafar, M.W.; et al. Analyzing the association between innovation, economic growth, and environment: Divulging the importance of FDI and trade openness in India. *Environ.*

Sci. Pollut. Res. **2020**, *27*, 29539–29553. https://doi.org/10.1007/s11356-020-09112-5

21. Rahman, Z.U.; Ahmad, S.; Khan, A. Bridging the EPC and IPAT in the presence of natural resources in China: Considering asymmetries in environmental-related technologies and unemployment. *Resour. Policy* **2025**, *103*, 105523. https://doi.org/10.1016/j.resourpol.2025.105523
22. Tang, N.; Arthur, N. Technological advancement, environmental regulations, and sustainable development: The role of energy efficiency and CO_2 emissions. *Sustain. Dev.* **2026**, *34*, 5616–5631. https://doi.org/10.1002/sd.70654
23. Espoir, D.K.; Sunge, R.; Alola, A.A. Exploring ecological footprint drivers in Africa: Fresh insights from advanced machine learning techniques. *Comput. Econ.* **2026**. https://doi.org/10.1007/s10614-025-11210-w
24. Rees, W.E. Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environ. Urban.* **1992**, *4*, 121–130. https://doi.org/10.1177/095624789200400212
25. Wackernagel, M.; Onisto, L.; Bello, P.; et al. National natural capital accounting with the ecological footprint concept. *Ecol. Econ.* **1999**, *29*, 375–390. https://doi.org/10.1016/S0921-8009(98)90063-5
26. Galli, A.; Kitzes, J.; Wermer, P.; et al. An exploration of the mathematics behind the ecological footprint. *Int. J. Ecodyn.* **2007**, *2*, 250–257. https://doi.org/10.2495/ECO-V2-N4-250-257
27. Wackernagel, M.; Schulz, N.B.; Deumling, D.; et al. Tracking the ecological overshoot of the human economy. *Proc. Natl. Acad. Sci. USA* **2002**, *99*, 9266–9271. https://doi.org/10.1073/pnas.142033699
28. Borucke, M.; Moore, D.; Cranston, G.; et al. Accounting for demand and supply of the biosphere's regenerative capacity: The national footprint accounts' underlying methodology and framework. *Ecol. Indic.* **2013**, *24*, 518–533. https://doi.org/10.1016/j.ecolind.2012.08.005
29. Wackernagel, M.; Rees, W. *Ecological Footprint: Reducing Human Impact on the Earth*; New Society: Gabriola Island, BC, Canada, 1996.
30. Galli, A. On the rationale and policy usefulness of ecological footprint accounting: The case of Morocco. *Environ. Sci. Policy* **2015**, *48*, 210–224. https://doi.org/10.1016/j.envsci.2015.01.008
31. Rao, A.; Sharma, G.D.; Radulescu, M.; et al. Environmental apprehension under COP26 agreement: Examining the influence of environmental-related technologies and energy consumption on ecological footprint. *Int. J. Environ. Sci. Technol.* **2024**, *21*, 7999–8012. https://doi.org/10.1007/s13762-024-05526-7
32. Sadiq, M.; Wen, F.; Dagestani, A.A. Environmental footprint impacts of nuclear energy consumption: The role of environmental technology and globalization in ten largest ecological footprint countries. *Nucl. Eng. Technol.* **2022**, *54*, 3672–3681. https://doi.org/10.1016/j.net.2022.05.016
33. Nikou, V.; Sardianou, E. The determinants of ecological footprint of production: A spatial panel data estimation. *Sustain. Futur.* **2025**, *9*, 100508. https://doi.org/10.1016/j.sftr.2025.100508
34. Obekpa, H.O.; Alola, A.A.; Adejo, A.M.; et al. Examining the drivers of ecological footprint components: Is pursuing food security environmentally costly for Nigeria? *Ecol. Indic.* **2025**, *170*, 113009. https://doi.org/10.1016/j.ecolind.2024.113009
35. Zeb, A.; Shuhai, N.; Ullah, O. Socioeconomic determinants of ecological footprints: Bridging the gap between developed and developing nations. *Environ. Dev. Sustain.* **2025**, *56*, 1–30. https://doi.org/10.1007/s10668-025-06081-y
36. Ahmed, S.; Ahmed, K.; Ismail, M. Predictive analysis of CO_2 emissions and the role of environmental technology, energy use and economic output: Evidence from emerging economies. *Air Qual. Atmos. Health* **2020**, *13*, 1035–1044. https://doi.org/10.1007/s11869-020-00855-1
37. Sharma, V.; Dhamija, A.; Haseeb, M.; et al. Transitioning towards a sustainable environment: The dynamic nexus between economic complexity index, technological development and human capital with environmental quality in India. *Environ. Sci. Pollut. Res.* **2023**, *30*, 87049–87070. https://doi.org/10.1007/s11356-023-28310-5
38. Daubechies, I. The wavelet transform, time-frequency localization and signal analysis. *IEEE Trans. Inf. Theory* **1990**, *36*, 961–1005. https://doi.org/10.1109/18.57199
39. Torrence, C.; Compo, G.P. A practical guide to wavelet analysis. *Bull. Am. Meteorol. Soc.* **1998**, *79*, 61–78. https://doi.org/10.1175/1520-0477(1998)0792.0.CO;2
40. Grinsted, A.; Moore, J.C.; Jevrejeva, S. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Process. Geophys.* **2004**, *11*, 561–566. https://doi.org/10.5194/npg-11-561-2004
41. Razi, U.; Afshan, S.; Cheong, C.W.H.; et al. Dynamic connection between energy prices, Malaysia's economic growth, and ecological footprint: An evidence from morlet wavelet approach. *Geol. J.* **2024**, *59*, 1000–1017. https://doi.org/10.1002/gj.4906
42. Adebayo, T.S.; Sevinç, H.; Sevinç, D.E.; et al. A wavelet-based model of trade openness with ecological footprint in the MINT economies. *Energy Environ.* **2024**, *35*, 2178–2197. https://doi.org/10.1177/0958305X221150489
43. Ozcan, B.; Kılıç Depren, S.; Kartal, M.T. Impact of nuclear energy and hydro electricity consumption in achieving environmental quality: Evidence from load capacity factor by quantile based non-linear approaches. *Gondwana Res.* **2024**, *129*, 412–424. https://doi.org/10.1016/j.gr.2023.05.014
44. Bilgili, F.; Önderol, S.; Kuşkaya, S.; et al. Renewable energy and technology adoption: Mitigating CO_2 emissions through implementation strategies. *Nat. Resour. Forum* **2025**, *49*, 1478–1535. https://doi.org/10.1111/1477-8947.12441
45. Dai, S. Understanding automation's impact on ecological footprint: Theory and empirical evidence from Europe. *Environ. Resour. Econ.* **2025**, *88*, 503–532. https://doi.org/10.1007/s10640-024-00938-y
46. Cetin, M.; Ozturk, I.; Sumerli Sarigul, S.; et al. Nexus between technological innovation and environmental pollution in selected OECD countries. *Nat. Resour. Forum* **2025**, *49*, 841–862. https://doi.org/10.1111/1477-8947.12458
47. Adebayo, T.S. Achieving the targets of sustainable development goals 7 and 12 in Norway: An application of wavelet tools. *Environ. Prog. Sustain. Energy* **2025**, *44*, e14634. https://doi.org/10.1002/ep.14634
48. Ahmad, Z.; Baig, I.A.; Husain, S.; et al. How technological innovation and electricity consumption affect environmental quality? A road map towards achieving environmental sustainability. *Environ. Sci. Pollut. Res. Int.* **2023**. https://doi.org/10.1007/s11356-023-28055-1
49. Chakraborty, P.; Chatterjee, C. Does environmental regulation indirectly induce upstream innovation? New evidence from India. *Res. Policy* **2017**, *46*, 939–955. https://doi.org/10.1016/j.respol.2017.03.004
50. Cholette, P.-A. *Adjusting Sub-Annual Series to Yearly Benchmarks*; Statistics Canada, Working Paper No. 85-12; Statistics Canada: OT Ottawa, ON, Canada, 1983; pp. 1–14. Available online: https://publications.gc.ca/site/eng/9.837714/publication.html (accessed on 28 October 2026)
51. Denton, F.T. Adjustment of monthly or quarterly series to annual totals: An approach based on quadratic minimization. *J. Am. Stat. Assoc.* **1971**, *66*, 99–102. https://doi.org/10.1080/01621459.1971.10482227
52. Adebayo, T.S. Response of sectoral CO_2 emissions to climate and economic policy uncertainties: A multi-frequency quantile analysis. *Appl. Econ.* **2026**, *58*, 3922–3941. https://doi.org/10.1080/00036846.2025.2490857
53. Sethi, S.R. Wavelet-based techniques to analyze the dynamics of petroleum consumption and CO_2 emissions: Implications for environmental sustainability and policy. *Technol. Sustain.* **2026**, *5*, 78–93. https://doi.org/10.1108/TECHS-09-2025-0200

54. World Bank. *India's Urban Infrastructure Needs to Cross $840 Billion Over Next 15 Years: New World Bank Report*; World Bank: Washington, DC, USA, 2022. Available online: https://www.worldbank.org/en/news/press-release/2022/11/14/india-s-urban-infrastructure-needs-to-cross-840-billion-over-next-15-years-new-world-bank-report (accessed on 16 October 2026).
55. IEA. *India Energy Outlook 2021*; OECD Publishing: Paris, France, 2021. Available online: https://www.iea.org/reports/india-energy-outlook-2021 (accessed on 16 October 2026).
56. PIB. *Balanced Use of Fertilizers: A Key Enabler of Sustainable Farming*; Press Information Bureau, Government of India: New Delhi, India. Available online: https://www.pib.gov.in/PressReleasePage.aspx?PRID=2221117&reg=3&lang=2 (accessed on 16 October 2026).