JustRE Alliance

Global South Alliance for a Just Transition to Renewable Energy

The Implementation Gap: Anticipating missed renewable energy targets through media-sentiment and social resistance index

In partnership with

SEI Stockholm Environment Institute

Executive summary

The success of the global energy transition depends as much on social viability in the territories as on capital mobilization; however, accumulated social resistance remains a blind spot in most implementation models. When communities interpret new renewable projects through the lens of past experiences —where prior infrastructure often promised development but delivered displacement or environmental impact—, a systemic friction emerges that halts permitting and extends timelines for years.

Against this backdrop of social friction, the current context of renewable deployment must be assessed: achieving the International Energy Agency's Net Zero Emissions (NZE) scenario requires deploying 35.9 TW of renewable generation capacity globally by 2050 (up from 4.9 TW today). Yet emerging and developing economies capture less than 17% of global clean energy investment (excluding China), and many countries continue to experience a significant gap between planned and deployed renewable energy capacity. Behind this "implementation gap" lies a risk that conventional models underestimate: accumulated social resistance. The literature has shown that community conflicts halt permits and extend timelines, generating financial losses of up to USD 40 million per project and reducing Net Present Value by between 24% and 37%, and that managing conflict proactively is four times more cost-effective for projects.

To make visible, manage, and anticipate the difficulties caused by social resistance, **this document proposes a Composite Social Resistance Index (CSRI),** a metric that integrates local media coverage data (from the Global Database of Events, Language and Tone - GDELT) and historical socio-environmental conflict records (from the Environmental Justice Atlas - EJAtlas) tested across nine Global South countries, namely Colombia, Chile, Ethiopia, Indonesia, Kenya, Peru, Senegal, Thailand, and Vietnam. **This analytical tool translates territorial friction into actionable quantitative data for monitoring renewable energy projects portfolios and public policy.** In doing so, it explicitly speaks to the study's central Implementation Gap (IG)—defined as the distance between planned and actually installed renewable capacity in a country—used as the main dependent variable capturing implementation deficits in wind and solar deployment.

The results of this report should be interpreted as evidence of potential relationships rather than definitive causal estimates. The analysis is limited to the nine Global South countries for which historical electrical planning data was identified, underscoring a broader challenge: the limited availability and transparency of generation expansion data across many countries in the Global South, which constrains the evaluation of transition targets and progress. Although the report applies econometric methods and therefore includes some specialized terminology, it has been written in accessible language to ensure that its findings can inform a broad audience engaged in energy transition policy and practice.

Key findings

- **Three-year early warning:** Negative media noise about renewable energy in a country anticipates implementation deficits three years in advance. This translates into lags of 40–60% for planned wind capacity and 35–50% for planned solar capacity.

- **Two speeds of territorial risk:** Social risk operates across two distinct dimensions that require separate approaches. Media sentiment is highly volatile, acting as a short- to medium-term tactical risk. By contrast, the historical memory of past conflicts is a permanent structural scar, defining each country's baseline entry complexity and operating conditions.

- **Technological differentiation:** Implementation barriers are not technologically neutral. While solar energy deployment shows greater global convergence, likely due to its modular standardization and lower visual impact, trajectories for wind energy deployment are highly dependent on local geographic particularities, land governance, and community history. This is consistent within the sample of countries studied.

- **Context matters more than geography:** The implementation gap does not follow predictable regional patterns and does not respond uniformly to global shocks. Countries within the same region often display radically different trajectories, while countries across regions may exhibit similar dynamics. Variance decomposition confirms that changes in the implementation gap are driven primarily by country-specific temporal dynamics rather than structural differences between countries.

Recommendations

For public policy makers:

- **Integrate social viability metrics:** Ministerial dashboards could monitor social acceptance in real time alongside installed-GW targets, using the media sentiment index proposed in this study, helping to anticipate bottlenecks.

- **Design asymmetric regulatory frameworks:** Licensing and public consultation regulatory frameworks should not treat all technologies equally. Wind projects require participation frameworks far more tailored to local context than solar projects.

- **Ensure data transparency:** Preserving and publishing capacity expansion targets or expectations, and tracking them historically, is essential to rigorously evaluate each nation's energy transition commitments.

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For investors and project developers:

- **Incorporate media monitoring into the risk matrix:** Using media sentiment index makes it possible to identify early warnings, providing a three-year window to adjust financial expectations and strengthen community engagement before the construction phase.

- **Segment due diligence:** It is essential to distinguish between historical socio-environmental liability (structural risk) and current public pressure (dynamic risk) in order to avoid underestimating the long-term effort or over-diagnosing transient circumstances, and to manage community expectations appropriately.

- **Concessional capital as a catalyst for closing the implementation gap:** The analysis demonstrates empirically that concessional capital—originating from official development assistance—has a statistically significant effect in reducing the implementation gap, particularly in wind technology. This means that multilateral climate funds and concessional loans do much more than incentivize commitments or ambitious planned-capacity targets in emerging economies; they are the catalyst that allows those national plans to overcome territorial friction and become effectively installed capacity—building local capabilities, strengthening regulatory frameworks, and closing technical and conceptual gaps.

Content

Executive summary 2

1 Why does the gap between planned and implemented matter? 6

2 What research has established on social resistance and renewable energy deployment 8

3 Methodology 10

3.1 The Implementation Gap (IG) 11

3.2 The Composite Social Resistance Index (CSRI) 11

3.3 Isolating the effect of social resistance: Multiple Regression Model with Fixed Effects (MRMFE) 12

4 Preliminary findings on the behavior of the implementation gap 13

5 Findings of the Multiple Regression Model with Fixed Effects (MRMFE) 16

5.1 Temporal variability and final specification of each model 16

5.2 Media sentiment as an early warning signal of renewable energy deficits 17

5.3 What the control variables reveal about the investment environment 19

5.4 Interpretation of results from the Media Sentiment Index (MSI) 20

6 What the results imply for understanding renewable energy upscaling 23

7 Conclusions, recommendations, and Implications for decision-makers 25

8 Limitations: What this study cannot yet answer 27

9 Next steps 28

10 Technical annex: methodological note 29

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1 Why does the gap between planned and implemented matter?

The success of the global energy transition depends as much on social viability as on capital mobilization; however, accumulated social resistance remains a blind spot in most implementation models. When communities interpret new renewable projects through the filter of past experiences, where previous infrastructure often promised development but delivered displacement, exclusion or socioenvironmental impacts, a systemic territorial friction emerges. This friction can delay permitting processes and slow implementation for years.

It is under this premise of social friction that we must analyze the current context of renewable deployment. Most countries have undertaken energy transition initiatives to mitigate the impacts of anthropogenic global warming. The IEA's NZE scenario introduces a challenging reality: to maintain the threshold of 1.5°C of temperature increase above pre-industrial levels, the pace of renewable capacity expansion must be radically accelerated and, actual capacity added should be equal or mayor than planned capacity. Counting MW will not be enough if there is a continuous implementation gap over time.

On the financing side, the volume of investment required in electricity generation from renewable sources and in grids must reach between 2.1 and 2.8 trillion dollars annually between 2025 and 2035 (IEA, 2025; Naran et al., 2024). Yet in 2023, only 196,000 million dollars reached emerging markets and developing economies (EMDEs), of which only 22% came from private capital (Naran et al., 2024). In Latin America and the Caribbean, the situation was more critical as the region captures only 5% of global private investment in clean energy (IEA & Olade, 2025). Moreover, fiscal deficits in EMDEs are approximately 60% larger than in the pre-pandemic period; the cost of domestic private capital is double that of advanced economies; and international investors perceive combinations of risk — currency, political, regulatory, social — that drive risk premiums to levels that hinder the deployment of renewable energy projects (IEA, 2025).

The social and territorial risks that are significantly harder to quantify. Community opposition, unresolved land-use disputes, and the legacy of past socio-environmental conflicts can delay projects, increase development costs, and undermine the realization of planned capacity. These dynamics contribute directly to the implementation gap, yet they remain largely absent from conventional deployment and investment models (Institute for Human Rights and Business, 2025).

In this context, this report examines the implementation gap through the lens of social resistance. It proposes an empirically grounded approach based on the construction of an index designed to examine the disparity between installed and planned renewable energy capacity since the signing of the Paris Agreement in 2015, tested across nine Global South countries. To achieve this objective and capture the dynamic nature of social risk, it is methodologically necessary to adopt a fixed-effects panel econometric model.

This analytical approach allows for the observation of the same countries over a decade (2015-2024), isolating the specific impact of social resistance on the implementation gap and separating it from permanent structural variables, such as institutional history, geography, or the baseline regulatory quality of each country. For policymakers and investment portfolio structurers, this tool acts as a statistical filter that separates the noise, making it possible to quantify how temporal fluctuations of a Media Sentiment Index (MSI) within the same territory alter the capacity implementation of generation projects.

The accumulated evidence on the costs of ignoring the social dimension

Research over the last five years has radically transformed the understanding of social resistance to renewable energy projects. It is no longer a qualitative variable that companies must "manage." It is a financial risk with documented magnitude.

Delays caused by community conflicts generate average financial losses of between USD 25 and 40 million per project — equivalent to a reduction of 24% to 37% of the average Net Present Value of the investment (Feyertag & Bowie, 2021). The cost of confronting a social conflict can be up to four times greater than that of mitigating it from the outset (Feyertag & Bowie, 2021). In the United Kingdom, cumulative losses from social opposition to renewable projects were estimated at GBP 23,000 million by 2019 (Energy Institute AT HASS, 2021). In Ireland, generation expansion models that omit social acceptance produce systems that are 33% more costly (Tong Koecklin et al., n.d.).

These are not isolated findings. A retrospective assessment of 31 European countries between 1990 and 2019 demonstrates that social factors explain up to 27% more of renewable expansion outcomes than conventional techno-economic models (Fisch-Romito et al., 2025). An empirical analysis of 12,475 projects in 48 countries confirms that investors manage their portfolios dynamically, and that site characteristics, including the social dimension, condition their execution decisions (Gumber et al., 2024).

What is missing and what this study attempts to address is a quantitative index, comparable across countries and years, that allows social resistance to be integrated into the monitoring and management of renewable energy projects in Global South countries.

2 What research has established on social resistance and renewable energy deployment

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Social resistance to renewable energy projects has come a long way in academic literature, from a phenomenon labeled with the pejorative term "Not In My Back Yard" (NIMBY) to a variable with demonstrable financial weight. This shows not only the formalization of the problem, but also its degree of importance in the current context, its economic effect on society and the potential to capture associated benefits.

Since the foundational work of Wüstenhagen et al. (2007), which conceptualized social acceptance at the community level as a three-dimensional phenomenon (procedural justice, distributive justice, and trust in project developers), an extensive body of research has documented that opposition is neither irrational nor episodic. It is cumulative, inherited, and dynamic. Communities learn from past conflicts. They forge their own vocabulary — "ecological debt", "environmental racism", "food sovereignty" — that emerges directly from experiences with previous projects (Martinez-Alier et al., 2016). This collective learning acts as a reservoir of latent resistance that can be activated by new projects, decades after the original conflicts.

Theoretical frameworks such as bounded rationality (Klaes & Sent, 2005), energy justice (Heffron & McCauley, 2017), and the sustainable livelihoods approach (Natarajan et al., 2022) have contributed to explaining why historically marginalized communities respond with greater intensity to the externalities of infrastructure projects. A structured review of 47 cases of community conflict in large-scale renewable projects concludes that conflict is multicausal and structural, emerging from the combination of project size and proximity, impacts on livelihoods and land use, the absence of genuine consultation, and competition for water resources (Institute for Human Rights and Business, 2026).

The SPEED (Socio-Political Evaluation of Energy Deployment) framework demonstrated that the integration of media analysis and focus group participation substantially improves understanding of the determinants of technological deployment (Stephens et al., 2008). The World Bank has used the Global Database of Events, Language and Tone (GDELT) database to correlate news tone with mass protest events, validating the pertinence of approaches based on natural language processing for the analysis of social mobilization (World Bank Group, 2026).

These precedents open the possibility of constructing a quantitative index of social resistance based on media coverage that is comparable across countries, updatable, and replicable with publicly accessible data. Also, that can be empirically validated as a determinant of the implementation gap between planned and effectively installed capacity in wind and solar energy. That is what this study attempts to build.

From this review, it is posited as a hypothesis that social acceptance — or its absence — acts as a latent variable throughout the entire project life cycle, is sensitive to negative cumulative effects stemming from previous projects, and manifests dynamically through *de facto* channels. It also leaves evidence and traces in media outlets that influence decision-makers, project developers, and the academic community, in cycles of expansion and contraction fed back by media attention and the comparative economic factors available to a renewable energy project developer monitoring their portfolio.

3 Methodology

In line with the conclusion of the state-of-the-art review, this study assumes that social conflict is inherited and that latent resistance exists toward the development of large-scale renewable energy projects. This resistance coexists with exogenous and endogenous factors that project developers evaluate comparatively and cross-sectionally. The methodological challenge therefore consists of approximating, in an indirect manner, the behavior of social conflict or opposition and integrating it with explanatory variables that also influence the pace of generation capacity deployment.

To validate social opposition as an explanatory variable of the gap between planned and effectively installed capacity in wind and solar energy (the implementation gap), the study proposes a **Multiple Regression Model with Fixed Effects (MRMFE)**. Its indexes are constructed from two data sources: sentiment analysis of local media coverage on renewable energy using the **GDELT database** and the **historical records of socio-environmental conflicts reported in the Environmental Justice Atlas (EJAtlas)**. The MRMFE is appropriate as it allows the effect of regressors to be verified and isolated in a controlled manner, separating out the effects of each country's unobserved heterogeneity (D.Allison, 2009). Control variables are market factors and institutional factors selected based on their frequency of appearance in literature as determinants of investment and of the deployment of solar and wind generation capacity (e.g., wholesale electricity price, debt-to-GDP ratio, GDP growth rate, state legitimacy, regulatory quality, among others). Regarding the time horizon, the model uses 10 years of data spanning from the signing of the Paris Agreement (2015) to 2024.

In this section, we briefly describe the methodology and main indexes while the technical annex provides more conceptual details on the methodological development of the RFME and the construction and rationale of the proposed indexes. Therefore, **for more methodological depth you may consult the technical annex at the end of this document.**

3.1 The Implementation Gap (IG)

Before measuring social resistance, this study operationalizes the phenomenon it seeks to explain: **the difference between what a country planned to install in renewable energy (wind and solar) and what it actually installed**. This distance is the Implementation Gap (IG) which is calculated as the difference between actual added capacity and planned capacity for each country and year:

$$IG = \ln(\textit{actual added capacity}_{it} + 1) - \ln(\textit{planned capacity}_{it} + 1)$$

Negative values of the gap indicate an implementation deficit (the country executed less than planned). Positive values indicate that execution exceeded planning. The gap is calculated separately for wind energy (IGwind) and solar energy (IGsolar), given that both technologies face distinct implementation barriers with differentiated heterogeneity patterns.

3.2 The Composite Social Resistance Index (CSRI)

The core of the proposal is the construction of the Composite Social Resistance Index (CSRI), a quantitative metric that evaluates the social friction faced by the deployment of renewable energy projects, equitably integrating two fundamental dimensions of territorial risk. The CSRI is composed of the **Socio-environmental Conflict Memory (SCM) index** built from the EJAtlas database, and the **Media Sentiment Index (MSI)**, which represent the tone of news extracted from GDELT for each year in each country.

$$CSRI_{it} = w_1 SCM_{it} + w_2 MSI_{it}$$

The MSI captures the emotional record of media coverage on renewable energies in a country over a year. The result is an annual signal that reflects, in a single figure, whether that country's media ecosystem treated renewable energies with a predominantly favorable or adverse framing during that period, conditional on there being active coverage of the topic. For its part**, the SCM index captures the long-term legacy of socio-environmental conflicts** and is constructed using data from the EJAtlas, a global database of socio-environmental conflicts. By consolidating current public opinion and the historical socio-environmental liability into a single indicator, the CSRI provides decision-makers and investors with a robust empirical variable to anticipate the community barriers that widen the gap between planned and actually installed electricity generation capacity.

The SCM index captures a clearly documented fact: communities do not forget. A conflict recorded in 2003 does not disappear from collective memory in 2015. It leaves an institutional imprint in resistance repertoire, in expectations about the behavior of project developers, in the interpretive frameworks that communities apply to new projects, and in some cases in rulings that serve as legal precedent. It conditions the reception of future investments in the same territory. In the Global South, where many territories have accumulated decades of extractive projects with unresolved socio-environmental impacts, this inherited memory can be as determinant of current resistance as the conflicts of the ongoing year.

3.3 Isolating the effect of social resistance: Multiple Regression Model with Fixed Effects (MRMFE)

A multiple regression model with fixed effects is used to identify the specific effect of social resistance on the implementation gap. The model attempts to separate social resistance from the effects of macroeconomic conditions, institutional governance, financial flows, and unobserved heterogeneity. The general equation of the model is:

$$IG_{it} = \beta_0 + \beta_1 CSRI_{it} + \beta_2 SL_{it} + \beta_3 RQ_{it} + \beta_4 WS_{it} + \beta_5 LU_{it} + \beta_6 CPI_{it} + \beta_7 IFF_{it}$$

$$+ \beta_8 EP_{it} + \beta_9 GDPR_{it} + \beta_{10} GDP_{it} + \mu_i + \alpha_t + \varepsilon_{it}$$

Country fixed effects (μ_i), for example, absorb everything that permanently differentiates one country from another such as institutional history, political culture and geography, without needing to measure it directly. Year fixed effects (α_t) absorb common global shocks, such as the COVID-19 pandemic or tensions in the renewable equipment supply chain.

The control variables are Market Factors and Institutional Factors. Market Factors include international financial flows for renewable energy (IFF), wholesale electricity price (EP), debt-to-GDP ratio (GDPR), and GDP growth rate. Institutional Factors include state legitimacy (SL), regulatory quality (RQ), and corruption perception index (CPI). Two variables were considered in the initial specification and subsequently discarded for statistical reasons: Water Stress (WS) and Land Use (LU). This does not mean that water stress or land use pressure are irrelevant to renewable project deployment; it means that their effects are absorbed by the permanent structural characteristics of each country, and that their temporal dynamics cannot be identified with the panel size available.

4 Preliminary findings on the behavior of the implementation gap

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The behavior of the implementation gap in the Global South is not uniform, does not follow predictable regional patterns, and does not respond in a synchronized manner to global shocks. Consequently, **renewable energy acceleration strategies require differentiated and context-sensitive approaches, rather than homogeneous recipes replicated across regions**.

Figure 1 shows the behavior of the implementation gap for the nine countries analyzed. Negative values indicate that, in a given year, the renewable capacity effectively installed was lower than the capacity previously planned, reflecting implementation deficits. Conversely, positive values indicate that installed capacity exceeded the originally projected targets or forecasts. Values close to zero indicate that installed capacity are close to the originally projected targets or forecasts.

Figure 1. Evolution of the implementation gap for wind and solar generation capacity.

The following three findings are drawn from **Figure 1** based on the exploratory analysis:

- **Within-region heterogeneity across countries:** even among countries sharing relatively similar macroeconomic contexts, the trajectories of the implementation gap are markedly distinct. In Latin America, for example, Colombia exhibits a systematic and stable wind energy implementation deficit throughout the entire analyzed period, while Peru shows high volatility with positive peaks in 2016–2017 and 2023. Chile, for its part, maintained values close to zero for years, but over the last three years has shown a growing trend toward implementation deficits in wind capacity. Three countries from the same Latin American macroeconomic context, three completely distinct trajectories. This heterogeneous behavior is not specific to this region or its countries; it also manifests in the Sub-Saharan Africa and Southeast Asia countries studied.

- **Cross-regional heterogeneity:** the observed patterns also vary significantly across regions of the Global South. In Sub-Saharan Africa, Kenya records the most pronounced wind capacity implementation boom in 2018, exceeding the planned capacity for that year, yet followed by a sustained decline toward strongly negative values in 2019–2024. In Southeast Asia, Vietnam evidences an ascending trajectory toward positive values in 2021–2022, possibly associated with the wind-solar energy boom driven by feed-in tariff mechanisms, while Indonesia exhibits the deepest deficit in the Asian set of countries. Finally, Latin America shows a marked difference with respect to the other regions, showing a sustained deficit trend for wind energy and a recovery trend for solar energy.

- **Absence of a common temporal pattern across countries:** if global temporal shocks, such as the COVID-19 pandemic in 2020, supply chain tensions in 2021–2022, or changes in international interest rates, were the primary determinant of the gap, a synchronized movement across the nine countries would be expected in those years.

Statistically, the preceding behavior was confirmed in the variance decomposition of the dependent variables, finding that their changes respond primarily to temporal dynamics within each country and not to structural differences between countries. Accordingly, the fixed effects estimator — which operates precisely on that temporal dimension — has sufficient signal to identify which variables explain why the same country widens or narrows the gap between planned and effectively installed capacity in different years.

An additional finding emerges from this technological contrast:

- **The solar implementation gap shows greater cross-country convergence than the wind implementation gap.** Countries differ more among themselves in how they implement wind energy than in how they implement solar energy. This suggests that solar energy deployment, favored by globally standardized modules and homogeneous declining costs, faces more similar barriers across countries; while wind deployment, more dependent on local conditions such as resource location, territory, land governance, and community history has more idiosyncratic trajectories. This difference has direct implications for policy design and raises the question: should investment attraction instruments and social risk management frameworks be technologically differentiated?

5 Findings of the Multiple Regression Model with Fixed Effects (MRMFE)

The study tested three specifications of the Social Resistance Index independently: the Media Sentiment Index (MSI) based exclusively on media sentiment from GDELT data, the Socio-environmental Conflict Memory index (SCM) as an independent regressor and the Composite Social Resistance Index (CSRI) as a combination of the MSI and the SCM under equal weighting. Accordingly, six models are estimated in total — one pair per index (one for wind energy and one for solar) — each sharing the same pipeline estimation architecture.

5.1 Temporal variability and final specification of each model

Each regressor considered had sufficient temporal variation to be identified by the fixed effects estimator. A regressor whose variance is almost entirely structural (that is, reflecting permanent differences between countries rather than annual fluctuations) contributes no useful signal to the within estimator and must be excluded.

The Media Sentiment Index (MSI) has the highest temporal signal of all the social resistance indexes: 63% of its variation is dynamic, changing from year to year within each country. The Socio-environmental Conflict Memory components — both in the CSRI and in the independent SCM — have ratios of 0.22 and 0.21 respectively, meaning that 78–79% of their variation is structural across countries. In other words, **the MSI changes rapidly; media noise can spike in a given year due to news about an auction, for instance, and drop the following year, or vice versa in the event of unfavorable news coverage. In contrast, the SCM shows minimal year-over-year variation, demonstrating that the scars of socio-environmental conflict persist over time**, which is consistent with the literature and empirical evidence regarding cumulative socio-environmental conflict. Therefore, both indices could lead to different strategies.

While media narratives can shift rapidly from year to year, the legacy of socio-environmental conflicts remains remarkably persistent, highlighting the need to address both short-term perceptions and long-standing grievances.

Additionally, it was considered that the changes in regressors had a temporally lagged effect on the implementation gap. Accordingly, the determination of the optimal lag for the control variable in each model was performed through a systematic exploration of lags of 0 to 4 years, evaluating each specification with the Akaike Information Criterion (AIC) calculated on the residuals of the within estimator (Stock James; Watson Mark, n.d.; Yum, 2021).

5.2 Media sentiment as an early warning signal of renewable energy deficits

One of the most significant findings of the study is that **the media sentiment index (MSI) predicts renewable implementation deficits three years in advance, consistently for both wind and solar energy.** When the MSI of a country exceeds its historical mean, the model estimates that **the gap between planned and installed renewable capacity widens in a range of 40–60% for wind energy and 35–50% for solar energy three years later. In practical terms, countries experiencing more adverse media sentiment subsequently deploy a significantly smaller share of the renewable capacity they had originally planned.** The effect holds when expressed both in terms of the original scale of the index and in terms of the standard deviation that the MSI records within the same country over time, which confirms that the result is not dependent on the unit of measurement chosen for interpretation.

The three-year horizon is not arbitrary and is consistent with the propagation cycle described in the literature on social conflicts and energy permitting. Negative media narratives do not immediately translate into implementation deficits. Negative media noise in year *t* translates into the media framing of the conflict, which formally materializes in year *t+1* through resistance, including litigation, demonstrations, blockades, among others. This, in turn, activates the collective memory of the conflict; producing, in year t+2, the suspension of permits and licenses; and an observable implementation deficit in t+3. The robustness of this horizon across technologies (that is, the same lag in wind and solar energy) makes this pattern difficult to attribute to specification artifacts.[1]

Negative media sentiment provides a three-year early warning of implementation risks. Countries with above-average levels of negative media coverage experience renewable deployment deficits of 40–60% in wind energy and 35–50% in solar energy relative to planned capacity.

[1] A specification artifact is a result that appears robust but was in fact inadvertently produced by researcher decisions during the model-building process, rather than by a genuine relationship in the data. The consistency of a three-year lag in the MSI across the implementation gaps of different technologies rules out this type of situation.

The interpretation of the above results is further supported by a supported by the following empirical and statistical validation, which provide evidence about of the estimated MSI and the reliability of statistical inference despite the limited sample size. First, a technical feature of relevance for the robustness of the MSI is that the difference between the coefficients of the fixed effects estimator and the random effects estimator is less than 10% for both technologies (wind and solar energy). This indicates that the MSI is not confounded with the permanent structural characteristics of countries, but rather effectively captures temporal variation. Second, the inflation of the standard error upon applying the CR2 correction[2] is less than 10% in wind and solar — the most moderate of the six models. This indicates that the bias introduced by the reduced panel size into the inference of the MSI is limited. On the other hand, the lack of formal significance under the CR2 correction does not indicate the absence of a signal. It indicates that the nine-country panel does not have sufficient statistical power to exceed the formal threshold with the most conservative correction available.

In conclusion, for the MSI, the difference in statistical significance between the conventional estimator and the CR2 correction is only 7 percentage points — reflecting primarily the penalty imposed by working with nine countries rather than twenty or thirty, and not a signal that the effect is fragile or unstable. From a decision-making perspective, an investor or policy formulator who discards the MSI because its CR2 statistical significance does not cross the 10% threshold is applying the same standard that would reject a seismic alert because the most conservative sensor recorded 6.7 instead of the 7.0 threshold and in doing so, would be accepting a higher risk of missing a real signal in exchange for a stricter but structurally unattainable level of statistical certainty given the panel size.

In the case of the CSRI, coefficient differences exceed 30% in both wind and solar, signaling that the temporal variation of the composite index is insufficient to separate the effect of the regressor from the individual heterogeneity absorbed by the fixed effects. Sign analysis qualifies this result differently for each technology. The Socio-environmental Conflict Memory index (SCM) as an independent regressor shows the most pronounced standard error inflation of the set upon applying the CR2 correction.

The consistency of a positive sign in the wind energy model between estimators can be interpreted as suggestive evidence of the direction of the effect: **in years with greater historical accumulation of socio-environmental conflicts, the wind implementation gap tends to be wider. This also implies that a country’s past in terms of socio-environmental conflict conditions its ability to implement renewable projects in the present, regardless of its current media sentiment, regulatory quality, or investment flows.** Under the theoretical conflict cycle, this is plausible because conflict memory activates expectations of delays among developers, which may induce overplanning of capacity, more detailed or postponed licensing processes, or deferral of investment decisions. But this mechanism requires additional validation given the sign change observed in solar energy before being reported as a robust result.

[2] CR2 correction = Cluster-Robust variance estimator of order 2. For more details, see section 10.3 of the technical annex.

The historical memory of socio-environmental conflicts is likely a real determinant of territorial resistance to renewable projects, but it operates primarily as a structural characteristic of countries — absorbed by the fixed effects — and not as a signal that fluctuates from year to year. To capture it empirically as a regressor, panels with a greater temporal dimension are needed.

5.3 What the control variables reveal about the investment environment

Among the control variables, the wholesale electricity price with a one-year lag is the only one that exceeds the significance threshold under the CR2 correction in the wind energy model. The positive sign reflects that high electricity prices induce the planning of greater wind capacity or the acceleration of execution for projects already underway, which ultimately can lead to a narrower implementation gap (holding other factors constantly). For solar energy, the signal is opposite and with a three-year lag. In this case, solar projects, which tend to have shorter construction times, do respond to price signals by increasing the volume of proposed or submitted projects that are not fully executed, which ultimately widens the implementation gap for this technology.

In short, a higher electricity price acts as a signal that materializes wind projects one year later and reduces the implementation gap, while in solar energy projects higher prices widen the implementation gap for this technology with a three year-lag.

For its part, international public financial flows for wind energy show the expected sign — **more low-cost concessional capital reduces the implementation gap.** This confirms the critical role of official development assistance flows in renewable deployment in the EMDEs, and indicates that international climate finance mechanisms have a measurable effect on effective execution. For solar energy, however, the coefficient shows the opposite sign, a result that is not consistent with the expected direction of the finance–deployment relationship and warrants further analysis before drawing conclusions about the mechanism at play.

Greater access to low-cost international public finance is associated with smaller implementation gaps in wind energy, confirming the importance of concessional climate finance for turning plans into projects.

Institutional variables (SL, RQ, CPI) do not reach significance under the CR2 correction. This does not imply that regulatory quality or corruption perception do not matter for renewable deployment — the literature consistently shows that they do —; rather, their temporal variation within each country over the analyzed period is relatively limited, making it difficult to identify their effect with a reduced panel of nine countries.

5.4 Interpretation of results from the Media Sentiment Index (MSI)

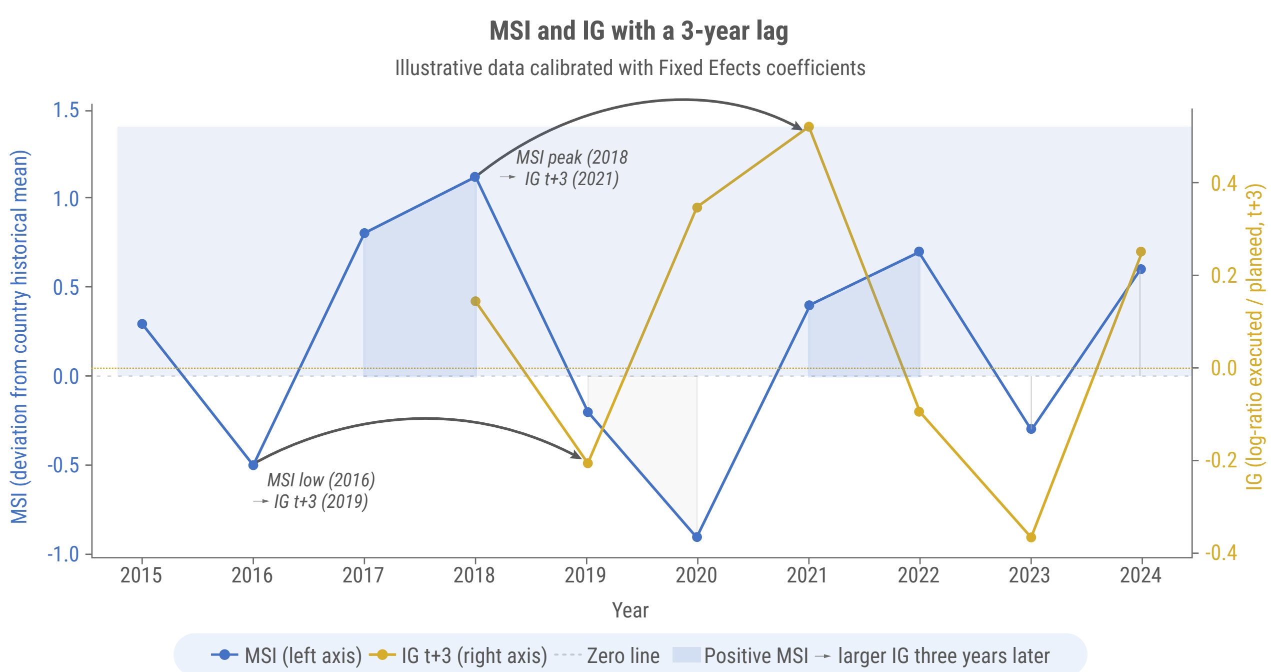
The MSI has two properties that operate independently and must be read separately: its absolute level in a given year (that is, whether the value for media tone is positive or negative in gross terms) and its change relative to the country's own historical mean (whether that year was unusually positive or negative for that country). The fixed effects model uses only the second; accordingly, the question the MSI answers is: when the MSI in a country is above (or below) its historical mean, what happens to the implementation gap? This section offers answers to this question.

Values above the MSI's historical mean

The MSI captures the predominant media framing of renewable energy in a country over a given year: positive values reflect a favorable framing (e.g., coverage of agreements reached, investment, economic development); negative values reflect an adverse framing (e.g., coverage of protest, conflicts, litigation). **The model identifies a robust relationship between the MSI and the Implementation Gap (IG) with a three-year lag**. **When a country's MSI improves, the IG tends to be higher and positive three years later —implementation moves closer to, or surpasses, the planned target—; when the MSI deteriorates, the IG tends to be lower —the implementation deficit deepens or slows**.

Reminder: In this study, higher Implementation Gap (IG) values represent better implementation performance (deployment closer to or exceeding planned capacity), whereas lower IG values indicate larger implementation shortfalls.

Figure 2. Illustration of the MSI-IG relationship and the 3-year lag



Note: illustrative series generated. The Fixed Effects estimator operates on within-country deviations, not on absolute MSI levels.

Figure 2 illustrates this relationship using hypothetical data. The blue line (left axis) traces the MSI — the annual deviation of media sentiment from a country's own historical mean — while the orange line (right axis) shows the implementation gap three years later. Two annotated arrows make the propagation mechanism explicit. When the MSI reaches its peak in 2018 (favorable media framing), the IG rises in 2021 indicating that executed capacity met or slightly exceeded the planned target. Conversely, when the MSI falls to its lowest point in 2016 (adverse media framing), the IG drops to a negative value in 2019 reflecting a deficit between planned and executed capacity. The shaded blue areas highlight years of positive MSI, consistently followed by upward IG movements three years later.

How to read the MSI–Implementation Gap relationship

The Media Sentiment Index (MSI) measures whether a country's news coverage of renewable energy is favorable or adverse relative to its own historical average. The Implementation Gap (IG) measures whether a country executed more or less renewable capacity than planned. The table below translates the model's three-year lag into actionable language.

MSI signal	What the media is saying	IG outcome 3 years later	What it means in practice
FAVORABLE **MSI above country's historical mean (positive deviation)**	News highlights agreements, investment, job creation, and successful community engagement. The public narrative treats renewables as an opportunity.	IG rises — becomes less negative or turns positive. Capacity installed moves closer to, or exceeds, the planned target.	Lower permitting friction, stronger investor confidence, and faster project execution. The territory is more likely to absorb planned capacity.
ADVERSE **MSI below country's historical mean (negative deviation)**	News focuses on protests, litigation, land conflicts, environmental harm, or broken promises. The public narrative treats renewables as a threat or injustice.	IG falls — becomes more negative. Capacity installed falls significantly short of the planned target.	Higher permitting delays, community blockades, litigation risk, and investor retreat. The territory struggles to convert plans into operating capacity.

When the MSI improves

A rising MSI can produce a positive IG for distinct reasons, and the model cannot distinguish between them with the available data. Various reasons may be behind this behavior, including:

- **Real acceleration of execution driven by accumulated social pressure and conflict.** More favorable media coverage on renewable energy (e.g., agreements reached, effective compensation, successful consultation processes) facilitates permitting, licensing, and community acceptance, accelerating actual construction beyond the planned pace.

  In some Global South contexts, sustained coverage of renewable energy projects does not paralyze implementation but, on the contrary, activates it. When conflict reaches sufficient media visibility, regulators and developers accelerate or adjust consultation, compensation, and project-adjustment processes to recover public legitimacy. This institutional response —which occurs only when pressure is visible— can result in faster and more socially robust implementation than what would have occurred without conflict.

  The literature on procedural justice in infrastructure projects (Wüstenhagen et al., 2007) documents this effect: genuine consultation processes, although slower in the short term, produce more stable agreements and fewer execution conflicts in the medium and long term. An adverse MSI may be the signal that this genuine process is underway.

- **Post-conflict agreements unlock stalled projects.** When an active conflict reaches negotiation, media coverage often adopts a constructive tone. This media shift often coincides with the release of projects that had been administratively blocked, whose backlogged execution accelerates beyond the prevailing planning pace.

- **Editorial bias in low press-freedom contexts can overstate actual favorability.** In these contexts, a favorable MSI may coexist with social tension that is underreported in the media. This limitation does not invalidate the observed empirical relationship —the MSI still predicts the direction of the IG— but it qualifies its interpretation as a measure of genuine social acceptance.

When the MSI deteriorates

A declining MSI is associated with a lower (or negative) IG three years later. Various reasons may be behind this behavior, including:

- **Administrative and judicial blockage of execution.** A more adverse media climate often coincides with active litigation, community blockades, and the precautionary suspension of licenses and permitting, which directly delay construction and contract the capacity actually executed.

- **Erosion of investor confidence:** A more adverse media climate raises the perceived regulatory and social risk among financiers and investors, which can translate into more restrictive financing conditions or the postponement of final investment decisions.

6 What the results imply for understanding renewable energy upscaling

The results of this study provide empirical evidence in three dimensions of scientific relevance for the field of energy transition planning in the Global South.

First: the MSI opens a new line of quantitative real-time monitoring of social acceptance

The MSI is the first quantitative approximation of a social resistance index for renewable energy deployment built from global media coverage data (GDELT) for Global South countries. Its positive and consistent direction across technologies — greater unfavorable media noise is associated with an implementation deficit three years later — validates the proposed theoretical mechanism and opens a quantitative research line for monitoring the social acceptance of the energy transition in real time. **This contribution has methodological value independently of formal statistical significance, given that it demonstrates the technical feasibility of operationalizing a socially complex construct using publicly accessible and replicable data.** Renewable energy project developers, financiers, and public authorities could incorporate this type of monitoring into their portfolio risk management systems, with continuous updating and without the costs of conventional opinion surveys.

Second: Wind and solar deployment respond to distinct logics that policies rarely distinguish

The goodness-of-fit results[3] — within R^2 of around 15–20% in the wind models and 11–18% in the solar models — are consistent with the findings of similar fixed effects studies on renewable deployment in country panels that report analogous levels recognized as acceptable in this literature (Escoffier et al., 2021; Hao & Shao, 2021). The slightly better fit for wind than for solar energy simply reflects that wind deployment varies more over time and across countries, giving the model more "signal" to capture compared with solar, whose patterns are more stable and therefore harder to distinguish with the same set of explanatory factors.

[3] The goodness-of-fit (R^2) of a model tells us how much of what we actually observe in the real world the model is able to explain or capture. Think of it as a measure of how closely the model's predictions mirror reality: the higher the percentage, the more of the actual variation in renewable deployment across countries and over time the model accounts for.

The contrast between technologies contributes to the literature by empirically documenting that both follow distinct implementation logics in Global South economies during 2015–2024. Wind deployment follows markedly distinct trajectories across countries: each country responds to its own conditions of territory, governance, and accumulated historical conflict, producing implementation patterns that cannot be explained solely by common global factors — a result consistent with the greater geographic heterogeneity of the wind resource potential compared to solar (Roth & Schill, 2023).

Solar deployment, in contrast, shows greater cross-country convergence: by depending on globally standardized modular technology and a cost reduction that operates relatively homogeneously across markets, the solar energy implementation gaps between countries are substantially smaller than the wind energy ones. **This structural difference between technologies has direct implications for the design of investment attraction policies and technology-differentiated risk management frameworks. Treating both technologies identically loses precision precisely where it is most needed.**

Third: The historical memory of conflicts is a structural, not temporal, determinant of social acceptance

The difficulty in validating the Composite Social Resistance Index (CSRI) and the Socio-environmental Conflict Memory (SCM) index as independent regressors in the fixed effects estimator suggests that the effect of the historical memory of socio-environmental conflicts operates primarily in the structural between-country dimension and not as a temporally identifiable signal over a ten-year period.

Countries with denser histories of socio-environmental conflicts have structural conditions of greater resistance — absorbed by the model's fixed effects as part of their institutional architecture — without this translating into detectable annual fluctuations in a ten-year panel. This distinction between structural resistance and dynamic resistance has implications for the design of interventions and in part confirms the initial hypothesis of latent conflict inherited from other projects. **Policies oriented toward rebuilding long-term territorial trust are distinct — in nature, not only in scale — from project-by-project risk management tools.**

7 Conclusions, recommendations, and implications for decision-makers

For policymakers

Incorporate social acceptance metrics into monitoring and tracking systems for national energy expansion plans. Energy expansion plans measure targets in installed MW. They rarely measure the social climate toward the projects. The gap between what was planned and what was executed, documented in this study for nine countries, signals that this omission carries quantifiable costs. Public authorities could develop monitoring dashboards that complement installed capacity progress reports with social acceptance indexes calculable from publicly accessible data, enabling national and local authorities, project developers, and financiers to implement proactive measures that mitigate delays between planning and execution.

Differentiate administrative and participatory frameworks by technology. Given that wind energy deployment exhibits greater national heterogeneity and greater sensitivity to local factors, consultation processes, community participation frameworks, and licensing timelines for this technology should be more territorially context-specific than those applied to solar energy. An energy policy that treats both technologies identically loses precision precisely where it is most needed.

Invest in publicly accessible energy information systems as a condition of governance. The main limitation on expanding this study to more Global South countries was the absence of verifiable official data on historical planned capacity and targets. Public authorities that do not publish or preserve their historical expansion targets hinder research and prevent their own inhabitants from evaluating compliance with transition commitments. Preserving generation capacity expansion plans, roadmaps, and records of awarded auctions, among other public documents, holds immense academic, public, and sectoral value. Furthermore, there is great value in tracking the targets and objectives of past generation expansion plans, as Kenya has demonstrated in several Strategic Plans published by its Ministry of Energy.

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For project developers and financiers

Include media sentiment monitoring in portfolio risk management systems. The MSI, built from publicly accessible and real-time updatable data, offers an operational approximation of an anticipatory signal for social resistance risk. High unfavorable media activity toward renewable projects in a country may signal implementation difficulties three years in advance. This timeframe should be capitalized to adjust portfolio decisions, reinforce community participation strategies, recalibrate execution timelines, and even exploit opportunities.

Distinguish between structural social risk and dynamic social risk in due diligence. This study suggests that historical conflict memory and contemporary media sentiment are distinct phenomena with distinct impact horizons. While conflict memory is structural, media sentiment is dynamic. Due diligence instruments that treat both as equivalent may underestimate long-term risk or over-diagnose short-term risk, with equally costly consequences.

Recognize concessional capital as an execution lever, not only as a financing mechanism. Low-cost international public financial flows show a positive and statistically significant effect on the wind energy implementation gap: more concessional financing is associated with a smaller gap between planned and executed capacity. Multilateral climate funds, risk guarantees, and concessional lending not only enable planning, they can also accelerate effective implementation. Designing them with that explicit objective, and measuring them with that indicator, could substantially improve their documentable impact.

8 Limitations: What this study cannot yet answer

This study offers suggestive, not conclusive, evidence. Its results are methodologically rigorous within their limits, and those limits must be stated clearly. **The nine-country panel reflects an information deficit, rather than a sampling choice.** The main barrier to expanding the sample was the absence of verifiable historical planned capacity data in official documents. This constraint reduces the statistical power of the model; it does not compromise the conceptual validity of the study or the internal consistency of the proposed indexes. The nine countries in the panel are those (from a larger sample of 12) for which it was possible to reconstruct those series. Also, they are not representative of all EMDEs or the Global South.

The statistical correction for small samples makes inference more honest, but also more conservative. With a sample of nine countries, the CR2 correction with Satterthwaite degrees of freedom adjusts confidence intervals in such a way that the conventional 10% significance threshold is not reached in the MSI models. This does not invalidate the signal; it establishes that more countries are needed for formal statistical confirmation (N > 15 countries to overcome the limitations of the Hausman test evaluation and CR2 correction).

The model controls for long-term endogeneity, but not for short-term reverse causality. It is possible that prolonged implementation gaps exacerbate community resistance, generating a feedback cycle. The three-year lag structure of the MSI reduces this risk without formally eliminating it. Analysis with instrumental variables is methodologically desirable and falls outside the scope of the present study given the size of the panel.

Geographic representativeness is partial and asymmetric. The nine countries cover Latin America, Sub-Saharan Africa, and Southeast Asia, but exclude Global South regions with distinct dynamics. For Southeast Asian countries where official translations were not available, large language models (Gemini and DeepSeek) were used as search and translation tools, introducing an additional level of uncertainty into the construction of variables for that region.

9 Next steps

Expanding the temporal and geographic panel. With T ≥ 20 years and N ≥ 20 countries, it would be possible to statistically validate the Socioenvironmental Conflict Memory (SCM) as a temporal regressor and obtain more robust estimates of the MSI effect. The availability of Global South energy data (accessibility, standardization, transparency) is an enabling condition for that expansion — not only for research, but for accountability regarding transition targets.

Developing the MSI as a real-time monitoring tool. The GDELT database is updated in real time. With the appropriate analytical infrastructure, the MSI could be calculated monthly for the panel countries, offering an early warning signal with operational value for project developers and public authorities (at a marginal cost significantly lower than that of any conventional opinion survey).

Exploring within-country heterogeneity. This study operates at the national level. However, social resistance is fundamentally local. The same country may have territories with high acceptance and regions with intense resistance. While this study seeks to capture local dynamics indirectly through media sentiment analysis and the historical memory of socio-environmental conflicts, these proxies cannot fully reflect the complexity of project-specific interactions. Future research should therefore explore subnational analyses and incorporate more granular, project-level information. This would allow the capture of internal heterogeneity and the production of more specific recommendations for the design of community participation frameworks, subject to the availability of energy planning data at the provincial, regional and/or project level.

Exploring in other areas of energy system: The proposed methodology and set of indexes can be tested in other segments of electrical system expansion, such as transmission projects. If it is possible to historically map data on planned and actual transmission capacity expansion, the methodology could provide valuable insights in this specific area.

10 Technical annex: methodological note

This section shows the description of the primary variables, the process of calculating the proposal index, and the final formulation of the RFME model, and is a comprehensive extension of **section 3.**

10.1. The Implementation Gap

This study uses as the dependent variable (i.e., the one upon which the effects of social resistance and the other regressor or control variable are reflected): the difference between what a country planned to install in renewable energy (wind and solar[4]) and what it actually installed. This distance — the Implementation Gap (IG) — is calculated as the logarithmic difference between actual added capacity and planned capacity for each country and year:

$$IG = \ln(\textit{actual added capacity}_{it} + 1) - \ln(\textit{planned capacity}_{it} + 1)$$

Where:

***Actual added capacity$_{it}$*:** is the actual capacity added for technology i in year t for each country in the study.

***Planned capacity$_{it}$*:** is the additional capacity projected by the planner or expected by the market according to connection requests, depending on the country,for technology *i* in year *t*.

Negative values of the gap indicate an implementation deficit (the country executed less than planned). Positive values indicate that execution exceeded planning. The gap is calculated separately for wind energy (IGwind) and solar photovoltaic energy (IGsolar), given that both technologies face distinct implementation barriers with differentiated heterogeneity patterns.

Planned capacity data were reconstructed from official documents published by Ministries of Energy, planning bodies, and, in some cases, vertically integrated state-owned companies — that

[4] We focused on wind and solar photovoltaic energy sources because they are the cleanest technologies with the lowest environmental impact. Furthermore, they were widely promoted after the signing of the Paris Agreement.

is, public companies that manage several segments of the electricity system, from generation to distribution and commercialization. Reconstruction was the greatest operational challenge of the study. An initial sample of 12 candidate countries was reduced to nine because for the remaining countries it was not possible to reconstruct the historical generation capacity planning series. Colombia, Chile, Ethiopia, Indonesia, Kenya, Peru, Senegal, Thailand, and Vietnam — three per major region of the Global South — were the countries studied.

10.2 The Proposed Indexes

10.2.1 The Composite Social Resistance Index (CSRI)

The core of the proposal is the construction of the Composite Social Resistance Index (CSRI), composed of the Media Sentiment Index (MSI), which represent the tone of news extracted from GDELT for each year of the study in each country and the Socio-environmental Conflict Memory (SCM) indicator built from the EJAtlas database. The CSRI integrates the two components with equal weighting (50/50), given that no consolidated empirical basis exists for assigning greater weight to one or the other:

$$CSRI_{it} = w_1 SCM_{it} + w_2 MSI_{it}$$

Where:
$\boldsymbol{w_1} = \boldsymbol{w_2} = 0.5$, the weighted share assigned arbitrarily to each indicator
$\boldsymbol{SCM_{it}}$: Socio-environmental conflict memory in country *i* in year *t*
$\boldsymbol{MSI_{it}}$: Media sentiment indicator in country i in year t

In summary, the CSRI is a quantitative metric that evaluates the social friction faced by the deployment of renewable energy projects, equitably integrating two fundamental dimensions of territorial risk. By consolidating current public opinion and the historical socio-environmental liability into a single indicator, the CSRI provides decision-makers and investors with a robust empirical variable to anticipate the community barriers that widen the gap between planned and actually installed electricity generation capacity.

10.2.2 The Media Sentiment Index (MSI)

The MSI captures the emotional record of media coverage on renewable energies in a country over a year. The result is an annual signal that reflects, in a single figure, whether that country’s media ecosystem treated renewable energies with a predominantly favorable or adverse framing during that period, conditional on there being active coverage of the topic.

The Media Sentiment Index (MSI) is constructed from two layers of data extracted from GDELT, joined via the URL of each news item. The MSI captures the emotional record of media coverage of renewable energy in a country over a year. The data layers are:

Content layer: extracts the emotional tone (*V2Tone*) and thematic taxonomy (*V2Themes*) of each article.
Events layer (gdelt-bq.gdeltv2.events): geocoded records rated using the Goldstein Scale (*GoldsteinScale*) and diffusion volume (*NumMentions*).

From the *V2Themes* field in GDELT, a thematic filter is applied that segments each news item into one of three mutually exclusive categories:

Table A1. Terms used in the GDELT database query to filter news content.

Category	Topics searched in V2Themes
Resistance	protest, conflict, indigenous, human rights, blocked, strike, riot, displacement, eviction, lawsuit, legal, contamination, violence
Acceptance	job_creation, economic development, infrastructure, cooperation, investment, partnerships, agreement, sustainable, growth, approval
Neutral	Any other case not captured by the preceding filters

Note: The evaluation is sequential; if a news item contains topics of both polarities, it is classified as Resistance because that condition is evaluated first. It is acknowledged that automatic translation and the lexical richness of GDELT introduce noise, but the designed filter is deliberately broad to maximize capture sensitivity.

Duplicate Control and Extraction of Impact per News Item

To avoid distortions from repeated reports on the same news item within the events layer, daily data are first aggregated at the unique URL level. For each news item, the following are extracted mathematically:

Its average severity level: $\overline{Goldstein_i} = Average(Goldstenin)$
Its impact or virality: $M_u = Max(NumMentions)$

Calculation of Weighted Components

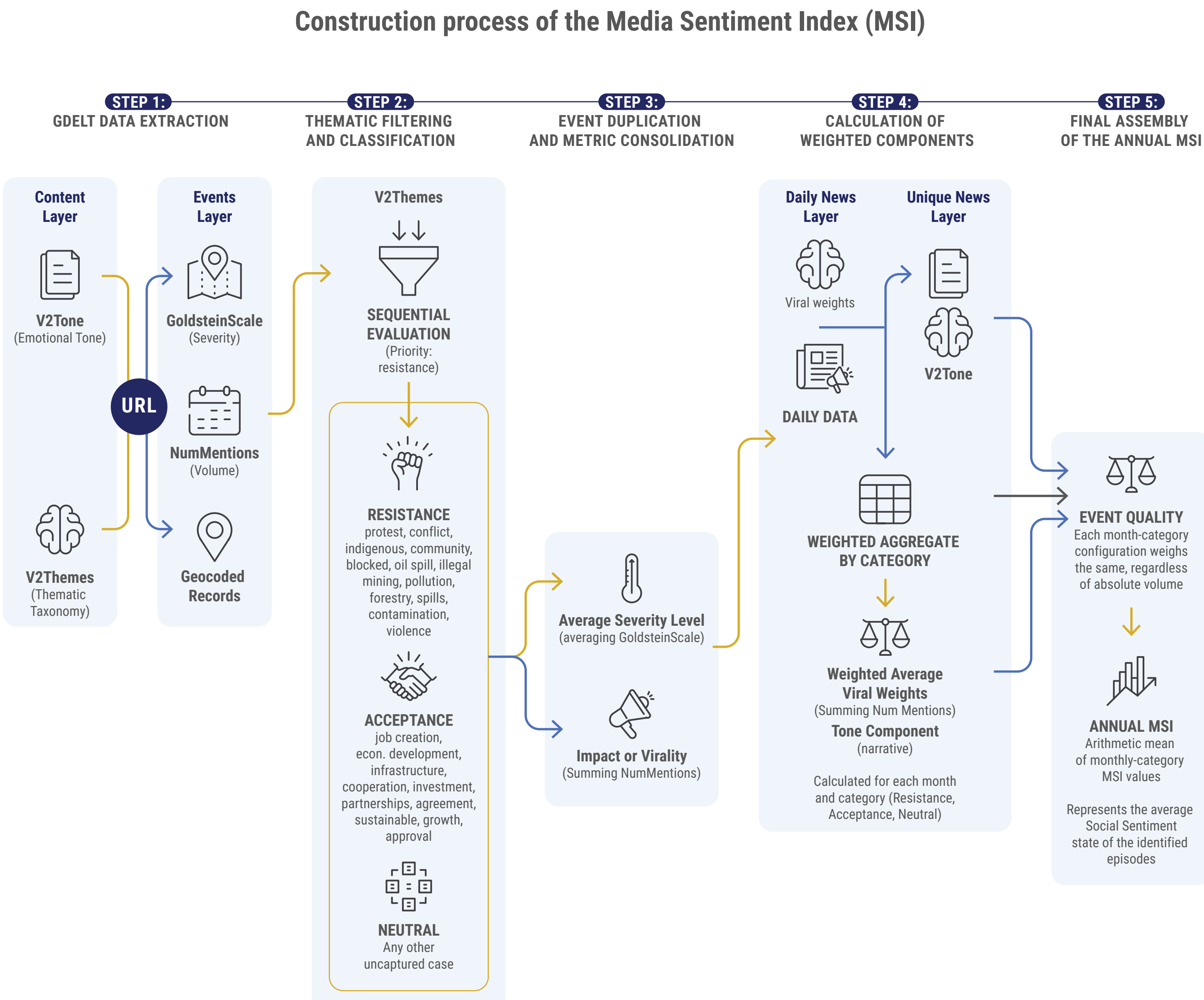
Once unique news records have been matched, this news layer is intersected with the content layer. Subsequently, for each month and category (Resistance, Acceptance, Neutral), the weighted average is calculated as a function of each news item's virality, as:

$$\text{tone component} = \frac{\sum_{i \varepsilon N} (tone_i * m_i)}{\sum_{i \varepsilon N} m_i)}$$

Tone Component (narrative)

Finally, the annual indicator is constructed as the arithmetic average of the monthly tone component values across the three categories (Resistance, Acceptance, Neutral). This procedure implies a logic of event equality: each month-category configuration is weighted uniformly, regardless of its absolute media volume. Consequently, the annual MSI does not represent the weighted emotional impact of the total media ecosystem, but rather the average Social Sentiment of the identified episodes throughout the period. Figure A1 represents the workflow presented in the preceding paragraphs.

Figure A1. Workflow diagram for the construction of the MSI (produced with nano banana based on the MSI construction process).



10.2.3 Socio-environmental Conflict Memory Indicator (SCM)

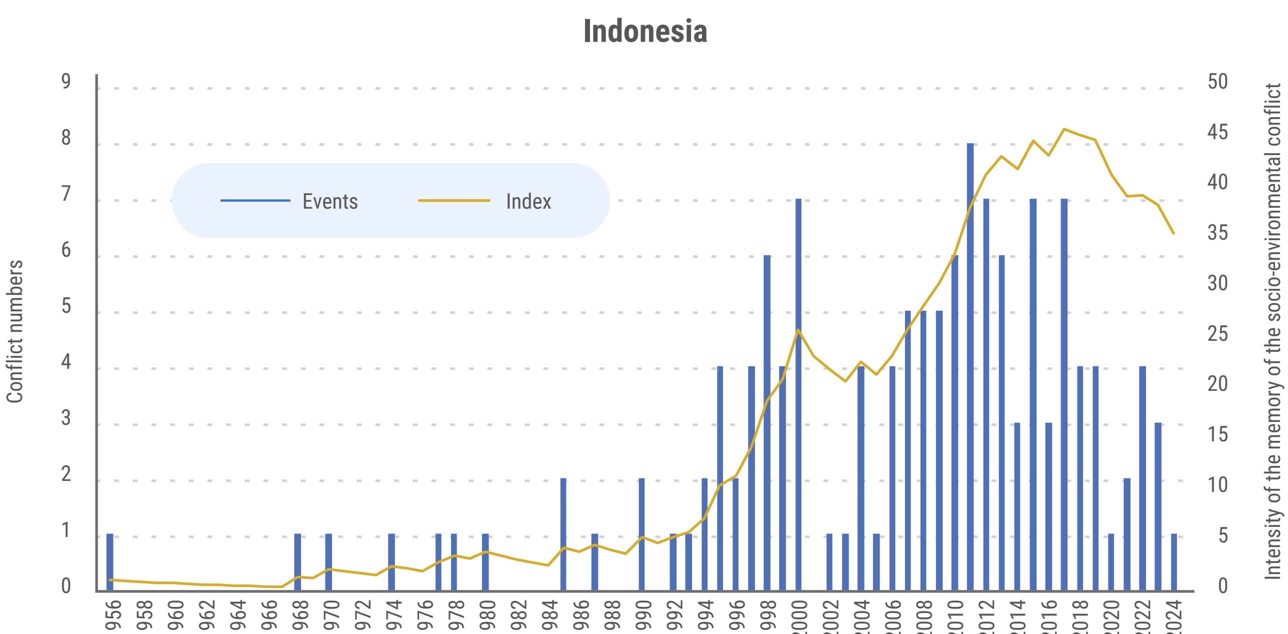
The historical component is constructed from EJAtlas data, a global database of socio-environmental conflicts. The indicator assumes that the influence of past conflicts diminishes gradually over time, applying an annual decline rate[5] of 10% to the cumulative impact — a concept commonly used in perpetual inventories. This behavior is accepted as reasonable on the basis of academic evidence and the long-term persistence of territorial resistance memories in the Global South (Martinez-Alier et al., 2016):

$$SCM_{i,t} = number\ of\ events_{it} + (1-\delta) * SCM_{i,t-1}$$

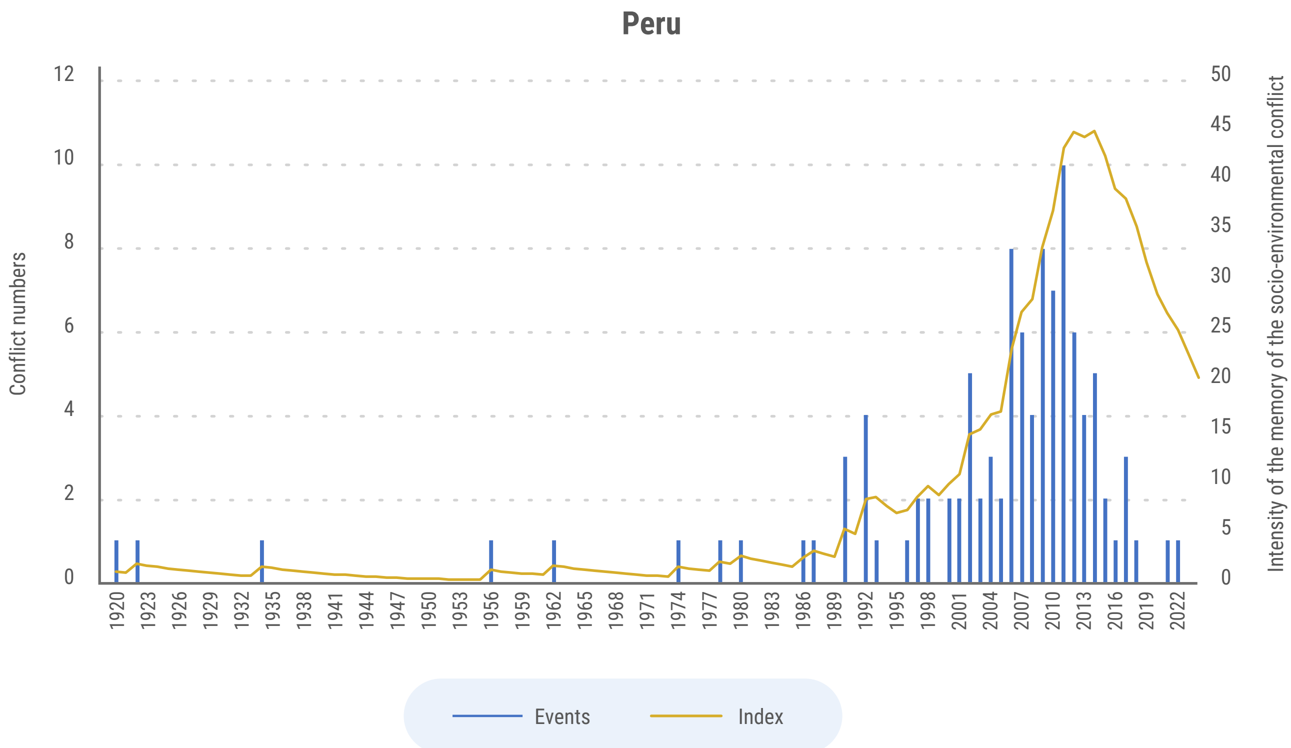
Where:
$\boldsymbol{SCM_{i,t}}$= conflict memory indicator in country i in year t
$\boldsymbol{\delta}$ = 10% decay rate
$\boldsymbol{SCM_{i,t-1}}$ = accumulated value of the conflict memory indicator in country *i* in year *t*

This indicator reflects the persistence of collective memory: past conflicts shape expectations, institutional trust, and community responses to new projects. In contexts where extractive activities have left unresolved socio-environmental impacts, this inherited conflict memory can be as influential as current events in shaping resistance to renewable energy development.

Figure A2. Behavior of the Socio-environmental Conflict Memory Indicator for 3 countries in the study. In blue, the annual number of conflict records in EJAtlas; in mustard, the behavior of the SCM (own elaboration with EJAtlas data).



[5] The 10% decline rate is a moderate estimate, given that there are active conflicts with more than 100 years of history. See, for instance: https://climatetrackerlatam.org/historias/tocopilla-despues-del-carbon-las-cicatrices-de-la-contaminacion-y-una-transicion-injusta/


Peru
Conflict numbers
0
2
4
6
8
10
12
Intensity of the memory of the socio-environmental conflict
0
5
10
15
20
25
30
35
40
45
50
1920
1923
1926
1929
1932
1935
1938
1941
1944
1947
1950
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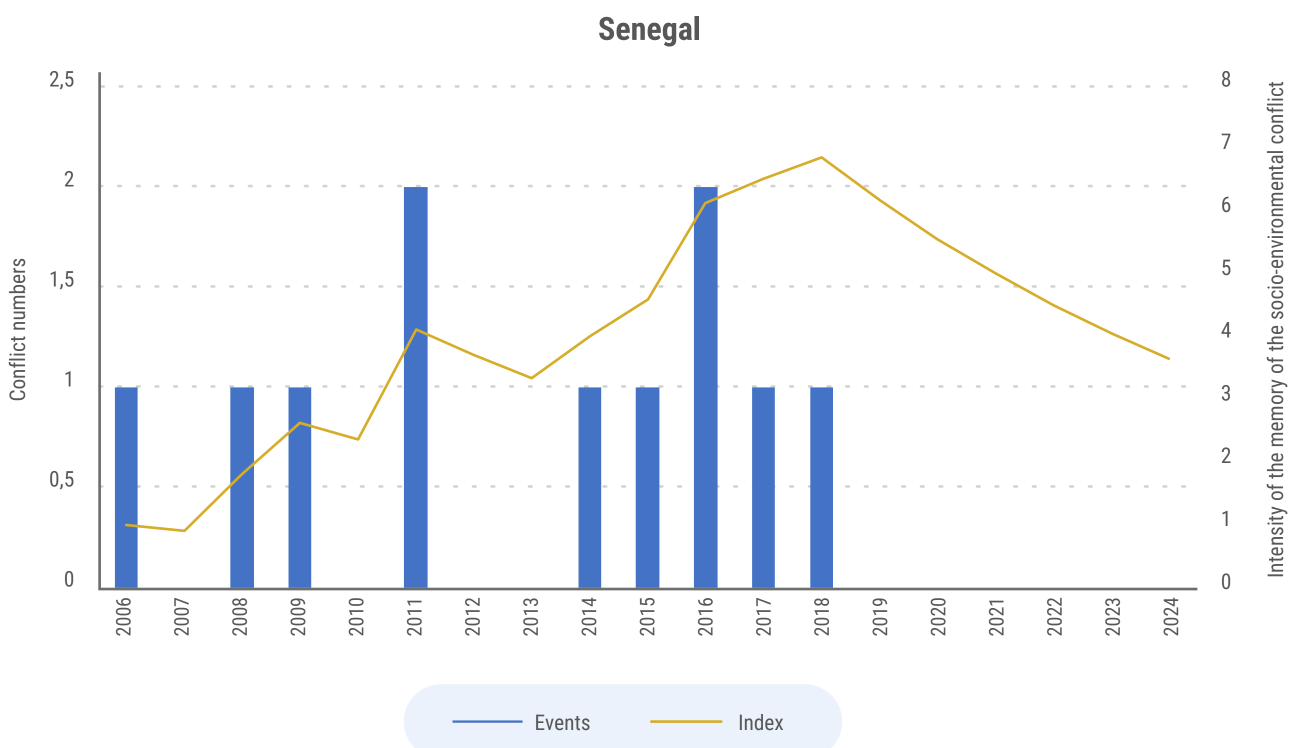
2022
Events
Index


Senegal
Conflict numbers
0
0,5
1
1,5
2
2,5
Intensity of the memory of the socio-environmental conflict
0
1
2
3
4
5
6
7
8
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Events
Index

10.3 Isolating the Effect of Social Resistance: Multiple Regression Model with Fixed Effects (MRMFE)

To identify the specific effect of social resistance on the implementation gap — separating it from the effects of macroeconomic conditions, institutional governance, financial flows, and unobserved heterogeneity — a multiple regression model with fixed effects is used. The general equation of the model is:

$$IG_{it} = \beta_0 + \beta_1 CSRI_{it} + \beta_2 SL_{it} + \beta_3 RQ_{it} + \beta_4 WS_{it} + \beta_5 LU_{it} + \beta_6 CPI_{it} + \beta_7 IFF_{it}$$

$$+ \beta_8 EP_{it} + \beta_9 GDPR_{it} + \beta_{10} GDP_{it} + \mu_i + \alpha_t + \varepsilon_{it}$$

Where:
β_0: Intercept
$\beta_1 - \beta_{10}$: coefficients of the control variables estimated by the MRMFE
μ_i: Country fixed effects.
α_t: Year fixed effects.
ε_{it}: Idiosyncratic error term.

Country fixed effects (μ_i), for example, absorb everything that permanently differentiates Colombia from Kenya — institutional history, political culture, geography — without needing to measure it directly. Year fixed effects (α_t) absorb common global shocks, such as the COVID-19 pandemic or tensions in the renewable equipment supply chain.

The control variables are Market Factors and Institutional Factors. Market Factors include international financial flows for renewable energy[6] (IFF), wholesale electricity price[7] (EP), debt-to-GDP ratio[8] (GDPR), and GDP growth rate.[9] Institutional Factors include state legitimacy[10] (SL), regulatory quality[11] (RQ), and corruption perception index[12] (CPI).

Two variables were considered in the initial specification and subsequently discarded for statistical reasons: Water Stress[13] (WS) and Land Use[14] (LU). Both have more than 90% of their variation concentrated in structural differences between countries — not in temporal fluctuations — making them invisible to the fixed effects estimator. This does not mean that water stress or

[6] The financial flow information provided by The Energy Progress Report was used as an approximation; these are defined as the sum of official loans, donations, and capital investments made by "DAC countries" (ODA recipients listed by the Development Assistance Committee). For more information https://trackingsdg7.esmap.org/about-us

[7] Retrieved from: https://www.global-climatescope.org/

[8] Retrieved from: https://data.imf.org/en/Data-Explorer?datasetUrn=IMF.RES:WEO(6.0.0)&INDICATOR=GGXWDG_NGDP

[9] Retrieved from: https://data.imf.org/en/Data-Explorer?datasetUrn=IMF.RES:WEO(9.0.0)&INDICATOR=NGDP_RPCH

[10] Retrieved from: https://fragilestatesindex.org/indicators/p1/

[11] Retrieved from: https://www.worldbank.org/en/publication/worldwide-governance-indicators/interactive-data-access

[12] Retrieved from: https://www.transparency.org/en/about

[13] Retrieved from: https://data.apps.fao.org/aquastat/?lang=en

[14] Retrieved from: https://datos.bancomundial.org/indicator/AG.LND.AGRI.ZS

land use pressure are irrelevant to renewable project deployment; it means that their effects are absorbed by the permanent structural characteristics of each country, and that their temporal dynamics cannot be identified with the panel size available.

Some data sources presented missing values (such as the electricity price for 2015–2016, regulatory quality for 2024, and international financial flows for 2024) that were estimated using the average of available values in adjacent years. This strategy may attenuate correlations and underestimate the variance of the affected variables (Little & Rubin, 2019). Compared to the alternative of eliminating observations — which would have compromised the statistical viability of the fixed effects model — the estimation of missing values is the methodologically least costly option for a panel of this size (D.Allison, 2002; Hair et al., 2019).

Finally, for a fixed effects model to be mathematically viable, it must satisfy sufficient **degrees of freedom (df):**

$$df = n_{eff} - N - K,$$

where *neff* is the number of effective observations after the elimination of missing values generated by the lags, N is the number of estimated fixed effects, and K the number of explanatory variables. For the 9-country panel with *neff* ≈ 81 effective observations and K = 8 explanatory variables in the final specification, the model has 64 residual degrees of freedom, equivalent to approximately 10 within observations per estimated parameter — exceeding the 5:1 benchmark commonly used in applied regression (Baltagi, 2021) which implies enough to make an estimate.

$$df = 81 - 9 - 8 = 64$$

Nevertheless, given that the number of clusters is small (N = 9 countries), classical clustered standard errors (CR1) systematically underestimate the true variance of the estimators because the degrees-of-freedom correction factor is insufficient with few clusters. The Bias-Reduced Linearization (CR2) correction is therefore applied, which guarantees first-order unbiasedness of the estimator variance regardless of the number of clusters (Pustejovsky & Tipton, 2018). All analyses were implemented in R 4.6.0 on Google Collaboratory, following a reproducible and documented pipeline.

The choice between the fixed effects and random effects estimators was addressed through the two-stage procedure recommended by Wooldridge (n.d.) and Baltagi (2021). The Hausman test was non-significant across all six models, which would in principle suggest the efficiency of the random effects estimator. However, with N = 9, the Hausman test lacks sufficient statistical power (Arellano, 2003; Colin Cameron & Miller, 2015); a non-significant result does not validate the random effects estimator — it only indicates that the test lacks the power to detect the difference.

Two empirical validation criteria were accordingly adopted through direct comparison of coefficients. The first evaluates the magnitude of changes between the coefficients of both estimators: differences exceeding 30% signal correlation between unobserved individual effects and regressors, invalidating the orthogonality assumption of the random effects estimator (Wooldridge, n.d.). The second evaluates directional consistency: a sign change between the coefficients of both estimators constitutes an inconsistency of the regressor.

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SEI Stockholm Environment Institute

INSPIRE Initiative for Social Performance in Renewable Energy

FORUM FOR THE FUTURE

ICM INICIATIVA CLIMÁTICA DE MÉXICO

Responsible Energy Initiative

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