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Environmental rebound effect of wind and solar technologies in the Colombian household sector

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Abstract

Decarbonizing the national energy system by increasing the amount of non-conventional renewable resources (NCRRs) is one of the strategies of the Colombian government to meet the compromises declared in the last conference of the parties (COP 26) (Glasgow 2021). Concretely, it is expected that at the end of 2023, the shares of NCRRs in the power grid will increase from <1% to 12% through wind and solar power. However, the expected environmental savings may be partially or totally offset by the environmental rebound effect (ERE). This study assesses the ERE generated in the household sector due to increased shares of wind and solar power in the Colombian power grid. Our results reveal an ERE between 1.9% and 8.2% for the climate change (CC) category, which depends on the model (wind or solar) and the approach applied to test it. Backfire effects were observed in all the models for the respiratory effects impact category with levels ranging from 119,469% to 376,605%. Service sectors contribute with about 27% (combined approach) and 47% (single approach) of the total ERE in the CC impact category. We highlight the importance of rebound mitigation policies to mitigate the potential negative effects of the ERE and the reinforcement of desired effects such as economic growth and social welfare.

KEYWORDS
energy efficiency, households, industrial ecology, life cycle assessment (LCA), rebound effect, renewable energy

1 | INTRODUCTION

The Colombian greenhouse gas (GHG) emissions accounted for about 280 Mton in 2018. From these total emissions, electricity and heat production contributed with about 8.7% (IDEAM et al., 2021). Combustion of fossil fuels represented around 17% of the power grid, while the hydro and the non-conventional renewable resources (NCRRs) such as small hydro, wind, and solar power accounted for 82% and less than 1% of the power grid, respectively (UPME, 2020a) (Figure 1). Consequently, the Colombian government plans a sizeable increase in the share of NCRRs in the power grid to meet the rising energy demand and decarbonize the sector in the coming years. It is expected that the NCRRs will reach a 12% share of the total power grid at the end of 2023 (UPME, 2021, 2022a, 2022b).

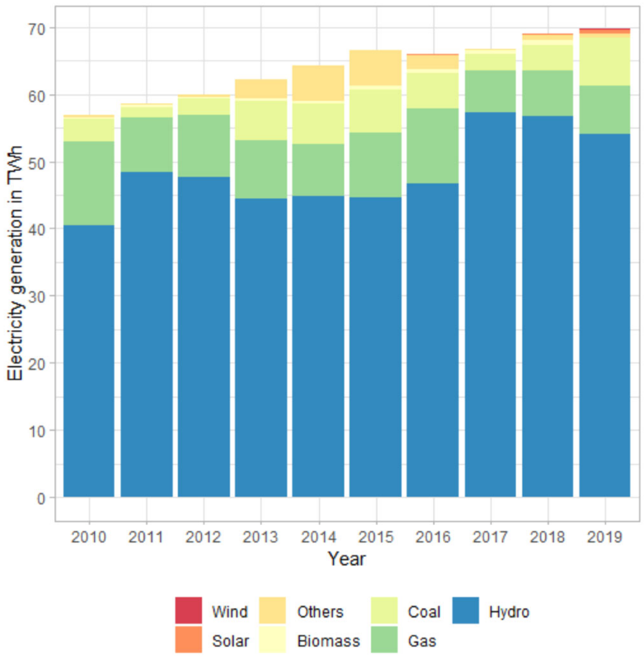

FIGURE 1 Colombian yearly electricity demand by energy sources and CO_2 emissions Eq for the year 2010–2019. Based on National energy yearbooks (UPME, 2020b). Underlying data for this figure can be found in Supporting Information, Data S1.3

By increasing the shares of NCRRs in the power grid, the Colombian government seeks several targets. First, it aims to protect the electricity supply against climatic variations such as the "El Niño" (south oscillation ENSO), which alters the reservoir levels and the electricity cost (Velez-Henao & Garcia-Mazo, 2019). Second, it attempts to considerably reduce the GHG emissions coming from the energy sector as one of the key strategies to reduce the GHG emissions by 50% by 2030 (Ministerio de Ambiente y Desarrollo Sostenible, 2021).

While the injection of NCRRs into the power grid will help to decarbonize the production of electricity and ensure affordable prices by displacing fossil fuels (Gielen et al., 2019; Kaberger, 2018; Turconi et al., 2013), the total environmental savings for such initiatives may be totally or partially offset by the environmental rebound effect (ERE). The ERE accounts for the "environmental consequences of changes in demand as a response to efficiency changes from technical improvement" (Vivanco, Mcdowall, et al., 2016, p. 61) and allows to systematically measure the environmental impacts (e.g., climate changes, acidification, eutrophication) caused by an improvement in the efficiency of a particular service (e.g., electricity). It has been studied in different contexts such as reusing smartphones in the United States (Makov & Vivanco, 2018), energy efficiency improvements in the household sector in the United States, Spain, and China (Freire-González & Vivanco, 2017; Freire-González et al., 2017; Thomas & Azevedo, 2013; Wen et al., 2018), electric cars and high-speed transport technologies (Liu et al., 2021; Spielmann et al., 2008; Vivanco & Voet, 2014; Vivanco et al., 2015, 2016), green consumption in Australia (Murray, 2013), and recently in NCRRs technologies in Colombia (Vélez-Henao et al., 2020).

Thus, a presumable drop in the current electricity prices may cause an increase in the disposable income, and consequently the demand (direct rebound effect) and in the trade of other goods and services such as food or housing (indirect rebound effect) (Greening et al., 2000). This chain of events ends up counteracting the expected environmental savings. It has been previously shown that an increase of 3% of the shares of the wind power on the Colombian power grid leads to an increased ERE and significant backfires (ERE > 100%), implying that the ERE had suppressed the environmental savings achieved by producing additional environmental issues (Vélez-Henao et al., 2020). While the importance of considering the effects of the ERE in environment–energy policy designs has been previously highlighted, the ERE caused by the introduction of solar technologies into a power grid remains unexplored.

The goal of this study is to generate empirical evidence of the ERE produced by increasing the shares of solar and wind power in the Colombian power grid. Furthermore, we overcome methodological limitations presented in previous estimations of the ERE for wind power (Vélez-Henao et al., 2020). Thus, our work extends the current knowledge regarding the role of the NCRRs in achieving sustainable goals such as the SDGs by analyzing the ERE of different energy sources based on the same methodological approach.

Our study is relevant to both practitioners and policymakers. Practitioners will gain insights into the estimation of the ERE for several environmental–energy policies. Policymakers will obtain valuable information about the potential consequences of introducing NCRRs into an energy system.

2 | MATERIAL AND METHODS

2.1 | Non-conventional renewable resources into the Colombia power grid and the consumption sector

The study focuses on the ERE generated by the household sector due to increased shares of solar and wind technologies in the Colombian interconnected power grid. These technologies are more relevant than other NCRRs (i.e., small hydro and biomass) since a significant amount of solar and wind power is expected to enter in operation in the short term. Particularly, the introduction of an additional 2.1 GW of NCRRs to the power grid (about 1.1 GW wind and 1 GW solar) (UPME, 2021, 2022a, 2022b) is expected by the end of 2023. We consider the commissioning of 1 GW of generating power of wind or solar energy in the national grid. A simulation of the energy system yield based on marginal production costs and the capacity factors of the selected was performed to estimate the new energy mix configuration and electricity prices (see supporting information, Data S1). It is worth mentioning that two electric zones operate in Colombia, the interconnected (studied here) and the non-interconnected (i.e., unelectrified or off-grid areas), which are out of the scope of this study. In the latter, an injection of NCRRs may increase the electricity cost due to additional expenses earned to ensure the reliability of the system, for example, storage and backup devices. This scenario is mainly observed in the pacific coast, part of the Atlantic region, and the amazon zone in Colombia, which represent about 53% of the territory (IPSE, 2022). These areas are characterized by high exposure to environmental harms and risk (known as environmental justice [EJ] communities; Holifield, 2001).

The reference year selected for the analysis is 2019, the most updated year from which the electricity demand was not affected by the Covid-19 pandemic (UPME, 2020a). We started our analysis with the total installed capacity in 2019 (17.5 GW) (reference model) and we compared it against the system set after the introduction of 1 GW of wind power (model 1) and 1 GW of solar power (model 2), respectively (see supporting information, Data S2). For simplicity, no increment of the electricity demand was included. The yearly savings obtained from the difference between the actual price and the new calculated price (model 1 and 2) was used to estimate the ERE.

The electricity price in the household sector (UPME, 2020a) is the product of all the costs (margins included) of the supply chain (i.e., generation, transmission, distribution, and commercialization), and an additional component that accounts for the losses and restrictions on the grid (CREG, 2005). It is assumed that all the components but the generation will remain constant.

For completeness, two different approaches to estimate the ERE were followed. A combined approach takes into account the direct and indirect ERE separately, as done in Vélez-Henao et al. (2020) and many others (Freire-González & Vivanco, 2017; Freire-González et al., 2017; Thomas & Azevedo, 2013; Vivanco & Voet, 2014; Vivanco et al., 2015; Wen et al., 2018). A single approach uses solely the marginal budget shares (MBS) to calculate the ERE, and therefore does not differentiate between the direct and indirect effects, as done in Vélez-Henao et al. (2020) and others (Brännlund et al., 2007; Makov & Vivanco, 2018).

2.2 | Model overview and rebound effect calculation

The method for the estimation of the ERE (Figure 2) initiates with a policy intervention (injection of NCRRs into the power grid), which induces different effects: (1) technical changes, (2) economic benefits, and (3) consumption adjustments. The energy model provides information regarding the technology mix (technical chances) observed under the reference, the wind, and solar models. The differences between the estimated electricity prices associated with these models provide information regarding the potential monetary savings (economic benefits) induced by the technical changes.

The consumption adjustments effect (direct and indirect) is estimated as follows. The direct ERE is obtained by calculating the additional electricity consumed in physical units (kWh) by estimating the price elasticity of electricity. Additionally, a process-based LCA model is applied to estimate the environmental impact intensity per kWh based on the technology mix obtained from the energy model. Similarly, the indirect ERE is calculated by estimating the monetary savings available to re-spend (total savings—additional consumption of electricity) and the MBS to allocate the savings into the different consumption categories. Finally, an environmentally extended input–output (EEIO) model is used to calculate the environmental burdens caused by the additional consumption.

2.3 | Energy model

The energy model considers the marginal costs and the amount of electricity produced by each power station based on the installed capacity and the capacity factor of all the power stations operating in 2019, in the Colombian power grid (see supporting information, Data S1). The capacity factor of the different resources (e.g., hydro, coal, gas, wind, solar) was estimated based on the information published by the operator of the system (XM, 2019). The information to determine the marginal cost by power station (i.e., installed cost, fixed and variable cost of operation and maintenance) was obtained from CAISO (2018), EIA (2019), and IRENA (2018).

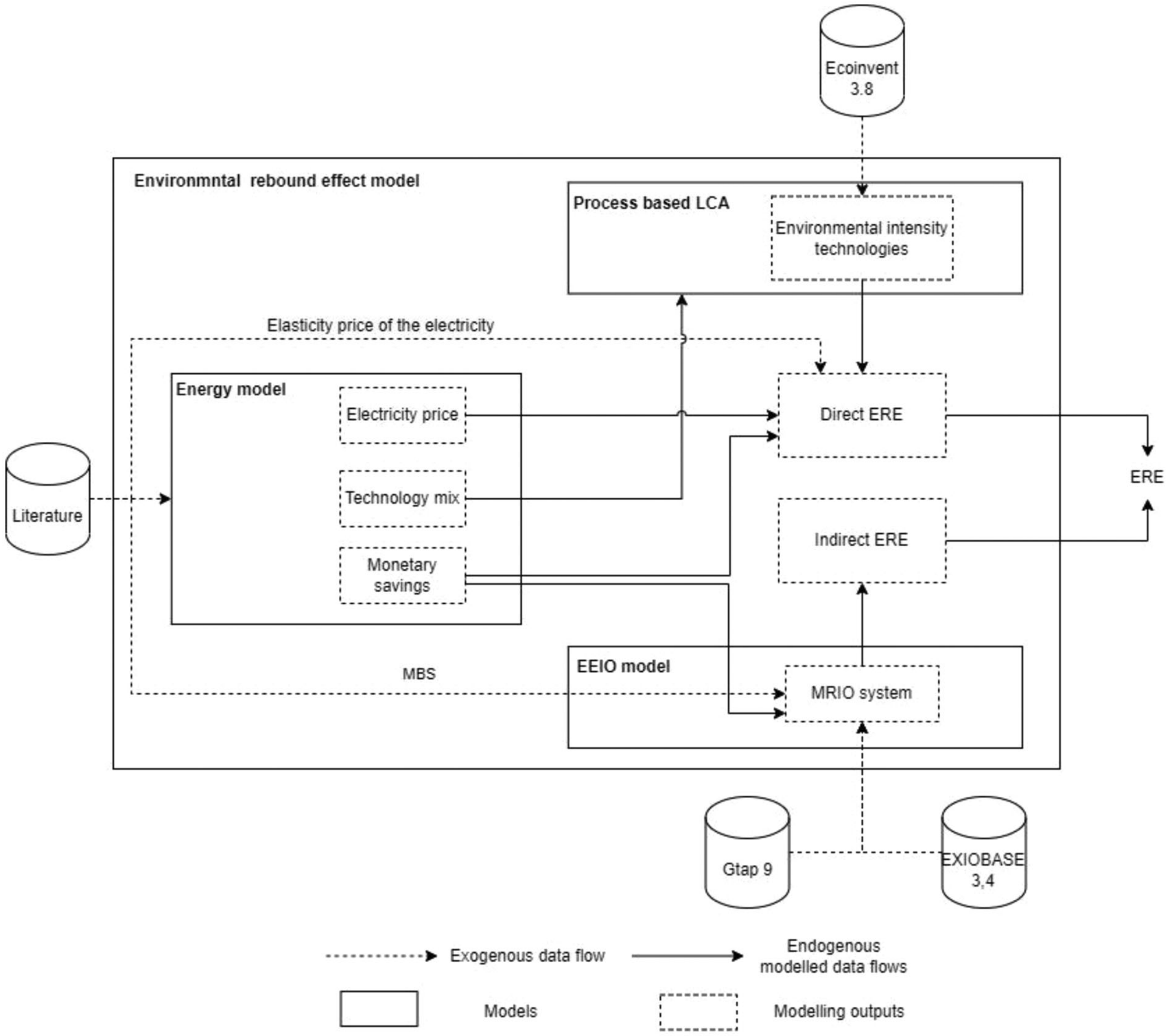

FIGURE 2 Overview of the proposed method to calculate the environmental rebound effects

The cost of the generation component is fixed as the cost of the last power station dispatched to meet the electricity demand (70.1 TWh). In the case that imports are needed, the cost of importation is fixed as the final price of the generation component (see supporting information, Data S1).

The monetary savings obtained for the injection of 1 GW of a particular NCRR were calculated as the differences between the final price of electricity in the reference model and the improved models, multiplied by the electricity demand (see supporting information, Data S3).

2.4 | Environmental rebound effect model

The ERE is generally expressed as a percentage of the environmental savings that are "taken back" (Velez-Henao, 2021; Vélez-Henao et al., 2020) as:

$$\mathrm{ERE} = \left(\frac{\mathrm{PS} - \mathrm{AS}}{|\mathrm{PS}|}\right) * 100 \tag{1}$$

with

$$\mathrm{AS} = \mathrm{PS} - (\mathrm{PS} + \mathrm{ERE}) \tag{2}$$

where PS is the potential environmental savings from increasing the shares of a particular NCRR on the power grid, and AS is the actual savings, including the rebound effect. Thus, the ERE is expressed as:

$$\mathrm{ERE}^{\mathrm{e}} = \mathrm{ERE}^{\mathrm{e}}_{\mathrm{dir}} + \mathrm{ERE}^{\mathrm{e}}_{\mathrm{ind}} \tag{3}$$

where $\mathrm{ERE}_{\mathrm{dir}}$ accounts for the consumption of electricity (direct rebound effect) and $\mathrm{ERE}_{\mathrm{ind}}$ represents the additional consumption associated with other goods and services (indirect rebound effect). *e* represents the environmental burden. Additionally, the two effects can be expressed as:

$$\mathrm{ERE}^{\mathrm{e}}_{\mathrm{dir}} = \Delta \mathrm{d}_{\mathrm{dir,ts}} \mathrm{b}^{\mathrm{e}}_{\mathrm{ts}} \tag{4}$$

$$\mathrm{ERE}^{\mathrm{e}}_{\mathrm{ind}} = \sum_{\mathrm{s}\,=\,1,\ldots,\mathrm{n}} \Delta \mathrm{d}_{\mathrm{ind,i}} \mathrm{b}^{\mathrm{e}}_{\mathrm{i}} \tag{5}$$

with:

$$\Delta r = \Delta d_{\mathrm{dir,ts}} + \sum_{s\,=\,1,\ldots,n} \Delta d_{\mathrm{ind},i} \tag{6}$$

where $\Delta d_{\mathrm{dir,ts}}$ from Equation (4) denotes the change in demand (in monetary terms) for a given technology shares in the power grid *ts*, and b^{e}_{ts} represents the environmental impacts per kWh. These are obtained from process-based LCA coefficients as the sum of the impact factors of each energy technology (e.g., wind, solar, hydro) multiplied by their respective percentage shares in a given power grid. Δd_{ind} denotes the change in demand (in monetary terms) for a consumption category *i*, *b* refers to the environmental burdens per unit of demand, *n* equals the total number of consumption categories, and Δr corresponds to the total change in real income due to the increasing shares of wind or solar power into the power grid.

$\Delta d_{\mathrm{dir,ts}}$ (Equation 4) is estimated in most cases through econometric approaches, that is, elasticity estimations (Sorrell et al., 2009). Thus, $\Delta d_{\mathrm{dir,ts}}$ can be approximated by Sorrell and Dimitropoulos (2007) and Sorrell et al. (2009):

$$\Delta d_{\mathrm{dir,ts}} = -\eta_{\mathrm{p_E}}(E) - 1 \tag{7}$$

where $\eta_{\mathrm{p_E}}$(E) represents the price elasticity of energy demand. Additionally, the direct cost effect calculated using Equation (7) is translated into environmental burdens through the coefficient b^{e}_{ts} from Equation (4).

To calculate the ERE_{ind}, an EEIO model is used in combination with the MBS. The MBS allows determining how the additional savings are re-spent in each consumption category *i* (e.g., food or clothing). Thus, the indirect effect can be calculated by multiplying the remaining change in real income (Δr_{r}), by individual MBS, among each consumption category *i* as:

$$\mathrm{RE}_{\mathrm{ind}} = \Delta d_{\mathrm{ind}} = \sum_{s\,=\,1,\ldots,\mathrm{n}} \Delta r_{\mathrm{r}} \mathrm{MBS}_{\mathrm{i}} \tag{8}$$

with:

$$\Delta r_{\mathrm{r}} = (d_{\mathrm{ats}} - d_{\mathrm{ts}}) - \Delta d_{\mathrm{dir,ts}} \tag{9}$$

where RE_{ind} is the rebound effect in monetary units, *d* is the electricity demand in monetary terms for a given power grid in ts (original power grid without the introduction of additional NCRR), and its corresponding alternative ats (power grid with the additional NCRR). Additionally, the monetary values are translated into environmental indicators by applying an EEIO model:

$$\mathrm{ERE}_{\mathrm{ind}} = \mathrm{RE}_{\mathrm{ind}}\ \mathrm{EII} \tag{10}$$

with

$$\mathrm{EII} = \mathrm{SL} = \mathrm{S}(\mathrm{I} - \mathrm{A})^{-1} \tag{11}$$

where $\mathrm{ERE}_{\mathrm{ind}}$ represents the indirect ERE, in environmental units, $\mathrm{RE}_{\mathrm{ind}}$ is the indirect effect of the additional expenditure in monetary terms. EII is the environmental impact intensity (i.e., the environmental impact per monetary unit) of each consumption category *i*. *L* is the Leontief inverse matrix, *S* the set of coefficients of environmental intensities. For more detail regarding the EEIO model see Miller and Blair (2009). For more details regarding the ERE model applied, see Vélez-Henao et al. (2020).

2.5 | Data sources

To estimate the direct rebound effect, that is, $\Delta d_{\text{dir,ts}}$ (Equation 7), a value of −0.834 for the price elasticity of the electricity from Vélez-Henao et al. (2022) was used since it is the only measure available in the literature for the direct rebound effect associated with the household electricity consumption in Colombia. Thus, a 1% decrease in the electricity price will lead to a 0.834% increase in the electricity demand. Additionally, to estimate the environmental burdens per kWh consumed, that is, (b^{e}_{ts}) (Equation 4) the APOS (allocations at point of substitutions) variant was taken from the ecoinvent 3.8 database (Wernet et al., 2016) (see supporting information, Data S4).

The estimations of the indirect rebound effect ERE^{e}_{ind} (Equation 5) were performed using several databases such as EXIOBASE and GTAP. The cost of the electricity was estimated through the energy model applied (generation), while the cost of other components of the supply chain was obtained from the superintendency of domiciliary public utilities (SUI) database.

The final price of the electricity was estimated as the sum of the generation cost (model estimation) and other components of the supply chain (i.e., transmission, distribution, commercialization, losses, and restrictions) obtained from the SUI database (SUI, 2019) (see supporting information, Data S5).

The MBS were obtained from the National Administrative Department of Statistics (DANE). The MBS for the Classification of COICOP 2-digit classification (12 categories) at the national level was extracted from the national household budget survey for 2017 (the updated information available at the moment of this study) (DANE, 2018) (see supporting information, Data S6). Concordances between the COICOP and the GTAP database were obtained from Oswald et al. (2020).

The Global Trade Analysis Project (GTAP) 9 database containing 57 industries across 140 regions (including Colombia) was used to develop the EEIO system (Aguiar et al., 2016). The construction of an MRIOT, using the GTAP database, was performed following the procedure described by Peter et al. (2011), from which the variant with endogenous international transport pool was obtained. The specific tool used, "GDX_to_MRIOT_GTAPAgg," can be found on GitHub (2018). Since current GTAP environmental extensions are limited to CO_2, the environmental extensions from the EXIOBASE 3 database (Stadler et al., 2018) were used in this study (Somé et al., 2018) (see supporting information, Data S7). EXIOBASE 3 contains 163 industries. As a consequence, a many-to-one concordance between the two databases is needed. Country concordances have been obtained from the GTAP website (GTAP, 2019), while sectoral concordances were obtained from the EXIOBASE Zenodo repository (Stadler et al., 2021).

The methodology used to perform the life cycle inventory impact assessment (LCIA) was taken from the International Reference Life Cycle Data System (ILCD) (European Commission, 2014). It was provided by ecoinvent, a robust and widely used approach among LCA practitioners. Concretely, the ERE is presented for the following categories: CC, climate change (kg CO_2-Eq); A, acidification (mol H+-Eq); E, ecotoxicity (CTUh.m3.yr); MEUT, marine eutrophication (kg N-Eq); TEUT, terrestrial eutrophication (mol N-Eq); CE, carcinogenic effects (CTUh), NCE, non-carcinogenic effects(CTUh); OD, ozone layer depletion (kg CFC-11-Eq); POC, photochemical ozone creation (kg ethylene-Eq); and RES, respiratory effects (kg PM2.5-Eq), expressed as a change in a given environmental indicator.

3 | RESULTS

EREs are present for both models (wind and solar) and approaches (combined and single), with values ranging from 0.12% (MEUT) to 376,605% (RES) across impact categories (Figure 3). Generally, the injection of wind power (Figure 3a,b) generates higher EREs than solar power injections (Figure 3c,d). Similarly, the EREs in the combined approach (Figure 3a,c) are significantly higher than those obtained by the single approach (Figure 3b,d) in all the impact categories, except from the RES category.

Backfire effects were observed for the RES impact category ranging from 119,469% to 376,605% in the two models independent of the approach following.

In the combined approach (Figure 3a,b), the direct rebound effect (electricity consumption) is responsible for the 0.01% (RES) and 95% (MEUT) of the total ERE across the different impact categories (42% in the CC category). The direct effect is slightly similar in both models (see supporting information, Data S8). The environmental impacts associated with the indirect effect are mainly ligated to the consumption categories of housing services and miscellaneous. Taking CC as an example, they represent the 21.15% and 11.90%, respectively, of the total ERE across impact categories in the wind model and around the 20.45% and 11.93% of the total ERE in the solar model.

The environmental impacts associated with the indirect rebound effect in both approaches are mainly dominated by 10 of the 57 industries analyzed (Figure 4). Taking CC as an example, the sugar (SGR) sector contributes with 67% and 83% of the impacts in the consumption category of food and beverages and alcoholic beverages and tobacco, respectively. Similarly, the public administration, defense, education, and health (OSG)

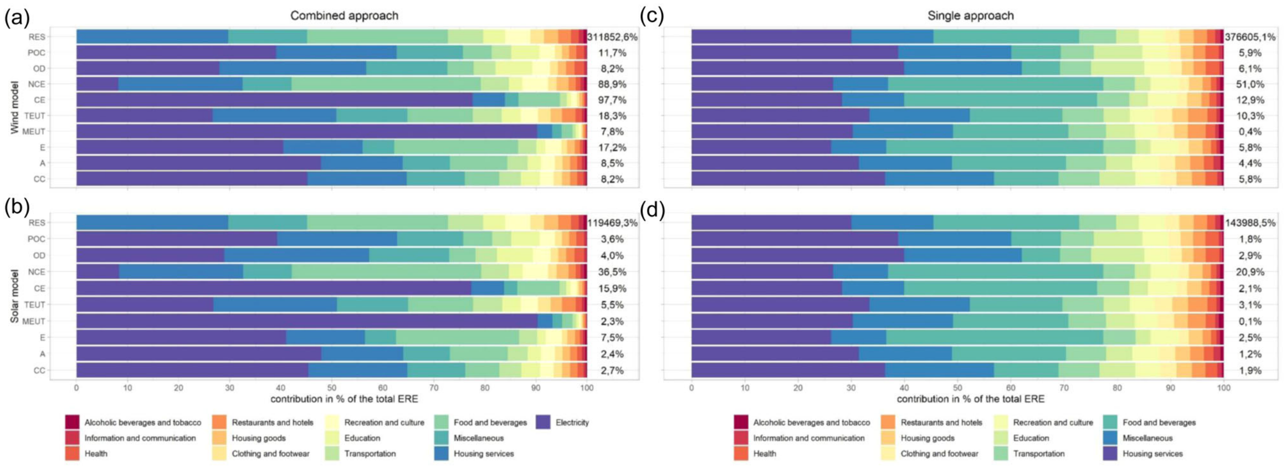

FIGURE 3 Environmental rebound effect by model and approach. (a, c) wind model, (b, d) solar model. (a, b) (combined model). (c, d) (single model). (a) freshwater and terrestrial acidification (in mol H+-Eq), CC, climate change (in kg CO_2-Eq); CE, carcinogenic effects (in CTUh); E, ecotoxicity (in CTUh.m3.yr); MEUT, marine eutrophication (in kg N-Eq); NCE, non-carcinogenic effects (in CTUh); OD, ozone layer depletion (in kg CFC-11-Eq); POC, photochemical ozone creation (in kg ethylene-Eq); RES, respiratory effects, inorganics (kg PM2.5-Eq); TEUT, terrestrial eutrophication (mol N-Eq). Underlying data for this figure can be found in Supporting Information, Data S8.1

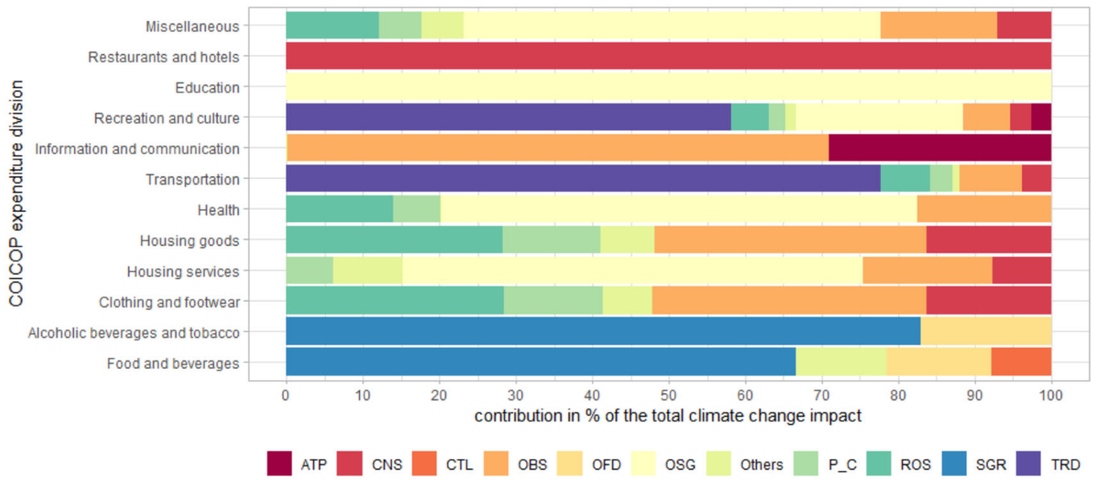

FIGURE 4 Environmental rebound effect contribution in percentage by economy sector (GTAP industries sector) and consumption categories (COICOP classification) for the climate change impact category. Bovine cattle, sheep and goats, horses (CTL), sugar (SGR), food products (OFD), petroleum, coal products (P_C), construction (CNS), trade (TRD), air transport (ATP), business services (OBS), Recreational and other services (ROS), public administration, defense, education, health (OSG), others (rest of the 47 sectors). Underlying data for this figure can be found in Supporting Information, Data S8.2

sector represents 62% and 100% of the total impacts in the consumption category of health and education, respectively. The trade sector (TRD) accounts for 78% and 58% of the total impact generated for the consumption categories of transport and recreation and culture, respectively. Additionally, the business services (OBS) sector contributes with 36% of the total impacts in the consumption categories of clothing and household goods and 71% in the consumption category of information and communications.

In the single approach, five industries are responsible for 96% of the total impacts associated with the housing services consumption category: OSG (60%), OBS (17%), construction (CNS) (8%), petroleum, coal products (P_C) (6%), and electricity (ELY) (5%).

4 | DISCUSSION

Wind or solar power brings environmental benefits to the energy system. Taking CC as an example, there are total savings per kWh of 12.93 gr CO_2-Eq (wind model) and 10.18 gr CO_2-Eq (solar model) when compared to the reference model (238.80 gr CO_2-Eq/kWh). These savings are a consequence of the displacement of about 1% of the shares of fossil fuels from the power grid (see supporting information, Data S2) and the decrease of energy imports from Venezuela, which has a power grid more dependent on shares of fossil fuels (39%) than Colombia (ecoinvent, 2019). It is worth mentioning that the energy model applied does not account for externalities, for example, costs of fuels, maintenance, or drawbacks that may affect the production of electricity. Thus, it is likely that imports are needed to satisfy the demand, as has been the case historically (UPME, 2020a).

The ERE in the wind model is about two and three folds bigger than that obtained from the solar model, independent of the type of approach applied (Figure 3). This response is due to a higher capacity factor for the wind power (39%) in comparison with the capacity factor of the solar power (21%), that is, electricity produced by wind technologies is higher than that produced with solar technologies during the course of a year based on a same installed capacity. For this reason, the injection of 1 GW of wind technologies (model 1) displaces more fossil fuels from the reference model than the injection of the 1 GW of solar technologies (model 2). Thus, the monetary savings derived from model 1(0.05 US cent/kWh) are bigger than those obtained with model 2(0.01 US cent/kWh).

The environmental impacts related to the indirect rebound effect are the product of two components, the EII of the economic sectors and the MBS of the consumption categories (see supporting information, Data S9). Taking CC as an example, on one hand, the environmental impacts associated with the housing services are due to a high EII of 61.22 kg CO_2-Eq per US dollar and its MBS of 24%. On the other hand, the impacts associated with health are the product of an EII of 0.08 kg CO_2-Eq per US dollar, and an MBS of 2%. Education and transport have similar MBS around 10% but different intensity emission factors (0.20 kg CO_2-Eq per US dollar and 1.56 kg CO_2-Eq per US dollar, respectively).

Backfire effects are present in the RES impact category independent of the model or approach applied. This result is derived from a higher AS (3.55E + 04 kg PM2.5-Eq) than the PS (1.13E + 01 kg PM2.5-Eq) (Equation 1) and is explained by the large emissions coefficients in EXIOBASE. The observed high emissions per monetary unit are largely due to a combination of completeness and aggregation issues (Joshi, 2000; Lenzen, 2000). Completeness means that EXIOBASE accounts for economic sectors and flows that are systematically omitted in LCI databases. Aggregation implies that every industry incorporates heterogeneous production technologies and products regarding input materials and environmental impacts (Suh, 2004; Suh & Huppes, 2005). Then, the estimations associated with the indirect rebound effect may be overestimated. For example, in the GTAP database, the ELY industry aggregates all the energy supply chain (production, collection, and distribution) and this provokes a significant difference between the RES emissions estimated with the process-based LCA (2.04E-07 kg PM2.5-Eq, 14 kWh per dollar) and the one estimated with the EEIO model (1.27E-02 kg PM2.5-Eq).

The impacts associated with electricity consumption are defined by the modeling approach applied. Taking CC and the wind model as examples, the impacts per kWh in the combined approach (0.20 kg CO_2-Eq/kWh) are significantly lower than those obtained with the single approach (3.47 kg CO_2-Eq/kWh). These differences are due to two factors: the amount of savings re-spent on electricity and the environmental impact coefficients associated with the production of electricity in each modeling approach. In the combined approach, the electricity consumption is a function of the monetary savings and the price elasticity of electricity. Whereas, in the single model, the electricity consumption is a function of the MBS. Thus, 17% of the total savings obtained are re-spent on electricity in the former case, whereas only 0.02% of the total savings are re-spent on electricity in the latter. Furthermore, the impact factors assigned to the electricity consumption in the combined model are obtained from ecoinvent, whereas in the single approach, the impact factors are obtained from EXIOBASE.

The results of the ERE in this study are consistent with previous reports since they describe both high variability of magnitudes and a backfire effect. As examples: for CC in transport innovations in Europe (227% ≤ ERE ≤ 900%) (Vivanco et al., 2015) and smartphones in the United States (27% ≤ ERE ≤ 46%) (Makov & Vivanco, 2018), for freshwater eutrophication in electric cars (−834,869% ≤ ERE ≤ 377%) (Vivanco & Voet, 2014), for water consumption in energy efficiency improvements in the Spain household sector (1,191% ≤ ERE ≤ 1,628%) (Freire-González & Vivanco, 2017), and for CO_2 emissions in green consumption patterns in Sweden (ERE = 25%) (Alfredsson, 2004).

In contrast to our previous estimation of the ERE for wind resources in Colombia (Vélez-Henao et al., 2020), this study provides a more conservative ERE for environmental categories such as CC, A, E, MTUE, MTUE, OD, and POC. Taking CC and the results for 2019 as an example, a total ERE between 220% (combined approach) and 216% (single approach) was estimated previously (Vélez-Henao et al., 2020), whereas, values in the present study are in the range of 8.25 and 5.77%, respectively. Similarly, our former study provided values for RES in the range of 151% (combined approach) and 516% (single approach), contrasting the values between 313,195% (combined approach) and 376,605% (single approach) found in this study.

The observed variations are due to the methodological and data constraints presented in the former work (Vélez-Henao et al., 2020). From the methodological aspect, we previously applied a simplified energy model (51% of the total power installed capacity for the year 2018 without imports). Thus, the estimated monetary savings are in the range of 4%, which is significantly higher than the value estimated here (<1). Therefore, monetary savings available to re-spend are higher in the former study. Additionally, the value of the price elasticity used in the former study (−0.959) is higher when compared with the one applied in the present study (−0.834). Thus, the results imply that more electricity is consumed in the former study. Data constraints are mainly associated with the assumption and approximations used to estimate the ERE. The impact coefficients used to calculate the direct rebound effect were taken from ecoinvent 3.4 for a Brazilian region. Moreover, the data to estimate the MBS have more aggregate information regarding the household expenditure than that applied in this study.

This study improves some data limitations presented before (Vélez-Henao et al., 2020). First, novel information about the ERE from solar energy is provided. Second, more reliable data for estimating the technology mix, the electricity price, and the monetary savings were applied by expanding the energy model to account for the whole Colombian interconnect power system (including electricity imports). Third, environmental coefficients for electricity production in Colombia were obtained from ecoinvent 3.8. Four, more desegregated information for the MBS was used (moving from 8 to 12 categories in this study). Finally, the price elasticity of the electricity used to estimate the direct rebound effect was updated with an improved estimation (Vélez-Henao & Uribe, 2022).

Future improvements of the presented models can address sources of potential bias associated with data availability and the modeling limitations. In this study, the monetary savings per kWh were calculated by assuming that all supply chain costs were fixed, the generation being the only exception. However, this may not be the case along all the country mainly because wind and solar stations are commonly located in isolated areas as is the case of the Guajira region at the north of Colombia. In this region, new transmission lines are needed (UPME, 2020c). Therefore, additional costs associated with transmission and distribution may increase or reduce the potential for monetary savings. As an example, an increase of 4% (transmission), 1% (distribution), 2% (commercialization), 3% (losses), or 10% (restrictions) ceteris paribus would reduce the potential savings estimated for the wind model.

The MBS used here corresponds to data for the 12 consumption categories at the national level. This information is aggregated data and does not differentiate between the level of consumption among cities or households' income levels. Moreover, due to the lack of data to compute an ideal demand system (AIDS) model (a common approach among economists and rebound effect practitioners to study consumption behaviors; Deaton & Muellbauer, 1980), the MBS was estimated as the expenditure proportion of each category to the total values.

Colombia imports electricity from Ecuador (177 MWh). However, information in ecoinvent was only available for Venezuela. This may bias our results due to the technology mix differences between the two countries. As an example, 39% of the electricity produced in Venezuela comes from fossil fuels, while in Ecuador the amount of fossil fuels in the grid accounts for 17% (Ecoinvent, 2019).

Thus, eight additional models were estimated to account for the variability of the results to the MBS and imports sources. The MBS (8 consumption categories) estimated with an AIDS model and provided by Vélez-Henao et al. (2020) were used. Additionally, imports from Venezuela were replaced for the electricity production of Ecuador. Our new results suggest that the level of aggregation of the MBS may significantly affect the ERE (see supporting information, Data S8.3). Particularly, results have a relative variation (Coefficient of variation (CV)) ranging from 0.15% (CE) in the combined approach for the solar model to 30.86% (OD) in the single approach for the solar model (see supporting information, Data S8.5). The differences found here are mainly due to the re-distribution of the savings across the consumption categories. For example, the MBS for clothing increased from 4.5% (12 consumption categories) to 20.4% when 8 categories were used. Similarly, housing services move from 24% to 6.5%, and transport moves from 9.6% to 16.81% when the MBS are aggregated into 8 categories. Contrasting these findings, our new results suggest that the source of imports does not change significantly the expected behavior of the system (see supporting information, Data S8.4). The coefficient of variation ranges from 0.43% (NCE) for the wind in the single approach to 7.54% (OD) for the solar model independent of the approach followed (see supporting information, Data S8.5). This result reflects the fact that electricity imports accounted for less than 0.3% of the total electricity demand in 2019, but the imports of energy are avoided in the wind and solar models.

Limitations arise from the inherent uncertainties involved with using EEIO models, such as the degree of sectoral aggregation, the linear production function assumption, constant technical coefficients, and temporal lags between emission data and IO tables (Thomas & Azevedo, 2013). Moreover, limitations stem from using the environmental extensions of EXIOBASE 3.4 in the GTAP9 database, because both databases differ on the base year and level of industry aggregation, among other differences (Tukker et al., 2018).

Future research should focus on gathering data to better estimate the MBS across the different consumption categories. More desegregated data (COICOP 3 digits classifications) at the national and regional levels, as well as data for the different household income levels. Moreover, effort should be made in estimating the cost of the other components of the electricity supply chain different from the generation derived from the injection of NCRRs to better estimate the potential savings for introducing NCRRs in the power grid. Thus, a more realistic approximation to the ERE is needed. Finally, effort should be in estimating the ERE of the NCRRs, including biomass and small-hydro, at different levels of penetration into the power grid, for example, scenarios where the shares of NCRRs are 12%, as is expected in the short-term (UPME, 2021, 2022a, 2022b), but also conservative (e.g.,10%), optimistic (e.g., $\geq$15%), and climate change scenarios. Such analysis will extend the knowledge regarding the ERE of green technologies providing valuable information to practitioners and policymakers.

5 | CONCLUSIONS

Increasing the shares of NCRRs into the power grid up to 12% by the end of 2023 is the key strategy of the Colombian government to decouple climate change from development, protect the energy system against climatic phenomena such as the "El Niño" (south oscillation ENSO), and reduce the GHG emissions by 50% by 2030. Although such strategy represents a clear commitment of the Colombian government to keep climate change below 2°C, it is unclear if the expecting environmental gains may be totally or partially offset by the ERE. Our results reveal variable ERE ranging from 0.12% (MEUT) for the solar model when a single approach (indirect effect by allocating all the savings into the EEIO model) is used, to 97%

(NCE) for the wind model when a combined approach (direct plus indirect effect by combined process-based LCA and EEIO model) is applied. Additionally, backfire effects were observed for the RES category (between 119.469% and 376.605%) in both models, independently of the approach applied. Taking CC as an example, we observed that the electricity consumption in the combined approach is responsible for about 42% of the total ERE, while in the single approach it represents 1.3% of the total ERE. Service sectors such as OSG and OBS produce about 20% and 7% (combined approach) and 35% and 12% (single approach) of the total ERE.

Compared to developed countries, developing countries have a higher rate of growth, the cost of the energy is higher, and the consumption of essential energy services such as lighting is far from saturation; thus rebound effects are expected to be considerably higher than in developed countries (van den Bergh, 2011). Therefore, ERE mitigation policies are relevant. For example, subsidy schemes to disincentivize the additional consumption of electricity proved to have a positive effect in controlling the electricity demand in Colombia when the energy system was at risk of rationing due to the “El Niño” phenomenon in 2016–2017. This scheme penalized the additional consumption of electricity (above the average consumption of the last months previous to the emergency) with an additional cost in the price of the electricity. Moreover, environmental taxation and energy pricing policies may also have positive effects. Particularly, energy pricing policies may prevent consumers perceive the economic gains obtained from the efficiency improvement, limiting the additional consumption of electricity (Freire-González & Puig-Ventosa, 2015). However, such policies may counteract the desired effects of the rebound effect such as fomenting economic growth and increasing social welfare. Thus, attention must be given when designing a mechanism to mitigate the ERE, especially because such mitigation actions may trigger additional ERE.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available in article supporting information.

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