An Integrated Framework for ESG Assessment and Action Planning in Eco-Industrial Parks

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Abstract. Eco-Industrial Parks (EIPs) are increasingly regarded as important instruments for promoting more sustainable forms of industrial development. Their performance, however, cannot be understood only in terms of environmental efficiency, since it also depends on social conditions, governance arrangements, shared infrastructures, and the quality of coordination among multiple actors. This makes the assessment of EIPs particularly challenging and highlights the need for approaches capable of integrating environmental, social, and governance (ESG) dimensions within a single analytical framework. This paper proposes a two-phase methodological framework for assessing and improving ESG performance in EIPs. The first phase is diagnostic and measures deviations between observed performance and predefined targets derived from regulations, institutional benchmarks, and best practices. The second phase is prescriptive and uses Goal Programming to identify the most effective improvement strategies under economic, technical, and organizational constraints. In this way, the framework links sustainability assessment with the definition of intervention priorities and the selection of feasible actions. The main contribution of the paper lies in adapting ESG logic to the territorial and multi-actor nature of eco-industrial parks, while also connecting performance evaluation with decision support. The framework is presented as a methodological proposal that may support more operational and integrated forms of sustainability governance in industrial areas, although its usefulness still requires empirical testing in different EIP contexts.

Keywords: Eco-Industrial Parks · ESG assessment · Goal Programming · sustainability assessment · industrial symbiosis

1 Introduction

In recent years, Eco-Industrial Parks (EIPs) have gained increasing attention as a sustainability-oriented model for rethinking industrial areas. Unlike conventional industrial parks, EIPs are not simply clusters of firms located in the same area, but organized systems in which environmental and economic performance also depends on shared

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infrastructures, coordinated management of energy, water, and waste, and structured relationships among firms, park managers, and public actors [1]. Their functioning therefore reflects not only firm-level behavior, but also wider territorial and organizational conditions, including the capacity to activate industrial synergies and to connect industrial development with local sustainability goals [2, 3].

This broader understanding has important implications for assessment. The sustainability of an eco-industrial park cannot be reduced to eco-efficiency alone, since it also depends on organizational arrangements, working conditions, governance capacity, stakeholder relations, and the park's interaction with the surrounding territory. Recent studies have in fact shown that EIPs may contribute not only to resource efficiency and impact reduction, but also to green innovation, resilience, and more integrated forms of territorial development [4, 5]. Consequently, the evaluation of EIPs requires approaches that can jointly take into account the different dimensions involved [6, 7].

In this respect, the Environmental, Social and Governance (ESG) perspective offers a useful conceptual basis. Originally developed in responsible investment and later extended to sustainability reporting and accountability systems, ESG provides an integrated framework for considering environmental impacts, social implications, and governance mechanisms together. This orientation is also consistent with recent developments in the European reporting framework, which increasingly emphasize integrated sustainability approaches [8, 9].

However, applying ESG logic to EIPs is not straightforward. Most ESG tools were designed for individual firms, financial markets, or investment portfolios, whereas eco-industrial parks are collective and territorial systems in which performance emerges from shared assets, interdependencies, and multi-actor governance processes [10, 11]. This makes direct transfer difficult and requires methodological adaptation. A further issue concerns the broader ESG literature itself, where the heterogeneity of indicators, measurement approaches, and weighting systems often limits comparability across results [12, 13]. If this is already problematic for individual firms, it becomes even more so in the case of EIPs, where sustainability performance depends on system-level relationships that exceed the boundaries of any single organization.

Against this background, the key methodological challenge is not only to build ESG indicator systems at park scale, but also to understand how assessment can support decision-making. In the case of eco-industrial parks, this means linking the measurement of performance to the identification of priorities and to the selection of feasible intervention strategies under economic, technical, and organizational constraints [14].

2 Aim

This contribution proposes a two-phase methodological framework for the assessment and improvement of Environmental, Social and Governance (ESG) performance in Eco-Industrial Parks (EIPs). Its aim is to address a gap that is still present in the literature, namely the limited availability of approaches capable of explicitly linking sustainability assessment with the selection of intervention strategies consistent with economic, technical, and organizational constraints.

To this end, the paper develops an approach based on Goal Programming, which is considered suitable for managing multiple and heterogeneous objectives expressed through explicit targets. The framework performs a dual function:

1. a passive phase, aimed at assessing ESG performance by measuring deviations from targets defined on the basis of regulatory references, institutional benchmarks, and best practices;
2. an active phase, aimed at identifying the most effective intervention strategies for reducing such deviations through an optimization model that incorporates costs, priorities, budget constraints, minimum performance thresholds, and dependency relationships among actions.

Within this perspective, the originality of the proposed framework does not lie in the development of a new optimization technique, but in the integrated adaptation of ESG logic to the territorial and multi-actor nature of EIPs. Compared with existing indicator-based approaches, the framework does not limit the assessment to the construction of a sustainability profile or a composite score. Instead, it explicitly measures deviations from predefined ESG targets and uses these diagnostic results as inputs for a constrained decision-support model. In this sense, the contribution is both methodological and operational: it connects ESG performance assessment, priority identification, and action selection within a single structured procedure.

In this way, ESG assessment is interpreted as a decision-support tool for the sustainable governance of territorial production systems.

The remainder of the paper is structured as follows. Section 3 reviews the main strands of literature on EIPs, sustainability assessment, and Goal Programming. Section 4 presents the proposed methodology, describing both the passive and the active phases of the framework. Finally, Sect. 5 concludes by discussing the main implications, limitations, and possible directions for future research.

3 Background

The literature on Eco-Industrial Parks (EIPs) initially developed around the concept of industrial symbiosis, understood as a set of cooperative relationships through which co-located firms exchange energy, materials, by-products, and services, thereby improving the overall efficiency of the system. Early studies were mainly concerned with clarifying the concept itself and identifying the conditions under which symbiotic relationships emerge and persist. Over time, attention shifted towards the role of exchange networks, shared infrastructures, and coordination among actors, showing that EIPs should not be understood as simple agglomerations of firms, but as more complex territorial systems [15–17]. More recently, this view has been further expanded by studies that interpret EIPs as socio-technical transition processes, in which infrastructures, organizational capabilities, collective learning, and policy conditions evolve together [2, 19]. This evolution in the literature has gradually moved the debate beyond symbiotic exchanges alone and towards the broader issue of how the sustainability of these systems can be assessed.

This question has been addressed by a growing body of work on EIP performance assessment. Several studies have proposed environmental, economic, and social indicators to evaluate park sustainability and to support the construction of more coherent

monitoring frameworks. Felicio and Amaral (2013) [20], for instance, applied environmental indicators to eco-industrial parks, while Lütje and Wohlgemuth (2020) [21] developed a quantitative system to monitor progress towards sustainability targets in industrial symbiosis contexts. Koch et al. (2022) [22] used performance assessment as a strategic support tool for energy and waste recovery in an eco-industrial park. Taken together, these contributions suggest a gradual shift from descriptive accounts of symbiotic practices towards more structured approaches to sustainability measurement.

At the same time, EIP research has increasingly incorporated optimization models to support the design of industrial park configurations, exchange networks, and restructuring strategies. Many of these studies rely on MILP (Mixed-Integer Linear Programming) formulations or integrated network models to balance economic costs, environmental gains, and, in some cases, social impacts. Genc et al. (2019) [19], for example, proposed a socio-ecological approach to support the transition of industrial zones towards eco-industrial configurations, and Genc et al. (2020) [23] later developed an integrated optimization, location, and food-web analysis model inspired by natural systems for circular eco-industrial park design. Despite their relevance, however, recent reviews point out that these modelling approaches still tend to focus on material and energy flows, network structure, and environmental efficiency, while much less attention is paid to fully integrated ESG-oriented frameworks [24].

In this context, Goal Programming (GP) deserves more attention than it has so far received in EIP studies. As an extension of linear programming for multi-objective problems, GP makes it possible to define each objective in terms of a target and to measure deviations from that target while incorporating priorities, weights, and resource constraints [25–28]. Its potential has already been recognized in several fields related to sustainable planning and environmental management. Reviews have highlighted its use in sustainable energy planning, where economic, environmental, and social goals must be balanced within a consistent decision framework [29]. Other studies have shown its relevance in resource management and multicriteria decision-making contexts characterized by competing objectives and explicit constraints [30]. In fields closer to territorial planning and sustainable investment, optimization-based decision-support models have also shown how these techniques can help connect sustainability criteria with the selection of feasible alternatives [31]. Although GP has not yet been widely applied to eco-industrial parks, it appears particularly suitable when sustainability is interpreted both as distance from explicit targets and as a problem of choosing interventions under economic, technical, and organizational constraints.

4 Methodology

The proposed methodological approach is structured in two phases and is designed to connect ESG performance assessment with the identification of improvement priorities in Eco-Industrial Parks. The first phase is diagnostic: it measures the extent to which observed performance differs from a set of reference targets. The second phase is prescriptive: it supports the selection of the most effective improvement strategies under economic, technical, and organizational constraints. Figure 1 summarizes the overall structure of the proposed methodological framework.

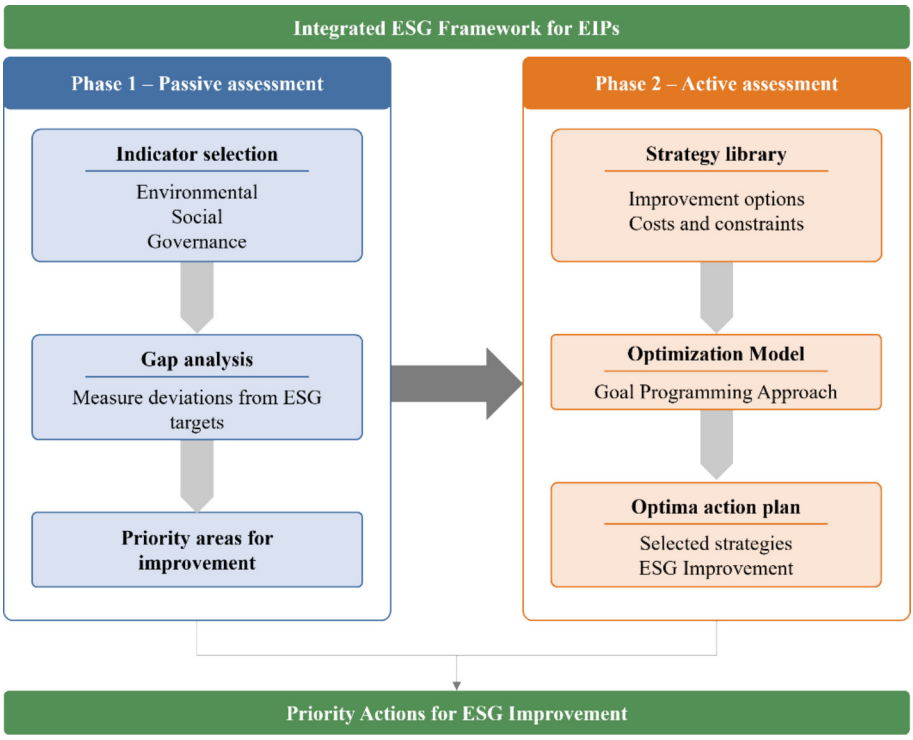

Fig. 1. Overview of the proposed two-phase framework for ESG assessment and improvement in Eco-Industrial Parks.

The framework is based on Goal Programming (GP), a mathematical programming technique developed to address multi-objective problems in which each objective is expressed as the achievement of a predefined target. Unlike traditional linear programming, which is oriented towards the optimization of a single objective function, GP makes it possible to deal simultaneously with heterogeneous objectives by measuring deviations from desired levels. In its classical formulation, for each objective j, the relationship between observed value, target, and deviations can be expressed as:

$$f_j(\mathrm{x}) + d_j^- - d_j^+ = g_j$$

where $f_j(\mathrm{x})$ represents the value of the objective function, g_j the desired target, and d_j^- and d_j^+ the negative and positive deviations from that target, respectively. In the present framework, this logic is adapted to ESG assessment by taking the individual indicator as the unit of analysis; accordingly, the index j denotes the ESG indicator under consideration, each associated with a corresponding reference target.

On this basis, the methodology is divided into two phases. The first is intended to measure the distance between observed ESG performance and predefined sustainability targets. The second uses those results to identify the most appropriate intervention strategies within a constrained decision space.

4.1 Phase 1 – Passive Assessment

The passive phase is aimed at identifying ESG gaps with respect to predefined targets. It includes two main steps: the construction of the indicator system and the formalization of the assessment model.

The first step consists in selecting a set of indicators capable of representing, in an integrated way, the environmental, social, and governance dimensions of the industrial park. From a methodological point of view, these indicators may be divided into two groups. The first includes mandatory indicators, associated with targets derived from binding regulations, recognized standards, or institutional references. The second includes strategic voluntary indicators, which do not necessarily correspond to mandatory thresholds but are useful for capturing aspects that are relevant to the overall ESG quality of the park.

As shown in Table 1, the indicator system may include variables related to environmental performance, social conditions, and governance arrangements. The examples reported in the table should not be interpreted as a fixed or exhaustive set, but rather as an operational template that can be adapted to different contexts depending on data availability, local priorities, and decision needs.

For each selected indicator j, three elements are defined: the observed value x_j, the reference target g_j, and the weight w_j. Targets may derive from regulatory sources, institutional benchmarks, international standards, or best practices. In order to ensure transparency and replicability, indicator selection should follow explicit criteria. In particular, indicators should be selected according to: i) relevance to the environmental, social, or governance dimension under analysis; ii) measurability and data availability at the park scale; iii) comparability across parks or over time; and iv) actionability, namely the possibility of linking the indicator to concrete improvement strategies.

Normalization is required because the selected indicators may be expressed in different units and scales. Depending on the nature of the indicator, benefit-type variables can be normalized so that higher values correspond to better ESG performance, while cost-type or pressure indicators can be transformed so that lower original values correspond to higher normalized scores. When regulatory thresholds or institutional benchmarks are available, normalized values may also be expressed in relation to the corresponding target. Observed values are therefore normalized onto a common scale, for example within the interval [0, 1], so that originally heterogeneous variables can be treated jointly.

Weights should be assigned through a transparent procedure, such as expert judgement, stakeholder consultation, pairwise comparison, or a combination of these approaches. They reflect the relative importance attributed to the different indicators within the overall evaluation framework. In order to test the robustness of the results, alternative weighting scenarios or sensitivity analyses may also be considered.

Once the indicator system has been defined, the passive assessment is formalized through a classical GP model. At this stage, the purpose is not to reward performance beyond the target, but to measure shortfalls with respect to regulatory thresholds, institutional benchmarks, or best practices. For this reason, the model considers only negative deviations. For each indicator j, the observed normalized value x_j is compared with the corresponding normalized target g_j; the variable d_j^- measures the residual gap with

Table 1. Illustrative examples for constructing the ESG indicator system in the passive assessment phase.

Dimension	Category	Examples of indicators	Possible target references
Environmental	Mandatory	Share of energy from renewable sources; energy efficiency measures; presence of renewable energy plants; waste recovery in a circular economy perspective; reduction of CO_2 emissions; active water-saving systems	EU directives and regulations; institutional benchmarks; applicable technical standards
Environmental	Strategic voluntary	Park territorial extension; environmental certifications; sustainable facilities; hydrogen production systems from waste; sustainable mobility initiatives; monitoring of indirect emissions; CO_2 capture and reuse projects	Sectoral best practices; international guidelines; internal improvement targets
Social	Mandatory	Corporate welfare services; training, equality, and inclusion programmes; collaboration with schools and universities; average employee tenure; community relations; onboarding and professional development programmes	International standards; EIP guidelines; ESG/social reporting references
Social	Strategic voluntary	Number of firms located in the park; number of direct employees; hosted events; territorial engagement initiatives	Comparative benchmarks; organizational targets; territorial development objectives
Governance	Mandatory	Risk management structure; anti-corruption training; code of conduct; whistleblowing procedures	Existing regulation; compliance standards; corporate governance references
Governance	Strategic voluntary	Sustainability board; transparent governance systems; voluntary sustainability reporting; governance-related recognitions and certifications	Voluntary standards; UNIDO/GRI/OECD guidelines; accountability and reputation goals

respect to that target, while the weight w_j expresses the relative importance attributed to the indicator within the overall evaluation framework.

The objective function is therefore:

$$\min \sum_{j=1}^{n} w_j \cdot d_j^-$$

Subject to:

$$x_j + d_j^- \geq g_j \qquad \forall j$$

with:

$$d_j^- \geq 0 \qquad \forall j$$

In this formulation, the larger the value of d_j^-, the greater the distance of indicator j from its target. The objective function therefore provides a synthetic measure of the overall distance of the system from a condition of full alignment with ESG objectives. No logical interdependency constraints are introduced at this stage, since the model is exclusively evaluative and does not yet simulate intervention scenarios.

For clarity, Table 2 summarizes the main variables and parameters used in the passive assessment phase.

Table 2. Variables and parameters of the passive assessment model

Symbol	Description	Domain
j	Index of ESG indicator	$j = 1, \ldots, n$
n	Total number of ESG indicators considered	Positive integer
x_j	Observed and normalized value of indicator j	$x_j \in [0, 1]$
g_j	Normalized target value of indicator j	$g_j \in [0, 1]$
d_j^-	Negative deviation of indicator j from its target	$d_j^- \geq 0$
w_j	Weight assigned to indicator j	$w_j \in [0, 1]$

The output of the passive phase consists of a synthetic measure of ESG performance, the identification of the indicators showing the largest deviations from their targets, and, consequently, the identification of priority areas for improvement.

4.2 Phase 2 – Active Assessment

The second phase is prescriptive and aims to transform the diagnostic results into a coherent set of priority actions. If the first phase measures the distance from ESG targets, the second phase is concerned with identifying which strategies should be implemented in order to reduce those distances as effectively and realistically as possible.

To make this phase operational, a library of improvement strategies must first be constructed on the basis of the gaps emerging from the passive phase. Each strategy should be described at least in terms of its expected ESG improvement, its total implementation cost, and any dependency, precedence, or compatibility relationship with other strategies. In practical terms, strategies may concern energy and environmental infrastructures, welfare and training measures, governance and control mechanisms, or actions aimed at strengthening relations with the surrounding territory and stakeholders.

The construction of the strategy library represents a key operational step of the active phase. Strategies should be derived from the priority gaps identified in the passive assessment and should be defined in collaboration with park managers, firms, public authorities, and technical experts. For each strategy, the expected ESG improvement may be estimated through technical assessments, benchmarking of similar interventions, expert elicitation, feasibility studies, or evidence from previous projects. Implementation costs should include not only direct investment costs, but also operating, maintenance, coordination, and transaction costs where relevant. Dependency relationships should also be made explicit. Some actions may require preliminary enabling measures, while others may be mutually exclusive or complementary. For example, the installation of advanced monitoring systems may be a prerequisite for more complex energy optimization measures. Including these relationships in the model allows the strategy selection process to better reflect real implementation conditions.

The model is formulated as a selection problem with binary variables, in which each strategy represents an option that may or may not be activated depending on available resources. More specifically, for each strategy *j,* the parameter $DESG_j$ represents the expected improvement in ESG performance associated with its implementation, while C_j^{tot} denotes the total cost of the intervention. The decision variable y_j takes value 1 when the strategy is selected and 0 otherwise. The set of selected strategies must also satisfy an overall available budget B.

The objective function is therefore aimed at maximizing the overall ESG improvement associated with the selected strategies:

$$max \sum_{j=1}^{m} \Delta ESG_j y_j$$

subject to the budget constraint:

$$\sum_{j=1}^{m} C_j^{tot} y_j \leq B$$

where m denotes the total number of strategies considered. Additional logical interdependency constraints may also be introduced, for example:

$$y_i \leq y_k$$

whenever intervention i requires the prior implementation of intervention k. This formulation makes it possible to represent conditions that are typical of real contexts, where not all desirable actions can be implemented simultaneously and where some strategies are feasible only if accompanied by enabling measures or preliminary investments.

Table 3 summarizes the main variables and parameters used in the active assessment phase.

Table 3. Variables and parameters of the active assessment model

Symbol	Description	Domain
j	Index of the improvement strategy	$j = 1, \ldots, m$
m	Total number of strategies considered	Positive integer
$DESG_j$	Expected ESG performance improvement associated with strategy j	Normalized value, [0, 1]
C_j^{tot}	Total implementation cost of strategy j	Non-negative monetary value
yj	Binary decision variable associated with strategy j	$y_j \in \{0, 1\}$
B	Overall available budget	Non-negative monetary value

To clarify the interaction between the two phases, a simplified illustrative example may be considered. Suppose that the passive phase identifies the largest ESG gaps in three areas: renewable energy production, employee training, and governance transparency. The active phase would then translate these gaps into a set of possible strategies, such as installing photovoltaic systems, introducing training and inclusion programmes, or strengthening whistleblowing and reporting procedures. Each strategy would be associated with an expected ESG improvement, an implementation cost, and possible dependency conditions. Under a limited budget, the optimization model would select the combination of actions that maximizes the overall ESG improvement while respecting the available resources and any logical constraints.

The output of the active phase consists of the optimal set of selected strategies, the overall improvement achievable under the given constraints, and, more broadly, an argued basis for defining intervention priorities. In this way, ESG assessment is no longer confined to a descriptive exercise, but becomes part of a decision-support process that is more closely aligned with the operational conditions of eco-industrial parks.

5 Conclusions

Assessing sustainability in Eco-Industrial Parks (EIPs) requires tools that can reflect their territorial, multi-actor, and multidimensional nature. Because EIPs operate through the interaction of firms, shared infrastructures, governance arrangements, and local dynamics, their performance cannot be adequately understood through descriptive assessments alone.

This paper has proposed a two-phase framework based on Goal Programming. The first phase is designed to measure deviations from predefined ESG targets, while the second uses those results to support the selection of improvement strategies under explicit economic, technical, and organizational constraints. In this way, the framework connects assessment and intervention within a single methodological structure.

The main contribution of the proposed approach lies in its adaptation to the specific characteristics of eco-industrial parks. By combining ESG indicators, reference targets, weighted priorities, and constrained action selection, the framework offers a more operational perspective on sustainability assessment. ESG evaluation is therefore treated not only as a reporting exercise, but also as a potential support tool for governance and decision-making.

From a practical perspective, the framework may support different stakeholders involved in the governance of EIPs. Park managers can use it to identify priority ESG gaps and to allocate resources among competing interventions. Firms located within the park can benefit from a clearer understanding of collective sustainability objectives and of the actions required to achieve them. Public authorities may use the framework to define transparent criteria for incentives, monitoring procedures, or policy support measures. Finally, investors and financial actors may rely on the model to better connect ESG performance with feasible improvement plans.

The operationalization of the framework requires reliable data collection procedures, agreement on shared targets, transparent weighting mechanisms, and a periodically updated strategy library. For this reason, the model should be understood not only as an assessment tool, but also as a structured process for supporting dialogue, coordination, and decision-making among the actors involved in EIP development.

At the same time, the framework should be regarded as a methodological proposal that still requires empirical application and refinement. Its effectiveness depends on several factors, including data availability and quality, the definition of context-sensitive targets, the transparent assignment of weights, and the realistic estimation of costs, expected improvements, and dependencies among strategies. For this reason, further research should test the model in different EIP contexts and assess its robustness through comparative applications and sensitivity analyses [31–33].

Overall, the paper suggests that a closer connection between performance assessment and action planning may represent a useful direction for advancing ESG-oriented approaches to eco-industrial parks and, more broadly, for supporting more integrated forms of sustainability governance in territorial production systems.

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