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The Nexus between Hydropower Energy and Environmental Quality: Evidence from Granger Causality and Wavelet Coherence

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Abstract

This study examines the relationship between hydropower energy and environmental quality in Indonesia over the period 1965–2024 using Granger causality and wavelet coherence approaches. Environmental quality is proxied by ecological footprint (EFP), greenhouse gas emissions (GHG), and carbon dioxide emissions (CO_2). The findings reveal that unidirectional causality runs from EFP and CO_2 to hydropower. In contrast, bidirectional causality is observed between hydropower and GHG. Furthermore, the wavelet coherence results show that these relationships are time-varying and frequency-dependent, broadly supporting the Granger causality findings while revealing how they evolve across different time horizons. Overall, the findings indicate that hydropower development in Indonesia is primarily driven by ecological footprint and carbon emissions, while its relationship with GHG emissions is characterized by mutual interaction, highlighting a differentiated and time-varying linkage across environmental indicators. This suggests that hydropower planning should be more closely aligned with environmental trends rather than treated as an independent driver of environmental improvement.

1. Introduction

Hydropower is one of the most established and widely utilized sources of renewable energy and has long been considered an important component of the global transition toward low-carbon development [1–3]. As a mature and relatively reliable technology, hydropower can enhance energy security, support electricity system stability, and reduce dependence on fossil-fuel-based power generation [4–6]. Compared with conventional thermal power plants, hydropower generally produces lower operational carbon emissions and is therefore often regarded as a potentially important instrument in climate change mitigation strategies [7–9]. However, the environmental implications of hydropower are not uniformly positive. Large-scale dam construction may disrupt river ecosystems, alter land-use patterns, affect biodiversity, and, in some cases, contribute to methane emissions through reservoir formation under specific ecological conditions [10, 11]. These contrasting features suggest that hydropower should not be viewed solely as a clean energy solution, but rather as an energy source with potentially mixed environmental consequences.

This dual character is particularly relevant in the case of Indonesia. Since the late 1960s, Indonesia has experienced rapid economic growth, industrialization, and rising energy demand [12–14]. Over the period 1965 to 2024, this structural transformation has been accompanied by increasing fossil fuel consumption and

Table 1. Variable description.

Variable	Description	Unit of Measurement	Data Source
HYDRO	Electricity generation	Terawatt-hours (TWh)	OWID [15]
CO2	Carbon dioxide emissions	Metric tons	OWID [15]
GHG	Greenhouse gas emissions	Metric tons	OWID [15]
EFP	Ecological footprint	Total global hectares (gha)	GFN [16]

intensifying environmental pressure [17, 18]. Although coal continues to dominate the national electricity mix [19], hydropower has increasingly been promoted within renewable energy policy as part of efforts to diversify the energy structure and reduce carbon intensity [20]. Indonesia, therefore, represents a particularly relevant case for examining the hydropower–environment nexus. As one of the largest economies in Southeast Asia, the country combines persistent fossil fuel dependence, growing environmental stress, and substantial hydropower potential within an evolving energy transition agenda [8, 20, 21]. These conditions make Indonesia more than a simple single-country application; rather, it provides an important setting for assessing whether hydropower development tends to precede environmental improvement or whether it mainly expands in response to worsening environmental conditions.

The literature on the energy–environment nexus provides important insights [22–24], but the evidence remains fragmented across indicators, methods, and geographical contexts. Some studies report that renewable energy deployment contributes to lower emissions and better environmental outcomes [4, 8, 25–27], while others show that these effects depend on the structure of the energy system, institutional settings, and broader macroeconomic conditions [5, 6, 28, 29]. More specifically, several empirical studies suggest that hydropower development can improve environmental quality by reducing CO_2 emissions, GHG emissions, and ecological footprint across countries [30–32]. However, much of the extant literature relies on conventional time-domain approaches that estimate average relationships over the full sample period and may overlook nonlinearities, cyclical interactions, and time-varying dynamics across different horizons. In addition, relatively limited attention has been given to Indonesia as a distinct national context, despite its importance in the regional energy transition.

A key limitation in the literature concerns how environmental quality is conceptualized and measured, as it cannot be adequately captured by a single indicator [33]. To address this, the present study adopts three complementary proxies: CO_2 emissions, total GHG emissions, and EFP. CO_2 emissions reflect energy-related carbon intensity [34–37], while total GHG emissions provide a broader measure by incorporating additional gases such as methane and nitrous oxide [35, 38, 39]. Ecological footprint captures wider environmental pressure related to land use, resource consumption, and biocapacity constraints [40, 41]. Together, these indicators allow for a more comprehensive assessment of the hydropower–environment nexus. Conceptually, the study is further grounded in the distinction between proactive and reactive energy transition dynamics, where hydropower development may either precede environmental improvement or follow rising environmental pressure.

Against this background, this study examines the dynamic relationship between hydropower and environmental quality in Indonesia over the period 1965 to 2024 using Granger causality and wavelet coherence techniques. Its contribution lies in applying these complementary approaches to a multidimensional and country-specific analysis. Specifically, the study provides evidence from an underexplored national context, evaluates environmental quality using three complementary indicators, and captures both predictive relationships and their variation across time and frequency horizons. In doing so, it offers a more comprehensive understanding of the hydropower-environment nexus and a firmer empirical basis for aligning renewable energy planning with environmental dynamics in emerging economies.

2. Materials and Methods

2.1. Data and Variable Sources

This study examines the dynamic relationship between hydropower generation and environmental quality in Indonesia over the period 1965 to 2024, using annual observations. As presented in Table 1, hydropower is measured by electricity generation from hydro sources in terawatt-hours (TWh), which reflects the contribution of hydropower to the national energy mix. Environmental quality is proxied using three complementary indicators in order to capture different dimensions of sustainability. Carbon dioxide (CO_2) emissions, measured in metric tons per year, represent energy-related carbon intensity and direct fossil fuel combustion. Total greenhouse gas (GHG) emissions, expressed in metric tons of CO_2 equivalent per year, provide a broader measure of aggregate emissions dynamics by incorporating gases beyond CO_2. Ecological footprint (EFP), expressed in global hectares, captures wider environmental pressure associated with land use, resource consumption, and biocapacity constraints. The data are obtained from Our World in Data (OWID) and the Global Footprint Network (GFN), which are widely used and consistent secondary sources for long-run environmental and energy analysis.

The empirical analysis employs these annual series at two frequencies. All time-domain procedures, including the unit root, cointegration, lag selection, and Granger causality tests, are conducted directly on the original annual observations, ensuring that the causal inference is based exclusively on observed data. For the wavelet coherence analysis, in contrast, the annual series are transformed into quarterly frequency (1965Q1–2024Q4) using linear interpolation to provide a denser temporal grid for localizing dynamics across time and frequency. It should be noted that linear interpolation does not create new observed within-year information but rather distributes the annual values smoothly across quarters.

2.2. Granger Causality and Wavelet Coherence Test

To examine the relationship between hydropower generation and environmental quality, this study employs both Granger causality and wavelet coherence techniques, which capture complementary dimensions of interaction. First, Granger causality is implemented within a vector autoregressive (VAR) framework to assess whether past values of one variable contain statistically significant information for predicting another variable beyond its own lagged values [27, 42]. In this study, the test is applied to hydropower and each environmental proxy, namely CO_2 emissions, total GHG emissions, and EFP. The null hypothesis states that one variable does not Granger-cause another, and rejection of the null indicates the existence of a predictive relationship, either unidirectional or bidirectional. It is important to emphasize that Granger causality does not establish structural causation; rather, it identifies predictive associations conditional on the lag structure of the model [43, 44].

Before estimating the Granger causality model, several pre-estimation diagnostics were conducted to ensure the appropriateness of the empirical specification. First, stationarity was assessed using the Augmented Dickey–Fuller (ADF) [45] unit root test. Second, if the variables were found to be non-stationary in levels but stationary after first differencing, the Johansen cointegration test was conducted to determine whether a stable long-run equilibrium relationship existed among them [46]. Third, the optimal lag length of the VAR model was selected using standard information criteria, including the Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan–Quinn Criterion (HQ) [47, 48].

To complement the time-domain analysis, wavelet coherence is employed to investigate localized co-movement between hydropower and each environmental indicator in time-frequency space. Unlike traditional econometric methods that estimate average relationships over the full sample period, wavelet coherence allows the strength of association between two variables to vary simultaneously across time and frequency [49]. Because the ability of the wavelet transform to localize dynamics improves with the density of observations, the analysis is conducted on the interpolated quarterly series (1965Q1–2024Q4), providing the finer temporal grid required to trace how these co-movements evolve across short, medium, and long run horizons. Because the interpolation generates no new within-year information, coherence features at periods below approximately two years cannot be fully separated from patterns induced by the interpolation itself and are treated as suggestive evidence only, while the substantive conclusions rest on the bands of two years and above, which are unaffected by the interpolation. Statistical significance is evaluated at the 5% level using Monte Carlo simulation [49, 50], and the cone of influence is used to identify regions where the estimates may be affected by edge effects, with results outside this region interpreted with caution. Phase-difference analysis is used to indicate relative lead-lag patterns within statistically significant coherence regions, but it is not interpreted as evidence of structural causation. In the wavelet coherence plots, arrows pointing to the right indicate in-phase movement, arrows pointing to the left indicate anti-phase movement, and the vertical tilt of the arrows identifies the leading variable [51–53]. By combining Granger causality on annual data with wavelet coherence on the quarterly series, this study provides a comprehensive framework for identifying predictive linkages as well as their variation across time and frequency in the hydropower-environment nexus [52, 54, 55].

2.3. Study Workflow

Figure 1 presents the analytical workflow of the study in a clear five-step sequence. The process begins with data collection and construction, followed by variable summary and preliminary tests to assess the statistical properties of the series and determine their suitability for dynamic analysis. The next stage applies the Granger causality approach to identify predictive relationships among the variables, while wavelet coherence is then

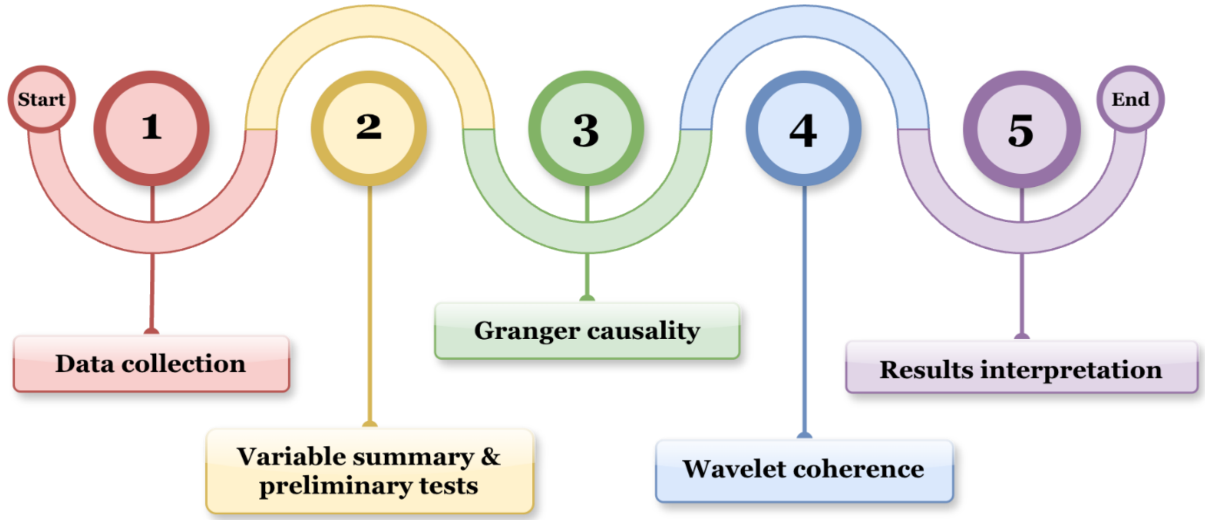

Figure 1. Flow analysis of the study.

Table 2. Descriptive statistics.

Variable	HYDRO	CO2	GHG	EFP
Mean	9.1236	276,008,973	1,302,906,348	261,224,381
Median	8.5588	220,712,625	1,251,771,700	239,024,721
Max.	27.3	812,220,200	3,027,978,500	519,217,435
Min.	1.0607	23,374,952	559,361,540	128,243,445
Std. Dev.	7.4113	220,734,782	545,831,919	114,308,930
Obs.	60	60	60	60

employed to capture their time-varying and frequency-dependent co-movement. The final stage focuses on interpreting the combined findings from both approaches, allowing the study to provide a more comprehensive understanding of the hydropower–environment nexus in Indonesia.

3. Results and Discussion

3.1. Variable Summary and Preliminary Tests

Table 2 shows the descriptive statistics of the variables used in the analysis, based on 60 annual observations covering 1965–2024. Hydropower generation (HYDRO) has a mean of 9.1236 TWh and a median of 8.5588 TWh, indicating a fairly stable central tendency, although the wide gap between the minimum (1.0607 TWh) and the maximum (27.3 TWh) reflects substantial growth over time. The standard deviation of 7.4113 further confirms considerable variability in hydropower output over the study period. For CO_2 emissions, the mean annual level is 276,008,973 tons with a median of 220,712,625 tons, indicating a right-skewed distribution driven by higher values in later years, as confirmed by the maximum of 812,220,200 tons against a minimum of 23,374,952 tons. Total GHG emissions are even larger in both magnitude and dispersion, with a mean of 1,302,906,348 tons, a maximum exceeding 3 billion tons, and a standard deviation of 545,831,919, indicating notable growth and volatility during the sample period. Similarly, EFP has a mean of 261,224,381 global hectares, a maximum of 519,217,435, and a standard deviation of 114,308,930, reflecting considerable fluctuation in overall environmental pressure. Across all variables, the wide ranges between minimum and maximum values point to the structural transformation of energy use and environmental dynamics in Indonesia from 1965 to 2024, while the complete and consistent set of observations confirms the suitability of the data for empirical analysis.

All variables are non-stationary at levels according to the ADF test, as indicated by probability values above conventional significance levels. After first differencing, however, all variables become stationary, with HYDRO, CO_2, GHG, and EFP statistically significant at the 1% level, as reported in Table 3. These results confirm that all series are integrated of order one, I(1), and are therefore appropriate for subsequent cointegration analysis.

The Johansen cointegration results indicate no evidence of a long-run equilibrium relationship among the variables. As reported in Table 4, both the trace and maximum-eigenvalue statistics fail to reject the null hypothesis of no cointegration, with probability values of 0.1459 and 0.1646, respectively, at the "None" specification. The subsequent hypotheses also remain statistically insignificant at the 5% level. These findings indicate that no cointegrating relationship exists among

Table 3. ADF unit root test results.

Variable	Level		1st Difference	
	t-stat.	**Prob.**	**t-stat.**	**Prob.**
HYDRO	-0.4081	0.9005	-9.6001***	0.0000
CO2	-1.8934	0.3332	-8.0612***	0.0000
GHG	-1.7421	0.4051	-11.6555***	0.0000
EFP	1.3243	0.9985	-7.9028***	0.0000

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

Table 4. Johansen cointegration test results.

Hypothesized No:	Eigenvalue	Trace Stat.	Prob.	Max-Eigen Stat.	Prob.
None	0.3298	42.4745	0.1459	23.2132	0.1646
At most 1	0.1918	19.2613	0.4743	12.3515	0.5134
At most 2	0.0995	6.9099	0.5882	6.0758	0.6035
At most 3	0.0143	0.8340	0.3611	0.8340	0.3611

Note: probability values are based on MacKinnon-Haug-Michelis [56]; no cointegrating relationship is detected at the 5% level.

Table 5. Lag optimum test results.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-17.7209	NA	2.59e-05	0.7899	0.9358	0.84631
1	212.9359	419.3760*	1.06e-08*	-7.0159*	-6.2859*	-6.7336*
2	220.8578	13.2512	1.43e-08	-6.7221	-5.4082	-6.2140
3	232.3219	17.5089	1.73e-08	-6.5572	-4.6593	-5.8232
4	245.6791	18.4572	2.00e-08	-6.4611	-3.9793	-5.5013
5	252.0027	7.8183	3.07e-08	-6.1092	-3.0434	-4.9236

Note: * represents the optimal lag recommended across the selection criteria.

Table 6. Granger causality results.

Null Hypothesis	F-stat.	Prob.
CO2 does not Granger Cause HYDRO	4.4172**	0.0401
HYDRO does not Granger Cause CO2	0.9878	0.3246
GHG does not Granger Cause HYDRO	13.8899***	0.0005
HYDRO does not Granger Cause GHG	10.4280***	0.0021
EFP does not Granger Cause HYDRO	7.4227***	0.0086
HYDRO does not Granger Cause EFP	0.1886	0.6658

Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

HYDRO, CO_2, GHG, and EFP over the study period. Given that all variables are I(1) but not cointegrated, the subsequent Granger causality analysis can appropriately focus on the stationary first-differenced series without requiring a VECM specification.

The lag length selection results indicate that lag 1 is the optimal specification for the model. As presented in Table 5, all selection criteria, including LR, FPE, AIC, SC, and HQ, consistently select lag 1 as optimal. This agreement across the criteria supports the use of a one-period lag to capture the dynamic relationships among the variables while avoiding unnecessary model complexity. Accordingly, lag 1 is adopted for the subsequent Granger causality analysis.

Taken together, the preliminary diagnostics provide a coherent statistical basis for the causality framework adopted in this study. The ADF tests establish that all four series are integrated of order one, becoming stationary only after first differencing. The Johansen procedure then finds no evidence of a cointegrating relationship among the variables, implying that no long-run equilibrium mechanism or error-correction term needs to be embedded in the causal specification. Under these conditions, estimating a vector error correction model would be inappropriate, and the standard pairwise Granger causality test applied to the stationary first-differenced series constitutes the correct and fully specified framework. With the lag order set to one, as unanimously indicated by the selection criteria, the pairwise Granger tests reported below can be interpreted as valid evidence of short-run predictive relationships between hydropower and each environmental indicator.

3.2. Granger Causality Results

The Granger causality results are reported in Table 6, while detailed visualizations of these results are presented in Figure 2. The relationship between hydropower and CO_2 emissions is unidirectionally predictive. The null hypothesis that CO_2 does not

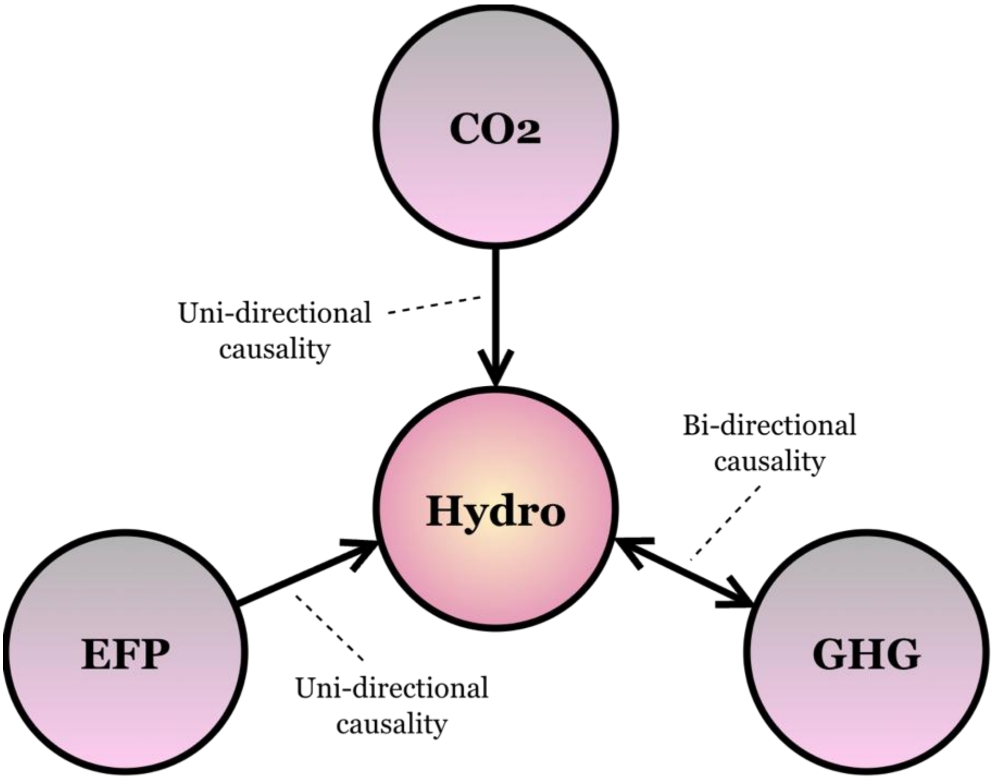

Figure 2. Overview of the Granger causality results.

Granger-cause hydropower is rejected at the 5 percent level, whereas the reverse hypothesis cannot be rejected. This result suggests that historical CO_2 emissions carry predictive information for hydropower growth, but hydropower does not predict future changes in CO_2 emissions over the sample period. Put differently, rising carbon emissions appear to act as a leading indicator of renewable energy generation, consistent with a policy response to carbon-intensive growth. By contrast, hydropower generation carries no detectable predictive power for the subsequent evolution of CO_2 emissions, suggesting that its share in the overall energy structure has remained too limited to influence aggregate carbon emission patterns in a statistically discernible way.

The Granger causality results for hydropower and total GHG emissions reveal a predictive relationship in both directions at the 1 percent significance level. Both null hypotheses are rejected, confirming that past GHG emissions predict the development of hydropower and that past hydropower generation predicts GHG emissions. This feedback mechanism implies a dynamic interaction between renewable energy growth and aggregate GHG trends. On the one hand, rising GHG emissions appear to drive the development of hydropower; on the other hand, hydropower carries predictive information for future GHG movements, reflecting its role within the overall emission structure. This bidirectional causality indicates a more intertwined relationship than that observed for CO_2.

Lastly, the Granger causality results for EFP and hydropower indicate a unidirectional predictive relationship running from EFP to hydropower. The null hypothesis that EFP does not Granger-cause hydropower is rejected at the 1 percent significance level, whereas the null hypothesis that hydropower does not Granger-cause EFP cannot be rejected. This means that past EFP values are a strong predictor of hydropower development in Indonesia, and not vice versa. The finding suggests that mounting ecological pressure can prompt policymakers to expand hydropower capacity as part of environmental management strategies. Nevertheless, hydropower development offers no predictive information about the broader ecological sustainability processes represented by the ecological footprint measure.

3.3. Wavelet Coherence

To complement the Granger causality results, wavelet coherence is employed to trace how the strength and direction of the hydropower–environment nexus evolve jointly across time and frequency. In Figures 3–5, warmer colors denote stronger local correlation between the two series, the thick black contours enclose regions that are statistically significant at the 5% level against red noise, and the lighter-shaded area outside the white curve marks the cone of influence (COI), within which edge effects render the estimates unreliable. Phase arrows convey the lead–lag structure: arrows pointing right indicate that the series move in phase, arrows pointing

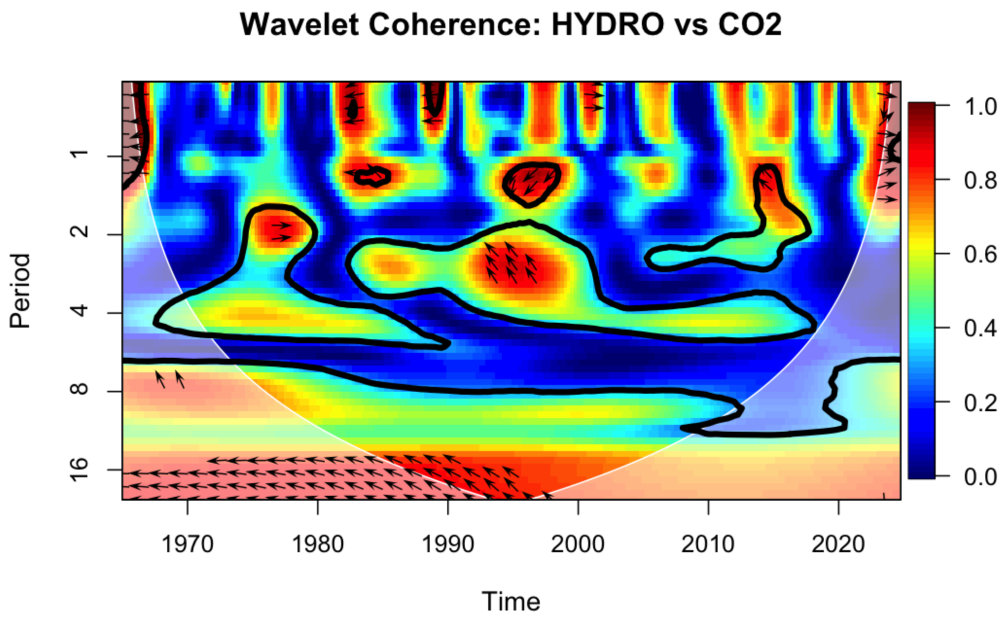

Figure 3. Wavelet coherence: Hydropower vs. CO_2.

left indicate an anti-phase relationship, a downward tilt indicates that hydropower leads the environmental indicator, and an upward tilt indicates that the environmental indicator leads hydropower. Because the series are sampled at a quarterly frequency, the vertical axis expresses the period in years, the finest resolvable period is half a year, and the longest reliably estimated period is approximately sixteen years. Throughout this section, periods below two years are referred to as the short run, two to eight years as the medium run, and above eight years as the long run.

3.3.1. Hydropower vs. CO_2 Emissions

The wavelet coherence between hydropower and CO_2 emissions (Figure 3) is dominated by two well-defined structures. The first is a broad long-run region at the 12–16-year band that is already present at the left edge of the sample in the mid-1960s and persists until the mid-1990s, with coherence in the range of 0.7–0.8. The phase arrows in this region point predominantly to the left, revealing an anti-phase relationship, and from the mid-1980s onward they acquire a clear upward tilt, indicating that CO_2 emissions lead hydropower at these long horizons. In economic terms, sustained increases in carbon emissions precede subsequent adjustments in hydropower development, consistent with hydropower expansion acting as a delayed structural response to mounting emission pressure. Because the lower-left portion of this region approaches the cone of influence, its earliest segment should be read with some caution, although the core of the region lies safely inside the reliable area.

The second prominent structure is a medium-run island at the 2–4-year band stretching from approximately 1983 to 2000, whose core of high coherence (0.8–0.9) is concentrated around 1993–1998. Within this core the arrows point upward and slightly to the right, again identifying CO_2 as the leading variable while the relationship transitions toward phase alignment. This episode coincides with the period of rapid industrialization preceding the Asian financial crisis, when emission dynamics plausibly conditioned energy-sector investment cycles. In addition, three smaller and more transitory features are visible: an in-phase pocket around 1976–1979 at the 2-year band with rightward arrows, brief high-frequency bursts near 1983–1984 and the mid-1990s at periods of about one year, and a moderate region around 2013–2017 at the 1.5–2.5-year band, indicating that the linkage re-emerged in a weaker, cyclical form during the recent renewable-expansion period.

Crucially, at no point does the plot display a sustained significant region in which the arrows tilt downward, that is, in which hydropower systematically leads CO_2. The time–frequency evidence therefore corroborates the unidirectional Granger causality running from CO_2 to hydropower: carbon emissions carry predictive content for hydropower development, particularly at medium and long horizons, whereas hydropower does not systematically anticipate carbon emissions.

3.3.2. Hydropower vs. GHG

Of the three environmental proxies, total GHG emissions display the strongest and most persistent coherence with

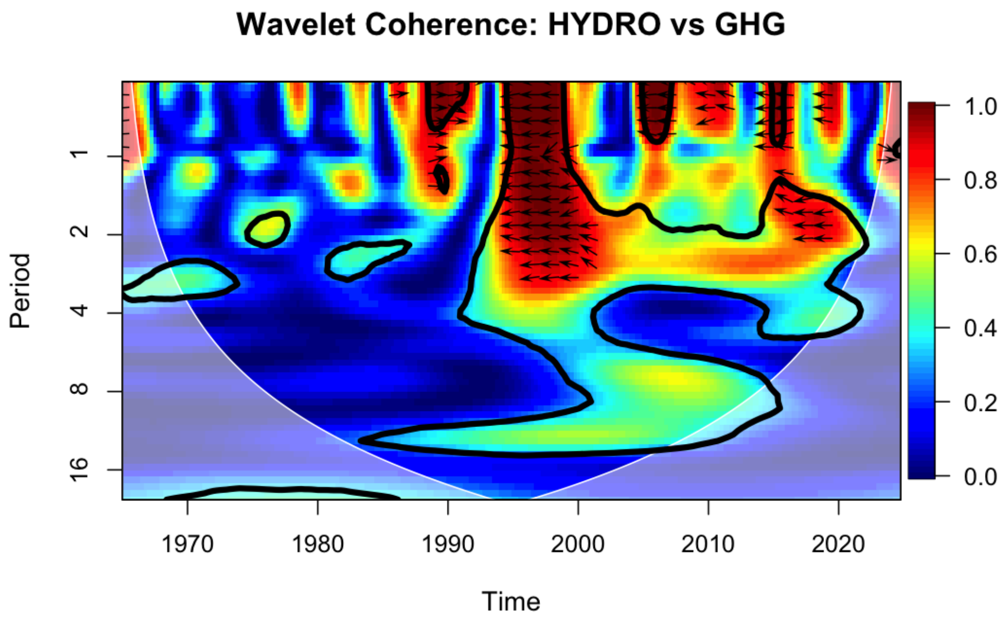

Figure 4. Wavelet coherence: Hydropower vs. GHG.

hydropower (Figure 4), although this dominance is concentrated at high frequencies rather than at long horizons. The most striking feature is a vertical column of near-unity coherence spanning roughly 1994–2000 and extending from periods below half a year up to about three years. Within this column the arrows point overwhelmingly to the left, establishing a strong anti-phase relationship, while their tilt alternates between left-up and left-down. This alternation is the time–frequency signature of a shifting lead–lag structure, in which GHG emissions lead hydropower in some sub-periods and hydropower leads GHG in others, and it maps directly onto the bidirectional Granger causality reported in Section 3.2. The timing of this episode, which brackets the Asian financial crisis, suggests that macroeconomic disruption jointly reshaped emission trajectories and energy-supply decisions at business-cycle frequencies.

A second strong region emerges at the 1–3-year band between approximately 2013 and 2022, with coherence of 0.7–0.9 and arrows again pointing left, showing that the short-run anti-phase linkage re-intensified during the recent decade of renewable-energy policy activism. These two major regions are connected by recurrent significant spikes at sub-annual periods around 1989–1991, 2005–2006, and 2009–2011, which indicates that, unlike the CO_2 case, the hydropower–GHG relationship is repeatedly reactivated at short horizons throughout the sample.

At lower frequencies, an elongated significant band at periods of roughly 8–14 years extends from about 1985 to 2015. Its coherence is moderate (0.4–0.6) and the sparse, direction-varying arrows preclude a firm attribution of leadership, while its right-hand edge approaches the COI. This band is therefore best characterized as evidence of a persistent but moderate long-run co-movement with a time-varying lead–lag structure, rather than as a region of strong long-run causality. Taken together, the GHG results combine the widest frequency coverage, the highest peak coherence, and alternating phase leadership, confirming that the hydropower–GHG nexus is the most dynamic of the three and is best described as a feedback relationship.

3.3.3. Hydropower vs. EFP

The coherence between hydropower and the ecological footprint (Figure 5) is moderate and discontinuous, with significant regions scattered mainly across the short- and medium-run bands. The strongest feature is a high-coherence region (0.8–1.0) at the 1.5–2.5-year band spanning approximately 1973–1983. The arrows there point predominantly straight to the left, identifying a pronounced anti-phase relationship in which hydropower and ecological pressure move in opposite directions over short cycles; the occasional vertical tilts are mixed, so the leadership within this region is episodic rather than uniform. Read jointly with the Granger results, this episode is consistent with short-run ecological pressure conditioning subsequent hydropower activity during the early phase of Indonesia's hydropower build-out.

In the medium run, three additional structures are visible. A band at the 3–4-year period accompanies the

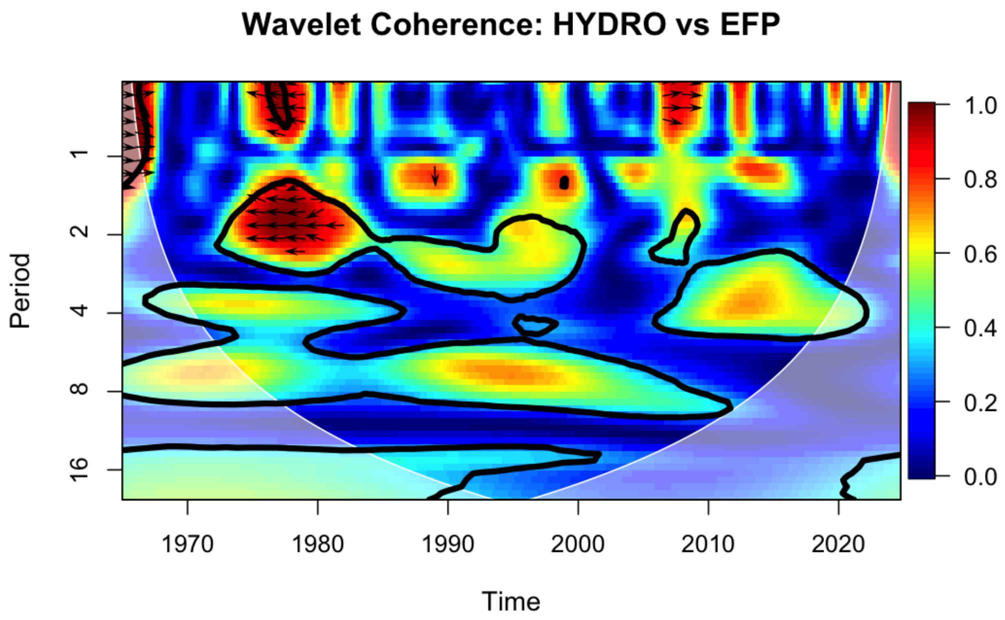

Figure 5. Wavelet coherence: Hydropower vs. EFP.

sample from the mid-1960s to the mid-1980s with moderate coherence, although its earliest portion lies close to the COI. A more clearly interior region occupies the 6–8-year band from roughly 1985 to 2005, with a yellow-to-orange core around 1990–1998, indicating a recurrent medium-cycle association during the 1990s. Finally, a policy-relevant region appears between 2005 and 2020 at the 3–5-year band, with coherence of 0.6–0.8, showing that the hydropower–footprint linkage resurfaced at medium horizons precisely during the era of accelerated renewable deployment; its right-hand portion, however, borders the COI and should be interpreted accordingly. Phase arrows outside the strong 1970s region are sparse, which limits fine-grained lead–lag inference at these horizons.

By contrast, the long-run band above 12 years exhibits only weak and fragmented coherence, and the corresponding contours lie largely at or beyond the edge of the COI. There is thus no evidence of a stable structural synchronization between hydropower and the ecological footprint at long horizons. Overall, the EFP results portray a relationship that operates in cyclical, short-to-medium-run episodes—in the 1970s, the 1990s, and again after 2005—rather than as a continuous long-run dynamic, in line with the unidirectional causality from EFP to hydropower detected in the Granger analysis.

3.4. Discussion

In this study, the dynamic interaction between hydropower development and environmental quality in Indonesia is examined by integrating Granger causality and wavelet coherence methods. Through the analysis of CO_2 emissions, total GHG emissions, and ecological footprint, both energy-specific and broader dimensions of sustainability are captured. The following discussion elaborates on the differences in predictive relationships and time-frequency dynamics across these environmental indicators.

To begin with CO_2 emissions, the evidence shows that carbon intensity is a key predictor of hydropower development. The Granger causality results indicate that CO_2 emissions predict hydropower, whereas hydropower does not predict CO_2 emissions, implying that changes in renewable generation follow, rather than lead, the accumulation of carbon emissions, and that policy has been responsive to rising environmental pressure. The wavelet coherence in Figure 3 supports this interpretation at two distinct horizons. In the long run, a broad significant region at the 12–16-year band accompanies the sample from the mid-1960s to the mid-1990s in an anti-phase configuration, and the upward tilt of the phase arrows from the mid-1980s onward identifies CO_2 as the leading variable, confirming that long-run carbon trajectories carried strong predictive information for hydropower during Indonesia's early development decades. In the medium run, a 2–4-year island spanning 1983–2000, with peak coherence around 1993–1998, shows CO_2 leadership re-emerging at business-cycle frequencies during the period of rapid industrialization, while only a weaker and short-lived echo of this linkage reappears around 2013–2017. Crucially, at no horizon does the plot display a sustained region in which hydropower leads CO_2, which is consistent with the continuing dominance of fossil fuels in the Indonesian power system: the share of hydropower has remained too limited to exert a detectable predictive influence on aggregate carbon trends. Based on these results, this finding differs from the studies by Ummalla & Samal [28], Maulidar et al. [20] and Idroes et al. [8], which found a bidirectional causality between hydropower and CO_2 emissions in Indonesia and the Southeast Asian region. While Bello et al. [31] and Saadaoui et al. [57] reported a unidirectional causality running from hydropower to CO_2 emissions.

When turning to total GHG emissions, the interconnection becomes markedly more dynamic. The Granger causality tests establish predictive relationships in both directions, and the wavelet coherence in Figure 4 reveals where this feedback is generated: not at long horizons, but primarily at short ones. The dominant feature is a column of near-unity coherence spanning roughly 1994–2000 at periods below three years, in which the anti-phase arrows alternate between upward and downward tilts—the time–frequency signature of a lead–lag structure that switches direction, with GHG emissions leading hydropower in some sub-periods and hydropower leading GHG in others. The timing of this episode, bracketing the Asian financial crisis, suggests that macroeconomic disruption jointly reshaped emission trajectories and energy-supply decisions at business-cycle frequencies. The same short-run anti-phase linkage re-intensifies at the 1–3-year band between 2013 and 2022, coinciding with the recent decade of renewable-energy policy activism, and is repeatedly reactivated by sub-annual bursts around 1989–1991, 2005–2006, and 2009–2011. At lower frequencies, a moderate but persistent band at 8–14 years extends from about 1985 to 2015 with direction-varying phase leadership, indicating that the feedback also operates, more diffusely, over longer cycles. Taken together, the wider frequency coverage, higher peak coherence, and alternating leadership confirm a deeper structural interdependence between hydropower development and aggregate emission dynamics than is observed for CO_2 or the ecological footprint. Based on our results, we do not find existing literature that reports evidence of bidirectional Granger causality between hydropower and GHG emissions.

Lastly, with respect to the ecological footprint, the results indicate that hydropower responds to broader environmental pressure rather than shaping long-term sustainability outcomes. The Granger causality output identifies a one-way predictive relationship from the ecological footprint to hydropower, implying that ecological degradation anticipates renewable-energy expansion. The wavelet coherence in Figure 5 shows that this reactive pattern operates in recurrent episodes rather than continuously: the strongest region appears at the 1.5–2.5-year band during 1973–1983, in a pronounced anti-phase configuration consistent with short-run ecological pressure conditioning hydropower activity during the early build-out phase; a medium-cycle association occupies the 6–8-year band from roughly 1985 to 2005; and the linkage resurfaces at the 3–5-year band between 2005 and 2020, precisely during the era of accelerated renewable deployment. By contrast, coherence in the long-run band above twelve years is weak, fragmented, and largely confined to the edge of the cone of influence, indicating that hydropower development is not structurally synchronized with long-term ecological outcomes. Considering that the ecological footprint aggregates land use, resource utilization, and biocapacity demands, these findings suggest that hydropower development alone has not been sufficient to alter Indonesia's overall sustainability trajectory. The present findings differ from those reported by Alola et al. [58] and Adebayo et al. [59], which documented a unidirectional causality from hydropower to the ecological footprint; however, they are supported by Yıldırım et al. [60], who found that the ecological footprint Granger-causes hydropower.

Across the three indicators, distinct time–frequency patterns emerge in the hydropower–environment nexus in Indonesia. The CO_2 linkage is concentrated at medium- and long-term horizons and is predominantly unidirectional, while the GHG linkage is stronger and more frequently observed, particularly at shorter horizons, with evidence of bidirectional interactions. In contrast, the EFP linkage is less persistent and concentrated at short- and medium-term horizons, with limited long-run synchronization. These heterogeneous patterns suggest that hydropower has predominantly responded to environmental pressures rather than consistently preceded changes in environmental quality. They also demonstrate that the relevant time horizons differ across environmental indicators, providing important insights for the timing and coordination of energy and environmental policies discussed in the following section.

3.5. Policy Recommendations, Limitations and Future Research

From a policy perspective, the findings suggest that hydropower should not be treated as a standalone driver of environmental improvement. Instead, its role appears to be closely linked to evolving environmental pressures and broader emissions dynamics. This implies that hydropower planning needs to be more closely aligned with environmental trends and integrated within the wider energy system. In particular, the effectiveness of hydropower in improving environmental outcomes depends on how it interacts with carbon emissions and the overall energy structure rather than on expansion alone. Therefore, policy strategies should focus on coordinated energy planning, where hydropower development is considered alongside other components of the energy transition rather than as an isolated solution.

This study has several limitations. First, the analysis is based on aggregated national-level data, which may mask regional heterogeneity and localized environmental impacts. Second, the focus on hydropower excludes other renewable energy sources and institutional or policy-related factors that may influence the energy-environment relationship. Third, the wavelet coherence analysis relies on quarterly series obtained through linear interpolation of annual data, so that fine-grained dynamics at the shortest horizons should be interpreted with caution. Fourth, while the study captures time-varying dynamics through wavelet coherence, it does not incorporate structural breaks or nonlinear modeling approaches. In addition, recent advances in machine learning and clustering techniques have shown potential in identifying nonlinear patterns and hidden structures in energy-environment data [39, 61–64], but these methods are not explored in the present study. Future research could address these limitations by incorporating multiple energy sources, applying nonlinear and structural break models, integrating machine learning approaches, and extending the analysis to sub-national or comparative regional contexts.

4. Conclusions

This study examined the dynamic relationship between hydropower and environmental quality in Indonesia over the period 1965 to 2024 using Granger causality and wavelet coherence approaches. The findings indicate that this relationship is not uniform across environmental indicators or time horizons, underscoring the importance of viewing environmental quality as a multidimensional construct rather than a single aggregate measure. A central insight is that environmental pressure precedes energy responses: hydropower development appears to be driven by rising ecological footprint and carbon emissions, as evidenced by unidirectional causality, indicating that Indonesia's renewable energy expansion has historically followed environmental degradation rather than anticipated it. In contrast, the relationship with GHG emissions is characterized by bidirectional causality, suggesting that hydropower is both shaped by and embedded within the country's broader emission dynamics. The wavelet coherence results further reveal that these relationships are time-varying and frequency-dependent, implying that the environmental signals to which hydropower responds operate at different horizons, from short-run ecological cycles to long-run emission trajectories.

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