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Influence of Solar Power Farm Expansion on Land Use Transition Trajectories and Carbon Sink Resilience

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Abstract

The European Union has set ambitious goals for renewable energy, leading to a significant expansion of solar power farms across member states. This growth, however, has introduced notable challenges, particularly regarding land use changes and the preservation of carbon sinks. In 2009, the National Renewable Energy Action Plan (NREAP) mandated that each EU member state develop specific incentives to encourage the growth of solar power farms. These measures aimed to increase the share of solar energy in the overall energy mix and to reduce environmental pollution. A thorough evaluation of the NREAP's implementation is essential to understand its effects on solar expansion, land competition, and land use changes, especially those that support carbon sink preservation. This study analyzes panel data from all 27 EU member states, covering the period from 1990 to 2023. The research employs a heterogeneous timing difference-in-difference model to assess how transformation policies have influenced the expansion of solar power farms, with particular attention to environmental pollution reduction and biodiversity conservation within the EU27. The analysis indicates that, compared to Central and Eastern EU member states, Western EU countries have implemented NREAP policies that significantly affect land use change and carbon sink capacity. These policy-driven changes are associated with higher population densities in Western EU member states. The effectiveness of these policies was confirmed through a placebo test, supporting the validity of the findings. Based on the results, the study offers recommendations to further enhance the competitiveness of offshore solar power projects. These suggestions aim to support sustainable energy development while maintaining environmental and biodiversity objectives.

Keywords: Solar power; Land use change; carbon sink; renewable energy; environmental pollution

1- Introduction

The National Renewable Energy Action Plans (NREAPs) across the EU have significantly influenced land use changes through their promotion of solar power farms, with both direct and indirect impacts shaped by policy targets, technological choices, and sustainability considerations. NREAPs, under the EU Renewable Energy Directive (2009/28/EC), set binding national targets for renewable energy shares, including solar power (Chatzipanagi et al., 2023). For instance, Finland aimed for 38% renewable energy by 2020, while Ireland targeted 16%. To meet these goals, member states have incentivized solar power deployment through subsidies, feed-in tariffs, and streamlined permitting processes. However, this has intensified competition for land, particularly between solar power farms and agriculture or biodiversity conservation. Ground-mounted solar power farm installations, which dominate current EU solar power capacity, often convert agricultural land (Chatzipanagi et al., 2023). In the UK, 95% of solar farms are on agricultural land, with 2/3 on arable fields. Similarly, Italy's agrivoltaic auctions revealed strong market demand for solar power projects on farmland, driven by 40% installation subsidies and 20-year feed-in tariffs. This trend raises concerns about food security and ecosystem fragmentation, especially in countries like Germany, where 60% of suitable solar power land is excluded due to settlement proximity regulations (Searchinger et al., 2022).

When natural carbon sinks in the EU are converted to solar power farms, land use changes can release significant amounts of carbon dioxide (CO_2) and other greenhouse gases (GHGs) stored in ecosystems. Here's a detailed breakdown: Direct Carbon Emissions from Ecosystem Destruction; (1) Forest Conversion, EU forests store ~92 tonnes of carbon per hectare in biomass alone. Clearing forests for solar power farms releases CO_2 from decomposing vegetation and soil (Searchinger et al., 2022). For example, a 2021 study estimates land-use changes for solar power farm expansion in the EU could emit 0–50 grams of CO_2 per kilowatt-hour (g CO_2/kWh) of electricity generated, depending on the ecosystem converted. (2) Wetland and Peatland Disturbance, Peatlands store twice as much carbon as global forests, but release CO_2 when drained or disturbed. Drained peatlands in the EU contribute 4% of global anthropogenic GHG emissions. Restoring them can turn them back into sinks, but solar power development on rewetted peatlands requires careful management to avoid re-releasing stored carbon.

Soil Carbon Loss: (1) Soil Organic Carbon (SOC) Depletion, Construction activities (e.g., grading, excavation) disrupt soil structure, accelerating decomposition of organic matter. A 2022 study in Italy found that after seven years, solar power panels reduced SOC by 61% under panels compared to adjacent areas. Soils under solar power farms also showed lower microbial activity and nutrient loss, indicating long-term degradation. (2) Regional Variability, Soils in colder/wetter regions (e.g., Nordic countries) store more organic carbon and are more vulnerable to disturbance. The EU Joint Research Centre (JRC) estimates artificial land uses like solar power farms contribute to negative soil carbon budgets, particularly in high-organic soils.

Indirect Emissions and Ecosystem Impacts (Fritsche et al., 2017); (1) Indirect Land Use Change (ILUC), Converting carbon-rich land for solar power might displace agriculture or forestry elsewhere, triggering deforestation and carbon release in other regions. For example, biofuel-driven ILUC has historically caused higher emissions than direct savings. (2) Biodiversity Loss, Destruction of habitats like grasslands or wetlands reduces ecosystem resilience, potentially releasing stored carbon over time as secondary effects (e.g., invasive species altering carbon cycles).

In summary, the development of solar power farms in the EU presents a complex interplay of challenges and opportunities tied to land use dynamics: Land Competition and Permitting Delays, Environmental and Social Trade-offs, Balancing Food Security and Energy Needs, and Economic and Technological Barriers. The European Union's Land Use, Land Use Change, and Forestry (LULUCF) framework aims for 310 million tonnes of CO_2 equivalent removals by 2030, but current trends show declining carbon sinks due to forest harvesting and climate stressors. Solar power farm expansion on natural sinks could exacerbate this gap.

This research question focuses on the core issue of the impact of solar power farm expansion on land use change in the EU from the perspective of carbon sinks and energy security. It can prompt an in-depth exploration of the specific influence mechanism of land use change brought about by solar power farm projects on carbon sinks due to forest harvesting and climate stressors, as well as the study of strategies to address the challenges of ensuring efficient carbon sinks while promoting the development of solar power farms. Therefore, this research questions as follows: (1) To what extent does the large-scale policy implementation of solar power projects on land use change in the EU affect carbon sink in the EU during the period between 1990 and 2023? (2) To what extent do different EU27 member states benefit in terms of carbon sink from the integration of solar power farms and biodiversity conservation policy?

Accordingly, this research objective can be stated as follows: (1) To explore how solar power farm expansion policy in the EU is influenced by land use change for the period between 1990-2023, and to what extent this NREAP policy impacts land use change, considering variations across different member states, biodiversity conservation systems, and geographical regions. (2) To compare the experiences of different EU27 member states in implementing solar power farm projects and considering biodiversity conservation, and assess which models and policies are most effective in safeguarding biodiversity conservation. (3) To analyze the social, economic, and environmental dimensions of solar power farms policy in the EU region, and understand how these dimensions interact to influence carbon sink during the period between 1990 and 2023.

By segregating the EU27 members into two groups based on economic structure and development, this research can identify the differences and characteristics of different economies within the EU. Group 1 is the European Union industrial countries (Western EU14) and consists of economically developed and diversified economies with high GDP per capita, advanced service-oriented structures, and strong innovation capacities. The EU14 members, such as France, Germany, Italy, and the Netherlands, are notable for their proactive approach to biodiversity conservation policy, while these nations have been developing regulatory frameworks, implementing support schemes, and hosting pilot projects (see Figure 1).

Group 2 is European Union emerging countries (Central and Eastern EU13), which includes economies in transition or with underdevelopment economies, which have lower GDP per capita, industrial structures in the process of transformation, and relatively lower innovation capacities. EU27 policies like the European Green Deal and the Common Agricultural Policy (CAP) strongly influence EU13's newer economies. These policies push for renewable energy adoption and biodiversity conservation, creating a framework for a carbon sink. Therefore, the increase of EU-wide policies regarding biodiversity conservation has greatly increased the adoption of renewable energy projects in EU13 economies. For example, countries within the Central and Eastern European region are beginning to implement solar power farm projects and are creating legislation to support the growth of the sector.

Research on EU solar power farm expansion, land use change, and carbon sinks using the difference-in-difference (DID) method is significant and novel in the following ways: (1) this study addresses critical gaps in reconciling the EU's renewable energy targets (e.g., 40% renewables by 2030) with carbon sink conservation, a key pillar of its climate goals (carbon neutrality by 2050). Quantifying the trade-offs among solar farm expansion, land use shifts, and carbon sink impacts informs policy (NREAPs) and integrates fragmented research on energy, land use, and carbon cycles. (2) The DID method enables causal inference by isolating the net effect of solar farm-induced land use change on carbon sinks, controlling for confounding variables (e.g., economic structure, implemented policy, applied technology) that correlational studies miss. (3) This study also integrates multi-scale dynamics and unpacks understudied feedbacks, enhancing robustness and practical relevance for sustainable energy transitions. The remainder of this study is organized as follows. The Literature Review section examines recent research in the field, considering both empirical and theoretical perspectives. The Data and Methodology section outlines the model specification and details the panel data estimators employed in the analysis. The Empirical Results section presents the estimation outcomes derived from the panel data methods. Finally, the Discussion and Conclusion section provides an analysis of the findings, discusses their implications, and offers concluding remarks.

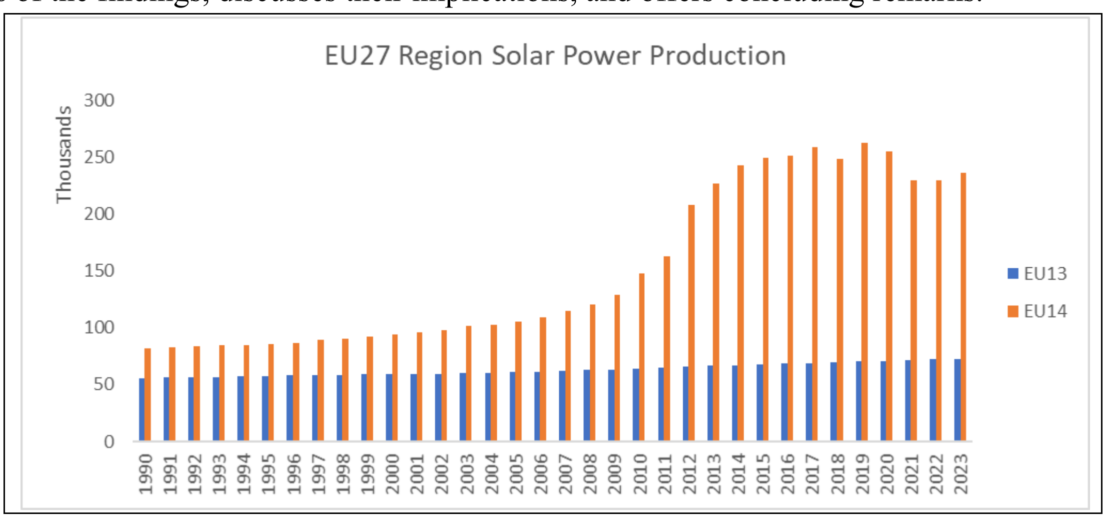

Figure 1 Solar power production in the EU27 states (EU13 and EU14) during the period 1990-2023

2- Literature Review

Recent research by Zhang et al. (2024) has identified unavoidable land-use conflicts between solar farms and forests. While the expansion of solar farms poses a threat to the capacity of forests to sequester carbon and maintain essential ecosystem services, the overall extent of these conflicts is relatively small but geographically widespread. Xu et al. (2024) further examined the environmental effects of solar farms, focusing on changes in albedo, vegetation, and land surface temperature through remote sensing. Their findings indicate that large, high-capacity solar farms intensify impacts on both albedo and land surface temperature. These effects are influenced by geographic and climatic conditions and vary depending on the type of concentrating solar power technology used. In contrast, Lovering et al. (2022) reported that the current global energy system occupies only 0.4% of ice-free land, a figure much lower than the 30–38% attributed to agriculture. However, the authors caution that a transition to more extensive low-carbon energy technologies could significantly alter global landscapes, especially as global energy consumption is projected to double by 2050 alongside widespread electrification of transport and industry.

In the United States, studies by Yavari et al. (2022), Buckley Biggs et al. (2022), and Levin et al. (2023) have evaluated the potential impacts of expanding ground-mounted photovoltaic solar energy on land cover and areas critical for animal movement. Their research suggests a considerable overlap between solar energy development and land important for animal migration, with much of the development expected to occur on land valuable for climate-change-induced migration. In Ireland, Geoghegan and O'Donoghue (2023) analyzed the economic returns of converting agricultural land to renewable energy production. Using multiplier analysis, they found that biomethane production offers the highest multiplier effect, while solar photovoltaic systems provide the lowest. In South Korea, research by Kim et al. (2022) and Ko (2023) demonstrated that rural opposition to landscape changes caused by solar farms has been a significant factor prompting county governments to impose restrictions. Counties with higher solar farm density are more likely to adopt such measures. The studies also highlight that national renewable energy initiatives may encounter local policy barriers if adverse effects on communities are not addressed.

In Tropic of Cancer and Turkey, Marzouk (2022) assessed the competitiveness of photovoltaic and concentrated solar power technologies in the Tropic of Cancer, concluding that photovoltaic systems with horizontal single-axis tracking are most effective for land use in low-latitude regions. In Turkey, Coruhlu et al. (2022) integrated geographic information systems and analytical hierarchy processes to evaluate solar energy potential in environmental planning. Their findings indicate that allocating high-potential solar areas for other purposes, such as buildings or hospitals, may hinder the long-term development of renewable energy. Both forests and solar power farms are essential for meeting the climate objectives of the Paris Agreement. However, the large land requirements of solar farms can create conflicts with other land uses. Tölgyesi et al. (2023) and Zhang et al. (2024) assessed these conflicts globally, using simulation models and remote sensing data. They found that 9.14% of solar farms, representing 4.9% of total solar farm area, conflict with forests. Additionally, the capacity factor of solar farms decreases as forest coverage increases, primarily due to greater cloud formation and reduced solar radiation.

Dinesh et al. (2022) and Carvalho et al. (2022) reviewed grassland management practices within solar farms in temperate regions, focusing on soil carbon dynamics. Their analysis indicates that practices such as plant removal and prolonged mineral fertilization are likely to result in long-term soil carbon loss. In the Sahara and the Amazon Basin, Power et al. (2023) modeled the impact of a Saharan solar farm on the terrestrial carbon cycle. Their results show an enhanced carbon sink in Northern Africa, particularly the Sahel, but a weakened carbon sink in the Amazon basin. In China, Yu et al. (2022) and Gao et al. (2022) conducted a case study in Qinghai province, which has significant solar and wind resources and high carbon sequestration potential. The province shifted from rapid carbon emissions growth (2000–2015) to achieving carbon neutrality during the 13th Five-Year Plan (2015–2020). Land management interventions contributed to this transition by preventing ecosystem degradation and promoting biomass growth and soil carbon sequestration.

In Pakistan, Danish et al. (2025) examined the effects of land use and land cover changes on soil properties and carbon sequestration in the upper Himalayan region of Gilgit. They observed significant changes in soil organic carbon, bulk density, electrical conductivity, temperature, and moisture, although pH changes were not significant across soil depths. In Fiji, Avtar et al. (2022) analyzed land use changes and projected forest carbon sequestration using remote sensing and geospatial modeling. The study found ongoing deforestation over the past two decades, with further declines in forest area expected by 2040, primarily due to conversion to agriculture. In Europe, Winkler et al. (2023) reported that Eastern Europe accounted for approximately 0.41 gigatons of above-ground biomass carbon sink per year from 2010 to 2019, representing 78% of the European total. However, this carbon sink is declining, mainly due to changes in land use, land management, and increasing natural disturbances. In Finland, Lehtonen and Rämö (2023) explored how Finnish agriculture, traditionally focused on livestock, could reduce greenhouse gas emissions by over 40% by 2050. Achieving this reduction would require moderate changes in diets and land use, supported by productivity growth and policy reforms.

H1: Policies designed to promote solar power farm development contribute to an increase in both the expansion of land use change and the capacity of carbon sinks.

H2: Policies that do not actively promote solar power farm development are associated with a decrease in both the scale of land use change and the potential of carbon sinks.

While the EU and some member states have introduced policies related to solar power farms, such as France and Germany. However, there is a lack of in-depth research using the Diff-in-diff approach to explore the impact of these policies on the development level of solar power and the ecological impacts. The current literature did not precisely measure how these policies affect the solar power farms in the EU27 region. Without this evaluation, it is difficult to provide an empirical basis for policy optimization in the EU market. Moreover, there is no research applying the DID method to compare EU27 members that have adopted specific photovoltaic technologies with those that have not. Without such research, it is impossible to determine the actual ecological and environmental effects of these technologies in practice. This restricts the further quality improvement of these solar power farms in the EU. Lastly, the solar power approach involves the interests of multiple parties, including energy developers, landowners, stakeholders, and agricultural farmers. Although it is theoretically possible to create new value, the actual value-distribution mechanism remains unclear. Existing studies have not used the DID method to analyze the changes in the benefits of each party under different economic models and policies.

Solar power farms offer unique advantages in resource utilization and sustainability, while the DID method provides a rigorous framework to quantify their competitive edge by isolating causal effects from confounding factors. Therefore, the novelty of energy economic analysis via the DID method is as follows: (1) Define treatment groups (regions/projects with offshore solar) and control groups (similar regions without), ensuring comparable natural and economic conditions. (2) Gather pre- and post-development data on indicators like power generation cost, efficiency, environmental impact, ecological impact, and economic benefits. (3) Verify that indicators for both groups followed similar trends before the intervention to ensure DID validity. (4) Compare policy implementation pre-post differences between groups to estimate the causal impact of solar power farms on land use change and carbon sink. (5) Conduct statistical inference and sensitivity tests (e.g., using different control groups or periods) to ensure result reliability.

3- Method and data

3.1. Data collection

This study examines the key factors influencing the development of solar power farms in EU27 countries, as well as their ecological and environmental impacts. The analysis employs the difference-in-differences (DID) methodology, utilizing data spanning from 1990 to 2023. The treatment period for countries implementing relevant policies is defined as 2010 to 2023. The empirical analysis draws on data from EU24 countries over the period from 1990 to 2023. The DID approach was selected to assess the effects of policy interventions, specifically focusing on the implementation of the National Renewable Energy Action Plan (NREAP) in 2010. In this context, a dummy variable distinguishes between treated countries (assigned a value of 1 during the NREAP policy period) and control countries (assigned a value of 0). SP (Solar Thermal Collectors' Surface): Measured in thousands of square meters, this variable represents the total surface area of solar thermal collectors. LUC (Forest Area): Defined as land covered by natural or planted stands of trees at least five meters tall, regardless of productivity. This excludes tree stands in agricultural production systems (such as fruit plantations and agroforestry) and trees located in urban parks and gardens.

GDP (Gross Domestic Product): Calculated as the sum of gross value added by all resident producers, plus any product taxes, and minus any subsidies not included in the product values. CO2 (Carbon Dioxide Emissions): Includes emissions resulting from the combustion of fossil fuels and cement production, as well as emissions from the consumption of solid, liquid, and gaseous fuels and gas flaring in marine activities. HDI (Human Development Index): Measured by government expenditure on education as a percentage of GDP. PD (Population Density): Calculated as the midyear population divided by land area in square kilometers, based on the de facto population definition, which includes all residents regardless of legal status or citizenship. All variables were sourced from the World Development Indicators and Eurostat. For further details, refer to Table 1.

Table 1. Variable explanation list

Variable	Symbol	Source	Variable	Unit of Measurement
Land Use Change	LUC	Eurostat	Independent	Forest area loss as % of land area
Dummy Variable	Intercept	WBD	Independent	Treated = 1, Controlled = 0
Solar Power Output	SP	Eurostat	Dependent	Thousand Square Meters
Human Development Index	HDI	WBD	Independent	Education Expenditure % of GDP
Carbon Dioxide Emission	CO2	Eurostat	Independent	Metric tons per capita
Population Density	PD	WBD	Independent	% / m^2
Economic Growth	GDP	Eurostat	Independent	Current US dollars

3.2. Theoretical background

Land use change (e.g., converting forests to solar farms or agricultural land to urban areas) is governed by theories of resource allocation, opportunity cost, and property rights. Based on opportunity cost and land allocation theories, land is a scarce resource with competing uses (e.g., solar power, agriculture, forestry, urban development). The opportunity cost theory of using land for solar is the value of the next-best alternative (e.g., crop yields from farmland or carbon sequestration from forests). Efficient land use requires balancing these costs against Solar's benefits (e.g., clean energy). Also, from a non-market valuation of land ecosystems perspective, many land-based services (e.g., carbon sequestration, biodiversity) lack market prices, leading to undervaluation and over-conversion to commercial uses (e.g., solar farms). Economic tools to quantify these non-market values include: (1) Hedonic pricing, inferring value from property prices (e.g., proximity to green spaces increasing home values). (2) Contingent valuation method, survey-based estimates of willingness to pay for preserving land ecosystems.

The analysis employs the widely recognized Difference-in-Differences (DID) approach, as utilized by Upton and Snyder (2017), Abadie (2018), and Xu (2017). This method is applied to both cross-sectional and panel data for EU14 and EU13 countries, covering two distinct periods: 1990–2010 and 2011–2023. The primary rationale for selecting the DID methodology is its ability to provide unbiased estimates of the impact of solar power within the EU27 region. This ensures that the results obtained are both robust and reliable. Let y(i, t) denote the outcome of interest for country i at time t. Observations are made for each country before the treatment period (t = 0) and after the treatment period ($t = 1$). During these periods, countries that are exposed to the treatment are identified by the indicator $D(i, t) = 1$. Conversely, countries not exposed to the treatment are assigned $D(i, t) = 0$. $D(i, t) = 1$: Indicates countries that receive the treatment, specifically the EU14 countries in this study. $D(i, t) = 0$: Refers to countries that do not receive the treatment, serving as the control group. According to Abadie (2018), countries can only be classified as untreated ($D(i, t) = 0$) for the relevant period. The DID estimator is typically implemented using a linear parametric model, following the procedures outlined by Card (1985) and Abadie (2018). It is assumed that the outcome variable is generated according to the variance process specified in the subsequent equation.

$Yi,t = \mu i,t = \delta(t) + \alpha \cdot Di,t + \eta(i) + vi,t$ (1)

Equation (1) includes several key elements, each representing a distinct aspect of the model: $\delta(t)$: This term captures the component that is specific to each point in time. α: This parameter reflects the effect of the treatment within the model. $\eta(i)$: This denotes the component that is unique to each country. $v(i, t)$: This term represents country-specific shocks. These shocks have an average value of zero within each period (where $t = 0, 1$) and are directly correlated over time. $y(i, t)$ and $D(i, t)$: These are the observable variables in the analysis.

$P(Di,t = 1|\text{-}\mu i,t)=P(Di,1) =1$ (2)

For $t = 0, 1$, by applying addition and multiplication operations to the conditional expectation $E[\eta(i) \mid D(i,1)]$ as presented in Equation (1), the expression is transformed as follows:

$Yi,t = \delta(t) + \alpha Di,t + E[\eta(i)| Di,1] + \varepsilon i,t$ (3)

From Equation (3); $(i,t)=\eta(i)\text{-} E[\eta(i)]| D(i,1)]+v(i, t)$. It should be noted that $\delta (t)=\delta (0) + (\delta(1)-\delta (o)t$, And; $E[\eta(i)]| D(i,1)]=E[\eta(i)]| D(i,1)=0]+E[\eta(i)] | D(i, 1) =1]\text{-} E[\eta(i)] | D(i,1)=0]D(i,1)$. Let $\mu= E[\eta(i)]| D(i,1)=0] +\delta(0)$, $\tau= E[\eta(i)]| D(i, 1) = 1]\text{-} E[\eta(i)]| D(i,1)=0]$, and $\delta=(\delta(1) - \delta (o)$. Equation (4) is concluded as below:

$$Yi,t = \mu + \tau Di,1 + \delta t + \delta Di,t + \varepsilon i,t \quad (4)$$

The constraints applied to Equation (2), specifically setting $t = 0, 1$, indicate that the expectation $E[1, D(i,1), t, D(i, t)]$ holds under the condition that the error term $\varepsilon(i, t)$ equals zero. This assumption is essential for the identification strategy within the model. The variables presented in Equation (4), along with the parameter δ, can be estimated using the ordinary least squares (OLS) method. This approach provides a straightforward means to obtain consistent parameter estimates under the specified assumptions. Furthermore, the structure of the equation allows for the selection of treated countries based on their level of dependence, as indicated by the condition $D(i,1) = 1$ and the country-specific variable $\eta(i)$. This facilitates targeted analysis within the empirical framework. Equation (4) may also be further simplified, as demonstrated below:

$Yit = \delta + \delta_i \times TREAT_i + \delta_{it} \times POST_t + \beta^{2\times2}{}_t TREAT_i \times POST_t + U_{it}$ (5)

In this analysis, Yit denotes the outcomes for several key indicators: solar power (SP), land use change (LUC), carbon dioxide emissions (CO2), gross domestic product (GDP), population density (PD), and the Human Development Index (HDI). The term δiTREATi identifies countries that have received the treatment at time i. Similarly, δitPOSTt refers to countries that have been exposed to the treatment after its implementation. The interaction term, β2×2tTREATi×POSTt + Uit, captures the combined effect of the treatment dummy for a group of countries and the post-treatment dummy for the same group within the regression model. This section brings together both EU13 and EU14 member states that have experienced the treatment, both before and after its introduction. The objective is to identify the factors influencing solar power adoption and land use change in the context of ecological sustainability. The variable Uit represents the country-specific, unrelated transitional component associated with green energy investments. The methodology employed is known as the difference-in-differences (DID) approach. Based on the condition outlined in Equation (2), the analysis proceeds to Equation (6), as presented below.

$$\delta = \{E[Yi,1|Di,1=1]-E[Yi,1|Di,1=0]\} - \{E[Yi,0|Di,1=1]-E[Yi,0|Di,1=0]\} \quad (6)$$

Model formulation is essential when analyzing cross-sectional data pairs, specifically (Y(i, t), D(i, 1)) for t = 0, 1. In this context, the study utilizes panel data to capture differences before and after a particular event across various countries. The observed outcome is represented by the difference between Y(i, 1) and Y(i, 0). To estimate the parameter δ, the ordinary least squares (OLS) method is applied. This approach allows for a straightforward estimation of the effect by comparing outcomes over time within the same units.

$$\delta = E[Yi,1-Yi,0|Di,1=1] - E[Yi,1|Yi,0,Di,1=0] \quad (7)$$

Based on Equation (2), when considering t = 0, 1, the difference v(i,1) - v(i,0) represents an average that does not depend on D(i,1). As a result, if none of the countries receive treatment, the mean outcomes would exhibit the same variations as those observed in the treated countries. Abadie (2018) notes that this modeling approach can be restrictive, particularly when the treated and untreated groups possess different, unbalanced explanatory variables that influence the dynamics of the outcomes. This limitation may affect the validity of the results when there is significant heterogeneity between groups. To address these concerns, it is useful to draw an analogy to the foundational work of Ashenfelter (1978). By accounting for variations among the countries under study and managing heterogeneity, the model proposed by Ashenfelter and Card (1985) offers a framework designed to accommodate these complexities:

$$Di,1 = \begin{cases} 1, \text{if } yi,1 - k + ui < Y \\ 0, \text{otherwise} \end{cases} \quad (8)$$

From a model parameters and policy implications perspective, here are the key variables: K represents a positive integer; Y denotes a constant value; u(i) refers to a random variable. In the context described above, countries with relatively low solar power farm output are expected to implement new policies aimed at increasing their solar energy production. This shift typically occurs following the treatment period and is driven by the requirements of the Paris Accord as well as concerns raised by environmental advocacy groups. The objective is to encourage these countries to enhance their solar power output as part of broader efforts to reduce environmental pollution. The Difference-in-Differences (DID) methodology is applicable under the condition (i, 1−k). Under this framework, the effect on the group receiving the treatment is outlined below:

$$f(\theta,Di1)=\begin{cases} -Yi1, Di1 = 1 \\ \mid Yi0 \mid, Di1 = 0 \end{cases} - [E(Yi0 \mid Xi, Di1 = 1) - E(Yi0 \mid Xi, Di1 = 0)] \quad (9)$$

The equation X(i) = (i, 1-k) defines a vector, X(i), which represents the observable characteristics of each country. As outlined in this article and in Abadie (2018), these characteristics are established at the initial time point, t = 0. Equation (9) addresses the sequence in which countries are matched for analysis. Specifically, it compares each group of treated countries, denoted by i, to individual countries that have not received the treatment. The outcome covariate, Yi, for each treated country is considered in this matching process. The matched outcome, estimated as bYi, is then assigned a weight corresponding to its closest counterpart in the comparison group. This approach ensures that the analysis accurately reflects the relationship between treated and untreated countries.

$$\widehat{Yi} = \sum_{j \in C^0(Pi)} w_{ij}\, y_j \qquad (10)$$

$C_0(P_i)$ denotes the set of treated neighbors indexed by *i* within the group where $D = 0$. The term W_{ij} refers to the weight assigned to each untreated individual *i* when making comparisons with their treated counterparts. In general, the matching estimator for the Average Treatment Effect on the Treated (ATT), denoted as ATT(S_{10})**,** can be expressed as follows:

$$\widehat{ATT} = \frac{1}{\#[D=1 \cap (S10)]} \sum_{i \in \{Di=1\} \cap S10} (Yi - \widehat{Yi}) \quad (11)$$

E {Y|treated on S_{10} − E {Y|weighted/untreated

4- Results

To evaluate the potential for scaling up offshore solar farms across the EU27 countries, a normality test was performed on the dataset. The Jarque-Bera test was selected to examine both skewness and kurtosis. The results indicated a statistically significant normal distribution, as demonstrated by a p-value of 0.00. This finding confirms that the residual errors in the analysis are normally distributed. The outcomes of the Jarque-Bera normality test, as analyzed using EViews, are presented in Table 2. Following the confirmation of normality, the difference-in-differences (DID) estimator was employed to further analyze the data (refer to Table 3). The DID approach offers several advantages: (1) It enables direct comparison between entities with similar characteristics, ensuring methodological consistency; (2) It accounts for both observed and unobserved differences among countries; (3) It is straightforward to implement and does not rely on parametric assumptions.

Table 2 summarizes the descriptive statistics, including covariance and normality test results. Among the variables analyzed, carbon emissions (CO2) and onshore solar power farms (OSP) recorded the highest mean values. This highlights the strong relationship between these two factors within the study model. The human development index (HDI) for the countries examined is relatively low, suggesting that human capital plays a limited role in the connection between solar farm development and land use change in the EU context. In contrast, the mean values for economic growth (GDP) and land use change (LUC) are moderate, reflecting the contribution of solar power to both the energy and environmental sectors. Population density (PD) data further emphasize the importance of a healthy living environment. This factor is crucial for the successful development of solar power farms and for addressing environmental pollution and biodiversity loss.

Table 2: Summary statistics and normality test

	CO2	LUC	GDP	HDI	PD	OSP
Mean	4.726	1.444	1.528	0.679	2.023	3.770
Median	4.737	1.51	1.540	0.683	2.030	3.724
Maximum	5.981	1.867	1.752	0.932	3.214	5.055
Minimum	2.000	0.038	0.218	0.286	1.214	3.000
Std. Dev.	0.563	0.343	0.082	0.100	0.385	0.247
Observations	918	918	918	918	918	918
Normality Test	Skewness	Kurtosis	Jarque-Bera	Probability	Observation 918	
Residual	0.041	3.358	2.828	0.000		

Table 3 presents the intercept dummy variable for both treated countries and the relevant time periods, as outlined in Equation (5). This variable is included to provide a counterfactual perspective regarding the hypothesis that all countries, regardless of treatment status, would receive an equivalent level of renewable and sustainable energy policies. The dummy variable is defined as follows: D = 1 for countries that have received the treatment, and D = 0 for those that have not. The statistical analysis indicates that this dummy variable is significant, with a p-value of 0.000. These results suggest that both treated and untreated countries demonstrate a strong tendency to attract further development of solar power farms and to implement renewable and sustainable energy policies. Such measures are directed at mitigating environmental impact and supporting a transition toward sustainable development. For additional details, refer to Figure 2 and Figure 3.

Table 3 Regression with a dummy variable for the intercept (treat*post) t-statistic test

Variable	Coefficient	Std. Error	t-Statistic	Prob.

INTERCEPT	7.287***	0.047	154.791	0.000
R-squared	0.826	Mean dependent var		3.774
Adjusted R-squared	0.813	S.D. dependent var		0.2477
S.E. of regression	0.107	Akaike info criterion		-1.560
Sum squared resid	9.775	Schwarz criterion		-1.213
Log-likelihood	782.352	Hannan-Quinn criteria		-1.428
F-statistic	62.346	Durbin-Watson stat		0.049
Prob(F-statistic)	0.000			

The parallel trend test is an essential prerequisite for applying the time-varying point Difference-in-Differences (DID) methodology. In this study, the event study approach is employed to conduct the parallel trend test within the time-varying DID framework. Figure 2 presents the dynamic effects observed in the analysis. In the four periods preceding the implementation of the NREAPs policy, the coefficients associated with the dummy variables do not differ significantly from zero. This outcome suggests that, before the policy intervention, the trends in NREAP strategies for both the treatment and control groups remained relatively stable. Following the introduction of the NREAPs policy, the coefficient of the relevant variable rises above one. This result indicates that the NREAP strategies for both the control and treatment groups experienced notable changes attributable to the policy's implementation.

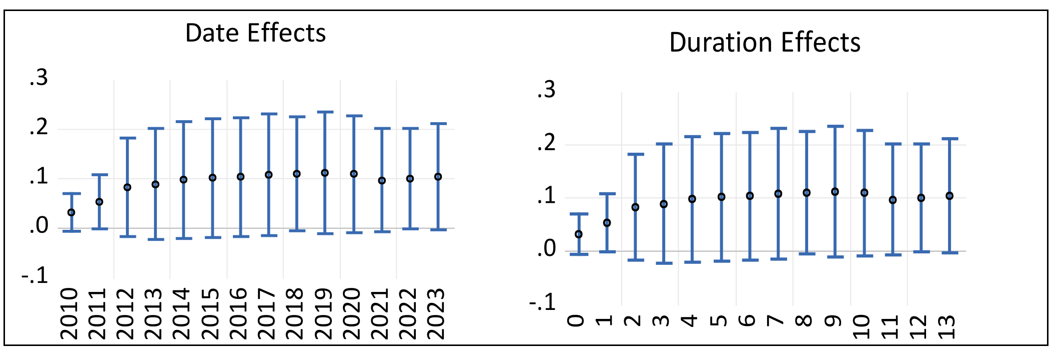

Figure 2: Parallel trend test. The vertical dashed line shows the "event year" of 2010, and the horizontal dashed line shows the zero-value axis.

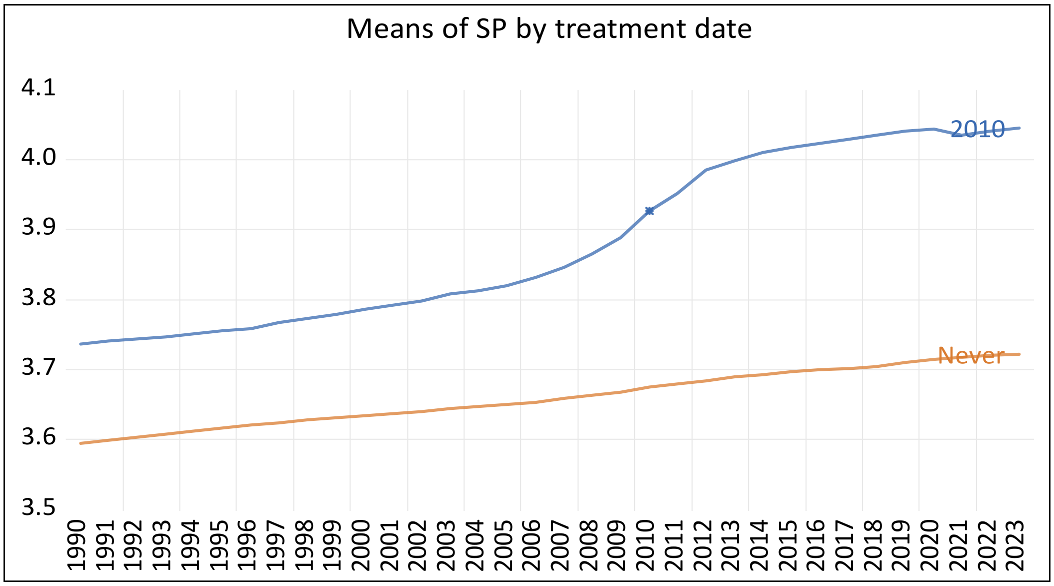

Figure 3 presents policy implementation profiles, detailing the adverse events that impacted both treatment countries (indicated in blue) and control countries (indicated in red) between 1990 and 2023. The analysis distinguishes events occurring before and after the baseline year of 2010. The primary hypothesis of this study was that the effectiveness of the National Renewable Energy Action Plan (NREAP) in expanding solar power farms would result in different patterns of land use change and carbon sink responses compared to those observed in control countries. To examine this, the research addressed two hypotheses separately: first, the impact of negative coping strategies under the NREAP, and second, the effect of positive adaptive or transformative NREAP strategies.

The study employed the Ordinary Least Squares (OLS) model, as shown in Table 4, and the Fixed Effect-Ordinary Least Squares (FE-OLS) model as a robustness check in Table 5. The analysis controlled for Central and Eastern European countries (EU13) and treated Western European countries (EU14) as the primary group of interest. Given the specific responses of EU27 member states to the NREAP, the research also considered the characteristics of these states, particularly in relation to negative coping strategies. The focus was placed on three main models: EU27, EU14, and EU13. For each of the three principal models presented in Tables 4 and 5, the study identified countries that reported being affected by the relevant policies at the baseline. The corresponding coping strategies under the NREAP were then analyzed. The OLS and FE-OLS models used to test the difference-in-differences (DiD) approach yielded non-conclusive results overall.

In Table 4, the DiD variable (intercept) was found to be statistically significant and positive for both the EU27 and EU14 groups, indicating a greater likelihood of adopting positive, strengthening NREAP strategies. In contrast, for the EU13 control group, the DiD variable (intercept) was not significant and was negative. Similarly, in Table 5, the DiD variable (intercept) remained statistically significant for the EU27 and EU14, while it was not significant for the EU13 group. The empirical results support the initial hypothesis regarding NREAP strategies. The implementation of these policies has facilitated the expansion of solar power farms and contributed to an increased share of renewable energy, thereby enhancing energy security within the EU27 region. The findings are particularly conclusive for positive responses, as the propensity to adopt adaptive or transformative NREAP strategies is higher among the EU27 as a whole and among the treatment countries (EU14), compared to the control group (EU13).

Table 4 Testing the effect of NREAPs on coping strategies for land use change, using OLS models. Test completed for the three main models: EU27 States overall (Model 1); Western European Union States EU14 (Model 2); and Central and Eastern European Union States EU13 (Model 3).

Model	EU27		EU14		EU13	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
CO2	-2.583***	0.883	-0.324***	0.056	-0.080***	0.019
GDP	0.124	0.081	0.073	0.051	0.133***	0.018
HDI	0.313***	0.067	0.658***	0.088	0.148**	0.072
INTERCEPT	0.282***	0.016	0.284***	0.026	-0.0002	0.021
LUC	0.195***	0.029	0.158***	0.0438	0.257***	0.040
PD	0.246***	0.026	0.026	0.030	0.432***	0.041
Constant	5.406***	0.827	3.269***	0.346	1.479***	0.166
Observation	918		476		442	
Number of groups	27		14		13	
F-statistic	79.842		69.390		49.816	
Prob(F-statistic)	Prob>F=0.000		Prob>F=0.000		Prob>F=0.000	
R-squared	0.344		0.470		0.407	
Control	YES		NO		YES	
Treat	YES		YES		NO	
Intercept	YES		YES		YES	

In Table 4, there is a significant positive influence of NREAPs strategies on solar power farms; an increase in NREAPs application by 1% will bring about an increase in solar power supply by 0.284% in EU14 states, and 0.282% in the EU27 states overall. In the EU14 states, this research observes that NREAPs policy implementation contributes to an increase in the share of HDI and LUC by 0.658 and 0.158 for a 1% increase in solar power production. Among the other variables, a 1% increase in solar power was associated with a decrease in CO2 by 0.324%.

The Difference-in-Difference estimation outcomes for the alteration in NREAPs policies with the reflection on the solar power production are reported in Table 5; the most influenced group measure is shown to be the EU14 treatment group by 0.187%, the EU27 region by 0.299%, and no significant evidence for the EU13 (controlled group). After its treatment in the EU14 countries, an observed change of -0.209% in CO2, 2.206% in LUC, and 1.418% in PD was recorded in the years following the treatment for each 1% increase in solar power production in the EU14.

In Table 5, among the three NAREP measures considered, the EU13 controlling group is the least affected by the NREAPs policies implementation. In the year following the NREAPs policies boosting the EU27 region overall, there is an estimated change in GDP and PD by 0.063% and 0.359% for a 1% increase in solar power production. Moreover, an observed change of -0.948% in LUC was recorded for each 1% increase in solar power production.

Table 5 Testing the effect of NREAPs on coping strategies for land use change, using FE-OLS models. Test completed for the three main models: EU27 States overall (Model 1); Western European Union States EU14 (Model 2); and Central and Eastern European Union States EU13 (Model 3).

Model	EU27		EU14		EU13	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
CO2	-2.719***	1.013	-0.209**	0.095	-0.008	0.017
GDP	0.046	0.097	0.019	0.086	0.063***	0.010
HDI	0.328***	0.069	0.052	0.116	0.020	0.032
INTERCEPT	0.299***	0.020	0.187***	0.024	0.012	0.007
LUC	0.1875***	0.030	2.206***	0.377	-0.948***	0.155
PD	0.240***	0.027	1.418***	0.442	0.359***	0.066
Constant	5.686***	0.937	4.264***	0.769	2.3701***	0.228
Observation	918		476		442	
Number of groups	27		14		13	
F-statistic	12.416		55.967		353.554	
Prob(F-statistic)	Prob>F=0.000		Prob>F=0.000		Prob>F=0.000	
R-squared	0.355		0.699		0.937	
Control	YES		NO		YES	
Treat	YES		YES		NO	
Intercept	YES		YES		YES	

5- Discussion

When comparing EU14 western states (treatment group) and EU13 central and eastern states (control group), the greatest augmentation in solar power farms production policies is achieved in EU14 states (see Table 5). For example, an average annual increase in solar power production of 0.187% and 0.012% is observed in the EU14 and EU13 countries, respectively, following the implementation of the NREAPs policy. The outcome is consistent with earlier studies such as Nieto Morone et al. (2025) and Abdoos et al. (2025). The NREAP policy plays a more significant role in driving solar power farm production in EU14 compared to EU13, primarily due to four key differences: (1) EU14 countries (e.g., Germany) established renewable energy policies (like early versions of the EEG) and NREAP-related measures much earlier, building experience and industry momentum, while EU13 countries often faced delays in policy development. (2) EU14 nations (e.g., the Netherlands) set higher, clearer renewable energy targets (including for electricity) in their NREAPs, strongly guiding solar energy growth, whereas EU13 targets for solar were often lower or less defined. (3) EU14 countries (e.g., France, Italy) offered long-term, high-value subsidies (e.g., 20-year price supports with billions in funding) for solar projects, while EU13 support was frequently less intensive or shorter in duration. (4) EU14's mature power grids and stable renewable energy demand facilitated smoother grid integration and market access for solar farms, reducing barriers, whereas EU13 often struggled with underdeveloped grids and weaker market demand, limiting NREAP's impact.

Similarly, raising solar power farms production drives an average annual change of about 2.206% and -0.948% in LUC for EU14 and EU13, respectively. The outcome aligned with earlier research such as Yavari et al. (2022), Buckley Biggs et al. (2022), and Levin et al. (2023). Land use change from solar power farms is greater in EU14 than in EU13 due to several key factors: EU14 has a longer history of solar deployment with greater cumulative capacity, driven by earlier and stronger policy support that prioritizes large-scale, land-intensive projects. Additionally, EU14 benefits from more established land-use frameworks, allowing repurposing of underutilized land and mature grid infrastructure to accommodate such projects. In contrast, EU13 lags in large-scale solar development due to later policy adoption, focus on smaller-scale solar, competing land demands, and weaker grid infrastructure, resulting in less land use change for solar farms. For example, to meet its NREAP target of 14.5% renewable energy by 2020, the Netherlands expanded solar farms on low-yield agricultural land and reclaimed areas. The *Solarpark Zeeland* spans 100 hectares, producing 70 MW, and is part of a broader strategy to repurpose underutilized land for renewables. Its dense population and limited available space make efficient land use for solar a priority, leading to concentrated land conversion for large projects. On the other hand, Romania has a growing solar capacity, and it focuses more on smaller-scale projects. For example, rooftop solar installations dominate, with utility-scale farms remaining limited. The *Solar Park Craiova* is one of the larger projects, but covers only ~30 hectares (generating 20 MW)—far smaller than EU14 counterparts. Policy delays (e.g., inconsistent subsidy frameworks) and weaker grid infrastructure in rural areas have hindered large-scale development, reducing land conversion.

Expectedly, due to the promotion of solar power farms under the NREAP policy led to an average annual mitigation of about -0.204% and -0.008% in CO2 for EU14 and EU13, respectively. These results aligned with previous research by Paraschiv and Paraschiv (2020), Ciais et al. (2022), and Maier et al. (2023). EU14 experiences higher land use change from solar power farms and a greater reduction in carbon sinks compared to EU13 due to key differences in solar development patterns and land conversion. EU14's larger, more established solar farms—driven by earlier policies, robust infrastructure, and ambitious targets—often replace carbon-rich land (e.g., agricultural fields, low-lying vegetation areas) that naturally sequesters carbon, eliminating these important carbon sinks. In contrast, EU13’s smaller, slower solar growth focuses on less carbon-intensive land (e.g., degraded sites, rooftops) with minimal carbon-sequestering capacity, resulting in both less land use change and little loss of carbon sinks. For Example, Germany’s Solarpark Meuro (mentioned earlier) covers 160 hectares of former agricultural land. This land, once used for crops like wheat or barley, sequestered carbon through plant growth and soil organic matter. Converting it to a solar farm eliminated that ongoing carbon uptake, resulting in a significant local reduction in the carbon sink. On the other hand, EU13’s solar growth is slower and more focused on small-scale projects (e.g., rooftop solar) or solar farms on already degraded land (e.g., abandoned industrial sites with little vegetation). These areas were not significant carbon sinks to begin with, so converting them to solar causes minimal loss of carbon-sequestering capacity. As of Romania’s Solar Park Craiova (30 hectares) is built on a former gravel quarry, land that was already barren and had negligible carbon storage. Its development caused little reduction in the local carbon sink. Moreover, Bulgaria’s Solar Park Stara Zagora (25 hectares) uses land previously used for low-productivity grazing (with sparse vegetation), which sequestered far less carbon than the agricultural or wetland areas converted in EU14.

Moreover, after boosting solar power farms under the NREAP umbrella, a significant piece of evidence for an annual increase in PD is achieved in the EU14 and EU13. In more detail, an average annual escalation of about 4.264% in PD for EU14 and 2.470% in PD for EU13. This result contradicts earlier research by Manowska and Nowrot (2022), Oudes et al. (2022), and Amer et al. (2023). Population density around solar power farms is higher in EU14 compared to EU13 due to key differences in land availability, infrastructure, policy priorities, and community engagement. The EU14 countries, being more densely populated and land-scarce, site solar farms on marginal land (e.g., brownfields, low-yield farms) close to populated areas, as remote "empty" space is limited. Their mature, dense power grids—concentrated around population centers—also encourage solar development near communities to minimize transmission costs. Policies prioritize efficient land use and community co-location, supported by local engagement (e.g., citizen cooperatives), further pushing farms into populated regions. For example, A 50 MW solar farm in the Netherlands (EU14) near the town of Zeeland (population ~20,000) sits on reclaimed land 10 km from residential areas, due to grid proximity and land scarcity. In contrast, EU13 has abundant, sparsely populated rural land and less developed grids, allowing solar farms to be sited in remote areas where land is cheap. Policies focus more on rapid scaling using available remote land, with less emphasis on proximity to communities, and local participation is often weaker. This results in solar farms in less populated regions. Thus, EU14’s constraints and priorities drive solar farms closer to populations, while EU13’s conditions lead to more isolated developments. For example. A 20 MW solar farm in Romania (EU13) near Craiova is 30 km from the city, in a rural area with scattered villages (population density <50 people/km^2), where land is abundant and cheap.

Next, the increase of solar power under the NREAP policy led to an average annual escalation of about 0.019% (insignificant) and 0.163% (significant) in GDP for EU14 and EU13, respectively. This was consistent with previous research by Taveira-Pinto et al. (2021), Fratila et al. (2021), and Bădîrcea et al. (2021). EU13 countries are in a rapid growth phase for solar deployment, fueled by late-stage adoption of renewable policies, EU structural funds, and lower labor/land costs. This drives heavy investment in large-scale solar farm construction, local manufacturing (e.g., module assembly), and grid expansion—all of which directly boost GDP through labor, materials, and services spending. Their focus on domestic projects with high local content amplifies these economic impacts. In contrast, EU14 has mature solar markets with slower growth, where expansion has shifted from large-scale new projects to optimizing existing infrastructure. Its solar sector focuses more on high-value but low-volume activities (e.g., R&D, advanced component production) and export-oriented industries, which contribute less to domestic GDP. Reduced subsidies and higher costs (labor, regulations) further limit immediate economic gains from solar. Thus, EU13's "catch-up growth" in solar drives greater GDP contributions, while EU14's maturity and structural focus result in more modest impacts. For example, Poland (EU13) added 4.6 GW of solar capacity, the fourth-highest in the EU in 2023. This growth was driven by EU-funded auctions and private investments in rural solar farms, creating 40,000+ jobs and generating €1.2 billion in GDP from manufacturing and construction. While Germany (EU14), despite installing 14 GW in 2023, Germany's solar GDP contribution was limited by: (1) Automation in manufacturing (e.g., robotized module production at Q CELLS factories). (2) Grid congestion leading to curtailment of solar output, reducing revenue for developers.

Table 6 presents the results of a carefully executed placebo test, which was carried out using a random sample of 27 countries. The estimated coefficients and their corresponding p-values were systematically recorded. These steps were taken to enhance the reproducibility of the findings and to reduce the potential impact of unobserved variables on the outcomes of the regression analysis. Key results: (1) All estimated coefficients from the placebo test were consistently less than one; (2) The distribution of these estimates was centered near zero. This pattern suggests that the conclusions drawn from the analysis are unlikely to be explained by other unmeasured factors. Nevertheless, it is important to emphasize that this interpretation remains theoretical at this stage. Additional research is necessary to fully assess whether any confounding variables could affect the validity of the regression results.

Table 6 Testing the effect of NREAPs on coping strategies for land use change, using Placebo tests. Test completed for the three main models: EU27 States overall (Model 1); Western European Union States EU14 (Model 2); and Central and Eastern European Union States EU13 (Model 3).

Model	EU27		EU14		EU13	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
CO2	-0.035	0.026	0.237***	0.022	0.102	0.602
GDP	0.163***	0.022	-2.703	4.408	0.065***	0.010
HDI	0.244***	0.038	-0.250**	0.101	0.020	0.032
INTERCEPT-	-	0.018	-	0.020	0.013*	0.007

Random	0.181***		0.239***			
LUC	-0.018	0.028	-0.108**	0.050	-0.956***	0.156
PD	0.094***	0.025	0.010	0.034	0.364***	0.066
Constant	2.109***	0.180	5.242	4.127	2.220***	0.673
Observation	918		476		442	
Number of groups	27		14		13	
F-statistic	129.269		53.231		353.351	
Prob(F-statistic)	Prob>F=0.000		Prob>F=0.000		Prob>F=0.000	
R-squared	0.459		0.405		0.937	
Control	YES		NO		YES	
Treat	YES		YES		NO	
Intercept- Random	YES		YES		YES	

6- Conclusion and Implications

This study examines the expansion of solar power farms and associated land use changes in the EU27 countries from 1990 to 2023. The primary focus is on assessing progress toward establishing a carbon sink, in line with the objectives set by the National Renewable Energy Action Plans (NREAPs). To determine whether there were differences in solar power commitments among EU27 countries during two distinct periods—1990 to 2009 and 2010 to 2023—the study utilized a difference-in-differences approach. This method involved formulating a counterfactual hypothesis and analyzing the outcomes by categorizing the countries into two groups: the EU13 (Eastern and Central European Union Members) as the control group, and the EU14 (Western European Union Members) as the treated group. The analysis accounted for time-varying factors that could influence the results. Fixed effects were controlled to ensure the robustness of the findings. The empirical results indicate that, after controlling for fixed effects, the regression coefficient for the difference-in-differences analysis was significantly positive at the 0.00 significance level (refer to Table 3, Table 4, and Table 5). Additionally, a placebo test was conducted to validate these findings, with results presented in Table 6. The findings demonstrate that the primary objectives of the NREAPs—namely, promoting the expansion of solar power farms and enhancing the economic benefits of renewable energy sources, particularly in relation to reducing carbon dioxide emissions—have been effectively achieved. However, these developments have also led to notable changes in land use and have implications for the carbon sink potential within the region.

When comparing EU14 western states (treatment group) and EU13 central and eastern states (control group), the greatest augmentation in solar power farm expansion is achieved in EU14 states. Leading to that, in the year after boosting NREAPs policy implementation, the average annual escalation of solar power farm expansion, land use change, carbon dioxide mitigation, and population density is higher in the EU14 treatment group in comparison with the EU13 control group. In the year after boosting NREAPs policy implementation, an average annual reduction of land use change was observed more clearly in EU13 states (due to the lags in large-scale solar farm expansion) compared to those in the EU14 states (due to the massive proportion of solar power farm expansion in the renewable energy mix). On the other hand, an average annual increase in economic growth is observed to be higher in the EU13 states in comparison with those in the EU14 states.

Western EU14 countries, such as Germany and Italy, face intense land competition due to their relatively scarce land resources. There is an urgent need to formulate more stringent land-use regulations for solar power farms. For example, specific zoning laws could be implemented to designate certain marginal lands, like brownfields (former industrial sites), as priority areas for solar power farm expansion. This would help to reduce the encroachment of solar farms on prime agricultural lands and biodiversity-rich - rich areas. Western EU14 members need to be more cautious about the carbon sink effects of solar power farm expansion. Since the conversion of land for solar farms, especially in areas with high-carbon-stock soils like semi-natural grasslands, can lead to significant carbon emissions, measures should be taken to protect existing carbon sinks. For instance, they could be required to use no-till farming methods under solar panels to preserve soil structure and carbon content. The construction of solar power farms in Western EU14 has already shown negative impacts on biodiversity, such as the reduction of plant and soil biodiversity in semi-natural grasslands. Solar power farm projects should be designed in a way that maximizes the protection of local ecosystems. This could include leaving buffer zones around sensitive habitats, or incorporating biodiversity-friendly design features like creating small ponds or planting native wildflowers within the solar farm boundaries to support pollinators and other wildlife.

Eastern and Central EU13 countries like Romania and Hungary have more abundant land resources, which provide great potential for solar power farm expansion. However, bureaucratic hurdles and unclear permitting processes are currently slowing down this expansion. Governments should streamline the approval procedures for solar power farm projects. For example, setting up one - stop - shop platforms where developers can submit all necessary documents and get approvals in a more coordinated and efficient manner. These Eastern and Central EU13 countries can take better advantage of EU27 funds, such as those from the Cohesion Policy, to promote the integration of solar energy development with land use. For instance, funds could be used to conduct comprehensive land surveys to identify the most suitable areas for solar farms, especially on degraded agricultural lands. The construction of solar power farms in Eastern and Central EU13 can play a crucial role in revitalizing rural economies. Many rural areas in this region have faced issues such as population decline and low - low-productivity agriculture. Solar farms can bring new economic activities. For example, in some parts of Poland, the establishment of solar farms has led to the creation of jobs in construction, operation, and maintenance (See Chart 1).

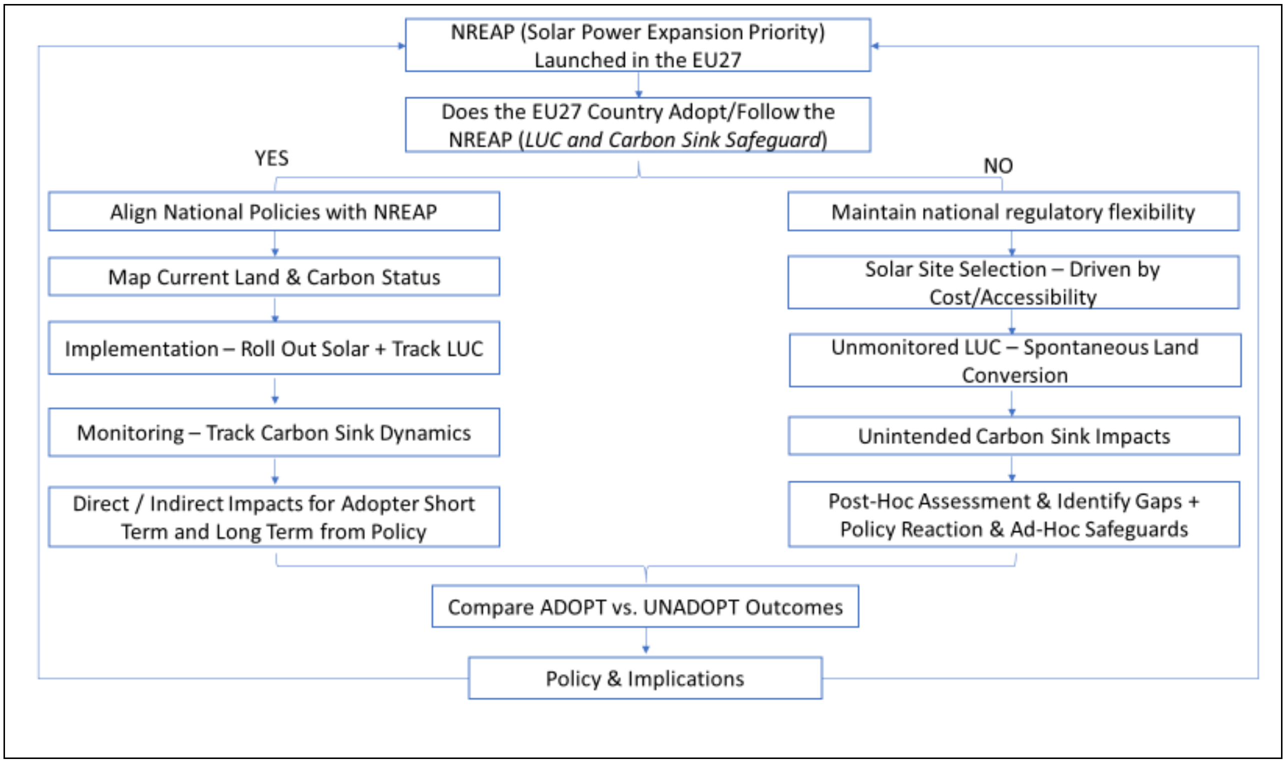

Chart 1: The Impacts of the NREAP on the Solar Power and Associated LUC & Carbon Sink in European Countries (Adopters vs. Non-Adopters of the Policy)

This study assessed the effectiveness of NREAP policies in enhancing solar power within the EU27, with a focus on reducing land use change and increasing carbon sink capacity. However, several limitations should be acknowledged. The sample size selected for this research may not fully represent the broader European context. As a result, the generalizability of the findings is limited. The outcomes observed may reflect the specific economic structures of EU27 member states during the study period and may not necessarily apply to other European countries outside the EU. Further research is necessary to gain a more comprehensive understanding of the dynamic effects resulting from NREAP policy upgrades. In particular, employing time series and panel data analysis could help determine whether the observed increase in offshore solar power production is both immediate and sustained, or if it fluctuates over time. Additionally, adaptation to new regulations in solar power project expansion may involve a period of adjustment and learning. Consequently, the full impact of NREAP upgrades on solar power consumption patterns may only become evident after a significant time lag. A dynamic analytical approach would also facilitate a more detailed examination of the rebound and pre-bound effects discussed in this study.

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Authors' contributions:
M.A. (Mohd Alsaleh) gathered the data and estimated the panel cointegration model and the

competitive advantage of the external factors on the solar power industry in the EU27 region; Wang Xiaohui (W.X.) presented the EU27's health environment and renewable energy sector industry and put together all the numerical results; M.A. contributed with conclusions and recommendations as well as with the limitations of the study and further research; A.S. Abdul-Rahim (A.S.A.R) conducted the literature review; and was responsible for the overall writing process.

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Data is available upon request.

Competing interests:
The author declares that they have no competing interests.

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The authors declare the provided manuscript has not been published before nor submitted to another journal or preprint server for consideration of publication.

Consent to participate:
The authors declare that the manuscript does not report studies involving human (or animal) participants, human (or animal) data, or human (animal) tissue.

Consent to publish:
The authors declare that the manuscript does not contain any person's data in any form (including any individual details, images, or videos).

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